Staffordshire University
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The Effectiveness of Active Labour Market Policies in Reducing Unemployment in Transition Economies

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Abstract

The aim of this thesis is to investigate the effectiveness of Active Labour Market Policies (ALMP) in reducing unemployment in European transition and non-transition economies. The theoretical framework proposed to analyse the effectiveness of ALMPs in reducing unemployment indicates that these policies affect unemployment through several different mechanisms. ALMPs can facilitate the matching process, increase productivity, increase labour supply and competition in the labour market, reduce welfare losses of the unemployed and serve as a stimulus to unemployed individuals' willingness to work. This research is based on both a country-level analysis using a sample of European transition and non-transition economies (for 2005-2015) and individual-level analysis using cross-sectional data (2012) for Kosovo. The country-level analysis assesses the ALMP effectiveness using two different strategies. The first one investigates the effect of ALMP expenditure (as share of GDP) on the flow from unemployment to employment using a Fixed-Effects panel model and finds a positive effect, in line with expectations. The economic significance of this finding, however, is questionable since the increase in the outflow from unemployment is relatively small. The second strategy investigates whether the ALMP expenditure (as share of GDP) reduces the unemployment rate in a dynamic panel analysis, using a Generalised Methods of Moments (GMM) estimator. This strategy, also, investigates the relative effectiveness of different measures by separately including variables to account for: *Training, Employment Incentives, Supported Employment and Rehabilitation, Direct Job Creation and Start-Up Incentives.* The results from the second approach find no significant effect of any of the ALMPs in reducing the unemployment rate. The analysis of the ALMP effectiveness at the individual level in Kosovo explores the following measures: *On the Job Training, Internship Scheme and Institution and Enterprise Training*. This analysis focuses on the following outcomes: beneficiaries' probability of finding a job post-participation; beneficiaries' probability of increasing job search and beneficiaries' probability of having an employment contract. The empirical findings indicate that participation in one of these active measures is associated with a higher individual's probability of being employed compared to a non-participant, however the results differ subject to model specification. In addition, the findings also suggest that among employed individuals those that participated in ALMPs are more likely to be in informal employment. Finally, an assessment of the policy implications for European economies seeking to increase and sustain employment through active measures is provided based on the empirical evidence presented in this thesis.

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Abbreviations

AIC - Akaike Information Criteria

ALMP – Active Labour Market Policies

ATE – Average Treatment Effects

ATET – Average Treatment Effects on Treated

BIC - Bayesian Information Criteria

CEE – Central and Eastern Europe

CEEC – Central and East European Country

CIA - Conditional Independence Assumption

CIS - Commonwealth of Independent States

EBRD – European Bank for Reconstruction and Development

EPL – Employment Protection Legislation

ETE – European Transition Economies

EU – European Union

FE – Fixed Effects

FEDK – Fixed Effects Driscoll Kraay

FEVD - Fixed Effects Vector Decomposition

GDP – Gross Domestic Product

GLS – Generalized Least Squares

GMM – Generalized Method of Moments

IET – Institution and Enterprise Training

IIA – Independence from Irrelevant Alternatives

ILO – International Labour Organisation

IPW – Inverse Probability Weighting

IPWRA – Inverse Probability Weighting – Regression Adjustment

IRS – Increasing Returns to Scale

IS – Internship Scheme

IV – Instrumental Variable

KAS – Kosovar Agency of Statistics

LFP – Labour Force Participation

LFS – Labour Force Survey

LSDVC – Least Squares Dummy Variable Estimator

MIMIC – Multiple Indicator and Multiple Cause

MLSW – Ministry of Labour and Social Welfare

NAIRU – Non-Accelerating Inflation Rate of Unemployment

NEET – Youths Not in Employment, Education or Training

NGO – Non-governmental organizations

OECD – Organisation for Economic Co-operation and Development

OJT – On the Job Training

OLS – Ordinary Least Squares

PES – Public Employment Offices

PLMP – Passive Labour Market Policies

PSM – Propensity Score Matching

P-VAR – Panel Vector Autoregressive

RA – Regression Adjustment

RAE – Roma, Ashkali and Egyptian

RE – Random Effects

RTS – Returns To Scale

SEE – South Eastern Europe

SME – Small and Medium Enterprises

TE – Transition Economies

UNDP - United Nations Development Programme

VIF – Variance Inflation Factor

VTC – Vocational Training Centre

WDI – World Development Indicators

WE – Western Economies

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I would like to take this opportunity to express my gratitude to the people without whom this thesis would have not been possible.

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Undertaking this PhD has been a truly life-changing experience for me.

I dedicate this thesis

to my parents, Hamide and Jahja, for their encouragement,

to my husband, Ermal, for his love and support and

to my precious little one, Nili, who filled my life with joy.

Chapter 1

Unemployment and Active Labour Market Policies in Transition Economies: Introduction and Context

1.1 Introduction

The main purpose of Active Labour Market Policies (ALMPs) is to provide means for skill enhancement and intensify job-search activity which would improve employment prospects of the unemployed. ALMP help ensure the return of the unemployed in the labour market as fast as possible with the most optimal job match. During the last decade, in part due to the global financial crisis, unemployment has reached one of the most daunting levels in the history of the European economies. This issue is even more pronounced in many of the European transition economies because of the already high unemployment inherited from the period of break-up of socialist system and transition to the market system. During the process of transition, the issue of skill mismatch made high rates of unemployment a persistent feature of their labour markets.

In the current economic situation, European economies have put a greater emphasis on policies dedicated to improving human capital having realised how essential they are to achieving higher rates of employment, improving the quality of work and raising labour productivity. Some authors have argued that raising expenditure on ALMPs along with improving coordination of employment strategies in European economies can help reduce unemployment rates both in short and long-term (Calmfors et al., 2002; Van Vliet and Koster, 2011). According to Banociova and Slavomira (2017, p.3), *'a country that supports expenditures on ALMP in long-term has a more stable employment development than a state that provides smaller contributions for labour market measures, particularly in the times of negative economic development'*.

Section 1.2 of this chapter introduces the aim and objective of the thesis while section 1.3 discusses the structure of the thesis. The characteristics and trends of the labour market indicators are discussed in section 1.5.1 and 1.5.2 and the extent of expenditure on active labour market policies (ALMPs) in section 1.6.1. The labour market indicators and the level of expenditure on ALMPs are analysed in the light of the data provided by Eurostat, International Labour Organisation (ILO), Organisation for Economic Co-operation and Development (OECD) and World Bank. Since there is considerable variation, the data for the European Union – 15

Western European countries[1], Central and Eastern Europe (CEE)[2] and South East Europe (SEE)[3] are compared. In accordance with the focus of this thesis, this chapter also discusses separately the labour market indicators and the expenditure on ALMPs for Kosovo in sections 1.5.3 and 1.6.2.

1.2 Aims and objectives of the thesis

ALMPs are designed to address skill mismatches and labour imbalances, increase productivity and prepare the unemployed for the rapid changes in the labour market. An essential attribute of ALMPs is to enhance human capital and shift from an 'employment' to 'employability' paradigm, i.e., their aim is not merely to provide the unemployed with a job, but to enhance their skills so they become capable of finding and retaining employment. Investigations of ALMP effectiveness to increase employability in western economies are numerous, but evaluations of these policies in European transition economies are still rare and lack the use of sophisticated methodology. The critical review of empirical studies provided in sections 2.3 and 4.4.1 highlights that there are relatively few studies analysing the ALMP effectiveness in transition economies, either at the individual or country level. The poor quality and unavailability of data has impeded the thorough research of the ALMP effectiveness in transition economies. The data from administrative records typically do not provide detailed information needed by current evaluation methodologies for the micro-econometric analysis and follow-up surveys are also rare. Studies based on experimental designs are largely missing for transition economies even though they are considered as the 'gold standard' in evaluation methodology.

In most cases there is the possibility that an individual could be eligible to participate in more than one active measure, hence the relative effectiveness of these policies should be analysed in an econometric framework that allows for multivalued treatment. Until recently, the evaluation methodology did not allow for multivalued

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[1] The 15 EU Western Countries consist of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.

[2] Central and Eastern European (CEE) is the group of countries comprising: Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, the Slovak Republic, Slovenia, and the three Baltic States: Estonia, Latvia and Lithuania.

[3] The South East Europe (SEE) 6 consists of Albania, Bosnia and Herzegovina, Montenegro, FYR Macedonia Kosovo and Serbia. Kosovo is excluded from the discussion here since it will be discussed separately in section 1.3.3.

treatment. The estimation technique used for the individual level analysis in this research project uses a more sophisticated evaluation technique which allows analysis of this aspect. To the best of authors' knowledge this is the first study to use a double robust estimator to assess the ALMP effectiveness. This estimator allows for both the treatment model to address the selection issue and the outcome model to account for variables affecting the outcome. Also, this research project fills a gap in literature for transition economies, as the first study using an advanced econometric methodology to analyse the effectiveness of ALMPS in Kosovo. Finally, to the best of authors' knowledge, there are no studies that analyse the effect of participation in an ALMP on an individual's probability of finding employment in the formal sector as opposed to the informal sector. The empirical analyses in chapters 5 and 6 of this thesis aim to fill this gap in the literature.

There are also very few empirical studies using country level data to investigate this topic for transition economies. This thesis contributes to the empirical literature by assessing the ALMP effectiveness in increasing matching efficiency and reducing unemployment rate for transition economies. In order to compare the effectiveness of ALMPs between transition and non-transition economies and due to the limited data for transition economies, the country level analysis was extended to include the European non-transition economies.

Motivated by these gaps in the literature explained above, the aim of this thesis is to investigate the effectiveness of ALMPs in transition and non-transition economies in reducing unemployment. The following objectives were set to accomplish the aim of the thesis:

1. To provide a comprehensive and critical review of the theoretical framework of unemployment and the multiple effects of ALMPs in reducing it;
2. To provide a critical review of the empirical studies analysing the effectiveness of ALMPs in European Transition and Non-Transition economies;
3. To empirically analyse the effectiveness of ALMP expenditure as share of GDP in reducing unemployment at the economy-wide level in European transition and non-transition economies;

4. To critically review different evaluation methodologies and empirical studies analysing the ALMP effectiveness at the individual level in addressing the issues of the missing counterfactual and selection bias;
5. To empirically evaluate the overall and relative effectiveness of three active measures implemented in Kosovo: On-the-Job Training, Institution and Enterprise Training and Internship Scheme on finding employment, searching for jobs and, conditional on being employed, having an employment contract.
6. To synthesise policy recommendations for improving the effectiveness of these policies as a tool to reduce unemployment among vulnerable groups such as youths and the low-skilled unemployed.

1.3 Structure of the thesis

In order to address the above objectives the remainder of the thesis is structured as follows. The aim of **chapter 2** is to develop a theoretical framework to analyse the relationship between ALMPs and unemployment and to review empirical studies which have investigated ALMP effectiveness at the economy-wide level. To address the first objective of the thesis, this chapter analyses the underlying theories of unemployment, utilising the NAIRU framework developed by Layard, Nickell and Jackman (1991) and the hysteresis hypothesis. A modified version of NAIRU by Calmfors (1994) is used to analyse the multiple effects of the ALMPs in the labour market. Given that this thesis places a particular focus on the European transition economies, this chapter will discuss the theoretical explanations of the causes and consequences of the high unemployment rates in transition economies comparing the structuralist view of unemployment and the hysteresis hypothesis. Furthermore, this chapter argues that the transition economies may be characterised by multiple equilibria in the labour market which can result in an economy getting stuck in a ‘bad-job/low-skill equilibrium’. One characteristic of the latter can be the presence of a large informal sector. The empirical studies reviewed in chapter 2 reach no agreed consensus regarding the effectiveness of these policies. This theoretical and empirical review will be used as the basis for empirical analysis of the effects of ALMPs at the individual (chapters 5 and 6) and the economy-wide level (chapter 3).

Having critically reviewed previous theoretical and empirical research on the ALMP effectiveness, **chapter 3** continues to addresses objective three and investigate the following research question: *Are ALMPs in European economies (transition and non-transition) effective in reducing unemployment at the economy-wide level?* To answer this question, chapter 3 employs two empirical strategies using two separate datasets to assess the ALMP effectiveness for European transition economies and non-transition economies. The first one assesses the efficiency of the ALMP expenditure as share of GDP in matching the job-seekers with vacancies using static panel modelling techniques. The second strategy assesses the efficiency of these policies in reducing the unemployment rate using a dynamic panel modelling approach.

Assessing the effectiveness of ALMPs at the individual level is not an easy task because of the missing counterfactual data (an individual cannot be in two different states: beneficiary and control at the same time). Hence, **chapter 4** addresses objective four by critically discussing various evaluation methodologies employed in microeconomic policy analysis. This chapter also partially addresses objective two by reviewing the empirical studies investigating the effectiveness of ALMPs at the individual level.

Having discussed the evaluation methodology and reviewed the empirical research on the effectiveness of ALMPs, **chapter 5** addresses objectives five and six and answers the following research question: *Which of the following three active measures, On the Job Training (OJT), Institution and Enterprise Training (IET) and Internship Scheme (IS), is more effective in increasing an individual's probability of undertaking active job search, finding employment and having an employment contract in Kosovo?* This chapter employs two different empirical strategies. The first one is a multinomial probit regression model with a three category dependent variable which equals zero if the individual is unemployed at the time of the survey, one if the individual is employed with an employment contract and two if the individual is employed without an employment contract. Given that the beneficiaries of these active measures are selected based on a certain set of criteria, a potential issue in this empirical investigation is selection bias. Hence, the second empirical investigation addresses selection bias using the Inverse Probability Weighting – Regression Adjustment (IPWRA). This approach is a doubly robust estimator which uses both treatment and outcome models and it can achieve unbiased estimates even if one of the models is incorrectly specified. Another novelty of this empirical approach is that it allows for a multiple treatment model thus this evaluation study is the first one to assess the effectiveness of multiple active measures in the same framework.

In order to analyse the overall effectiveness of the active measures, **chapter 6** extends the analysis of the previous chapter by using an additional dataset, Labour Force Survey (LFS) for Kosovo, to create a control group. This chapter also addresses objective five and six and answers the following research question: *To what extent the active measures implemented in Kosovo affect the beneficiaries' probability of finding employment and receiving an employment contract?* This empirical analysis uses the same evaluation methodology as chapter 5, IPWRA, to assess the ALMP effectiveness.

Chapter 7 provides the conclusion to the thesis, synthesising the main findings of this research and contributions to knowledge of the theoretical and empirical analysis. Based on these findings policy recommendations with regard to increasing ALMP effectiveness in Kosovo are discussed. This chapter also analyses the limitations of the research programme reported in this thesis and develops suggestions for further research on this subject.

1.4 Transition process and the labour markets of European transition economies

This section provides a brief overview of the impact of the transition process on the labour market indicators in European transition economies. A more comprehensive discussion about the transition process and unemployment is provided in section 2.3.

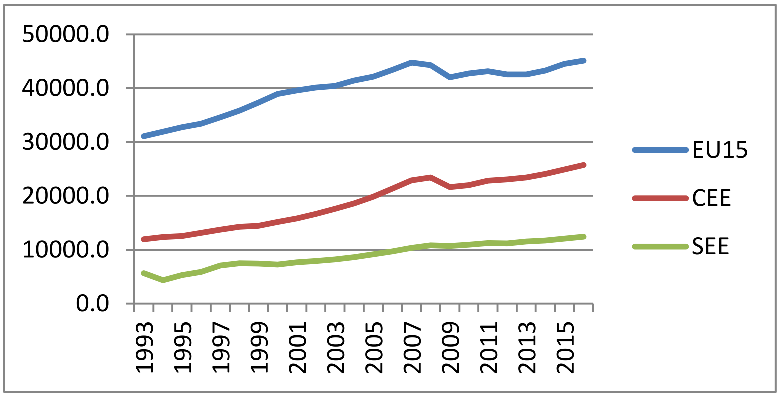
During the pre-transition period, open-unemployment did not exist; it was during the transition process that unemployment emerged and became a persistent feature of most of the transition countries (Boeri, 1997; Nesporova, 2002). The rise of unemployment was a direct consequence of the dramatic collapse of output that transition economies were facing with the shift from the rigid trade relationships of the central planning system to a market economy (Burda, 1993; Lehman and Muravyev, 2011).

The fall in labour demand, which continued after the initial fall of output, was also a consequence of the inefficient use of labour resources or labour hoarding in the pre-transition period which became apparent after privatisation (Adam, 1982; Bruck et al., 2007). Labour hoarding can be defined as "*a situation where an establishment is paying for more worker-hours than is necessary to produce current levels of output*" (Pissarides, 1991, p. 3). Though the labour hoarding is not easy to be estimated a number of studies suggest that between 15 to 30 percent of the employed in CEE countries were hoarded labour (Gora, 1991; Nesporova, 1991).

In most of the transition economies initially non-agricultural self-employment was non-existent, while most of the employment was concentrated in large conglomerates (Boeri, 1998). The restructuring of labour markets involved large job losses in heavy industries and agriculture, while light manufacturing and services were being developed (Boeri, 1992). Almost six million people lost their jobs in the Central and Eastern European countries (CEECs) and many withdrew permanently from labour market (Hoti, 2003). According to researchers, the skills acquired in the state sector were often not suitable for employment in the private sector which induced persistence in unemployment – many skills have become obsolete due to changes in new forms of firm organization and technology (Burda, 1993; Boeri, 1997, Nesporova, 2002). Hoti (2003) argues that the occupational adjustment requires time and this is what makes unemployment in transition countries persistent.

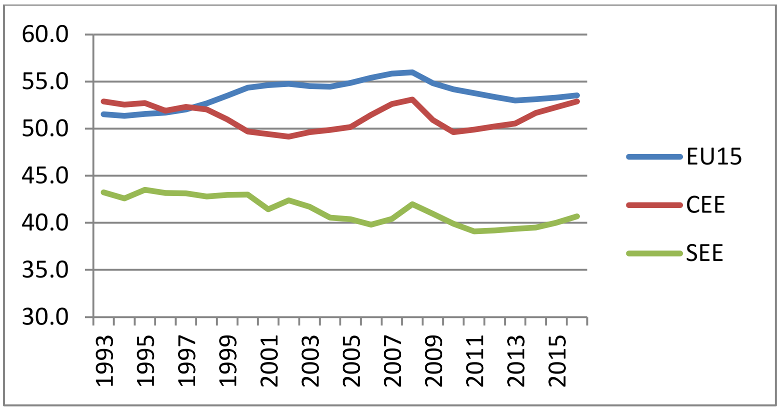
As figure 1.1 shows, in general, the transition countries experienced robust economic growth from the mid-90s, which was faster than that of the EU15 until the global financial crisis. The labour markets of European countries responded to the decline in output during the financial crisis by a sharp decrease in employment rates, a rapid rise in unemployment rates, a reduction in working hours and fall in real wages (Burda, 1993; Leon-Ledesma and McAdam; 2004; Lehman and Muravyev, 2011). Figures 1.1 and 1.2 show that there are differences between the CEE and SEE in growth of GDP per capita and the employment to population ratio. During the first stages of transition, SEE countries experienced the deepest recession and still remain the slowest growing. The cause of this slow recovery in this region has mainly been attributed to the conflict in the Former Yugoslavia.

Figure 1.1 GDP per capita for EU15, CEE and SEE countries, 1993 to 2016



Source: World Bank database (2018)

Figure 1.2 Employment to population ratio for EU15, CEE and SEE countries, 1993 to 2016



Source: World Bank database (2018)

The nature of jobs has also changed during the transition process: informal, temporary and casual employment has increased. A study by Schneider and Williams (2013) found that although the shadow economy had fallen from 37.9% in 1999 to 33.7% of official total GDP in 2007 for transition countries, the shadow economy in those countries remained larger than the average of 116 developing countries (26.2%) and the 25 OECD countries (13.0%). The average level of informality of the CEE countries had fallen further by 2015 to about 23%, however, it still remained higher than EU15 average (13.5%). Among the European transition economies, Bulgaria has the highest informality with 31% of the official GDP while the Czech Republic and Slovakia with lowest with about 15% of the GDP (Schneider, 2015).

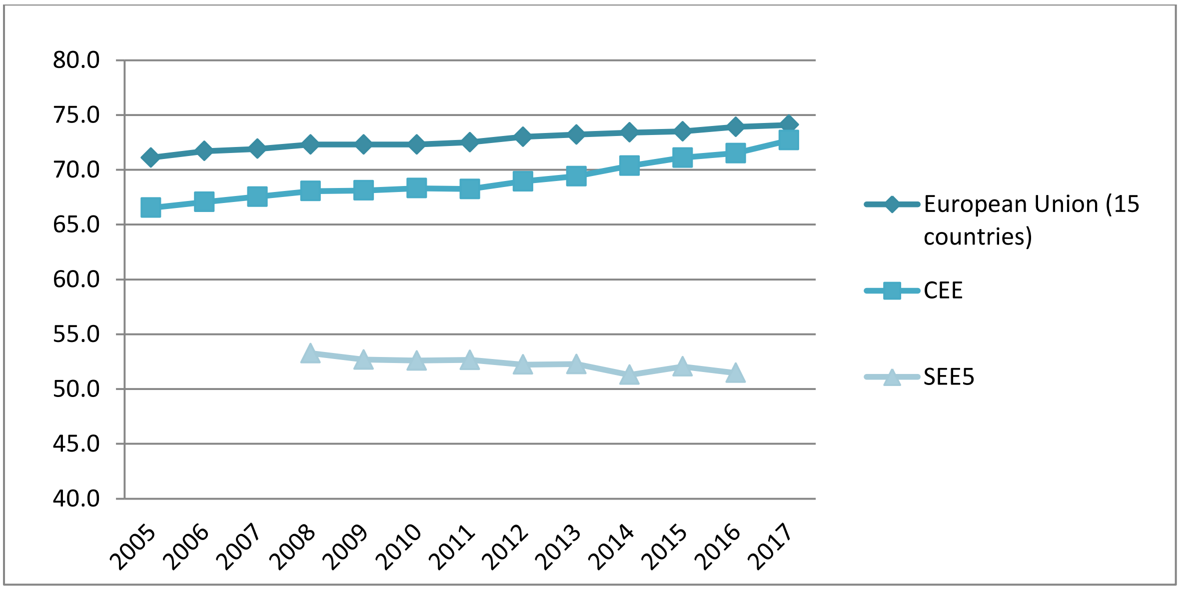
1.5 Labour market indicators

The previous section identified that after nearly three decades of transition and more than a decade of the start of the global financial crisis unemployment remains an important issue in both developed and transition European economies. Considering that this thesis focuses on European countries, this section will examine the gravity of unemployment issue in these countries. Section 1.5.1 and 1.5.2 will discuss the labour force participation and unemployment rate, respectively, for EU15 compared to CEE and SEE countries. A specific summary of the labour market in Kosovo is provided in a separate section, 1.5.3.

1.5.1 Labour Force Participation

During the first stages of the transition period, CEECs together with high and persistent unemployment, typically experienced a huge fall in labour force participation. Due to a lack of job opportunities, some unemployed became discouraged and withdrew from the labour market. From the macroeconomic point of view, the cost of the low labour force participation rates is similar to that of high unemployment since both reduce the labour force available and as such diminish growth potential. As figure 1.3 shows that since 2005 the labour force participation (LFP) rates for CEECs have increased continually, almost reaching those in EU Western economies.

Figure 1.3 Labour Force Participation Rate, % of total working age population



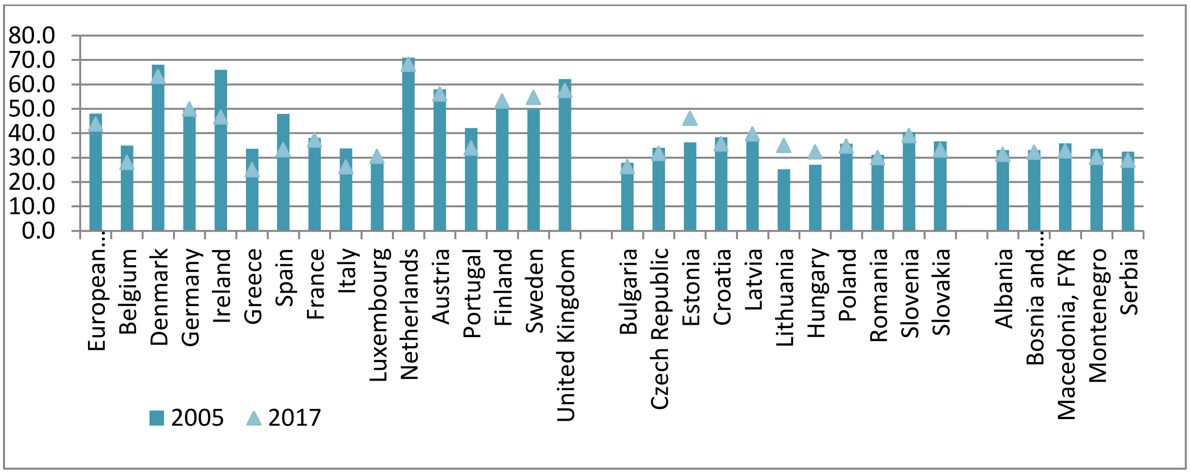
Source: Eurostat (2018) for EU countries and ILO (2018) for SEE

According to the Eurostat database (2018), in 2017 the economically active labour force accounted for more than 72% of the working age population in EU transition economies compared to 74% in EU Western Economies. However, the LFP figures for South East Europe 6[4] (presented in figure 1.3 only from 2008 to 2016 due to missing data) suggest that participation rates are much lower compared to both CEE and EU economies, with an average of just 54% of the working age population. Apart from Kosovo, the labour force participation rate in Bosnia and Herzegovina remains the lowest among the transition countries at just 43.2% on average in 2016 and has not changed much since 2005.

Considering age, one apparent trend is that the participation of the population aged 15 to 24 in the labour market is decreasing over time in the EU 15; the participation of this group has dropped from about 48% in 2005 to about 43% in 2017 (Eurostat database, 2018). However, as figure 1.4 shows, there are notable differences among countries where the participation of youth in Ireland dropped from 66% in 2005 to 46% in 2017 or in Spain from 47% to 33%. On the other hand, the participation rates for CEECs remained on average constant; however, it increased from 36% in 2005 to 46% in 2017 in Estonia and from 25% to 35% in Lithuania. As figure 1.4 shows, the participation rate of this group in SEE countries has fallen. A particularly large reduction is observed in Albania where it fell from 50% in 2002 to just 31% in 2015 (ILO database, 2018). This may be partly explained by the substantial increase in higher educational enrolment by young cohorts in the region that led to their delayed entry into the market (World Bank, 2013b).

[4] Kosovo is excluded from the discussion here since it will be discussed separately in section 1.3.3.

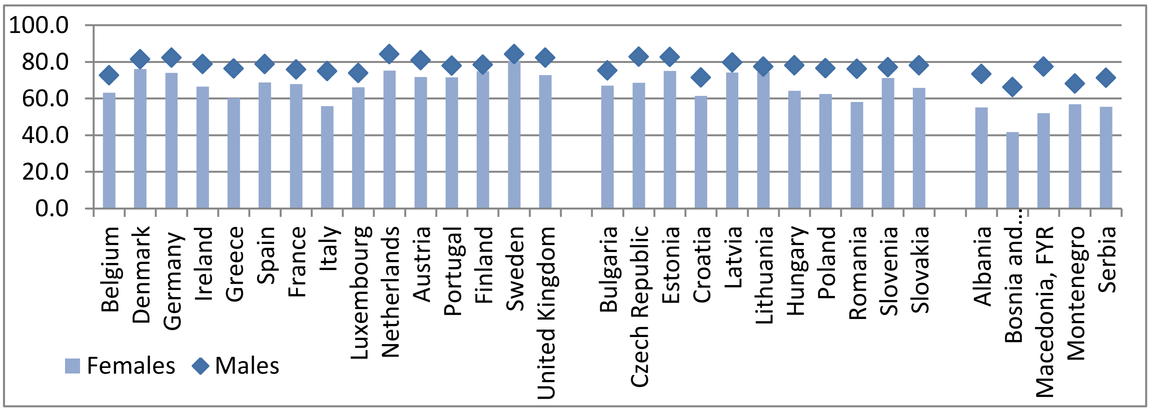
Figure 1.4 Youth Labour Force Participation aged 15-24



Source: Eurostat (2018) for EU member states and ILO (2018) for SEE.
Note: For SEE countries the figure presents data for 2008 and 2015 due to missing data.

During the socialist period, the female labour force participation rates in CEECs, except for Western Balkan Countries, were very high by international standards (Nesporova, 2002; Lehman and Muravyev, 2011). The transition process initially reduced both female and male LFPs and brought down female labour force participation to the EU level and that of males well below to that of the EU level. Female LFP is also low in the SEE region but here there are additional explanatory factors to the transition process that include cultural reasons and traditional roles assigned to women. Also, the social benefit system is seen as cause of inactivity in some cases such as that of Montenegro, where the introduction of life-long benefits for mothers of at least three children in 2016 resulted in more than 15,000 women applying for this benefit, consequently causing many of them to withdraw from the labour market (World Bank, 2017). Women's LFP in Albania fell in comparison to pre-transition period but remained on average constant from 2005 to 2016 at about 47%. The lowest female participation rate in the Western Balkans countries is that of Bosnia and Herzegovina with about 32%. In Croatia and Bulgaria the female participation rates remained quite unchanged during this period at around 45%. As seen in figure 1.5, the gender differences in labour force participation in the CEECs, in general are much larger than those in EU 15, expect for Italy where the gender gap is 19.1 percentage points (pp) compared to Romania (18 pp) and Poland, Czech Republic and Hungary (14 pp). The gender participation gap in SEE is considerably larger compared to both EU15 and CEECs. Apart from Kosovo, which is discussed in the next section, the gender gap for FYR Macedonia and Bosnia and Herzegovina are the largest among the European transition countries of around 25 and 24 percentage points in 2015 (ILO, 2018).

Figure 1.5 LFP rates by gender (%) for EU15, CEECs (2017) and SEE (2015)



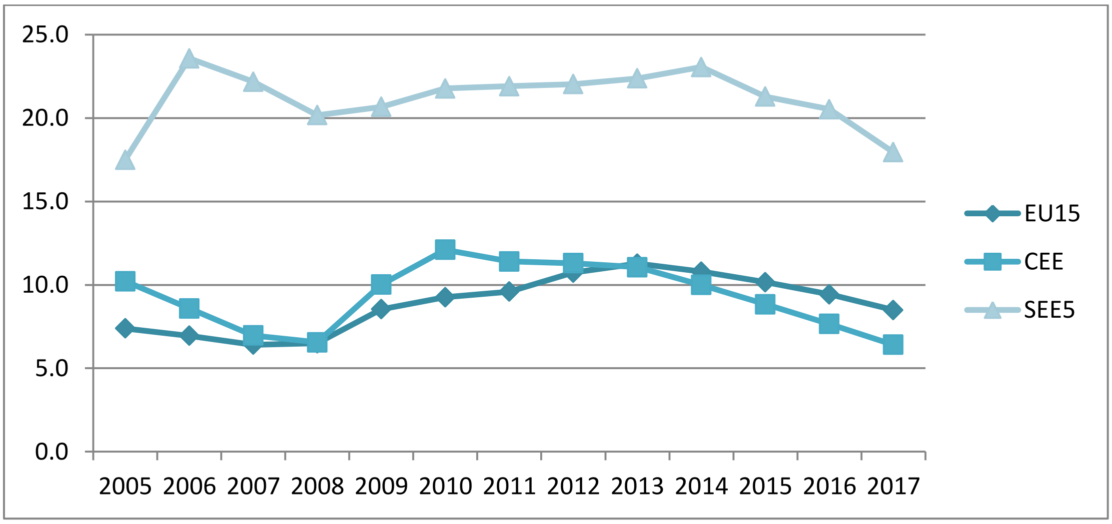
Source: Eurostat database (2018) for EU member states and ILO (2018) for SEE.

Considering the analysis of the educational attainment in most of the transition countries the highest proportion of the labour force consists of workers with completed secondary education. According to the Human Capital theory, educational achievement is considered to be crucial determinant of the labour supply. In the post-transition period secondary and tertiary education have become more valuable and skills obtained in higher education increase the probability of gaining employment considering the structural changes in the pattern of employment (Boeri and Terrell, 2002). Countries with the highest proportion of those who have only completed primary education in the SEE region are FYR Macedonia with more than 28 percent, followed by Bosnia and Herzegovina and Kosovo with 20% of the labour force in 2012 (ILO database, 2018). The proportion with completed higher education in Montenegro's labour force was just over 10% followed by Serbia with 12.5% compared to FYR Macedonia with about 19% in 2017 (ILO database, 2018).

1.5.2 Unemployment Rates and Duration

As discussed in section 1.3.1 before the start of transition in the CEECs unemployment was not common. Masked unproductive employment was mainly in the public administration sector and in inefficient state-owned enterprises. Privatization of the state-owned enterprises led to a drastic increase in unemployment and displacement of the labour force, some of who left the labour force forever (Mickiewicz, 2010). The first rise in unemployment was concentrated in agriculture and heavy industry, which was initially expected to be absorbed by the expansion of light manufacturing, construction and services (OECD, 1992; Mickiewicz, 2010). In most of the CEECs job-destruction in the public sector was not followed by an equal amount of job-creation in the private sector leading to an employment decline (World Bank, 2005; Kovtun et al., 2014). In recent years, the unemployment in CEECs has fallen from the double digits, the only country still having double digit unemployment rate in Croatia with 11.1% while the Czech Republic has the lowest unemployment rate of 2.9% in 2017. However, unemployment in the South East Europe 5 is the highest amongst the European transition countries, and it remains a major economic and social challenge (ILO database, 2018). As can be seen in figure 1.6, even though the unemployment rate has fallen in these countries since 2005, it still quite high compared to the average of EU15 and CEE countries with an average of 18% in 2017. Apart from Kosovo, the countries with the highest unemployment rate in the region are Bosnia and Herzegovina (BiH) at about 25% and Former Yugoslav Republic of (FYR) Macedonia with 23%.

Figure 1.6 Unemployment rate for EU15, CEE and SEE

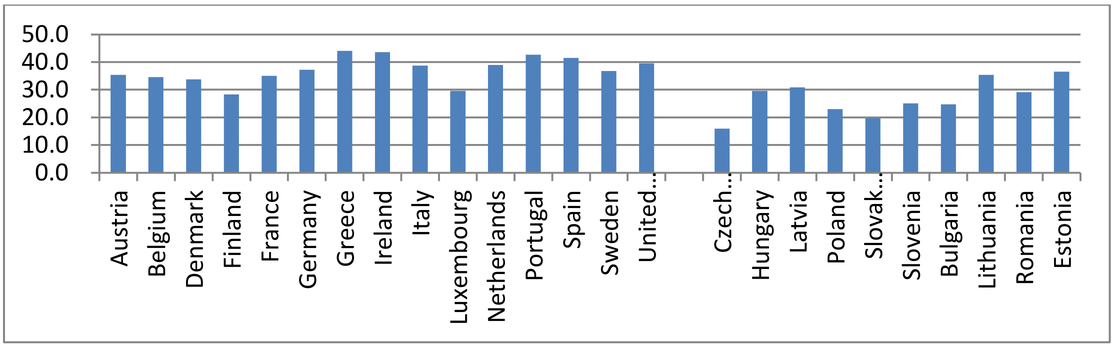


Source: Eurostat database (2018) for EU15 and CEECs and ILO database (2018) for SEE

Long-term unemployment, consisting of persons who are unemployed for one year or more, is very high in most of the transition countries and has been increasing in some of them since 1995 (Eurostat database, 2018). The persistent low-job creation in the private sector in the SEE has increased the possibility of persistent unemployment. In CEECs more than 42% of the unemployed have been searching for a job more than one year which has dropped from 54% in 2005 (Eurostat database, 2018). However, the data show that there are differences in long-term unemployment between CEECs where Slovakia has the highest figure of long-term unemployed with 62% while Poland the lowest with 31% of the total unemployed. SEE countries exhibit much higher long-term unemployment; in FYR Macedonia and Montenegro the proportion of long-term unemployment is more than 77% (Eurostat database, 2018). The 'true' unemployment rates in CEECs may be lower than the figures provided by Labour Force Survey, since a significant number of workers considered unemployed may actually work in the informal sector. However, some potential workers are disheartened or discouraged from seeking employment and withdraw from the labour market. This is particularly true for Western Balkan countries (KAS, 2017; GoS, 2016).

As discussed in section 1.4, in post-transition economies labour markets are characterized by a high degree of skill mismatch due to slow skill adjustments during periods of restructuring (Bejakovic and Mrnjavac, 2014). This mismatch further adds to the difficulties of improving the labour market as the jobseekers will need to acquire necessary skills in order to benefit from the available employment opportunities.

Figure 1.7 Qualification mismatch in EU15 and selected CEECs, 2015



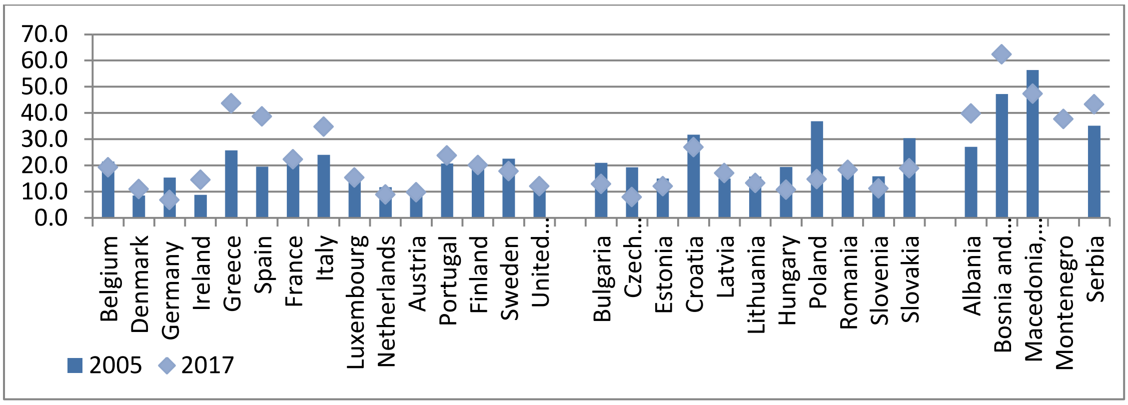
Source: OECD database (2018)

As seen in figure 1.7, the qualification mismatch[5] was, on average in 2015, much higher in the EU15 than in the CEECs. Given that this measure captures both, over-qualification and under-qualification, one may suggest that the mismatch in EU15 might be primarily due to over-qualification.

[5] The OECD measures the qualification mismatch indicator by comparing each individual's education level to the level required in their occupation. The 'normal' qualification level that is required in an occupation is defined as the qualification level that is most observed among people employed in that occupation. People can be over-qualified when their qualification level exceeds the one that is usually required in their occupation, or under-qualified, when they have a qualification level below.

Unemployment among youths is even higher than the general unemployment. In comparison to adults, young workers face a disadvantageous labour market situation. The 2017 youth unemployment rates for Greece (43%), Spain (38%) and Italy (34%) are higher than any of new EU member states where the highest rate is that of Croatia (27%). As mentioned in a World Bank report (Bogetic et al., 2012) and illustrated in Figure 1.8, youth unemployment is a particularly daunting problem for the SEE countries. In several SEE states youth unemployment rates is almost 50% for FYR Macedonia while 62% for Bosnia and Herzegovina, much higher than the two extreme cases in the Eurozone: Greece and Spain (EBRD, 2013; ILO database, 2018).

Figure 1.8 Youth Unemployment rate for EU15, CEEC and SEE, 2005 and 2017



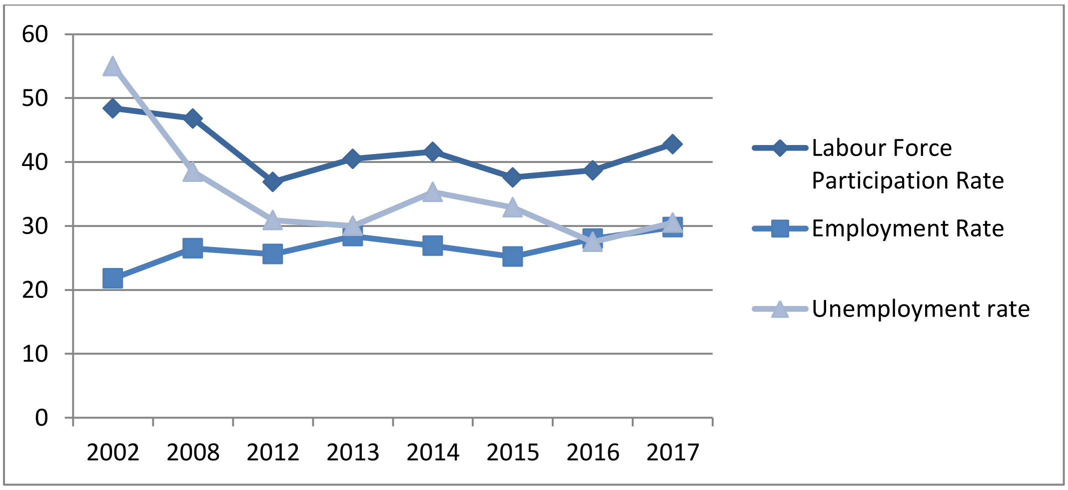
Source: Eurostat (2018) for EU member states and ILO (2018) for SEE.
Note: For SEE countries the figure presents data for 2008 and 2015 due to missing data for 2005 and 2017. Data for Montenegro for 2008 is missing.

1.5.3 Labour market indicators in Kosovo

As pointed out in the introduction of this chapter, this thesis gives particular emphasis on the analyses of the effectiveness of ALMPs in the reducing unemployment in Kosovo. Hence this section will provide a brief analysis of the labour market indicators. In comparison to other transition countries, Kosovo has a distinct history which is reflected in the current labour market situation. Kosovo was one of the last countries to start the transition from a central to a market economy (Hoti, 2017). Before Yugoslavia was dissolved, Kosovo was the poorest region in the country with a per capita social product of a quarter of the country’s average in 1989 (Bevc, 1993). During the period 1989 – 1999 the occupation of Kosovo by Serbia led to the country’s isolation and a massive dismissal of workers from their jobs of up to 145,000 workers (Hoti, 2017). During 1990 to 1995, the GDP contracted by 50% compared to its pretransition level (Hoti, 2017). Kosovo's post 1999 economic recovery has been very slow in tackling the inherited structural unemployment problem and the depleted human capital stock. Kosovo is known for its young population and also large-scale emigration which affect the size and the age composition of the labour force (Hoti, 2017). Nearly one third of the population is under the age of 15 which implies that there are a large number of new entrants into the labour force each year.

The labour market performance in Kosovo is the poorest when compared to other Balkan countries and European Union member states. As figure 1.9 shows, low labour force participation (LFP) remains one of the most critical issues in the labour market in Kosovo. Of those of working age, in 2017 only 42.8% were participating in the labour force (economically active) meaning that they were either employed or unemployed (i.e., actively seeking work and available to work) (KAS, 2017). Part of the reason for the difference between Kosovo and Balkan countries is that Kosovo has a very young population and has experienced a significant expansion of higher education in recent decades, thus many of these young people are still in education and categorized as inactive. The discouragement of the labour force participants is widely persistent, out of the 733,341 inactive population, 165,712 people did not search for a job because they did not believe that there are job opportunities for them (KAS, 2015).

Figure 1.9 Main labour market indicators: Kosovo, 2002 to 2017

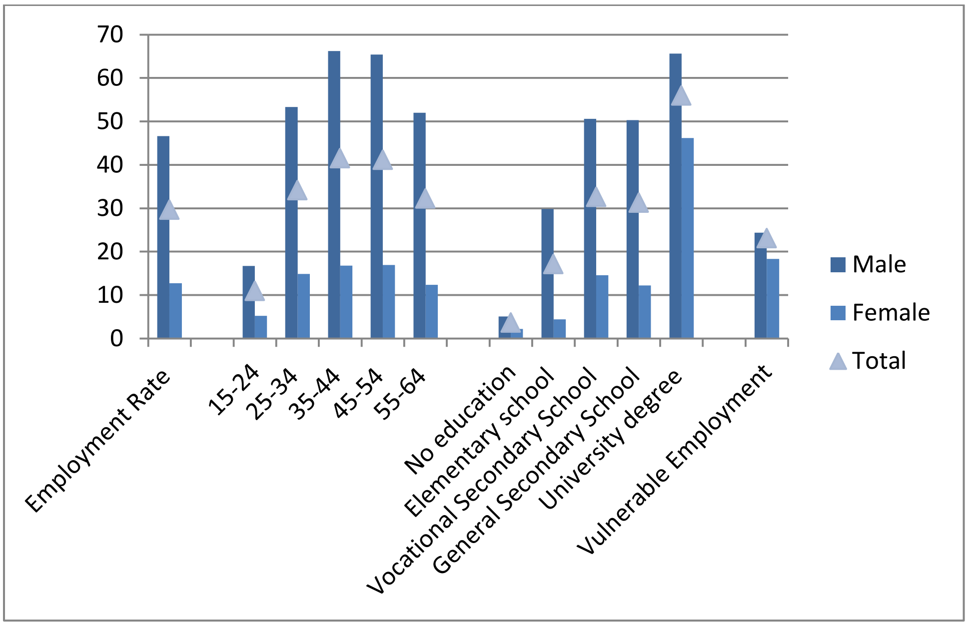


Source: KAS (2002 to 2017)

Participation is much lower among women than that of men, just over 20% for women compared to 65.3% for men. Apart from low labour demand, family responsibilities and the absence of (affordable) childcare are among the reasons for the low women participation in the labour force (Democracy for Development, 2015). In addition, women's low LFP in Kosovo is also related to stereotypical gender roles that certain occupations are not considered suitable for women. As noted by a World Bank report (2002) in times of limited labour demand and social policies to support women, they become more easily discouraged than men and withdraw from the labour market.

Only 29.8% of the working age population was employed in 2016; only 12.7% of working age women were employed compared to more than 46% of men (KAS, 2017). Despite being low, the employment rate has been increasing steadily over the years from about 21% in 2002 to almost 30% in 2017 (see figure 1.10). Across different age groups the employment rate was highest among 35-44 years old (40.5%). The lowest employment rate is among the young population (15-24 years old) at just over 11.2%, where the employment rate for young women is only 5.2% while around 12% for young men. Figure 1.10 also shows that the higher the level of education the higher possibility of being employed; about 57% of those who have university degree are employed

Figure 1.10 Employment rate (% of active population) by age, gender and education, 2017

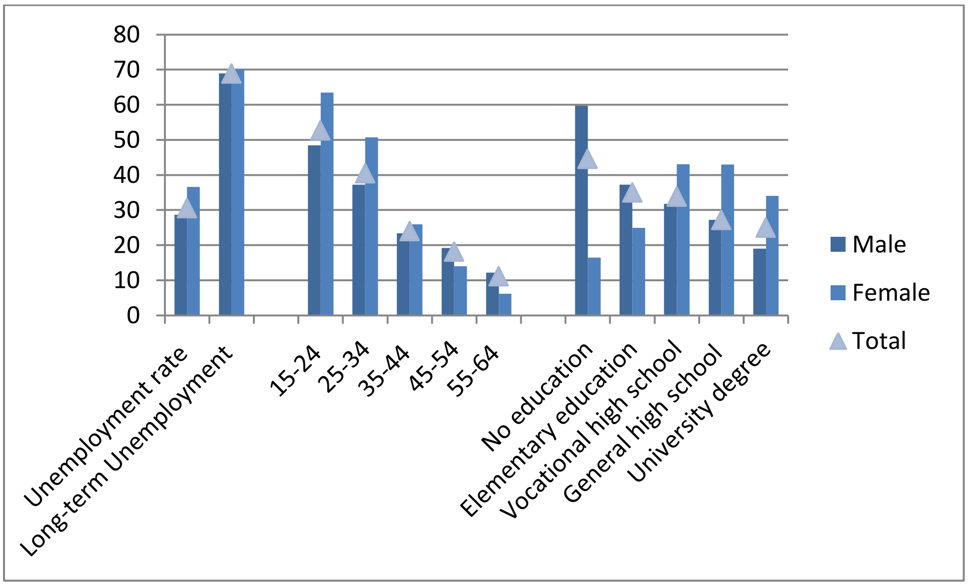


Source: KAS (2017)

In addition to the low employment rate in Kosovo, vulnerable employment, which refers to self-employment without employees or those who are employed in any family business without pay is around 23.1% of total employment. Men are more likely to have vulnerable employment (24.4%) compared to women (18.3%). In terms of the contractual agreement, more than 78% of respondents in the LFS had an individual contract. With regard of those who have a contract, more than 70% had a temporary contract (no gender differences) and only 5% of the employed were entitled to the benefits of the social security schemes in the job.

Of the entire working age population, according to the LFS 2017, the unemployment rate in Kosovo was 30.5%, it was higher for women (36.6%) than for men (28.7%). As presented in figure 1.11, the unemployment rate in Kosovo has dropped significantly since 2002 from 55% to about 30% in 2017. The majority (71.5%) of unemployed have been unemployed for more than a year. According to the LFS (2017), the likelihood of becoming long-term unemployed increases with age and women are also more likely to become long-term unemployed compared to men, except for young women. With regard to the age groups, the unemployment rate of the youth population is the highest among all age groups at about 52.7%, where 63.5% of women of this age are unemployed compared to 48.4% of men. The likelihood of a young person being unemployed is twice as high as that of older workers and the difference is more pronounced among males.

Figure 1.11 Unemployment rate (% of active population) by age, gender and education, 2017

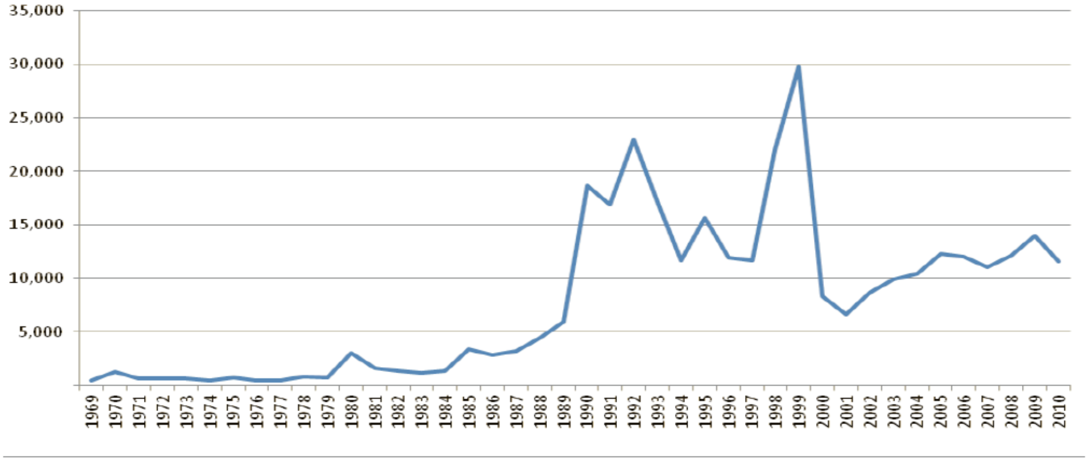


Source: KAS (2017)

This exceptionally high youth unemployment in Kosovo is related to the weak demand for labour (Corbanese and Rosas, 2007). Even though the rate of job creation has been improving in Kosovo, the amount of new vacancies is not rising at the pace of the inflow of the new labour participants (USAID/UNDP, 2009). In Kosovo the share of youths aged 15 to 24 not employed, not in education and not in training (NEET) is very high of more than 27% of the young population (KAS, 2016). This raises concerns about their future employability and detachment from the labour market. Despite lack of good job opportunities, there are other factors which might have affected youth unemployment and idleness such as low quality of education and incompatibility of education programmes with the labour demand, lack of practical work during school, lack of career counselling, limited information about the labour market demand and lack of networking (MLSW, 2017). This makes the young entrants to the workforce often relatively unskilled and poorly prepared, in terms of both job-related and employability skills (USAID, 2009; MLSW, 2017).

A significant emigration of its population has been an integral part of Kosovo throughout history. As presented in figure 1.12, the emigration of Kosovo population increased dramatically in the 1990s' due to the conflict in former Yugoslavia which resulted in a grave political and socio-economic situation in Kosovo. Given poor employment opportunities in Kosovo during this period, emigration was considered as the only option to escape unemployment and poverty, to contribute towards household income and increase their welfare. According to Human Rights Watch during this period there was a 'forced emigration of 350,000 Kosovo Albanians' and it was mainly the young population who escaped the country (Gollopeni, 2016). The emigration culminated in 1999 when an estimated 850,000 Kosovo Albanians were evicted from their homes to the neighbouring countries (Albania, FYR Macedonia and Montenegro) leading to mass emigration. While the largest number of refugees returned to Kosovo after the conflict was over, about 100,000 ethnic Serbs left Kosovo to Serbia and the north of Kosovo (Elsie, 2011). According to KAS (2014), in 1998 and 1999, 51,728 Kosovo Albanians (21,973 and 29,755, respectively) or about 13.6% of all emigrants left the neighbouring countries to Europe and other countries (Haxhikadrija, 2009).

Figure 1.12 Emigration of the Kosovo population (expressed in number of people), 1969 to 2010



Source: KAS (2014)

The emigration during the 1990s was mainly due to the political situation while socio-economic situation was the main reason for emigration during the other periods of migration. The latest stage of migration was in 2014 and 2015 when approximately 100,000 citizens left Kosovo towards Western European countries mainly due to low job opportunities and the loss of hope for better domestic economic prospects in the near future (Gollopeni, 2016). According to Kosovo Agency of Statistics (2014), in 2011, 21.4% of Kosovo's population was living abroad (that was approximately 381,000 persons).

The level of remittances received by transition countries have frequently been a vital source of external finance for these countries after incoming foreign direct investment (World Bank 2006; Hoti, 2009). Kosovo was ranked as one of the countries with the highest percentage of remittances on GDP; in 2014, 16.1% of GDP comprised of remittances while this percentage dropped in 2015 to 13% (Ministry of Economic Development - MED, 2018). Most of the remittances are used for consumption like food and clothing (35.4%), other expenditure on such as electrical equipment, cars and weddings (24.8%), renovating houses and buying new ones (19.6%) while a smaller amount of remittances goes on education and medical care (10.6%) (MED, 2018). Education is one of the accelerators of the countries' economic growth and many studies suggest that the number of high-school drop-outs has fallen due to the remittances (MED, 2018).

The emigration of population affects the composition and size of the labour force and it also affects the skill composition of labour left in the country of origin. In a study of 24 countries with large scale emigration, the share of highly skilled emigrants was not more than 10% of the population (Adams, 2003). More specifically, a study by Hoti (2009) suggests that 7.4% of Kosovar individuals with completed higher education (about 11,000) live out of the country. Many studies have emphasised a positive relationship between education and emigration since it gives people the incentive to acquire higher education in order to be marketable internationally (Ivļevs and King, 2010). This is commonly referred to as the 'brain drain' and it is considered as damaging to the country of origin as much as the emigration (Hoti, 2009). Emigration of highly skilled workers makes the country less attractive to foreign direct investment, it affects the level of income and increases the fiscal burden of people left in the country etc. Skilled and unskilled workers are frequently complementary in the process of production and the absence of the former can make the later less productive (Docquier and Rapoport, 2004; Hoti, 2009). Given peoples' incentive to migrate and the lower employment opportunities in their home country, the ALMP participants in Kosovo, analysed in chapters 5 and 6, might also use the training acquired to emigrate to countries where their new skill can be utilised.

1.6 Types of ALMPs

Having so far discussed the labour market indicators in European countries with particular attention to Kosovo, this section investigates the ALMPs which are recognised as one of the essential policy instruments to alleviate labour market mismatch and to fight high unemployment rates. This section provides a brief discussion of the types of ALMPs and their aim in the labour market, with an extended analysis of the multiple effects of these policies being provided in section 2.2.3. The following section sheds light on the level of ALMP expenditure in EU15 and transition economies. This serves as starting point for the analysis of the relationship between ALMPs and unemployment in the following chapter.

ALMPs are a group of policies used by governments to promote employment, growth and equality (Calmfors et al., 1994; Rueda, 2006). The main aim of these policies is to enhance labour supply, increase labour demand and improve the functioning of the labour market. Policy makers recognize ALMPs as potentially being a direct instrument in reducing unemployment through enhancing information exchange, increasing the skills and employability of the unemployed and improving the matching of vacancies and job-seekers (Calmfors et al. 2002). Moreover, these policies can affect labour demand by reducing the hiring costs, thus facilitating job-creation in the labour market. Some policy-makers view ALMPs not as a cure for large-scale unemployment, but rather as a treatment for specific types of unemployment or specific groups of unemployed individuals. The multiple effects of ALMPs are analysed in detail in Chapter 2.

There is a wide variety of ALMPs among European countries. Kluve (2006) classified ALMP interventions into six core categories; the same classification that was suggested and is now used by the OECD and Eurostat.

1. *Training* is the most common active policy encompasses classroom training, on-the-job training and work experience. The primary aim of the training programmes is to enhance human capital through improving skills needed for employment and to increase the productivity of the participants. This measure can either provide more general knowledge such as language courses and basic computer courses, or specific vocational programmes that can also increase occupation-specific skills such as craft and operative skills.
2. S*ubsidised private sector employment* that comprises measures that increase job-opportunities in the private sector. This measure aims to alter workers and/or employers behaviour with regard to private sector employment. The most common measure is the wage subsidy which aims to encourage employers to increase job-opportunities for new workers and/or to maintain those jobs that are under threat of being made redundant The financial subsidy is typically paid to employers but may be paid directly to supported employees for a fixed period of time, and is often targeted at the long-term unemployed. This category also encompasses grants for self-employment and start-up businesses, which can include a combination of training, financial support and management advising for a fixed period of time (Kluve et al., 2006).
3. *Subsidised public sector employment* (public works) aims to offer job opportunities in the public sector through direct job creation. These measures are usually targeted at disadvantaged groups with the objective of keeping the

participants in the labour market and preventing loss of human capital during the period of unemployment.

4. *Job search assistance and sanctions* aim to increase the effectiveness and intensity of the job search process (Card et al., 2010; Butschek and Walter, 2013). The main objective of job search assistance is to increase the efficiency of the job matching through job search courses, job clubs, counselling and monitoring and sanctions applied in the case of noncompliance with requirements. This active measure can be managed by private agencies but historically public job search services have dominated provision. In many countries the Public Employment Services (PES) predominantly target long-term unemployed and disadvantaged groups while private agencies target white-collar and more privileged employees. This active measure includes also benefit sanctions or specified reductions in (or loss of) unemployment benefits if the unemployed refuse to accept an offered job or do not apply sufficient effort in their job search.

The first four active measures are descriptions of the programme types while the next two focus on specific target groups for ALMPs. In many countries, ALMPs have been used to address inequality and are targeted at disadvantaged individuals in the labour market (Card et al., 2010).

5. *Youth programmes* include the above mentioned active measures applied specifically to the young unemployed usually aiming to increase their employability skills (World Bank, 2008), e.g. through training programmes, subsidies and job search assistance.
6. *Measures for the disadvantaged groups* such as training may be used to assist specific groups of unemployed. Examples of such measures include support for females enter male dominated occupations and increase their income level (Bergman and Van den Berg, 2006),support for immigrants and minorities' in the labour market through language and induction courses and subsidised employment (Butschek and Walter, 2013).

In practice, classifying actual programmes into these categories is frequently difficult since most national programmes combine two or more active measures targeted to the same group (Calmfors et al, 2002). Measures that encourage desirable behaviour such as training, job search assistance and subsidies are usually called ‘’carrots’’ while imposing threats on the unemployed such as benefit sanctions are called ‘’sticks’’ (Kluve and Schmitt, 2002).

1.6.1 ALMP expenditure in EU member states

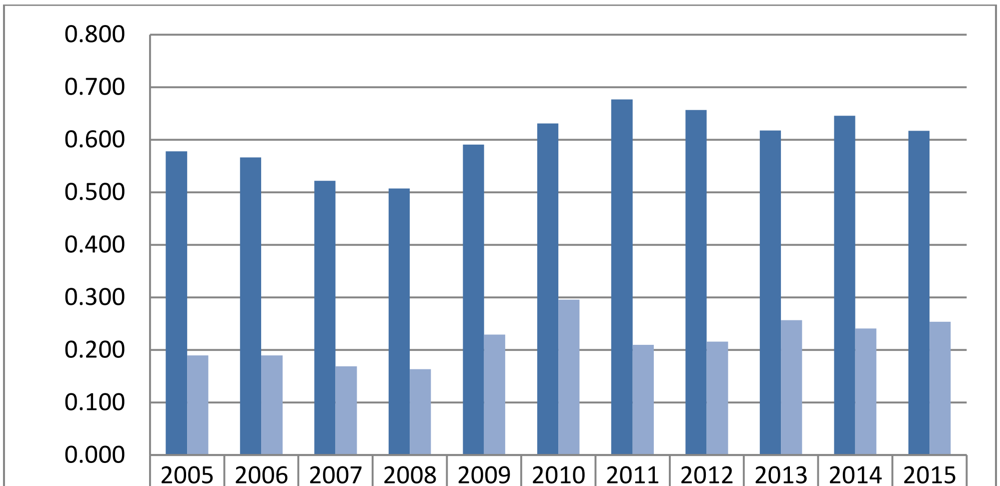
Transition countries’ labour markets are characterised by specific features which affect the potential of ALMPs to improve labour market performance. For instance, the extent and speed of structural changes means that any feasible implementation of ALMPs would not be sufficient to absorb the workers displaced during transition period. The limited capability of the labour markets in transition economies to create new jobs led to a stagnant pool of unemployment with the tendency to become long-term unemployment. As discussed in section 1.3.2, most of the transition economies are characterised by chronic long-term unemployment. In developed countries the unemployed workers are disproportionately from marginalised groups, those with low attachment to the labour market or who face trouble finding employment at the beginning of their working life. In contrast, the pool of unemployment in transition countries typically contains large numbers of the core labour force, those possessing large stock of human capital and who have high attachment to the market. The stagnant pool of unemployment further led to high deterioration of human capital. Job competition in transition labour markets is much stronger than in developed countries thus the unemployed who participate in the active programmes may not have the same experiences and outcomes as those in other countries (Lehman and Kluve, 2008).

ALMPs became popular in European countries in the 1990s and have continued to increase in scale and scope, however there is heterogeneity in the expenditure dedicated to these measures. Figure 1.13 presents the ALMP expenditure as share of GDP for both the EU15 and CEECs[6]. As the graph shows, the EU 15 countries allocate considerably more expenditure on ALMPs as a % of GDP than the new member states. In CEE countries, regardless of their generally high unemployment, the spending on ALMP is limited, which is not surprising since transition countries have faced great fiscal pressures. As seen in figure 1.13, on average in 2015 the

[6] Comparative data for ALMP expenditure in SEE is not available.

ALMP expenditure as percentage of the GDP in CEE countries was 0.24% compared to 0.62% in the EU15. During the Global Financial Crisis an intensification of ALMP expenditure was undertaken in many EU countries, despite the budget constraints and capacity issues which have constrained their growth (Gama et al. 2015). However, after 2012 there was no significant increase in these expenditures (Numanovic et al., 2016).

Figure 1.13 ALMP Expenditure as a share of GDP; EU15 and CEE

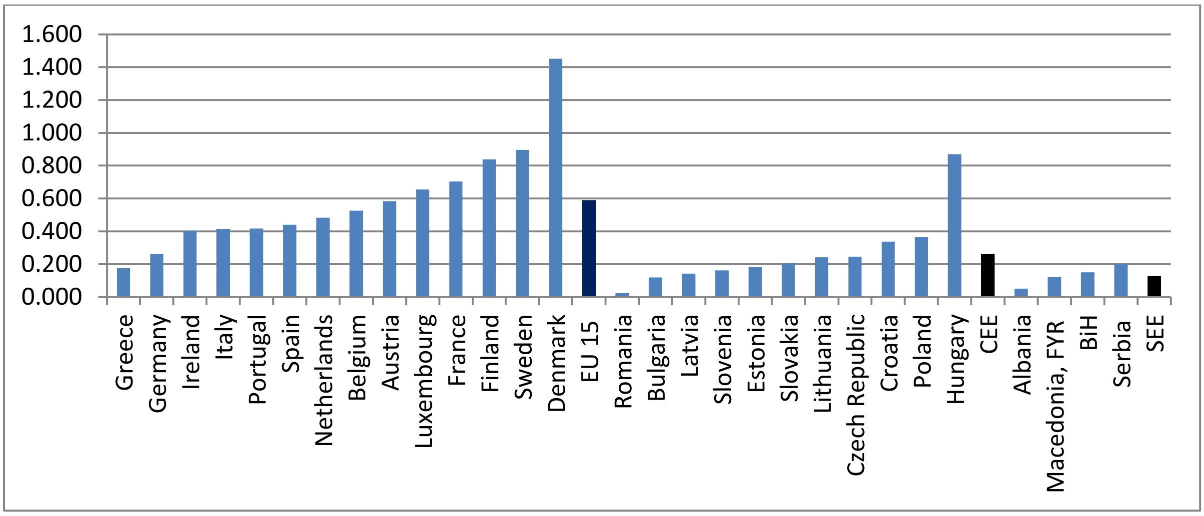


	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
EU15	0.578	0.567	0.522	0.507	0.591	0.631	0.677	0.656	0.617	0.645	0.617
CEE	0.190	0.190	0.169	0.163	0.229	0.295	0.210	0.216	0.257	0.241	0.254

Source: Eurostat database (2018)

Although the data in figure 1.13 reflect some general trends in total expenditure on ALMPs, the difference between countries cannot be easily generalised. Figure 1.14 shows that Denmark is the highest spender among the EU15 countries allocating more than 1.4% expenditure as share of GDP while Greece allocates only 0.18%. Amongst the CEECs only the level of ALMP expenditure in Hungary is comparable with those of high spenders in the EU 15 with 0.79% of GDP, whereas all other countries are low spenders, with Romania spending only 0.019%, and Latvia and Estonia spending about 0.10% of GDP in 2015. Despite the fact that Balkan Countries in recent years have considerably increased the amount spent on active policies, it is still much lower than that of the EU 15. The level of expenditure of the ALMPs in Serbia was about 0.2% of country's' GDP while Albania spent only 0.05% in 2015 (Numanovic et al., 2016).

Figure 1.14 ALMP Expenditure as a share of GDP; EU15, CEE and selected SEE, 2016

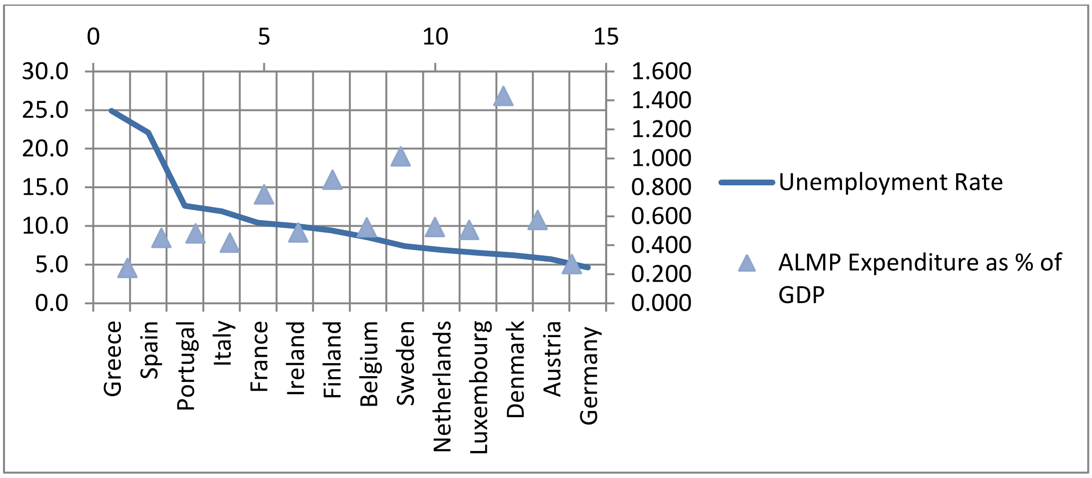


Source: Eurostat (2018) for EU member states and Numanovic et al., (2016) for SEE countries.

Note: Data for UK is not available. Data for Italy, Albania, Bosnia and Herzegovina (BiH) FYR Macedonia and Serbia are for year 2015.

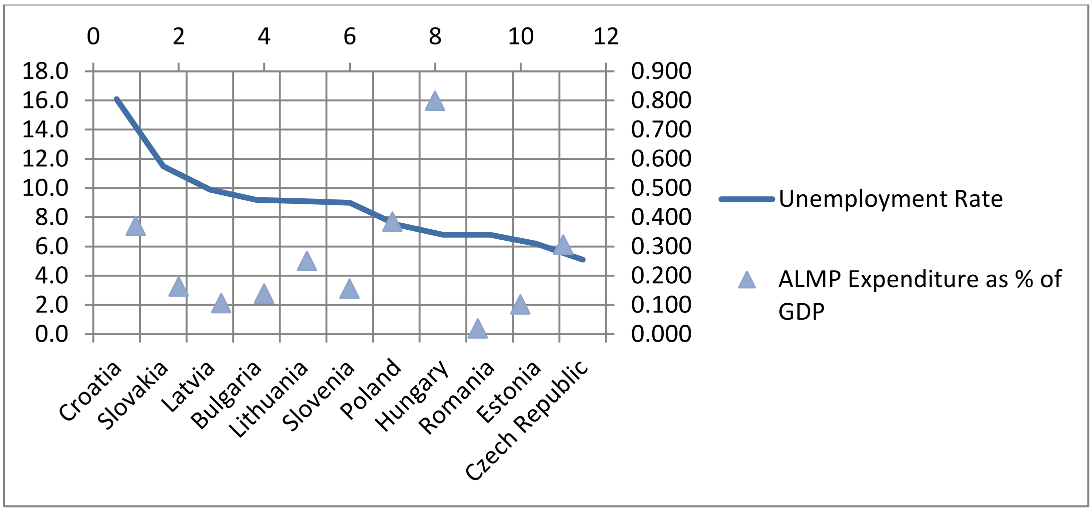
Figures 1.15 and 1.16 tend to capture the relationship between ALMP expenditure as share of GDP and unemployment rates for both the EU 15 and CEE for 2015. Figure 1.15 shows that there might be pattern relating the ALMP expenditure and unemployment rate for EU 15 countries. Figure 1.15 shows that the low spenders on ALMP as a % of GDP tend to have high unemployment rates, such as Greece, Spain, Portugal and Italy whereas countries that allocate more expenditure to ALMPs such as Finland, Sweden and Denmark tend to have lower unemployment rates. On the other hand, in the CEECs no clear relationship between ALMP expenditure and unemployment rate can be observed.

Figure 1.15 Unemployment rate and ALMP Expenditure as a share of GDP for EU15 countries, 2015



Source: Eurostat database (2018)

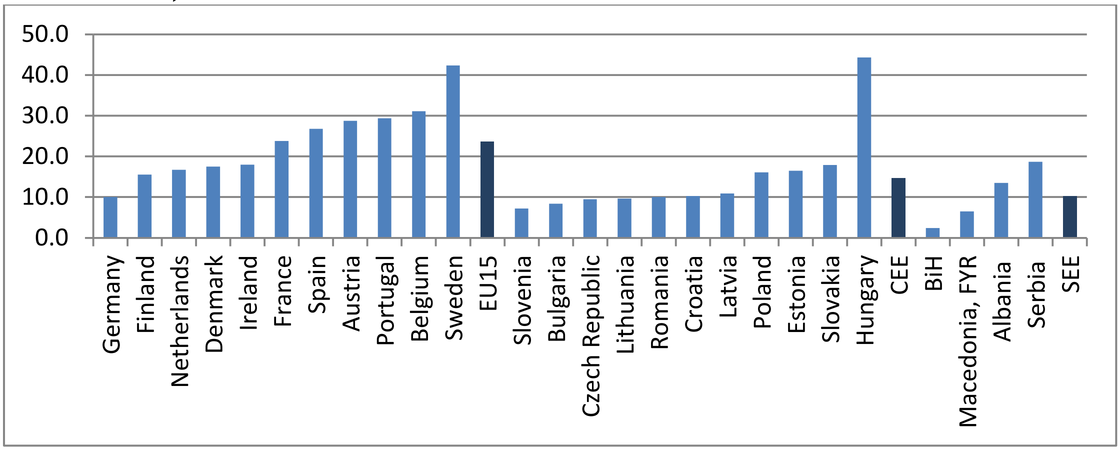
Figure 1.16 Unemployment rate and ALMP Expenditure as a share of GDP for CEE countries, 2015



Source: Eurostat database (2018)

Figure 1.17 shows that the coverage rate of the unemployed persons by ALMP (the share of registered unemployed benefiting from ALMPs in a given year) also varies greatly between countries. Except for Hungary (44.3%), every other country in CEE and SEE is below the EU average (23.6%). The lowest activation coverage is that of BiH and FYR Macedonia, the activation policies cover only 2.4% and 6.5% of registered unemployed respectively (Numanovic et al., 2016). The low coverage in these countries can partially be explained by the high unemployment which suggests that the number of unemployed assisted by these policies is too small and inadequate for these labour markets characterised by many challenges.

Figure 1.17 ALMP Coverage rate of unemployed persons (%); EU15, CEE and selected SEE, 2016



Source: Eurostat (2018) for EU member states, Numanovic et al., (2016) for Albania, BiH and FYR Macedonia and Gerovska (2017) for Serbia.

Note: Data for UK, Greece, Italy and Luxembourg is not available. Data for Ireland and Netherlands is for year 2014, Albania, Bosnia and Herzegovina (BiH) and FYR Macedonia is for year 2015.

As explained in section 1.4, active measures mainly target the low-skilled, long-term unemployed and marginalised groups and those groups that have problems entering the labour market. In a well-functioning implementation of the active policies, the predetermined target groups should be set so as to minimise deadweight and substitution effects[7]. Candidates for participation in active measures are usually selected based on particular criteria where all the registered unemployed from a given target group can apply. According to Steendam et al. (2010), the implementation of active measures in Germany and Belgium were especially successful partially due to well-defined target groups and the selection of participants based on the criteria. On the other hand, the ALMPs in transition countries, such as Albania, FYR Macedonia and BiH, did not follow the pre-set criteria for selection, but rather recruited from all the unemployed. Numanovic et al. (2016) emphasise that the targeting was not sufficiently personalised in these countries and there is no well-established institutional mechanism that could identify the needs of the job-seekers and help them through the employment process. The ILO (2014) also highlighted that in Albania vulnerable groups have limited inclusion in the active measures with current policies being poorly targeted on this category of job-seekers.

[7] The substitution effect leads to the substitution of one category of workers with the ALMP beneficiaries because they are less costly. The deadweight effect leads to employing the same individuals that would have been employed even in the absence of such programmes. More details about these two effects are provided in section 2.2.3.

1.6.2 ALMPs in Kosovo

One of the main objectives of the Ministry of Labour and Social Welfare in Kosovo is to increase employment through ALMPs (MLSW, 2017). However, the number of registered unemployed benefiting from ALMPs in Kosovo remains relatively low, mainly due to the limitations of the budget and staff of the Employment Agency of Kosovo. According to MLSW (2017), only about 10% of the 101,773 registered unemployed in 2016 benefited from ALMPs. The number of the ALMP beneficiaries, however, seems to be increasing since in 2015 only 6,966 registered unemployed benefited from these policies compared 10,419 in 2016. Table 1.1 presents the ALMPs in Kosovo during 2016, where vocational training in VTC (Vocational Training Centre) is the largest active measure with 7.6% of total registered unemployed.

Table 1.1 The number of ALMP participants in Kosovo, 2016

Indicator	**Classification by Eurostat**	**Number of participants in 2016**	**% of registered unemployed in 2016**
Employment through ALMPs	**Active Labour Market Programmes**	**1,781**	**1.8%**
Of which:			
Public jobs	Creating jobs	819	0.80%
Salary subsidy	Incentives for permanent employment	474	0.50%
Apprenticeship work	Labour market measures: Support to interns	434	0.40%
Self-employed	Incentives for self-employment	54	0.10%
Vocational training	**Active Labour Market Programmes**	**7,687**	**7.60%**
Of which:			
Vocational training in VTC	Institutional training	6736	6.60%
On-the-job training	Training on the job	951	0.90%

Source: MLSW (2017)

Similar to many Balkan Countries, ALMPs in Kosovo were introduced through support of international funds such as European Agencies, the German Government, the Swiss Government, the Government of Finland, the Luxembourg Government and United Nations Development Programme (UNDP) etc. Due to data unavailability, this thesis will focus only on a fraction of ALMPs implemented in

Kosovo, those implemented by UNDP in cooperation with the Ministry of Labour and Social Welfare. While this section briefly depicts the ALMPs implemented by UNDP, section 5.2 provides an extensive examination of the design and targeting and detailed data analysis of the active measures investigated.

This ALMP programme launched in 2007 (which was a continuation of the Employment Project which was implemented from 2005) and was targeted mainly at low-skilled young women and men aged 15 to 29 without previous work experience. The programme was implemented in seven regions in cooperation with regional and municipal employment offices and private sector enterprises. The programmes' prime objective was to increase the employability of youths in Kosovo. The ALMPs funded by the UNDP in Kosovo comprise the measures presented in table 1.2.

The total number of beneficiaries up to June 2016 was 13,285. The active measure with the largest number of beneficiaries is On the Job Training with 4,429 beneficiaries, the Public Works projects with 3,194 followed by Wage Subsidies and the Internship Scheme with 2,794 and 1,175 respectively (UNDP, 2014). From the total number of beneficiaries at least 50% were women, 21% were from minorities and 56% were from rural areas.

Table 1.2 ALMPs implemented by UNDP and MLSW in Kosovo during 2005 – 2016

Active labour market measures	No. of beneficiaries in total since 2005
Public Works projects	3194
On the Job Training (OJT) 2007	4429
Pre-Employment Training (PET) 2007 – 2008	79
Wage Subsidies (WS)	2794
Internship Scheme (ISch)	1175
Institution and Enterprise based training (IET) 2008	373
Training at a local school 2007 – 2008	40
Professional practice in enterprise for VET students	1138
The Self-Employment Programme	63
Total Beneficiaries	**13,285**

Source: Active Labour Market Programme for Youth, UNDP, 2016

The above-mentioned interventions applied in Kosovo helped young people to establish interaction with labour market for the first time through enhancing employability and vocational skills. According to the UNDP's Annual Report (2014) the ALMP programmes have successfully provided equal opportunities to youths and the disadvantaged and integrated minorities and other low-skilled groups into the labour market. In 2008 and 2012, two different external evaluations of the programmes concluded that the ALMPs generated positive benefits and they increased the chances of the participants getting employed (Mukavilli, 2008; Kavanagh, 2012). Even though the ALMPs implemented were considered successful, the Labour Force Survey results show that the youth unemployment rate in Kosovo still remains high. Both of the previous evaluation studies were largely at a descriptive level of analysis, providing only a comparison of descriptive statistics between treatment and control groups. Kavanagh (2012) uses a control group of only 150 individuals in comparison to 1,082 treated which raises doubt as to the reliability of the analysis. Mukavilli (2008) uses a more balanced sample, though the latter is small, 399 individuals where 100 are control individuals. Neither of the studies used an advanced evaluation methodology to assess the ALMP effectiveness thus they do not account for potential selection bias. Chapters 5 and 6 use the same data as Kavanagh (2012), though the latter will also utilise the Labour Force Survey data collected in 2012 while employing the most recent evaluation methodology.

1.7 Conclusions

This chapter provided the initial analysis of the labour market indicators and ALMP expenditure and coverage in European transition and non-transition economies. Given the focus of this thesis, particular emphasis was given to Kosovo. Transition economies experienced a large drop in labour force participation rates and an increase in unemployment during the first stages of transition process. Labour force participation has increased steadily in CEE economies almost reaching those in Western European economies in recent years. The unemployment rate in CEE has also dropped continually during the last decade and on average it is lower than that of the EU15. The unemployment rate in SEE, however, still remains very high and the long-term unemployment rate is also much higher than in the other regions as is the size of the informal sector. This chapter also assessed expenditure on ALMPs, comparing the expenditure of European transition and non-transition economies. The figures presented in section 1.6.1, point out that transition economies allocate considerably less expenditure, as a % of GDP, to ALMPs compared to non-transition economies. It is also observed that the non-transition economies allocating higher expenditure to ALMPs have lower unemployment rate. This pattern of the relationship between ALMP expenditure and unemployment rate, however, is not observed in transition economies. The transition economy with the most daunting problem of unemployment is Kosovo, despite its high unemployment rate the expenditure allocated to ALMP is very low compared to other countries in the region.

The first part of this chapter presented the aim, objectives and the structure of this research project. Given the high unemployment rates in transition economies and the goal of ALMPs in enhancing individuals' skills and improving employment opportunities, this thesis aims to analyse to what extent these policies can reduce unemployment in European transition and non-transition economies. Section 1.2 pointed out the lack of empirical studies for transition economies, especially those employing more advanced evaluation methodologies. This thesis fills this gap in the literature by evaluating ALMPs in European transition and non-transition economies using the most recent techniques. The following chapter will critically analyse the theoretical framework through which the effectiveness of ALMPs can be empirically investigated.

Chapter 2

Theoretical Framework for the Analysis of ALMPs and the Review of Empirical Studies of the effectiveness of ALMPs at the Country Level

2.1 Introduction

Chapter 1 provided an introduction to the state of the labour markets in European transition economies, with special reference to Kosovo. It focused on the factors influencing their high rates of unemployment and the types and scope of Active Labour Market Policies (ALMPs). One of the main objectives of this second chapter is to provide a critical assessment of the theory of the Non-Accelerating Inflation Rate of Unemployment (NAIRU) based on the framework of Layard, Nickell and Jackman (1991) and the role of ALMPs in reducing unemployment. Layard, Nickell and Jackman is the most commonly used theoretical framework to analyse the NAIRU. This theoretical framework will be used to set the ground and critically review the arguments for analysing the multiple effects of the ALMPs at the individual and economy-wide level. The hysteresis hypothesis of unemployment will be critically analysed. Given the context of European transition economies, a less restrictive version of NAIRU, the structuralist view of unemployment, will be developed to evaluate the nature of unemployment.

A major gap in the theoretical and empirical literature is the analysis of the effectiveness of ALMPs in the context of countries with high informal employment. An important objective of this chapter is to provide a concise and critical assessment of the arguments associated with the relationship between ALMPs and informal employment and what are the mechanisms through which ALMPs could provide incentives for the switch from informal to formal employment.

Chapter 1 observed that disadvantaged labour and, particularly, youth unemployment is one of the main targets of the ALMPs. However, the literature review shows that youth unemployment has not been the focus of empirical studies resulting in a gap between the aims and the results of these policies. Data unavailability in European transition economies frequently limits empirical studies assessing the effectiveness of ALMPs on youth unemployment. This chapter has a particular focus on investigating the theoretical explanations of the causes of youth unemployment in transition economies with particular emphasis on Kosovo.

The rest of this chapter is organised as follows. Section 2.2 reviews two theoretical approaches, the traditional NAIRU theoretical model and the Hysteresis hypothesis and provides a thorough discussion on the effects of ALMPs in the context of

Layard-Nickell-Jackman model. Section 2.3 discusses the causes and characteristics of unemployment in labour markets in transition economies which will be followed by a review of the empirical studies that assessed whether the nature of unemployment in transition economies conforms more to the structuralist or the hysteresis hypothesis. Since the empirical analysis in chapter 3 will also include European non-transition economies, section 2.5 will review more recent empirical studies for these countries. The theory of the duality of the labour markets in the context of transition economies is analysed in section 2.6 while section 2.7 provides a discussion of the causes of youth unemployment in transition economies. Finally, in section 2.8 the conclusions of the chapter are summarised.

2.2 A Theoretical Framework for the Analysis of ALMPs

In the theoretical field there are currently two main unemployment hypotheses: the Non-Accelerating Inflation Rate of Unemployment (NAIRU) and Hysteresis. The first emphasises the presence of a Non-Accelerating Inflation Rate of Unemployment (NAIRU) which is the equilibrium rate of unemployment and hypothesises that there is no long-run trade-off between unemployment and inflation (Ball and Mankiw, 2002). This view of the NAIRU is that there is a level of the unemployment rate below which the inflation rate accelerates while above it the inflation rate decelerates; thus if the unemployment rate is always equal to the NAIRU, the inflation rate will be constant in the long-run aside from the effects of short-run shocks (Fair, 1999). This theory was firstly proposed by Phelps (1968) and Friedman (1968) who argue that shocks have only temporary effects on the equilibrium rate and unemployment will tend to get back to that rate in the long-run. The traditional view of the NAIRU implies that the equilibrium unemployment rate changes slowly over time due predominantly to demographic factors. A less restrictive version of the NAIRU was developed by Phelps (1994) which allows the equilibrium rate to deviate in response to shocks in the underlying economic factors determining the equilibrium rate such as: the real interest rate (Blanchard, 1999), productivity growth (Pissarides, 1990) and the labour market institutional framework such as the generosity of the unemployment benefit system, other non-wage income, etc. (Marjanovic and Mihajlovic, 2014). This is referred to as the Structuralist view and suggests that most shocks cause a temporary divergence from the natural rate of unemployment but if the shock is strong enough it might cause a shift in the equilibrium rate to a higher level. According to Papell et al. (2000) the structuralist view suggests that unemployment is stationary around a process that is subject to structural changes.

The increase of unemployment during the oil shock in the 1970s made the hysteresis hypothesis popular. This hypothesis states that shocks may have a permanent effect on the unemployment rate over the long-run path. The hysteresis hypothesis implies that after a shock the unemployment rate may never return to the previous equilibrium rate because of labour market rigidities explained by insider-outsider interactions and by human capital depreciation and social stigma related to the long-term unemployed (Blanchard and Summers, 1986, 1988; Layard et al., 1991). Thus, this hypothesis emphasises that unemployment is not a stationary process. Additionally, it is also possible to observe a 'persistence' in unemployment which implies a very slow speed of adjustment and it needs a long period of time to revert to the equilibrium rate after the shock.

Considering the high unemployment rate in transition economies, discussed in Chapter 1, it is important to observe the nature of unemployment and assess whether it is better explained by the NAIRU or the Hysteresis hypotheses in order to design appropriate measures directed to reduce unemployment. If unemployment patterns are in accordance with the NAIRU, then it can be reduced through institutional measures such as a reduction in unemployment benefits, increasing labour market flexibility and labour mobility, reducing the strictness of the employment protection, introducing more active labour market policies to enhance skills through labour training and so on. If the unemployment in transition economies exhibits more hysteresis effects, besides applying the same policies as to reduce the NAIRU, policies should also be directed at increasing aggregate demand through monetary and fiscal policies.

Both hypotheses concerning the determinants of the unemployment rate will be critically reviewed in the following sections. Sub-section 2.2.1 will establish the determinants of NAIRU in the Layard, Nickell and Jackman (1991) approach which is most commonly used when analysing the macroeconomic effect of ALMPs. Sub-section 2.2.2 will provide a critical discussion on the hysteresis hypothesis and the implications of the insider-outsider hypothesis. A review of the effects of ALMPs at the economy level is provided in section 2.2.3.

2.2.1 Layard, Nickell and Jackman's approach to the NAIRU

The most popular version of the NAIRU is the model developed by Layard, Nickell and Jackman (1991). This model assumes an economy of imperfectly competitive profit-maximising firms facing exogenously determined product market conditions and predetermined capital and technology (Layard et al., 1991). The model assumes that firms and labour have a certain bargaining power to set the price of output in the case of firms and the price of supplied labour in the case of workers. The model is consistent with the efficiency wage framework or a wage bargaining model.

The equations of price and wage setting introduced below illustrate the main points of the model. According to Blanchard (2006), the price-setting and wage-setting relations resemble the labour demand and labour supply in a neoclassical model of labour market analysis.

$$p - w = \beta_0 + \beta_1 (y_d^e - \bar{y}) - \beta_2 (p - p^e) - \beta_3 (k - l) \qquad 2.1$$

$$w - p = \gamma_0 + \gamma_1 u - \gamma_2 (w - w^e) - \gamma_3 (k - l) + Z_w \quad \text{where } \gamma_3 = \beta_3 \qquad 2.2$$

where p is the aggregate value added price (GDP deflator), w is the aggregate level of wages, p^e and w^e are the expectations of the future prices and labour costs, respectively, y_d^e is the level of expected demand in the economy, $\bar{y}$ is the level of output in the economy corresponding to full utilisation of resources, u is the aggregate unemployment rate, l is the fixed labour force, k is the capital stock and Z_w is the is the effect of wage-push factors such as unions and the generosity and coverage of unemployment benefits.

The behaviour of firms is captured by equation 2.1, where the firms set prices as a mark-up over labour costs $(p - w)$ which depend on demand conditions, i.e. on the difference between expected demand and the level of output in the economy corresponding to full utilisation of resources $(y_d^e - \bar{y})$, the difference between the actual aggregate value added price and expected price $(p - p^e)$ and productivity $(k - l)$. As expressed by equation 2.2, real wages $(w - p)$ are influenced by firm specific factors such as the productivity $(k - l)$, on one hand, and the labour market specific factors such as the difference between the actual and expected wages $(w - w^e)$, the unemployment rate u, and wage-push factors Z_w, including union bargaining strength and unemployment benefits. Layard et al. (1991) note that an important assumption of the model is that the measure of productivity in the price mark-up and wage equations are exactly the same, which suggests that the capital and labour are perfect substitutes for each other.

Equations 2.3 and 2.4 below present the aggregate side of the economy.

$$y_d - \bar{y} = -\alpha u + \varepsilon \tag{2.3}$$

$$y_d = \sigma_1 x + \sigma_2(m - p) \tag{2.4}$$

Where ε is the technology shock, y_d is the actual aggregate demand, x stands for exogenous demand factors such as monetary or fiscal policy shocks, and m is the money stock. $(y_d - \bar{y})$ expresses the difference between the actual aggregate demand and the level of output corresponding to full utilisation of resources. Equation 2.3 expresses the relationship between the output and the unemployment rate which suggests that for a given ε, a rise in the unemployment rate will be accompanied by a fall in the output. Equation 2.4 expresses the relationship between the aggregate demand and the exogenous real factors such as fiscal policies denoted by x and nominal money balances $(m - p)$.

In the long-run, it is assumed that the expectations regarding future wage and price are fulfilled thus there are no wage and price surprises, thus $w = w^e$ and $p = p^e$ and no difference between expected and actual demand $y_d = y_d^e$. Substituting equation 2.4 into 2.1 and equating equation 2.1 with 2.2 will give the long-run unemployment and wage equilibrium presented in equations 2.5 and 2.6.

$$u^* = \frac{\beta_0 + \gamma_0 + Z_w}{\beta_1 + \gamma_1} \tag{2.5}$$

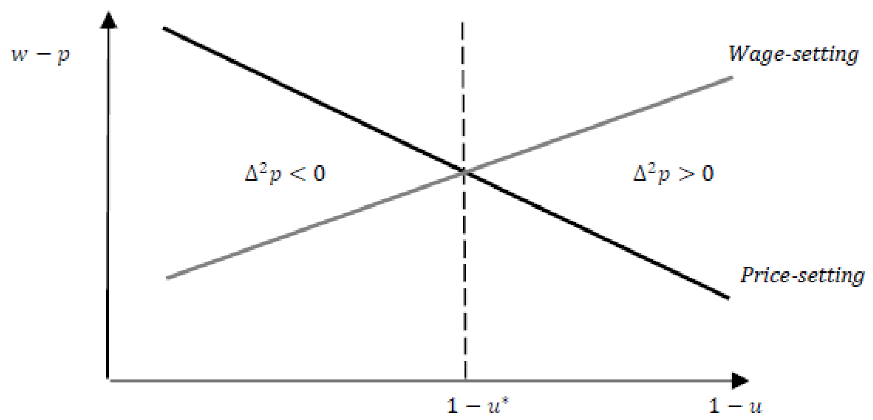
$$(w - p)^* = \frac{(\beta_0 \alpha \gamma_0 - b_0 \gamma_1)}{\gamma_1 + \beta_1 \alpha} + \frac{\beta_0 \alpha Z_w}{\gamma_1 + \beta_1 \alpha} + \beta_3(k - l) \tag{2.6}$$

From equation 2.5, one can see that unemployment equilibrium is determined by the exogenous wage pressure Z_w and the parameters of the wage and price equations 2.1 and 2.2, β_0 and γ_0 respectively. The equilibrium level of unemployment does not depend on the difference in growth rates of capital and labour, the latter only influences the real wage as seen in equation 2.6. This follows from the equality of the coefficients of the trend productivity expressions in the price and wage equations. Layard et al. (1991) explain that if these coefficients were different it would give unemployment a trend dependent upon productivity growth. However, these authors acknowledge that such a trend is not observed in the data hence their assumption. The long-run equilibrium level of unemployment is not influenced by either monetary or fiscal policies. A key feature of the model is that the exogenous demand side policies do not influence this equilibrium as described in equation 2.5.

In the short-run, however, expectations may not be achieved which causes the level of unemployment to diverge from its equilibrium rate. This generates the negative relationship between inflation and unemployment; when the unemployment falls below the natural rate, the inflation rate rises and vice versa. Thus u^* in equation 2.5 may be presented as the Non-Accelerating Inflation Rate of Unemployment – NAIRU.

A graphical representation of the NAIRU is presented in Figure 2.1 which is based on Layard et al. (1991). It presents the price setting curve which is the graphical illustration of equation 2.1 and the wage-setting curve corresponding to equation 2.2. The point where the two setting curves intersect represents the equilibrium thus both workers and firms have fulfilled price and wage expectations. To the right of the intersection, the inflation rate rises while on its left it falls.

Figure 2.1 Layard–Nickell-Jackman Framework



Source: Layard et al. (1991)

Layard et al. (1991) also incorporated the hysteresis hypothesis into their NAIRU model by introducing the short-run change of unemployment in the price and wage-setting equations, Δu. This term stands for the unemployed workers fired in the last period which captures the influence of recently laid-off workers on real wages and equilibrium unemployment. The hysteresis hypothesis was pioneered by Blanchard and Summers (1986) when analysing the persistent high unemployment rates in Europe during the 1970s and 1980s. Blanchard and Summers (1986) argued that if uncommonly large shocks can increase unemployment rate for a sufficient length of time, it is likely that the level of NAIRU will increase. The model by Blanchard and Summers (1986) implies that it is the bargaining power of the remaining employees (insiders) that sets the new wage level for the whole labour market which will determine the level of unemployment. The greater the bargaining power of the insiders, the higher the wage level and the higher the unemployment rate. The following section will discuss the hysteresis hypothesis and the sources of the insider power that can determine the wage level and unemployment rate.

2.2.2 The Hysteresis hypothesis and Insider-Outsider theory

Some scholars suggest that the labour market displays a form of hysteresis (Blanchard and Summers, 1986; Layard et al., 1991; Ball and Mankiw, 2002; Gali, 2015). An aggregate shock, such as negative productivity shock or an external globalisation shock, would influence unemployment by causing it to diverge from its natural rate and then could have a permanent effect on it, since the unemployment rate will not return to the initial equilibrium after the shock (Blanchard and Summers, 1986; Cuestas and Ordonez, 2011).

The insider-outsider theory assumes that there is a long-term employment relationship between firms and their workers. According to Blanchard and Summers (1986, 1987) and Lindbeck and Snower (1988), the main element of the insider-outsider theory is wage rigidity and the power of the insiders in the wage-setting mechanism. Blanchard and Summers (1986) point out that unemployment hysteresis/persistence can result from the 'membership rule' which considers the employed as the insiders who ignore the outsiders (the unemployed) in wage-setting. Insiders are concerned with maintaining their desired level of wages in their current jobs while not ensuring employment opportunities for outsiders. An unanticipated negative structural shock increases the unemployment level which will reduce the number of insiders in the labour market. Even though some previous workers lose their insider status, the smaller group of insiders will in the future set wages at the level to maintain this new lower level of employment.

According to Lindbeck and Snower (1988), insiders' power comes about as the result of the turnover costs which make it costly for employers to recruit new employees to replace current ones. Considering that insiders have experience and accumulated skills during their working period in the firm, it will be costly to fire insiders and hire outsiders who will require additional costs such as greater supervision, additional job-specific training and so on. In addition, insiders' turnover requires costly firing procedures and severance payments. Taken together these turnover costs give power to insiders since these costs may not be recovered in the form of lower unit labour costs associated with new workers. Hence the larger the turnover costs for the employer, the more power insiders will gain in setting wages above the market clearing level. Given the higher wages, jobs become more attractive which will result in higher labour supply relative to labour demand leading to a higher involuntary unemployment. The key point made by Lindbeck and Snower (1988) is that not only are these turnover costs likely to be significant, they are highly likely to be influenced by insiders. Since the employers have to bear some of these costs, they may not have an incentive to replace insiders with outsiders. Lindbeck and Snower (1987, 1988, 2001) also emphasise that insiders may increase cooperation with each other (individually or collectively) in the production process in order to boost their wage level. This cooperation will not take place with potential undesired entrants (outsiders) which would further lower the productivity of the outsiders.

As explained by Blanchard and Summers (1986), the existing employees hold 'membership status' as insiders in the firm. Lindbeck and Snower (1988) extended the basic framework to allow for the membership status to be acquired and lost at different rates. The recently unemployed workers may maintain their status and new employees may need to be employed for a continuous period of time to acquire that status. Layard et al. (1991) also categorise the long-term unemployed as outsiders, arguing that the short-term and long-term unemployed are not comparable in a sense that human capital can deteriorate the longer the individual is unemployed. The long-term unemployed subsequently can be less competitive in the labour market and less attractive to the employer (Calmfors and Lang, 1995; Dobbie, 2006; Gali, 2015). Additionally, the individual might get accustomed to being unemployed and reduce their job-search intensity (Ball and Mankiw, 2002; Leon-Ledesma and McAdam, 2002). Employers frequently use the duration of unemployment as a screening mechanism when hiring new employees so the longer one is unemployed the lower chances to be considered employable (Dobbie, 2006).

In conclusion, under the hysteresis hypothesis in addition to reforming the structure of labour market, such as labour market institutions, wage bargaining legislation and union power, policy makers can seek to reduce unemployment through engineering a number of positive shocks to the labour market through stimulating aggregate demand.

The following section will analyse the various effects of ALMPs based on the theoretical approach of Layard, Nickell and Jackman (1991) outlined above. This section will be followed by a discussion on the nature of unemployment in transition economies and a review of empirical studies that discuss whether unemployment in these countries conform to the structuralist or hysteresis hypotheses.

2.2.3 Effects of Active Labour Market Policies at the Economy Level

The effectiveness of ALMPs needs to be analysed in a framework where the determinants of the labour market equilibrium are explicitly addressed. The labour market analysis developed by Layard et al. (1991) is now used as that base theoretical framework for assessing the economy wide effects of the ALMPs in the labour market framework. Calmfors (1994) modified the LNJ model to make a distinction between regular employment in the labour market and participation in active programmes. In this model, the proportion of individuals in the labour force who participate in active measures are deducted from the regular labour force. This is illustrated in the Figure 2.2 by a leftward shift of labour force curve. The difference between unemployment at the initial equilibrium point (point A in Figure 2.2) and the reduced labour force is referred to as open unemployment. Thus, regular employment refers to the employment excluding participants in the active programmes, even though from the employee point of view the subsidised jobs are perfect substitutes for regular employment (Calmfors, 1994). According to Calmfors et al. (2002), ALMP effects can influence the labour market either through the wage-setting or the price-setting schedules.

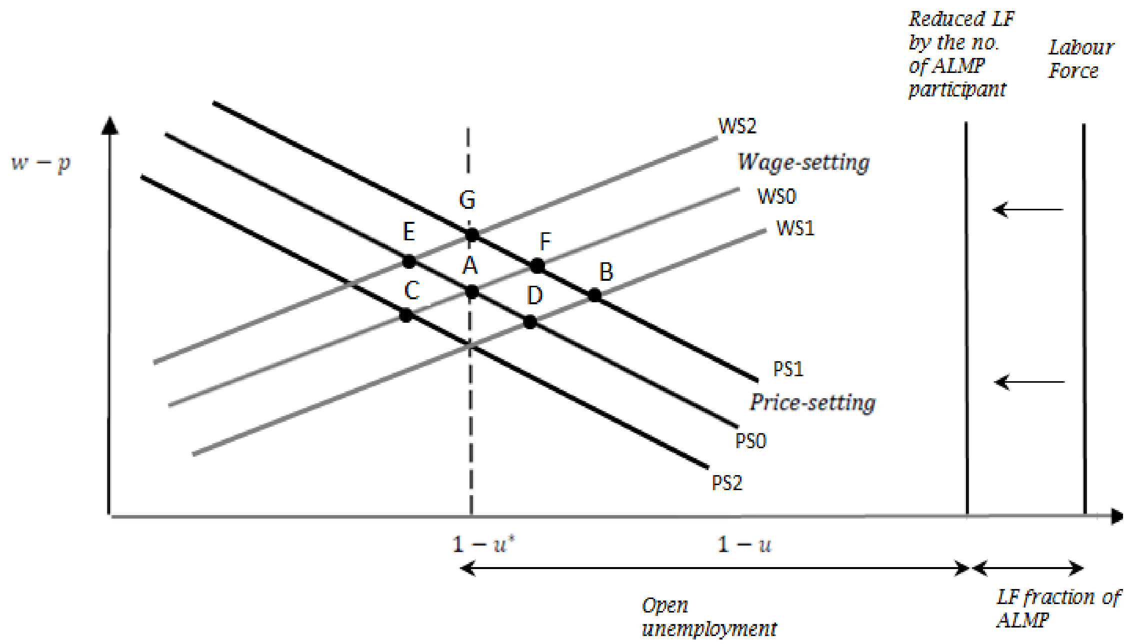
Using this framework, the following effects of ALMPs will be discussed and illustrated in Figure 2.2 and in equation 2.5:

- Effects on the matching process
- Productivity effects
- Effects on labour force and competition in the labour market
- Deadweight loss and substitution effects
- Reduced welfare losses for the unemployed
- Work – test effects

Effects on the matching process - Active labour market policies traditionally are thought to facilitate the matching process in the labour market which has frequently been regarded as their primary function (Calmfors et al., 2002; Card et al., 2010; Schmidl, 2014; Escudero, 2018). This is achieved through several channels.

Firstly, ALMPs may enable the qualifications and skills of the beneficiaries to be better adapted to the structure of the demand for labour. More particularly, as explained in Chapter 1, this would be the effect of training and re-training programmes, where the beneficiaries can acquire skills based on the requirements of unfilled jobs. Secondly, through participating in the active programmes, the unemployed individuals' job-search activity may be encouraged and better targeted. Finally, active labour market programmes can substitute for the regular employment experience and thus reduce employers' uncertainty about the employability of the beneficiaries. This effect would be predominantly attributed to subsidised employment and on-the-job training.

Figure 2.2 Economy wide effects of ALMPs on wages and regular employment



The number of unemployed job-seekers relative to that of vacancies would be likely to decrease when a better matching process is achieved in equilibrium. This would affect both the wage-setting and price-setting schedules in the model. The initial equilibrium is point A in Figure 2.2. The firms' costs decline because vacancies are filled more quickly and due to that, firms provide more vacancies which is equivalent to an increase in the labour demand. This effect can be interpreted as a rightward shift in the price-setting curve from PS0 to PS1 in Figure 2.2, thus from equilibrium point A to equilibrium point F. In the equation of the equilibrium unemployment 2.5, this effect is depicted by a decrease in parameter β_0 which captures firm's mark-up of prices on their costs.

$$u_F^* = \frac{(\beta_{0F} \downarrow) + \gamma_0 + Z_w}{\beta_1 + \gamma_1} \qquad 2.7$$

Furthermore, the same effect also deteriorates the position in the wage bargaining process of the existing employees (or unions) relative to firms. The argument is that since the firm can expect to fill the vacancy easier, the firm has a better bargaining position relative to existing employees. Since this effect improves the matching effectiveness, it reduces the employers' incentive to attract labour by pushing up wages. Thus this can induce a downward shift of the wage-setting curve from WS0 to WS1 in Figure 2.2. This is illustrated in Figure 2.2 as a shift in the equilibrium from point A to B and in the equation 2.8 by a decrease in parameter Z_w which captures the bargaining position of existing employees relative to firms. Both effects increase regular employment but the net effect on real-wage is unclear.

$$u_B^* = \frac{\beta_0 + \gamma_0 + (Z_{wB} \downarrow)}{\beta_1 + \gamma_1} \qquad 2.8$$

The effect on the matching process might be negative given the reduced search behaviour of the active programme participant, i.e. the so-called lock-in effects (Van Ours, 2001; Schmidl, 2014). The job search intensity of participants in ALMPs is highly likely to decrease during the training period. Except for job search assistance, the lock-in effect has been found to be important for all types of active measures, especially for subsidised employment (Van Ours, 2001, 2002; Sianesi, 2008; Schmidl, 2014). One must also take into account that search intensity might have been reduced before participating in the programmes. In such cases, the search intensity of the beneficiary before and during ALMP participation is expected to be lower than that of the openly unemployed (Holmlund and Linden, 1993; Hamalainen, 2002; Sianesi, 2008; Schmidl, 2014).

Productivity effects - One of the most desired effects of active policies is the increase in the productivity of the job-seekers (Hamalainen, 2002; Kluve et al., 2007; Card et al., 2017). As pointed out in Chapter 1, active measures are mainly targeted at the long-term unemployed and disadvantaged labour in general. Taking into account that the productivity of the targeted individuals is frequently relatively low due to human capital deterioration or other reasons, one of the aims of the active programmes is to offset this tendency through training. Subsidised employment also serves the same purpose through increasing the beneficiaries' experience and additional learning on-the-job. The consequent effect of the increase in productivity on employment is uncertain. When the labour becomes more efficient, the scale effect tends to increase employment because of the tendency to extend output because unit labour costs fall, ceteris paribus. The fall in unit labour costs is captured by a decrease in parameter β_0 in equation 2.9. This effect would result in a rightward shift on the price setting schedule from PS0 to PS1 thus leading to a higher regular employment. The new equilibrium point is reflected by a shift from point A to point F in Figure 2.2.

$$u_F^* = \frac{(\beta_{0F} \downarrow) + \gamma_0 + Z_w}{\beta_1 + \gamma_1} \quad 2.9$$

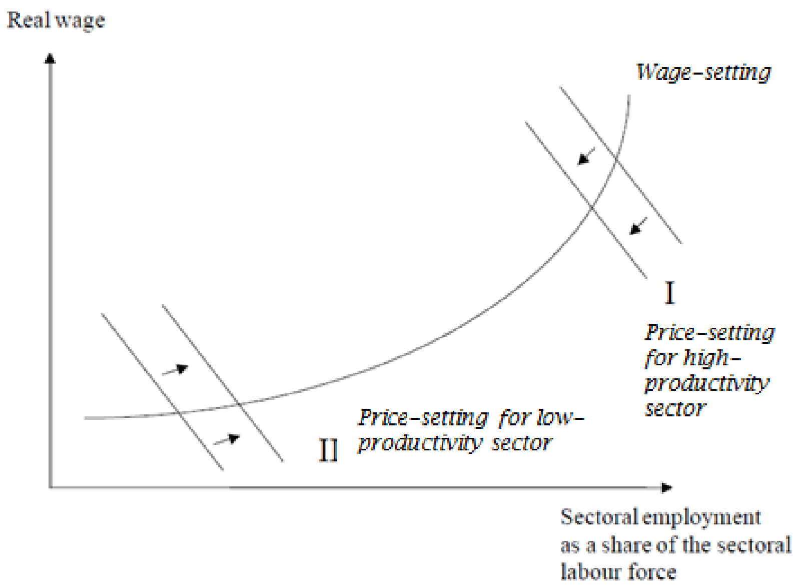
On the other hand, since a given output can be produced with a smaller number of workers, the substitution effect tends to reduce the number of employees. These effects make the result of productivity effects on regular employment ambiguous. The increase in productivity might also increase the beneficiaries' reservation wages which results in real wages going up at any given level of regular employment i.e. a leftward shift of the wage-setting schedule from WS0 to WS2. This is illustrated in Figure 2.2 as a shift from point A to point G and in equation 2.10 by an increase in parameter $Z_w$which reflects a higher level of real wages but leaving the employment rate unchanged.

$$u_G^* = \frac{\beta_0 + \gamma_0 + (Z_{wG} \uparrow)}{\beta_1 + \gamma_1} \quad 2.10$$

According to Calmfors et al. (2002), the net effect of the increase in productivity on the wage and price settings depends on the magnitude of these two opposing effects of active policies.

Another important potential effect of active policies is to transfer labour from low productivity to high productivity sectors through training and other programmes which aim to enhance the skills of the unemployed (Calmfors et al., 2002; Speckesser, 2004; Card et al., 2010; Card et al., 2017). When the skills of the unemployed are enhanced it is expected that labour supply transfers from low to high productivity sectors. This effect is presented in Figure 2.3. The economy consists of two sectors: a low-productivity sector (price schedule I) and a high-productivity (price schedule II) sector. Figure 2.3 shows that the wage-setting curve has different slopes corresponding to these two sectors. The higher the employment rate in the sector the steeper the wage-setting curve, meaning that employers will have to offer higher wages to employ higher-productivity labour. Labour demand is assumed to be higher in the high-productivity than in low-productivity sector. After the successful completion of active programmes low-productivity labour will be transferred to the higher-productivity sector. Calmfors et al. (2002, p.17) point out that "*the labour demand as a share of sectoral workforce at a given real wage falls in the high productivity sector where labour supply increases, and rises in the low-productivity* *sector where labour supply decreases*". This result is illustrated as a shift of the labour demand (price-setting curve) to the left in the high productivity sector and a shift to the right for the low-productivity sector. Thus, the demand for high-productivity labour falls while the demand for low-productivity labour increases. Having in consideration that the wage-setting schedule has a steep slope, the high productivity workers will face a substantial fall in the real wages while the low productivity workers will face only a marginal increase of real wages. On the other hand, employment of low-productivity workers can increase by a larger amount than the fall of the employment of high-productivity workers. Therefore, the net effect on employment of the reallocation of the labour force between the two sectors is expected to be positive.

Figure 2.3 Reallocation of unemployed between high-productivity and low-productivity sectors



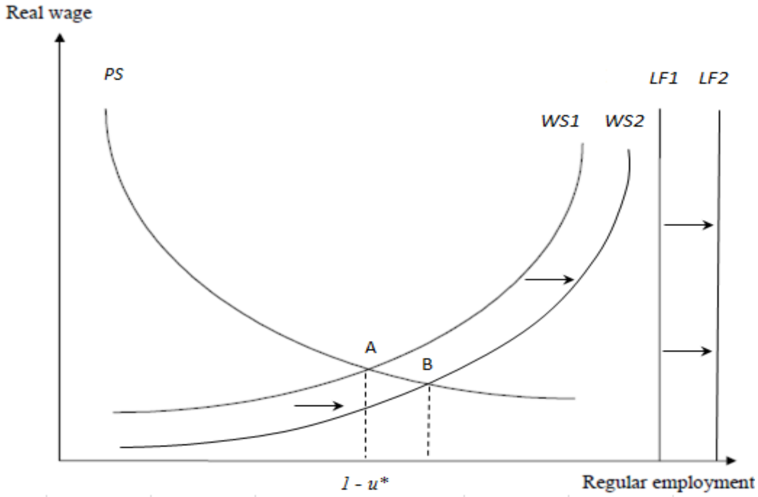
Source: Calmfors et al. (2002)

Effects on labour force and competition in the labour market - One of the most important effects of the ALMPs is to preserve the size of the labour force since due to the discouragement amongst the unemployed, especially long-term unemployed, in the absence of such policies the labour supply will tend to shrink, other things being equal. Figure 2.4 illustrates the anticipated effect of active measures on labour force participation. Participating in active programmes increases the motivation to actively search for jobs which counteracts the "discouraged-worker effect" of unemployed. Active measures tend to increase labour force participation, hence a positive labour supply effect would be illustrated with a rightward shift of the labour force curve (the vertical curve presented in Figure 2.4). However, in the absence of a secondary effect this would result in a higher unemployment level.

The effect of active policies on increased competition for jobs can be analysed within the insider-outsider framework (Blanchard and Summers, 1986; Calmfors, 1994; Calmfors and Lang, 1995). As discussed in Chapter 1, active programmes target the outsiders in the labour market, typically the young unemployed, long-term unemployed, people out of labour force, women, immigrants etc. It is the increased competition from outsiders following a successful active programme that discourages insiders from putting upward pressure on wages. The lower level of real wage would incentivise employers to raise the employment level resulting in a rightward shift of the wage-setting curve. Thus, an initial increase in the unemployment rate which raises competition for jobs in the labour market puts downward pressure on real wages and subsequently results in firms hiring more workers. This effect is shown in equation 2.11 by an increase in parameter $\gamma_1$which captures the increase in the unemployment rate and illustrated in Figure 2.4 with a shift from WS1 to WS2 resulting in equilibrium point change from A to B[8]..

$$u_D^* = \frac{\beta_0 + \gamma_0 + Z_w}{\beta_1 + (\gamma_{1D} \uparrow)} \qquad 2.11$$

Figure 2.4 The effect of ALMPs on labour force and competition in the labour market



Source: Calmfors et al., (2002)

[8] In Figure 2.2 this effect is also illustrated with the shift from equilibrium point A to point D.

Deadweight loss and substitution effects[9] - Active policies might also have unintended negative effects in the labour market such as crowding-out regular employment (Dahlberg and Forslund, 1999, Kluve et al., 2006; Schmidl, 2014). Two such unintended effects induced by active policies are: the substitution and deadweight effect. The first effect leads to the substitution of one category of workers with another because relative wage costs have changed, in this case in favour of the active programme beneficiaries. The deadweight effect leads to employing the same individuals that would have been employed even in the absence of such programmes. These effects are most likely to occur in case of subsidised employment and job creation schemes. These effects are expected to reduce regular employment which results in a leftward shift of the price-setting curve from PS0 to PS2 in Figure 2.2 and a new equilibrium point from A to C which tend to reduce real wages (Calmfors, 1994; Calmfors et al., 2002).

$$u_C^* = \frac{\beta_0 + \gamma_0 + Z_w}{\beta_1 + \gamma_1} \qquad 2.12$$

Reduced welfare losses for the unemployed – Active policies' objective is to increase the welfare of participants since it increases their expected future level of income. Additionally, beneficiaries may experience improved emotional and psychological well-being compared to remaining unemployed (Calmfors et al., 2002). Beneficiaries may perceive participation in the active programmes as meaningful thus increasing their well-being. Another objective of active programmes is to improve their future income and prospects in the labour market and increase their probability of getting a job and remaining employed thus participation in these programmes decreases the risks of future 'unemployability'. All of the above effects of ALMPs reduce the welfare difference between having and not having a job, so that they increase the wage pressure under the process of collective and individual wage bargaining. The individual workers acquire wage bargaining power relative to employers since now they possess more employable skills. Trade unions have also an incentive to negotiate higher wages because even if workers risk losing their jobs as a consequence of wage rises they face better opportunities of finding alternative

[9] According to Kluve et al. (2007) another negative effect of ALMPs is the displacement effect. This effect tends to crowd out from the market firms or workers receiving no subsidies. Because it is less costly for the subsidised firm to increase its output, the unsubsidised firm becomes less competitive in the market and reduces the regular employment. In the context of this thesis, the displacement effect is regarded as another substitution effect.

employment. This is reflected in the equation 2.13 with an increase in wage push factor Z_w which leads to an increase in real wages and higher unemployment. This effect is illustrated in Figure 2.2 as an upward shift of the wage-setting curve where the equilibrium unemployment moves from point A to point E.

$$u_E^* = \frac{\beta_0 + \gamma_0 + (Z_{wE} \uparrow)}{\beta_1 + \gamma_1} \qquad 2.13$$

Work-test effects – A certain number of recipients of unemployment benefits may not be interested in searching for work and thus are not expected to be willing to participate in active programmes. In a labour market with high unemployment it is not easy to identify the individuals who are not willing to be employed. Thus participating in the active measures may serve as a 'work test' for the eligibility of unemployment benefits, since those who are not interested in being employed will prefer to continue receiving unemployment benefits. In countries where participation in the active programmes is mandatory to obtain the unemployment benefits, this work-test effect is expected to reduce aggregate unemployment. However, according to Calmfors and Skedinger (1995), this effect is not expected to substantially reduce the number of benefit claimants or the amount of the open unemployment since those who are placed in the programmes in order to renew their unemployment benefits are not really interested in remaining in the labour market. In such cases, it is expected to seriously weaken the efficiency of active programmes in terms of re-employment probabilities.

In conclusion, active measures may have a number of different effects in the labour market. The above discussion reveals that it is likely to be quite difficult to assess the net effect of active measures since these individual effects may counteract each other. In the context of transition economies, the effects of ALMPs are likely to be even more complex to assess due to the peculiarities of the labour markets in these countries and their high unemployment rates and large informal sectors.

The next section provides a discussion of the causes of unemployment and the characteristics of unemployment in transition economies followed by a review of studies which assessed the structuralist vs. hysteresis hypothesis of the nature of unemployment in these economies. This section will be followed by a critical literature review of empirical studies assessing the employment effects of active measures at the economy level in transition countries.

2.3 Unemployment and the Transition process

As Chapter 1 established, the labour markets in European transition countries initially showed relatively high unemployment rates, which in many cases reached double-digit figures. During the early period of transition, the fall in output came as a consequence of the institutional and structural changes associated with economic transition, economic liberalisation and the emergence of product market competition. The process of these structural changes that shook labour markets in transition countries led to a rise in unemployment (Boeri, 2001; Boeri and Terell, 2002; León-Ledesma and McAdam, 2004; Munich and Svejnar, 2009; Cuestas and Gil-Alana, 2010; Cuestas and Ordonez, 2011; Kovtun et al., 2014).

In the literature the evolution of unemployment in transition countries has been explained by two basic mechanisms: reallocation and restructuring (Blanchard, 1997; Mickiewicz and Bell, 2000; Mickiewicz, 2010). Reallocation refers to the process through which the resources like capital and labour are being allocated from the state to the private sector. The elimination of state subsidies resulted in a contracted output and shrunk labour demand in the state sector (Blanchard, 1997). The liberalisation was also associated with the removal of restrictions and taxes on the new private firms. However, the initial result of liberalisation was an adverse shift of demand for labour by state firms rather that a favourable shift of private demand for labour, and therefore an increase in unemployment.

Because of the lack of incentives in command planning, many enterprises in the pre-transition economies were too large, their products were of poor quality and there was extensive hoarding of capital and labour. Thus, the restructuring of these enterprises was necessary to improve productivity and to increase international competitiveness. According to Blanchard (1997), the deep restructuring in the transition economies had two relevant dimensions. First, the existing employees did not have the right skills for the international open market so had to be replaced. A considerable number of plants were being shut down and even those that were successfully privatised did not retain all their original employees Second, the capital equipment of the public firms in communist countries was typically old and technologically obsolete. Restructuring during transition required a large capital enhancement to replace the old one. Since the state firms now faced severe financial constraints from governments and were unlikely to restructure, in order to raise the capital and enhance workers' skills governments were motivated to start programmes for large-scale privatisation.

However, the privatisation plans were mostly limited in scope and frequently very slowly implemented especially in heavy industry and mining (Mickiewicz, 2010). One of the obstacles to privatisation seemed to have been the opposition of insiders, the employees of the enterprises who had power vis-à-vis government to block the privatisation process. The employees perceived the privatisation as putting their jobs at risk while those remaining employed would be paid lower wages. The Russian privatisation process attempted to overcome this obstacle by enlisting the support of insiders in the firm and by giving them a large stake in the privatisd firms (Blanchard, 1997). This approach was also followed in some Commonwealth of Independent States (CIS) countries and to a lesser extent in CEE countries.

With respect to accessing new capital, enterprises had incentives to generate profit and use these earnings to buy new equipment. These earnings, however, were usually insufficient to extend the technology and equity financing was mostly not available. Equity investors were not interested in investing in enterprises where the majority of the stakeholders were employees who might end up using new funds to increase their own wages. In slow-reform countries, there were a large majority of enterprises or sections of industry that operated under strict budget constraints due to their support of existing employees in these old enterprises. As a consequence, they were not able to finance new investment. Thus, the capital shortages in transition economies caused insufficient labour demand leading to unemployment hysteresis. This lack of efficient and prolonged restructuring caused persistent high unemployment in the slow-reform transition economies (Mickiewicz and Bell, 2000; Mickiewicz, 2010).

In transition economies, especially those in South Eastern Europe, employment protection legislation consists of a very basic job security law and provides very limited coverage of the areas commonly regulated in the EU, while the enforcement of these laws is typically not prioritised by governments (Kolev and Saget, 2005;

Corbanese and Rosas, 2007; Mojsoska-Blazevski, 2016). Weak enforcement of employment protection legislation (EPL) in transition economies undermines the incentives that EPL provides for employers and employees to invest in human capital which in turn will result in negative effects on basic employment security for workers, productivity, competitiveness and overall efficiency.

In Kosovo labour legislation does not include unemployment assistance and provides a very limited social safety net which comprises of two broad categories. The first one is the pension system (old-age assistance programme) while the second category is the social assistance which comprises two sub-categories: the first for families where no one is able to work and the second for families with a child under 5 where only one member is able to work, but cannot find a job. The coverage and effectiveness of this safety net is inadequate to provide insurance for the unemployed and the loss of earnings during unemployment. The common argument that a rigid labour market is caused by excessive labour legislation does not explain high unemployment in all ETEs. E.g. Kosovo has a low index of labour market regulation with the labour market freedom index for Kosovo in 2018 being 58 ranking as moderately free from regulation (Heritage Foundation, 2018).

Chapter 1 provided a detailed discussion of labour market indicators which showed that labour markets in transition economies suffered from high youth unemployment, large regional disparities in unemployment, long-term unemployment spells and low employment to population ratios. During the communist era, large enterprises were frequently the main providers of jobs for an entire region. Large regional disparities in unemployment emerged when many of these large enterprises collapsed during early transition. The population in communist countries tended to be attached to a specific locality and their reliance on local social networks further limited their geographical mobility (Mickiewicz, 2010). On the other hand, during early transition transport fares increased, further increasing the immobility of labour force between regions which contributed to the stagnant regional unemployment differentials.

Economic restructuring in transition economies has also triggered skills mismatch in the labour market (Bartlett, 2013). As discussed above, the new jobs created frequently require different skills from those inherited from the communist era. The privatisation of the state enterprises, the new Small and Medium Enterprises (SME) and foreign direct investment which brought new technology also required more adaptable and soft skills. On the other hand, the educational and training systems in transition economies has not been developed to meet the new requirements of the labour market (Arandarenko and Bartlett, 2012; Bartlett, 2013). Even if individuals hold the right qualification from the official educational system, they might not have the skills required to effectively perform in that particular occupation (Kupets, 2015). This skill mismatch plays an important role in the persistence of the long-term unemployment since skill mismatch typically increases with the length of the spell of unemployment.

The high share of long-term unemployment along with persistent regional differences and lack of relevant skills and geographical mobility provide an indication that labour markets in transition economies frequently exhibit structural mismatches which is related to an overall economic imbalance reflecting structural problems in the economy. According to Nesporova (2002), although cyclical unemployment can be evident during economic recessions it is less important than structural unemployment, while frictional unemployment is not a significant source of unemployment in most European transition economies. The rest of this section provides a review of empirical studies assessing whether the unemployment in transition countries displays characteristics in line with the structuralist or hysteresis hypothesis.

There has been a growing interest in recent years to test whether the unemployment in European transition countries fulfil the structuralist view or the hysteresis hypothesis; the evidence is rather mixed. Using aggregate data for twelve transition countries, Leon-Ledesma and McAdam (2004) employed stationarity tests controlling for structural breaks and business cycle effects. The findings from this study suggest that unemployment dynamics in these countries are structuralist in nature, meaning that temporary shocks do not have any permanent effect on unemployment rate. However, the authors observed the existence of multiple equilibria around which the economy fluctuates after large shocks. This pattern is especially evident for the Czech Republic, Lithuania and Slovakia. Furthermore, Camarero et al. (2008) applied unit root tests with structural breaks for Central and Eastern European Countries (CEEC) and found evidence against the unemployment hysteresis and in support of the structuralist view of unemployment that temporary shocks induce slow adjustments to the equilibrium rate of unemployment but do not have permanent effects on it. The same result was found when using panel data and also when testing separately for each country. Cuestas and Ordonez (2011) applied panel unit root testing for eight CEEC that joined the EU in 2004 and found evidence to support the validity of the structuralist theory in four out of eight countries: Hungary, Poland, Latvia and Slovenia.

Moreover, when testing for co-movement of the unemployment rates in these countries, evidence suggests there are common factors that drive the unemployment rate in transition countries which might be related to the process towards their integration in the European Union. Gozgor (2013) also applied a unit root test for ten CEEC, however they found evidence to support the validity of hysteresis hypothesis for these countries. Marjanovic and Mihajlovic (2014) used unit root tests, panel unit root tests and also structural break analysis and find mixed results for CEEC. When applying unit root tests they found evidence to support hysteresis theory for all transition countries, except Bulgaria, Estonia, Lithuania and Romania. The results from panel unit root testing suggest mixed results for transition countries. Since the observation period of this study (monthly data for period 2000 to 2013) was subject to some crisis event, these authors raised concerns that their results might lead to wrong conclusion. Marjanovic and Mihajlovic (2014) divided the period of observation into two sub-periods to identify when structural breaks may have occurred. The results provide evidence that before the great recession of 2007, unemployment in transition countries showed hysteresis behaviour, while after the recession the unemployment rate become stationary at higher levels.

Bukowski et al. (2013) investigated the impact of shocks and rigidities in the labour market. This empirical study employed a Structural Vector Error Correction Model, using a panel of quarterly data from 1996 to 2007. The investigation concluded that positive labour demand shocks determine increases in employment and reductions in unemployment in the short-run. Positive labour supply shocks were found to increase unemployment; this is especially the case in Poland which may be the result of specific institutional factors such as their welfare system (Nesporova, 2002). The rigidity of wages was found to be an important factor determining unemployment in transition countries.

Lehman and Muravyev (2009) analysed the impact of labour market institutions on labour market outcomes in European transition economies. Such institutions include employment protection legislation, active labour market policies, duration of unemployment benefits, the tax wedge on labour and union density. The results show convincing evidence that stronger employment protection legislation depresses the employment-to-population ratio and it substantially increases youth unemployment. Findings from the study indicate a smaller impact of other labour market institutions and policies on labour market outcomes.

Cazes (2002) investigated the effects of labour market institutions on different labour market outcomes for both transition and OECD countries. The investigation of Cazes also put emphasis on the strictness of employment protection legislation in transition countries considering that labour market in many of these countries have been rigid and granted workers a higher degree of job security. The study found that high collective bargaining coverage and payroll taxes tend to increase the long-term unemployment while the presence of more powerful trade unions seems to increase the overall unemployment rate. The findings also suggest that a long duration of unemployment benefits and high labour taxes increase youth unemployment rates. Cazes found that stronger employment protection legislation might reduce both employment rates and labour force participation rates.

The evaluation of ALMPs at the economy wide level in transition economies have utilised mainly the matching function which attempts to capture the efficiency of matching under the assumption that these policies increase search and matching efficiency. The following section provides an introduction to the conceptual framework of this approach and a review of empirical studies using matching function in European transition economies.

2.4 Conceptual Framework of the Matching Function and a Review of Empirical Studies for Transition Economies

As section 2.2.3 discussed, raising the efficiency of the matching process between the unemployed and employers (through enhancing their human capital, re-locating jobs or workers and/or increasing the search intensity of the job-seeker) is regarded as one of the main functions of active policies. Human capital enhancement may be a crucial element where the labour market displays structural mismatches, which are likely to be especially important in transition countries. Most of the empirical research in assessing the effects at the economy level of ALMPs in European transition countries has focused on modelling matching functions. As utilised in these research studies, the matching function typically regresses the exit from unemployment to employment, i.e. the number of successful matches between the previously unemployed and unfilled vacancies, on the vacancy stock, the unemployment stock and a set of variables measuring ALMPs.

The matching function is attractive for empirical studies since it enables modelling of the mismatch in the labour market with minimum complexity. This approach summarizes the mechanism of bringing together firms who advertise vacancies and the unemployed who are searching for jobs through employment agencies, reading advertisements in the newspapers or utilising their social networks. As Petrongolo and Pissarides (2001, p. 391) review, '*the key idea is that this complicated exchange process is summarised by a well-behaved function that gives the number of jobs formed at any moment in time in terms of the number of workers looking for jobs, the number of firms looking for workers, and a small number of other variables*'. The simplest form of the matching function is $M = m(U,V)$, where M is the number of matches created or jobs filled in a given period of time, U is the number of unemployed workers searching for a job while V is the number of open vacancies.

Layard et al. (1991) acknowledge that the matching function accounts for the mismatch that measures the degree of heterogeneity in the labour market across different dimensions such as the skill groups, industrial sectors and regions. It is often encountered that the skills possessed by workers are not compatible with those required in current vacancies which lengthens the duration of search. Industrial sector mismatch would prevail when industries require specific skills which may not be available amongst current job-seekers. Regional differences in unemployment may also be persistent because of low labour and/or job mobility. Layard et al. (1991) also suggest that there might be additional imbalances caused by temporary structural shocks such as those which arise from the business cycle. However, since both reflect imbalances of labour demand and supply, Layard et al. (1991) suggest that, for practical purposes, they should be referred by the generic term 'mismatch'. The concept of mismatch bears some relationship to the concept of structural unemployment which by definition is the unemployment arising from fast structural changes such as those experienced by transitional economies.

The microeconomic foundation of the matching function is based on the search phenomena of the economic agents in attempt to create efficient matching. Efficient matching can be defined as the ability of unemployed to find a match in a relatively short period of time. The average time that it takes for a match to be created depends on how the firm and worker search for a match. In matching function models returns to scale are likely to play an important role.

The empirical analysis of the matching function is similar to the Cobb-Douglas production function; so when the sum of the coefficients of unemployment and vacancy stocks is equal to unity, it implies constant returns to scale (CRS) while when it exceeds (is less than) unity it implies increasing (decreasing) returns to scale (IRS). It is usually assumed that the matching function ensures CRS, meaning that an increase in size of labour market in terms of vacancies and unemployed workers would increase the matching efficiency at the same magnitude. Some models use a matching function allowing IRS which indicates positive externalities with respect to labour market size (Munich et al., 1998; Stevens, 2002). Petrongolo and Pissarides (2001) emphasise that because of the heterogeneity of workers and jobs, the transition probabilities and the mean duration of unemployment spells and unfilled vacancies will differ across the labour market. According to Petrongolo and Pissarides (2001) the dependence of the mean transition probabilities on the number of workers and firms engaged in search is an externality and the matching function can give a measure of the extent of these search externalities. If the elasticity with respect to unemployment in the matching function equation ($M = m(U,V)$) is η_U and the elasticity with respect to vacancies is η_V; then $\eta_U - 1$ measures the negative externality of unemployed towards other unemployed workers (congestion externality – when a rise in new entrants in the unemployment pool reduces the matching efficiency of the existing unemployed or the employed workers who search while being employed) while the η_U measures the positive externality from the unemployed to firms (an increasing search and matching intensity with rising unemployment). Similarly, the positive externality from firms on searching unemployed (thick-market effect) is measured by η_V and negative externality of firms on other firms (congestion externality) is measured by $\eta_V - 1$. When IRS prevails, there could be more than one equilibrium because of strong positive externalities of high search intensity (Munich et al., 1998). In one equilibrium, firms and workers put more search effort to create a match which creates higher returns from the search effort while in another equilibrium the search effort from both firm and workers can be low resulting in a low matching rate and higher unemployment.

Some studies suggest that labour markets in CEE countries may be characterised by multiple equilibria which makes the matching function with IRS an appropriate choice to analyse the labour market in these countries (Munich et al., 1998, Munich and Svejnar, 2009). Appendix 2.1 examines how multiple equilibria may prevail in a labour market according to Snower's (1994) model and provides an explanation of why CEE countries may have been caught in a low-skill, bad-job equilibrium.

Based on the theoretical model of Snower (1994), multiple equilibria can result in a 'low-skill, bad-job equilibrium' and a 'high-skill, good-job equilibrium'. Snower argues that labour market can fall into a 'low-skill, bad-job trap' which entails a preponderance of jobs that are associated with low wages, low productivity and little opportunity to acquire training or enhance human capital. In this context, firms do not provide a lot of skilled vacancies because there is not enough skilled labour and these vacancies would be difficult to fill. Snower refers to this as the 'vacancy supply externality'. Similarly, workers are not incentivised to acquire skills since there are few skilled vacancies and as such the skills would be likely to remain under-compensated. This is regarded as the 'training supply externality'. If firms provide skilled vacancies it raises the workers' returns to education and training, however firms do not pay for the workers' education. By the same argument, workers who acquire training and education increase firms' returns to opening vacancies for skilled jobs. Snower argues these two externalities reinforce one another and can induce an insufficient level of training.

Snower's (1994) model suggests that the higher the aggregate number of skilled workers and vacancies for skilled jobs the higher the average wage paid to workers. Since high-skilled workers are more productive it means that more is being produced in this sector and the firms will also generate higher profit. Thus, a policy implication for countries with a high proportion of low skilled workers and seeking to move to the good-job equilibrium is to subsidise education in order to produce higher skilled workers or to subsidise skilled employment directly in firms. In the context of this thesis, the shift to the good equilibrium may be assisted by increased subsidises for training, wage subsidies for skilled workers and other ALMPs. However, since the bad-job equilibrium is likely to be a stable one, Snower (1994, p.19) argues that small subsidies may not be enough to shift from the bad to the good equilibrium and only a '*'big push' in the form of sufficiently large skilled employment subsidies is required before the sector can be propelled toward the high-skill, good-job equilibrium'*.

The dependent variable in studies using a matching function can be the total outflow from unemployment, the flow from unemployment to employment, or the total number of hires (Petrongolo and Pissarides, 2001). A major limitation of using this approach is that data on outflows from unemployment into employment is usually unavailable, so the measure on total outflows from unemployment is usually used in these studies ignoring other flows in the labour market such as outflows from unemployment to inactivity and job-to-job flows. The former are likely to be relatively large in early and mid-transition. Studies have also included additional explanatory variables that may influence matching in a systematic way such as variables to account for regional differences and district size, demographic variables, level of education, level of wages (Coles and Smith, 1996) and output per head (Munich et al., 1998) etc.

Usually, a distinction is made between ordinary and augmented matching functions where the latter take into account that workers and jobs are heterogeneous. Lehman (1995) uses the augment matching function to account for the search effectiveness of the unemployed workers. The search effectiveness is dependent on different factors with one of them being ALMPs which, as discussed in section 2.2.3, are assumed to have positive effect on matching efficiency. The size of ALMPs is measured in the model in various ways such as the expenditure on ALMPs at the regional or country level, the number of the unemployed participating in active programmes during a specified period, number of hours a worker spent in a subsidised job, etc.

Studies have also discussed the appropriateness of the assumption that not only the stocks of unemployment and vacancies influence the efficiency of matching (Petrongolo and Pissarides, 2001; Coles and Petrongolo, 2002). These studies argue that flows (inflows of new vacancies and unemployed in a certain period in the labour market) play an important and significant role in explaining the efficiency of matching. This is referred to as stock-flow matching. Coles and Smith (1996) make a sharp distinction between the stocks and inflows; they argue the unemployed stock should not be matched with the stocks of vacancies because they were participants in the previous matching round but did not match. The analysis of stock–flow matching can be better understood when analysing the entrance of new unemployed individual into the labour market. The new entrant in the unemployment pool searches for a job in a bulk of advertisements before deciding to apply. Coles and Smith assume that there is a positive probability that even after applying for all the advertised jobs there will be no match because the unemployed does not meet the requirement of the employer. So, for a new entrant into unemployment there are two possibilities; the unemployed may achieve a match or they will continue to remain in the unemployment pool. In the first case, that would mean that the new entrant (the inflow) in the unemployment pool is matched with a vacancy in the existing vacancy stock. On the other hand, if the new entrant does not find a suitable match with the existing stock of vacancies, it is reasonable to believe that he might have to wait for the new inflows into vacancies to create a match. In this case, it is the vacancy inflow that is matched with an unemployed in the existing stock of unemployment.

According to Munich and Svejnar (2009), the matching function captures the unemployment dynamics assessing the extent to which high unemployment in transition countries is a result of the following three causes: a) economic structural mismatch, (b) macroeconomic policies or external shocks and (c) the ongoing transition from planned to market economy. The first cause suggests that the high unemployment is a result of an inefficient matching created by poorly designed labour market policies and institutions which tend to reduce individuals' search effort, increase skills depreciation, induce high reservation wages or geographical mismatch. In such cases, both unemployment and vacancy stocks tend to be high simultaneously. The second factor implies that high unemployment is caused by low demand for labour resulting from tight macroeconomic policies or external contractionary shocks such as a globalisation shock; this would be marked by a low vacancy stock relative to the inflows into unemployment which will cause high unemployment. While the third factor causing high unemployment implies that due to the unfinished transition process, net job destruction in firms is still ongoing; thus it would be manifested with high unemployment stock caused by high inflows into unemployment relative to the number of vacancies.

Munich and Svejnar (2009) estimate a matching function of the outflows from unemployment with three explanatory variables: the number of unemployed in a district, the number of individuals flowing into unemployment and the number of vacancies in a district during a period of time, for five transition countries and one Western country (the Czech Republic, Hungary, Poland, Slovakia, East and West Germany). The main limitation of the study is that it uses total outflows from unemployment rather than outflows to employment thus it fails to identify the specific job-related flows in the labour market. The results from the estimation of the matching function show that the coefficients on unemployment, vacancies and inflows to unemployment vary across these countries. The results from the estimation of the matching function show positive but small coefficients for the vacancy stock and large positive and significant coefficients for unemployment stock suggesting that unemployment stock is an important determinant of the outflow. In the second specification a variable measuring inflows into unemployment was included in the model. The coefficients of the inflows into unemployment range from 2.0 for Poland to 4.3 for Slovakia compared to the coefficients for existing unemployment stocks which range from 0.74 for Czech Republic to 2.59 for Poland. Based on the larger magnitude of the coefficients of inflows to unemployment compared to existing unemployed, this result suggests a higher efficiency of matching for newly unemployed.

The estimation of returns to scale suggest that there is increasing returns to scale for all but one of these countries ranging from 2.40 for Hungary to 1.56 for West Germany (the sum of coefficients of three explanatory variables should exceed unity in order to have increasing returns); Poland is an exception with constant returns to scale. Because the coefficient of inflows to unemployment is the highest among the three explanatory variables, it is this coefficient that generates increasing returns. Given the low vacancy stocks, this might suggest that it is the new entrants into the unemployment pool who disproportionately match with the existing vacancies, while those previously unemployed remain unmatched; which leads to a high matching efficiency but also high long-term unemployment. In general, the study finds evidence to support the hypothesis that in transition countries high unemployment might be a result of the low number of vacancies and high inflows to unemployment. As these authors emphasise, this outcome is consistent with the hypothesis that unemployment in transition countries is predominantly caused by tight macroeconomic policies and external shocks (which cause the low number of vacancies, e.g. low labour demand relative to unemployment and inflows) and on-going restructuring in transition countries (high number of inflows into unemployment).

Table 2.1 provides a summary of the empirical studies assessing ALMP effectiveness in transition countries at the economy-wide level. Only two empirical studies have employed panel regression analysis to assess the economy-wide effects of ALMPs: Cazes (2002) for 8 European Transition countries while Lehman and Muravyev (2009) extended the sample to 27 transition countries. Cazes (2002) and Lehman and Muravyev (2009) for CEEC and CIS transition countries found considerable evidence that an increase in the expenditure on ALMPs will lead to a reduction in the overall unemployment rate and especially the youth unemployment rate.

The results for transition economies using a matching function are influenced by the methodology used in terms of the model specification, the inclusion of additional control variables that affect the outflows from unemployment, whether they use static or dynamic models and the extent to which they account for endogeneity of the explanatory variables. Some of the studies employing matching functions found evidence of positive effects; other empirical studies have not detected any impact, while some even found evidence of a negative impact of ALMPs on outflows from unemployment. When using the matching function approach, Burda and Lubyova (1995) found positive but modest effects of expenditure on ALMPs on outflows from unemployment for the Czech and Slovak Republics. However, these results should be taken with caution since the study does not account for demand conditions. Positive effects of expenditure on employment subsidies and public works per members on the outflow from unemployment of the regional labour force were found by Munich et al. (1998) for the Czech but not for Slovak Republic, though this difference is predominantly attributed to different demand conditions in the two countries. In their study, Munich et al. account for the economic activity in the regional level by the ratio of industrial output to the labour force, the number of firms with fewer than 25 employees per member of labour force and the ratio of the value of agricultural production to industrial production.

Table 2.1 Summary of studies on economy wide effects of ALMPs for European Transition Economies and selected Western Economies

Studies of European transition economies based on chronological order (year of publication)

Study	Country	Data	Dependent Variable	Estimation technique	Results
Boeri and Burda, 1995	Czech Republic	Regional Employment Offices 1991 – 1994	Number of individuals flowing from unemployment into jobs	**Matching Function: Dynamic Panel models** ALMP variables: Spending on programmes at the district level per year, inflows of positions (i.e., available slots in the various programmes) and inflows per quarter of persons into ALMP programs (i.e., filled positions).	Small positive effect of all ALMPs on exits from unemployment into jobs.
Burda and Lubyova, 1995	Czech and Slovak Republics	Regional Employment Offices 1991 - 1994	Number of individuals flowing from unemployment into regular employment	**Matching Function** ALMP Variable: Regional ALMP spending.	Modest positive effect of ALMPs on exit rates from unemployment into employment.
Lehman, 1995	Poland	Regional Administrative data	Outflow of the registered unemployed into regular un-subsidised jobs	**Matching Function: Ordinary Least Squares (OLS)** ALMP variable: Stock of participants in training and re-training measures	Insignificant effects of ALMPs.

Puhani and Steiner, 1996	Poland	LFS and National Labour Office (NLO) 1992 – 1994	1. Outflow rates from unemployment into employment and 2. Outflow rates from employment into unemployment	**Matching Function: Random and Fixed Effects** ALMP variables: Regional expenditure on public works, intervention works and public training.	No significant effect of ALMPS exp. on the outflow rates from unemployment to employment. Intervention works and public training expenditure raises the outflow rate from employment into unemployment.
Munich, Svejnar and Terrell, 1998	Czech and Slovak Republics	Regional Administrative data	The number of individuals flowing from unemployment in certain district and time	**Matching Function:** ALMP variable: Expenditures on ALMP per members of district labour force.	Small positive effects of ALMP expenditure on outflows from unemployment
Puhani, 1999	Poland	Labour Force Survey and Ministry of Labour 1992 – 1996	1. Outflow rates from unemployment into employment and 2. Outflow rates from employment into unemployment	**Matching Function: Dynamic Panel models** ALMP variable: Regional ALMP expenditure.	Small positive effect of public training programmes in reducing unemployment
Dmytrotsa, 2003	Ukraine	National Employment Offices 2000 - 2002	Outflow from unemployment	**Matching Function: OLS** ALMP variable: Number of registered unemployed placed in different measures; Amount of information given by the PES.	Positive effect of increasing exit from unemployment for public works and training programmes.
Dmitrijeva and Hazans, 2007	Latvia	Regional Employment offices 1998 - 2003	Outflows from the pool of registered unemployed into regular employment	**Matching Function:** ALMP variable: The share of trained and re-qualified unemployed in the pool.	Positive and statistically significant impact of the share of trained unemployed on outflows to employment.
Jeruzalski and Tyrowicz, 2009	Poland	Regional Administrative data 2000 - 2008	Log of monthly outflows to employment out of unemployment (unemployed de-registered due to commencing employment).	**Matching Function: Two Stage Stochastic Frontier and Difference-in Difference.** ALMP variable: The share of registered unemployed participating in ALMPs.	Significant negative effects of ALMPs in outflows to employment (high lock-in effects or essential ineffectiveness of ALMPs).

Tomic, 2012	Croatia	Regional Administrative data 2000 - 2011	Number of employed persons from the CES Registry during the month	**Matching Function: Stochastic Frontier Estimation** ALMP variable: Share of persons in ALMP in total number of unemployed in each regional office at the year end	ALMP variable is significant and positive but very small

Studies of European non-transition economies based on chronological order (year of publication)

Study	Country	Data	Dependent Variable	Estimation technique	Results
Anxo et al. (2001)	France and Sweden	Regional level data	1. Employment demand decrease due to hiring / stock of employment demands at the end of the month (DEFM) (France) 2.Number of unemployed people leaving unemployment towards employment/ unemployment stock at the end of the month (Sweden)	**Matching function : Fixed Effects** ALMP variable: Inflows to four different ALMPs.	Positive but small effect of ALMPs. Better work when targeted at long-term unemployed.
Hujer et al., 2002	West and East Germany	Regional Administrative data 1999-2001	Job Seekers Rate – the rate of total job seekers and ALMP participants relative to the labour force	**Dynamic modelling for West Germany – diff. and sys GMM and OLS and within estimator for East Germany** ALMP variable: The stock of participants in a specific type of programme relative to the total rate of job seekers	Negative effects for vocational training and job creation schemes. Insignificant effect; questionable results due to the small dataset.
Hujer and Zeiss, 2005	West Germany	Regional Employment office data 2003 – 2004	Outflow from unemployment to employment	**Matching Function: Dynamic Panel models, GMM.** ALMP variable: Inflows from unemployment into job creation schemes.	Job creation schemes reduce the inflows into regular employment in the first 12 months after a programme extension (suggesting lock-in effects). In the period between 12 and 18 months after a programme extension it does not affect the inflows into employment.

Altavilla and Caroleo (2006)	Italy	Regional Administrative data 1996 - 2001	Unemployment rate and Labour Force Participation	**GMM and Panel Vector Autoregressive** ALMP variable: The total number of participants in a programme in a particular region divided by the total working-age population in the same region	ALMPs significant in reducing unemployment rate and increasing participation rate.
Hujer and Zeiss (2006)	West Germany	Regional Administrative data 2003-2004	The flow from unemployment to employment	**Matching function: Stock-flow combination (GMM;** choice of lags higher than the training period to avoid the locking-in effect)	Small regional level effect (possible substitution effect when compared to the microeconomic effect on the individual where the effect is significant in increasing individuals' probability to get employed.
Hujer et al., (2007)	West Germany	Regional Administrative data	Outflows of unemployed individuals into regular, non-subsidised employment	**Matching function: Dynamic model (GMM) with spatial effects using two different weights**	Insignificant or negative effects of the policies.
Altavilla and Caroleo, (2009)	Italy	Regional Administrative data 1997 - 2007	Employment rate and Participation rate	**Panel factor-augmented vector autoregressive** ALMP variable: The ratio between the number of participants in ALMP and the working-age population in the same region.	Increase the job reallocation and boost reemployment. Increase labour force participation. ALMPs are effective only in regions with lower labour market rigidity.
Dauth et al. (2010)	Austria	Regional level data 2001-2007	1.The number of matches in a region and 2. The regional job-seeker rate	**Matching Function: Difference and System GMM** ALMP variable: The stock of participants in a certain programme relative to the number of job-seekers.	Positive effects of job schemes in the non-profit sector, wage subsidies, and apprenticeships on the regional matching function and the job-seeker rate.
Arranz et al., (2013)	Spain	Regional Administrative data 1987 – 2010	1. Levels of employment (total employment and temporary employment), 2. Unemployment and labour force,	**Difference and system GMM** ALMP variable: Incentivized contracts to	Expenditure on job-creation programmes and the number of participants in vocational training programmes have little or no effect on

			employment rate (employed population as a proportion of the working-age population), 3. Unemployment rate (unemployed population as a proportion of the labour force), 4. Temporary employment rate (number of temporary contracts divided by the number of workers in wage employment) and 5. Labour market transitions (flows between unemployment and employment, and between temporary and permanent employment).	promote permanent jobs; No. of participants in vocational training; Expenditure on job-creation programmes; No. of indirectly incentivized contracts.	the transitions from unemployment to employment. Incentivised contracts to promote permanent jobs have small positive effect on transitions from unemployment to employment and from temporary employment to permanent employment.

Studies using samples of mixed countries, based on chronological order (year of publication)

Study	Country	Data	Dependent Variable	Estimation technique	Results
Cazes, (2002)	19 OECD and 8 transition countries (Bulgaria, Czech Republic, Estonia, Hungary, Poland, Russian Federation, Slovakia, Slovenia)	OECD database and National sources	Five dependent variables: 1. Unemployment rate 2. Long-term unemployment rate 3. Youth unemployment rate 4. Employment rate 5. Labour Force Participation rate	**Panel data regressions** ALMP variable: The ratio of GDP spending on ALMP to the unemployment rate.	Significant ALMP effects: reduces unemployment rates and increases employment and labour force participation rates.
Estevao (2003)	15 Industrial Countries	National level data 1985 - 2000	The share of the working-age population employed in the business sector.	**Ordinary Least Squares (OLS)** ALMP variable: ALMP expenditure as share of GDP	Increase business employment. Direct subsidies to employment creation are more effective in raising employment rates in the business sector than expenditures on training or PESs.

Bassanini and Duval (2006)	21 OECD countries	National level data 1982 – 2003	1.Unemployment rate and 2. Employment rate	**Fixed Effects and Instrumental Variable approach** ALMP variable: ALMP expenditure as share of GDP	In general increases employment rate and reduces unemployment rate. The most consistent result is that of training programmes.
Lehman and Muravyev, (2009)	Eastern Europe and Central Asia (27 countries)	OECD, EUROSTAT for EU member states and World Bank and IMF for SEE and CIS countries 1995 – 2008	1.Employment to population Ratio 2. Unemployment rate 3. Long-term unemployment rate 4. Youth unemployment rate	**Random and Fixed Effects** ALMP variable: The expenditure of ALMP as a percentage of GDP.	ALMP significant in reducing youth unemployment rate, long-term unemployment and unemployment rate.
Oesch (2010)	21 OECD Countries	National level data 1991 – 2006	Unemployment rate of unskilled workers.	**OLS** ALMP variable: ALMP spending as % of GDP divided by unemployment rate	ALMP expenditure reduces unemployment rate of unskilled workers.
Murtin and DeSerres (2014)	11 OECD countries	National level data 1985-2007	Unemployment outflow rate (measured as the number of hires divided by the number of unemployed)	**Matching function; Instrumental variable approach. 1st stage OLS dep. Var. labour market tightness, 2nd stage instrumental variable. 1st stage OLS, 2nd stage differences GMM.** ALMP variable: Spending on ALMPs per unemployed worker normalized by a proxy of average income (GDP per worker).	No effect of ALMPs on unemployment outflow rate.
Escudero (2018)	31 OECD countries	National level data 1985 - 2010	1.Unemployment rate, 2. Employment rate, 3. Labour force participation of the overall and low-skilled population and 4. Low-skilled unemployed rate.	**Instrumental Variable approach** ALMP variable: Expenditure on ALMPs per unemployed person.	In general, positive effect of ALMP on the labour market: reduce unemployment and increase employment and participation rate.

Taking into consideration that the matching mechanism can work differently in different regions, Puhani (1999) ran separate regressions for industrial, agricultural and modern regions however the evidence of the effects of ALMPs did not differ. Jeruzalski and Tyrowicz (2009) critiqued the study of Puhani (1999) arguing that it used data from a period when Poland was experiencing an overall reduction in unemployment (period from 1992 to 1994). Thus, they point out that the positive effects found in Puhani (1999) might not present the real effect of ALMPs in this country. In contrast, Jeruzalski and Tyrowicz (2009) used data for a period with both an increase and decrease in unemployment (period from 2000 to 2008) and found strong evidence that an increase in number of participants in training programmes, subsidised private employment and public works reduced the outflow from unemployment into employment for Poland.

In order to account for regional differences, Lehman (1995) included dummy variables to indicate whether a region belongs to heavily industrialised, agricultural or developed region. Lehman found no evidence that the stock of the unemployed in public training and re-training and public works programmes impact on the flow out of unemployment to employment for Poland in any of the observed regions. Results from Kwiatkowski and Tokarski (1997), for the same country, found negative effects of expenditure on public works and loans to enterprises on outflows from unemployment, no effects of training and start-up loans but positive effects of expenditure of public works on outflows from unemployment. Lenkova (1997) also found no evidence that increasing the number of participants in training led to an increase in the flow out of unemployment for Bulgaria. A limitation of both Lenkova (1997) and Kwiatkowski and Tokarski (1997) is that they do not account for demand conditions or region-specific differences.

Munich et al. (1998) emphasise that empirical studies that have not controlled for region size have biased results. The reason for this is that the region size is likely to be correlated with the matching parameters. The higher correlation of unemployment and vacancy stock with the regional level characteristics, the greater the likelihood of incorrect estimates. Munich et al. (1998) refer to this as spurious scale effect. The spurious effect can be avoided if the study uses panel data together with region-specific time-invariant effects (Puhani, 1999; Dimitrijeva and Hazans, 2007; Jeruzalski and Tyrowicz, 2009). In contrast to most of the empirical studies using a matching function which do not control for region specific characteristics and demand conditions, Munich et al. (1998) control for the following regional variables: the proportion of unemployed who have secondary or tertiary education, the density of population in the region and a range of variables to account for labour demand and economic activity and the distance from the district capital to account for labour mobility. The study did not find any significant effect of ALMPs in outflow from unemployment.

Since ALMPs induce can externalities in the labour market, such as substitution effects and deadweight loss, macroeconomic studies are capable of capturing these effects by using aggregate data. Two of the studies conducted in transition countries have found that these externalities may be significant. To assess whether active programmes have any indirect effect or whether they can prevent unemployment to occur in the first place, Puhani and Steiner (1996) and Puhani (1999) use two dependent variables: the outflow from unemployment into employment and the outflow from employment into unemployment. Puhani (1999) finds evidence of a weak positive effect of expenditure of ALMPs on outflows from employment into unemployment suggesting that these active programmes induce substitution effects; i.e. firms might want to fire workers who are employed without a subsidy in order to hire unemployed individuals whose wage is partially subsidised. Findings from Puhani (1999) indicate that an increase of €100 on the expenditure on public training and intervention works will lead to one employee being substituted by an unemployed individual who has completed one of these active measures. Nevertheless, Puhani and Steiner (1996) and Boeri (1996) emphasise that ALMPs can still serve a purpose to promote equality if they are targeted at the disadvantaged groups.

Some of these studies recognise that ALMP variables might be endogeneous if more resources are allocated to regions within a country where the unemployment rate is high the results might be biased through this reverse causation (Boeri and Burda, 1996; Puhani, 1999; Dmitrijeva and Hazans, 2007; Jeruzalski and Tyrowicz, 2009). Puhani (1999) addresses the issue of endogeneity by using lagged, instead of current, ALMP expenditure to account for the fact that it takes some time until such expenditure can have an effect on the labour market. Similarly, Dmitrijeva and Hazans (2007) argue that the issue of endogeneity can be accounted for by using a variable that measures the number of unemployed who have completed training. So, for instance, if there is an increase in ALMP expenditure in period t in response to current worsening labour market, while participants expect to complete the training in 4 months, these individuals will only appear in the fourth lagged variable (when using monthly data) thus arguing that the outcome of participants will not be affected by the current increase in expenditure on ALMP. This approach, however, is only applicable when studies use monthly data which is common for studies using regional level data but not for those using country level data. However, this might not be a good approach to account for endogeneity. Munich and Svejnar (2009) argue that the explanatory variables in the matching function are pre-determined by the matching process of the previous periods, thus they suggest that in order to obtain consistent estimates, a study needs to apply the first difference approach of estimation of the matching function ($\Delta M_{it} = \Delta U_{it-1} + \Delta V_{it-1} + \Delta \varepsilon_{it}$). According to Munich and Svejnar (2009) further lags of the ΔU_{it} will be uncorrelated to $\Delta \varepsilon_{it}$ arguing in favour of the method of estimation with instrumental variables. Boeri and Burda (1995) also use dynamic panel data models to account for endogeneity when assessing programme effectiveness for the Czech Republic and find small positive effects of ALMP expenditure on exit rates from unemployment.

Jeruzalski and Tyrowicz (2009) and Tomic (2012) both employ a two-stage stochastic frontier estimation technique. The estimations include monthly and year dummies. In the first stage of the estimation only the explanatory variables of unemployment and vacancies stocks and flows are included, along with monthly and year dummies. The second stage estimates technical efficiencies[10] by accounting for the characteristics of local labour markets and different individual search intensities (Ibourk et al., 2004). The covariates included in the second stages include the vacancy to unemployment ratio to capture the labour market tightness, regional unemployment rate, share of females in total unemployment, share of young individuals in the pool of unemployed, share of long-term unemployed, share of low-skilled and high-skilled unemployed among the jobless, size of the labour market, net income per capita and a measure to account for ALMP coverage rate (Tomic,

[10] Technical efficiency can be defined as the ratio of observed output to maximum feasible output. If technical efficiency is equal to 1 it shows that the individual obtains the maximum feasible output, while it is smaller than 1 provides a measure of the shortfall of the observed output from maximum feasible output.

2012) or number of ALMP participants (Jeruzalski and Tyrowicz (2009). Tomic (2012) found a positive, but very small, effect of active measures, while Jeruzalski and Tyrowicz (2009) found a negative effect of active measures on matching efficiency.

In conclusion, most of the studies using a matching function are limited in a sense that they do not account for aggregate demand. An additional limitation of the studies using a matching function is that the dependent variable is usually outflows from unemployment. This data limitation does not allow one to observe the direction of transitions of labour, i.e. whether the unemployed transitions to employment, to inactivity or if there are any job-to-job transitions. Munich at al. (1998) argue that when using regional level data, not accounting for regional specific characteristics would lead to biased coefficients while very few of studies in transition economies account for such differences. Based on this argument, Munich et al. (1998), Lehman (1995) and Dmitrijeva and Hazans (2007) used regional dummies to account for region specific effects, Tomic (2012) used regional population density as a proxy to account for the size of social network and flow of information, Jeruzalski and Tyrowicz (2009) used the size of labour market (the total number of unemployed, inflows and job offers), while Puhani (1999) ran separate regressions for different regions.

With regard to effects of ALMPs at the economy wide level, the results are mixed. This may be a result of the: different methodologies used, different measurements of the ALMP variable, different control variables included in the models, the different period of data analysed or how studies have accounted for potential endogeneity. Findings from Puhani (1999), Dmytrosa (2003) and Dmitrijeva and Hazans (2007) suggest that training induce positive transitions from unemployment to employment while Lehman (1995) found no evidence of training on transition to employment. Lehman (1995) and Kwiatkowski and Tokarski (1997) found evidence to suggest that private subsidised employment increases the outflows from unemployment. The results from Jeruzalski and Tyrowicz (2009) suggest that all active measures reduce the outflow from unemployment to employment.

The following section provides a critical review of recent empirical studies for non-transition economies, their methodologies and the data used. It will also review studies using mixed samples combining both transition and non-transition economies. Finally, it will provide a brief comparison of the results between studies of transition and non-transition economies.

2.5 Review of Empirical Studies for Non-Transition Economies

The evidence on the effectiveness of the ALMPs in reducing unemployment (or increasing employment) from studies using data for non-transition economies appears to be far from conclusive. Studies using regional and national level data differ in terms of the estimation technique used, the time frequency of the data, the dependent variable and also the definition of the independent variables. This section will review a set of recent studies (published since 2000) of the effectiveness of active policies in non-transition countries. This section will initially review the studies using regional level data for single country samples (based on chronological order) followed by the studies using national level data for samples with mixed countries. The summary of the reviewed studies are provided in Table 2.1.

In order to compare the effectiveness of different ALMPs in France and Sweden, Anxo et al. (2001) use monthly regional level data, applying a fixed effect model using different model specifications for the two countries depending on the data availability. The dependent variable used in the analysis of ALMP effectiveness for France is the '*ratio between the employment demand decrease due to hirings and the stock of employment demands at the end of the month'* while for Sweden is the '*ratio of the flow from unemployment to employment and unemployment stock at the end of the month*'. One advantage of this study is that it distinguishes between three different ALMPs: (i) employment creation schemes in the public sector; (ii) wage subsidy schemes in the private sector; and (iii) training schemes. The evidence from this study suggests that ALMPs have in general a positive impact on outflows from unemployment to employment. According to the results, the most effective measure in both countries are employment creation schemes in the public sector. Wage subsidies and training measures seem to have a smaller aggregate impact. It might be possible that the effect of training is underestimated because training is generally heterogeneous and the analysis of their aggregate effect is more complex. Also, as argued in section 2.2.3, the effect of training takes longer to materialise due to lock-in effect. This study does not assess the effectiveness of ALMPs in the medium or long-term but only the period instantly after the completion of the measures. From the review of other studies, it can be observed that both wage subsidies and training measures might be more effective in medium or long-term hence suggesting that there might be a lock-in effect related to these results (Van Ours, 2001; Dauth et al., 2011; Schmidl, 2014). Anxo et al. (2001) ignore completely the simultaneity bias by arguing that this is an issue only in the unemployment equations and not in the matching function, because in the latter the dependent variable is not the direct object of political decisions. Another justification why this study does not address the issue of simultaneity is that the authors claim there is no clear joint variation of the unemployment and the number of ALMP participants for the time period analysed. A limitation of this study is that the dependent variables, especially the one for France, are quite complex and difficult to interpret.

A study by Hujer et al. (2007) investigates the aggregate effect of various ALMPs in West Germany using monthly regional level data for a two-year period from 2003 to 2004. This study uses a dynamic specification of the matching function while accounting for spatial interactions, assuming that the changes in employment exit probabilities in one region depend on the changes in labour market conditions in the neighbouring regions. In addition, Hujer et al. are able to use detailed information on the duration of employment spells of participants after the completion of the measures. This analysis accounts for different ALMPs in Germany: training programmes, job creation schemes, measures promoting qualifications and wage subsidies. The ALMPs are measured as the stock of participants in the different programmes while the dependent variable is the outflows of unemployed individuals into regular, unsubsidised employment. The study additionally accounts for possible endogeneity of the ALMPs by including several lagged values of the policies in the matching equation. The evidence from the study suggests in general a negative to insignificant effect in the both short and long-run of the ALMPs analysed. According to Hujer et al. an explanation for this may be that after the measure ends, firms replace the former subsidised employees/trainees as the measure ends with new subsidized employees/trainees.

To assess the effectiveness of different ALMPs in reducing the unemployment rate, youth unemployment rate and increasing the employment rate in Italy, Altavilla and Caroleo (2006) use monthly regional level data from 1996 to 2002. The study employed three different estimation techniques: Fixed Effects (FE), a dynamic panel modelling (difference and system Generalised Methods of Moments - GMM), and Panel Vector Autoregressive (P-VAR). They also distinguished between different active policies considered: mixed cause contracts (work contracts that include the training of the worker during working hours), subsidies for long-term or short-term employment (these subsidies consist of reducing payroll taxes or transferring a part of unemployment benefits to the employers), incentives for the stabilization of short-term contracts (these measures are used to transform short-term contracts like internship contracts into long-term contracts) and incentives for self-employment. The variables measuring active policies have been constructed as the total number of participants in a programme in a particular region divided by the total working-age population in the same region. The results from the dynamic specification suggest that the active policies analysed are effective in reducing unemployment and increasing employment and there is no great discrepancy between the results from GMM, FE and P-VAR estimators. Additionally, the results from the P-VAR suggest that the unemployment rate in North and South regions of Italy respond differently to ALMP shocks (an increase in ALMP participants to working-age population ratio). The authors argue that this might be due to a higher degree of labour market rigidity in the South, which might suggest that the efficiency of the labour market should be improved.

Dauth et al. (2010) also uses a matching function to assess the effectiveness of various ALMPs in Austria on a rich quarterly data at regional level from 2001 to 2007 using a dynamic specification. To control for further influences on the variables of interest, the authors add data on the structure of job-seekers such as the shares of different age and qualification groups, the shares of female, long-term job-seekers and the share of job-seekers with a migration background. To take into account a possible lock-in effect, several temporally lagged values of the policy variable were also included. Since the effects of different ALMP programmes can vary, the authors include the individual programmes as shares of all-jobseekers. Since the ALMPs of one region could also affect the labour outcome of other regions, the authors include a spatially lagged dependent variable. The study found that the regions with the larger shares of job-seekers older than 50 and younger than 25 had fewer matches compared to those with higher shares of job-seekers between the age 25 and 50. The same applies to the regions with large share of females and long-term job seekers. The study found mixed evidence with regard to the effectiveness of the ALMPs. The most effective measure in Austria for the period observed were a wage subsidy and apprenticeship scheme (this measure provides internship training positions to challenged young persons), while there was no evidence that vocational training, active job search and orientation and job training measures had any significant effect on the matching process. There was a strong negative effect of job schemes in non-profit organisations and the authors argue that this might be due to stigmatisation of participants. The findings also suggest that active measures with long-duration tend to be more likely to have lower matches hypothesised to be due to lock-in effects.

Some of the recent studies use large samples of mixed countries such as Bassanini and Duval (2006), Estevao (2007), Oesch (2010), Murtin et al. (2014) and Escudero (2018), all these studies use data at national level for non-transition economies except for the last one which uses both transition and non-transition economies. Even though these studies use different estimation techniques and have different sample sizes, the overall findings point to the effectiveness of ALMPs in reducing unemployment or increasing employment and labour force participation. In a few cases the results become statistically insignificant but none of them found evidence of a negative effect of these policies. Many of the studies using mixed samples are aware of the potential endogeneity problem when assessing the effectiveness of ALMPs and have tried to control for it using instrumental variable methods. A common limitation of the studies using mixed samples is that they rarely disaggregate between various ALMPs, leaving the studies unable to distinguish the effectiveness of individual policies.

Bassanini and Duval (2006) using static panel models on a sample of 21 OECD[11] countries do not find consistent effects of ALMPs. This study applies separate model specifications for the unemployment and employment rates using ALMP expenditure as share of GDP to assess the effectiveness of ALMPs. When using fixed effects, the ALMPs are found to be statistically significant in reducing unemployment and

[11] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States.

increasing employment rates. However, when using an instrumental variable approach (IV), where the ALMP variable is instrumented by its lagged values, the results become insignificant. Bassanini and Duval also examine the effect of different ALMPs, decomposing them into five categories: public employment services (PES) and administration, training programmes, youth measures, subsidized employment and measures for the disabled. The findings suggest the effect of training programmes is the only ALMP which is significant and consistent in all specification models in increasing the employment rate and reducing the unemployment rate.

In his study, Estevao (2007) analyses the effects of ALMPs on increasing the business employment rate (the share of working-age population employed in the private sector). The study argues that the business employment rate is a better measure (dependent variable) compared to the unemployment rate. This is because it avoids overestimating the policy importance of ALMPs by automatically excluding cyclical increases in public sector employment, which do not represent real improvements in labour market functioning. Estavao used a panel dataset of 15 industrialised countries[12] for 1985 – 2000 in a linear regression specification accounting for a set of institutional and other control variables. To account for the potential endogeneity of ALMPs, the study also uses the lagged values of ALMP expenditure as share of GDP but the results were not different from the basic specification. The overall findings suggest a positive effect of ALMPs on increasing the business employment rate (employment in the private sector).

Oesch (2010) focuses particularly on the unemployment rate of low-skilled workers to analyse the ALMPs effectiveness and policies such as wage-setting institutions, employment regulation, monetary policy and also globalization effects. This study also uses OLS regressions for 21 OECD[13] countries during the 1991 – 2006 period divided into four periods. The econometric analysis does not address the endogeneity of the ALMPs or the persistent nature of the unemployment rate, however the findings consistently supported the hypothesis that investing in ALMPs results in a

[12] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, the Netherlands, New Zealand, Norway, Spain, Sweden, the United Kingdom, and the United States.
[13] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom, Norway, Switzerland, Australia, Canada, New Zealand and the United States.

lower unemployment rate of low-skilled workers. The main limitation of this study is that it uses OLS, which in case of panel data produces biased and inconsistent results because the country specific effects are omitted and potentially correlated with other regressors.

Murtin et al. (2014) assess the effectiveness of the labour market policies on the unemployment outflow rate (the number of hires from the pool of unemployed divided by the number of unemployed) for 11 OECD countries[14] for a period between 1985 and 2007. This is one of very few studies which use a matching function for cross-country analysis of the effectiveness of ALMPs. Murtin et al. use a two-stage instrumental variable approach where in the first stage the dependent variable is the labour market tightness measured as *v/u* (vacancy to unemployment) ratio. The study instrumented the labour market tightness by business cycle shocks (measured by the output gap) as well as labour market institutions that are considered to have an impact on market tightness but not on matching efficiency which include the tax wedge and its interaction with the characteristics of wage bargaining systems. In the second stage estimation the unemployment outflow rate is estimated on predicted market tightness and a set of other institutional variables such as the characteristics of unemployment benefit systems and the degree of employment protection. The study found consistent evidence to suggest that ALMPs increase labour market tightness however the effect of ALMPs on matching efficiency is not significant.

Escudero (2018) increased the sample to 31 OECD countries (including some transition economies) using annual country-level data over the period 1985 - 2010. This study uses a set of dependent variables such as the unemployment rate, employment rate, labour force participation rate and the share of low-skilled unemployed in total unemployed. The author argues that using the latter dependent variable would assess whether ALMPs are providing incentives to the unemployed for acquiring new skills or to enterprises for enhancing the demand for low-skilled workers. An advantage of this study is that it particularly focuses on the low-skilled unemployed and marginalized groups. Escudero applies the instrumental variable approach to account for the endogeneity of the policy variables using real

[14] Australia, Belgium, France, Germany, Japan, Norway, Portugal, Spain, Sweden, the UK and the USA

expenditure on ALMPs per unemployed person as the instrument. In order to control for multicollinearity, the study included a set of active policies (training, employment incentives, supported employment and direct job-creation) into one cluster while start-up incentives and job-rotation and job-sharing are included separately in the model. Another advantage of this study, which is absent in any other study analysing the effectiveness of ALMPs, is that it accounts for different aspects of implementation of the policies in trying to explain the differences in the performance of ALMPs between countries. Three different measures of the ALMP implementation were included in the specification. The first one is the overall expenditure on programme administration as a percentage of total expenditure on ALMPs. The second measure is the continuity in the implementation of programmes measured by the dynamics of ALMP expenditure; this is captured by the difference between the fluctuations (measured by the standard deviation) in real GDP growth and the growth rate of ALMP spending. The third variable measures the timing of the ALMP expenditure, i.e. whether the policies are implemented in a counter-cyclical or pro-cyclical manner. To assess this, a dummy variable was created taking the value of one if expenditure on ALMPs ran parallel to changes in the unemployment rate and counter the economic trend (policies were implemented counter-cyclically) and zero otherwise. The main limitation of the clustering of different ALMPs is that the separate effect of the individual policies cannot be estimated.

The results from this study point to positive effectiveness of the policy cluster on all dependent variables. Most importantly, the findings from this study suggest that these ALMPs particularly improve the labour market outcomes for the low-skilled unemployed. The findings suggest that the start-up incentives are effective in reducing general unemployment and increasing employment, however with a lower magnitude and lower significance than in the case of the low-skilled unemployed. Importantly, the findings for the implementation variables also suggest that an increase in the share of administrative expenditure on ALMPs, which potentially indicates quality of administration, is associated with a reduction of unemployment and increase in employment and participation rates. Additionally, the study also included interaction terms between the policies and the implementation variables and found interesting results suggesting that when the ALMPs are implemented counter-cyclically (counter the economic trend), the effect of ALMP expenditure on reducing unemployment will be higher.

Similar to the studies for transition economies reviewed in the previous section, studies for non-transition economies also do not find a consensus with regard to the effectiveness of ALMPs. Given that one of the main goals of ALMPs is to increase matching efficiency, studies using single country sample usually employ the matching function approach for both transition and non-transition economies, although they differ in the estimation technique used. Altavilla and Caroleo (2006) found that employment creation schemes in public sector are the most effective among other measures in increasing matching efficiency. On the other hand, the results from Dauth et al., (2010) suggest that employment schemes in non-profit organisations have negative effect in matching efficiency possibly resulting from stigmatisation of the beneficiaries. Subsidies in the private sector are found to have more positive effect in increasing employment (Estevao, 2003; Altavilla and Caroleo, 2006; Bassanini and Duval, 2007; Dauth et al., 2010). However, some studies suggest that these measures are likely to induce deadweight and substitution effect (discussed in more details in section 2.2.3) hence the net effect of these policies could be small or even zero (Estevao, 2003; Bassanini and Duval, 2007; Arranz, 2013; Escudero, 2018). Estevao (2003) suggests that subsidies in the private sector could be more effective in reducing unemployment if they are better targeted and if they are implemented with better monitoring process. To avoid deadweight and substitution effects, these subsidies would be more effective if they target specific unemployed groups such as low skilled and long-term unemployment rather than general unemployed (Anxo et al., 2000; Altavilla and Caroleo, 2006; Arranz, 2013; Escudero, 2018). Similar results for subsidies in the private sector were found also for transition economies (Lehman, 1995; Kwiatkowski and Tokarski, 1997).

The results for training measures for non-transition economies are mixed, similar to those for transition economies. Studies suggest that vocational training, on the job training and general training have very small or no effect at all in increasing employment (Anxo et al., 2001; Estevao, 2003; Hujer et al., 2007; Dauth et al., 2010; Arranz et al., 2013). Anxo et al., (2001) argue that the ineffectiveness of training might be due to the lock-in effect and it is expected that this measure might become effective only in the long-run. However, in their study, Dauth et al., (2010) even after taking account of this issue still find the same result. In contrast, some studies have found evidence to suggest that training measures are the most favourable among all the active measures in increasing employment (Bassanini and Duval, 2007; Escudero, 2018).

Active job search and counselling seem to have a positive effect in increasing employment in the short-term (Bassanini and Duval, 2007; Escudero, 2018). According to the results of some studies, the self-employment and start-up measures also seem to be effective (Altavilla and Caroleo, 2006; Escudero, 2018).

The focus of this research is to analyse the effectiveness of ALMPs in transition countries which are characterised by large informal sectors. The next section will review the empirical studies which investigated the existence of informal labour markets in transition economies.

2.6 Labour Market Duality and Informal Labour Markets

The estimations of Schneider et al. (2010) suggest that the size of informal employment is relatively large in the transition countries. Recently, there has been an increased interest in investigating the effectiveness of ALMPs in countries with large informal sectors even though there is no established theory of the interaction between ALMPs and informal employment. This section will focus on the segmented labour market and the causes of informal employment, followed by a review of empirical studies estimating the existence of segmented market in transition economies.

The dual labour market theory was developed by Doeringer and Piore (1971) who directed their analysis towards the continuing poverty and unemployment amongst segmented and disadvantaged workers in poorer urban areas in the United States of America. The development of the dual labour market theory came after the failed attempts by government to increase the economic participation of marginalised workers such as women and minorities. Doeringer and Piore (1971) conceptualised the labour market as consisting of two different sectors with high within sector mobility but restricted mobility between sectors. The theory of labour market duality supports the idea that the two labour market sectors are able to function independent of each other because both sectors are divided by demand and supply side processes. In this context, the supply side refers to the characteristics of the worker such as level of education and the level of skills but also their perceived and actual attitude towards work. While the labour demand side comprises of the characteristics of jobs such demand for certain level of education and skills and employment protection and security.

Doeringer and Piore (1971) distinguished the two sectors according to individual and job features and refers to them as primary and secondary sectors. The privileged members of the labour market are allocated to the primary sector which is regulated and offers employment protection and job security. The employment in this sector is stable, provides relatively high wages and good advancement prospects. Additionally, the primary sector also offers individuals bargaining power and the protection of the trade unions which is an important feature of the job security of the employees.

The secondary sector comprises mostly of low-skilled jobs which usually do not need specific training to perform the job. According to the dual labour market theory, it is raw labour power that is required in this sector. Workers do not have employment protection and also do not have the possibility to complain because of lack of support from the trade unions. The secondary sector is very much unregulated and there are no seniority privileges as in the primary sector. Additionally, individuals who work in the secondary sector display a certain set of individual characteristics which are different from those in the primary sector. The individual's manners such as poor discipline, carelessness and high absenteeism make the workers in the secondary sector less reliable and trustworthy.

The literature on the dual labour market argues that disadvantaged individuals in the labour market, such as women, youth, ethnic minorities and people coming from poorer social class are trapped in the informal sector of the labour market. Peck (1996) argues that workers are social actors and their employment prospects are predetermined out of the labour market. In a society where females are viewed as the child bearers while the males are expected to be the breadwinners of the family, their constructed social gender identities reflect also their prospects in the labour market (Bauder, 2001). This typically reflects the situation in many European transition economies shown in Chapter 1, where males are more prone to be engaged in formal employment when they are head of the family and have children while females in same circumstances would be more likely to be informally employed. Further, the allocation of workers to jobs is a reflection of the ‘social class situation’ where the social groups tend to remain in the same social class. Because of social closeness, the entrance to the two sectors is controlled by social groups such as gender, ethnic and groups of different social class. In European transition economies it is the most deprived social class and unskilled workers are over represented in the informal employment (Kogan, 2011). Migrants and minorities, for instance, face higher barriers to entry in the formal employment because they do not always have information and appropriate social network about the vacancies and formal jobs (Julia et al., 2015). Cultural differences also play an important role in allocation of the labour force into the two sectors. Bauder (2001) and Jackson (2012) link the cultural identification with economic opportunity and labour market outcomes. The cultural aspect associated with behaviour, norms and ethics influence individuals to pursue different educational goals and occupational choices which in turn will impact their opportunities in the segmented labour market. When recruiting, employers use the level of completed education and related characteristics, such as full-time or part-time education, private versus public, whether the workers dropped out of school, as a screen. In spite of representing workers’ productivity, these educational biographies represent the workers’ vulnerability which are more prone to be taking up jobs in the informal sector (Kogan, 2011). As discussed in Chapter 1, in European transition economies workers with lower education level comprise the largest share in the informal sector.

However, Fields (1990) and Maloney (2004) acknowledge that the informal sector also attracts a segment of workers who participate in this sector by choice. Fields (1990) divided the informal sector into two subsectors, one which consists of disadvantaged workers where entrance is easy (the easy-entry informal sector) and the second where there are barriers to entry such as requirement of higher capital and skills (the upper-tier informal sector). The upper-tier sector entails long-term relationships between employers and employees, operates flexible hours and locations and employment of family members in this sector tends to be preferred. Typical upper tier informal sector activities are individually-owned and operated taxi cabs. There is a relatively high cost involved in purchasing a taxi which entails barrier to entry, hours of work can be regular or irregular and the owner can employ an additional driver to operate during the night shift (Fields, 1990). The easy-entry subsector is better understood as opportunity of last resort or as a survival strategy for the excluded workers, while in the upper-tier subsector workers participate voluntarily.

In contrast to the view of dual labour market, the two sectors might not necessarily be divided by the entry restrictions but the features of two sectors may co-exist in the same labour market (Maloney, 1999; 2004; Cunningham and Maloney, 2001). Maloney (2004) argue that informal workers make the decision to enter the labour market taking into consideration both sectors; the worker then will choose whichever sector offers a higher earning opportunity and also other higher benefits. In this context, Maloney (2004) argues that there is high mobility of workers between the two sectors. When Maloney (2004) and Fields (1990) argue the voluntary engagement of workers in the formal sector, they use this argument only for those who are self-employed or micro-entrepreneurs. As observed from the information analysed in Chapter 1, in transition economies informal self-employment is fairly rare and informal workers are overwhelmingly informal dependent employees (Slonimczyk, 2014). In this context, informal employment in transition economies is predominantly characterised by easy-entry informal rather than upper-tier informal markets.

There is a considerable literature which analyses the factors that contribute to the emergence of informal labour markets. Regulatory distortions in formal labour markets, such as a relatively high minimum wage and strong union bargaining agreements may keep the wage in the formal sector above the market clearing level. Labour costs might also increase when taking into account benefits and severance pay which would result in inflated wages. High tax burdens and social security contributions increase the size of the informal sector; the larger the difference between the labour costs and the after-tax earnings the stronger the incentive to engage in informal employment (Schneider and Enste, 2000; Eilat and Zinnes, 2002; Schneider and Williams, 2013). Thus, labour market regulations and policies may tend to increase artificially labour costs and cause the labour market sector to be divided. Subsequently, those who are not able to get an employment in the formal sector will be subject to find work in the informal sector.

There are a few empirical studies that have analysed the labour market segmentation in transition economies. Haltiwanger and Vodopivec (1999) estimated labour market transition during the early transition period and found evidence to suggest that Estonia experienced high levels of mobility between informal and formal sectors. Earle and Sakova (2000) used multinomial logit analysis to distinguish between employers and own-account self-employed while comparing both groups to employees and the unemployed in six transition economies (Bulgaria, Poland, Czech Republic, Slovakia, Hungary and Russia). They distinguished between employers who are considered as genuine business owners and own-account self-employed whose background is more ambiguous. Earle and Sakova suggest that own-account self-employed are typically engaged in the informal economy. This study also examined the earnings differences between individuals in different labour market states. The findings suggest positive earning differentials of own-account self-employed compared to employees for all six transition countries and also positive selection into informal self-employment suggesting that these workers have a comparative advantage at being micro-entrepreneurs.

Pages and Stampini (2007) also analysed wage differentials in three transition countries (Albania, Ukraine and Georgia) but found no evidence of a positive formal wage premium to informal salaried jobs and also found high mobility from informal to formal salaried jobs. In contrast, the findings from this study suggest that there is very low mobility between informal self-employment jobs and formal employment which suggest that there exist barriers to movement in both directions.

Another study for Serbia used regression-based models to identify the determinants of the level of main job earning inequality between formal and informal sector (Krstic and Sanfey, 2010). The findings suggest that there is greater inequality of earnings in the informal sector relative to the formal sector. One possible reason for this is the minimum wage which was enforced in the formal sector during the period examined (2002 – 2007). The findings from the study suggest that there is high between-group earnings inequality of the same educational level of informal and formal workers. The earnings inequality increased between 2002 and 2007, which highlighted the growing advantage of the formal employment.

Lehman (2015) analysed the labour market segmentation of the Russian labour market employing two different approaches. The first approach used is the wage gap regression to assess if there is any wage gap between workers who are employed in formal and informal sectors. In order to assess whether there are barriers between formal and informal sectors, the second approach used is an estimation of mobility probabilities between labour market states. In order to assess the wage difference the study divided the informal employees into groups of high and low skilled. The study also assessed if individual 'subjective' risk attitudes are linked to the labour market states. Findings from the wage regressions suggest that low skilled informal employees experience a significant wage penalty, while informal employees with high skills have the same wages as their formal counterparts. This finding suggests that the labour market for high skilled workers is integrated, while low skilled informal workers are faced with a segmented labour market. When analysing the mobility of workers in different sectors, Lehman divided employment into five distinct states: involuntary informal dependent employment, voluntary informal dependent employment, formal dependent employment, informal and formal self-employment. The study found strong evidence to suggest that formal employees are the most risk-averse while self-employed and informal employees have the highest propensity to take risk.

Empirical evidence on the existence of segmented labour markets in transition economies is mixed and no straightforward conclusion can be drawn. From the empirical findings one can argue that in transition economies there exist earning differential for low-skilled workers (Krstic and Sanfey, 2010; Lehman, 2015), however the same result is not found for high-skilled workers (Pages and Stampini, 2007; Lehman, 2015). When analysing the mobility between informal and formal sectors, findings from Pages and Stampini (2007) indicate that there is low mobility between the two sectors while those from Haltiwanger and Vodopivec (1999) indicate high mobility. However, when analysing informal self-employment, the findings from Earle and Sakova (2000) and Pages and Stampini (2007) suggest that there is low mobility between informal and formal self-employment suggesting that the labour market for self-employment is highly segmented.

Considering the large informal sectors in transition economies there are significant additional policy implication for the effectiveness of ALMPs. According to Katz (1996), the effects of lowering labour costs are conceptually equivalent to providing wage subsidies to employers. Katz suggests that the effect of a reduction of labour costs is only clear cut when the supply is perfectly elastic or perfectly inelastic. In an extreme case, when the labour supply is perfectly elastic the result will be the increase in employment. In a pool of low skilled unemployed or informal workers, and where there is a statutory minimum wage, firms will expand employment without having to raise wages. While, in the other extreme, when the labour supply is perfectly inelastic the result will be an increase in wages because the subsidies will be passed on to employees, however no additional jobs will be created. As explained by Lehman and Muravyev (2012), the most realistic scenario in European Transition Economies is when the labour supply is positively elastic, a reduction of labour cost can lead to higher level of employment. Based on the empirical evidence, Katz (1996) argues that low skilled workers face higher elasticity of labour demand and supply than skilled workers. Thus, an increase in wage and direct subsidies for low skilled workers would provide an incentive to firms to employ more formal workers as opposed to informal ones and comply with employment legislation such as providing written contracts for their workers. Lehman and Muravyev (2012) argue that in the case of high structural unemployment this effect would be particularly large because these subsidies will reduce the skill mismatch.

Transition economies' labour markets might be characterised by multiple equilibria. As explained in Snower's model (1994), the good equilibrium consists of a predominance of high-skill workers in the formal sector, while the bad equilibrium consists of a high proportion of low-skill workers in the informal sector. Taking into consideration that low-skilled workers are more likely to be engaged in the informal sector in transition economies, wage subsidies can improve employment prospects for this category of workers through lowering labour costs of the firm. Access to such subsidies provides incentives for a firm to switch from informal to formal sector. Skills enhancement of the informal workers through training or labour counselling, as active measures, might also improve their employment prospects in the formal sector. As discussed in section 2.2.3, training and on-the-job training increase employee's skills which in turn increase their productivity and as a consequence will assist a transfer of the low-skilled labour from low-productivity (i.e. informal sector) to high-productivity sector (formal sector). In this context, ALMPs perform best when designed to target the low-skilled, that are mainly concentrated in the informal sector in transition economies, and as such ALMPs provide incentives for the firms to employ more formal workers rather than informal ones.

2.7 Conclusions

This chapter has provided a critical review of different theories of unemployment and the effectiveness of ALMPs at the economy wide level. It also discussed the causes of high unemployment rates and large informal employment in transition economies and provided a detailed discussion on empirical methodology widely used to evaluate the ALMP effectiveness at the economy level. Section 2.2.3 concluded that there is a considerable number of identified effects of ALMPs: effects on the matching process, productivity effects, effects on labour force and competition in the labour market, deadweight loss and substitution effects, reduced welfare losses for the unemployed and work-test effects. The effects of ALMPs have been analysed based on the theoretical framework of Layard, Nickell and Jackman (1991). The discussion of the effects of ALMPs concluded that these effects can counteract each other and can also cause negative externalities in the labour market. Having found no explicit theoretical explanation of the effectiveness of ALMPs in the context of high informal employment, this chapter sought to analyse the role of active measures as incentives for firms to switch from informal to formal employment. This chapter also discussed the causes of general and youth unemployment in European transition economies and reviewed the empirical evidence assessing the nature of unemployment in these economies. The findings from the empirical studies are mixed, with most inclining to support the structuralist hypothesis of unemployment in transition economies. The matching function approach is the empirical methodology mostly employed for the analysis of ALMPs at the economy wide level. Matching functions have been acknowledged in the empirical literature as an appropriate approach to analyse the matching efficiency in the labour market in transition economies since they allow for Increasing Returns to Scale. As discussed in this chapter, labour markets in transition economies might be characterised by multiple equilibria; with many ETEs, especially in South Eastern Europe, being trapped in a low-skill bad-job equilibrium.

The conceptual framework of the matching methodology has been critically assessed in this chapter and will be used in Chapter 3 as the basis for the empirical analysis to evaluate the effectiveness of ALMPs in selected European transition economies. The discussion in this chapter also provides the theoretical framework for the empirical evaluation of ALMP at the individual level which will be conducted in Chapters 5 and 6.

Chapter 3

The effectiveness of ALMPs in reducing unemployment, with particular reference to the role of the size of the informal sector

3.1 Introduction

The analysis of the underlying theoretical framework and review of the empirical studies using matching function discussed in Chapter 2 provide the basis for the empirical analysis to be conducted in this chapter. As argued in Chapter 2, active labour market policies can impact on the labour market either through the wage-setting or the price-setting schedules. Specifically, ALMPs have been argued to have the following potential effects on the labour market: effects on the matching process, productivity effects, effects on the size of the labour force and the level of competition in the labour market. The review of the empirical research of the transition context studies indicated that there is currently no solid consensus with regard to the effectiveness of ALMPs. Thus, this chapter provides additional empirical evidence in assessing the effectiveness of different active labour market policies at the economy-wide level.

Most of the empirical studies assessing the effects of ALMPs have employed a *matching function.* These investigations have typically used the *flow from unemployment to employment as the dependent variable* and have employed regional administrative data on a quarterly or monthly basis. Because for the selected sample of countries, neither quarterly nor monthly data is available for variables measuring ALMPs, this chapter will utilise only annual level data for the period 2010 to 2015 for European transition economies. The sample was further expanded to account for European non-transition economies in order to compare the effectiveness of ALMPs between the two groups of countries and due to the limited data available for transition economies. The second empirical approach will use a different dependent variable and estimation approach: separately including variables to account for the following active measures: training, employment incentives, supported employment and rehabilitation, direct job creation and start-up incentives. Data and model specifications of the two approaches are developed separately and the final models will be presented at the end of each discussion.

This chapter is organised as follows. Section 3.2 provides a description of the active policies analysed in this empirical chapter. Section 3.3.1 provides a discussion of the model specification and data sources, while 3.3.2 will discuss the possible endogeneity of the ALMP variable. Section 3.3.3 will provide an explanation of the estimation methodology used for the first model which will be followed by section

3.3.4 which discusses the key descriptive statistics for the matching function and the main empirical findings. Section 3.4.1 will provide the model specification for the second approach where the dependent variable is the unemployment rate. Section 3.4.2 provides a discussion of the estimation methodology used for dynamic panel models, their key advantages and possible limitations. Findings from the second model will be provided in section 3.4.3 while section 3.5 presents the conclusions of this chapter.

3.2 Classification of Active Labour Market Policies according to Eurostat

The ALMP variables are derived from Eurostat databases. Policy categories used in this chapter thus follow the Eurostat classification and definitions (Eurostat, 2016). These categories are:

1. *Labour market services – "are all services and activities undertaken by the PES together with services provided by other public agencies or any other bodies contracted under public finance, which facilitate the integration of unemployed and other jobseekers in the labour market or which assist employers in recruiting and selecting staff"* (Eurostat, 2018, p.13). This service covers the ad hoc information about the available vacancies, training and other forms of assistance together with job-brokerage services for employers. Labour market services also include individualised counselling aiming to provide a planned path for job-seekers towards durable (re)employment. These services also include all the administration, management and coordination of the employers and servicers engaged for all categories of ALMPs.
1. *Training* – includes different forms of training aiming to improve the employability of target groups. There are three categories of training which are defined depending on the amount of time participants spend in the classroom or workplace with purpose of instruction. The first one is institutional training which covers measures where majority of the time is spent in the training institutions (at least 75% is spent on school, college, training centre etc.). The second form of training is the workplace training which covers those activities that are mostly spent in the workplace with

purpose of instruction by the supervisor (75% in the workplace) or entirely based on learning by doing or learning by experience. The third category is where training in which the time is more evenly split between on and off-the-job.

2. *Employment incentives* – "*covers measures that facilitate the recruitment of unemployed persons and other target groups, or help to ensure the continued employment of persons at risk of involuntary job loss"* (Eurostat, 2018, p.17). These are subsidies for open market jobs which might exist or can be created, most likely in the private sector but also in public and non-profit sectors. The subsidy typically covers some remuneration for the employed person while a majority of the labour costs is covered by the employer.
3. *Supported employment and rehabilitation* – "*covers measures providing subsidies for the productive employment of persons with a permanently (or long-term) reduced capacity to work*" (Eurostat, 2018, p.18). This measure consists of subsidies for the employment of individuals with a long-term unemployment, disabled job-seekers, those who are going through rehabilitation after an accident or illness, recovering drug-addicts and other groups who are not work-ready and may benefit from rehabilitation.
4. *Direct job creation* – "*covers measures that create additional jobs, usually of community benefit or socially useful, in order to find employment for the long-term unemployed persons otherwise difficult to place"* (Eurostat, 2018, p.19). This usually refers to subsidised jobs for temporary, non-market jobs which would not exist without the help of public intervention. This subsidy aims to assist the unemployed by increasing their employability.
5. *Start-up incentives* – "*covers measures that promote entrepreneurship by encouraging the unemployed and other target groups to start their own business or to become self-employed"* (Eurostat, 2018, p. 20). This form of subsidy can be distributed through cash benefits or indirect loans, provision of facilities, business advice etc. These measures may also support new businesses to take on their first employees from the target groups. Start-up incentives are accounted as ALMPs only when they target specified groups of unemployed or non-participants, generally available business start-up subsidies are not included in this category.

The following section provides an explanation of the approach taken in the first empirical investigation of this chapter. Section 3.3.1 provides the model specification while section 3.3.2 discusses the potential endogeneity of the ALMP variable and assesses the instrumentation strategies used by previous empirical studies. Following this discussion, section 3.3.3 provides an explanation of the estimation techniques for panel data employed in this empirical investigation. while section 3.3.4 discusses the empirical results.

3.3 Empirical Approach for Model 1 – Matching Function

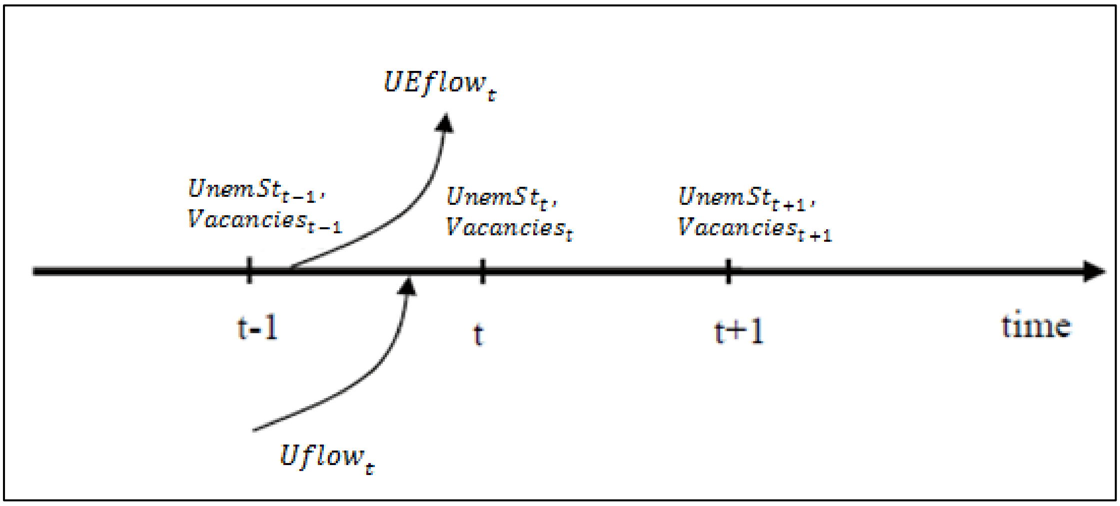
In order to provide an overview of the effects of the ALMPs on the national labour markets this chapter will use two model specifications. The first model is a matching function where the dependent variable is the outflow from unemployment to employment, i.e. the number of matches made between the unemployed and unfilled vacancies. This section will discuss the specification of the model of the outflows from unemployment to employment, where the key variable of interest is measured as total expenditure on ALMPs as percentage of GDP. The section below provides a discussion of the model specification.

3.3.1 Model Specification

As elaborated in Chapter 2, the effectiveness of ALMPs is most appropriately assessed through the matching function approach. The suitability of the matching function approach lies in the minimal complexity of this approach. A matching function summarizes the mechanism of matching the vacancies advertised by firms and the unemployed who are searching for jobs through employment agencies, reading advertisements in the newspapers or utilising their social networks. The simplest form of a matching function is a model where the dependent variable is the outflow from unemployment to employment and it is regressed on two main explanatory variables: (i) the number of unemployed workers searching for a job and (ii) the number of open vacancies. A detailed explanation of the matching function and its' appropriateness in assessing the effectiveness of ALMPs is provided in section 2.4.

It was argued in Chapter 2 that not only do the stocks of unemployment and vacancies affect the efficiency of matching but also the flow of new entrants into the pool of unemployment and flows of the new vacancies into the existing stock of vacancies. Chapter 2 explained that the unemployment stock at period t cannot be simply matched with the vacancy stock at time period t. Hence in order to find a match, the existing unemployed may wait until the next period when new vacancies (flow of new vacancies) are opened and similarly the existing vacancies may remain open until new entrants join the unemployment pool (inflows to unemployment pool) (Coles and Smith, 1996; Petrongolo and Pissarides, 2001). Following this argument, only the lagged values of unemployment and vacancy stocks are included in the model. With regard to the flow independent variables, due to data limitations, only the variable accounting for the flows of new entrants into the unemployment will be included in the model. The stock-flow matching is depicted in Figure 3.1.

Figure 3.1 The process of stock-flow matching



Source: Munich and Svejnar (2009), p.10.
Note: UEflow is the number of people transitioning from unemployment to employment and *Uflow* is the number of people transitioning to the unemployment pool.

Theories of search and matching generally do not suggest a specific functional form but most of the studies use a Cobb-Douglas function written in a deterministic form of discrete observations as following:

$$lnUEflow_{i,t} = \beta_0 + \beta_1 lnUnemSt_{i,t-1} + \beta_2 lnVacancies_{i,t-1} + \alpha_i + \varepsilon_{i,t} \qquad 3.1$$

The observational unit is the country i, at year t. The dependent variable, $lnUEflow_{i,t}$, is the flow from unemployment to employment during period t, $lnUnemSt_{i,t-1}$ and $lnVacancies_{i,t-1}$ are the number of unemployed and vacancies at the end of period $t-1$, respectively, α_i is the unobserved time invariant country specific effect and $\varepsilon_{i,t}$ is the idiosyncratic error term. This form of matching function will be augmented to account for the effects of ALMP expenditure as a share of GDP and control variables which are presented in table 3.1 and are discussed individually below.

According to Munich and Svejnar (2009), unless the matching function exhibits constant returns to scale, not controlling for respective labour market size may lead to biased coefficients (omitted variable bias). The bias arises from the positive correlation between $UEflow_i, UnemSt_i, Vacancies_i$, and the labour force size $LFor_\mathrm{i}$. The direction of bias would be negative if the unemployment and vacancy stocks are positively correlated with labour force size and matching displays increasing returns to scale. On the other hand, a positive bias would be present in case of negative correlation of these variables or decreasing returns to scale. The bias is greater the greater is the correlation between the measures with the labour force size. Hence, labour force size, $LFor_\mathrm{i}$, is included in the model to adjust for the labour market size and avoid the omitted variable problem.

As the review of the empirical studies emphasised in Chapter 2, an individual recently entering unemployment (flow into unemployment) typically has a higher probability to match with existing vacancies (stocks) compared to those that were unemployed in period *t-1*, since it is expected that a match would have happened already if the previous period's vacancies were suitable (Coles and Smith, 1996; Petrongolo and Pissarides, 2001; Coles and Petrongolo, 2003). To reflect this 'stock-flow' matching and assess the matching efficiencies of the new entrants, two flow variables accounting for the new entrants in the unemployment from the inactive state, $IUflow_\mathrm{i,t}$, and from employment, $EUflow_\mathrm{i,t}$, are typically included in the model. As section 2.3.1 pointed out, empirical studies for transition economies so far did not distinguish between the flows into unemployment from different labour market states. When comparing the two flows, individuals transitioning from employment to unemployment would typically be more attached to the labour market, thus it is expected that they would have higher matching efficiency compared to those transitioning from an inactive state to unemployment. Due to being inactive for a certain period, workers recently joining the labour market might face a longer search period before finding a job because they have less information about the open vacancies. Moreover, employers might prefer hiring those who until recently were employed rather than those who were inactive because the former may be expected to be, on average, more productive.

Different groups of the unemployed may have different search intensities, might be more adaptable and might have different willingness to accept specific job offers such as those for temporary jobs and also, employer attitudes may differ towards these groups (discrimination and expectations regarding potential productivity). Given the analysis presented above, the specific groups included in the model are the share of young unemployed (*ShYoungUn), the* share of long-term unemployed (*ShLongUn*), and the share of unemployed women (*ShWomen).* Several studies using a matching function argue that the share of youths in total unemployment is expected to increase the number of transitions from unemployment to employment due in part to youths usually demonstrating higher adaptability and higher search intensity (Jeruzalski and Tyrowicz, 2009; Tyrowicz and Wojcik, 2010; Tomic, 2012). In addition, young people are more likely to accept temporary jobs and they are expected to move in and out of employment more often compared to their older counterparts. The share of long-term unemployed as percentage of total unemployment is included in the model because the long-term unemployed (more than one year) might be expected to have different unobserved characteristics compared to those short-term unemployed. As discussed in Chapter 2, the long-term unemployed may be discouraged, stigmatised as being less-productive and have deteriorated human capital. According to Tomic (2012), the share of long-term unemployment may capture both business cycle effects and more structural difficulties (employers' behaviour, skill or occupational mismatch). An increase in the share of long-term unemployment is expected to reduce the number of individuals transitioning from unemployment to employment, ceteris paribus, thus the sign of this variable is expected to be negative. Women are also expected, ceteris paribus, to have lower search efficiency and experience lower matching compared to men (Tomic, 2012; Barnichon and Figura, 2015). This is because of discrimination in the labour market: some employers tend to prefer men for certain occupations for reasons unrelated to potential productivity (Anker, 1997). Also, women are expected to spend more time with childcare and other family responsibilities hence reducing their search intensity. Due to occupational segregation and perceived and actual discrimination, women may reduce their search for higher paying and more desirable positions but disproportionately search for temporary jobs and lower ranking jobs. In this context, Tomic (2012) argues that labour markets with a larger percentage of females searching for jobs will tend to have lower matching efficiency.

The augmented matching function will include a variable measuring the expenditure on ALMPs as share of GDP, *ALMPExp*. The effects of ALMPs were extensively discussed in section 2.2.3; it is expected that an increase in the ALMP expenditure as a percentage of GDP will increase the number of individuals transitioning from unemployment to employment. As also discussed in Chapter 2, Snower (1994) argues that there should be a large infusion of ALMPs in the labour market in order for these policies to be effective in shifting the bad-job equilibrium to the good-job equilibrium. Hence, the size of ALMPs might exhibit nonlinear relationship with the dependent variable and the quadratic form of ALMP is included in the model to adjust for this potential nonlinear relationship.

Control Variables

A control variable measuring Passive Labour Market Policies (PLMP) (the total of Out-of-Work income maintenance and support and Early Retirement policies) measured as expenditure on PLMP as a percentage of GDP (*PLMPExp*)[15] is included in the model based on the theoretical rationale that more generous unemployment benefit systems affect the willingness to accept a job via different mechanisms (Scarpetta, 1996; Nickell, 1997, Cazes, 2003). Bassanini and Duval (2006) argue that higher unemployment benefits available to the unemployed for a longer period reduce job search intensity thus weakening the job-matching process. Also those unemployed receiving unemployment benefits will tend to have higher reservation wages, thus reducing the effectiveness of these unemployed as potential fillers of vacancies since it becomes more costly for employers to hire new workers. Nickell (1997) also points out that when unemployment is high and more persistent,

[15] A variable measuring the expenditure per PLMP beneficiary was considered to be included in the model instead of the PLMP expenditure as share of GDP. However according to Eurostat (2016), data on the number of beneficiaries are not reliable, hence variable expenditure per PLMP beneficiary could not be calculated.

countries may increase the level of benefits to support the unemployed, so the causality is not from benefits to unemployment but rather the other way around. However, the empirical evidence does not show a clear consensus with regard to this relationship (Scarpetta, 1996; Nickell, 1997; Cazes, 2002; Nunziata, 2002; Lehman and Muravyev, 2009). It is expected that an increase in PLMP expenditure as percentage of GDP will reduce the number of individuals transitioning from unemployment to employment, i.e. will reduce matching efficiency.

As argued in section 2.4, a variable measuring the size of the informal economy (*Informality*) is included in the model to assess its effect on the matching efficiency. Schneider and Williams (2013) emphasise that there is a dispute regarding the most appropriate methodology to assess the scope of the informal economy since because of its' nature it is quite difficult to measure. This investigation uses estimates of the size of informality by Schneider (2015) based on the MIMIC (Multiple Indicator and Multiple Cause) estimation procedure. Schneider and Williams (2013) explain that the informal economy can be estimated quantitatively based on the causes and indicators of the informal economy. The causes of informal economy include the level of the tax burden and the intensity of regulation, while indicators include money demand, official national income figures and total hours worked in the economy. According to Buehn and Schneider (2012), the relationship between unemployment and the size of the informal economy is theoretically ambiguous. When the unemployed search and take jobs in the informal labour market the behaviour of unemployment depends on whether or not informal workers are considered unemployed in official statistics. In the case when the informal worker is considered unemployed, the flow from unemployment to employment estimate would not change. On the other hand if informal workers are considered employed, the flow from unemployment to employment increases and one would observe a positive relationship between the dependent variable (*lnUEflow*) and the size of the informal economy (*Informality*). The data used for this empirical analysis are based on national Labour Force Surveys which are designed to cover informal employment. Considering the arguments presented above, the expected sign of informal economy is positive: i.e. the higher the informal economy the higher the flows from unemployment to employment. It can also be argued that there might be a reverse causality between the informality variable and the dependent variable which could result in endogeneity. Schneider and Williams (2013) argue that higher unemployment might give rise to informal employment because those unemployed who are unable to find a job in the formal sector will be compelled to work in the informal sector. Having argued a possible endogeneity issue, the lagged value of variable *Informality* is included in the model.

GDP growth (*GDPgrowth*) is another control variable included in the model specification to capture the labour demand fluctuations within countries. The values of this variable are expressed in annual percentage growth rate of GDP at market prices based on constant 2010 U.S. dollars. Following the theoretical arguments of Cazes (2002) and Lehman and Muravyev (2009), GDP growth aims to better account for macroeconomic shocks and demand fluctuations. It is expected that an increase in GDP growth, ceteris paribus, increases the number of transitions from unemployment to employment[16].

The model also incorporates the relationship between the matching efficiency and the level of the economic freedom. The testable hypothesis is that countries with greater economic freedom have a larger number of transitions from unemployment to employment. Greater economic freedom encourages a higher level of entrepreneurial activity and creation of small businesses (Kreft and Sobel, 2005). It also affects the transitions from unemployment to employment by reducing the regulatory and financial costs on employers in the country (Karabegovic and McMahon, 2008). This investigation will use the Economic Freedom Index (*EcoFreeIndex)* constructed by the Heritage Foundation which is based on a set of 10 different aspects (Property rights, Freedom from corruption, Fiscal freedom, Government spending, Business freedom, Labour freedom, Monetary freedom, Trade freedom, Investment freedom, Financial freedom). The economic freedom indices are based on a 10 point scale with higher values representing greater freedom. The expected sign of this variable is positive, i.e. the higher the economic freedom of a country, the larger the number of matches.

Labour Freedom Index (*LabFreeIndex*) is included in the model to account for various aspects of the legal and regulatory framework of a country's labour market,

[16] GDP growth may not affect transitions into employment positively if at the same time productivity increases proportionately (Nordhouse, 2005; Balls, 2008).

including regulations concerning minimum wages, laws inhibiting layoffs, severance requirements and measurable regulatory restraints on hiring and hours worked. This index is also derived from the Heritage Foundation and is also based on a 10 point scale with higher value of the indicator representing a more flexible labour market. In general, empirical research supports the argument that rigid labour markets have the tendency to hinder job creation and tend to be associated with higher levels of unemployment (Nickell, 1997; Bassanini and Duval, 2006; Bernal-Verdugo et al., 2012) and those mostly affected are the young unemployed (Botero et al., 2004). It is expected that greater labour market freedom, ceteris paribus, increases the number of transitions from unemployment to employment. The model uses lagged values of *EcoFreeIndex* and *LabFreeIndex* because it is believed that a lag exists between the time when the government policies are implemented and the effect of these policies on the labour market, hence it is reasonable to model the transition from unemployment to employment as a function of previous period's government policies (Heckelman, 2005; Garrett and Rhine, 2011).

Given that education has a major influence in the labour market outcomes (Card, 2001; Grossman, 2006; Oreopoulos and Salvanes, 2009), this investigation will test the hypothesis that more educated individuals are more likely to find jobs than their less educated counterparts. The level of education is included in the model with two variables that capture the share of labour force that attained or completed secondary (*EduSecondary*) or tertiary education (*EduTertiary*) as the highest level of education. An increase in share of individuals in the labour force with higher levels of education, ceteris paribus, is expected to increase the number of transitions from unemployment to employment.

The Population Density (*PopDensity*) variable intends to capture the probability that a contact is established between the right worker and employer (Ibourk et al., 2004; Tomic, 2012). The variable measuring population density serves as a proxy for the size of social networks and the efficiency of information transmissions. Ibourk et al. (2004) argue that the population density variable tends to adjust for the effects 'labour market thickness'. A thick labour market represents a higher and more effective number of participants in the market, employers and workers, which tends to improve the search efficiency either through increasing returns to scale in search or through increased flexibility in each agent's choice of where to search (McLaren, 2003). Coles and Smith (1996) argue that search efficiency improves in a labour market with a higher population density because the communication between parties close to each other requires lower effort and costs. However, Kano and Ohta (2005) suggest that the heterogeneity of the job seekers and vacancies may be higher in more densely populated areas increasing search frictions. Thus there might be difficulties in the matching process despite the agents being close to each other in a geographical sense. Ibourk et al. (2004) and Wahba and Zenou (2005) introduce the quadratic form of the population density variable. Wahba and Zenou (2005) conclude that as long as population density remains an (undefined) 'reasonable size', it has a positive impact on matching efficiency, but this effect might become negative for labour markets with very high population densities. Following this argument, the quadratic form of *Popdensity* is included in the model to capture the potential nonlinear relationship between population density and the dependent variable. It is expected that an increase in population density increases the number of transitions from unemployment to employment up to a point and then have a negative impact of the matching efficiency.

In order to examine the difference in matching efficiency between transition and non-transition economies an additional variable (*Transition*) is created: a dummy variable taking value of 1 if it is a transition or post-transition economy and 0 otherwise. Also, an interaction term between *Transition* and *ALMPExp* (*TransAlmp)* is also introduced to examine potential differences in the effectiveness of ALMPs in the two groups of countries.

$$\begin{aligned} lnUEflow_{i,t} = {} & \beta_0 + \beta_1 lnUnemSt_{i,t-1} + \beta_2 lnVacancies_{i,t-1} + \beta_3 lnEUflow_{\mathrm{i,t}} \\ & + \beta_4 lnIUflow_{\mathrm{i,t}} + \beta_5 ShYoungUn_{\mathrm{i,t}} + \beta_6 ShLongUn_{\mathrm{i,t}} \\ & + \beta_7 ShWomenUn_{\mathrm{i,t}} + \beta_8 ALMPExp_{\mathrm{i,t}} + \beta_9 ALMPExp_{\mathrm{i,t}}{}^2 \\ & + \beta_{10} PLMPExp_{\mathrm{i,t-1}} + \beta_{11} Informality_{\mathrm{i,t-1}} + \beta_{12} GDPgrowth_{\mathrm{i,t}} \\ & + \beta_{13} LabFreeIndex_{\mathrm{i,t-1}} + \beta_{14} EcoFreeIndex_{\mathrm{i,t-1}} \\ & + \beta_{15} EduSecondary_{\mathrm{i,t}} + \beta_{16} EduTertiary_{\mathrm{i,t}} + \beta_{17} PopDensity_{\mathrm{i,t}} \\ & + \beta_{18} PopDensity_{\mathrm{i,t}}{}^2 + \beta_{19} Trans_{\mathrm{i,t}} + \beta_{20} TransAlmp_{\mathrm{i,t}} + \alpha_i \\ & + \varepsilon_{i,t} \qquad 3.2 \end{aligned}$$

Variable description, labels, the expected signs and data sources are summarised in table 3.1 presented below.

Table 3.1 Variable Specifications and Expected Signs – 1st approach

Variable Name	Variable Description	Expected Sign	Data Source
Dependent Variable			
UEflow	The flow from unemployment to employment at the end of period t, i.e. the number of successful matches		EUROSTAT
Main Variables of Interest			
UnemSt	The number of unemployed at the end of the period		EUROSTAT
Vacancies	The number of job vacancies at the end of the period		EUROSTAT
IUflow	The number of new entrants from inactive to unemployment stock at the end of the period		EUROSTAT
EUflow	The number of new entrants from employment to unemployment stock at the end of the period		EUROSTAT
ShYoungUn	The share of youth unemployment in total unemployment	+	EUROSTAT
ShLongUn	The share of long-term unemployment in total unemployment	-	EUROSTAT
ShWomenUn	The share of women unemployment in total unemployment	-	EUROSTAT
ALMPExp *1.TrainSh* *2.EmpIncSh* *3.SupportSh* *4.DirectJobSh* *5.StartupSh*	Active labour market policies measured as expenditure as percentage of GDP and Different types of active policies measured as share of ALMPExp: 1. Share of expenditure on training in total ALMP expenditure, 2. Share of expenditure on employment incentives in total ALMP expenditure, 3. Share of expenditure on supported employment and rehabilitation in total ALMP expenditure, 4. Share of expenditure on direct job creation in total ALMP expenditure 5. Share of expenditure on start-up incentives in total ALMP expenditure.	+	EUROSTAT
Control Variables			
LFor	Total labour force comprises people aged 15 and older who meet the International Labour Organization definition of the economically active population: all people who supply labour for the production of goods and services during a specified period. It includes both the employed and the unemployed.	+/-	WORLD BANK
Informality	MIMIC index measure of the size of the shadow economy.	+	Schneider (2015)
PLMPExp	Passive labour market policies measured as expenditure as a % of GDP	-	EUROSTAT
PopDensity	Population density is midyear population divided by land area in square kilometres. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.	+	WORLD BANK
EduSecondary *EduTertiary*	1. Labour force with secondary education - The share of the total labour force that attained or completed secondary education as the highest level of education. 2. Labour force with tertiary education - The share of the total labour force that attained or completed tertiary	+ +	WORLD BANK

	education as the highest level of education.		
GDPgrowth	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.	+	WORLD BANK
LabFreeIndex	A quantitative measure that considers various aspects of the legal and regulatory framework of a country's labour market, including regulations concerning minimum wages, laws inhibiting layoffs, severance requirements, and measurable regulatory restraints on hiring and hours worked.	+	The Heritage Foundation
EcoFreeIndex	The overall measure of economic freedom based on 10 different aspects (Property rights, Freedom from corruption, Fiscal freedom, Government spending, Business freedom, Labour freedom, Monetary freedom, Trade freedom, Investment freedom, Financial freedom).	+	The Heritage Foundation
Transition	Dummy variable taking value of 1 if it is a transition economy		
TransAlmp	Interaction term between *Transition* and *ALMPExp*		

3.3.2 Endogeneity of Active Labour Market Policies and Potential Instrumental Variables

In macroeconomic evaluation studies of ALMP effectiveness in reducing unemployment and improving matching efficiency, a fundamental issue is that ALMP cannot be treated as strictly exogenous. The level of ALMP expenditure may depend on the labour market situation, so it is not only ALMP expenditure that may affect the unemployment rate but it is also possible that the unemployment rate affects the level of ALMP expenditures, e.g. governments base their ALMP expenditure decisions on the magnitude of the problem they face. Ignoring the latter could lead to a correlation of the ALMP variable with the error term and consequently to inconsistent estimates of the effects.

In attempting to address this causality issue, studies have applied different approaches and used different instrumental variables. Scarpetta (1996) and Elmeskov et al. (1998) have used a time invariant variable measuring the average ALMP expenditure per unemployed person relative to GDP per capita over the period of the available data. Since these are time invariant country-specific averages over the observed period of time, the authors argue that there is no endogeneity bias. An issue with this approach is that it requires the assumption that country-specific effects are randomly distributed. Similarly, Blanchard and Wolfers (2000) apply country-specific effects while using the same instrumental variable as Scarpetta (1996) and Elmeskov et al. (1998). This approach seems not suitable because, this empirical analysis needs variation in ALMP expenditure over time in order to estimate its effect on the unemployment rate. This is especially important for the second model of this empirical analysis, given the long period of data used (2005 to 2014). When analysing ALMP effectiveness for the Czech Republic, Boeri and Burda (1996) use quarterly data while using the average of ALMP expenditure per unemployed for a period of four quarters. In conducting a cross-country analysis, Escudero (2018) assumes that the ALMP expenditure as a share of GDP is not endogenous if each government commits a given fraction of GDP to ALMP which does not change with the unemployment rate, effectively assuming away the possibility of endogeneity.

To create an instrument for the ALMP expenditure variable, Nickell and Layard (1999) and Boone and Van Ours (2004) have renormalized the percent of GDP expenditure on ALMP on the lagged unemployment rate.[17] Boone and Van Ours (2004) also introduced shares of expenditure on separate ALMP categories in total expenditures as explanatory variables. Whereas the variable measuring the ALMP expenditure may be subject to endogeneity, share variables are not expected to be endogenous.

Potential instrumental variables proposed in previous studies include political factors, the proportion of welfare recipients, national unemployment rate and vacancy rate (Hagen, 2003; Hujer and Zeiss, 2005; Escudero, 2018). It has been argued that left-wing political parties have a stronger preference for expenditure on ALMP than liberal-conservative parties (Calmfors and Skedinger, 1995; Büttner and Prey, 1998; Hagen, 2003; Escudero, 2018). Hagen (2003) when analysing the matching efficiency of ALMPs in Germany, uses the proportion of votes in the national election for liberal-conservative parties as an instrument to account for the potential endogeneity of the ALMP measure. Escudero (2018) uses a set of different indicators of the political party in office: the first one is the cabinet composition measured as the percentage of right-wing or left-wing parties in total cabinet posts

[17] The instrumental variable is: $Z_{i,t} = \frac{almp_{i,t}}{u_{i,t-1} \cdot l_{i,t-1}}$, where u is the unemployment rate and l is the labour force.

weighted by the days in office while the second indicator corresponds to the Schmidt-Index which takes the value of 1 to 5 depending on whether there is a dominance of right-wing or left-wing parties in office. Other instruments used by Escudero (2018) include a continuous variable accounting for the number of years that have passed since a change in government in that country and an indicator taking the value of 1 if a reform to ALMPs was put in place in that year in the country and 0 otherwise. Despite their wide use in empirical studies, these particular instrumental variables may not to be appropriate when analysing the effectiveness of ALMPs in transition economies. One reason is that the political system in many transition economies is not defined strictly based on a left-right dimension as in the Western economies.

Another instrumental variable proposed by Hagen (2003) and Escudero (2018) is the national unemployment rate. They argue that because it is the central issue in determining the judgement by the voters, then a government might seek to reduce open unemployment by increasing the number of participants in active measures. Since this variable is used as the dependent variable in the second model and is highly correlated with the dependent variable in the first model in this empirical analysis, it cannot be used as an instrument. Hagen (2003) also argues that the national vacancy rate[18] can be used as instrumental variable arguing that with a reduction in the national vacancy rate, government might increase the ALMP expenditure in an attempt to reduce unemployment, thus this instrumental variable might serve as a business cycle indicator. In the first model, the level of vacancies is used as one of the components of the matching functions thus the vacancy rate is not an appropriate instrument. Another instrumental variable used by Munich and Svejnar (2009) is the share of unemployed who are within 0-3 months before the expiration of their unemployment benefits. They argue that the ALMP funds are often allocated preferentially to those who lose their entitlement to unemployment benefits. Munich and Svejnar (2009) include another variable as an instrument to account for ALMPs which is the share of high-school graduates in the total population of their age cohort arguing that a significant portion of ALMP funds is in employment subsidies for school leavers. This study is specifically modelled for

[18] Measured as: Number of job vacancies / (number of occupied posts + number of job vacancies) * 100

Germany and both these instrumental variables are appropriate for this country but not necessarily for other countries. Hence, these instrumental variables may not be appropriate to use for the empirical analysis in this chapter. In general, the instrumental variables mentioned above which are commonly used to account for endogeneity when assessing the ALMP effects at the economy level do not provide an adequate set of instruments. They typically have hardly any predictive power of the effectiveness of ALMP measures and are still likely to be correlated with the residual term of the regression equation. Most of the studies analysing the effectiveness of the ALMPs at the economy wide level suggest a lagged ALMP variable as the more appropriate instrumental variable (Puhani and Steiner, 1996; Puhani, 1999; Hagen, 2003; Hujer and Zeiss, 2003; Munich and Svejnar, 2009). Puhani and Steiner (1996) argue that it takes a period of time until the ALMP policies can show any effect on the labour market. In this context, they suggest that lagged policy variable adjusts for endogeneity of the ALMPs. Thus, the dynamic panel model seems to be the preferred model when analysing ALMP effectiveness (Puhani, 1999; Hujer and Zeiss, 2003; Hujer et al., 2004; Munich and Svejnar, 2009). Hujer et al. (2004) also point out the importance of the number of lags to be included in the specification. In Hujer et al. (2004) where they use quarterly data in a dynamic panel model (system Generalised Methods of Moments), they include four lags of the ALMP measure because, in context of their study, ALMPs have a duration of about 8 to 10 months. Boeri and Burda (1995) also apply a dynamic panel in a quarterly dataset; however, in attempting to avoid endogeneity, they use the yearly average of ALMP expenditure per unemployed. As discussed in Chapter 2, Munich and Svejnar (2009) apply three different estimators for several Central and Eastern European economies (Czech Republic, Slovakia, Hungary and Poland). They use a monthly dataset and apply fixed and random effects, instrumental variable estimator and a dynamic panel data model for a matching function approach. Considering the possible endogeneity of the ALMP measure and that of other components of matching function, unemployment and vacancies, it is concluded that dynamic panel modelling is the preferred approach because the ‘internal instruments’ account for endogeneity.

In order to address the potential endogeneity of ALMP expenditure, we applied an instrumental variable approach using two different instruments: the lagged value of

ALMPExp and variable Cabinet Party Composition Index which takes value of 1 to 10 depending on whether there is a dominance of left-wing or right-wing parties in the cabinet (*CompGov*). The endogeneity test from instrumental variable approach suggested that *ALMPExp* can be treated as exogenous in the model specification including all explanatory variables in the matching function (the estimation from instrumental variable approach can be seen in Appendix A3.8). However, taking into account theoretical considerations that the *ALMPExp* is likely to be endogenous we use the lagged value *ALMPExp* in FEDK and FEVK and difference GMM which accounts for endogeneity. The following section provides a detailed discussion of estimators which will be used in the first model while section 3.4.2 will discuss the estimation approach for the second model.

3.3.3 Estimation Methodology

According to Baltagi (2005), using panel data would be beneficial to the analysis since it provides more information, more variability, less collinearity among the variables, more degrees of freedom and it also the accounts for heterogeneity among the units and the dynamics of adjustment. The most commonly used methodological approach using panel data are fixed effects (FE) and random effects (RE). A crucial assumption of the random effects estimator is that the unobserved individual effect, α_i, is assumed to be uncorrelated with the explanatory variables whereas the fixed effects estimator allows for correlation between the unobserved individual effect and the explanatory variables. In the case when the cross-country component is assumed to be correlated with the explanatory variables, the FE estimator allows for the constant term to vary across different countries while the coefficients from the RE would be biased and inconsistent. Hausman (1978) introduced a test to determine the appropriateness of the random effects estimator (Greene, 2002; Wooldridge, 2009). The rejection of null hypothesis of the Hausman test suggests that the fixed effects are favoured (Greene, 2002; Wooldridge, 2009).

A potential problem for the fixed effects estimator is the cross-sectional dependence, i.e. the dependence of errors across different sectional units. This may be a result of spatial dependence, omitted unobserved common components (common shocks) or economic differences (Pesaran, 2004; Sarafidis et al., 2009).[19] Cross-sectional dependence is a common feature of panel data analysis because during the periods of global shocks, such as those observed in the 1970s and Global Financial Crisis in 2008, labour markets across countries are influenced (Gabrisch and Buscher, 2006; Bakas and Papapetrou, 2012).[20] In the presence of cross-sectional dependence, not correcting for cross-sectional dependence would result in statistically spurious results (Pesaran, 2004). An alternative to the standard FE estimator which corrects for cross-sectional dependency is proposed by Driscoll and Kraay (1998). According to their results from Monte Carlo simulations, the estimation from the Driscoll-Kraay estimator provides standard errors which are simultaneously robust to autocorrelation heteroscedasticity, and cross-sectional dependency (Driscoll and Kraay, 1998; Hoechle, 2007). Autocorrelation and heteroskedasticity are highly likely to be present in panel data analysis. Heteroskedasticity is likely to be present because countries with differences in terms of their level of economic development and size are included in the sample. Autocorrelation can also occur in panel data since errors associated with a given period may carry over from the previous time period. Hoechle (2007) emphasises that one should be cautious when using Driscoll-Kraay estimator in panel models which contain a large cross-section but only a very short time dimension.

An important disadvantage of the fixed effects estimator is the inability to estimate the time-invariant variables because it uses a transformation to remove the unobserved country specific effect and all the time-invariant explanatory variables before estimation (Wooldridge, 2009). The fixed effects vector decomposition (FEVD) is an estimator which allows for time-invariant variables and slowly moving variables through time. It is a three-step estimator where in the first step the standard FE is estimated with time-variant variables. The second step uses unit effects which is extracted from the regression in the previous stage, and is estimated on time-invariant and slowly changing variables. During this stage it becomes possible to decompose the unit effects into the observed component which is explained by these

[19] It is important to emphasise that for unbalanced panel data it is not possible to verify the presence of cross-sectional dependence.

[20] Theoretically, studies suggest it is reasonable to think that there is cross dependency of the countries included in the sample. There is some empirical evidence that suggests that there are common factors and interdependence of labour markets in European countries (Cuestas and Gil-Alana, 2011; Gozgor, 2013).

variables and the unobserved component which is the unexplained part. In stage three, it uses all time-variant and time-invariant explanatory variables and the residuals (unexplained part) from the stage two in a pooled OLS model. Plümper and Troeger (2007) after conducting a series of Monte-Carlo simulations suggested that this estimator is preferred to pooled OLS and RE in treating time-invariant and slowly changing variables. They suggest that this estimator has better finite sample properties and it produces more accurate estimates. Plümper and Troeger (2007) argue that even inconsistent FEVD estimates might be more reliable than consistent FE estimates because the presence of slowly changing variable in a FE setting can produce imprecise coefficients. Moreover, they argue that a FEVD estimator is more efficient because it produces a smaller within and between variance.[21] In the case of this empirical investigation using FEVD becomes possible to account for time-invariant variables in our model, such as *Transition* (dummy variable accounting for transition or post-transition economies in the sample), and the slowly-changing variable *TransALMP* (the interaction term between *Transition* and *ALMPExp*).

Munich and Svejnar (2009) suggest that in panel data analysis a suitable within transformation of equation (3.1) can be used to remove the unobserved effect using both mean deviations from country specific means (fixed effects) and first differences. In the matching function, explanatory variables, unemployment and vacancy stock, are predetermined by the previous matching process through flow identities. Following Munich and Svejnar's (2009) argument that the components of the matching function (*UnemSt, Vacancies*) are predetermined by their previous values but also considering the endogenous nature of *ALMPExp* variable, Generalised Method of Moments (GMM) would be the ideal choice in this case. However, it could not be used due to a small sample size.

The following section presents evidence from the matching function with fixed effects estimator using lagged level of the explanatory endogenous variable *ALMPExp*. Moreover, all the models for this analysis have been augmented by including a set of time dummies to account for universal time-related shocks

[21]In contrast, some studies criticised this estimator suggesting that the efficiency gains are not as evident as argued by the previous study (Breusch et al., 2011; Greene, 2011). Greene (2011) emphasised a drawback of this estimator being its unreliability because it produces small standard errors. However, Plümper and Troeger (2011) argued that the updated Stata ado file has taken into account this critique and the new standard errors are closer to the true sampling variance.

(Roodman, 2006). According to Sarafidis et al., (2009), these dummies are expected to diminish the cross-sectional dependence arising from time shocks. Assuming that all countries are affected by these shocks in the same way, the time-dummies will remove the 'homogenous' component of the cross-sectional dependence.

3.3.4 Empirical Results

To empirically test the hypotheses developed in this chapter, a panel dataset consisting of 14 European transition and non-transition economies for the period 2010 to 2015 is used. The choice of countries and time period for this empirical analysis was determined by data availability. The data for the dependent variable, the flow from unemployment to employment, is available only for 2010 to 2015 and for the following European transition economies: Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia. While data for the European non-transition economies are only available for the Netherlands, Sweden and Norway. The analysis using a matching function should ideally be conducted with frequent periods of observation such as quarterly or monthly. However, the variables measuring the expenditure of ALMPs are not available quarterly for country level analysis and this empirical investigation is therefore compelled to use annual data.

The descriptive statistics in table 3.2 show that some of the variables have a high number of missing values so a major concern for this empirical analysis is the low number of observations. It seems that there are missing values for more recent years since the data have not been collected for some of the variables. From table 3.2 one can observe that there are some variables that exhibit a large difference between the transition and post-transition economies (TE) and western economies (WE). Table 3.2 shows that the TEs unemployment consists of a large share of long-term unemployed. The mean of variable *ShLongUn* shows that almost 50 percent of unemployment stock is comprised of individuals who have been unemployed for more than a year in TEs. The same variable for WE in the sample is 25 percent. There is also a difference between two sets of countries for the variable *ShYoungUn* where the young unemployed as share of total unemployment stock in transition economies is only 19.3 percent compared to 34 percent for western economies. There is a considerable difference between the two sets of countries in the expenditure on Active and Passive Labour Market Policies; table 3.2 shows that western economies have higher expenditure as percentage of GDP dedicated to both Active and Passive LMPs compared to transition economies. The *Informality* variable shows that transition economies have much higher informality size with the mean of the MIMIC index of 24.7 compared to western countries with 12.5.

Table 3.2 Descriptive Statistics for Transition and Non-Transition Economies – 1st approach

Variable	Obs	Mean	Std. Dev.	Min	Max
Transition Economies: Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia					
lnUEflow	66	10.53	.77	9.21	12.44
ALMPExp	54	.24	.16	.02	.77
lnUnemSt	66	12.54	.88	10.64	14.39
lnVacancies	57	9.60	.88	7.60	11.47
lnEUflow	66	10.25	.74	8.98	12.18
lnIUflow	66	10.34	.92	8.98	12.49
lnLFor	55	14.83	.96	13.44	16.72
ShLongUn	66	49.61	9.16	31.1	70.2
ShYoungUn	66	19.27	3.66	12.46	27.62
ShWomenUn	66	45.57	3.65	36.69	53.35
PopDensity	66	84.23	34.94	30.95	136.62
PLMPExp	54	.42	.18	.13	.91
Informality	66	24.72	5.12	14.1	32.6
GDPgrowth	66	1.95	2.17	-3.79	7.6
LabFreeIndex	66	61.77	11.81	39.4	85.5
Western European Countries: the Netherlands, Sweden and Norway					
lnUEflow	18	11.14	.69	10.12	11.79
ALMPExp	17	.68	.26	.37	1.08
lnUnemSt	18	12.52	.79	11.35	13.39
lnVacancies	17	11.26	.32	10.82	11.79
lnEUflow	18	10.89	.69	9.74	11.74
lnIUflow	18	11.38	.62	10.51	12.17
lnLFor	15	15.41	.51	14.77	16.01
ShLongUn	18	24.78	8.07	17.7	42.9
ShYoungUn	18	34.01	4.19	25.73	38.82
ShWomenUn	18	46.08	2.98	39.78	51.03
PopDensity	18	178.39	232.53	13.39	503.02
PLMPExp	17	.87	.60	.33	2.20
Informality	18	12.50	2.32	9	15.1
GDPgrowth	18	1.68	1.62	-1.06	5.99
LabFreeIndex	18	53.48	6.25	44.6	66.3

The variance inflation factors (VIFs) presented in table 3.3[22] and the correlation matrix in appendix A3.1 indicate that there is high collinearity between some of the variables. Flow variables, *lnUEflow*, *lnEUflow* and *lnIUflow*, *lnUnemst*, *Vacancies*

[22] The final models also include the quadratic terms of *ALMPExp* and *Popdensity*.

and *lnLFor* are by definition correlated with each other. From the correlation matrix in appendix A3.2, it is observed that correlation among these variables goes up to 0.97. With regard to the VIF values, when the VIF value is higher than 10 it indicates a problem of multicollinearity (Kutner et al. 2004). Appendix A3.1.2 shows that there are variables that pass this threshold. According to Wooldridge (2009), to deal with potential multicollinearity one should increase the sample size or drop variables that are causing the problem. In the case of this empirical analysis, it is impossible to increase the sample, whilst dropping variables may cause omitted variable bias.

The variable with the highest VIF value is *lnLFor*, however as explained in section 3.2 it is a key variable in the matching function and not including this variable in the model would result in biased coefficients. The variable with the second highest VIF value is *EduSecondary* with 51.71 and from the correlation matrix it can be observed that it is highly correlated with variable measuring the share of long-term unemployment *ShLongUn* and with *EduTertiary,* thus this variable is dropped from the model. In order to gain degrees of freedom, a choice was made between variables *EcoFreeIndex* and *LabFreeIndex*[23]*;* the latter is kept in the model because *LabFreeIndex* captures the government policies, the labour laws and regulations which more directly tend to improve labour market performance. Furthermore, combining the flow variables, *lnEUflow* and *lnIUflow*, into one variable was considered however, it does not significantly improve the collinearity diagnostics therefore they are included separately in the final model (see Appendix A3.1.2). Variables *ShLongUn* and *ShYoungUn* are also highly correlated with each other while variable *ShYoungUn* is also highly correlated with *lnVacancies.* Dropping the share variables, *ShYoungUn, ShLongUn* and *ShWomenUn* from the model improves the mean VIF. These three variables assess the matching efficiency of these subgroups of unemployed, however, they are not considered essential in this empirical analysis. Hence, the first specification includes these variables and the second does not. The VIF collinearity diagnostics of the final model are presented in table 3.3. The mean VIF value has dropped significantly from 27.91 from the initial model to 14.05. The only variables with VIF values above threshold of 10 (Kutner et al., 2004) are components of the matching function (*lnLFor, lnUnemst, lnVacancies,*

[23] Neither of these variables has high VIF value nor are highly correlated with other variables.

lnUEflow, lnEUflow and *lnIUflow),* which are expected to be correlated with each other, but are essential and hence they are kept in the model.

Table 3.3 VIF Collinearity Diagnostics – 1st approach

Variable	VIF	1/VIF
lnLFor	56.66	0.017649
lnIUflow	20.37	0.049101
lnEUflow	19.80	0.050512
lnVacancie~1	19.53	0.051207
lnUnemplST~1	14.52	0.068868
PopDensity	8.94	0.111806
PLMPExplag1	8.09	0.123612
ALMPExplag1	6.44	0.155202
EduTertiary	5.08	0.196992
Informalit~1	5.00	0.200001
GDPgrowth	2.10	0.476909
LabFreeInd~1	2.04	0.489056
Mean VIF	14.05	

Following the analysis of different estimation methodologies presented in section 3.3.2, the empirical results and diagnostic tests from the preferred estimator will now be presented. The first estimations for RE and FE are presented in appendix tables A3.2.1 to A3.2.3 in the appendix section A3. The Hausman test was used to determine the appropriateness of the RE estimator for this empirical analysis[24]. The null hypothesis of no systematic differences between the FE and RE coefficients is rejected, though with a borderline p-value = 0.089. Thus, the FE estimator is considered the more appropriate approach.

The next step is to check the diagnostic tests of the models. The results from several diagnostic tests (modified Wald test for group wise heteroskedasticity, the Wooldridge test for autocorrelation in panel data and the test for serial correlation in the residuals) suggest that there is no presence of serial correlation but there is the presence of heteroscedasticity in the errors in the econometric models (see Appendix A3.2.4 and A3.3.4). For unbalanced panel data the cross-sectional dependence cannot be tested, however, as argued in section 3.3.2, panel data usually are subject to this issue. In order to be sure that the effects of cross-sectional dependence are

[24] Option *sigmamore* is used as it is recommended by Cameron and Trivedi (2009) which specifies that both covariance matrices, from FE and RE estimates, are based on the estimated disturbance variance from the efficient estimator.

rectified, the Fixed Effects Driscoll-Kraay (FEDK) estimator is used. As discussed in the previous section, this estimator corrects for heteroscedasticity, cross-sectional dependence and serial correlation even though serial correlation is not an issue in this case. The estimated results from FEDK are presented in table 3.4.

Table 3.4 Estimated Results

	(1)	(2)	(3)	(4)
	FEDK	FEDK	FEVD	FEVD
VARIABLES	lnUEflow	lnUEflow	lnUEflow	lnUEflow
ALMPExplag1	0.369*	0.269*	-0.0159	-0.439
	(0.118)	(0.0868)	(0.258)	(0.398)
lnUnemplSTlag1	0.227	0.476***	0.419**	0.742**
	(0.135)	(0.0784)	(0.166)	(0.321)
lnVacancieslag1	-0.112	-0.159	0.00986	-0.135
	(0.143)	(0.156)	(0.121)	(0.229)
lnEUflow	0.0969	0.0558	0.299	-0.0838
	(0.101)	(0.108)	(0.178)	(0.386)
lnIUflow	0.431	0.435*	0.353**	0.754*
	(0.189)	(0.139)	(0.147)	(0.360)
lnLFor	1.443	-0.264	-0.233	-0.684
	(1.027)	(0.991)	(0.330)	(0.638)
ShYoungUn	0.00873		0.0163	
	(0.00734)		(0.0173)	
ShLongUn	0.0152		-0.00512	
	(0.00774)		(0.00556)	
ShWomenUn	0.00461**		-0.00584	
	(0.000852)		(0.0117)	
PLMPExplag1	0.0674	-0.0402	0.140	0.0350
	(0.157)	(0.148)	(0.208)	(0.574)
Informalityl1	-0.168	-0.104	-0.0151	0.0231
	(0.145)	(0.134)	(0.0188)	(0.0363)
GDPgrowth	-0.0164	-0.0124	-0.0175	-0.0108
	(0.0120)	(0.00907)	(0.0141)	(0.0260)
LabFreeIndlag1	0.0129**	0.0124**	0.00520	0.0121
	(0.00262)	(0.00268)	(0.00662)	(0.00880)
EduTertiary	0.0134	0.0175*	0.0232	0.0614**
	(0.0128)	(0.00736)	(0.0134)	(0.0232)
PopDensity	0.0334	0.0788**	0.00412	0.0285
	(0.0361)	(0.0193)	(0.0103)	(0.0192)
PopDen2	-2.35e-05	-7.57e-05***	-8.37e-06	-5.45e-05
	(3.85e-05)	(1.08e-05)	(1.78e-05)	(3.32e-05)

Transition			0.0254	-2.350
			(0.850)	(1.940)
TransAlmp			0.216	-0.569
			(0.271)	(0.462)
Constant	0	0	1.230	3.477
	(0)	(0)	(2.637)	(4.923)
Observations	49	49	49	49
R-squared			0.997	0.996
Number of groups	14	14	14	14
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Because within estimators do not allow for time-invariant variables, an alternative estimator is used. The discussion provided in section 3.3.2 introduced Fixed Effects Vector Decomposition as the estimator with similar features with fixed effects that produces consistent estimates for the coefficients of the time invariant variable, *Transition* and slowly changing variable, *TransAlmp*. The preferred models for interpretation remain FEDK models 1 and 2 because they address the issues mentioned in the previous paragraph while FEVD models 3 and 4 will be referred to only for time-invariant variables.[25]

Table 3.5 presents the means of the variables and the calculations of the effects of the selected independent variables of interest on the dependent variable for models 1 and 2. This will help to establish a clearer idea of the scale of the effects. As may be seen from table 3.4, the estimated coefficient of the lagged value of *ALMPExp* is significant and has the expected sign in models 1 and 2. Since the quadratic term of *ALMPExp* was insignificant in all the specifications and considering the small sample size used for this analysis this variable was excluded from the final specifications (Appendix A3.4.5 and A3.4.6 provides estimations with the quadratic term of ALMP). Because it is highly unlikely that ALMP expenditure as share of GDP will increase by 1 percentage point during a single year (this would imply a huge increase), the results for this variable will be interpreted using an increase of 0.1 percentage point.

[25] Year dummies are included in the models, however they are not presented in table 3.4.

Table 3.5 Calculation of the effects of the selected variables

	Mean	**An increase by 0.1 pp**	**An increase by 1 %**	**Model 1**	**Model 2**
UEflow	63900	-	-	-	-
ALMPExp (%)	0.3548	0.4548		0.0369*63900 = 2357.91	0.0269*63900= 1718.91
UnemSt	307055.6		3070.556	-	(0.476*63900)/100 = 304.164
IUflow	65055.56		650.5556	-	(0.435*63900)/100 = 277.965

The estimated results presented in table 3.5, suggest that an increase by 0.1 percentage point of expenditure on ALMPs as a share of GDP, from a sample mean value of 0.35 to 0.45 (see table 3.5), will increase the flow from unemployment to employment in the following year by 3.69 percent, ceteris paribus; to be more specific it would increase the number of matches made each year by about 2,358 on average. As seen in table 3.4, in model 2 (where variables *ShLongUn, ShYoungUn and ShWomenUn* are excluded from the model*) ALMPExp* has a somewhat smaller coefficient; an increase by 0.1 percentage point of expenditure on ALMPs as a share of GDP will increase the flow from unemployment to employment in the following year by 2.69 percent, thus it would increase the number of matches made each year by 1,718 on average.

While the estimated coefficients on the main components of the matching function, unemployment stock and flow from inactivity to unemployment, are significant only in model 2, other components of the matching function are insignificant in both models. The elasticity of flows from unemployment to employment with respect to the unemployment stock is highly significant in model 2 where the share variables *(ShLongUn, ShYoungUn and ShWomenUn)* are excluded from the model which suggests that a part of the effect of unemployment stock might be captured by these variables. The estimated results from model 2 suggest that an increase by 1 percent in the unemployment stock from the mean value in the sample, i.e. an increase by about 3,070 persons in the unemployment stock, is associated with outflows to employment increasing by 0.476 percent from the mean value, or approximately by 304 persons each year, ceteris paribus.

The variable measuring the flow from inactivity to unemployment is significant at 10 percent significance level only in model 2 while that measuring the flow from employment to unemployment is insignificant in both models. The estimated results suggest that an increase by 1 percent of *IUflow* from the mean value in the sample, or an increase by 650 persons who join the unemployment pool from inactivity, is associated with an increase in the number of matches made by 277, other variables remaining constant. Based on the results presented in table 3.5, more than 42 percent[26] of those who enter the unemployment pool from inactivity get employed in the same year compared to approximately 10 percent of those already in the unemployment pool in line with the expectation that new entrants might have better matching efficiency compared to those already in the unemployment pool.

In view of the theoretical discussion in chapter 2, the results in table 3.6 present returns to scale (RTS) for matching function, i.e. whether the following terms are jointly significant and equal unity, $RTS = \beta_1 lnUnemSt_{i,t-1} + \beta_2 lnVacancies_{i,t-1} + \beta_3 lnEUflow_{\mathrm{i,t}} + \beta_4 lnIUflow_{\mathrm{i,t}}$. When the sum of coefficients equals to unity it implies constant returns to scale, meaning that an increase in the size of labour market in terms of one of the matching function components would increase the matching efficiency by the same magnitude. When the sum of coefficients is lower than the unity, the labour market exhibits decreasing returns to scale meaning that an in increase in labour market would increase the matching efficiency by a lower magnitude. Finally, when it exceeds unity it implies increasing returns to scale where positive externalities of the search intensity of unemployed workers and vacancies might prevail, creating more than one possible equilibrium. In this analysis, the hypothesis that the sum of these coefficients is not significantly different from 0 is rejected in all the estimated models (see table 3.6 below, and table A3.5 in appendix 3). However, while the sum of the coefficients from models 1 and 2 point to decreasing returns to scale (0.64 and 0.81) the sum of coefficients from models 3 and 4 suggest that there is increasing returns to scale in the matching efficiency (1.08 and 1.28).

[26] The ratio of employed people to those entering unemployment pool from inactivity is 277.9/650.5= 0.4272; the ratio of employed people to those the unemployment stock 304.164/3070.556=0.099.

Table 3.6 Returns to Scale (RTS)

lnUEflow |	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Model (1) |	.6421577	.1653083	3.88	0.030	.1160728	1.168242
Model (2) |	.8081077	.1892566	4.27	0.024	.2058087	1.410407
Model (3) |	1.08037	.2345406	4.61	0.000	.5773303	1.583409
Model (4) |	1.276409	.4374473	2.92	0.010	.3534757	2.199342
Model (5)[27]|	1.310651	.161662	8.11	0.004	.7961702	1.825132
Model (6) |	1.141365	.2996006	3.81	0.032	.1879018	2.094827

However, the estimation of RTS should be interpreted with caution because the sample includes both transitional and non-transitional countries with different labour market characteristics. The reviewed studies for transition economies reviewed in Chapter 2 consistently found evidence to suggest that the labour markets in these countries experience increasing returns to scale, thus multiple equilibria, but such a pattern is not observed in non-transition economies. Hence, additional regressions were run only for transition countries using the same specification as in model 1 and 2 (see Appendix A3.5); the sample was reduced to only 37 observations. The RTS estimations from these additional models are presented in table 3.6 as model 5 and 6. These estimations both point to increasing returns to scale suggesting that in transition economies labour markets might exhibit multiple equilibria consistent with the results from other empirical studies (Camarero et al., 2008; Munich and Svejnar, 2009) However, the sample is small and these results should be treated with caution.

With regard to control variables, in model 1 variables *ShWomenUn* is significant but does not have the expected sign while *LabFreeIndex* is significant and has the expected sign. In model 2, *LabFreeIndex, EduTertiary, PopDensity* and its' quadratic term are significant and have the expected signs. The coefficient of *ShWomenUn* suggests that an increase in share of women in the pool of unemployment by 1 percentage point is associated with an increase of matching efficiency by 0.4 percent. This result might suggest that women accept more often temporary jobs compared to their male counterparts. The lagged value of *LabFreeIndex* is significant in both models 1 and 2 and has the expected sign; this result suggests that an increase by 1 unit of *LabFreeIndex* will increase the transitions from unemployment to employment by 1.29 percent in the following year in model 1 and 1.24 percent in model 2, other variables remaining constant. The variable *EduTertiary* is significant at 10 percent level only in model 2. An increase

[27] Models 5 and 6 only include transition countries; see appendix A3.3.2 for estimated results.

in the share of individuals who have attended or completed tertiary education as the highest level of education in the labour force by 1 percentage point will increase the matching efficiency by 1.75 percent. In accordance with our expectations, the estimated population density coefficients imply a concave relationship between matching efficiency and density. The calculation of the turning point suggests that if population density increases beyond 1,676 people per square kilometre then it would impact negatively the flow from unemployment to employment[28]. Other control variables are consistently insignificant. As explained above, FEVD is used to account for the invariant variable *Transition* and slowly changing variable *TransAlmp*. These variables are insignificant in both models.

Due to the small sample size used for analysis of the matching efficiency, it was not possible to distinguish between the effects of different types of ALMPs. The following section will expand the analysis of the effectiveness of ALMPs using a GMM estimator for a larger number of countries included in the sample and with a longer time period.

3.4 Empirical Approach for Model 2

3.4.1 Model Specification

As argued by Munich and Svejnar (2009), GMM would be a better choice for the matching function considering that the components of the matching function (*UnemSt and Vacancies*) have a dynamic nature thus are in part predetermined by their previous values and the endogenous nature of the *ALMPExp* variable. However, it was not possible to utilise this approach since the data for the dependent variable (the flow from unemployment to employment – *lnUEflow)* and the main variables composing the matching function (*lnVacancies, lnEUflow, lnIUflow*) are available only for a short period of time and for a limited number of countries thereby restricting the size of the sample. The small size of the sample also does not allow an assessment of the effectiveness of different types of ALMPs (training, employment incentives, supported employment and rehabilitation, direct job creation and start-up incentives).

[28] Turning point = - Popdensity/(2*Popden2)= -0.0788168/ (2*(-0.0000235)) =1,676.95

Hence, the second empirical approach (GMM) uses a different model specification where a new dependent variable is used, the unemployment rate (*UnemRate*). The data for the second empirical approach is available for a longer time-span and for a higher number of countries which allows overcoming the disadvantages of the first empirical approach – the endogenous nature of the *ALMPExp* and the dynamic nature of the dependent variable *UnemRate*. The justification for using this second approach is thus twofold. Firstly, to assess the effectiveness of the ALMPs in reducing the unemployment rate in a larger dataset for a higher number of countries and the larger sample allows a comparison of the effectiveness of the different types of ALMPs mentioned above.

As in the matching function model, the quadratic form of ALMP is included in the model to account for a possible non-linear relationship between ALMP expenditure and the unemployment rate. Since an increase in ALMP expenditure as a share of GDP is expected to reduce the unemployment rate, see Section 2.2.3, the expected sign for *ALMPExp* is negative while the expected sign for the square term of *ALMPExp* is positive.The dependent variable for this analysis is the unemployment rate, *UnemRate,* defined as the unemployment as a percentage of the active population.

Table 3.7 presented at the end of this section summarizes the variable description, labels, the expected signs and data sources.

Control Variables

Studies consistently have argued that the relatively high unemployment benefits for a relatively long duration have a positive effect on the unemployment rate (Scarpetta, 1996; Nickell, 1998; Elmeskov et al., 1998; Nunziata, 2002; Bassanini and Duval, 2006). Unemployment benefits may increase the unemployment rate via two mechanisms. First they reduce job search intensity, thus reducing the willingness of the unemployed to accept job offers. Secondly, because they lower the economic cost of being unemployed, unemployment benefits put upwards pressure on workers' reservation wages thus reducing the number of filled vacancies and increasing job separations (Bassanini and Duval, 2006). The variable *PLMPExp*, measured as the PLMP expenditure as share of GDP, is included in the model to account for this relationship. The expected sign of this variable is positive, thus an increase in

PLMPExp is expected to lead to an increase in unemployment rate. As argued in section 3.3.1, unemployment benefits are frequently higher when the unemployment level is high and persistent, pointing out the potential endogeneity of this variable (Nickell, 1997). Following this argument *PLMPExp* is treated as endogenous.

The variable *Informality*, as in the model specification for matching function, is based on Schneider's (2015) MIMIC estimation procedure. In this model specification the size of informality and unemployment rate are expected to have a negative relationship, thus an increase the size of informal economy might attract unemployed to search for jobs in the informal sector thus reducing the unemployment rate[29]. Additionally, as explained in section 3.3.1, there is potential reverse causality between the two variables: a high unemployment rate may give rise to a larger informal economy as due to lack of jobs in the official sector, the unemployed turn to the informal sector for job opportunities. Thus, *Informality* should be treated as endogenous.

In order to control for the possible influence of demographic factors on the unemployment rate, this specification also includes the variable *PopDensity*[30]. Population density tends to capture the geographical concentration of economic activity and the size of social networks, i.e. a labour market with higher population density tends to reduce the unemployment rates (Coles and Smith, 1996; Ibourk et al., 2004; Lahtonen and Hynninen, 2005; Tomic, 2012). On the other hand, a high population density may also have an adverse effect on the unemployment rate because labour markets with a higher population density are associated with higher labour supply. In a labour market with a constant labour demand, all other variables remaining equal, higher population density, i.e. higher labour supply will tend to increase unemployment rate. Thus the expected sign of this variable for this model specification is ambiguous.

According to theoretical expectations, the likelihood of being unemployed is unequally divided among groups with different education qualifications (Card, 2001; Oreopoulos and Salvanes, 2009; Nunez and Livanos, 2010). Less educated people

[29] As argued in section 3.3.1, informal workers are considered employed by the Labour Force Survey, thus an increase in the informal employment will lead to a reduction of the unemployment rate.
[30] A variable measuring population growth, *PopGrowth*, was also considered, however this specification did not have the correct diagnostic tests.

tend have higher unemployment rates compared to better educated people. *EduTertiary*, measured as the share of labour force with tertiary education as their highest level of education, is included in the model to test the hypothesis that a higher share of individuals in the labour market who have completed higher education will have a negative effect on the unemployment rate.

It is assumed that the unemployment rate is partly determined by the demand conditions which in this specification is captured by the growth rate of GDP (Cazes, 2002; Lehman and Muravyev, 2009; Escudero, 2018). Theoretically, it is expected that an increasing demand has a negative impact on the unemployment rate, although this effect might not be immediate. As Levine (2013) pointed out, as long as GDP growth exceeds the growth in labour productivity then employment will rise, and if employment growth is more rapid than labour force growth, the unemployment rate will fall. Thus over an extended period of time, the relationship between GDP growth and unemployment rate is expected to be negative. *GDPgrowth* is included in the model to account for this relationship.

As discussed in section 3.3.1, the Labour Freedom Index (*LabFreeIndex*) accounts for various aspects of the legal and regulatory framework of the labour market (see also table 3.7 for details of the variable definition). Theoretically, labour markets with lower flexibility will obstruct job creation and will tend to keep labour markets rigid, especially at the turning points of the business cycle (Tasci and Zenker, 2011). More rigid labour institutions are consistently found to be associated with higher unemployment rate over a longer period of time (Nickell, 1997; Bassanini and Duval, 2006; Tasci and Zenker, 2011; Bernal-Verdugo et al., 2012). Following this argument, the expected sign of *LabFreeIndex* is negative, i.e. a higher degree of labour market freedom, ceteris paribus, is expected to reduce the unemployment rate. Because there the current implementation of labour market policies will need a period of time to have an effect on the labour market the lagged value of *LabFreeIndex* is included in the model.

Table 3.7 Variable specifications and expected signs – 2nd approach

Variable Name	Variable Description	Expected Sign	Data Source
Dependent Variable			
UnemRate	Unemployment as a percentage of the active population		EUROSTAT
Main Variables of Interest			
ALMPExp *1.TrainSh* *2.EmpIncSh* *3.SupportSh* *4.DirectJobSh* *5.StartupSh*	Active labour market policies measured as expenditure as a percentage of GDP and Different types of active policies measured as a share of ALMPExp: 1. Share of expenditure on training in total ALMP expenditure, 2. Share of expenditure on employment incentives in total ALMP expenditure, 3. Share of expenditure on supported employment and rehabilitation in total ALMP expenditure, 4. Share of expenditure on direct job creation in total ALMP expenditure 5. Share of expenditure on start-up incentives in total ALMP expenditure.	-	EUROSTAT
Control Variables			
Informality	MIMIC index measure of the size of the shadow economy.	-	Schneider (2015)
PLMPExp	Passive labour market policies measured as expenditure as a % of GDP	+	EUROSTAT
PopDensity	Population density is midyear population divided by land area in square kilometres. Population is based on the de facto definition of population, which counts all residents regardless of their legal status or citizenship.	+/-	WORLD BANK
EduTertiary	Labour force with tertiary education - The share of the total labour force that attained or completed tertiary education as the highest level of education.	-	WORLD BANK
GDPgrowth	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.	-	WORLD BANK
LabFreeIndex	A quantitative measure that considers various aspects of the legal and regulatory framework of a country's labour market, including regulations concerning minimum wages, laws inhibiting layoffs, severance requirements, and measurable regulatory restraints on hiring and hours worked.	-	The Heritage Foundation

3.4.2 Estimation Methodology – Generalised Methods of Moments (GMM)

Since the data used for this empirical investigation is panel data, there are several estimators that can be utilised including standard Fixed Effects (FE) and Driscoll-Kraay FE and Generalised Methods of Moments (GMM). As discussed in Chapter 2, unemployment is persistent over time since the current rate of unemployment is dependent upon the past rate of unemployment, thus possible endogeneity is an issue. It is necessary to apply a dynamic panel analysis in this case since the unemployment rate is determined by an adjustment of the unemployment rate toward a 'natural' or 'equilibrium' rate of unemployment which will differ across states (Heckman, 1981; Layard et al., 1991; Mühleisen and Zimmermann, 1994; Hyslop 1999; Arulampalam et al., 2000; Stewart, 2007; Frijters et al., 2009). The inclusion of the lagged dependent variable on the right-hand side of the equation will allow us to examine the state dependence of unemployment from the previous rate of unemployment. Given the possible endogeneity using FE or OLS would be subject to different drawbacks and the best possible choice would be a dynamic model (Munich and Svejnar, 2009; Escudero, 2018). When using an OLS estimator, particularly when not controlling for country specific effects, the most severe issue is endogeneity. Nickell (1981) established that OLS and FE estimates of the lagged dependent variable's coefficient in a dynamic panel model are biased because they are correlated with the error term and this possible bias cannot be ignored. As discussed by Baltagi (2005), the OLS estimator tends to be upward biased with respect to the autoregressive parameter thus violating the classical OLS assumption. In contrast to the OLS estimator, the within estimator, such as FE, accounts for country specific effects correlation by transforming the data so that the country specific effect is removed. However, this transformation is appropriate for static models only, generating biased results in dynamic panel data models because it produces a correlation between the lagged dependent variable and the error term. This bias has been corrected by Kiviet (1995) and Bruno (2005) who suggested applying least squares dummy variable estimator (LSDVC). However, the disadvantage of this approach is that it assumes that explanatory variables are exogenous thus it is not appropriate in this empirical study. As discussed in section 3.3.2, variable *ALMPExp* is expected to be determined by a policy reaction function, i.e. the level of ALMP expenditure is determined by the level of unemployment for each country. In order to handle the endogeneity issue a dynamic panel model is applied, as suggested by Arellano and Bond (1991) and Blundell and Bond (1998).

A common strategy to deal with the above-mentioned problem is to use a difference or system GMM estimator (Arellano and Bond, 1991; Blundell and Bond, 1998). According to Roodman (2009), the GMM estimator is an appropriate methodological approach for samples with shorter time periods (*T*) relative to the number of groups (*N*). Moreover, this approach is appropriate for samples where the independent variables are not strictly exogenous; have heteroscedasticity and autocorrelation within groups and are not normally distributed.

The sample used for this empirical analysis has a time-dimension (*T*) of 9 years and number of groups (*N*) of 28 countries. The time period available is from 2005 to 2014, though a few countries in the sample such as Croatia and Malta have data available only for a shorter time period. The time period used in this chapter seems to be larger than the period used previously by Arellano and Bond (1991) and other studies (Blundell and Bond, 1999; Mangan et al., 2005; Pugh et al., 2008). This seems to not be a concern, because as suggested by Hayakawa (2008), the GMM estimator can generate efficient estimates even with a time dimension of 20. Roodman (2006, p.42) argues that 'if T is large, dynamic panel bias becomes insignificant, meanwhile, the number of instruments in difference and system GMM tend to explode with T'. The unbalanced panel dataset of 28 countries included in this analysis is quite low compared to Monte Carlo simulations based on Arellano and Bond (1991) where they use about 140 groups. However, according to Roodman (2006) 'large number of groups' has no precise definition, but a panel with number of groups lower than 20 would be worrisome. Based on Roodman (2006), the panel data used for this chapter passes the 'threshold' of the number of groups and time dimension.

As discussed in section 3.3.2, empirical studies have difficulty justifying the appropriate external instruments for ALMPs for countries under analysis. GMM is specifically designed to account for endogeneity of the explanatory variables through the matrix of internal instruments. Arellano and Bond (1991) suggest estimating a first difference model where the differenced lagged dependent variable is instrumented by either the level or the first difference of the second lag of the dependent variable. This would be valid under the assumption that the error term in not serially correlated and the lag of explanatory variables are weakly exogenous. If the error term in the differenced equation is correlated with the first difference of the lagged dependent variable ($\Delta y_{i,t-1}$), Anderson and Hsiao (1982) suggest using the lag of the second difference ($\Delta y_{i,t-2}$) or second lagged level ($y_{i,t-2}$) of the dependent variable as instrument. Arellano and Bond (1991) suggest that in the first difference model the lagged dependent variable can be instrumented not only the first lagged level but also for longer lags such as $y_{i,t-3}$, $y_{i,t-4}$ etc. Arellano and Bond (1991) and Kiviet (1995) conclude that lagged levels as instruments are more efficient with relatively smaller variances compared to levels or differences. Evidence from the Monte Carlo simulations from Arellano and Bond (1991) suggest that the estimates from GMM estimators yield much smaller variances compared to other estimators using instrumental variables hence the main approach used in the empirical analysis will be GMM.

A potential shortcoming of the difference GMM estimator is that the coefficient estimated may be biased if variables follow a random walk (Roodman, 2009), if the explanatory variables are persistent over time and if the time dimension of the sample is small (Blundell and Bond, 1998). Some studies have identified some further limitations of the GMM estimator, arguing that the lagged levels may be weak in explaining the dynamic nature of the dependent variable especially when the dependent variable is persistent (Ahn and Schmidt, 1995; Blundell and Bond, 1998). According to Roodman (2006), the difference GMM would perform poorly when the dependent variable follows a random walk because past levels cannot predict the future changes suggesting that the lagged levels are not good instruments for differenced dependent variable. Another disadvantage of the difference GMM, when using unbalanced panel data, is that it magnifies the gaps in the data and it does not make use of all available information i.e. when one observation is missing it means two observations will be lost because the difference cannot be calculated.

In order to address these problems, a system GMM estimator is developed to combine two different equations; (i) the equation of first differences, (ii) the equation in levels (Arellano and Bond, 1991; Blundell and Bond, 1998). A system GMM estimator increases the efficiency of the estimates by allowing for exploitation of additional moment conditions from the data in levels (Arellano and Bover, 1995). Additionally, when the dependent variable follows a random walk, studies argue that the past changes are a better predictor of future levels than the levels (Blundell and Bond, 1998; Roodman, 2006). System GMM also performs better for unbalanced panel data because it makes use of more information than the difference GMM and allows for inclusion of time invariant variables as opposed to difference GMM which wipes out all the time invariant variables. However, despite the noted advantages of system GMM, it proved not to be feasible in the sample used for this empirical analysis because it uses a higher number of instruments compared to the number of countries. Hence, the estimator used for this analysis is the difference GMM because it uses a smaller number of instruments.

As mentioned earlier in this section, the GMM estimators allow for heteroscedasticity, autocorrelation and do not require any assumption about the distribution (Greene, 2002; Roodman, 2006). There are two options in GMM that can produce robust estimation; one-step and two-step estimation. In the one-step estimation, standard errors are robust to heteroscedasticity and autocorrelation within individuals using a covariance matrix which is independent of the estimated parameters (Roodman, 2006). The two-step estimation constructs a sandwich proxy for the covariance matrix with initial parameter obtained from one-step estimation and the second step where this matrix is used to reweight the moment conditions (Roodman, 2006). Two-step GMM estimation is robust to heteroscedasticity and within-individual autocorrelation. An important issue with the two-step estimation is that when the number of instruments is large and the sample is small size, the standard errors are found to be downward biased (Arellano and Bond, 2001; Bond, 2002; Windmeijer, 2005). In this case the Windmeijer (2005) finite sample correction, which is superior to the cluster-robust one-step standard errors; without correction the standard errors tend to be severely downward biased. This correction is found to greatly reduce the problem of bias, especially for difference GMM estimator for which the simulation is performed. Hence, based on this discussion, the efficient *two-step difference GMM estimator* will be used with Windmeijer (2005) robust standard errors with small-sample correction using option '*two robust small'*. Furthermore, Sarafidis et al. (2009) suggest that all models should include time dummy variables to control for possible cross-sectional dependency arising from spatial dependence, common shocks and economic distance.

As mentioned previously in this section, because the first difference equations (both in difference and system GMM) are constrained to lose information when using unbalanced panel data, Arellano and Bover (1995) suggest using a common transformation called the 'forward orthogonal deviations'. Roodman (2006, p.20) notes that "*the orthogonal deviations, instead of subtracting the previous* *observations from the contemporaneous one, it subtracts the average of all future available observations of a variable*", thus it minimizes data loss in unbalanced panels because it uses all the information available. In this context, Rodman (2006) also suggests that the lagged observations remain valid instruments because they are not involved in computation of the orthogonal deviations. Therefore, as suggested by Roodman (2006), since unbalanced panel data is used for this empirical analysis and in order to preserve the sample size, orthogonal deviations will be applied using option '*orthog'*.

A major drawback of GMM estimators is that they may use a large number of instruments which may overfit endogenous variables, weaken the diagnostics used for validity of the instruments and provide biased estimates of the covariance matrix of the moments. There is no specific guidance on what is the optimal number of instruments; however, the general rule of thumb proposed by Roodman (2006) is that the number of instruments should be lower or equal to the number of groups in the sample. According to Roodman (2006), the instrument matrix can restrict the lag ranges that are used in generating the set of instruments, thus the number of instruments will be reduced. Roodman (2006) suggests this can be done by using the '*collapse'* option.

As discussed above, the instrumentation of the dependent variable in a dynamic model is justified because it is predetermined within the model by the previous values of other regressors, while being independent of their present values. This instrumentation can also be used to address the issue of endogeneity of the explanatory variables which are correlated with the past error terms. The validity of the instruments for treatment of endogenous variables is diagnosed with the Sargan and Hansen tests of overidentifying restrictions, which are robust to heteroscedasticity. According to Roodman (2009), the p-value of the Hansen test of overidentifying restrictions approaching unity and those lower than 0.25 should be viewed with caution. Difference in Hansen test is also used to test the subset of instruments for individual variables since it can affect the overall Hansen test.

The GMM estimator can create a large number of moment conditions and a large number of instruments; the estimator creates an instrument for each variable, for each period and each lag distance of the corresponding period (Roodman, 2006). The instruments as lags of the explanatory variables are used under the assumption that errors are not autocorrelated, which would mean that they are correlated with the instruments. Considering this, to ensure the validity of the instruments a test for autocorrelation is used, first-order and second-order serial correlation (referred to as *m1* and *m2*), which examines the hypothesis of no second-order serial correlation in the error terms. The GMM estimator requires that there is first-order serial correlation but no second-order serial correlation in the residuals.

3.4.3 Empirical Results

As discussed above, the dataset for this model is larger, comprising of a larger number of countries and longer time period. The descriptive statistics in table 3.8 show that this dataset is unbalanced since some of the variables have a number of missing values for some countries. However, there is no indication of data missing for a specific reason other than randomly, thus this not expected to influence the reliability of the estimations. Table 3.8 shows that there are some differences in the summary statistics between transition and non-transition countries which might affect the final estimated results for this empirical analysis.

The collinearity diagnostics do not suggest there is cause for concern. From table 3.9 one can see that the mean VIF value is 4.47 while none of the individual VIF values exceed the threshold of 10. The correlation matrix presented in Appendix A3.5 also shows that correlation among independent variables is not likely to cause multicollinearity in this case.

Table 3.8 Descriptive Statistics for Transition and Non-Transition Economies - 2nd approach

Transition Economies: Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia and Slovakia					
Variable	Obs	Mean	Std. Dev.	Min	Max
UnemRate	143	10.001	3.73	4.3	19.8
ALMPExp	122	.21	.142	.019	.768
TrainSh	122	25.45	23.38	.130	91.30
EmpIncSh	122	27.93	18.33	.757	82.61
SupportSh	122	11.45	17.96	0	64.96
DirectJobSh	122	28.12	23.36	0	91.28
StartupSh	120	7.22	9.76	0	44.59
PLMPExp	123	.37	.21	.08	1.35
Informality	143	25.93	5.32	14.1	35.9
GDPgrowth	143	2.98	4.62	-14.81	11.89
LabFreeIndex	121	61.02	11.79	39.4	85.5
EduTertiary	132	23.42	7.09	10	39.7

PopDensity	143	85.02	34.06	30.95	136.62
Western European Countries: Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom					
Variable	Obs	Mean	Std. Dev.	Min	Max
UnemPActPop	234	8.18	4.48	2.5	27.5
ALMPExp	213	.54	.33	.03	1.56
TrainSh	213	39.73	19.02	7.73	80.21
EmpIncSh	213	30.62	21.19	2.91	85.35
SupportSh	208	16.53	18.51	0	74.71
DirectJobSh	194	10.74	11.12	0	49.33
StartupSh	212	3.75	7.16	0	43.81
PLMPExp	216	1.24	.68	.16	3.05
Informality	234	16.41	5.75	7.5	28.7
GDPgrowth	234	1.28	2.82	-9.13	8.46
LabFreeIndex	198	60.11	15.20	31	100
EduTertiary	216	29.34	7.86	10.8	47.8
PopDensity	221	153.62	123.07	12.5	503.02

Table 3.9 VIF Collinearity diagnostics – 2^{nd} approach

Variable	VIF	1/VIF
TrainSh	9.94	0.100554
SupportSh	9.42	0.106180
DirectJobSh	8.47	0.118106
EmpIncSh	7.97	0.125412
PLMPExp	2.98	0.335200
ALMPExp	2.94	0.340154
PopDensity	1.94	0.516439
Informality	1.87	0.534752
LabFreeIndex	1.25	0.797896
EduTertiary	1.22	0.820811
GDPgrowth	1.13	0.884683
Mean VIF	4.47	

Based on the model discussed in section 3.4.1, the empirical estimation utilised the empirical software STATA using the *xtabond2* command developed by Roodman (2009). Both system and difference estimators were considered, however only difference GMM was feasible in the case of this analysis because it uses a smaller number of instruments compared to system GMM (the estimation from system GMM is provided in the Appendix A3.7.3). The lagged dependent variable, *ALMPExp* and its square term and *PLMPExp* are treated as endogenous and as such are instrumented with their own lagged levels. The choice of lags is determined by model diagnostics. The initial specifications included a minimum number of lags, i.e. starting from one lag for the lagged dependent variable and other variables. Since the initial specification failed diagnostic tests for instrument validity, higher order lags (three or four lags) are included until the specification achieves acceptable diagnostics. In addition to limiting the number of lags, as suggested by Roodman (2006), collapsing the instruments is used to reduce the count of instruments and to obtain more parsimonious model. Considering the potential endogeneity of *Informality* and *LabFreeIndex*, they are also specified as endogenous and instrumented through internal instruments via GMM. However, the specification failed the instrument validity tests and increased the number of instruments higher than the number of cross-sectional units (see Appendix A3.4). Both these variables are instrumented with their first lagged levels in the instrumental variable equation. The results show that the Hansen J test of overidentifying restrictions take the value of 0.310 and 0.370 in the two models respectively, suggesting the validity of the instruments for treatment of the endogenous variables. The null hypothesis of autocorrelation in differences of errors is rejected for the autocorrelation in differences of errors. It is also important to check the validity of subsets of instruments; the difference-in-Hansen test also known as C-test (Baum, 2006). The null hypothesis of the difference-in-Hansen is that the specified variables are proper instruments, i.e. that the set of examined instruments is exogenous. The results suggest that there is no sufficient evidence to reject the hypothesis (see Appendix A3.7.1 and A3.7.1).

The difference-in-Hansen test was also conducted in order to test for cross-sectional dependence. The results suggest that the null hypothesis of the validity of the instruments for lagged dependent variable cannot be rejected in both models. Following the suggestion of Bond et al. (2001), an additional test of the validity of dynamic panel estimation is performed to check whether the lagged dependent variable lies between the lower bound of FE and upper bound of OLS estimates. As appendix A3.7.3 shows, both model specifications satisfy this condition. Having analysed all these diagnostic tests, it is concluded that the model is well specified which can be used for interpretation of the results presented in table 3.10. As discussed in the previous section, the preferred estimator is two-step robust difference GMM which accounts for heteroscedasticity.[31]

Having obtained the final specification with acceptable diagnostics, the final estimated results are presented in table 3.10. The F-test for the joint significance of the independent variables rejects the null hypothesis, suggesting that the independent variables collectively have explanatory power with respect to the dependent variable.

The dynamic specification, through the lagged dependent variable, contains the history of the independent variables. This variable is highly significant in both models, suggesting that there is a high persistency of the unemployment rate. The coefficient of the lagged dependent variable suggests that a 1 percent increase in unemployment rate in the previous period is associated with an increase of about 0.80 percent in the unemployment rate in current period. The results in table 3.10 show that the variables of interest, *ALMPExp* and its quadratic term are not significant in either of the models 1 or 2. Model 2 includes variables measuring the share of each individual ALMPs (*TrainSh, EmpIncSh, SupportSh* and *DirectSh,* while *StartupSh* is a left out of the regression as the omitted category) to assess whether different active policies are effective in reducing unemployment rate. These variables *TrainSh, EmpIncSh, SupportSh* and *DirectSh* are also insignificant in model 2. The insignificant result might be because the dataset is combined to account for two different sets of countries which have distinctive differences. As discussed in section 2.4 and 2.5, different ALMPs might have different effects in different contexts and for different sub-groups of unemployed and those differences might cause the overall insignificance.

Of the control variables, *GDPgrowth* is significant in both models. The estimated results indicate that an increase in the *GDPgrowth* of 1 percent will reduce the unemployment rate by 0.32 percent, other variables remaining constant (0.34 in model 2). Variable *LabFreeIndex* is significant in model 1 and in line with our expectations, an increase in the labour freedom index of 1 unit will reduce the unemployment rate by 0.05 percent. Other control variables have signs in line with our expectations but are insignificant in both models.

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[31] There is no need to test for a normal distribution because the GMM estimator does not rely on that assumption.

Table 3.10 Estimated results from Difference GMM

VARIABLES	Model 1 *UnemRate*	Model 2 *UnemRate*
L.UnemRate	0.803***	0.811***
	(0.0898)	(0.125)
ALMPExp	-1.766	-2.654
	(4.305)	(5.008)
ALMPEx2	0.654	1.866
	(1.844)	(1.944)
TrainSh		-0.00624
		(0.0294)
EmpIncSh		0.000588
		(0.0286)
SupportSh		0.0227
		(0.0252)
DirectJobSh		0.00301
		(0.0378)
PLMPExp	1.507	1.220
	(1.019)	(1.102)
Informality	-0.284	-0.0840
	(0.731)	(0.655)
GDPgrowth	-0.320***	-0.340***
	(0.0537)	(0.0449)
LabFreeIndex	-0.0545**	-0.0243
	(0.0260)	(0.0220)
EduTertiary	-0.0696	-0.00906
	(0.0641)	(0.0577)
PopDensity	0.0306	0.0428
	(0.0297)	(0.0324)
Observations	211	194
Number of CountryID	28	27
F-test	F(21, 28) = 300.67 Prob > F = 0.000	F(25, 27) = 1230.04 Prob > F = 0.000
Arellano-Bond (AR1) test	Pr > z = 0.008	Pr > z = 0.016
Arellano-Bond (AR2) test	Pr > z = 0.163	Pr > z = 0.182
Sargan test	Pr > chi2 = 0.404	Pr > chi2 = 0.553
Hansen test	Pr > chi2 = 0.310	Pr > chi2 = 0.371
No. of Instruments	23	27

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.5 Conclusions

This chapter has applied two different empirical approaches. The first one is the matching function using FEDK and FEVD in a panel dataset for 11 countries for years 2010 to 2015 while the second approach is a dynamic panel data estimator, difference GMM, using a panel data for 28 countries for years 2005 to 2014. Section 3.3.2 provided a critical review of the endogeneity of the ALMP variable and discussed possible choices for the instrumental variables used by empirical studies. However, the instrumental variables used by empirical studies were argued not to be the optimal choice for this empirical analysis.

As discussed in section 3.3.2, the preferred empirical approach in previous studies analysing the effectiveness of the ALMP was a matching function using a dynamic panel estimator because it addresses the potential endogeneity of the ALMPs. Since the data for matching function component variables are not available for a long period, the dynamic panel estimator could not be applied hence FEDK and FEVD using the first lag of the *ALMPExp* were applied. The results from FEDK suggest that an increase in ALMP expenditure as a share of GDP will increase the flow from unemployment to employment, however this effect is not economically significant. Consistent with the findings from other studies, the estimated results from FEDK, when using a restricted sample of transition countries only, point to increasing returns to scale in the transition from unemployment to employment, suggesting that transition economies' labour markets might exhibit multiple equilibria. Same results are also found when using FEVD.

The second approach uses a larger dataset with a larger number of countries included in the sample and a longer time period. With the larger dataset it became possible to include variables which measure expenditure on individual ALMPs: training, employment incentives, supported employment and rehabilitation, direct job creation and start-up incentives. The difference GMM estimations did not find any evidence of a significant relationship between *ALMPExp* and unemployment rate. Variables measuring the shares of different types of ALMPs to total ALMP expenditure are also insignificant. As discussed above, one possible explanation for the insignificant results might be that different ALMPs have different effect in different contexts and for different sub-groups, hence cancelling out their effect. The results also show that the lagged value of the dependent variable, the unemployment rate, is highly significant with a coefficient one of 0.8 which suggests that the unemployment is highly persistent. As argued in section 2.2, when unemployment exhibits persistency, besides applying labour market policies, the focus should be on increasing aggregate demand to stimulate job creation. Having found no significant effect of ALMP expenditure at the country level on the transitions from unemployment to employment and reducing the unemployment rate, the following empirical chapters 5 and 6 will investigate the effect of the ALMPs at the individual level on increasing an individual's probability of being employed, having an employment contract and actively searching for jobs.

Chapter 4

A Review of Evaluation Methodology and the Microeconomic Empirical Studies for Transition Economies

4.1 Introduction

Having analysed the labour market in the European transition and non-transition economies in chapter 1 and established the potential importance of ALMPs as a factor in reducing unemployment in chapter 2, the thesis followed with an empirical analysis of the effectiveness of ALMPs in the European countries at the country level in chapter 3. This chapter will provide an assessment of the methodology applied in evaluating ALMPs in preparation for the upcoming empirical analysis in chapters 5 and 6. The aim of this chapter is to: (i) analyse the evaluation methodologies employed in microeconomic policy analysis and identify the key assumptions within the common frameworks; and (ii) review the empirical evidence specifically for European transition economies.

The central problem faced by microeconomic evaluation is the issue of counterfactual data since an individual cannot be in two different states at the same time. Thus, the key role of this chapter is to examine the evaluation problem and the construction of counterfactuals for the reliability of the results, since it is the important part of making the comparison between two different states. It is crucial to understand whether a particular active programme has been successfully designed, targeted and implemented and at the same time to evaluate the impact of ALMPs on the participants' future labour market outcomes. Assessing the effectiveness of the ALMPs is not an easy task and it remains a concern to researchers. The evaluation analysis becomes even more difficult in a quickly changing environment, which is the case in most transitional economies. There have been a substantial number of evaluations of ALMP effectiveness in Europe conducted by independent researchers and researchers commissioned by government bodies, though there are very few evaluations for transition economies. The evaluation studies in transition economies have mostly used different matching estimators and have had less focus on other evaluation methods.

According to Heckman et al. (1999), the choice of the most appropriate estimator depends on three factors: the assignment of individuals into the programmes, the quality of data available and the specific question to be answered. In social experiments the assignment of the participants into the programmes is performed randomly, hopefully assuring balance in observed and un-observed characteristics of the treated and control persons i.e. the characteristics of the two groups are similar hence comparable (Heckman et al., 1996; 1999). In contrast, in observational studies the assignment into the programmes is not random and thus causes possible selection bias. Choosing from the wide range of available evaluation methods when analysing the microeconomic effectiveness of active policies is a big challenge for researchers

Heckman et al. (1996; 1999) place a high emphasis on the importance of the quality of data to produce unbiased impact estimates. The observational data should ideally be obtained from the same source for the treatment and control groups and it should provide a rich set of variables. Evidence from some studies suggests that evaluations using observational data produce different estimates and generate conclusions which deviate from those drawn from experimental studies (LaLonde, 1986; Smith and Todd, 2005). Since social experiments are considered to represent the 'gold standard', researchers have tried to find an evaluation method that by using observational data will produce unbiased results just as social experiments ideally do. However, some studies found evidence that matching estimators succeed in replicating experimental results while also arguing that this method does not represent a 'magic bullet' that can solve the selection problem in every case (Deheija and Wahba, 2002; Smith and Todd, 2005).

The chapter is organised as follows. Section 4.2 provides a detailed explanation of the evaluation problem, with particular emphasis given to the construction of the counterfactuals. This section will provide arguments for using Propensity Score Matching and more specifically how this method may correct for any selection bias followed by an assessment of the efficiency of different matching methods. Section 4.3 will provide a review of the evaluation methodologies used when investigating the effectiveness of ALMPs at the individual level while section 4.4 reviews the evaluation methodologies adopted to date in transition economies. Section 4.5 provides the conclusions of the chapter.

4.2 Evaluation Methodology: The evaluation problem and the construction of counterfactuals

Most microeconomic evaluation studies of active labour market policies are based on the potential–outcome approach to causality (Rubin, 1974; Heckman et al., 1999;

Caliendo et al., 2011; Schmidl, 2014;) persons are expected to occupy one of two mutually exclusive states: treated or un-treated. The individual indicator D_i is associated with the indication of receiving a treatment, where $\mathrm{D}_i = 1$ if a person participates in the programme and $\mathrm{D}_i = 0$ otherwise. The ideal assessment is what would happen to individual i in the labour market if i participated in a programme ($\mathrm{D}_i = 1$) relative to the state when i did not participate in a programme ($\mathrm{D}_i = 0$). The second term is not possible to observe.

The outcome for the individual i who has participated is denoted as $\mathrm{Y1}_i * \mathrm{D}_i$ while the outcome in the case where the individual i has not participated in a programme is $\mathrm{Y0}_i * (1 - \mathrm{D}_i)$. Where increasing the employability of those undertaking treatment is the key objective of the intervention then the labour market outcomes can be defined as ''0'' if not employed and ''1'' if employed which gives the possibilities of an individuals' outcome before and after the treatment as $(0,0)$, $(0,1)$, $(1,0)$ or $(1,1)$. The evaluation analysis seeks to assess the *causal impact* of the treatment on labour market status. The actual outcome (Y_i) for individual i can be written as:

$$\mathrm{Y}_i = \mathrm{Y1}\ _i * \mathrm{D}_i + \mathrm{Y0}_i * (1 - \mathrm{D}_i). \qquad 4.1$$

The individual treatment effect would be given by the difference

$$\Delta i = \mathrm{Y1}_i - \mathrm{Y0}_i \qquad 4.2$$

Equation 4.2 is the fundamental e*valuation problem*. To evaluate the impact of the treatment, both outcomes with and without the treatment need to be observed. Unfortunately, the outcome of both states of one individual at the same time can never be observed. The outcome of the treated individual had he not been treated ($Y0_i$) is not observable hence it needs to be estimated which also implies that the treatment effect cannot be directly observed but needs to be estimated.

Some studies, focus on the population average treatment effect on the treated (ATT) (Caliendo et al., 2011; Schmidl, 2014) which is formally given by:

$$\mathrm{ATT} = \mathrm{E}(\Delta|\mathrm{D} = 1) = \mathrm{E}(\mathrm{Y1}|\mathrm{D} = 1) - \mathrm{E}(\mathrm{Y0}|\mathrm{D} = 1) \qquad 4.3$$

The final term of equation 4.3, $E(Y0|D = 1)$, is the expected outcome had treated individuals not participated in any programme. This is regarded as the counterfactual outcome that is impossible to be observed. Thus, the evaluation problem is the problem of finding an appropriate counterfactual that can be identified from the observational data. The only distribution of the individual outcomes that can be directly observed are the frequency distribution of the outcome $Y1_i * D_i$ for participants and the outcome $Y0_i * (1 - D_i)$ for non-participants. The frequency distribution of the outcomes of both individuals in different groups can be observed by the set of the individuals' characteristics X_i and also by the outcome of the pre-treatment period Yt'_i; the pre-treatment period is denoted as t'. Taking into account this conditioning information will allow correcting for selection on observable characteristics. Therefore, constructing an appropriate control group of non-participants will help to alleviate the evaluation problem.

In order to understand the identifying assumptions of the evaluation approaches used in the literature, a brief explanation of experimental and non-experimental designs is provided below.

Experimental studies completely replicate the intervention that will be implemented in the field; these studies provide, in principle, a convincing approach to the evaluation problem. The main idea of the experiment is the randomised selection of individuals into treatment and control groups. Individuals who would have chosen to participate in the programme would be excluded from the programme participation through a random mechanism. The process is under considerable control of the researcher about the individual compliance with the programme. As a consequence, randomization will generate a complete balancing of the relevant observable and un-observable variables across treatment and control groups (when the sample size is sufficiently large enough), which will enable comparability between the groups and does not require any sophisticated statistical analysis.

Non-experimental or observational studies are not conducted under the control of the researcher. This evaluation design gathers information on the labour market outcome(s) of participants and non-participants and utilises this information to achieve results similar to those from the experimental design. In this case the selection or assignment into the active programmes is done by labour office administrators or individuals may select themselves for programmes they anticipate to be beneficial for themselves. While the randomised experiment guarantees the balancing of observables and un-observables of the treatment and control individuals, the non-experimental study tends to use the observable information while the remaining difference in characteristics will be attributed to chance. Accordingly, the difference in the means of outcomes for participants and non-participants will be attributed to the programme effect.

In non-experimental designs, the treated and untreated are selected groups that would be likely to have different outcomes even in the absence of the programme, thus leading to a selection bias problem (Rodríguez-Planas and Benus, 2010). Even when treated and untreated individuals have comparable observed characteristics, the two groups are likely to differ in unobserved characteristics (Hämäläinen, 1999). The problem of selection bias can be diminished through imposing some identification assumptions. The evaluation methods are designed to estimate the counterfactual and at the same time taking into account the problem of selection bias. Matching estimators, as one of the evaluation methods, will tend to balance the characteristics in the two groups when using observational data. While in contrast in the social experiments a difference in baseline characteristics may exist (Austin, 2011). According to Rosenbaum (1998), matching estimation is feasible where there are differences in the pre-treatment characteristics of the treated and untreated individuals that are important for the outcome. If treated and control individuals have similar pre-treatment characteristics the selection bias would not arise and as such a simple estimator would be sufficient to assess the difference in outcome.

The choice of which evaluation method to use is an important one because the impact estimates are sensitive to the estimator chosen and deviate from the benchmark of experimental estimates (LaLonde, 1986; Heckman et al., 1999). According to Smith and Todd (2005), this is not surprising since the different estimates are dependent on different identification assumptions about the outcome and participation used by different estimators. The following section provides an overview on the evaluation approaches commonly used in ALMP evaluations and alternative methodologies using observational data.

4.3 Evaluation strategies for observational studies

An evaluation approach involves a comparison between the treated and untreated individuals. Evaluation methods are designed to take into account the estimation of counterfactual outcomes as well as to control for selection bias. Despite the fact that the quality of data available is one determining factor, the choice of the evaluation methodology also depends on the mechanism by which the individuals are allocated to programmes. Blundell and Dias (2009) refer to this as the 'assignment rule' and it is an important component in the choice of the evaluation method used. Each method employs different assumptions and unless an appropriate method is being used the results will not be reliable (Blundell and Dias, 2009). The adequacy of each of the approaches, the data required and the necessary assumptions are briefly discussed below. This discussion will provide the motivation for the later use of Propensity Score Matching in the analysis of the effectiveness of ALMPs considering the available data.

Heckman et al. (1999) distinguish three prototypical solutions to the evaluation problem:

Before and after estimator – this is the most common approach for constructing a plausible counterfactual. It comprises a comparison of treated individuals with themselves in the pre-treatment period *t'*. The underlying identification assumption of this method is that taken over the population of all treated individuals, the average of actual outcome in period *t'* is equal to the population average of what these individuals would have experienced in period *t* had they not participated in the programme. It therefore requires considerable stability in the economic environment. The validity of this assumption may be violated due to the changes in the overall state of the economy between different points of time, or changes in the life cycle position of the cohort. Even the anticipation of the individual participating in a programme may change an individual's motivation and behaviour in the pre-treatment period. This type of study requires longitudinal or repeated cross-section data from the same population where at least one section is from the pre-treatment period.

Cross-section estimator – this method compares the labour market outcomes of treated and untreated individuals at the same point of time. The results from this approach would be biased when using non-experimental or observational data since there will presumably be permanent difference in personal characteristics of individuals who participated and those who did not. This approach would be more suitable in an experimental design where individuals are randomly selected in treatment and control groups in which case the characteristics of the two groups would be closely related. The main assumption of this approach is that, on average, individuals who do not receive treatment have the same no-treatment outcome as those who do, had they not been treated. This assumption will be satisfied if the participation in the programme is independent of outcomes in the no-programme state in the post-programme period (Heckman et al., 1999). In addition, this approach is not vulnerable to the problems that arise in the before-after estimator if the macroeconomic environment and aging process have the same effect on both participants and non-participants.

Difference-in-difference estimator **–** is defined as the difference in average outcome of the before and after the treatment of treated individuals minus the difference in average outcome before and after treatment of the control individuals. The interpretation of this technique is the difference of a simple estimator between the actual outcome and the outcome that would occur in the post-treatment period in a hypothetical case where the treatment group had no treatment. This is a widely used evaluation method and considered by many to be the most efficient method when combined with propensity score matching (Smith and Todd, 2005). However, it requires longitudinal or repeated cross-section data.

4.3.1 Matching estimation – Propensity Score Matching

Matching estimation is used to estimate the treatment effect based on observational data. This estimation is based on the principle that participants should be matched with non-participants (control group) conditional on pre-treatment observed covariates. The outcome is then compared between the matched pairs and the difference in outcomes is attributed to the treatment. There are two matching techniques: Exact Covariate Matching and Propensity Score Matching. Exact Covariate Matching creates matched pairs of treated and un-treated individuals based on identical covariates, i.e. identical age, gender, educational level etc. Matching can be difficult when the dimension of conditioning variables is large, i.e. the more variables used to match by the more difficult it gets to match individuals. This phenomenon is known in the literature as the 'curse of dimensionality' (Stuart, 2010; Todd, 2010). Since the dimensionality increases exponentially with the number of covariates *X*, it becomes impossible to find a match for each observation when more than a few variables are being used. This is a serious limitation of Exact Covariate Matching even in cases of a large sample since it leads to many individuals not being matched (Rosenbaum and Rubin, 1983; Blundell and Dias, 2009). Rosenbaum and Rubin (1983) suggest that it is sufficient to match on Propensity Scores, i.e. to match the treated and un-treated individuals by their probabilities to enter a given programme conditional on the observed covariates. Rosenbaum and Rubin (1983) have shown that if the Conditional Identification Assumption (CIA - explained below) is valid for the variables *X* it would also be valid for the estimated propensity scores. Replacing the set of variables *X* with the estimated propensity scores to match the observations will reduce the matching problem to only one dimension, that of propensity scores, thus simplifying the matching procedure. In this context, participants are similar to non-participants based on their propensity to be treated in a particular active programme but it does not necessarily mean that all the characteristics of the matched pair are exactly the same. The propensity score of each of the individuals is estimated from a bivariate model (either logit or probit) using a set of variables determining the treatment participation and the outcome. The set of variables to be accounted for in the propensity score estimation is discussed in more detail below. Rosenbaum and Rubin (1983) showed that matching on propensity scores, instead of matching on a high-dimensional matrix of potential characteristics, will also balance the characteristics of the two groups through balancing the propensity score values and will lead to a higher number of matched pairs. In other words, conditioning on the propensity scores allows one to replicate an experiment setting, conditional on observed covariates.

Regardless of the type of matching, matching estimation is based on two assumptions. The first assumption is the *Conditional Independence Assumption (CIA)* (also referred to as un-confoundedness or selection on observables) which denotes that there are sufficient observable data (X) such that the outcomes or the treatment effects (Y) are independent from the programme participation (D) (Rubin, 1974; Gerfin and Lechner, 2002; Christensen, 2009; Bonin and Rinne, 2014):

$$(Y0), (Y1) \perp\!\!\!\perp D| \qquad 4.4$$

The CIA is in general a strong assumption and obliges inclusion of a range of relevant independent variables influencing both participation in the active programmes and the outcome variables (Bryson et al., 2002; Bonin and Rinne, 2014). This assumption tends to mimic as much as possible the experimental approach of random assignment (Austin, 2011). According to this, it is assumed that the unobserved characteristics are trivial and do not particularly affect the outcome in the absence of treatment. Participants may adjust their behaviour in order to become eligible to participate in a programme and this information may not be observable to the evaluator. However, when a rich dataset is available this assumption is likely to hold and conditional on observable characteristics the selection process will mimic randomisation just as in an experimental setting.

The second assumption is *common support* or the *overlapping of the covariates* of the participants and non-participants. As explained by Schmidl (2014) this assumption "*requires that all characteristic values appearing in the treatment group also appear in the control group"* (p. 137). In the case when the characteristics are observable only for treated individuals, one is unable to predict how these characteristics are related to the outcome of the control individual. The condition is written as:

$$0 < P(D = 1|X) < 1 \qquad 4.5$$

Under these assumptions, the distribution of the counterfactual and the observed outcome for the participants and the comparison group are the same, conditional on the vector of covariates.

$$E(Y0|X, D = 1) = E(Y0|X, D = 0) \qquad 4.6$$

Even when using propensity scores instead of exact covariates to create matching pairs, the problem of finding quality matches does not disappear completely. The non-treated group may not have some of propensity scores similar to the treated group which may lead to omitting the treated observations from the sample resulting with a narrow common support. The essence of matching estimators is to compare similar individuals and the common support assumption assures that the matched treated and control individual share similar characteristics. In the absence of common support, incomparable individuals are likely to have different observable characteristics and are more likely to differ in unobservable characteristics. However, in an attempt to increase the quality of matching one may lose too many observations from the treated group which is important, particularly for multiple treatment programmes (Bryson et al., 2002).

One of the most important steps when evaluating with propensity score matching is choosing the relevant covariates X. The literature suggests that a rich set of variables that simultaneously affect the choice probabilities and the outcome should be included in the estimation of the propensity scores; however, there is no consensus regarding which variables to include (Heckman et al., 1999; Austin 2011). Possible sets of variables to be accounted for when estimating the propensity scores include: the set of all measured baseline covariates (i.e. variables which are not influenced or modified by the treatment such as age, gender, household condition, etc.); the set of variables that are associated with treatment assignment (this set of variables depends on the specific characteristics related to the assignment or selection on the programmes such as the admission criteria, distance from the employment/training centres etc.); the set of variables that affect the outcome (potential confounders, basically all the variables that affect the labour market state or earnings such as demographic variables, labour market histories, economic condition etc.); and the set of variables that affect both treatment assignment and outcome level (true confounders) (Austin, 2011). Brookhart et al. (2006) suggest that including the variables that only affect the treatment assignment will produce greater variance of the estimated treatment effect. In many settings, it is safer to include in the propensity score model all baseline covariates that affect both treatment assignment and the outcome (Austin, 2011). Steiner et al. (2010) also suggest that the optimal modelling strategy is to include a large set of covariates since this approach will be more likely to satisfy the CIA condition. The socio-demographic characteristics of potential participants along with their educational background are likely to be very important in the context of ALMP evaluations (Bonin and Rinne, 2014). Previous studies suggest that individuals' labour market histories are important determinants of the participation in active labour market programmes, as they are of the individuals' labour market outcomes (Heckman et al., 1999). Therefore, dummies representing different intervals of duration of unemployment before the treatment should be included in the analysis. As explained, selection bias may arise also from unobserved characteristics, such as motivation to participate in a particular programme and orientation to paid employment. It is more likely that highly motivated individuals will be more likely to get a job. On the other hand, selection bias may also be attributed to the role of administrative staff in selecting participants. In such cases administrators may choose the best of applicants to participate in a programme, thus the programme effects may be over-estimated. Therefore, controlling for differences in observable characteristics may yield unbiased results (Bryson et al., 2002). As recognised by Bryson et al. (2002), motivation to participate and get a paid job may be correlated with the pre-treatment unemployment duration; thus including this variable in the propensity score estimation may capture the motivation effect and thus reduce the bias.

Even though the discussion so far has implicitly assumed that individuals can participate only in one homogenous programme, the type of treatment may be heterogeneous in terms of duration, content of training courses or provider of courses.[32] The discussion in section 2.2.3 showed that labour market outcomes may be affected by the intensity and the quality of the programme that an individual has participated in and there may also be dynamic selection effects when participating in programmes one after the other (possibly to remain eligible for state transfer payments). Based on Rubin's model of binary choice of participation, more recent studies extended it to account for multiple treatment (Imbens, 2004; Hirano and Imbens, 2001; Gerfin and Lechner, 2002; Emsley et al., 2008; Tan, 2010). Gerfin and Lechner (2002) show that similar properties as in the binary treatment model (Rosenbaum and Rubin, 1983) also hold in the multiple treatment framework.

A relevant issue in the Propensity Score Matching technique is the choice of the matching algorithm. Previous evaluations suggest different algorithms for matching

[32] In the case where a person participates in more than one programme, the effect of each programme in isolation would be very difficult to assess.

of treated and untreated units and there is no consensus on which matching algorithm is superior to the other (Morgan and Harding, 2006). Appendix 4.1 provides an assessment of different matching algorithms, their advantages and disadvantages and identifies potential cases when these methods are more appropriate.

4.3.2 Inverse Probability Weighting – Regression Adjustment

Based on the assumptions outlined in section 4.2 and the previous discussion, the treatment and control groups can become comparable by conditioning on the propensity scores which then can identify the treatment effect. Section 4.3 focused on methods based on matching with propensity scores while this section will expand the discussion of methods based on *doubly robust* estimation, because of its' advantages in the case of analysing multiple treatment programmes. Given that the aim of chapter 5 is to investigate the relative effectiveness of three different active measures, the chosen method for this empirical analysis is a doubly robust model, the Inverse Probability Weighting – Regression Adjustment (IPWRA). This estimator produces the parameter of interest while allowing for multinomial treatment modelling. Given this major advantage, the IPWRA seems to be a suitable choice in our setting. The discussion on the multivalued treatment variable is a recent one (Imbens 2000 and Lechner 2001). The doubly robust approach has been discussed by Hirano and Imbens (2001), Emsley et al. (2008) and Tan (2010), but to the best of our knowledge there is no study that combines regression and weighting to evaluate the effectiveness of the active labour market programmes. However, a few studies have used this technique in other fields such as estimating the earnings returns to different educational programmes (Uysal, 2015).

IPWRA is a doubly robust model estimator because it uses one model to predict the treatment probability and an outcome model to predict the outcomes for each specific treatment. The IPW tends to adjust the outcomes of the control subjects by weighting them with the inverse of the estimated propensity scores. It creates weights similar to the sampling weights that are used to weight survey samples which are representative of specific populations. This estimator forms a synthetic sample in which the distribution of measured covariates is independent of the treatment assignment (Austin, 2011).

IPWRA uses a three-step approach to estimate Average Treatment Effects on Treated (ATET). The first is the estimation of treatment model and computation of the propensity score weights. These weights are defined by the inverse of the propensity score if the subject has joined a treatment and the inverse of 1 minus the propensity score if the subject is in the control group (received no treatment or received another treatment). The second step is to predict outcomes for each subject through fitting the weighted regression models of the outcome for each treatment. The third step is to produce the average treatment effects on the treated which is the difference in the means of specific treatment outcomes.

An estimation of the parameter of interest τ^{IPW}, using the inverse weights equal to $1/\widehat{p_i}$ if $D_i = 1$ or $1/(1-\widehat{p_i})$ if $D_i = 0$, is obtained as the difference between the average outcome of the treated and the reweighted average outcome of the non-treated. According to Lunceford and Davidian (2004) the doubly robust estimator is defined as follows:

$$\tau^{IPW-RA} = \frac{1}{N}\sum_{i=1}^{N}\frac{D_iY_i-(D_i-\widehat{p_i})m_1(\underline{X_i})}{\widehat{p_i}} - \frac{1}{N}\sum_{i=1}^{N}\frac{(1-D_i)Y_i+(D_i-\widehat{p_i})m_0(\underline{X_i})}{1-\widehat{p_i}} \qquad 4.7$$

Where $m_D(\underline{X_i}) = E(Y_i|D_i = D, \underline{X_i})$ for D = 0 or D = 1 are predicted values from the regressions of the outcome on the baseline covariates where the coefficient estimates and predicted values are obtained from the regressions carried out separately for each treatment group with the same model specification. This approach provides consistent estimates of the effects because the treatment is assumed to be independent of the potential outcomes after conditioning on the covariates.

The standard errors reported in the doubly robust estimators correct for the three steps in the process when producing the parameter of interest. A particular concern associated with IPWRA is that it is very sensitive to large values of the propensity scores as they receive disproportionately large weights in the construction of the counterfactual. However, the common support (overlap) assumption ensures that predicted inverse-probability weights do not get too large. This estimator deals with the poor properties of the finite sample by normalising the weights of the propensity scores to one (Imbens, 2004; Emsley et al., 2008; Uysal, 2015).

The most important advantage of this estimator is that it gives unbiased estimates if only one of the models, the treatment or the outcome model, is specified correctly (Bang and Robins, 2005; Emsley et al., 2008; Uysal, 2015). This allows for two opportunities to obtain the accurate results. The simulations of Emsley et al. (2008), Tan (2010) and Uysal (2015) demonstrated that the doubly robust estimates remain consistent even if one of the underlying models is mis-specified. Because of the frequency of model mis-specification, the doubly robust model is desirable.

4.4 Review of empirical studies

The previous sections provided a review of the available evaluation methodologies usually used to assess the effectiveness of the ALMPs. In addition, sections 4.3.2 and 4.3.3 reviewed in more depth the Propensity Score Matching approach and also offered justification for using this method in evaluating active measures. In chapter 2 it was argued that the ALMPs, including measures such as job search assistance, labour market training, and wage subsidies among others, have a potentially important impact in combating unemployment. Seeking to identify the evidence that allows us to draw a conclusion with regard to the effectiveness of the ALMPs this section provides a critical review of the recent studies that used Propensity Score Matching in European countries. In addition, the review will focus more specifically on studies for European transition economies.

4.4.1 Evidence from Europe with special reference to European transition economies

The adoption of ALMPs was seen as an important instrument to tackle the relatively high unemployment rates in transition economies. It is therefore valuable to question this perception and to assess what level and type of these policies could be appropriate in the context of the labour markets of transition economies. It is widely known that labour markets in these countries have different characteristics compared to those in Western countries (see chapters 1 and 2). There are relatively few studies analysing the impact or the effectiveness of ALMPs in the transition contexts and their results are diverse. Summaries of the main microeconomic evaluations in European transition economies and selected non-transition economies are presented in table 4.1. While in Western countries the quality of data has been increasing, the most important issue for transition economies remains the quality of the micro data.

Administrative records do not usually provide enough information to carry out micro-econometric evaluations, thus most of the studies in transition economies do not rely only on this data source. Follow-up surveys of the registered unemployed or participants of the programmes in general are also rare and do not support the ever increasing need to conduct a thorough micro-econometric evaluations. Most programme evaluations analyse only the partial effect on the treated. The mean effect of 'the treatment on treated' is measured by the labour market outcome, either employment probability or earnings after the treatment. Table 4.1 shows that for transition economies the outcome variable tends to be unemployment and employment probability, which is in line with the objective of these policies in ETEs, while only a few studies investigate the effect of active measures on the level of earnings. The methodologies of evaluation studies in transition economies tend to follow the same identification strategies as those in other European countries. The studies have relied either on hazard rate analyses or on different variants of selection on observables, mostly through different matching estimators. Matching estimators seem to be mostly used in transition economies (Puhani, 2002; Leetmaa and Vork, 2003; Rodriguez-Planas and Benus, 2006; Kluve et al. 2008; Bonin and Rinne, 2014; Mojsoska-Blazevski and Petreski, 2015; Bratti et al., 2017; Potluka, 2017; Štefánik et al., 2018; Popescu and Roman, 2018; Adamecz-Völgyi et al., 2018) along with duration models (Puhani, 2002; Van Ours, 2001; Micklewright and Nagy, 2005), with a few exceptions using selection models (Vodopivec, 1999; Petreski, 2018). The following sections provide a review of the main empirical studies of the effectiveness of ALMPs in transition economies.

In terms of the data used, European evaluations mostly use cross-sectional data controlling for selection bias. In recent years, active policies have become more diverse and policymakers seem to have increased their focus on measures for specific target groups. The majority of the micro-econometric evaluations are based on non-experimental designs, while with respect to the identification strategies most of the studies use matching estimators or duration models. Regarding the time-span effectiveness of the active measures, evaluations in European countries mostly focus on the short-term effects (outcomes six to twelve months after completion of the programme), while in more recent years some studies consider also the long-term effects (outcomes between two to three years after completion of the programme) (Mojsoska-Blazevski and Petreski, 2015; Card et al., 2017; Štefánik et al., 2018).

It is common for evaluation studies to estimate the impact of active measures on unemployment and employment probabilities rather than on earnings, which is consistent with the objectives of policies (the main objective of the European policies is to increase employment rather than alleviate poverty (Eurostat, 2018).

Table 4.1 Summary of studies on the effectiveness of ALMPs for European Transition Economies and selected Non-Transition Economies, based on chronological order (year of publication)

Study	Country	Measure	Target Group	Observation Period	Outcome of interest	Methods of estimation	Results
Van Ours and Lubyova, 1998	Slovak Republic	1)PUJ – publicly useful jobs (employment in public sector), 2)SPJ – socially purposeful jobs (subsidies in private sector) and 3) Training	Unemployed	1993 – 1998 Administrative data	Dummy variables 1. value 1 if: unemployed did not participate in ALMP but found job 2. value 1 if: unemployed participated in ALMP and then found job, 3. value 1 if: unemployed part. ALMP but did not find job 4. value 1 if: unemployed neither participated neither found job.	Multivariate Duration Models	Training and PUJ reduce duration of remaining unemployed. SPJ increase probability of being unemployed.
Puhani, 1998	Poland	1)Training, 2)Intervention Works (subsidies in the private sector) 3)Public Works	Registered unemployed	1992-1996 Labour Force Survey	Re-employment probability	Propensity Score Matching and Exact Matching Nearest neighbour without replacement And a Duration Model	Training : Positive effect for men. Significantly positive effect for women for one month only. Significant positive effect of Intervention works and Public works for men.
Vodopivec, 1999	Slovenia	1)Public works	Unemployed	1992 – 1996 Administrative	Exit in individuals labour market status after searching n	Heckman Two Stage Model	Participants have higher success rate of finding employment. Women after 6 to 12 months of job search have lower rate of

					months for a job. Three values: 0 if after n months is still unemployed; 1 if after n months is employed; 2 if after n months is out of labour force		being unemployed. Young participants: + Vocational education: -
Gerfin and Lechner, 2002	Switzerland	1)Training (5 types), 2)Employment Programmes(priva te and public; job creation which does not compete with regular jobs), 3)Temporary wage subsidy (in the regular labour market)	Unemployed , UI recipients	1997-1998 – Administrative data	The probability of being in employment and out-of-labour force	Propensity Score Matching (Multivalued treatment)	Temporary wage subsidy shows a positive effect, employment programmes show a negative effect and training has mixed results.
Leetmaa and Vork, 2003	Estonia	1)Training	Unemployed , UI beneficiaries	2000 – 2002 Administrative, Follow-up Survey	Employment, Earnings conditional on being employed	Propensity Score Matching Nearest neighbour with replacement	Training increases the employment probability and earnings.
Micklewrigh t and Nagy, 2005	Hungary	1)Job search monitoring	UI claimants	2003 – lasted four months Administrative, LFS	Employment hazard	Multivariate Duration Model	Large significant effect for women over 30. , The effect is even larger if women over 30 is married. Men and younger women: no effect
Dorsett, 2006	United Kingdom	Two stage programme: 1.Job-search activity 2. one of the options: 1) Subsidised employment,	Young unemployed	1998 Administrative data	Employment in the week starting 28 May 2001	Propensity Score Matching	Subsidised employment is more effective in securing unsubsidised employment than the other options available.

		2) Full-time education and training, 3) Environmental task force or voluntary sector					
Rodriguez-Planas and Benus, 2006	Romania	1) Training and retraining , 2) Small business assistance, 3) Public employment, and 4) Employment and relocation services	Disadvantaged and long-term unemployed	1999-2002 Administrative and Follow up Survey	Re- employment probability and earnings	Propensity Score Matching Kernel-based matching with a caliper of 1%. .	Training, small business assistance and employment relocation services have positive effects on re-employment probabilities and wages. Public employment programme has a negative effect.
Kluve, Lehman and Schmidt, 2008	Poland	1) Training, 2) Wage subsidies in private sector	Unemployed	1992–1996 Labour Force Survey	Out of labour force – 0, employed – 1 and unemployed -2	Exact Covariate Matching	Training increase employment probability for men and women, IW does not have any effect for women but has a negative effect on men.
Ramos et al., 2009	Spain	1)Training 2)Retraining 3)Personalised employment support 4)Social Guarantee programmes 5)Job Creation scheme 6) Integrated programmes	Unemployed	2005 Administrative data	The probability of being employment	Propensity Score Matching – Nearest neighbour without replacement	Participation increases the probability of becoming employed by more than 5%. Participating in more than one programme is more effective than participating in only one.
Christensen, 2009	Denmark	1)Public and private on the job-training, 2)Residual programmes (a combination of active measures targeted at the weakest	Unemployed 25-50 years, UI recipients	2002-2006 – Administrative data	The probability of being employed and earnings (indexed to 2005)	Propensity Score Matching	Training increases employment and earnings Women, middle age or older, and unskilled benefit the most from participation in these programmes.

		unemployed - specific in Denmark)					
Caliendo et al., 2011	Germany	1) JUMP Wage Subsidies, 2)Wage subsidies, 3)Short-term training, 4)Further training, 5) Preparatory training, 6) Job search assistance, 7) Job creation Scheme.	Young unemployed	2002-2008 Administrative data – detailed daily information	Short-term and long-term effects in employment	Propensity Score Matching – Inverse Probability Weighting – Matching with strata	Positive long-term employment effects for almost all measures aimed at employment. Insignificant effect on youth and low positive effect on low educated youth. Public sector job creation is found to be harmful for the medium-term employment prospects and ineffective in the long-run.
Borra et al., 2012	Spain	Combination of 1)Training, 2)Labour Orientation and 3) Work Placements	Registered unemployed	2004 Administrative data and Two follow-up Surveys in 2005 and 2008	Employment probability, Earnings, Job Security Working hours at different time periods (at 6 and 36 months of completion of the programme)	Propensity Score Matching Epanechinikov and Gaussian Kernel matching and Radius matching	Short-run (6 months): Positive effect on employment, job security and working hours. Long-term (36 months):No significant effect
Maibom et al., 2014	Denmark	1) More frequent meeting, 2) Job search assistance and 3) Early mandatory participation in activation programmes	Young uneducated and educated unemployed	2009 Administrative data	The probability of being in employment	Randomly Controlled Trial	For young uneducated there is negative impact of all measures on employment For young educated there is a positive effect for more frequent meeting (counselling), job search assistance but no effect for early activation.
ILO, 2014	Albania	1)On-the-job training, 2)Wage subsidies for job-seekers in difficulty (long-term unemployed, young,	Registered unemployed	2008 – 2013 Survey	The probability of being in employment	Propensity Score Matching Nearest neighbour matching with replacement; caliper of 0.0001.	All three programmes have a positive impact; the largest impact is that of wage subsidies for job-seekers in difficulty.

		unemployed with disability, older than 45 with lower level of education etc.) and 3)Internship programme					
Bonin and Rinne, 2014	Serbia	1)Vocational Training, 2)Temporary jobs	Unemployed, UI recipients	2005 – Survey	Unemployment, employment in a regular job including self-employment, employment in a seasonal job and Subjective wellbeing variables.	Propensity Score Matching using Nearest neighbour matching	The study does not find any effect of the programmes on the labour market outcomes. However, the survey was conducted a short period after the completion of the ALMPs, authors suggest that this might have affected the results. The positive Impact appears to be strong when judged by subjective well-being.
Mojsoska-Blazevski and Petreski, 2015	Macedonia	1)Self-employment programme, 2)Internship, 3)Training for known employer, 4)Training for deficient occupations, 5)Training for IT skills	Registered Unemployed	2012 Cross-sectional Survey data	Several outcome variables regarding employment and subjective wellbeing	Nearest Neighbour Matching with replacement and with caliper	Mixed results. Internship scheme and Training for known employer are more effective in increasing employment probability.
Caliendo et al, 2017	Germany	1)Short-term training, 2)Long-term training and 3)Wage subsidies	Registered unemployed	June 2007 – May 2008 Administrative and Survey data	The probability of being in employment and the level of earnings	Propensity Score Matching using Kernel matching and Inverse Probability Weighting	No effect of short-term and long-term training on employment probability and negative effects on earnings. Positive effects of wage subsidies on employment probability and earnings.
Popescu and Roman, 2018	Romania	1)Vocational training	Registered unemployed	2014 Survey data	The probability of being in employment	Propensity Score Matching and Inverse Probability Weighting	Positive but modest effect on employment probability

Štefánik et al., 2018	Slovakia	1)Training and 2)Internship schemes	Registered unemployed	January 2007 - April 2008 Administrative data	The probability of being in employment	Propensity Score Matching, Inverse Probability Weighting and Two-Stage Least Square Estimations Using An instrumental Variable	Strong positive effect in the long-term after completion of the active measures.
Potluka, 2017	Czech Republic	1)Public works in social enterprises	Unemployed	April 2010 - June 2014 Administrative data	The probability of being in employment	Propensity Score Matching	Positive effect increasing individuals' employment probability. Strong effect for women and beneficiaries older than 40 years.
Petreski, 2018	Macedonia, Serbia, Montenegro, Russia, Kyrgyzstan, Moldova and Armenia	1) Public employment support services	Young unemployed	2014 or 2015 Cross-sectional Survey data	Informal employment (measured by whether the individual had an employment contract) and wages	Two stage Heckman selection model	Public employment support services decrease probability of being employed in the informal sector. Insignificant results for wages equation.
Bratti et al., 2017	Latvia	1) Vocational training programme	Young unemployed	June 2013 - December 2015 Administrative data	The probability of being in employment	Propensity Score and Coarsened Exact Matching estimators.	Insignificant effect
Adamecz-Völgyi et al., 2018	Hungary	1)Supported employment programme	Disabled unemployed	January 2004 – December 2011 Administrative data	Probability of finding a job and not re-entering the unemployment registry	Propensity Score Matching Use time-window approach of matching the treated and controls	Positive significant effect on employment probability. Positive but smaller effect on not re-entering the unemployment registry.

The definition of the set of characteristics to be included in the propensity score estimation is a crucial part of the statistical analysis in Propensity Score Matching evaluations. The choice of variables to be included in the propensity score estimation varies across European countries and this is partly due to the limitations of available data. Variables that capture social demographic characteristics such as age, gender, educational attainments are commonly included in the propensity score estimation; rarely included are variables that capture living conditions and household situations. Due to fertility or other reasons, the effect of ALMPs may differ by gender and it is apparent that this covariate needs to be balanced for the two groups (Puhani, 1998; Bonjour et al., 2001). Rodriguez-Planas and Benus (2006) point out that the family composition and whether the person is the main breadwinner in the family is likely to impact upon the decision to participate and should be accounted for. Additionally, Caliendo et al. (2011) find evidence that characteristics such as being married and/or being a parent increases the probability of participation in active measures.

Covariates such as region and rural residence are usually included in the studies to capture regional heterogeneity in different geographic areas since it is considered that regions are an important determinant of participation in active programmes (Kluve et al.,2002; Dorsett, 2006; Rodriguez-Planas and Benus, 2006; Bonin and Rinne, 2014; Mojsoska-Blazevski and Petreski, 2015; Bratti et al., 2017). Regional variables capture the unobservable local aspects that are correlated with programme implementation, with local policies, local infrastructure and labour mobility which are relevant for participation decision and participants' future labour market experience. In order to capture the economic variation, more specifically, some studies include regional unemployment rates (Bonjour et al., 2001; Dorsett, 2006; Schmidl, 2014) and also regional GDP growth during the year of participation (Schmidl, 2014). Schmidl (2014), in addition, captures the seasonal labour market conditions by matching individuals by the calendar month of the entry into unemployment.

The empirical studies usually rely on meaningful approximations to account for unobserved characteristics (Kluve et al., 2002; Dorsett, 2006; Schmidl, 2014; Caliendo et al., 2017; Adamecz-Völgyi et al., 2018). The pre-treatment labour market histories and earnings have been found to be good variables to approximate labour market attachment and aspirations that may affect the programme participation (Bryson et al., 2002; Lechner et al., 2013; Bratti et al., 2017). The timing of entry into the programmes may vary for participants with different characteristics. As an important determinant of the decision to participate in active programmes, Caliendo et al. (2011) include the unemployment duration before participation over a period of 12 months for youths in Germany. However, due to the low number of monthly treatment entries, the study divided this duration into three strata (1 to 3 months of unemployment duration; 4 to 6 months and 6 to 12 months of unemployment duration) and only individuals with similar unemployment duration intervals were compared. Kluve at al. (2002) when using Exact Covariate Matching for Poland apply the time-window approach which matches the treated and control individuals based on their exact pre-treatment labour market state (being unemployed, employed or inactivity state) up to 12 months before participation and in addition to other covariates the study matches pairs of treated and untreated based on identical pre-treatment histories. Adamecz-Völgyi et al. (2018) in their study for Hungary also use the time-window approach to match the treated and controls attempting to capture the similar labour market conditions for the two groups. In a recent study for Germany, Caliendo et al. (2017) as well as using labour market histories they also control for other, usually, unobserved individual characteristics such as personality traits, attitudes, expectations, social networks and intergenerational information. However, their findings suggest that if comprehensive control variables, such as those usually used in modern ALMP evaluations, including labour market histories are accounted for in the treatment specification, then the addition of other usually unobserved variables add little explanatory power.

On the other hand, the empirical review of Heckman et al. (1999) suggests that when matching with pre-treatment earnings at different times result in biased estimates since the matching is created with serial correlated pre-treatment outcomes. In addition, Heckman et al., (1999) argue that when these variables are eliminated from the estimation, the estimates from non-experimental studies are consistent with those from experimental studies. Heckman and Smith (1999) argue that labour force dynamics, i.e. being unemployed or out of the labour force, rather than earnings determine the participation decision, and thus should be accounted for in the propensity score estimation.

There are a few studies that capture the impact of the quality of employment services in the effectiveness of active programmes (Dorsett, 2006; Schmidl, 2014). Schmidl (2014) account for the number of placement offers by the case workers and the last contact with the employment services which may be of particular importance to measure the labour market performance of youths. The findings of the study suggest that young unemployed with the lowest and the highest number of offers are less likely to participate in active programmes compared to those with average employment offers (Scmidl, 2014). Dorsett (2006) argues that the regional dummies included in the estimation would account for the job centre the participant attends, hence effectively controlling for the level/quality of services provided to the participants.

Main Findings by Programme

- ***Training***

Training usually accounts for the largest share of expenditure on active programmes in European countries. Accordingly, as Table 4.1 shows, more than half of these studies investigate the effectiveness of training as an active measure. Earlier studies usually did not differentiate between the types of training programmes implemented (general training[33] e.g. training to improve literacy skills and firm-specific training) and as such were unable to capture the relative effects of a specific training scheme (e.g. Puhani, 1998; Kluve et al., 2002; Leetmaa and Vork, 2003; Rodriguez-Planas and Benus, 2006). Hence, one may argue that the results of those studies do not provide any clear message to policy-makers as to which training scheme is more effective in reducing unemployment.

More recent studies conducted in European countries have differentiated between the types of training (e.g. Lechner, 2001; Schmidl, 2014; Mojsoska-Blazevski and Petreski, 2015). Schmidl (2014) investigated the effectiveness of short-term training (from two to eight weeks duration), long-term training (up to one year), participatory

[33] Lowenstein and Spletzer (1999) distinguish between general and specific training: ''...*general training is defined as a human capital investment that raises a worker's productivity at other employers to the same extent as at the employer that provides the training. Similarly, completely specific training is defined as a human capital investment that increases productivity only at the employer that provides the training.*''(Lowenstein and Spletzer, 1999, p.711)

training (a practical training within a company that tends to help participants to find and successfully participate in regular vocational training or unsubsidised education) and other active programmes for Germany using an IZA Evaluation Dataset. This administrative dataset (composed of more than twelve thousand observations for young ALMP participants only) provides detailed daily information on spells in employment and social security contribution, unemployment, labour market history, socio-demographic characteristics and participation in ALMPs. This amount of data allowed the author to estimate monthly treatment effects as the difference between the treated and control outcome; for most measures the outcome variable was the probability of becoming employed with the exception of participatory training for which the outcome was the probability to participate in a vocational training or unsubsidised education. The results from the study suggest that the participatory training does not improve the post-training level of completed education and training. The evidence suggests that training increases the probability of becoming employed by 10 percentage points. The study also finds evidence of lock-in effects of long-term programmes (participants reduce their effort to search for regular jobs during the period of participation) of up to 20 percentage points. The findings suggest that training programmes help to overcome the barriers which youths face in entering the labour market. A similar study for Switzerland using a very informative dataset from the local labour offices analysed the impact of basic short-term training and long-term training (Lechner, 2001). The study employed a matching method using multinomial choice model to obtain the propensity scores and found no clear evidence that the initial training (job counselling and courses in the local language) and further vocational training (a combination of trainings including information technology courses with longer duration than basic training) affected the probability of participants entering employment after completion.

The majority of the evaluations of training programmes in transition economies tend to find a positive effect in the short-term (6 to 12 months) as compared to the long-term effect (more than a year). The evidence from Poland suggests that individuals participating in training programmes have much higher prospects of getting employed than they would have in the absence of such measures. Puhani (2002) analysed the impact of different active programmes (training and employment subsidies) on employment using a Propensity Score Matching and Duration Model employing data from Polish Labour Force Survey (LFS) collected during 1992 to 1996. Training at the time the data was collected took place within companies and also at centres run by the employment offices. The training targeted a very wide range of the unemployed, from white collar to blue collar unemployed and the training lasted from 3 to 6 months. One important feature of all the active measures in Poland at that time was the link of participation in these programmes with the entitlement to unemployment benefits. Participating in one of the programmes made the participant eligible for another 12 months of benefit entitlement. The data allowed controlling for socio-demographic characteristics, education level, labour market history, occupation and industry of employment and place of residence. The results from the matching estimator suggest a positive effect on getting re-employed for participants in training for both genders although this effect is larger for men (20 percentage points for men compared to 10 percentage points for women). This finding is also supported by the duration model which suggests significant positive effects of training for both men and women – participation in training reduced unemployment duration by five months for men while two months for women. In addition, the results from the duration model suggest that training in comparison to private subsidies and public works was more effective.

Kluve et al. (2008) applied Exact Covariate Matching on the same Polish LFS dataset as Puhani (2002). To capture the treatment assignment, the study divided individuals' labour market history in quarters and matched individuals who were unemployed during at least one quarter over the sampling period. This approach tends to capture more effectively the changes in institutional set-up and economic conditions which are common in transition countries. The labour market history was also observed after the treatment; this information was condensed to summarize the post-treatment labour market outcome of each individual by the individuals' average employment rate over the three quarters after the treatment. Kluve et al. (2008) estimated the effects of treatment using two samples: the first one without accounting for the individuals' labour market history while the second taking that into account. The results suggest different effects from the two samples. According to the findings from the first sample, there is no significant effect of training while the results from the second one found that participants have higher post-treatment employment rates, by 14 percentage points on average, compared to those who did not participate. Moreover, this finding suggests that had the study not accounted for the individuals' labour market history, the true effect of the programmes would have not been accurately estimated. According to Kluve et al. (2008), training seems to be more effective than other programmes and also the trained participants in general seem to be equipped with better observable and unobservable characteristics enabling them to have better employment prospects.

An evaluation for Albania also suggests positive effect of on-the-job trainings (ILO, 2014). The study evaluates the impact of three different active programmes: on-the-job training, job-seekers in difficulty and an internship programme. It uses a cross-sectional data from the registered job-seekers who had participated between 2008 and 2013 or had been selected to participate in the future. The dataset provides a limited number of variables on personal characteristics, but no information on household or community characteristics except for the region variable dummies. The evaluation based on Propensity Score Matching uses age, gender, educational level, unemployment duration and regional controls to estimate the propensity scores. According to the results, participating in on-the job-training increases the probability of becoming employed by 55% after one year compared to non-participants. This estimated large effect however, should be interpreted with caution as the control group used for analysis was very small. Out of 730 individuals from the treated group 608 were out of common support (section 4.3.2 discusses the assumption of common support in more detail); only 50 individuals comprised the control group.

In contrast, the study evaluating the effect of training in Serbia by Bonin and Rinne (2014) does not find any effect of vocational training on participants' prospects of finding a job. Active measures evaluated in this study comprised of vocational training and also temporary jobs in the construction sector targeted at the long-term and disadvantaged unemployed. Participation in vocational training lasted for three months and was full-time. The study used a matching estimator based only on age, educational level and place of residence. The active programmes started in January 2004 while the data was collected through a survey in November 2005. However, the survey did not trace the individuals' employment histories which seem to be an important factor in assessing the effectiveness of ALMPs. The authors also suggest that one reason for the insignificant results may be that the survey was conducted only a short period after the completion of the vocational training thus the full effect was not captured.

Positive effects of general training and literacy skills on earnings and re-employment probabilities were found for Romania by Rodriguez-Planas and Benus (2006). Rodriguez-Planas and Benus used a very rich dataset from Romanian employment offices for registered unemployment during the period 1999 to 2002 followed by a survey of the participants and non-participants. Propensity Score Matching was used to create matching based on a wide range of covariates including socio-demographic characteristics, pre-treatment employment history, regional dummies and variables that capture local labour market conditions to measure the different employment opportunities in specific regions. The study also includes participants' earnings during the two years period prior to the survey as a proxy for productivity. Training targeted the disadvantaged unemployed and comprised vocational training, general education and literacy skills. Those who participated in active measures in Romania were entitled to one or two months of benefits after they have completed the programme. The findings from the study suggest that the effect on earnings is particularly large; training increases earnings of participants by 58% compared to non-participants. The study also found that training is more effective for young participants than for older ones. Furthermore, the evidence suggests that training has shortened considerably the duration of receiving unemployment benefits and made it almost non-existent among the training participants.

A more recent study, Mojsoska-Blazevski and Petreski (2015) employ a nearest neighbour propensity score matching using a cross-section dataset which allows assessing the impact of different training programmes designed and implemented specifically in the FYR Macedonia. These measures include training for known employer, training for deficient occupations and training for IT skills. The findings of this study suggest mixed effects. The most effective of the training programmes is the training for known employer which is found to improve the long-term employment, reduce the chances of non-employment at any time after the training and increases beneficiaries' wage. The least effective seems to be the training for IT skills which only improves the subjective well-being of the beneficiaries. According to the authors, this result might be due to a targeting issue where in training for IT skills there is a high share of long-term unemployed while for other active measure the participants seems to have had a much shorter spells of unemployment of less than 1 month.

Other studies using Propensity Score Matching to evaluate the effectiveness of training measures are Štefánik et al. (2018) for Slovakia, Popescu and Roman (2018) for Romania and Bratti et al. (2017) for Latvia. The first study also employs Inverse Probability Weighting and Two-Stage Least Square Estimations using an instrumental variable. Štefánik et al. (2018) find evidence to suggest that the vocational training programme increases participants' employment probability moderately in the medium-term of up to 36 months. After 3 years, the employment probability starts to grow to its maximum in the 54th month after the end of participation where the difference between treated and control is about 4 percentage points. Popescu and Roman (2018) also find a significant positive effect of vocational training programme on employment probability of 14 percentage points higher than that of a similar control individual. The findings from this study suggest that the effect is larger amongst younger beneficiaries than those older than 25, for women compared to men and for those who have lower education levels. These findings are in line with the expectations that the active measure might be more effective for the disadvantaged given that these individuals benefit more from the skill enhancement. Bratti et al. (2017) found a positive but insignificant effect of the vocational training programme for youths in increasing beneficiaries' employment probability. Bratti et al. suggest several possible explanations for this result. The data used for this study is from a period where there was an increase in the employment rate of youths in Latvia hence both treated and control might have found jobs independently from the vocational training. Additionally, in order to increase the effectiveness of this measure, the authors suggest that vocational training should be combined with a job-creation scheme such as tax rebates for employers hiring unemployed individuals.

Van Ours (2001) carried out a multivariate duration model using rich administrative data from registered unemployed from 1993 to 1998 in the Slovak Republic to analyse the effectiveness of training, public and private employment subsidies. The targets of this training were the disabled unemployed, older people, long-term unemployed, young workers and school leavers. The study accounted for pre and post-treatment durations of unemployment, personal characteristics, regional differences and a variable indicating whether the individual has participated in any of the programmes to estimate the transition rate to employment (the speed with which participants find a regular job) and the job separation rate (the speed with which they terminate a regular job). The analysis concluded that participating in training gives participants an advantage in getting a regular job. According to the findings, training participants have a 6 times higher job finding rate than non-participants. This high observed impact may have been a result of unemployed entering in training programmes only after they have been promised a job. Participation in training did not have any impact on the job-separation rate, suggesting that the trained workers were not more valuable to retain in the company than those employees who had not participated in any training scheme.

- ***Job Search Assistance/Employment Services***

There are very few studies evaluating the effectiveness of employment services in European transition economies. Job search assistance is typically the least costly active measure and most evidence from transition economies also suggests that this measure has a positive impact on labour market outcomes. Through raising motivation and through monitoring their job-search behaviour these programmes generally have a positive effect on the probability of an unemployed individual getting back to work.

The evidence for the Czech Republic suggests that the receipt of employment services reduces unemployment duration. Terrell and Storm (1999) utilised a duration model to assess both active and passive labour market programmes during 1992 to 1994 which was in general a period of developing labour market institutions. The analysis is focused particularly on one active programme called job brokering where the case worker assists the unemployed to set up interviews with potential employers. The methodology assesses the probability that someone finds a job with the assistance of the case worker comparing to the probability of someone finding a job without assistance. The evidence suggest that the unemployment duration is shortened only for unemployed groups with longer duration spells, especially women, minorities and the less educated.

Rodriguez-Planas and Benus (2006) found evidence of positive effects of employment services on employment outcome. This study evaluated the effectiveness of small business assistance and employment relocation services (consisting of job and social counselling, job search assistance, job placement services, and relocation assistance). The first one assisted displaced unemployed entrepreneurs to facilitate start-ups while the second helped recently unemployed to find employment. Their study suggests that participants in the employment relocation services in Romania had an 8.45 percentage points higher probability of being employed compared to non-participants. However, the positive impact of receiving employment relocation services was found for men but not for women. The findings for the small-business assistance also suggest positive effects; receiving this assistance increases the probability to become self-employed by 8.38 percentage points compared to those who did not receive it. This measure also reduced the period of receiving unemployment benefits by almost one month.

Micklewright and Nagy (2008) assess the effectiveness of an increase in the monitoring of job search for benefit claimers in Hungary during 2003. The experiment uses data from LFS and employment registers to randomly select individuals into treatment and control groups. The study includes actions from case workers to increase the intensity of job search activity of benefit claimants. The treatment group was asked to increase the number of visits to every three weeks; during these visits they were asked about the job search activity and reasons for those who admitted little or no search activity. There were no actual sanctions of no job search activity but the treated were uncertain of the implication of failure. Control individuals were not asked to change their intensity in job search activity and were required to have a visit in the employment offices only once every three months. Multivariate duration models were used to assess the exit rates to employment while accounting for personal observed characteristics, a vector of employment office dummies, dummy variables with different duration time intervals and dummy for membership of the treatment. According to the findings, the treated did not, in general, find a job more quickly than the control individuals. However, there were positive effects found for married women over 30.

A more recent study evaluated the effectiveness of employment services on the probability of being employed in the informal sector and the level of wages for seven transition economies (Macedonia, Serbia, Montenegro, Russia, Kyrgyzstan, Moldova and Armenia) (Petreski, 2018). This study uses a Heckman two stage selection model where the variable of interest is measured as a dummy variable taking value of 1 if the person received a public employment-support service in any of the following forms: advice on how to search for a job; information on vacancies; guidance on education and training opportunities; placement in education or training programs; and 0 otherwise. The study attempts to address the econometric challenges such as the selection into informal job and employment and the endogeneity of the variable measuring the public employment-support service. Petreski argues that the selection arises because persons who are informally employed may be systematically different from those who are unemployed and hence whose (in)formal-employment status is unobserved. In the first stage, the probability of having used at least one public employment service is regressed on a set of independent variables such as: marital status, the number of children living in the household, education of parents and the household's financial situation. The second stage uses the probability of being in informal work as the dependent variable. The study also attempts to address the selection issue where the second stage employs an instrumental variable that correlates with the endogenous regressor, but is not directly correlated with the outcome variable, informal employment. The study uses two instrumental variables: the country employment rate at the time the person finished schooling and the number of years since the person finished school. The findings suggest that public employment support services reduce the probability of being employed in the informal sector by 64% compared to a person that did not use this service. In addition, in order to assess the effectiveness of different ALMPs, the study separated the sample for each active measure using the same methodology. Education and training programmes are the most effectives in reducing the probability of being employed in the informal sector by more than 21% while advice and guidance reduce it by 15%. Providing information on the available job vacancies seems to have no effect on the probability of being employed in the informal sector.

- ***Public and Private Sector Employment Subsidies***

Evidence from the evaluations in transition economies suggests mixed results for private and public sector employment subsidies. Van Ours (2001) came to conclusion that the unemployed that had participated in public employment subsidies had significantly higher transition rates to a regular job and very low job separation rates compared to those that did not participate. Public employment schemes in the Slovak Republic mainly targeted the less qualified unemployed and lasted for 6 months at the beginning of observed period which was later extended to 9 months and after that to 12 months. The author argues that this effect may come as a result of signalling; participating in a public subsidy signals a positive attitude towards work to potential employers. In contrast, those who participated in the private employment subsidies had a lower transition rate to a regular job compared to nonparticipants. The private employment subsidies targeted the more qualified unemployed and was set for a duration of minimum two years period. Since the duration of this programme is quite long, the lock-in effect may be the explanation for its' negative effect. The findings of Van Ours (2001) suggest that females, the less educated and older participants had lower transition rates to employment i.e. lower speed with which they find regular jobs compared to similar non-participants.

Puhani (2002) suggests that participants of public and private employment subsidies are less likely to become employed than non-participants. In this study for Poland, the results from the duration model suggest that participation in these programmes decrease the transition rate into employment for both men and women but will also decrease the rate into inactivity for men. This latter finding may be a positive indication that at least these programmes increase labour market attachment. Rodriguez-Planas and Benus (2002, 2006) also investigate the effectiveness of public employment subsidies along with training, employment services and small business assistance using a propensity score matching estimator for Romania. In this evaluation, the public employment subsidies are the only active measure that did not have positive effect on increasing the employment probabilities or earnings. These public employment subsidies were offered in regions with very low employment prospects which is argued to be the main reason for their negative effect.

A more recent study by Adamecz-Völgyi et al. (2018) uses Propensity Score Matching to evaluate the effectiveness of wage subsidies designed to assist the disabled unemployed to enter and remain in the labour market through employment in public institutions in Hungary. The findings suggest that these policies are effective in increasing beneficiaries' employment probability by up to 25 percentage points compared to that of the control group. The effect is found to be larger for women compared to men. A similar study by Potluka (2017), which uses the same methodology for a dataset for Czech Republic, also finds positive effects of public works in social enterprises on increasing beneficiaries' employment probability of about 17 percentage points.

The evidence from a study in Slovenia conducted by Vodopivec (1999) suggests that there is an immediate positive effect of public works on employment. Vodopivec (1999) utilised a Heckman two stage selection model with a dataset from three different sources: the dataset from registered unemployed, the dataset on the receipt of benefits and the dataset of the participants of employment subsidies. The study controlled for personal characteristics, human capital characteristics and variable indicating participation to analyse their effects on the probability of leaving unemployment (taking three different states: 0 if unemployed, 1, if employed and 2 if out of the labour market). These policies gave priority to the long-term unemployed, low skilled, disabled unemployed and those living in material hardship. The findings suggest an immediate positive effect of public works on employment. However, this effect becomes insignificant after 3 months which may be due to stigmatisation of the participants. An important finding of the study is that it reduces the probability of becoming inactive, thus increasing labour market attachment.

- ***ALMPs for Youths***

As there is no evidence on specific youth programmes in transition countries, this section will review the evidence found for other European countries. Training programmes for youths have mixed effects, however mostly positive, results. The evidence from the meta-analysis conducted by Kluve (2010) suggests that active programmes that target youths in European countries are less likely to be effective than non-targeted programmes. Larson (2009) also found evidence that training programmes for youths in Sweden have short-term negative effects on the labour market while zero effects in the long-term. According to some studies, the most successful active programme for youths was the New Deal implemented in the UK (Blundell et al.; 2004, Dorsett, 2006). The New Deal for Youth Programme combined a job-search assistance programme with one of other four programmes: subsidised employment, full-time education and training, environmental task force or voluntary sector. Dorsett (2006) provides strong evidence, when analysing the New Deal for Youth Programme, that the combination of the two programmes job-search assistance and subsidised employment for young unemployed were more effective than training programmes and job creation schemes. Ehlert et al. (2012) also provides evidence that combination of different programmes had positive impact in the labour market. According to the authors, the combination of coaching, training and temporary work had positive impact, increasing the probability of finding employment. Van den Berg et al. (2012) also found evidence that meeting and consulting with case workers had a positive impact on job finding rates for young unemployed in Denmark. In addition, Schmidl (2014) suggests that a wage subsidy is the most effective programme in the long-term for young German unemployed while public sector job creation is found to be harmful for the participants.

- ***Explaining the divergence in the findings of evaluations***

From the discussion above one can observe significant differences in the results of the studies conducted in transition economies. The overall evidence suggests that training, as an active measure, has a positive short-term effect (6 to 12 months). One explanation for this finding is that since there is lack of necessary skills and qualifications of the unemployed in transition economies and particularly, since the long-term unemployed have experienced human capital depreciation, training helps directly to rebuild their human capital and increase their productivity. Training may work better than other active programmes since its primary aim is to reduce the skill mismatch and increase knowledge needed to get back to work.

The findings reveal that the impact of active measures varies widely between different subgroups in the population, emphasising the importance of targeting to maximise the effect of the measures. Taking into consideration the level of unemployment and extent of long-term unemployment in transition economies, most of active measures in these countries target the long-term unemployed and in general the more disadvantaged unemployed which is the case for Slovenia, Romania and Serbia (Vodopivec, 1999; Van Ours, 2001; Rodriguez-Planas and Benus, 2006; Bonin and Rinne, 2014; Mojsoska-Blazevski and Petreski, 2015, Bratti et al., 2017; Adamecz-Völgyi et al., 2018). In addition, the ALMPs in the Slovak Republic used different targeting for the active measures; public employment subsidies and trainings mostly target long-term disadvantaged unemployed, whereas private subsidies target more qualified participants. The findings from the studies in transition economies suggest that when targeting long-term and disadvantaged unemployed the impact on employment is positive while when targeting the more qualified the effect is either negative or there is no effect. The effects also seem to differ when comparing different age groups and gender; training and internship measures seems to be more effective for the younger unemployed than for older ones, while job-search assistance and vocational training seem to be more important for women than for men (Terrel and Storm, 1999; Micklewright and Nagy, 2008; Mojsoska-Blazevski and Petreski, 2015; Popescu and Roman, 2018). However, there seems to be no clear explanation why these active measures are effective for certain groups of unemployed and not for others.

Theoretically, the duration of the active policies is hypothesised to be an important determinant of their effectiveness due to lock-in effects: the participant reduces job-search effort for a regular job during the period of participation in employment subsidies, i.e. the longer the duration of the subsidy the lower probability of getting a regular job. Van Ours (2002) and Caliendo et al. (2017) compare different durations for subsidised employment for transition economies. The findings seem to be in line with the theory; short-term public employment subsidies (6 to 9 months and 9 to 12 months) seem to have a positive effect on getting employed and while the duration of the subsidy increases the effect becomes smaller. The study also suggests that private employment subsidies which last for a minimum of 2 years have negative effect on getting employed.

One particular feature of the effectiveness of the active measures is its relation to unemployment benefit entitlement. In Poland, participation in one of the active measures made the participant eligible for 12 months of benefits after the participation (Puhani, 2002; Kluve et al., 2008). This created a cycle of some unemployed workers participating in the active programmes in order to claim unemployment benefits afterwards. In both studies for Poland the results suggested negative effects of the public and private employment subsidies on employment probabilities. In the case of the Slovak Republic, the public employment subsidy also made the participants eligible for another round of benefits after completing the programme. This made participants shift between unemployment and subsidised employment making this subsidy ineffective. In contrast, the study for Romania, suggests in general positive effects when the participant receives unemployment benefits for only one or two months at most after completion of the active measure (Rodriguez-Planas and Benus, 2006). When there is no enforced link between passive and active policies no clear pattern of the effect of active measure can be observed.

Since regions vary in economic strength and as such vary in employment opportunities, it is very important for the studies to account for these differences. In labour markets where the employment prospects are low the expectation is that the active measure will not be very effective. Most of the studies include regional dummies to account for this variation. Some ALMPs are designed for specific regions with low economic conditions aiming to increase employment such as the case of public employment subsidies in Romania. As explained above, these employment subsidies had a negative effect on employment which is in line with the expectations; when the labour market performance is weak active measures would not help in reducing unemployment. A similar finding could be observed in the study for the Slovak Republic when evaluating the private employment subsidies.

It is crucial to note the potential importance of the labour market history of participants, because it is likely to capture unobserved characteristics such as motivation. Hence, when studies do not account for this variable the results might be biased. Studies that have used the same methodology to estimate the employment probabilities with and without labour history found quite different results (Kluve et al., 2008). Hence, the results of the studies that do not account for this characteristic should be interpreted with caution, such as studies for Estonia and Serbia (e.g. Leetmaa and Vork, 2003; Bonin and Rinne, 2014).

Puhani (2002) suggest that stigmatisation may have caused the negative results of public and private employment subsidies. When the programme stipend is paid to the employer and not to the unemployed, the employer may perceive participation in such programmes as a negative signal of an individual participants' productivity. The study for Slovenia also suggests that the negative result on employment may be due to the stigmatisation of participation in public works. This effect is argued since it is known to employers that participants in these programmes are the most disadvantaged unemployed and employers perceive them to have low productivity (Vodopivec, 1999).

The studies reviewed above, however, do not evaluate whether active measures have any impact at the aggregate level i.e. whether they reduce the overall unemployment rate. A positive effect on the individual level does not guarantee a positive effect at the aggregate level. It is important to account for displacement and substitution effects when assessing the effectiveness of active measures and it cannot be assessed through microeconomic evaluation. One method to assess these effects is through simulation of active measures in a model of a general equilibrium economy (Jongen et al., 2000; De Koning, 2007). However, assessing the impact of the active measures at the aggregate level is not easy to conduct as this methodology is more sensitive to flawed data and to the model specification than microeconomic analysis.

4.5 Conclusions

This chapter has provided a critical review of the evaluation methodologies used to assess the effectiveness of the ALMPs. After analysing the evaluation problem and the creation of counterfactuals the review has identified several approaches to address the issue of selection bias when analysing the effectiveness of ALMPs. The Propensity Score Matching approach is analysed in more details and arguments are provided as to how this approach tends to replicate the setting of an experiment which is highly desirable in these analyses. Further, different matching estimators are analysed and comparisons are offered as to which of the estimators is more appropriate to create quality matching pairs. Inverse Probability Weighing Regression Adjustment is argued to be the most appropriate choice of estimator in the context of this thesis. This method provides unbiased estimates if only one of the models, the treatment or the outcome model, is specified correctly and it also allows multiple treatment modelling in the same framework.

In addition, this chapter provides a critical review of studies which evaluate the effectiveness of ALMPs. The quality of data available remains one of the issues in evaluations in transition economies. The methodologies used for estimation are also diverse, however they have mostly focused on matching techniques and duration models. The review finds a wide range of results reported in studies conducted for different countries and did not provide a clear overview as to which programme is more effective and for which target group. Most of the studies from transition economies report that training as an active measure improves the employment prospects of the unemployed in the short term, however there is no solid evidence provided for the long term. At the same time, there is inconclusive evidence on the effectiveness of employment subsidies. Chapter 5 will examine the effectiveness of the three different active measures: (i) on-the-job training; (ii) internship scheme; and (iii) institution and enterprise training, targeted at the young unemployed in Kosovo. This evaluation provides additional evidence and contributes to the on-going debate on the effectiveness of a specific active measure targeted at particular unemployed groups.

Chapter 5

The Relative Effectiveness of ALMPs Aimed at Reducing Unemployment in Kosovo

5.1 Introduction

The empirical evidence presented in Chapter 4 provided a cross-country analysis of the effectiveness of different active labour market programmes with a special focus on transition countries. The review of empirical studies suggests that training programmes in general are the most effective in improving an individual's employment prospects; however, it is unclear which type of training is more effective. Together with internship measures, trainings seem to be relatively more effective when targeted at the young unemployed, while job-search assistance and vocational training seem to be more effective when targeted at women. Some studies also found that counselling and guidance on small business start-ups increases an individual's probability of being employed. The evidence from the review of general public works subsidies in the private sector is inconclusive. However, none of the studies have evaluated the relative effectiveness of different active programmes in transition economies, while there are very few relative effectiveness evaluations for European countries in general. Therefore, the aim of this chapter is to fill this gap in the empirical literature by providing an assessment of the relative effectiveness of the three different active measures in Kosovo. Since there is a range of active programmes in which an individual can participate, the choice of participation should be extended from 'participation vs. non-participation' into a multiple choice model (Lechner, 2001). As Chapter 2 elaborated, this approach provides information on whether participants of one programme would have performed better if they had participated in another programme. Therefore the main aim of this chapter is to evaluate the relative effectiveness of three active measures: On the Job Training (OJT), Internship Scheme (IS) and Institution and Enterprise Training (IET).

This chapter is organised as follows. Section 5.2 provides a description of the three active programmes delivered in Kosovo, the groups targeted by these programmes and their specific aims while section 5.2.1 provides a critical review of two previous evaluations of these programmes. Section 5.3 offers an overview of the available data and provides detailed descriptive statistics. Section 5.4 analyses the specification of three models of the main determinants of: the probability of being in employment at the time of the survey, the probability of actively searching for a job for those unemployed at the time of the survey and the probability of having a contract for those employed. The models specified in this section will be used for estimating the results of the multinomial choice analysis and for the main analysis of this chapter, the Inverse Probability Weighting – Regression Adjustment (IPWRA). Section 5.5 presents the findings from both estimation approaches. Section 5.6 offers the conclusion on the relative effectiveness of the active measures for Kosovo.

5.2 Programmes under consideration

As Chapter 1 elaborated in more detail, the implementation of active measures in Kosovo started in 2005 and continues to date. Up to 2013, 11,154 individuals benefited from active measures such as: public works, wage subsidies, pre-employment training, on the job training, internship scheme and institution and enterprise training. This chapter will analyse the relative effectiveness of the three most prevalent active measures. This section provides an overview of these three active programmes under consideration of the analysis which were implemented during the period of 2008 to 2010: *Institution and Enterprise Training (IET), Internship Scheme (IS) and On the Job Training (OJT*). While Chapter 1 provides more detailed information on the scale of the active measures for Kosovo, table 5.1 presents the population of the beneficiaries of the three programmes of interest during this period.

Table 5.1 Beneficiary population over the period 2008 to 2010 in Kosovo

	2008	**2009**	**2010**	**Total**	**%**
On the Job Training (OJT)	266	86	632	984	52
Internship Scheme (IS)	148	211	274	633	33
Institution and Enterprise Training (IET)	54	79	153	286	15
Total	468	376	1059	1903	100

Source: Kavanagh (2012)

Two of these programmes aimed to give priority to young job-seekers without skills, without previous work experience and with low levels of completed education, whilst the IS targeted university graduates. At the same time these active programmes aimed to balance the gender mix of participants and include ethnic minorities and individuals with disabilities. The aim of the programmes was to achieve 15% of minority participants. With regard to age, the programme’s strategic aim was to primarily target the age group of 15-29; however the age requirement was often modified to achieve a more equitable representation either of women or minorities. These programmes targeted young job-seekers who had been unemployed for at least 6 months; this requirement was frequently not applied to minorities and women. Employers were required to make efforts to retain the interns after the completion of their programmes; not to displace current employees in order to employ the participants of the active programmes; and to provide training participants access to an experienced supervisor from the company during their placement.

Institution and Enterprise Training (IET) was aimed at supporting job-seekers by enhancing their skills and abilities through classroom training in the vocational training centres (VTC) and also acquiring job-specific skills and the essential knowledge in enterprises, providing the possibility of becoming a permanent employee in that enterprise. The target group for this scheme were young, low-skilled job-seekers who were registered unemployed for at least 6 months, had no previous work experience and had not had the benefit of attending and completing vocational training. The last criterion was changed subsequently to accept also those who had graduated from vocational training. Participants in this active measure firstly had to attend pre-employment training of one to three weeks at a VTC to enhance their employability skills, team-work skills, work readiness skills, information and communication technology and other non-vocational skills. During this period the trainer in association with the prospective company specified a list of skills that the trainee needed to acquire during the period at the company. Training at the company was designed to last 3 months and provide participants with specific vocational skills to enable them to remain employed at that company.

On the Job Training (OJT) mainly targeted vocational education students and provided career, occupational health and safety guidance by Public Employment Services, and practical learning and training in partner enterprises. OJT offered counselling and job-search assistance to potential participants for a four week period prior to participation in the training in order to assess the job-seekers' suitability for alternative employment opportunities. The employment adviser and the job-seeker then agreed on an employment plan specifying a suitable occupational profile for job-search. If the job-search was unsuccessful, participants were identified by the employment adviser as requiring further support. In agreement with the VTC and potential employers, the employment adviser prepared a training plan which outlined the competencies to be developed during the training period. OJT provided a 3 months period of training at companies. In both the OJT and IET programmes the employer was paid 50 euros per month for each participant, while the participant was paid 100 euro per month. This provided an incentive for the employer to train the participant as this amount was expected to cover the net cost of training job-seekers. In cases when at the completion of the training the participant was not accepted as a regular employee in the company, the employment services supported the job-seeker further through advising on other potential employment opportunities.

The target group of the *Internship Scheme (IS)* was young university graduates without work experience, registered as unemployed for at least 6 months and who lived in poor family conditions or received social assistance benefits. This programme aimed to help the participants to acquire necessary job experience, gain skills and knowledge to perform in the workplace and become unsubsidised employees. The interns worked for 6 months in a public institution or private enterprise, mainly in human resources, accounting and administration departments. Initially, employment service advisers screened and referred job-seekers to employers. After the completion of the internship the employer was expected to hire the intern; if the intern was not employed then their adviser supported the job-seekers in finding another job.

With regard to the design of the active measures, IET programme was designed to partially take place in VTC-s as classroom training (up to three weeks) where the participant was expected to enhance employability skills, team-work skills, work readiness skills, information and communication technology and other non-vocational skills. The rest of the IET programme would take place in the enterprise. The design of the OJT programme, on the other hand, required the training to be fully completed within the company. Private employers seem to prefer programmes where the candidates were required to complete the full training within the companies (Kavanagh, 2012). Having the candidate in the company during the whole training period was viewed to be more beneficial to the employer since it equips the participants with the specific skills required for that job.

5.2.1 Studies assessing the effects of ALMPs in Kosovo

There are two studies assessing the effectiveness of ALMPs in Kosovo. The first one is by Mukavilli (2008) which covers several ALMPs implemented during 2007 and the second study by Kavanagh (2012) which covers the ALMPs analysed in this empirical chapter.

Mukavilli analyses the effect of On the Job Training, Pre-Employment Training, Internship Scheme and Employment Subsidies by comparing the percentages of beneficiaries and control groups in employment and earnings. This study used a small sample of 299 out of 1426 beneficiaries and 100 control individuals. The report does not provide any information with regard to how the control individuals were selected for the study and whether they are suitable for comparison with the beneficiaries. Another limitation of this control group is that the some non-beneficiaries have claimed to have also participated in some training during this period which might have been organised by Non-Governmental Organisations (NGOs) or Donor organisations. The findings from the study suggest that the 46% of beneficiaries were employed at the time of the survey compared to 20% of the control group. More than 38% of OJT beneficiaries have remained employed in the same company where they completed their training. With regard to the earnings, non-beneficiaries seem to have earned more at the time surveyed of about 193 Eur per month compared 175 Eur per month for beneficiaries. The study also found that the targeting of beneficiaries was not strictly based on the pre-defined criteria. Except for the Internship Scheme which was targeted at young university graduates, other active measures targeted mainly young unemployed with less than secondary education. However, the beneficiaries seem to have completed higher levels of education compared to those in the control group. Mukavilli argues that there are several possible reasons for the issue with targeting: the lack of active measures for more educated unemployed, possible understating of the educational qualifications by applicants in order to become beneficiary, or issues with screening the applicants.

The second study assessing the effect of ALMPs in Kosovo is the study by Kavanagh (2012) which analyses three active measures: On the Job Training, Internship Scheme and Institution and Enterprise Training implemented during 2008 to 2010. This study used the same dataset which is being used for this empirical chapter. The methodology used in this study is also descriptive in nature where the effect is assessed based on simple comparison of descriptive means between beneficiary and control groups.[34] The findings from this study suggest that all three programmes are very well designed and improve the labour market prospects of the participants. With regard to relative effect of the active measures, participants of OJT will be more likely to get employed and remain employed in the same company compared to other two programmes. Similar to the first study, Kavanagh also suggest that there might be an issue of targeting and selecting the beneficiaries. According to Kavanagh (2012), IET programme seemed to have had issues with recruitment as most of the applicants did not meet this eligibility criterion (not having vocational education) and consequently most of the applicants were placed in OJT or IS. Afterward, this criterion was adapted to reflect candidates' level of education thus IET also accepted those who have completed vocational education. Even after adapting this criterion, the target number of participants was not met; only 27% of the initial target was achieved (Kavanagh, 2012). As explained by Kavanagh (2012), in order to increase the number of marginalised groups such as women, ethnic minorities, and disabled participants in the programmes, the eligibility criteria were frequently relaxed.

Both studies attempt to assess the effectiveness of the ALMPs only through descriptive statistics and do not use an advanced evaluation methodology. As explained in chapter 4, the experimental data used to analyse the effectiveness of these policies are usually not randomised and might be subject to potential selection bias. Neither of the studies reviewed above recognise this as a potential issue, hence their findings are likely to be unreliable. This chapter will analyse the effectiveness of the selected ALMPs in Kosovo by using an advanced evaluation methodology which attempts to address the problem of selection bias based on observable characteristics.

The following section will discuss the data used in this empirical analysis followed by the model specification for three models. These specifications will be used in both empirical approaches: multinomial probit and IPWRA.

[34] The control group used by Kavanagh (2012) was not available to use in this empirical chapter, hence chapter 6 will utilise LFS data to create a new control group.

5.3 Data and descriptive statistics

The evaluation analysis employs survey data from the Active Labour Market Programmes for Youths in Kosovo which was administered by the United Nations Development Programme (UNDP). The data used for the empirical investigation presented in this chapter is from a survey carried out by Riinvest, a professional research institution in Kosovo, in 2012 on behalf of the UNDP. The interviews were conducted face-to-face with a sample of those who had completed participation in these Programmes. This dataset contains information on individuals' socio-economic characteristics, level of education and previous labour market history. Table 5.2 presents descriptive statistics for individuals who participated in one of three categories of the active measures.

Interviewees had participated in one of these three programmes in 2008, 2009 or 2010. Since the dataset offers information on participants in three different years, it gives the opportunity to observe the treatment effect for different duration periods after completing the active programmes. During this three-year period 1903 job-seekers participated in the three programmes and out of them only 1081 could be contacted and surveyed[35].

As table 5.2 shows, the distribution of interviewees was similar to the total number of beneficiaries, OJT with 52% compared 55%, IS with about 33% compared to 29% and IET accounted for 15% of both those surveyed and total participants. More than 55% of the population of the beneficiaries started their programme in 2010, 20% started in 2009 while almost 26% started in 2008. The sample also consists of similar distribution; 53% of beneficiaries surveyed started the programme in 2010, 26% started in 2009 while 21% started in 2008.

[35] There is no information on whether those who dropped out of the active measures are included in the sample of the study or not.

Table 5.2 Descriptive statistics (selected variables)

	OJT			IS			IET		
No. of observation (share of beneficiaries)	**303**	**296**	**599 (52%)**	**160**	**153**	**313 (33%)**	**78**	**91**	**169 (15%)**
	Male	**Female**	**Total**	**Male**	**Female**	**Total**	**Male**	**Female**	**Total**
Active measure duration (in months)	3.81	3.92	3.86	3.94	4.12	4.03	3.62	3.94	3.78
	(1.29)	(.362)	(1.33)	(1.27)	(1.29)	(1.31)	(1.16)	(1.14)	(1.29)
Employment/training plan (discrete variable)	62.24	62.50	62.37	70.67	65.99	68.33	76.71	87.91	82.31
Certification (discrete v.)	66.34	70.95	68.64	75.63	71.90	73.76	58.97	70.33	64.65
Age (in years)*	26.83	26.08	26.46	26.65	25.99	26.32	27.03	25.99	26.51
	(4.59)	(4.01)	(4.33)	(3.97)	(2.94)	(3.52)	(4.76)	(2.76)	(3.85)
Education (discrete variables)*									
Primary School or lower	18.15	15.2	16.68	14.38	11.11	12.74	21.79	18.68	20.24
High School	44.88	37.5	41.19	43.75	45.1	44.42	50	38.46	44.23
Tertiary Education or higher	36.96	47.3	42.13	41.88	43.79	42.83	28.21	42.86	35.53
Unemployed before participation (discrete variables)	86.18	90.71	88.45	77.98	85.05	81.52	87.71	85.07	86.39
Unemployment duration before participation (discrete variables)									
Less than 6 months	19.65	12.58	16.12	6.33	10.45	8.39	10.42	9.26	9.84
6 to 12 months	29.48	22.52	26	22.78	10.45	16.62	33.33	12.96	23.15
12 to 24 months	15.03	16.56	15.8	10.13	8.96	9.55	18.75	9.26	14
More than 24 months	35.84	48.34	42.09	60.76	70.15	65.46	37.5	68.52	53.01
Unemployed (discrete v.)*	50.38	61.3	55.84	53.33	72.32	62.83	67.16	69.01	68.09
Active job search (discrete v.) *†	72.73	64.1	68.41	83.61	82.81	83.21	87.5	77.55	82.53
Employed (discrete variable)*	49.62	38.7	44.16	46.67	27.68	37.17	32.84	30.99	31.91
Contract (discrete variable)*‡	63.33	80.25	71.79	71.43	93.1	82.27	66.67	80	73.33
Region (discrete variables)									
Prishtina	14.85	19.59	17.22	10.625	7.84	9.23	21.79	32.97	27.38
Ferizaj	7.26	11.49	9.37	13.75	9.8	11.78	10.26	12.09	11.17
Gjakova	14.85	11.15	13	16.25	13.73	14.99	8.97	0	4.49
Gjilan	16.17	21.28	18.73	18.75	24.84	21.79	30.77	32.97	31.87
Mitrovica	15.51	11.15	13.33	16.25	17.65	16.95	3.85	5.49	4.67
Peja	8.91	10.14	9.52	12.5	19.61	16.05	8.97	4.4	6.68
Prizren	22.44	15.2	18.82	11.875	6.54	9.21	15.38	12.09	13.74

Notes: Standard deviations are presented in parenthesis in the second row of each of the selected variable. Discrete variables are measured in %. Averages are presented for continuous variables.

*At the time of the survey

† The variable measuring Active job search was constructed from the following question and includes only individuals who were unemployed at the time of the survey: “Have you actively searched for a job in the last four weeks?”

‡ The variable measuring whether an individual had an employment contract was generated from answers to the following question only for those who were employed at the time of the survey: “Do you have (an) employment contract at the current job?”

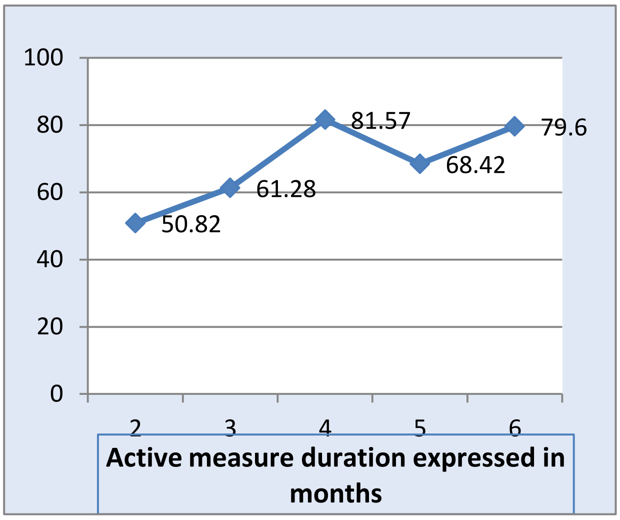
As pointed out, these active measures were designed to have specific durations; OJT and IET active measures were planned to take place over three months, while for IS it was six months. Figure 5.1 shows presents that there is a deviation from the initial plan for the duration of active measures.

Figure 5.1 Distribution of the duration for each active measure (months)

One possible explanation for this deviation might be related to the performance of the beneficiary during training, i.e. the beneficiaries might have been asked to stay longer in the training because they were performing better than those who left early or they were less successful and were asked to extend the training duration to achieve all of the learning outcomes. Another explanation might be that the firms and beneficiaries conspired to extend the training in order to continue to receive financial benefits from the government.

Table 5.2 shows that more than 82% of IET beneficiaries had an employment/training plan before training. In contrast, only about 68% of IS beneficiaries and 62% of OJT beneficiaries had the individual plan before training. This might indicate that this part of the process was not implemented as intended which calls into question the quality of the administration of these plans. The highest percentage of beneficiaries receiving a certificate of completion at the end of the training is for the IS beneficiaries with more than 75% for males and almost 72% for females. IET males have the lowest percentage of having a certificate of completion with about 59%. There seems to be a relation between receiving the certificate of completion and the duration of the active measure as figure 5.2 shows. As the duration of the active measure increases the percentage of individuals having a certificate increases. A possible explanation might be that receiving certificate might be related to the performance of the beneficiaries; i.e. duration of the measure may have been adjusted depending on how much time the beneficiary needed to complete the training successfully and receive the certificate.

Figure 5.2 Percentage of individuals receiving certificate of completion



In general, there are no substantial differences in the characteristics between the participants in three programmes. Table 5.2 shows that the mean age of interviewees was slightly above 26 years for each of three categories. There seem to be a very small difference in age between men and women. In terms of region, the highest number of participants is those living in region of Gjilan with 21% of the sample followed by Prishtina with 16% and Prizren with 15%. Gender seems to be balanced in OJT and IS programmes while there was a slightly higher percentage of women participants in the IET programme. Even though the aim was to achieve 15% participants from minority ethnic groups, the sample consists of 92% participants of Albanian ethnicity, 2% Serbian and 3.1% Roma ethnic participants and the rest are from other ethnic groups. Having in mind that these programmes targeted job-seekers receiving social assistance, one would expect to have a high number of this category of participants in the sample. However, only 8.9% of the sample consists of job-seekers on social assistance. Over 43% of the surveyed beneficiaries had two of household adult members registered unemployed, while only 10% have received remittances from the family members living abroad.

The level of education of the participants was also not as expected. The expectation was that OJT and IET participants would not have completed tertiary education. Even though the OJT and IET targeted groups were vocational students and low skilled young job-seekers, table 5.2 shows that about 42% of OJT beneficiaries and 35% of IET beneficiaries had completed more than secondary education. However, one explanation for this could be that since the completion of the programmes some individuals might have pursued higher education. Individuals who participated in the IS programme were expected to have a higher level of education since the target group was the new university graduates. In contrast, IS participants with a lower level of education seem to dominate. Table 5.2 presents a gender difference in education between men and women; more women from the sample seem to have completed the tertiary level of education than men. This seems to be the case for all three active measures. The largest gender difference in education is between the IET participants where 43% of women in the sample have completed tertiary level of education compared to only 28% of men.

Women seem to have been subject to higher unemployment before participating in the active measures; except for IET women participants. Table 5.2 shows that 88% of the IET male participants were unemployed before joining the programme compared to 85% of IET females. In contrast, larger percentage of IS and OJT females were unemployed compared to men. One of the criteria for eligibility for the programmes was to be unemployed before participating in the active measures. However, as table 5.2 shows, there seems to be a percentage of beneficiaries that 'were not' unemployed before training. This information was drawn from the question 'Were you unemployed before the training?'[36] . An explanation could be that they were employed in the informal sector before participating in active measures and did not report this to the Employment Office. As table 5.2 shows, many of those who answered the questions on their unemployment duration prior to treatment had long durations of unemployment; 67% of participants of IET were

[36] In the question 'In the period before participating in active measure, did you look for work?', about 21% of OJT, more than 16% of IS and 9.5% of IET beneficiaries responded that they were looking for work. This suggests that some beneficiaries were not actively looking for work independently before participating in one of the active measures (as a person being registered as unemployed is by definition looking for work through the Employment Office, which is a key eligibility criterion for participation in ALMPs).

unemployed for more than 12 months while there are 75% of participants of IS and 58% of OJT participants with the same duration of unemployment. Women, on average, were subject to a much longer unemployment duration than men, on average; 62% reported to have been unemployed for more than two years. Men reported shorter unemployment spells; 45% of them were unemployed for more than two years. The largest gender difference in unemployment duration is amongst the IET participants. Table 5.2 shows that 68% of women who completed IET programme seem to have been previously unemployed for more than 24 months compared to 37% of men. Table 5.2 shows that there are noteworthy differences between the unemployment before the participation in the programmes and current unemployment.

Almost 90% of the OJT participants reported to have been unemployed before participation while 55% of OJT participants were unemployed at the time of the survey. The difference of unemployment before and after completing the active programmes is narrower for the IS and IET programmes. At first sight, these figures may indicate that OJT was more effective than the other two programmes. Individuals in the sample seem to have had high job search activity at the time of the survey; IET and IS participants have higher job search activity (83% and 82%) than individuals participating in OJT programme (68%) which may also suggest that participants in OJT may have performed better in the labour market.

With regard to employment at the time of the survey, the data show that OJT participants had a higher percentage in employment than participants in the other two programmes. Forty four percent of OJT beneficiaries, followed by 37% and 31% of IS and IET were employed at the time of the survey. Mostly it is the private sector that offers employment to the participants. Out of 344 employed individuals in the sample, 63% were employed in the private sector followed by 20% employed in public enterprises, 10% in government agencies and slightly over 6% were self-employed.

It is important to emphasise that half of the employed from the sample have been in their current job for more than one year and more than half of them were employed at the companies in which they had been beneficiaries of one of the active programmes. Of those employed, 63% IS participants had been at the current job for at least a year compared to 56% of their IET and 44% of OJT counterparts. In addition, fewer of the OJT participants were employed in the company in which they were trained than participants in the other two programmes. It is worth pointing out that 78% of those who were employed at the time of the survey claimed to use the knowledge and skills gained from the active programmes in their current jobs.

Table 5.2 also confirms the importance of informality in the labour market in Kosovo. Despite OJT participants having a higher employment percentage, the data show that only 71% of the employed had a contract in their current job. The figures for other two programmes are slightly better; around 82% and around 73% of the IS and IET employed participants had employment contracts at their current job while 62% and 56% were entitled to health insurance and social security contributions and paid leave.

Table 5.3 shows that a higher percentage of female beneficiaries were inactive at the time of the survey compared to male beneficiaries of these three active measures. Considering that the average age of females in the sample is 26 and the fertility rate is highest for age-group 25 to 29 (KAS, 2011), this might be a possible explanation for the high percentage of inactivity of females in the sample. The employment figures for females who participated in OJT and IS are lower than those of males in the same active measures. However, this is not the case for female participants in IET. About thirty five percent of OJT male participants in 2008 were employed at the time of the survey however this figure declines sharply over the following two years.

Table 5.3 Labour market state by year of participation in the programme and by gender, at the time of the survey

		Inactive		**Unemployed**		**Employed**		**Total**
		Female	**Male**	**Female**	**Male**	**Female**	**Male**	
OJT	2008	4.9%	3.7%	22.2%	21.0%	13.6%	34.6%	100%
	2009	8.5%	3.6%	20.6%	27.3%	17.6%	22.4%	100%
	2010	14.1%	8.2%	27.0%	21.3%	11.3%	18.2%	100%
IS	2008	17.2%	11.1%	18.2%	19.2%	11.1%	23.2%	100%
	2009	16.4%	8.2%	17.8%	21.9%	12.3%	23.3%	100%
	2010	7.9%	6.3%	38.6%	28.3%	7.1%	11.8%	100%
IET	2008	14.7%	5.9%	20.6%	23.5%	20.6%	14.7%	100%
	2009	13.3%	6.7%	26.7%	36.7%		16.7%	100%
	2010	11.0%	6.0%	32.0%	25.0%	14.0%	12.0%	100%

A similar pattern, however a smaller decline, can be observed for IS participants. The data also suggest higher employment figures for females in all three programmes who completed their programme in 2008 compared to females who completed in 2010, however the differences are much smaller than those of males. The largest employment difference is for females who completed IET, ranging from 21% of those who participated in 2008, to 0 and 14% of those from 2009 and 2010, respectively. These figures may indicate that the active programmes might have more of a long-term rather than short-term effect for male participants than for their female counterparts. Other explanations for the differences across the years might be the variation of labour market conditions or the quality of the delivery of the active measures offered in particular years.

5.4 Model Specification

This chapter investigates the relative effectiveness of the three different programmes described in section 5.2. This section focuses on the specification of three probit models of the main determinants of: the probability of those surveyed being in employment, the probability of those respondents currently not in employment actively search for a job and the probability of those in employment having a contract. The objective of this section is: initially, to explain the justification for including variables in these model specifications for the multinomial probit estimation and secondly, to use these model specifications to create the outcome models for IPWRA approach. The multinomial probit model uses a three category outcome variable of the individual's state in the labour market (unemployed, contractually employed and employed without contractual agreement). This estimation serves as an initial analysis for evaluating the effects of the alternative programmes while the emphasis will be given to the IPWRA approach since it attempts to correct for a possible selection bias explained in more details in section 5.5.2. The justification for using multinomial probit as an initial analysis prior to the main estimation approach, IPWRA, in this empirical chapter is not only to investigate the relative effectiveness of the three active measures but also other relevant determinants of an individual's probability of being employed. Multinomial probit is chosen since it allows for a three category dependent variable differentiating between the probability of an individual not only being employed but rather the sector (formal/informal) in which he/she is employed which is an objective of the analysis in this chapter. On the other hand, as explained in details in section 4.3, IPWRA is chosen as the most appropriate evaluation methods to analyse the effectiveness of ALMPs for several reasons. Firstly, it addresses the possible selection bias. Secondly, IPWRA allows for a multiple-choice dependent variable for the treatment model, which is appropriate for this analysis because three different ALMPs are being assessed (OJT, IET and IS). And thirdly, in comparison to other evaluation methods, IPWRA has a doubly robust property meaning that even if one of the models, treatment or outcome model, is mis-specified, this method will still produce reliable estimates.

The dependent variable for the initial analysis, multinomial probit model estimating the probability to be in one of three labour market states, is defined as:

- Labour market state (Labstate): equals 0 if the individual is unemployed at the time of the survey, equals 1 if the individual is employed and has an employment contract and equals 2 if the individual is employed but has no employment contract.[37]

Since IPWRA does not allow for multinomial choice for the outcome model but only for the treatment model, this estimation uses three outcome models where the dependent variables are defined as follows:

- Employment (Emp): equals 1 if the individual is employed at the time of the survey, zero otherwise;
- Active job search (Actsrcat): equals 1 if the unemployed individual has actively searched for a job in four weeks before the survey, zero otherwise;
- Employment contract for those employed (Contract): equals 1 if the employed individual has signed an employment contract at the time of the survey, zero otherwise.

Models for three dependent variables are analysed and developed separately and the final model specifications will be presented at the end of each discussion. The model specification and the justification for each variable included in the employment

[37] If a respondent answers that he/she is inactive (in school, training, student, inactive due to family responsibilities) the survey was terminated. Hence, the inactive individuals at the time of the survey are excluded from the model since they do not answer a set of questions.

(*Emp*) model will be used for estimation of the multinomial probit model. Table 5.4 presents variable descriptions and their labels.

Table 5.4 Variables, names and specification

Information category	Specification details	
Dependent – Outcome variables	Employment (dummy=1 if the individual is employed at the time of the survey) Active job search for unemployed (dummy=1 if the individual has actively searched for a job in four weeks before the survey) Employment contract for the employed (dummy=1 if the individual has signed a contract with the employer at the time of the survey)	*Emp* *Actsrcat* *Contract*
Dependent variable of the treatment model	Types of the active measures the individual participated (dummy =1 if the individual received OJT; 2 if the individual received IS; 3 if the individual received IET)	*AmType*
Socio-demographic characteristics	Male (dummy= 1 if the individual is male) Age Minority (dummy = 1 if the individual is a member of a minority) Disability (dummy = 1 if the individual has disability) Received social assistance (dummy = 1 if the if the family of the individual receives social or disability assistance or pension at the time of the survey) Two members of the family unemployed (dummy =1 if two members of the family are unemployed at the time of the survey) Received remittances (dummy =1 if the individual received remittances at the time of the survey)	*Male* *Age* and *AgeSq* *Minority* *Disability* *Socialassist* *Twouunemp* *Remittance*
Education level	Education level at the time of the survey: - Four years or primary school completed - dummy=1 if the individual completed four years, primary school or is a high school drop-out - High school completed - dummy=1 if the individual completed high school - University and post-graduate degree – dummy=1 if the individual completed university or post graduate studies	*Primaryeduc* *Secondaryeduc* *Tertiaryeduc*
Active measure characteristics	- On the job training (dummy=1 if the individual received this active measure) - Internship scheme (dummy=1 if the individual received this active measure) - Institution and enterprise training (dummy=1 if the individual received this active measure) Year of completion of active measure - 2008 (dummy = 1 if the individual completed active measure in 2008) - 2009 (dummy = 1 if1 if the individual completed active measure in 2009) - 2010 (1 if the individual completed active measure in 2010) Duration of the active measure - 2 months - 3 months - 4 months - 5 months - 6 months Agreed on an employment plan before participation (dummy = 1 if the individual agreed on an employment plan) Received certificate after completion (dummy = 1 if the individual received certificate)	*OJT* *IS* *IET* *AM2008* *AM2009* *AM2010* *AMDuration* *EmPlan* *Cert*
Labour market history	Job-search 4 week prior to participation (dummy = 1 if the individual actively searched for job) Duration of unemployment before participation (dummy variables) - Less than 6 months - 6 to 12 months - 12 to 24 months - More than 2 years	*Jobsearchbt* *Undur6* *Undur12* *Undur24* *Undurmore24*
Regional characteristics	Regional dummy variables: - Prishtina - Mitrovica - Gjilan - Ferizaj - Gjakove - Peja - Prizren Regional Unemployment Municipality (dummy = 1 if individual lives in the city where the Vocational Training Centre is located)	*Pri* *Mit* *Gjil* *Fer* *Gjak* *Pej* *Prz* *Regunmp* *Vtcmncp*

__Model Specification for Employment__

The dependent variable of this specification is employment (Emp) which is a dummy variable taking the value of 1 is the individual is employed at the time of the survey and 0 otherwise.

Variables depicting participation in different active measures are included (*OJT* and *IS* compared to *IET*). As discussed in section 2.2.3, the duration of the active measures may induce lock-in effects for participants thus a continuous variable of the duration of the active measure is included in the model (*Amduration*), even though the active measures to be analysed do not last more than six months (Van Ours, 2001). As discussed in section 5.3, the duration of the active measures might also be dependent on the performance of the beneficiaries; the beneficiaries might have stayed longer if they performed well during the training or they were asked to finish their training in shorter period if they achieved all the learning outcomes. Another reason to include this variable is because the variation of active measure duration might have changed because beneficiaries and employers might have conspired to extend the duration in order to claim the financial benefits of the active measures. In this case, the expected sign of variable *Amduration* is ambiguous.

Variables indicating the year in which the participant completed the active measure are included in order to capture year-specific differences in labour market conditions, the duration of post-completion job search, and potentially the quality of provision of the active measures over the years (*AM2008* and *AM2009* compared to *AM2010*). There is no expectation on the signs of these variables. Variables on whether the individual along with employment office administrator/trainer[38] prepared a plan for skills to acquire during the training and for employment before participation (*EmPlan*) and whether he/she received a certificate (*Cert*) when they had finished their programme are also included in the model. The employment plan variable is a proxy for the individual's utilisation of employment office and VTC services which gives potential signals of the labour market performance, motivation and commitment to find a new job (Schmidl, 2014). *EmPlan* may also capture the quality of employment office and VTC services. Administrators are aware that close

[38] In this programme, each VTC had a designated trainer whose responsibility was to prepare the individual employment/training plans and monitor the implementation of these plans.

cooperation with the beneficiaries may result in a higher probability of being employed and higher success of the programmes. Hence it is expected that an individual who prepared a pre-treatment plan, *ceteris paribus*, will have a higher probability of being employed post-treatment. Receiving a certificate provides a signal of successful completion of the active measure and also the skill and ability level of the individual. Being certified by the training programme is expected, *ceteris paribus*, to increase the probability of being employed post-treatment.

As discussed in Chapter 1, the employment gender gap in Kosovo is very high: only 12.7% of working age women were employed compared to more than 46% of men (KAS, 2017). As explained in chapter 2, this gender difference might be partly explained by the strength of stereotypical gender roles and the social expectations for women in Kosovo and the perception that certain types of jobs are not suitable for women. Women are generally expected to take care of housework, children and the elderly. The LFS 2012 (KAS, 2012) reports that 28% of women decide not to participate in the labour market due to family or personal responsibilities compared to only 4% of men. Moreover, the average fertility rate is highest among the females aged 25 to 29 in Kosovo as suggested by KAS (2011). Considering that the dominant age group of interviewees in the sample is that in which female fertility is high in Kosovo it is expected that females will be less likely to participate in the labour market. Thus the expectation is that men (variable *Male*), *ceteris paribus*, are considered to have a higher probability of being employed compared to women.

Age and its squared term (*Age* and *AgeSq*) are also included in the model. According to neoclassical theory, age is considered as an important determinant of the labour supply and employment since it reflects experience in the labour market. The view in the model is that the probability of gaining employment increases with age at a diminishing rate (Pencavel, 1974). The human capital theory predicts that the probability of being employed increases with age due to an increase in productivity until it reaches a peak and then starts to diminish reflecting a decline in productivity and deterioration in human capital (Luong and Hebert, 2009). Age might not be a good proxy for experience in case of Kosovo due to high levels of unemployment and especially the high levels of long-term unemployment. However, this dataset does not offer a better measure for experience and therefore age and its' square are included in the model to account for a potential non-linear relationship between age and the probability of being employed.

There are empirical studies from other countries confirming persistent ethnic inequalities in the labour market (Julia et al., 2015; Zwysen and Longhi, 2018). The ethnic background represents differences in cultural background and other differences which might reflect a difference in employment opportunities. In the case of Kosovo the effect of the *Minority* variable is ambiguous, since a recent study for Kosovo suggests that minority women are more likely to participate in the labour market compared to Albanian women (Democracy for Development, 2015).

It is recognised from empirical studies that individuals with disability typically face more obstacles in finding regular employment (Patterson and Block, 2014; Ameri et al., 2018). Hence variable *Disability* (defined as a dummy variable equal to 1 if the individual has a disability) is expected to have a negative sign in the employment model.

It is a well-established theoretical and empirical proposition that education has a substantial impact on labour market outcomes such as earnings and employment (Becker, 1964; Brown, 1995; Oreopoulos and Salvanes, 2009; Riddell and Song, 2011). As discussed in section 2.4, the human capital gained through education is expected to increase productivity which is expected to subsequently lead to higher labour market performance. Two dummy variables representing secondary (*Secondaryeduc*) and tertiary (*Tertiaryeduc*) levels of education are included in the model (primary education, *Primaryeduc*, is the reference category). Higher levels of completed education are expected, other things being equal, to increase the probability of an individual being in employment post-treatment.

A variable depicting if the individual has two or more adult family members unemployed (*TwoUnemp*) is included in the model. The intention of this variable is to capture several potential mechanisms. This variable is a proxy for an individual's family connections to the labour market and also for individual's motivation to find a job. Some studies suggest that the main source of social capital for a youth is their family (Yan and Lam, 2006; Knight and Yueh, 2008; McGowan et al., 2015). If members of the family (most likely parents) of a young individual are unemployed they might lack the necessary social contacts to secure jobs for themselves and their family members. Moreover, the social position of their family might be of a great importance to access greater employment opportunities and it also might indicate the applicant's level of trust to those who are hiring. A recent study for Kosovo found that having an additional household member employed (as a proxy for social capital) increases women's probability of participating in the labour market by 9 percentage points, on average (Democracy for Development, 2015). According to the World Bank (2008), in Kosovo neither the unemployed nor enterprises rely to a significant extent on the public employment services as a mediator in the job search and employment process. As the extended internal labour market hypothesis predicts, firms usually use recruitment channels through existing employees who spread the knowledge of vacancies to their families (Manwaring, 1984). According to ILO (2007), 59% of young workers in Kosovo found jobs through family and friends' connections which confirm that informal networking is a preferred method for recruitment (21.5% were employed through direct recruitment from employer, 16.6% through advertisements while just 2.9% were placed through the Public Employment Services). On the other hand, variable, *TwoUnemp,* might also pick up an individual's motivation to become employed and support the family. The impact this variable might have on employment is twofold, it might increase the probability to be employed due to higher motivation or it might decrease this probability due to a lack of social capital, thus the expected sign of the coefficient is ambiguous.

The model also includes a dummy variable that controls if the individual's family receives remittances (*Remittance*). According to the neo-classical theory of labour-leisure choice, receiving remittances will, other things being equal, reduce the probability of an individual being employed in a family receiving remittances (Killingsworth, 1983). The individuals receiving the remittances are expected to increase their reservation wage[39] and as such are expected to reduce effort to find a job since they are less likely to receive a job offer with wages above their reservation level (Amuedo-Dorantes and Pozo, 2006). Previous research has found consistent evidence that receiving remittances is associated with a large decrease in the labour force participation of both men and women (Amuedo-Dorantes and Pozo, 2006; Kim, 2007; Shapiro and Mandelman, 2016). Similar findings are also found in a

[39] In a model of labour force participation, the reservation wage is the lowest wage rate at which a job-seeker is willing to accept employment.

study for the impact of remittances on labour force participation and employment in Kosovo. Findings suggest that being a remittance recipient is associated with a higher probability of being unemployed and not searching for job compared to a non-recipient (UNDP, 2012). On the other hand, receiving remittances might be a result of the individual coming from a poor family and he/she is unemployed. This, in turn, might translate into additional pressure to find employment. In contrast to findings of the negative effect of remittances on wage-employment, Funkhouser (1992) found evidence that remittances have a positive effect on self-employment. This is mostly evident when remittances are viewed by the receiving individual as a temporary source of income and are used to cover the start-up costs of self-employment which promises future incomes (Funkhouser, 1992; Adams and Page 2005; Shapiro and Mandelman, 2016). In the sample used for this chapter, self and wage employment are combined into one category, however the number of self-employed individuals in the sample is only 22 out of 344. Considering these arguments the sign of the variable *Remittance* is ambiguous.

The variable *Socialassist* (if the family of the individual receives social or disability assistance or a pension) is included in the model to account for non-labour income and family wealth.[40] Research findings suggest that welfare programmes, in general, decrease labour force participation and hence the probability of being employed (Moffit, 2002; Rejda, 2015; Farber and Valletta, 2015). Williams and Windebank (1998) suggest that the social benefits may induce a welfare dependency culture among the people who receive it and consequently will reduce the probability of being employed. Receiving social assistance for a long period of time induces a detrimental attitude and behaviour in terms of self-efficacy, morale, motivation and subsequently the level of skills which will make them less attractive in the labour market (Harvey, 2014; Abramovitz, 2017). Even though the level of social assistance in Kosovo is low, it is believed to increase dependency while also increasing the probability to work in low paid or low-quality jobs, often in informal employment (World Bank, 2015). On the other hand, this variable also indicates that the individual belongs to a poor family hence this might mean that an individual may put

[40] This variable is created from the question: 'Your family receives social assistance, disability benefits and pension?' From this question it is not exactly clear whether the beneficiary him/herself or someone within the family receives the benefits.

more effort into searching for a job or have a lower reservation wage. The overall effect of receiving social assistance on the probability of an individual being in employment is thus ambiguous.

The model also includes dummy variables controlling for the duration of unemployment before participation in one of the active measures. Three dummy variables measuring the individual's pre-treatment unemployment duration were included: whether the individual had been unemployed for less than 6 months (*Undur6)*, from 6 to 12 months (*Undur12)* and from 12 to 24 months (*Undur24).* Dummy variable measuring whether the individual had been unemployed for more than 24 months (*Undurmore24*is used as a reference category). As discussed in section 4.3.2 the inclusion of these variables in the model may capture unobserved characteristics of the individual, such as motivation for getting a job or labour market attachment (Bryson et al., 2002). As the review of empirical studies in section 2.5 suggests, there may also be a stigmatisation associated with a longer duration of unemployment because employers might perceive individuals with long unemployment spells as having lower productivity and/or motivation. Thus, shorter unemployment spells are expected, *ceteris paribus*, to increase an individual's probability of being employed post-treatment.

The model also includes regional dummies to account for the large regional differences labour market conditions in Kosovo. This set of variables is included in the model to account for variations in business activity, regional unemployment rates, specific labour market environment and the cost of living. This set of dummy variables represent the seven regions of Kosovo, the benchmark category being Prishtina (*Pri*) while the others being: Mitrovica (*Mit*), Gjilan (*Gjil)*, Ferizaj (*Fer*), Gjakove (*Gjak*), Peja (*Pej*) and Prizren (*Prz*). The omitted variable is Prishtina, since the interest is focused at the comparison of other regions with the capital city. It is expected that individuals living in regions other than Prishtina will have a lower probability of being employed due to the lower employment opportunities and level of infrastructure development in these regions (including transportation and childcare opportunities for women). The regional unemployment level (*RegUnemp*) was also initially included, but it was subsequently dropped from the model due to collinearity thus the regional differences are to be explained only through regional dummy variables.

The final specification for the employment model is:

$$EMP = f(OJT, IS, Amduration, AM2008, AM2009, Emplan, Cert, Male, Age, Agesq, Minority, Disability, Secondaryeduc, Tertiaryeduc, Twounemp, Remittance, Socialassist, Undur6, \ Undur12, Undur24, Fer, Mit, Gjil, Gjak, Pej, Prz) \qquad 5.1$$

Model Specification for Active Job Search

The dependent variable in this specification is a dummy variable taking a value of 1 if the individual in the sample has actively searched for a job in the four week period before the survey, and 0 otherwise. This variable was constructed from the question: *"Have you actively searched for a job in the last four weeks?"* This question was only asked to individuals who were unemployed at the time of the survey, thus the sample for this specification includes only unemployed individuals. The independent variables accounted for in this model are reviewed below.

Active measure types (*OJT* and *IS*, compared to the reference category *IET*), the duration of active measures (*Amduration*), year of completion of active measures (*AM2008* and *AM2009* compared to *AM2010*) and whether the participant prepared a training/employment plan (*EmPlan*) are included in the model to assess the impact of active measures and their characteristics on the probability to search for jobs. Having an *EmPlan* might increase the probability to search for a new job given that it may strengthen an individual's motivation and commitment to remain in the labour market.

As discussed in section 1.5.3, women in Kosovo face disproportionate house and childcare responsibilities which make them less likely to search for a job. Hence, other factors remaining constant, men (indicated by dummy variable *Male)* are expected to have higher probability to engage in active job search compared to women. The unemployment rate for youths in Kosovo is the highest among all age groups with 52.7% of youth population being unemployed (KAS, 2017). However, there is no evidence and thus no clear expectation on whether the young unemployed are more likely to engage in active job search. Variables *Age* and *AgeSq* are included in the model to account for effect of age on active job search.

In general, the unemployed from ethnic minorities are expected to have lower job search intensity due to discouragement from the discrimination they face in the labour market (Thomas and Renick, 1981; Kaas and Manger, 2012). Low social capital might also negatively impact their decision to search for a job. However, as discussed in the previous model specification, a recent study (see Democracy for Development, 2015) found evidence that ethnic minority women are more likely to participate in the labour market compared to Albanian women. Taking this finding into consideration, there is no clear expectation of the sign of the variable *Minority*.

Discrimination in the labour market, lack of workplace facilities necessary for disabled people and lack of meaningful employment opportunities are reasons for the discouragement of the disabled in the labour market (Burchadt, 2003; Patterson and Block, 2014). Hence, the expected sign of variable *Disability* in this specification is negative.

In the context of the individuals' labour-leisure choice, the higher the level of education completed the higher is the cost of not participating in the labour market, given that the potential wage will be higher if the individual is more educated (Riddell and Song, 2016; Ondoa, 2018). In this context, having a higher level of education is expected, other things being equal, to increase an unemployed individual's probability to search for a job.

Empirical studies also find evidence that those unemployed who receive remittances will increase their reservation wage and thus will be less likely to search for a job (Kim, 2007). According to a study, the average annual value of remittances in Kosovo is EUR 418 per capita in the household which may be considered high relative to local wage rates (Democracy for Development, 2015). As discussed in the employment model specification, *Emp*, it is expected that it is mainly individuals from poor families with little or no other income receive remittances. This might put pressure on the individual to search for jobs. Given these two counteracting mechanisms the expected sign of *Remittance* is ambiguous. Receiving social assistance (*Socialassist*), which is used as a proxy for family wealth, picks up the pressure of the individual to search for job more intensely thus it is expected to increase active job search.

Variables measuring unemployment duration spells are included in the model to pick up the individuals' motivation to participate in the labour market (*Undur6*, *Undur12* and *Undur24* reference category is *Undurmore24*). Individuals with shorter unemployment spells are expected, *ceteris paribus*, to have higher active job search under the assumption that these signal individuals' motivation to remain in the labour market thus they will be more willingly to search for jobs.

As in the previous model, regional dummy variables are included in the model to control for regional differences in labour market conditions. It is expected that individuals living in regions other than Prishtina, *ceteris paribus*, to have a lower probability to actively search for a job search since other regions offer lower employment opportunities and people might more easily become discouraged.

The final model for active job search model is specified as below:

$$Actsrcat = f(OJT, IS, Amduration, AM2008, AM2009, Emplan, \; Male, Age, Agesq, Minority, Disability, Secondaryeduc, Tertiaryeduc, Twounemp, Remittance, Socialassist, Undur6, Undur12, Undur24, Fer, Mit, Gjil, Gjak, Pej, Prz) \quad 5.2$$

Model Specification for Employment Contract

The dependent variable for the third model is generated from answers to the following question only for those who were employed at the time of the survey: 'Do you have an employment contract at the current job?' Therefore, this specification uses a dependent dummy variable indicating the incidence of informal employment, taking a value of 1 if the employed individual has an employment contract at the time of the survey, and 0 if the employed individual does not have an employment contract. The explanatory variables included in this specification are discussed below.

Active measure types (*OJT*, *IS* and *IET*) and their characteristics (*Amduration* and *Cert*) are included as in the previous models. The expected sign of variable *Cert* is positive since it signals a certain level of skills acquired from the training and also abilities thus employer may offer him/her better job opportunities.

Workers search for high quality jobs if they are possible, however their ability to acquire this kind of jobs depends on their bargaining power. As discussed in more detail in section 2.6, disadvantaged, low-skilled and workers with longer duration spells tend to have a lower probability of obtaining employment with a contract, are less likely to have health insurance and retirement benefits and are engaged in less secure jobs (McGovern et al., 2004; Julia et al., 2015). As pointed out in the literature review in Chapter 2, in most countries women are concentrated in lower quality, irregular and informal employment, such as domestic labour work and care assistance to the elderly, assistance in small family enterprises which does not offer social security and protection (Carr and Chen, 2002; Abramo and Valenzuela, 2006; Chen et al., 2006). In contrast, results from the Kosovo LFS (KAS, 2017) suggests that women in Kosovo are less likely to work in vulnerable jobs i.e. in unpaid family business or being self-employed without employees; 18.3% of employed women compared to 24.4% men (KAS, 2017). However, this is mainly driven by the fact that employed women in Kosovo are, in general more likely to be employed in the public sector. Since this is not the case for the sample being used in this empirical chapter (women in this sample are not mainly employed in the public sector), hence it is expected that men (*Male*), *ceteris paribus*, will be less likely to work without a contract compared to women.

Older workers are expected to have a higher probability to be in formal employment than their younger counterparts, other things being equal, because they are likely to have gained more labour force experience and seniority (Eilat and Zinnes, 2002; Schneider and Williamson, 2013; McCaig and Pavcnik 2015). According to McGovern et al. (2004), young workers usually tend to occupy low skilled jobs supporting the concept of ‘McJobs’. The Kosovo LFS (KAS, 2017) also suggest that 46.2.8% of Kosovo young workers (15 to 25 years of age) work without a contract compared to about 21% for all age groups. It is expected that the probability of having an employment contract, other things being equal, is lower for young individuals and it increases with age. A squared term of this variable is also included to test for potential non-linearity in the relationship.

Section 2.6 also emphasises that skilled workers are more likely to have higher quality jobs than low skilled workers (Kogan, 2011; Ondoa, 2018). Since the education signals the degree of skills acquired and the educated employees are expected to be more productive, they have more bargaining power thus the employers will tend to offer better job opportunities to them (Heywood and Wei, 2004; Chevalier et al., 2004; Backes-Gellner and Werner, 2007; Schneider and Williams, 2013). It is expected that higher levels of education, other things being equal, increase the probability of having an employment contract.

With regard to minorities, the discussion in section 2.6 emphasises that in addition to having barriers to being employed, they also face barriers to progress in their career and consequences such as wage differentials, contract types and stability in work, hours worked and self or part- time employment. Empirical studies confirm that minorities as disadvantaged groups are more likely to be employed in lower quality jobs than their counterparts (McCaig and Pavcnik, 2015; Julia et al., 2015). According to ILO (2007), there is a difference between Albanians and minorities in terms of the employment contracts. Young Serbs and the community of Roma Ashkali and Egyptian (RAE) reported twice as high informal employment compared to young Albanians. Discrimination has also been argued to be an important factor for disabled persons to be employed in the informal sector (Sanderson et al., 2017). Thus, the minority (*Minority*) and the disabled (*Disability*), if employed, are expected to be less likely to have an employment contract.

Variable *TwoUnemp* in this context picks up the pressure to be employed regardless of the work conditions; hence, if an individual have two or more members of the family unemployed, he/she will be more likely to be employed in the informal sector (without a contract). The impact of variable *Socialassist* on the quality of employment might be negative; working informally, rather than formally, may be preferred by social assistance beneficiaries since it enable them to remain eligible for benefits.

The set of duration variables (*Undur6*, *Undur12* and *Undur24* while reference category is *Undurmore24*) are included in the model, for the same purpose as in the previous models, to account for unobserved characteristics of the individual such as motivation, labour market attachment and employers' perception of his/her productivity. It is expected that employed individuals with longer unemployment spells, *ceteris paribus*, will more likely be employed in the informal sector.

Regional differences are also accounted through regional dummy variables as in the two previous specifications. Those residing in cities with higher unemployment rates are expected to be disproportionately employed in the informal sector, other factors remaining constant.

The final model specification for *Contract* is as follows:

$$Contract = f(OJT, IS, Amduration, AM2008, AM2009, Cert, Male, Age, Agesq,$$
$$Minority, Disability, Secondaryeduc, Tertiaryeduc, Twounemp, Socialassist,$$
$$Undur6, Undur12, Undur24, Fer, Mit, Gjil, Gjak, Pej, Prz) \tag{5.3}$$

Table 5.5 presents the expected signs of each variable in the three model specifications. The following section discusses the results from the multinomial probit and the IPWRA.

Table 5.5 Independent variable – expected sign

Variable	**Expected sign**		
Dependent – Outcome variables	EMP	ACTSRCAT	CONTRACT
Male	+	+	-
Age	+ up to a point; - after the turning point	?	- up to a point; + after the turning point
Minority	?	?	?
Disability	-	-	-
Family receives social assistance	?	+	-+
Two members of the family unemployed	-/+	+	NA
Received remittances	-	-	
Four years or primary school completed (omitted variable)			
High school completed	+	+	+
University and post-graduate degree	+	+	+
- On the job training			
- Internship scheme			
- Institution and enterprise training (omitted variable)			
Year of completion of active measure			
- **2008**			
- **2009**			
- **2010 (omitted variable)**			
Duration of the active measure	-/+	-/+	?
Agreed an employment plan before participation	+	+	NA
Received certificate after completion	+	NA	+
Duration of unemployment before participation			
- **Less than 6 months**	+	+	+
- **6 to 12 months**	+	+	+
- **12 to 24 months**	+	+	+
- **More than 2 years (omitted variable)**			
Regional dummy variables:			
- **Prishtina (omitted variable)**			
- **Mitrovica**	-	-	-
- **Gjilan**	-	-	-
- **Ferizaj**	-	-	-
- **Gjakove**	-	-	-
- **Peja**	-	-	-
- **Prizren**	-	-	-

5.5 Results

5.5.1 Multinomial Probit Model

The initial analysis uses a multinomial probit model to assess the relative effectiveness of the three active measures: On the Job Training (*OJT*), Internship Scheme (*IS*) and Institution and Enterprise Training (*IET*). The dependent variable used in this model is three categorical variable which: equals 0 if the individual was unemployed at the time of the survey, 1 if the individual was employed and had an employment contract and 2 if the individual was employed but had no employment contract at the time of the survey.[41] To use a dependent variable with another category of whether the unemployed were actively seeking for jobs at the time of the survey would be highly data demanding and was not possible with the data at hand.[42]

Both multinomial probit and logit were considered initially for estimation. Two tests were used to check whether the multinomial logit model violates the independence from irrelevant alternatives (IIA) assumption.[43] Comparing the coefficients of unrestricted with the first restricted model (where the category *formally employed* was excluded), the calculated standard Hausman test statistic is negative thus no conclusion can be drawn regarding the null hypothesis that the 'difference in the coefficients is not systematic' (see Appendix 5.1). In addition, a suest-based Hausman test was carried out to verify the difference of coefficients on the models; the results indicate that the null hypothesis that 'the odds are independent of other alternatives' cannot be rejected therefore there is no evidence of a violation of the IIA assumption. The same tests were carried out for the unrestricted and the second restricted model (where the category *informally employed* was excluded). For the second restricted model, output results from both tests indicate that there is no evidence of a violation of the IIA assumption.

Long and Freese (2006, p.191) suggest that the results from both tests used for IIA assumption (Hausman and suest-based Hausman test) should be consistent otherwise the results from these tests are unreliable, they quote McFadden (1973): a

[41] In the rest of the section category 1 and 2 of the dependent variable are referred to as formally and informally employed.
[42] 200 participants who were inactive at the time of the survey were not included in the sample.
[43] The IIA assumption implies that adding an additional alternative or changing the characteristics of one alternative does not change an individual's evaluation of one alternative relative to another (Wooldridge, 2010).

multinomial logit should be used only in cases where the outcome categories are "plausibly assumed to be distinct and weighted independently in the eyes of the decision maker". Additionally, Wooldridge (2002) suggests that the multinomial probit is preferred over the multinomial logit model since it relaxes the IIA assumption. Therefore, based on the considerations from the literature, the inconsistent results from the standard Hausman and suest-based Hausman tests the multinomial logit model seems not to be preferred and only the results from the multinomial probit model will be presented. [44]

The rest of this section presents the findings of the model on the determinants of individual's labour market status. The full results from the estimation of multinomial probit are presented in Appendix 5.2 while only the average marginal effects are interpreted based on suggestions by StataCorp (2013) and are presented in table 5.6. In order to interpret the multinomial probit coefficients, one set of coefficients is normalised to zero (the reference category), however such normalisation is not required when interpreting the average marginal effects. The average marginal effects are interpreted for all the three categories of the dependent variable *Labstate* (unemployed, employed in the formal sector and employed in the informal sector) and the sum of the average marginal effects for each variable should be equal to zero because in order for an increase in one category there should be a decrease in another category.

As the main aim of this chapter is to identify the relative effectiveness of active measures, the first variables to be interpreted are those associated with participation in three active measures (*OJT, IS*, *Amduration*, *AM2008*, *AM2009*, *Emplan* and *Cert*). Results indicate that, other things being equal, participating in OJT decreases an individual's probability of being unemployed when surveyed by 12.1 percentage points (pp) in comparison to participating in IET. An OJT beneficiary, other factors being constant, is more likely to be employed informally by 7 pp in comparison to an IET with similar characteristics. In contrast, participating in OJT seems not to significantly impact the probability to be formally employed though the sign is

[44] When analysing the effect of non-normality for probit models, Wooldridge (2002; 2012), argues that when estimating partial effects, it is practically irrelevant if the Beta estimates are inconsistent resulting from non-normality. Thus, focusing on the inconsistency of the Beta parameters "largely misses the point" of probit modelling.

positive. Participating in IS, holding other variables constant, decreases the probability to be unemployed by 9.9 pp compared to participating in IET, however it is statistically significant only at 10% significance level. Results also indicate that participating in IS does not have any different effect on the probability of being employed (neither formal nor informal) compared to participating in IET. Overall, the OJT programme, compared to the two other programmes, seems to have positively influenced the prospects of the participants; however the effect seems to be larger for the informal sector employment.

The duration of the active measure (*Amduration*) is found to have a statistically significant impact in increasing an individual's probability to be engaged in informal employment. Informal employment provides much-needed employment opportunities which are lacking in Kosovo's formal sector, though working conditions are often poor. Gaining an income, for most individuals, which supports the economic well-being of a worker and his/her family is the primary reason to work. Considering that receiving the social assistance is insufficient source of income to live a decent life in Kosovo, being informally employed is preferred relative to being unemployed. An increase of active measure duration by a month, other things being equal, increases an individual's probability to be informally employed by 2.8 pp. As discussed in section 4.4.2, some studies found strong evidence of negative effects of long-term active measures on the probability to find employment post-treatment, due to the 'lock-in effect' (Van Ours, 2001; Hamalainen, 2002; Sianesi, 2008; Schmidl, 2014). Yet, no study, to the author's knowledge, has examined the effect of active measure duration on informal employment thus these previous results should be taken with caution.

Results indicate that the impact of active measures becomes more pronounced over time. An individual who completed the programme in 2008 (*AM2008*), holding other variables constant, will have lower probability of being unemployed by 13.9 pp compared to an individual who completed in 2010. Completing in 2008 also increases an individual's probability to be employed in the formal sector by 11.7 pp compared to those who completed in 2010. *AM2008* is statistically significant at 1% significance level for both outcomes, unemployed and formally employed. Having participated in 2009, decreases an individual's probability of being unemployed by

8.4 pp while increasing his probability of being formally employed by 8.9 pp compared to an individual who completed in 2010.

Table 5.6 Average Marginal Effects from Multinomial Probit

	(1)	(2)	(3)
Variables	**Unemployed**	**Formally employed**	**Informally employed**
OJT	-0.121**	0.050	0.071**
	(0.047)	(0.043)	(0.031)
IS	-0.099*	0.072	0.028
	(0.054)	(0.049)	(0.036)
Amduration	-0.016	-0.011	0.028***
	(0.014)	(0.013)	(0.010)
AM2008	-0.139***	0.117***	0.022
	(0.045)	(0.040)	(0.029)
AM2009	-0.084**	0.090**	-0.005
	(0.038)	(0.035)	(0.025)
Emplan	-0.036	0.018	0.017
	(0.038)	(0.034)	(0.026)
Cert	-0.033	0.098***	-0.065***
	(0.037)	(0.034)	(0.023)
Age	-0.062**	0.019	0.042**
	(0.029)	(0.026)	(0.021)
Agesq	0.001*	-0.0001	-0.001*
	(0.001)	(0.001)	(0.001)
Male	-0.129***	0.026	0.103***
	(0.033)	(0.030)	(0.023)
Disability	0.278*	-0.226	-0.051
	(0.147)	(0.149)	(0.096)
Minority	0.233***	-0.117*	-0.116**
	(0.074)	(0.071)	(0.050)
Socialassist	0.142**	-0.147**	0.005
	(0.066)	(0.062)	(0.041)
Twounempl	0.075**	-0.092***	0.017
	(0.037)	(0.033)	(0.024)
Remittance	0.042	-0.065	0.023
	(0.060)	(0.056)	(0.038)
Secondaryeduc	-0.015	-0.018	0.034
	(0.049)	(0.046)	(0.028)
Tertiaryeduc	-0.053	0.171***	-0.117***
	(0.053)	(0.047)	(0.036)
Undur6	-0.277***	0.180***	0.096***
	(0.056)	(0.051)	(0.032)
Undur12	-0.017	0.022	-0.005
	(0.047)	(0.044)	(0.030)
Undur24	-0.114**	0.064	0.049
	(0.056)	(0.051)	(0.035)
Fer	0.129**	-0.040	-0.088**
	(0.061)	(0.055)	(0.040)
Gjak	0.177***	-0.106*	-0.070*
	(0.065)	(0.058)	(0.042)
Gjil	0.116**	-0.046	-0.069**
	(0.054)	(0.048)	(0.033)
Mit	0.385***	-0.335***	-0.049
	(0.065)	(0.063)	(0.036)
Pej	0.164**	-0.021	-0.143**
	(0.071)	(0.060)	(0.056)
Prz	0.228***	-0.159***	-0.068*
	(0.062)	(0.056)	(0.038)
Observations	751	751	751

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The discussion in section 4.4.2 pointed out that very few studies have analysed the short vs. long-term effects of active measures. Results obtained from the estimation presented in table 5.6 are broadly in line with these previous studies. This finding might also be explained by the economic environment and the quality of training over the period when the training took place, which could not be controlled for in the analysis. However, as Chapter 1 indicated, the labour market did not experience any significant changes during this period.

Having acquired a certificate of completion of the active measures (*Cert*) is associated with an increase in the individual's average probability of being in formal employment by 9.7 pp while it decreases the probability to be in informal employment by 6.5 pp. This result reflects the expectations that a certificate signals a higher level of individual's skills and competences which might imply higher productivity (Chan, 2013). As discussed in section 5.3, the percentage of individuals who received a certificate of completion increases with the time spent in training. This might indicate that receiving a certificate might reflect the individuals' ability to acquire more skills from the training. Furthermore, being certified may be perceived by companies as indicating that the individual have higher abilities and thus are less likely to be offered low quality jobs or informal jobs.

Having an individual plan on acquiring skills during the training (*Emplan*) seems not to be important for any of the outcomes since it is statistically insignificant. One explanation for this result could be that these individual plans might have not been well implemented and might not be of high enough quality to guide the beneficiary in acquiring the necessary skills and employment opportunities.

The signs of the marginal effects of variables *Age* and *AgeSq* are in line with the expectations of a non-linear relationship between age and an individual's probability of being unemployed: the probability of being unemployed reduces with age up to a certain point after which it increases. With regard to informal employment, there is also a non-linear relationship between age and the probability of being employed in the informal sector where the individual's probability of being employed in the informal sector increases with age up to a turning point after which it reduces. However, the squared terms of age are only significant at the 10 percent significance level.[45] In accordance with expectations, men are less likely to be unemployed and, if employed, they are more likely to be informally employed than women. Holding other variables constant, men are found to have a lower probability of unemployment by 12.8 pp. Moreover, men are more likely to be employed informally, other things being equal, by 10.3 pp.

As expected, having a disability increases the individual's probability to be unemployed by 27.8 pp compared to an individual without disability, although it is statistically significant only at 10% significance level. A possible explanation for this finding might be the low employment opportunities and social barriers that disabled individuals face in the labour market.

These results suggest strong evidence that being an ethnic minority is associated with a higher probability of being unemployed at 1% significance level, while being associated with a lower probability of being employed formally and informally at 10% and 5% significance level respectively. Holding other variables constant, being from an ethnic minority increases the probability to be unemployed by 23.3 pp while decreasing the probability to be in formal employed by 11.7 pp and informal employment by 11.6 pp, compared to being an Albanian. This finding is in line with empirical studies from other countries, suggesting that lower employment opportunities remain for minority ethnic groups (Julia et al., 2015; Zwysen and Longhi, 2018).

Results indicate that whether an individual's family receives social assistance and/or a pension is an important determinant of an individual's probability to be unemployed and formally employed. Findings indicate that if an individual's family receives social assistance and/or a pension, holding other things constant, increases an individual's probability of being unemployed by 14.2 pp and decreases an individual's probability of being formally employed by 14.7 pp. However, given that to receive the social assistance in Kosovo, it is a criterion that all family members should be unemployed, there is a potential endogeneity issue and this result should be treated with caution. Receiving remittances does not have a statistically significant effect for neither of the outcomes.

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[45] The turning point for the unemployment outcome= - Age/(2*AgeSq)= 0.062/(2*(0.001)) = 31;
The turning point for the informal employment outcome= - Age/(2*AgeSq)= - 0.042/(2*(- 0.001)) = 21

In accordance with the expectations of the social capital hypothesis, holding other variables constant, having two or more unemployed family members increases an individual's probability to be unemployed by 7.5 pp. Accordingly, other things being equal, it decreases an individual's probability to be in formal employment by 9.2 pp while it seems to have no impact on an employed individual's probability to be engaged in informal employment. A possible explanation for this finding might be the effect of nepotism which seems to be an important determinant of being employed in Kosovo. Another explanation could be that the individual might be discouraged from the labour market since he/she believes that the probability of being employed is low.

In accordance with theoretical expectations, having completed university, other things being equal, increases an individual's probability to be formally employed by 17.1 pp while decreasing the probability to be informally employed by 11.7 pp compared to having just primary level education. Having completed secondary education seems not to affect individual's labour market state compared to having primary education.

In general, results are in line with the evidence from the previous studies suggesting that an individual with shorter unemployment spells prior to entering training is more likely to be employed (Terell and Storm, 1999; O'Leary, 2001; Van Ours, 2002; Micklewright and Nagy, 2008; Kroft et al., 2013). There is evidence that having an unemployment spell of no longer than 6 months increases an individual's probability of being employed, both in formal and in informal employment, compared to having an unemployment spell of more 24 months. Results suggest that an individual's unemployment spells, *Undur12* and *Undur24*, are not statistically significant in determining the probability of being employed compared to *Undurmor24* (the reference category). In conclusion, the findings suggest that individuals who have been unemployed for up to 6 months have a higher probability of getting employed compared to those with longer unemployment spells (6 to 12 months, 12 to 24 months and more than 24 months).

Undur6 is statistically significant at 1% significance level for all three outcomes. Results indicate that an individual's probability of being unemployed, other things being equal, decreases by 27.2 pp for and individual with less than 6 months unemployment spell compared to one with more than 24 months unemployment spell. Having only 6 months unemployment spell also increases probability to be formally employed by 18 pp and to be informally employed by 9.6 pp. *Undur12* (having unemployment spell between 6 to 12 months) is not statistically significant in any of the outcomes. In contrast, having 12 to 24 months unemployment spell before participating in the active measures (*Undur24*) decreases an individual's probability to be unemployed compared to an individual with more than 24 months unemployment spell, other things being equal. The variable *Undur24* does not seem to influence an individual's average probability to be in formal nor informal employment.

Consistent with initial expectations, being from a region other than Prishtina (the base category) increases an individual's probability to be unemployed and decreases the probability to be employed (formally and informally). An individual's probability to be unemployed increases by 11.6 pp for individuals living in Gjilan, 12.9 pp for Ferizaj, by 16.4 for Peja, 17.7 pp for Gjakova, 22.8 for Prizren and 38.5 pp for Mitrovica in comparison to an individual living in Prishtina. With regard to the formal employment, being from Gjakova, Mitrovica and Prizren decreases the average probability to be formally employed, other things being equal. With regard to the informal employment, being from a region other than Prishtina, holding other variables constant, decreases an individual's probability of being informally employed.

5.5.2 Results from the Inverse Probability Weighting - Regression Adjustment

As explained in section 5.2, individual selection into different active programmes is not randomised. Selection is a general issue in a non-random sample such as the one being used in this empirical analysis. The selection of the participants into programmes was based on a set of pre-determined criteria such as age, individuals' unemployment spells, gender, the level of education etc. As emphasised by Winship (1992, p. 328) "*when observations are selected so that they are not independent of the outcome variables in the study, this sample selection leads to biased inferences about the processes*". This empirical analysis attempts to address the selection issue based on the observable factors. This estimation accounts for the type of the active programme that the individual participated in, the year of participation and the duration of the active programme participated and a set of individual characteristics. Certain unobserved factors might also influence the treatment model, hence a set of variables which may help to capture these unobserved effects are also included in the model.

Firms did not have any influence on selecting participants into programmes, but were allowed to choose the active measure in which they participated; hence the probability of selection bias arising from firms' actions is very small. The issue of selection bias can be diminished through imposing the assumptions discussed in section 4.3.2; i.e. the conditional independence assumption (CIA) which is also referred to as the un-confoundedness or selection on observables and the common support or the overlapping assumption. Explained in more details below, all the available relevant variables to control for selection into programmes are included in the selection model which makes the CIA a reasonable identification strategy in this context.

As explained in section 4.3.4, IPWRA models the treatment assignment and the outcome variable in the same estimator (Robins et al., 1995; Robins 2000; Bang and Robins 2005). This estimator has a doubly robustness property because it provides unbiased estimates even if one of the models (treatment or outcome) is mis-specified (Emsley et al., 2008; Wooldridge, 2009; Farell, 2015; Linden et al., 2016). If the outcome model functions are correctly specified and selection-on-observables (CIA) holds conditional on independent covariates, then the weighted estimators using any function of independent variables consistently estimate the coefficients on the control and treated sample. Therefore, even if the propensity score estimation is mis-specified, weighting by functions of propensity score does not cause inconsistency for estimating the parameters of the correctly specified outcome model (Wooldridge, 2009). The IPW estimator weights observations on the outcome variable by the inverse of the probability that is observed to account for the counterfactual. When the propensity score model is correctly specified, the IPW estimator (under selection-on-observables assumption) consistently estimates the solution to the unweighted population problem. In this case, even if the outcome model is mis-specified but the propensity model is specified correctly, IPWRA produces consistent estimates.

IPWRA is operationalised in a three-step process. First, the parameters of the propensity score model are estimated by multinomial logit modelling and the inverse weights are computed for each treatment level. Inverse probability weights are derived from the predicted propensity scores, where these are defined by the inverse of the propensity score if the individual receives treatment and the inverse of 1 minus the propensity score if the individual receives the control. Second, using the estimated weights, the outcome models are fitted by a weighted regression for each treatment level. Using the coefficients from this weighted regression, treatment specific predicted outcomes for each individual are obtained. The final step is to produce the average treatment effects on the treated which is the difference in the means of the specific treatment and control outcomes.

As discussed in Chapter 4, a crucial assumption, the conditional independence assumption[46], cannot be tested, thus it is required to include all the presumed important variables which affect both the outcome and treatment. Section 4.3.2 provides an extended discussion of the relevant variables to account in the treatment model. Emsley et al. (2008) recommend that the treatment model should include variables even if they are thought not to be confounders since it helps to improve the prediction of the propensity scores and lowers the bias. The availability of informative data is therefore crucial. Based on the selection process of individuals into active measures explained in section 5.2, the treatment model controls for all the likely important factors in the selection process, such as age, level of education, socio-demographic factors and regional variables. Section 4.3.2, explained the importance of including the past labour market histories since these variables may capture unobservable selection factors such as motivation and interpersonal skills. Assuming that the individuals' pre-treatment labour market histories might capture these unobservable effects, variables measuring an individuals' pre-treatment unemployment duration (*Undur6, Undur12 and Undur24*; *Undurmore24* is the reference variable) and pre-treatment job search activity (*Jobserachbt*) are included in the treatment model. In addition, the administrative staff may select participant with better prospects for getting employed after the completion of the training so as

[46] This assumption denotes that the unobserved characteristics are trivial and do not particularly affect the outcome in absence of the treatment; thus there are sufficient observable data such that the outcomes or the treatment effects are independent from the programme participation.

to improve the success rate of the active measures. Also, given that in Kosovo nepotism is common, the selection into programmes might have also been influenced by it. Besides the pre-treatment unemployment duration, the variable *Emplan* is included in the treatment model. This variable is used as a proxy for unobserved characteristics (individual's motivation and labour market skills) and might also be a signal of the closeness between the VTC administrator and the beneficiary. As pointed out in section 5.4, *Emplan* is also used as a proxy for the quality of employment and VTC services. Additionally, the variable *Vtcmncp* is included in the model which controls whether the individual lives in the city where the vocational training centres are located. This variable is a proxy for individual's proximity to the vocational training centre. Economic theory suggests that living closer to the vocational centre reduces the costs of attending and therefore, other things being equal, makes it more likely that the discounted expected benefits of attending the treatment exceed the expected costs (Heckman et al., 1999). Providing that there is a large number of variables accounted in the treatment model, it can be concluded that the CIA is a reasonable identification strategy in the context of this chapter. It has been suggested that the correct specification of the treatment model will increase the precision of the doubly robust estimators; therefore, we put particular emphasis on the treatment model and balancing the covariates in the treatment and control groups. The dependent variable of the treatment model is a three-category dummy variable which takes the value of 1 if the individual participated in OJT, 2 if the individual participated in IS and 3 if the individual participated in IET. The covariates chosen for propensity score estimation are as follows:

$$\begin{aligned} &Multitreatment = f(AM2008, AM2009, Emplan, Male, Age, Agesq, Minority,\\ &Disability, Secondaryeduc, Tertiaryeduc, Twounemp, Remittance, Socialassist,\\ &Undur6, Undur12, Undur24, Jobsearchbt, Vtcmncp, Fer, Mit, Gjil, Gjak, Pej, Prz) \end{aligned} \tag{5.4}$$

The best fitting treatment model is determined by the Akaike Information Criteria (AIC) using 'bfit' command in Stata (Burnham and Anderson, 2004).[47] This command generates a series of candidate multinomial logit models by maximum likelihood. These models range from a model including only the first independent

[47] Both Akaike and Bayesian Information Criteria (BIC) were considered, however considering the number of observations, AIC is used since it does not depend on the sample size (Burnham and Anderson, 2004).

variable specified in the model as a single covariate to a model including a fully interacted polynomial of the specified order. The sorted treatment model based on AIC is considered to be the best fit model and is chosen for the analysis below.

As an essential objective of the IPWRA is to balance the observable characteristics between treated and control subjects. A balancing diagnostic check has been performed to find out whether the treatment model specification has balanced the covariates or whether there is a difference in the distributions of the covariates. The diagnostics used to verify the balance of the covariates are based on the standardised differences in means and ratio of variances before and after weighting of the propensity scores for each covariate. Rubin (2001) suggest that the threshold for the standardised difference in means should be 0.25. This diagnostic test is used to verify the balance for weighted propensity scores for the three outcome models *Emp*, *Actsrcat* and *Contract*. Since the sample is restricted to account only for the unemployed and employed respectively for *Actsrcat* and *Contract*, the covariate balance should be tested separately for each model.

Figures 5.3, 5.4 and 5.5 show the non-parametric kernel density estimation with a triangular kernel and optimal bandwidth chosen by Stata for the propensity scores for each treatment for the whole sample. Table 5.7 presents the weighted standardised differences for these models.

Figure 5.3 Overlap graph of the probability assignment to the OJT programme

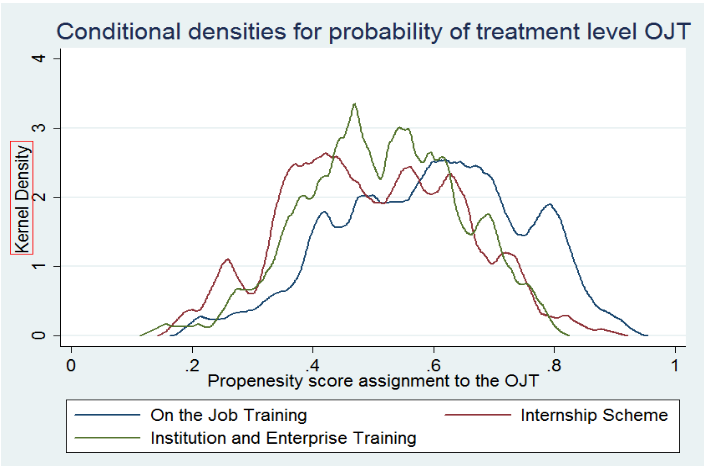


Figure 5.4 Overlap graph of the probability assignment to the IS programme

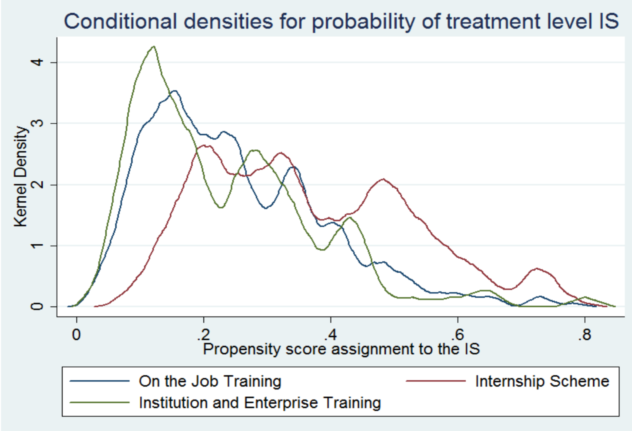
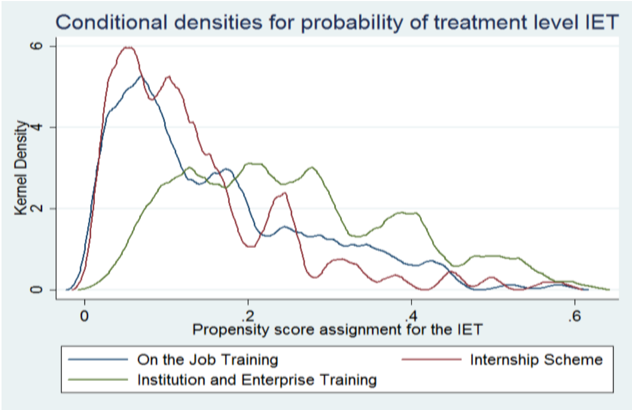


Figure 5.5 Overlap graph of the probability of assignment to the IET programme



For each treatment level, the overlap plots depict the estimated density of the predicted propensity scores for that specific treatment level conditional on other possible treatment level. IPWRA requires that the predicted propensity scores not to be bigger than one or smaller than zero and '*sufficient*' (undefined) propensity scores to be between this range. The three estimated Kernel density plots show that there is enough overlap and the estimated densities cover most of their respective masses. Therefore, there is no evidence that the overlap assumption (common support) is violated. However, this is the case only when the whole sample is accounted, thus only for *Emp* outcome. In the cases of the *Actsrcat* and *Contract* outcome models the sample is restricted to unemployed or employed individuals, respectively. The sample is reduced to 385 for *Actsrcat* and 284 for *Contract*. With the restriction of the sample the weighted propensity scores tend to be less balanced. Nine of the weighted standardised mean differences for *Actsrcat* and twelve for *Contract* are above the 0.25 cut-off recommended by Rubin (2001), thus the results for these two outcomes should be interpreted with caution (the imbalanced means are highlighted in table 5.7).

Table 5.7 Weighted characteristics of three different programme participants in the multivalued treatment model.

	Weighted Standardised Differences								
Outcome Variable	*Emp*			*Actsrcat*			*Contract*		
Sample size	775			385			284		
Variables	IS vs. OJT	IET vs. OJT	IET vs. IS	IS vs. OJT	IET vs. OJT	IET vs. IS	IS vs. OJT	IET vs. OJT	IET vs. IS
AM2008	-0.102	-0.027	0.079	-0.138	-0.224	0.218	-0.070	-0.366	-0.227
AM2009	0.000	-0.231	-0.211	-0.129	-0.296	-0.393	0.008	-0.025	0.270
Emplan	-0.067	0.118	0.101	-0.142	0.064	0.193	-0.057	0.157	-0.205
Age	-0.002	-0.014	0.117	-0.118	-0.182	0.146	0.071	0.019	-0.155
Male	0.047	0.239	0.074	0.067	0.187	0.207	-0.040	0.116	-0.106
Disability	0.026	0.087	0.069	0.019	0.041	0.027			
Minority	0.014	0.097	0.124	0.028	0.040	0.228	0.113	0.036	-0.088
Socialassist	-0.037	0.149	0.034	-0.115	-0.043	-0.312	0.029	-0.426	-0.367
Twounempl	-0.032	0.062	0.033	0.044	-0.029	0.054	-0.125	-0.282	-0.356
Remittance	0.003	-0.031	-0.051	0.022	0.268	0.213	0.003	-0.154	-0.217
Secondaryeduc	0.074	0.230	0.150	0.073	0.147	0.002	0.008	0.153	0.031
Tertiaryeduc	-0.029	-0.202	-0.153	-0.017	-0.128	-0.202	-0.030	-0.151	0.068
Jobserachbt	0.048	0.172	0.309	0.171	0.392	0.648	-0.038	0.423	0.561
Undur6	0.020	-0.011	0.033	0.018	0.063	-0.074	0.034	0.002	0.204
Undur12	0.027	-0.079	0.005	-0.010	-0.038	-0.249	0.113	0.084	0.176
Undur24	0.083	0.180	0.203	0.103	0.276	0.227	0.079	0.615	0.402
Vtcmncp	-0.042	-0.160	-0.057	-0.050	-0.058	0.156	0.034	0.190	-0.056
Fer	0.029	-0.142	0.010	0.170	-0.019	0.159	0.001	-0.103	-0.157
Gjak	0.091	0.038	-0.018	0.062	-0.083	-0.083	0.056	-0.025	-0.272
Gjil	-0.046	0.199	0.021	-0.028	0.274	-0.141	-0.076	0.131	0.024
Mit	-0.018	-0.187	-0.147	-0.205	-0.361	-0.260	0.149	-0.460	-0.344
Pej	0.013	0.138	-0.085	0.188	0.350	-0.046	-0.032	-0.163	-0.062
Prz	-0.036	-0.037	0.035	0.018	0.075	0.180	-0.104	0.017	0.419

The employment outcome model is specified as described in section 5.4.1. The same approach is followed for the *Actsrcat* outcome model. However, due to a loss of observations the regression model is specified differently for the *Contract* model. In the third outcome model, whether the employed individuals had an employment contract, variable *Disability* and the set of unemployment duration dummies (*Undur6, Undur12* and *Undur24*) are excluded from the model. In addition, the outcome model also excludes the following variables: *Socialassistt*, *Remittance* and *Twounemp*, since there is little variation in these variables for *Contract* model. Since the sample size shrinks to only 284 observations, the outcome model for *Contract* could not converge with these variables included in the model. As the multivariate treatment model has only recently started to be used, there is no discussion in the literature of the choice of diagnostics to account for in such cases, thus we follow the same approaches as in the binary treatment models (e.g. Austin, 2011).

The final results from IPWRA approach are presented in table 5.8 and Appendix 5.3, 5.4 and 5.5. In order to analyse all possible comparisons, (i.e. *OJT* vs. *IET, OJT* vs. *IS* and *IET* vs. *IS*), two control groups were considered; the first control group is those who completed OJT and the second those who completed IS.

Table 5.8 Average treatment effects on treated (ATT) and Potential Outcome Means (POM) for three outcome variables *Emp, Actsrcat* and *Contract*

	Variables	***Emp***		***Actsrcat***		***Contract***	
	No. of obs.	775		385		284	
		Average Treatment on Treated	Potential Outcome Mean	Average Treatment on Treated	Potential Outcome Mean	Average Treatment on Treated	Potential Outcome Mean
Control group: OJT	**IS vs. OJT**	-0.055 (0.043)		0.192*** (0.0642)		0.059 (0.060)	
	IET vs. OJT	-0.187*** (0.051)		0.105 (0.0690)		0.189*** (0.071)	
	OJT		0.432*** (0.033)		0.647*** (0.0542)		0.717*** (0.051)
Control group: IS	**OJT vs. IS**	0.013 (0.049)		-0.192*** (0.0416)		-0.104** (0.052)	
	IET vs. IS	-0.162*** (0.055)		-0.0887** (0.0388)		0.073 (0.062)	
	IS		0.422*** (0.045)		0.864*** (0.0262)		0.799*** (0.043)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Model specifications for outcome *Emp, Actsrcat* and *Contract,* are based on the specification in section 5.4, In order to gain more degrees of freedom, instead of using regional dummy variables, the variable measuring the regional unemployment rate, *Regunemp* is included in the outcome model. In specification of *Contract* model, due to small sample size few variables were dropped from the outcome model, *Twounemp*, *Disability*, *Socialassist and Remittance* and variables measuring the individual's unemployment duration, *Undur6*, *Undur12* and *Undur24.* Because it is crucial to attempt addressing the selection bias, the treatment model includes all the variables specified in equation 5.4, except for variable *Disability* for *Contract* model. The complete results of the three outcome models are provided in Appendix 5.3 to 5.5.

OJT as the control group: There seems to be no significant difference in the probability of being employed between participants of the IS and OJT programme. On the other hand, participating in the IET programme leads to a reduced probability to be employed, 18.7 pp lower from the average of OJT participants. Participating in an IS programme leads to a 19.2 pp higher probability of an unemployed participant being engaged in active job search at the time surveyed compared to the average of participants in OJT. Results also indicate that IET employed have an 18.9 pp higher probability of having an employment contract from the average probability of OJT employed.

IS as the control group: In case when IS was defined as the control group, the results suggest that participating in IET decreases an individual's probability of being employed by 16.2 pp compared to the average probability of being employed of IS participants. Participants in the IET programme who were unemployed at the time surveyed are also less likely to be engaged in active job search by 8.8 pp compared to the average job search probability of IS participants. OJT unemployed have a 19.2 pp lower probability to actively search for jobs compared to the average job search probability of IS participants. According to the findings, employed OJT participants are 10.4 pp less likely to have an employment contract compared to the average probability of having a contract of IS participants. As discussed, the model specification was modified and some variables were omitted due to issues with non-convergence thus this last result should be interpreted with caution.

In conclusion, these findings suggest a highly significant difference in the probability of being employed between OJT and IET participants. OJT participants are more likely to be employed, other factors being equal, compared to the IET participants. There seems to be no difference between OJT and IS on the probability of being employed at the time surveyed. When comparing the IET and IS programmes, the findings provide evidence suggesting that IET beneficiaries, other things being equal, had a lower probability of being employed compared to their IS counterparts. With regard to the job search activity at the time of the survey, the findings indicate that unemployed OJT are less likely to search for jobs, other factors being equal, than their IS counterparts. Furthermore, IET unemployed beneficiaries are less likely to search for jobs, other things being equal, compared to IS unemployed beneficiaries. Other factors being equal, an employed OJT participant is less likely to have an employment contract then an employed IET. For employed individuals in the sample, the difference in probability of having an employment contract is insignificant when comparing OJT and IS beneficiaries.

5.6 Conclusions

This empirical chapter used a cross-sectional dataset collected through a survey in 2012 to evaluate three different active measures, OJT, IS and IET, implemented in Kosovo from 2008 to 2010. This chapter utilised two methodologies. The first one is the multinomial probit model to evaluate the effectiveness of these policies and their characteristics such as the duration of the ALMPs, the year of completion, having received a certificate of completion and having prepared an employment/training plan. As argued in this chapter, the non-random data might be subject to selection bias, hence a second empirical approach, IPWRA was chosen since it attempts to address this issue based on observable factors.

The results from the IPWRA suggest that participating in OJT and IS increases the probability of being employed compared to participating in IET. The results are in line with those from the multinomial probit where both OJT and IS are found to reduce beneficiaries' probability of being unemployed. Beneficiaries of OJT, however, are also more likely to be employed in the informal sector compared to beneficiaries of IS and IET; this is also in line with the findings from multinomial probit which suggest that OJT beneficiaries are more likely to be employed in the informal sector. With regard to the characteristics of the active measures, the results from multinomial probit suggest that the longer the duration of the active measure the beneficiary is more likely to be employed in the informal sector. The impact of the active measures seems to diminish during the years of implementation; i.e. those who participated in 2008 and 2009 were less likely to be unemployed and more likely to be employed in the formal sector compared to those who participated in 2010. As discussed above, this may mean that the effect of the ALMPs is more pronounced in the long-term rather than shorter-term. Alternative explanations include changes in aggregate labour market conditions and/or changes in the actual or perceived quality of the active measures implemented in specific years. The findings from multinomial probit suggest that receiving a certificate also improves beneficiaries' probability of being employed in the formal sector and reduces the probability of being employed in the informal sector. On the other hand, having an employment/training plan before training had no impact on being employed in either formal or informal sector which puts in question the quality of these plans.

Given that the ALMPs in Kosovo are on a small scale, it is important not only to evaluate the effectiveness of participating in one of the measures relative to one another but rather to compare the outcomes of those who participate with those who do not. This would provide a clearer picture of the effectiveness of ALMPs in achieving their main objective, increasing employment prospects of the treated compared to that of the untreated. The analysis presented in the following chapter provides such a comparison.

Chapter 6

The overall effectiveness of ALMPs in Kosovo

6.1 Introduction

Chapter 5 empirically investigated the relative effectiveness of three active labour market measures implemented in Kosovo: On the Job Training (OJT); Internship Scheme (IS) and Institution and Enterprise Training (IET). That analysis used two different estimation techniques: Multinomial Probit and Inverse Probability Weighting – Regression Adjustment (IPWRA). This investigation came to the conclusion that participants in both OJT and IS had a higher probability, post-treatment, of being employed compared to their IET counterparts. On the other hand, employed IET participants were more likely to have an employment contract compared to participants in OJT, i.e. they were more likely to be employed in the formal sector. The empirical investigation in this chapter will extend the analysis of chapter 5 by assessing the overall effectiveness of the three policies compared to being a non-participant.

As elaborated in chapter 4, when using observational data ideally the control group data should be derived from the same data source. In the absence of a control group from the same source, the empirical analysis presented in this chapter will construct a control group acquired from the Labour Force Survey (LFS) for Kosovo for 2012, the same year as the UNDP data used in chapter 5. The estimation techniques used for this empirical investigation are Propensity Score Matching (PSM) and Inverse Probability Weighting – Regression Adjustment (IPWRA). Both estimation techniques attempt to address the potential selection bias. As discussed in chapter 4, while PSM uses only binary treatment assignment model, IPWRA allows us to extend treatment assignment from the 'participant vs. non-participant' analysis of PSM to a multivalued treatment assignment model while utilising an appropriate set of covariates which are available for both the treated and control groups. The combination of the two estimation techniques sheds light on the importance of multivalued treatment model and assessing the effectiveness of each active measure in comparison to the control group. Therefore the aim of this chapter is to further investigate whether being a participant in one of the three active measures improves the likelihood of gaining employment in general and being engaged in the formal labour market in particular compared to being a non-participant.

This chapter is organised as follows: section 6.2 provides the details on the construction of the control group, section 6.3 discusses the specification for both the treatment assignment and outcome models while section 6.4 provides descriptive statistics for the treated and control groups and presents the results from the PSM and IPWRA estimations. Section 6.5 provides a summary of conclusive remarks.

6.2 Construction of the Control Group

A key concern in any evaluation of the effectiveness of ALMPs is the construction of an appropriate control group based on the selection process that leads the unemployed to participate in the programme. Section 5.2 provides a detailed description of the three active measures in Kosovo along with the selection criteria specified for each of the measures, their duration and descriptive statistics of participants. In many studies evaluating programme effectiveness and also in the case of this analysis, the choice of the control group is constrained by data availability. This section will compare the LFS questionnaire used to construct the control group with the questionnaire from UNDP used to construct the dataset for participants in the active measures implemented in Kosovo and will assess the suitability of the control group for this evaluation.

Heckman et al. (1999) pointed out the desirability of deriving both the treated and control groups from the same data source. Using two different datasets for the treated and control might induce measurement differences due to the possibility of different definitions and instrumentations of the same outcome variable and covariates. This may add an important potential source of bias to the impact estimates reported for an active programme (Smith, 1997). In the case where a survey from a different source is used to construct the control group, it is important to ensure that the questions for the treatment groups closely match those for the control group. According to Card et al. (2011), even minor differences in question phrasing can lead to a quantitative difference in the measured outcomes. Hence, identical wording is desirable when constructing the dataset. This section identifies these differences and assesses how they can be mitigated. Table 6.1 presents the key differences in the questions in the two surveys which will be discussed in more detail here.

Questions about the labour market status of respondents are more detailed and precise in the LFS dataset compared to those in the UNDP data. The variable ***employed*** is constructed from the first questions presented in table 6.1. If an individual responded to options 3 to 6 in UNDP data and 1 to 5 in LFS data, the variable ***emp*** takes the value of one while if he/she responded to option 1 in UNDP survey and option 6 in LFS then the variable takes the value of zero. Those who responded as inactive in the UNDP data are excluded from the sample. From the LFS question '*Why did you not work last week?*', those who responded that they were in school, education or training, maternity leave, had illness or temporary disability, personal or family responsibilities are considered inactive and hence were also excluded from the sample.

From table 6.1, one can see that the questions measuring the variable *contract* are quite similar. The constructed variable *contract* is a dummy variable which takes the value of one if an employed individual responded that he/she has an employment contract in the UNDP survey. In the LFS data, the variable takes a value of one if the answer was options 1 to 4 to the question '*What kind of contract do you have?.* The variable *contract* takes a value of zero if an individual responded to options 2 and 5 in the respective surveys.

The variable measuring social assistance, *socialassist* is constructed from the question in the UNDP questionnaire: '*Does your family receive any kind of assistance (social assistance, assistance for disability, pension etc.)?*' while in the LFS questionnaire the question is '*Do you receive unemployment benefits?*'. In Kosovo, although there are no unemployment benefits per se, the eligibility criteria for social assistance are related to unemployment: families must fall within one of the following two categories: a) all family members are dependants[48] and b) there is a family member able to work (registered as unemployed) and there is at least one child under the age of five and/or an orphan under the age of fifteen. Thus, considering the criteria for social assistance in Kosovo, for practical purposes, the two indicators can be used interchangeably. Therefore, the variable *socialassist* takes

[48] Persons with disabilities rendering them unable to work for remuneration, persons who are sixty-five years of age or older, full-time carers of a person with disability, single parents with at least one child under the age of five etc.

the value of one if the respondent's household receives social assistance/unemployment benefits and zero otherwise.

Table 6.1 Differences of variable definition in the two datasets

Question in UNDP survey	Question in LFS	Variables constructed
Employment Today, you are: 1) Unemployed 2) Inactive (in school, training, student, engaged in family responsibilities) 3) Self-employed 4) Employed in a public agency (central or local) 5) Employed in a public enterprise 6) Employed in a private enterprise	**Employment** During last week, you have: 1) worked in a regular job (at least one hour) for pay (in cash or kind) 2) worked (at least one hour) in the non-agricultural sector 3) done any occasional job (at least one hour) for pay or profit 4) worked (at least one hour) on a farm (if at least part of the production is intended to be sold or bartered) 5) worked (at least one hour) on a farm (if the whole production is only for own consumption) 6) none of the above	**Variable *employed*** UNDP survey: The variable ***employed*** equals one for options 3, 4, 5, and 6, zero otherwise. LFS: The variable ***employed*** equals one for choices 1, 2, 3, 4, and 5, zero for option 6. Inactive respondents are excluded from the sample.
Contract (only for employed) Do you have employment contract? 1) Yes 2) No	**Contract (only for employed)** What kind of contract do you have? 1) Individual 2) Group 3) Collective with syndicate 4) Collective with employer 5) Without contract	**Variable *contract*** UNDP survey: The variable ***contract*** equals one for choice 1, zero for option 2. LFS: The variable ***contract*** equals one for options 1, 2, 3 and 4, zero for choice 6.
Received social assistance Does your family receive any kind of assistance (social assistance, assistance for disability, pension etc.)? 1) Yes 2) No	**Received social assistance** Do you receive unemployment benefits? 1) Yes 2) No	**Variable *socialassist*** UNDP survey: The variable ***socialassist*** equals one for option 1, zero for option 2. LFS: The variable ***socialassist*** equals one for option 1, zero for option 2.
Employment History Variable ***emp2011*** How many jobs did you have in 2011? Variable ***emphist*** Constructed from the following questions: - How many jobs did you have in 2008? - How many jobs did you have in 2009? - How many jobs did you have in 2010? - How many jobs did you have in 2011?	**Employment History** Variable ***emp2011*** What was your main activity status one year ago? 1) Carrying out a job, including unpaid work for family business or farm, including an apprenticeship or paid traineeship etc. 2) Unemployed 3) Pupil, student, in further training etc. 4) In retirement or early retirement 5) Permanently disabled 6) Fulfilling domestic tasks 7) Other inactive person Variable ***emphist*** Have you ever been in a regular employment before? (job as employee, self-employed, unpaid family member; purely occasional jobs or work during vacations should not be considered as previous work experience) 1) Yes 2) No	Variable ***emp2011*** UNDP survey: The variable ***emp2011*** equals one if the respondent was employed in 2011, zero otherwise. LFS: The variable ***emp2011*** equals one for option 1, zero otherwise. Variable ***emphist*** UNDP survey: The variable ***emphist*** equals one if the respondent has been employed at least once during period 2008-2011, zero otherwise. LFS: The variable ***emphist*** equals one for option 1 and if the respondent has been employed in 2011, zero otherwise.

Additionally, when constructing the dataset for programme evaluation, it is important to acquire information about the pre-treatment employment status variable in order to capture whether the two groups followed a similar outcome path prior to treatment. The design of the evaluation would be threatened if this is not the case, since there is no assurance that the employment path of the two groups would remain constant except for the impact of the treatment. Therefore, in order to generate a credible programme evaluation, it is necessary to find a control group for which the information on their employment status for several periods prior to joining the programme is available (typically at least a year and ideally a longer period) (Heckman et al., 1999; Card et al., 2011).

As discussed in section 4.4.1, the labour market history of the pre-treatment period has frequently been found to be a good proxy for an individual's motivation to find employment, their labour market attachment, interpersonal skills and employers' preference towards certain workers which might affect programme participation. In an attempt to capture these unobserved characteristics, two different variables are created. As Emsley et al. (2008) suggest, the treatment model should account for as many characteristics as possible, even if these factors are not strictly related to the treatment selection, in order to improve the prediction of the propensity scores and as such to lower the bias.

Considering the relevance of labour market history variables, we constructed two different variables which measure the employment history of the respondents in the sample. If an individual from the UNDP dataset claimed that he/she had at least one job during 2011 the variable *emp2011* takes value of one and takes the value of zero if he/she had no job at all during the same year. While if an individual in the LFS dataset responded that he/she was carrying out a job, including unpaid work for family business or farm etc. then the variable *emp2011* takes value of one, otherwise it takes a value of zero.

Also, to construct an additional variable, *emphist***,** the combined responses to the following questions in UNDP survey were used: '*How many jobs did you have in 2011?... in 2010?... in 2009? …in 2008?'*. If respondent was employed at least once during this period, variable *emphist* takes value of one while it takes value of zero if he/she was unemployed during the whole period. Considering the high long-term unemployment rate in Kosovo, one might argue that if a person was unemployed for the whole period 2008 to 2011 it is highly unlikely that this person was ever employed. Additionally, because the mean age of the sample of participants is about 26 and that of the control is about 29, a large group of young individuals might have not even been economically active 5 years prior to the survey, therefore, treating these individuals as unemployed for the whole period prior to the survey is a reasonable assumption in this case. To construct this variable for the control group from the LFS survey the combined responses to two questions were used. The first question, which was addressed only to the unemployed at the time of the survey in 2012, is: '*Have you ever been in a regular employment before?*'. If a respondent was in regular employment before, the variable *emphist* takes a value of one, otherwise the variable takes a value of zero. Since the first question does not collect information from those who were employed at the time of the survey, the second question used is the same one used to create the variable *emp2011* which is answered also by those who were employed at the time of the survey. Bearing in mind that six questions are used to create the variable *emphist*, it is clear that there are measurement differences, hence this variable is used only in the first specification and the results are interpreted with caution.

It should also be acknowledged that the LFS questionnaire does not have a question as to whether the individual surveyed has participated in any active labour market measure. Thus the estimation might induce contamination bias as some members of the control group are likely to have been participants of treatment being evaluated (Heckman et al. 1999). However, there is no clear suggestion from the studies that discussed evaluation methodology on how to proceed in such case. As chapter 1 explained, the number of people that participated in active measures from 2005 to 2012 was just 11,154. The argument for using LFS despite missing information about ALMP participation is that the number of participants in Kosovo is very small compared to more than one 1 million working age population, which is just 0.9 percent of total working age population (or compared to more than 400 thousand people actively seeking work in 2012) (KAS, 2012) making this source of bias negligible.

After considering all the measurement differences in the two surveys, the following section will discuss the model specification for the treatment and outcome models. Section 6.4 will present and discuss the empirical findings from the evaluation methodology.

6.3 Model Specification

This chapter assesses the overall effectiveness of the three active programmes described in chapter 5. Following the discussion in section 4.3.2, one of the most important points in evaluation methodology is the selection of relevant covariates for the treatment assignment model specification. Empirical studies using evaluation methodology suggest using a rich set of variables that affect treatment assignment. The potential set of variables include baseline covariates which are not influenced or modified by treatment, such as age and gender, while another set of variables include those that are related to the selection criteria for the treatment assignment. Section 5.2 provides a more detailed discussion of the selection of individuals into different active measures. This discussion suggests that the participants are not randomly selected into these programmes which might lead to a potential selection bias. As explained in section 4.3.2, controlling for all the relevant variables that affect the selection into these active programmes makes the conditional independence assumption (CIA)[49] a reasonable identification strategy. The second assumption of the evaluation methods "*require that all characteristic values appearing in the treatment group also appear in the control group*" (Schmidl, 2014, p. 137)[50]. Considering both assumptions, the choice of variables to be accounted for in both the treatment and outcome models will be restricted to those variables that are defined (measured) similarly in both the LFS and UNDP datasets.

In order to satisfy the CIA and considering the selection criteria of participants into the programmes, the treatment assignment model accounts for the main relevant factors in the selection process. Since active programmes under consideration for this analysis are targeted at the young unemployed, the variable age is accounted for in

[49] Also referred to as the un-confoundedness or selection on observables, CIA assumes that there are sufficient observable data such that the outcome or the treatment effects are independent from the programme participation. Under this assumption, it is assumed that the unobserved characteristics are trivial and will not affect the outcome in absence of the treatment.
[50] This is the assumption of common support or overlapping of the covariates of the participants and non-participants. See section 4.3.2 for more details.

the treatment model. The descriptive statistics of UNDP data in section 5.3 show that the age criterion was not strictly respected and sometimes participants in ALMPs were older than 35 in order to increase the number of women or ethnic minorities. Taking this into account, both samples are restricted to include individuals of working age who are younger than 40 years of age. The treatment model also accounts for gender because it was one of the criteria to select the more disadvantaged unemployed in the labour market. Individuals receiving social assistance and ethnic minorities were also targeted by these programmes considering their disadvantage in the labour market. Additionally, an important factor in the selection process of these programmes is the education level of participants. The OJT programme targeted those unemployed who have completed vocational education, the IET targeted those who had not had a chance to start or complete vocational education while the IS targeted those who had recently graduated from university and had no work experience. To account for the education level, two dummy variables are included in the model, *secondaryeduc* (equals one if individual completed secondary education, zero otherwise) and *tertiaryeduc* (equals one if individual completed tertiary education, zero otherwise) while *primaryeduc* (equals one if individual completed primary education, zero otherwise) is the benchmark category. As suggested by many studies, individuals' labour market history is also included in the treatment model since it might capture some unobserved characteristics such as motivation, skills and employers' preferences towards workers with certain characteristics (Heckman et al., 1999; Emsley et al., 2008; Kluve et al., 2008; Schmidl, 2014). Variables *emp2011* (equals one if individual was employed in 2011, zero otherwise) and *emphist (*equals one if individual was employed at least once during the period 2008 to 2011, zero otherwise) are included in the treatment model in an attempt to capture these unobserved effects. A variable measuring the family size, *hhsize*, is included in the treatment model since it is expected that individuals with larger families are more likely to participate in a treatment considering that they might feel more pressured to find employment. An interaction between the variable measuring household size and gender is also included in the model because it is expected that women are less likely to participate in the labour market and in training if the size of their families are large due to caring responsibilities.

Studies have also emphasised the importance of accounting for regional differences since, as explained in section 4.4.1, they capture the local aspects of programme implementation, local policies, infrastructure etc. which influence an individual's decision whether to apply for active programmes. The regional dummy variables, or a variable accounting for regional unemployment, are included in the treatment model, depending on the size of the sample of the outcome models. Since this empirical analysis uses two different outcome models, *employed* and *contract* (discussed in detail below), the sample for the latter outcome model will be restricted to account only for those who are employed. Due to this smaller sample for *contract* model, instead of using regional dummies, regional unemployment rates are included to gain more degrees of freedom and improve the balancing of covariates between the two groups.

Similar to the analysis presented in chapter 5, the variable *vtcmncp* (equals one if individual lives in the city where the vocational training centre (VTC) is located) was considered to be included in model to account for individuals' proximity to the vocational training centres. According to Heckman et al., (1999) living closer to VTCs reduces commuting costs and other costs related to attending the active programmes in the training centres. However, this variable could not be constructed for both the treated and control datasets. In section 5.5.2 it is emphasized that firms did not have any particular influence on the selection of participants into programmes, hence it is considered that the selection bias arising from firms' preferences is negligible in the context of this analysis. A relevant factor in determining an individual's programme participation and labour market status is nepotism which is considered to be widespread in Kosovo (Corbanese and Rosas, 2007). The prevailing culture of nepotism in Kosovo might have increased distorted selection into the treatment programmes, however no relevant proxy is available in either survey.

Interpersonal skills (which might also capture some unobservable characteristics) and an individual's health might also be relevant in determining programme participation and employment outcome. Neither of the questionnaires provides any information about these factors. However, these effects might be captured by variables measuring the individuals' employment history, *emp2011* and *emphist*. Also, some studies point out the importance of accounting for the influence of the behaviour of administrative staff in the employment offices in selecting participants into active programmes (see chapter 4). This might capture the closeness of the unemployed worker to the employment office and their persistence and motivation to remain in the labour market. Considering that the main relevant factors are included in the treatment model and assuming that the impact of the variables excluded is minimal, then one can assume that CIA is satisfied in the context of this empirical analysis.

Two dependent variables are used in the treatment model. The first one is a binary variable which equals 1 if an individual participated in one of the three active measures and 0 otherwise. The second is the multivalued variable with four categories which equals 0 if an individual is in the control group, equals 1 if he/she participated in OJT, equals 2 if he/she participated in IS and equals 3 if he/she participated in IET. The model specification for treatment selection is provided in the equation below:

$$Treatment = f(Age, Agesq, Gender, Socialassist, Minority, Secondaryeduc, Tertiaryeduc, Emp2011, Emphist, Hhsize, Hhsizegen, Region; Regunemp\ ) \quad 6.1$$

As discussed in section 4.3.4, IPWRA has a double robust property and even if one of the models (treatment or outcome) is mis-specified, this estimator will produce consistent estimates (Wooldridge, 2009; Emsley et al., 2014). This technique will use the following three steps to generate the average treatment effects on the treated. The first step is to estimate the parameters of the treatment model and compute inverse-probability weights using a multinomial logit model. Using these estimated weights, this technique will fit weighted regression models of the outcome for each treatment level and will predict treatment specific outcomes for each individual. The third step is the computation of the means of treatment predicted outcomes and the differences in the means of the treatment effects.

Model specification for Outcome models – Employment and Employment Contract

To estimate the overall effectiveness of the active measures, two outcome variables are used.

- Employment (*employed*): equals one if the individual was employed at the time of the survey, zero otherwise;
- Employment contract (*contract*): equals one if the employed individual had a signed employment contract at the time of the survey, zero otherwise.

The following subsection provides the model specification for each of the outcome models. Variable description and definitions are presented in table 6.2.

The variables age and its square term (*age* and *agesq*) are included in the model to account for a possible non-linear relationship between age and employment. Theoretically, age variables tend to capture the experience effect on employment probability suggesting that the probability of being employed increases with age, reaches a peak and starts to drop after that point. There are empirical studies that found evidence that youths are faced with higher levels of economic and social uncertainty and hence face a lower likelihood of finding a job, however their employment prospects increase with age (Russel and O'Connell, 2001; Bell and Blanchflower, 2015). As discussed in section 5.4, in Kosovo age might not reflect the experience considering very high levels of general and long-term unemployment. Disadvantaged groups in the labour market are more likely to accept low quality jobs, particularly jobs in the informal market. The expectation is that, other factors remaining constant, the probability of having an employment contract for a young person is low but increases with age. As explained in section 2.5.1, youths in transition economies, especially in Kosovo, usually transit from school to low paid jobs or informal employment (Corbanese and Rosas, 2007). Bosch and Maloney (2010) argue that youths use informal employment as a stepping-stone in the school to work transition in order to gain skills that would allow them to get employed in the formal sector in the future. Hence, suggesting that the probability of being employed in the informal sector is higher for young people but reduces with age. Thus, variables ***age*** and ***agesq*** are included in the employment contract model to account for this nonlinear relationship.

Table 6.2 Variables, names and specification

Information category	Specification details	*Name*
Dependent – Outcome variables	Employment (dummy=1 if the individual was employed at the time of the survey) Employment contract for the employed (dummy=1 if the employee had signed a contract with the employer at the time of the survey)	***employed*** ***contract***
Dependent variable of the treatment model	Multivalued treatment (dummy = 0 if the individual is part of the control group; 1 if the individual received OJT; 2 if the individual received IS; 3 if the individual received IET) Binary treatment (dummy = 0 if the individual is part of the control group; 1 if the individual received any of the three active measures)	***mtreatment*** ***btreatment***
Socio-demographic characteristics	Gender (dummy= 1 if the individual is male) Age Ethnicity (dummy = 1 if the individual is a member of an ethnic minority) Received social assistance (dummy = 1 if the if the family of the individual receives social, disability assistance or pension or unemployment benefits) Household size (continues variable measured in number of the household members)	***gender*** ***age* and *agesq*** ***ethnicity*** ***socialassist*** ***hhsize***
Education level	Education level: - Four years or primary school completed (dummy=1 if the individual completed four years, primary school or is a high school drop-out) - High school completed (dummy=1 if the individual completed high school) - University and post-graduate degree (dummy=1 if the individual completed university or post graduate studies)	***primaryeduc*** ***secondaryeduc*** ***tertiaryeduc***
Labour market history	Whether the individual was employed in 2011 (dummy =1 if the individual was employed in 2011) Whether the individual has been employed at least once (dummy = 1 if individual has been employed at least once)	***emp2011*** ***emphist***
Regional characteristics	Regional dummy variables: - Prishtina - Mitrovica - Gjilan - Ferizaj - Gjakove - Peja - Prizren Regional Unemployment Rate	***prishtina*** ***mitrovica*** ***gjilani*** ***ferizaj*** ***gjakova*** ***peja*** ***prizreni*** ***regunmp***

A gender variable is included in the model to account for gender differences in the probability of being employed. As elaborated in chapter 1, the female unemployment rate is substantially higher than that for males. The large employment gender gap in Kosovo can be explained by the prevailing social expectations about women. Women are more likely to withdraw from labour market due to household and caring responsibilities (KAS, 2017). Given this expectation and the prevalent gender stereotypes in Kosovo that they are more suitable for certain occupations, employers may prefer employing men to employing women. Thus, the expectation is that women have a lower probability of being employed compared to men ceteris paribus. Section 2.4 also emphasised that, in general, marginalised workers, such as women, are more likely to participate in the informal labour sector compared their counterparts (Chen, 2005; Jackson, 2012). This is related to social gender identities where the male who is the head of the family and has children is considered as the breadwinner of the house while women in the same situation are more likely to be engaged in vulnerable jobs. However, a report from KAS (2017) suggests that women in Kosovo are less likely to engage in informal jobs compared to men, however, as pointed out in chapter 5, this is mainly because women are more likely to be employed in the public sector. Given that in this sample women are not predominantly employed in the public sector, in this empirical analysis employed men are expected to be less engaged in the informal sector compared to women, other variables remaining constant.

The relationship between education and labour market performance has been theoretically established and analysed empirically by many studies (Becker, 1964; Card, 2001; Grossman, 2006; Oreopoulos and Salvanes, 2009; Bussemakers, 2017). Human capital formation is expected to translate into increased direct productivity, hence individuals with higher levels of education are expected to have a higher probability of being employed compared to those with lower levels of education, other factors remaining constant. Additionally, through the positive effect of income returns, education is expected to reduce the necessity to participate in the informal sector (Buehn and Farzanegan, 2013). With higher levels of education, employees have more bargaining power thus they will be more likely to have an employment contract (Heywood and Wei, 2004; Chevalier et al., 2004; Backes-Gellner and Werner, 2007; Corbanese and Rosas, 2007). Variables measuring the level of completed education *secondaryeduc* and *tertiaryeduc* are included in the model to account for the effect of education on the probability to be employed and the probability of having an employment contract if employed (*primaryeduc* is left out of the outcome regression as a benchmark category).

It has been widely recognised by empirical studies that ethnic minorities typically have lower employment opportunities due to their ethnicity (McCaig and Pavcnik, 2015). Ethnic minorities face barriers in the labour market due to their different cultural background, different language and other differences which might induce discrimination. The variable *minority* is included in the model in order to account for these differences. As explained in more details in section 2.4, ethnic minorities face greater barriers to enter the formal sector due to lack of information about vacancies in the formal market, lack of social networks and other related factors (Julia et al., 2015). They are also more likely to face barriers to professional advancement in their existing jobs and improving their employment status from informal to formal status (McGovern et al., 2004; Julia et al., 2015). Therefore, the expectation is that ethnic minorities, if employed, will be less likely to have an employment contract, ceteris paribus.

According to a number of empirical studies, if an individual's family receives social assistance, he/she is associated with a lower probability of participating in the labour market and as consequence a lower employment probability (Moffit, 2002; Farber and Valletta, 2015). There is disincentive for individual to find employment with higher levels of unemployment benefits and also benefits that cover long periods of unemployment (Nickell, 1997). Considering that in Kosovo the level of social assistance is quite low it is unclear whether it influences one's decision to join the labour force. Thus, the impact of variable *socassist* on the probability of being employed in the context of this analysis is ambiguous. In a study by World Bank (2015), receiving social assistance was found to increase the probability of actively searching for jobs in the informal market, hence they might feel pressured to be employed regardless of work conditions. With regard to the impact of this variable on the probability of having an employment contract, it is expected that if the family receives social assistance, the person is more likely to be employed in the informal sector rather than in formal one in order to continue to claim the social assistance, however small in the case of Kosovo.

The importance of accounting for an individual's labour market status history has been emphasised by many studies (Rodrigues-Planas and Benus, 2006; Kluve et al., 2008; Schmidl, 2014). Moreover, these empirical studies have highlighted that when an individual's status history is not accounted for in evaluations of ALMPs, the true effect of these policies cannot be estimated. An individual's labour market history is a relevant variable since it captures the unobservable characteristics of the individual such as motivation to find a job, non-schooling human capital and preference of firms towards specific potential workers (the review of literature in section 4.4.2 provides more discussion about the importance of this variable). To account for the above mentioned effects two variables, *emp2011* and *emphist*, are again included in the employment contract outcome model. It is expected that an individual who was employed during 2011 or at least once during period 2008-2011, other variables remaining constant, will have higher a probability of being employed in 2012 compared to their counterparts who were unemployed in those years. Also, if employed in 2012, it is anticipated that those employed during 2011 or at least once during period 2008-2011 will be more likely to be employed in the formal market, i.e. more likely to have an employment contract, compared to individuals who were unemployed.

The place of residence is a relevant variable to account for the differences in the demand and supply for labour in different regions. The regional differences are expected to arise due to variations in regional unemployment rates, in regional economic growth, total job opportunities and alternative jobs available in local labour markets. To assess the regional effect on the employment probability six dummy variables are included which represent the seven regions of Kosovo (Mitrovica, Gjilan, Ferizaj, Gjakove, Peja and Prizren), while the capital Prishtina is the benchmark category. The expectation is that individuals living in Prishtina, the capital city of Kosovo, will have a higher probability of being employed compared to those living in other regions due to their greater employment opportunities, lower commuting costs and better care facilities for children and elderly. In the *contract* model a variable measuring the regional unemployment rates is included instead because of a smaller sample and in order to gain more degrees of freedom. Other factors remaining constant, it is expected that regions with a higher unemployment rate increase an individual's probability of being employed in the informal sector.

A potentially important determinant of the future employment status is the household size, hence a variable accounting for family size, *hhsize*, is included in the model. In the context of Kosovo where public and private childcare facilities are scarce and expensive, it is expected that a larger household will increase a women's participation in the labour market and might also increase the probability of being employed. However, this depends on the health of the elderly in the family who alternatively might need to be taken care of. In order to observe the impact of family size on the probability of women's employment an interaction between household size and gender is included in the model, *hhsizegen*. The final specifications from outcome models, *employed* and *contract* are presented below:

$$Employed = f(age, agesq, gender, secondaryeduc, tertiaryeduc, socialassist, minority, emp2011, emphist, hhsize, hhsizegen, region) \quad 6.2$$

$$Contract = f(age, agesq, gender, secondaryeduc, tertiaryeduc, socialassist, minority, emp2011, emphist, hhsize, hhsizegen, regunemp) \quad 6.3$$

The following section will discuss the descriptive statistics of the covariates for the treated and control groups and will present empirical evidence of the treatment effects of the binary and multivalued treatment models using different estimation techniques.

6.4 Descriptive Statistics and Empirical Results

The descriptive statistics for the covariate variables are presented in table 6.3. The control group sample is much larger compared to the sample of three active measures with 6,906 observations for outcome variable *employed* and 2,943 for observations for outcome variable *contract*. When initially comparing the means of the variables between each active measure and the control group, the differences were quite substantial for some variables. Considering that the selection criteria for active measures were being young and unemployed the control sample was adjusted to account only for individuals within the same age range as that in the treated group. As explained in section 6.2, age is restricted to account for individuals of working age younger than 40 years of age. In this case, just 12 observations from the treatment group (individuals older than 40) are dropped from the sample[51]. Table 6.3 indicates that the mean of *age* is lower for the treated with an average of 26 years of age compared to the control group with more than 29 years on average. The mean

[51] The decision to restrict the age at 40 (rather than at 35 as per the programmes' eligibility criteria) was used in order not to reduce the sample for the treatment group further, as it is crucial to have as many treated individuals in the sample as possible.

values for the covariates do not show large differences except for the gender variable. After excluding the inactive individuals from the sample, the gender balance in the control group differs from that of the treatment group: the former is 75 percent male compared to 47 to 54 percent in the treatment samples.

Observational data covariates must be balanced either by matching or by weighting since, as explained in section 6.3, treatment assignment is related to specific covariates which consequently might affect the outcome results. The methodology used has to balance the observable characteristics between treated and control individuals thus a balancing check will be performed in order to assess whether these differences in means will be a problem.

Table 6.3 Descriptive statistics for treated group (OJT, IS and IET) and control group

	OJT		***IET***		***IS***		***Control group***	
VARIABLES	***(1) N***	***(2) Mean***	***(3) N***	***(4) Mean***	***(5) N***	***(6) Mean***	***(7) N***	***(8) Mean***
Outcome Dependent Variables								
employed	470	0.447	241	0.390	136	0.316	6,906	0.567
contract	192	0.698	85	0.788	41	0.732	2,943	0.850
Covariates								
age	470	26.27	241	26.50	136	26.51	6,906	29.41
agesq	470	702.5	241	715.4	136	713.7	6,906	902.9
male	470	0.540	241	0.548	136	0.478	6,906	0.748
socialassist	470	0.083	241	0.120	136	0.074	6,906	0.011
minority	470	0.064	241	0.083	136	0.081	6,906	0.063
secondaryeduc	470	0.398	241	0.427	136	0.434	6,906	0.627
tertiaryeduc	470	0.421	241	0.415	136	0.353	6,906	0.152
hhsize	470	6.226	241	6.071	136	6.022	6,906	7.716
hhsizegen	470	3.366	241	3.369	136	3.118	6,906	5.775
emp2011	470	0.343	241	0.303	136	0.338	6,906	0.577
emphist	470	0.579	241	0.506	136	0.684	6,906	0.614
gjakova	470	0.145	241	0.145	136	0.052	6,906	0.121
gjilani	470	0.206	241	0.199	136	0.257	6,906	0.063
mitrovica	470	0.134	241	0.166	136	0.059	6,906	0.096
peja	470	0.109	241	0.154	136	0.066	6,906	0.136
prizreni	470	0.162	241	0.104	136	0.125	6,906	0.163
ferizaj	470	0.113	241	0.149	136	0.132	6,906	0.123
prishtina	470	0.132	241	0.083	136	0.309	6,906	0.298

Because the aim of this chapter is to assess the outcome state of participants in ALMPs compared to the outcome state of the control individuals, initially the analysis will estimate a binary treatment model where the treatment dependent variable equals 1 if the individual was a participant and 0 if he/she is in the control group. Secondly, the multivalued treatment model will be used to assess the effectiveness of each active programmes, OJT, IS and IET, relative to being a non-participant. Both sets of estimations will use the following estimation techniques Inverse Probability Weighting (IPW), Regression Adjustment (RA), and the doubly robust estimator Inverse Probability Weighting - Regression Adjustment (IPWRA) because these methods allow for both binary and multivalued treatment models. For the binary treatment model Propensity Score Matching (PSM) with nearest neighbour will also be used (PSM uses a binary treatment model only, hence it cannot be used for multivalued treatment).

The fundamental evaluation problem is the construction of appropriate counterfactuals because an individual cannot be in both states, with and without treatment. Studies using propensity score methods have usually estimated the Average Treatment Effects on the Treated (ATET). ATET estimates the outcome of the treated individuals had they not been treated by any active measures. Section 4.2 has provided a more detailed discussion of the evaluation problem and appropriate counterfactuals.

The balancing diagnostics are provided before estimation results. For models using PSM, the following diagnostics are presented: standardized differences in means after matching, kernel density plots and propensity score plots. For models using IPW and IPWRA only standardized differences in means after weighting are presented, since kernel density plots are generated only for specific covariates while propensity score balance box plots can be generated only for models using PSM. Since both IPW and IPWRA use the same treatment model to generate weights their diagnostics are exactly the same, only one diagnostic will be presented for both techniques. RA estimation cannot generate any balancing diagnostics because this technique does not use a treatment assignment model, thus it does not use weighting nor matching methods but only uses the outcome model to generate the treatment effects. The differences in variance ratios before and after matching/weighting for all models are presented in Appendices A6.3 to A6.5. According to Rubin (2008), a perfectly balanced covariate has a mean standardized difference of zero while the acceptable threshold is the standardised difference of 0.25.

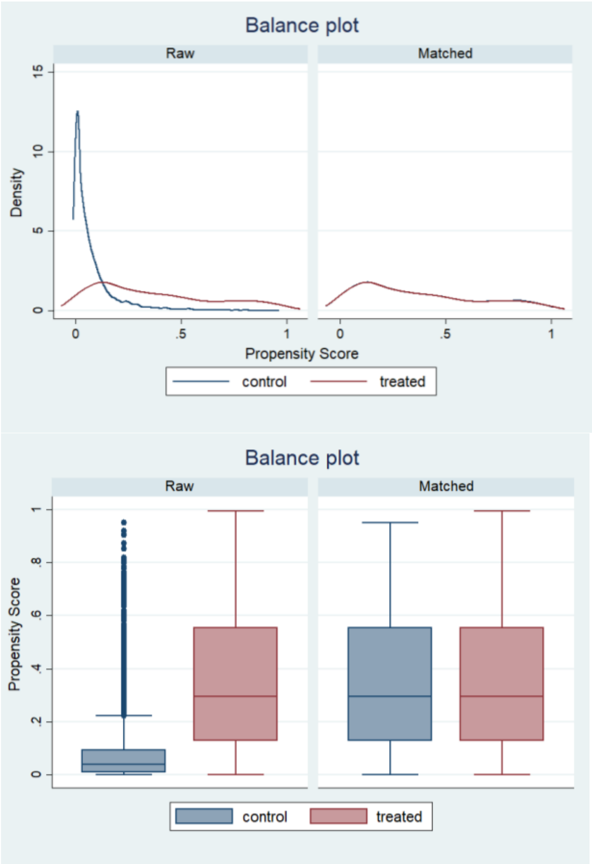
Evidence using the outcome dependent variable Employed

The balancing diagnostics for the outcome variable *employed* presented in table 6.4 suggest that the covariates have been balanced. The weighted standardised differences in means are all below the threshold of 0.25. The kernel density plots, which graph the model-adjusted estimated probability density functions of covariates, and diagnostics, which use box plots to verify whether the covariates are approximately equal, are presented in figure 6.1. The graphs show the kernel density functions and the box plots for PSM model before and after matching which suggest that the covariates have been balanced after matching. Therefore, one can conclude that the estimation techniques applied to the datasets achieve well-balanced covariates of the treated and control for treatment models.

Table 6.4 Weighted standardized differences in the means of the characteristics of treated and control in a binary and multivalued treatment model using PSM and IPWRA.

Outcome variable *employed*	**Binary treatment**		**Multivalued treatment**		
	PSM ATET	**IPWRA ATET**	**IPWRA ATET**		
	Treated vs. Control	**Treated vs. Control**	**OJT vs. Control**	**IS vs. Control**	**IET vs. Control**
age	-0.076	-0.081	-0.077	-0.062	-0.001
agesq	-0.078	-0.080	-0.077	-0.067	-0.004
gender	0.047	0.039	0.039	0.051	0.128
minority	0.099	0.016	0.018	0.014	-0.040
socialassist	0.161	0.163	0.160	0.183	0.173
secondaryeduc	0.072	0.067	0.058	0.071	0.116
tertiaryeduc	-0.086	-0.086	-0.076	-0.095	-0.138
emp2011	0.023	0.011	0.004	0.031	-0.047
emphist	-0.058	-0.031	-0.024	-0.033	0.042
hhsize	-0.057	-0.031	-0.034	-0.071	-0.050
hhsizegen	0.027	0.022	0.022	0.021	0.042
ferizaj	-0.042	-0.005	-0.007	-0.034	-0.024
gjakova	0.149	0.053	0.057	0.073	0.071
gjilani	-0.070	-0.064	-0.071	-0.037	-0.070
mitrovica	0.065	0.043	0.038	0.048	0.013
peja	-0.061	-0.021	-0.021	-0.001	0.003
prizreni	0.060	0.054	0.052	0.002	0.005

Figure 6.1 Kernel density and box plot using PSM for outcome model *employed*



The estimated average treatment effects on treated (ATET) using the binary and multivalued treatment model are presented in tables 6.5 to 6.8 (see Appendices tables 6.1 to 6.4). Initially, all variables discussed as relevant in section 6.3 are included in the model and the same sample is used for subsequent estimations. The complexity of how variable *emphist* is constructed, using two different questions for the control group and four different questions for the treatment group, is likely to create a measurement error because it is unable to capture individuals' potential employment prior to 2011. Because of this, the second set of estimations excludes the *emphist* variable and includes only *emp2011* (the results are presented in table 6.6). In order to observe whether the employment history variables have a predictive power for the treatment effects, both employment history variables are excluded from the estimations presented in table 6.7. Additionally, arguing that the effectiveness of the policies might be underestimated because the dependent variable *employed* captures only those who are employed in 2012, an additional dependent variable was constructed, *emp1112* (the period after the treatment), which equals one if the individual was employed in either 2011 or 2012 years and zero otherwise. The estimated results using this outcome dependent variable are presented in table 6.8.

Taking into consideration the doubly robust property of IPWRA, only results from this approach will be interpreted. The coefficients of the ATET in the first and second specification (tables 6.5 and 6.6) where at least one of the employment history variables are accounted for, suggest a significant positive effect of the active measures in the binary treatment model. The results from the specification 1 (where *emp2011* and *emphist* are included) suggest that participating in one of the active measures increases an individual's probability of being employed by 7.25 percentage points above the average of similar individuals had they not been participants, other factors remaining constant. The ATET from the multivalued treatment effect suggest that participating in OJT and IS increases an individual's probability of being employed by 9.91 pp and 8.79 pp respectively, above the average of similar individuals had they not been participants, other factors remaining constant. The ATET coefficient of the IET is insignificant. The results are very similar for specification 2 (where only *emp2011* is included), but with only slightly larger estimated coefficients.

When none of the employment history variables are included the estimated results suggest a significant negative effect of participation in each of these programmes. It appears that the negative treatment effects are due to omitted variable bias, since they disappear when employment history is controlled for. This result suggests the importance of controlling for employment history, which can in turn also capture unobserved beneficiary characteristics. The coefficient of the average treatment effects of IET is significant and negative only in specifications 3 (where *emp2011* and *emphist* are excluded) and 4 (where the dependent variable is *emp1112*). Participating in one of the active measures reduces an individuals' probability of being employed by 5.6 pp below the average of similar individuals in the control group, other factors remaining constant. The results from the multivalued treatment model suggest a significant negative treatment effect for IS and IET participants by 6 pp and 19.8 pp, respectively, other factors remaining constant. The results for specification 4 (using the dependent variable *emp1112*) suggest a positive treatment effect only when using PSM. The results of the binary model from other techniques are insignificant. The results from the multivalued treatment are more consistent across different methods; however, the OJT coefficient is significant only when using the IPWRA. The results from IPWRA suggest that participating in OJT increases the probability of being employed after treatment (in 2011 or 2012) by 4.6 pp above the average of similar individuals who had not participated in OJT, other factors remaining constant. The treatment effect for IET is negative, suggesting that having participated in IET reduces the probability of being employed after treatment by 13.2 pp below the average of similar individuals in the control group, other factors remaining constant.

Table 6.5 Specification 1- including both employment history variable *emp2011* and *emphist*. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for outcome model *employed*.

	PSM	***IPW***		***RA***		***IPWRA***	
	ATET	***ATET***	***PoMean***	***ATET***	***PoMean***	***ATET***	***PoMean***
Treated vs. Control	0.073***	0.079***		0.069***		0.073***	
	(0.025)	(0.020)		(0.017)		(0.018)	
Control			0.331***		0.340***		0.337***
			(0.019)		(0.016)		(0.017)
OJT vs. Control		0.102***		0.095***		0.099***	
		(0.027)		(0.024)		(0.024)	
IS vs. Control		0.094***		0.087***		0.088***	
		(0.033)		(0.030)		(0.030)	
IET vs. Control		-0.067		-0.043		-0.053	
		(0.042)		(0.039)		(0.041)	
Control			0.344***		0.351***		0.348***
			(0.024)		(0.021)		(0.022)
Observations	7,753	7,753	7,753	7,753	7,753	7,753	7,753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.6 Specification 2 – including only emp2011 variable. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for outcome model employed.

	PSM	***IPW***		***RA***		***IPWRA***	
	ATET	***ATET***	***PoMean***	***ATET***	***PoMean***	***ATET***	***PoMean***
Treated vs. Control	0.067***	0.079***		0.075***		0.080***	
	(0.025)	(0.018)		(0.017)		(0.017)	
Control			0.330***		0.334***		0.329***
			(0.014)		(0.016)		(0.016)
OJT vs. Control		0.105***		0.101***		0.106***	
		(0.024)		(0.024)		(0.024)	
IS vs. Control		0.089***		0.081***		0.083***	
		(0.032)		(0.029)		(0.029)	
IET vs. Control		-0.062		-0.035		-0.044	
		(0.041)		(0.037)		(0.035)	
Control			0.342***		0.345***		0.340***
			(0.022)		(0.021)		(0.021)
Observations	7,753	7,753	7,753	7,753	7,753	7,753	7,753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.7 Specification 3 - both employment history variables *emp2011* and *emphist* are excluded. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for outcome model *employed*.

	PSM	***IPW***		***RA***		***IPWRA***	
	ATET	***ATET***	***PoMean***	***ATET***	***PoMean***	***ATET***	***PoMean***
Treated vs. Control	-0.120***	-0.079***		-0.084***		-0.057***	
	(0.027)	(0.021)		(0.019)		(0.020)	
Control			0.489***		0.494***		0.466***
			(0.014)		(0.012)		(0.0139)
OJT vs. Control		-0.046*		-0.051**		-0.026	
		(0.026)		(0.025)		(0.026)	
IS vs. Control		-0.076**		-0.084**		-0.060*	
		(0.035)		(0.034)		(0.035)	
IET vs. Control		-0.223***		-0.229***		-0.198***	
		(0.045)		(0.043)		(0.042)	
Control			0.493***		0.498***		0.472***
			(0.015)		(0.014)		(0.015)
Observations	7,753	7,753	7,753	7,753	7,753	7,753	7,753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.8 Specification 4 - both employment history variables *emp2011* and *emphist* are excluded. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for outcome model *emp1112*.

	PSM	***IPW***		***RA***		***IPWRA***	
	ATET	***ATET***	***PoMean***	***ATET***	***PoMean***	***ATET***	***PoMean***
Treated vs. Control	-0.054**	-0.018		-0.020		0.006	
	(0.028)	(0.021)		(0.0199)		(0.021)	
Control			0.507***		0.509***		0.483***
			(0.014)		(0.012)		(0.014)
OJT vs. Control		0.026		0.023		0.047*	
		(0.026)		(0.025)		(0.026)	
IS vs. Control		-0.031		-0.032		-0.009	
		(0.036)		(0.035)		(0.035)	
IET vs. Control		-0.154***		-0.162***		-0.132***	
		(0.049)		(0.046)		(0.045)	
Control			0.511***		0.514***		0.489***
			(0.016)		(0.014)		(0.016)
Observations	7,753	7,753	7,753	7,753	7,753	7,753	7,753

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A relevant point worth emphasising is that when both employment history variables are excluded from the model, the results indicate a significant negative treatment effect. This might suggest that the employment history variables, *emp2011* and *emphist* are likely to capture individuals' unobservable characteristics which might affect the outcome and the treatment selection. As discussed in section 6.2, the individual's pre-treatment employment history would have been ideal to capture the unobservable effects and to create more comparable matches, however this variable was not available for the control group. Also, the questionnaire for the control group does not provide any information about participation of individuals in this group in any active measure. Even though, the participation in ALMPs in Kosovo might be small compared to the working age population or the labour force size, to some extent it still might have affected the estimated results.

Bearing in mind that the dataset used for this empirical analysis is constructed from two different sources for control and treatment groups and since the variables are constructed from different questions, the dataset is likely to contain measurement errors which might impose bias on the estimates. Therefore, one should not be hasty to draw any definite conclusions about the effectiveness of these ALMPs with regard to participants' employment probability for the case of Kosovo.

Evidence using the outcome dependent variable Contract

The next set estimations will use the second outcome dependent variable, *contract*, to evaluate the effectiveness of active measures in acquiring employment in the formal sector. The initial model specification included all variables discussed in the specification for the *contract* model in section 6.3. However, since including all the variables discussed imposes an imbalance in the propensity scores between the two groups, the dummy variables measuring the regional differences are replaced with a variable measuring the regional unemployment rate. The variable *emphist* is dropped from the model because it imposes imbalance on other covariates (the estimated model and balancing diagnostics including variable *emphist* and regional dummy variables are presented in Appendix table 6.5.1).

The balancing diagnostics are presented in table 6.9 and figure 6.2. The figure 6.2 presenting the kernel density plots and box plots of PSM model before and after matching suggests that the covariates have been balanced after matching. However, as figure 6.2 shows, it is worth pointing out that the propensity scores higher than 0.6 tend to be less balanced.

Figure 6.2 Kernel density and box plot using PSM for the outcome model contract

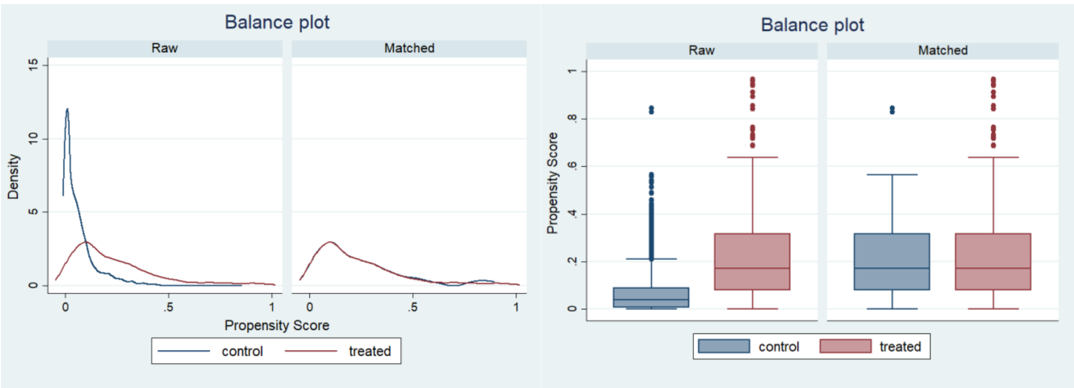


Table 6.9 Weighted standardized differences in means of the characteristics of treated and control in a binary and multivalued treatment model using PSM and IPWRA.

Outcome variable contract	***Binary treatment***		***Multivalued treatment***		
	PSM	***IPWRA***	***IPWRA***		
	ATET	***ATET***	***ATET***		
	Treated vs. Control	***Treated vs. Control***	***OJT vs. Control***	***IS vs. Control***	***IET vs. Control***
age	0.069	-0.010	0.001	0.026	0.196
agesq	0.062	-0.010	0.0002	0.029	0.201
gender	0.032	-0.057	-0.054	-0.070	0.197
minority	-0.078	0.011	-0.004	-0.030	-0.173
socialassist	0.027	0.018	0.040	0.028	-0.318
secondaryeduc	0.046	0.003	-0.005	-0.056	-0.078
tertiaryeduc	0.038	0.066	0.069	0.119	0.218
emp2011	0.066	0.027	0.004	-0.052	0.214
hhsize	0.040	-0.027	-0.027	0.007	-0.106
hhsizegen	0.070	-0.050	-0.047	-0.035	0.088
regunmp	-0.053	0.038	0.047	0.064	-0.035

Table 6.9 presents the balancing diagnostics for the outcome variable *contract* for PSM and IPWRA which suggests that the covariates are balanced between treatment and control group. The weighted standardised differences in means for covariates of the IET vs. Control are higher compared to OJT and IS vs. Control, however only the variable *socialassist* passes the threshold of 0.25 (it is highlighted in table 6.9). Nevertheless, since it is the only variable that is above the threshold it is not expected to significantly influence the outcome results. Considering that a balance of the covariates between the groups is a prerequisite for high-quality matching (weighting), only specifications with the balanced covariates will be discussed and interpreted.

The results from ATET for the outcome variable *contract* are presented in table 6.10 (see Appendices 6.5 and 6.6). The results are consistent in terms of the sign of the coefficients when using different estimation techniques. However, when using only the treatment model (PSM and IPW), the ATET seems to be underestimated while when using only the outcome model (RA), the ATET seem to be overestimated. The IPWRA estimated treatment effects using the binary treatment model suggest that an employed participant from one of the active programmes has a 9.2 pp lower probability of having a contract compared to the average of similar individuals who had not participated in any of the active programmes, other factors remaining constant. The IPWRA results using the multivalued treatment model indicate that the treatment effects is significant and negative only for the OJT participation. The result suggests that a participant in OJT, if employed, is less likely to have an employment contract by 12.5 pp below the average of similar individuals in the control group, other factors remaining constant. Though insignificant, the treatment effects for IET and IS are also negative.

Table 6.10 Specification 1 – using *emp2011*. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for outcome model *contract*.

	PSM	***IPW***		***RA***		***IPWRA***	
	ATET	***ATET***	***PoMean***	***ATET***	***PoMean***	***ATET***	***PoMean***
Binary treatment model							
Treated vs. Control	-0.081**	-0.053*		-0.104***		-0.092***	
	(0.034)	(0.029)		(0.026)		(0.026)	
Control			0.780***		0.830***		0.818***
			(0.021)		(0.013)		(0.014)
Multivalued treatment model							
OJT vs. Control		-0.089**		-0.134***		-0.125***	
		(0.036)		(0.033)		(0.033)	
IS vs. Control		0.037		-0.025		-0.009	
		(0.042)		(0.045)		(0.043)	
IET vs. Control		-0.044		-0.114		-0.059	
		(0.128)		(0.084)		(0.056)	
Control			0.787***		0.832***		0.823***
			(0.023)		(0.015)		(0.016)
Observations		4,023	4,023	4,023	4,023	4,023	4,023

In the second specification, where the *emp2011* is excluded from the model, the estimated results shown in table 6.11 are very similar to those of the previous one. An exception is that when using the RA method the treatment effect for IET becomes significant thus for an employed individual, participating in IET reduces an individuals' probability of having a contract by 11.6 pp below the average of similar individuals in the control group. The treatment effects from IPWRA in the second specification are slightly higher compared to the first one, however the difference is negligible. Considering that the sample for the outcome variable *contract* is restricted to employed individuals only, controlling for employment history seems to have no significant impact on the probability post-treatment of an employed individual having a contract.

Table 6.11 Specification 2 – excluding *emp2011*. Average treatment effects on treated (ATET) and Potential Outcome Means (PoMean) for the outcome model *contract*.

	PSM	IPW		RA		IPWRA	
	ATET	ATET	PoMean	ATET	PoMean	ATET	PoMean
Binary treatment model							
Treated vs. Control	-0.089***	-0.079***		-0.116***		-0.095***	
	(0.033)	(0.0271)		(0.024)		(0.025)	
Control			0.806***		0.842***		0.821***
			(0.0167)		(0.011)		(0.0133)
Multivalued treatment model							
OJT vs. Control		-0.121***		-0.154***		-0.134***	
		(0.033)		(0.031)		(0.032)	
IS vs. Control		0.001		-0.046		-0.022	
		(0.041)		(0.045)		(0.043)	
IET vs. Control		-0.042		-0.128*		-0.111	
		(0.086)		(0.0719)		(0.069)	
Control			0.819***		0.852***		0.832***
			(0.0179)		(0.013)		(0.015)
Observations	4,034	4,034	4,034	4,034	4,034	4,034	4,034

6.5 Conclusions

This chapter has focused on analysing the effectiveness of three different ALMPs implemented in Kosovo during the period 2008 to 2010: OJT, IET and IS. The effectiveness of these ALMPs has been analysed using several evaluation techniques to estimate the treatment effects in binary and multivalued treatment models. Following a discussion about selection bias in chapter 4 and the pre-determined selection criteria to participate in the above-mentioned active measures, the treatment model was specified to adjust for potential selection bias.

After achieving a balance of the propensity scores between the treatment and control groups, when using the same specification and assuming that all relevant variables are included in the model all estimation techniques arrive at a broadly similar conclusion. Because it is uncertain which of the models is correctly specified, from a practical standpoint, a doubly robust estimator was utilised because it increases the likelihood of estimating accurate treatment effects. Hence, only the results from IPWRA are discussed.

Depending on the model specification, the empirical findings from the analysis presented in this chapter suggest mixed results for the effectiveness of the active measures. The results suggest that participating in OJT and IS are associated with an increase in the probability of being employed compared to not participating in any active measure. The treatment effect of IET is negative when employment history is not controlled for, but becomes insignificant when accounting for employment history variables, suggesting that this result could be driven by omitted variable bias. The change in sign of the treatment effects after including the employment history variable indicate the importance of this variable which is in line with the findings of other evaluation studies reviewed in chapter 4. In addition to the findings from the employment probability model, the empirical findings from the binary treatment model suggest that participating in active measures is associated with employment in the informal sector. Furthermore, the evidence from the multivalued treatment model indicates that this effect derives predominantly from participating in the OJT. This empirical evidence might suggest that when labour market is characterised by low employment opportunities in the formal sector, ALMPs increase the probability of individuals post-treatment being engaged in the informal labour market.

However, the assumption of selection of unobservables (CIA) might have not been satisfied in this analysis since crucial factors influencing the selection into treatment, such as a pre-treatment employment history, could not be accounted for. The limitations of this empirical analysis also include the measurement errors caused by the different data sources used for treatment and control group. In the absence of a control group derived from the same source as that for treatment, this empirical analysis was compelled to construct a control group from an alternative source, the LFS. This is considered the most profound limitation of this empirical analysis since the questions in the two surveys are phrased differently thus creating measurement errors. Another relevant limitation of this analysis is the unavailability of information on whether individuals in the control group have participated in any ALMP at some point before year 2012, creating a specific bias in the estimates. Given the limitations presented, the estimated treatment effects could not be used as a convincing basis for drawing firm conclusions about the effectiveness of these ALMPs.

Chapter 7

Conclusions and Policy Implications

7.1 Introduction

The aim of this thesis was to empirically investigate the effectiveness of ALMPs in reducing unemployment in European transition economies (ETEs), in the context of labour markets with large informal sectors. Given that increasing unemployment became a persistent feature in most of the transition economies during the transition period, one of the objectives of the first chapter of this thesis was to discuss the rise and consequences of unemployment. Considering these high rates of unemployment, the first chapter also emphasised the potential importance of labour market policies, in particular ALMPs, in reducing unemployment. Following the discussion of the context analysis in chapter 1, this thesis had six inter related objectives:

1. To provide a comprehensive and critical review of the theoretical framework of unemployment and the multiple effects of ALMPs in reducing it;
2. To provide a critical review of the empirical studies analysing the effectiveness of ALMPs in European Transition and Non-Transition economies;
3. To empirically analyse the effectiveness of ALMP expenditure as share of GDP in reducing unemployment at the economy-wide level in European transition and non-transition economies;
4. To critically review different evaluation methodologies and empirical studies analysing the ALMP effectiveness at the individual level in addressing the issues of the missing counterfactual and selection bias;
5. To empirically evaluate the overall and relative effectiveness of three active measures implemented in Kosovo: On-the-Job Training, Institution and Enterprise Training and Internship Scheme on finding employment, searching for jobs and, conditional on being employed, having an employment contract;
6. To synthesise policy recommendations for improving the effectiveness of these policies as a tool to reduce unemployment among vulnerable groups such as youths and the low-skilled unemployed.

The second chapter established the theoretical framework to analyse the effectiveness of ALMPs. Since the theoretical framework developed for the Western economies is not fully appropriate in context of transition economies, the second chapter further established the theoretical relationship between the effectiveness of ALMPs and the size of the informal sector based on a review of the Layard, Nickell and Jackman (1991) and Snower (1994) models. Having found no consensus after a review of the empirical studies for transition economies the initial research question was formulated: ***whether ALMPs in European transition and non-transition economies are effective in reducing unemployment at the economy-wide level.*** This research question was addressed in chapter 3 using two methodologies: a matching function using a static panel model to assess the matching efficiency between the stock of unemployed and vacancies and a dynamic panel model to investigate the effect of ALMPs on reducing the unemployment rate. Because of data limitations, the analysis was extended to include European non-transition economies in order to achieve more reliable results.

Following a critical analysis of the effectiveness of ALMPs at the national level, the next research question was ***to investigate the relative effectiveness of three specific active labour market policies in Kosovo in increasing an individual's employment probability, the probability of unemployed of increasing active job search and the probability those in employment of having a contract***. In chapter 4 the evaluation and selection problems which can arise when evaluating the effectiveness of ALMPs at the individual level were discussed and the most appropriate methodologies to address these issues were considered. The empirical studies of the effectiveness of ALMPs at the individual level for transition economies, reviewed in chapter 4, had reached no definite conclusion. Hence, an empirical investigation was conducted in chapter 5, focused on addressing the second research question using a cross-section dataset for Kosovo employing two different methodologies: Multinomial Probit and to address the selection bias, Inverse Probability Weighting – Regression Adjustment (IPWRA). After assessing the relative performance of active policies, the final research question was to empirically investigate ***the overall effectiveness of the three active policies analysed in chapter 5 in increasing employment probability and the probability of having an employment contract.*** This investigation was conducted in chapter 6 using the same dataset as in the previous chapter and also using an additional dataset to construct the control group to assess whether the ALMP participants achieved a better performance in the labour market compared to that of non-participants.

This chapter will discuss the main findings of this research and synthesise the contribution to knowledge resulting from the empirical analysis. It will further examine the policy implications of the main findings and provide a discussion of the main limitations which have constrained the research analysis and how these may be addressed in future research work. This chapter is organised as follows. Section 7.2 presents the main empirical findings of the thesis with regard to the research questions presented above while section 7.3 provides a discussion on the main contribution to knowledge. Section 7.4 develops the policy implications resulting from the main findings of this research project. Section 7.5 discusses the limitations that have been encountered while conducting the empirical analysis and provides recommendations for further research in the future.

7.2 Main Empirical Findings

The discussion of the context of this research programme in the introductory chapter examined the state of the labour markets in European transition and non-transition economies, with a particular focus on Kosovo. The aim of this chapter was to analyse the differences in the labour market indicators of European transition economies compared to non-transition economies. The first chapter and section 2.3 established that the dramatic initial output collapse and the shift from the rigid labour markets of the central planning to market planning system were the main causes of the high rates of unemployment in early transition. The analysis of chapter 1 revealed that there is a substantial difference in the ALMP expenditure as a percentage of GDP between the transition and non-transition countries. Regardless of their generally high rates of unemployment, the spending on ALMP in European transition economies is comparable only to the lowest spenders in European non-transition economies. Balkan countries allocate an even lower amount of expenditure on ALMPs despite increases in recent years. After the global financial crisis, expenditure on ALMPs increased in EU countries but remained, on average, constant after the 2012 for both sets of countries.

Following this discussion, chapter 2 addressed the first objective of this research project by critically analysing the theoretical framework through which the ALMP effectiveness could be evaluated. This chapter initially evaluated the NAIRU framework developed by Layard, Nickell and Jackman (1991) which has been used as a basis for analysing the effectiveness of the ALMPs in Western countries. However, given the specific nature of labour markets in transition economies this theoretical framework was not considered to be completely appropriate for this investigation. The labour market in transition economies was argued to be characterised by multiple equilibria. In its simplest form, based on a model by Snower (1994), the equilibrium initially predominant in transition economies was argued to be a ‘low-skill bad-job equilibrium’ with low productivity workers, insufficient human capital and low wages because of scarce vacancies for skilled jobs. One of the initial findings of this research was that in many ETEs the bad-job equilibrium has been associated with a large informal labour market. This chapter also provided a concise and critical assessment of the mechanisms through which ALMPs could incentivise informal employers to switch to the formal sector. It is argued that the effect of ALMPs on the firm is similar to reduction in their labour costs. As examined in chapter 2, in a demand-constrained labour market (as that in many transition economies), a reduction in labour costs can increase the employment. The second objective of the thesis is also addressed in this chapter by critically reviewing the empirical studies that investigated the ALMP effectiveness at the country level. This topic is still not extensively investigated for ETEs mainly because of data unavailability hence only a handful of studies were reviewed. The findings for transition economies are inconclusive and no clear implications could be drawn. In contrast, the review of the empirical studies in Western European economies point to a generally positive effect of ALMPs on increasing employment and reducing unemployment.

Section 2.2.3, discussed in more details the theoretical explanations for the main effects of the ALMPs in the labour market where six possible effects were identified. The main function of ALMPs is raising the efficiency of the matching between the unemployed who are searching for jobs and employers who are searching for workers. These policies tend to increase the efficiency of matching through enhancing the human capital of participants, re-locating jobs or workers, increasing the search intensity of the job-seeker, reducing the hiring costs and reducing employers’ uncertainty about the employability of applicants hence allowing the firms to create more vacancies and fill them more quickly.

To answer the research question: *Are ALMPs in European economies (transition and non-transition) effective in reducing unemployment at the economy-wide level?*, chapter 3 addresses the third objective using two empirical analyses: the first one is the matching function using Fixed Effect estimator while the second is the dynamic panel analysis using difference General Methods of Moments. In order to investigate whether ALMPs in European economies have any influence on improving the matching process between the number of unemployed in the labour market and the number of unfilled vacancies, the first model in utilised outflows from unemployment to employment as the dependent variable. The estimation approach used for this empirical analysis was the Fixed Effects Driscoll Kraay (FEDK) standard errors, which is robust to cross-sectional dependency, heteroscedasticity and autocorrelation. Because of the inability of FEDK to estimate the time-invariant factors, an additional estimator, Fixed Effects Vector Decomposition (FEVD), was employed. This estimator allowed assessing whether the transition economies showed a different pattern of matching efficiency and also whether the ALMPs have the positive effect in reducing unemployment in transition compared non-transition economies. Following the theoretical expectations and the review of the empirical studies for transition economies expressed in chapter 2, this empirical analysis also analysed whether the labour markets in transition economies exhibit multiple equilibria.

The empirical evidence obtained from this investigation suggests that ALMPs in the selected countries of analysis have a statistically significant and positive effect on increasing matching efficiency between the unemployment stock and unfilled vacancies. However, this effect is quite small when translated into economic terms since only a relatively small number of unemployed were found to flow from unemployment into employment. In accordance with the evidence from other empirical studies (Munich and Svejnar, 2008; Camarero et al., 2008), this model also found evidence to suggest that the labour markets in transition economies might exhibit multiple equilibria. However, in contrast to the expectations, from the results provided in this empirical investigation there seem to be no relationship between the size of informality and matching efficiency. As argued in chapter 3, one possible explanation that this relationship could not be confirmed from the analysis at the national level is that the sample includes both transition and non-transition economies. The results from FEVD, however, do not suggest any significant effect of ALMPs in transition economies.

Given that current aggregate unemployment is partly determined by its values in previous time periods and also considering the potentially endogenous nature of the variable total expenditure of ALMPs as share of GDP, chapter 3 implemented a second empirical investigation of the effectiveness of these policies employing a dynamic panel analysis using difference GMM. This analysis assessed the effectiveness of the total expenditure on ALMPs as a share of GDP in reducing the unemployment rate. Additionally, using a larger dataset (i.e. including both European transition and non-transition economies) it became possible to assess the effectiveness of the five different ALMPs: training, employment incentives, supported employment and rehabilitation, direct job creation and start-up incentives. The results from this model could not confirm that the increased total expenditure of ALMPs as share of GDP had an impact on reducing the unemployment rate. The results also indicated that there were no significant differences in the effectiveness of the active measures analysed. Section 3.4.3 provides one possible explanation for the overall insignificance. As the review of empirical studies in chapter 2 revealed, the effectiveness of individual ALMPs is diverse and the same ALMPs might have not be effective in different countries, in different time periods and for different groups of unemployed. This diversity in the effectiveness of individual ALMPs might be a result of different targeting, different design specifics and different levels of economic development of countries where these policies are being implemented. Additionally, some of the ALMPs might also induce negative effects such as a deadweight effect (the beneficiaries of active measures were going to be employed even in absence of such measures) and substitution effect (the beneficiaries get employed at the expense of other potential workers). Based on the discussion in section 2.2, it was concluded that in order for the labour market policies and regulations to be effective in reducing the unemployment rate then unemployment should be predominantly structural or frictional in nature. In contrast, when the behaviour of unemployment is better explained by the hysteresis hypothesis then active labour market policies may have little or no effect and the policy focus should be primarily on increasing aggregate demand. Following this argument, one explanation for the findings of the empirical investigation in chapter 3 is that the aggregate demand for labour in many ETEs was low. However, referring to the literature review provided in section 2.3, the evidence from the empirical studies suggests mixed results about the dynamics of unemployment in transition economies; whether it is more likely to show hysteresis or a structuralist pattern. Thus, the argument that a lack of aggregate demand leads to the insignificant effect of ALMPs should be taken with caution. Additionally, one potential explanation for the insignificant effect of active policies analysed was argued to be the composition of the countries included in the sample where both transition (at different stages of transition) and Western European countries were analysed. Even though potentially important control variables are accounted for in the model, such as the level of economic growth, labour market institutions and policies, the level of education and the size of informality, there might be other factor missing in the specification which might have given rise to omitted variable bias.

By critically reviewing different evaluation methodologies and empirical studies which analyse ALMP effectiveness at the individual level and identifying the key assumptions within the framework, chapter 4 addresses objective 4 of this thesis. The main focus of this chapter is to analyse the evaluation problem and to identify a suitable evaluation technique for the construction of the counterfactual and accounting for selection bias. Chapter 4 concluded that the most appropriate evaluation technique in context of the analysis in this research project is the Inverse Probability Weighting Regression Adjustment (IPWRA). This estimator uses both treatment and outcome models which helps to address the selection bias and it allows evaluating different ALMPs in the same setting. The critical review of the empirical studies analysing the ALMP effectiveness at the individual level for transition economies suggests that training might be an effective measure in the short-term, however, no conclusion can be made for the long-term.

Chapters 5 and 6 address objective 5 of this thesis. To provide an insight on the effectiveness of ALMPs at the individual participant level, a cross-sectional dataset for Kosovo was used to assess the relative effectiveness of the active policies in increasing the probability of an individual to: be employed; be employed in the formal sector; or, if unemployed, undertake active job search. There were three active measures implemented in Kosovo during 2008 to 2010 which were the focus of chapter 5's investigation: on-the-job training (OJT), an internship scheme (IS) and institution and enterprise training (IET). In order to test the hypothesis that participation in an ALMP increases the probability of being employed in the formal sector as opposed to the informal one, the first methodology used in this chapter is the multinomial probit with a three category dependent variable which equalled zero if the individual is unemployed at the time of the survey, one if the individual is employed with an employment contract and two if the individual is employed without an employment contract.

The empirical evidence on the relative effectiveness of the three active measures suggests that participating in OJT and IS reduced the probability of being unemployment relative to participating in IET. Participating in OJT seems to have had a positive impact on increasing employed individuals' probability of engaging in the informal sector compared to participating in IET. The evidence from this empirical analysis also suggests that participating in an active measure for a longer period of time tends to increase participants' probability of being employed informally, i.e. being employed without a contract. As argued in section 5.2, participants in the investigated active measures were, typically, disadvantaged long-term unemployed and getting employed in the informal sector provides a necessary income for them. In a labour market with few employment opportunities in the formal sector, participants consider the alternative of employment in the informal sector, rather than remaining unemployed. The findings suggest that programmes implemented in more recent years are less effective in increasing a participant's probability of being in employment compared to the same programmes implemented earlier. One possible explanation for this result is that the quality of these programmes, actual and/or perceived, might have declined during the observed period or the specific labour market conditions might have influenced their effectiveness over time. Another finding of this empirical analysis is that having acquired a certificate increases an individual's probability of gaining employment in the formal market and reduces the probability of engaging in the informal labour market compared to an individual who did not acquire a certificate of completion. This finding might suggest that having a certificate signals to potential employers that the individual has a certain level of ability and as a consequence will be less likely to be employed in low quality jobs or informal market. In contrast, the variable used a proxy for quality of implementation of the ALMPs (whether the participants have an employment/training individual plan) is statistically insignificant. This might suggest that this part of the process of implementation might have not been of high enough quality to assist beneficiaries in acquiring skills and getting employed.

As explained in section 5.2, participation in these active measures was supposed to be pre-determined based on a set of selection criteria, making the estimation of the study subject to a potential selection bias. Hence, in attempting to adjust for selection bias, the second empirical analysis in chapter 5 employed a doubly robust evaluation technique, IPWRA, which uses both treatment selection and outcome models. This approach gives unbiased estimates if at least one of the models is specified correctly. As discussed in section 4.4, an additional novelty of this methodology compared to previous evaluation methodologies is that it allows an analysis of the effects of treatment in the context of multiple programmes. The analysis utilised three different outcome models where three dependent variables were used; the first one equalled one if the participant was employed at the time of the survey, zero otherwise, the second equalled one if the unemployed participant actively searched for jobs, zero otherwise and the third equalled one if the participant, conditional on being employed, had an employment contract, zero otherwise. The empirical evidence from IPWRA is consistent with the estimations from the multinomial probit, suggesting that IET participants had a lower probability of being employed compared to both OJT and IS. Nevertheless, employed OJT participants were more likely to be without an employment contract compared to participants in the other two active measures.

With regard to the relative effectiveness of these three active measures analysed, the evidence from all the estimations suggest that on-the-job training is the most effective in increasing the probability of being employed in both formal and informal sectors. It was argued that one possible explanation is the design of this programme: employers seem to prefer programmes that are designed to take place within firms during the whole period of training (Kavanagh, 2012). Another explanation could be that the quality and market-relevance of the training received by the employees is higher compared to the other two programmes. In contrast, institution and enterprise training was designed to divide the time allocated between the training at the vocational training centres to improve participants' soft and other employability skills and training at the companies to enhance job-specific skills. Another reason for the apparent ineffectiveness of IET might be related to the stigmatisation of the participants because this measure targets the most disadvantaged unemployed (those who did not have a chance to attend or complete vocational education and had no previous work experience). Additionally, these active measures, in general had irregularities in targeting participants. In order to accept more women and minorities the selection criteria were not strictly met, hence accepting older participants and those with unsuitable levels of education. Moreover, since there is no data that can provide an insight on the content and quality of the programmes, a definite judgment of the effectiveness of these policies cannot be made.

Chapter 6 also addresses objective 5 of this thesis by analysing the overall effectiveness of the above-mentioned ALMPs. The difference between relative and overall effectiveness of ALMPs is that the latter analyses the effects of participation in one of the policies in comparison to non-participation. In order to construct a control group of non-beneficiaries, this chapter utilised an additional dataset, the Kosovo Labour Force Survey data collected in the same year as the data for the beneficiaries. When constructing control groups from a source other than that used for the treatment group, it is likely that the dataset contains measurement errors due to differences in the two questionnaires. In order to minimise the measurement differences between the treatment and control datasets, variables with measurement differences were used in separate specifications and the results from these specifications were interpreted with caution. The empirical evidence suggests a significant positive treatment effect in increasing employment probability after treatment, however only when controlling for the individuals' employment history, which is in line with some evidence found in other studies (Kluve et al., 2008). Consistent with the empirical evidence from chapter 5, the most effective active measure in terms of employment probability was OJT followed by IS. When analysing the effectiveness of the active measures in increasing the probability of being employed in the formal sector, the empirical evidence from the binary treatment model suggests that, in general, participation in one of these three active measures reduces the probability of an employed individual having an employment contract compared to that for a non-participant. However, the findings from the multivalued treatment model suggest that out of these three active measures only the treatment effect for OJT is significant. This result also shows that the multivalued treatment model presents a clearer picture of the effectiveness of measures compared to the binary treatment model. The evidence provided in chapter 6 suggests that, in the context of a labour market with low formal employment opportunities, such as in Kosovo, participating in an active measure might increase a participant's probability of being in employment but participants may be employed in the informal sector. The empirical analyses suggest that particularly OJT participants in Kosovo were likely to be employed informally. The findings from chapter 6 indicate that an employed OJT participant has a lower probability of having an employment contract by 12.5 pp compared to the average of similar individuals in the control group. Differences in outcomes for participants of different measures may be related to the economic sectors in which they are implemented and also the occupation of the participant.

In conclusion, when analysing the relative effectiveness of the ALMPs, the evidence from the multinomial probit model are broadly consistent with the evidence from IPWRA where OJT is found to be the most effective in increasing an individual's probability of being employed followed by the IS programme. The evidence from the overall effectiveness of ALMPs also suggest that the OJT and IS measures are effective in increasing the probability of participants being employed compared to non-participants. The results, though, depend on the model specification used. When variables measuring the individual's employment history are not included in the model (even though in this analysis these variables tend to have measurement differences between treated and controls), the evidence indicates negative treatment effects for IET on the probability of being employed. This evidence suggests the importance of the unobserved characteristics captured by these variables in determining the individual's probability of gaining employment. When the probability of having an employment contract for those employed in the sample was analysed the results suggest that the employed OJT are more likely not to have an employment contract compared to the non-participants and also compared to IET. This result is consistent in all specifications and also in line with the findings in chapter 5.

7.3 Contribution to Knowledge

This thesis has made four main contributions to knowledge with regard to the evaluation of the effectiveness of ALMPs in increasing employment.

Firstly, this is one of very few studies that have incorporated into the evaluation of the effectiveness of ALMPs employment in the informal sector. The theoretical framework for assessing the effectiveness of ALMPs developed for Western economies, presented in chapter 2, was argued not to be entirely appropriate for the analysis in a transition economy context. Considering that the labour markets in many transition economies are better characterised by a low-skill, bad-job equilibrium, an augmented theoretical framework was required. The discussion in chapter 2 provides theoretical justifications that in transition economies this equilibrium is associated with a large informal sector. Given that the ALMPs, in general, target low-skilled, long-term and disadvantaged unemployed and because the informal sector tends to employ more of these categories of labour, it was argued that in this context, ALMPs such as wage and direct subsidies for low skilled workers could provide incentives to firms to switch to formal employment. Employers would benefit from such policies because they would lower firms' labour costs and therefore they would improve the employment prospects of participants in the formal sector**.** Consequently, employers would be induced to comply with employment regulations such as providing the participants with a written employment contract. This research fills the gap in the theoretical and empirical literature by addressing how the ALMPs perform in context of countries with large informal sectors. This relationship has not been assessed theoretically and to the best of author's knowledge there is only one study analysing it empirically. In contrast to the theoretical expectations discussed here, investigations at the individual level in chapter 6 find that the participants in ALMPs in a labour market characterised with large informal sector, if employed post-participation, are more likely to be so in the informal sector.

Secondly, this research makes a contribution to knowledge by using a more sophisticated estimation strategy, which allows for analysing the effect of participating in an ALMP in a multivalued treatment selection framework. To the best of our knowledge, this is the first research study to use this empirical approach in the ALMP microeconometric evaluation literature. Previous microeconometric evaluation methods were mostly concerned with the treatment effects of being or not being a participant in one of the active measures. As argued in chapter 4, ALMPs are heterogeneous in terms of content, quality, design, targeting of participants, duration etc. Thus, it is crucial to analyse these policies in a framework with a dynamic treatment selection, where the choice is not just participating vs. non-participating but a distinction is also made between which programme the unemployed participated in. This research fills the gap in the microeconometric evaluation of ALMPs by addressing the heterogeneity of the active labour market policies and the findings of chapters 5 and 6 confirm that this approach can lead to valuable insights.

Specifically, the results presented in chapter 6, suggest that a treatment effect based on multivalued pairwise comparison can give a clearer causal explanation of the effects of different active measures that could be used to rank them. The estimated results from the multivalued treatment models provide more detailed information with regard to which of the active measures are more effective in comparison to non-participation. On the other hand, the results from the binary model, which puts all three active measures into one category and treats them as being the same, are unable to reveal which of the three measures is more effective. Moreover, the evidence in chapter 6 suggests that the treatment effects of the three active measures, obtained from the multivalued treatment model might cancel each other out. Thus, the overall treatment effect from the binary model of participation vs. non-participation cannot always present the 'true' situation of the effectiveness of individual ALMPs.

Thirdly, this is the first critical evaluation study of the effectiveness of ALMPs to be conducted for Kosovo. As chapters 2 and 4 revealed, the effectiveness of ALMPs has generally been under-researched in transition economies, mainly due to the low quality and general unavailability of data. Given that the unemployment rate in Kosovo is the highest in region and in Europe, it is crucial to assess the relative effectiveness of active measures in attempt to increase the employment prospects of the unemployed. Moreover, Kosovo constitutes a country which has undergone conflict more than a decade ago which has distorted the labour market. This makes this analysis distinct from other similar studies in the transition context. ALMPs in Kosovo have been implemented only from 2005, and the findings of the study provide insights as to how to design more effective active measures. As discussed in chapter 5, there are two other studies assessing the effect of these ALMPs in Kosovo, however, neither of them used an advanced evaluation methodology such as the one used in this thesis; notably, they simply compare mean outcome variables of participants and non-participants, not controlling for participant characteristics and employment history and they do not account for the potential selection bias. Both studies reviewed in section 5.2.1 assess the effectiveness of the programmes only based on the percentage of the participants employed at the time of the survey. According to Kavanagh (2012), who uses the same dataset as this thesis, the most effective programme is the IS since 59% of previous participants were employed at the time of the survey, followed by IET with 42% and then OJT with 35%. Given that this study does not control for participant characteristics or use a modern evaluation methodology or address selection bias, the results provided by this study are unreliable. In contrast, as discussed in the previous section, when using an evaluation methodology which controls for relevant participant characteristics attempts to address selection bias, the findings from this thesis indicate that OJT is the most effective in increasing the individual's employment probability, followed by IS, while IET is usually found to be ineffective.

Fourthly, this research contributes to the empirical literature in assessing the effectiveness of ALMPs at the country level by employing a diversified empirical strategy. The review of theoretical framework emphasised the possible multiple effects of active measures in the labour market, hence the analysis at the country level presented in this research makes use of different approaches and different estimation techniques which allows more comprehensive inferences to be drawn. In this analysis, the choice of the estimation approaches was made based on the theoretical framework but also on the availability of data. As pointed out in chapter 2, the main effect of ALMPs is the effect on the matching process, thus the first approach used allows assessing the matching efficiency of these policies. Given the potential endogeneity of the ALMPs, the second approach uses a dynamic panel model to assess the impact of these policies in reducing unemployment rate. It is worth emphasising that there are very few studies analysing the effectiveness of ALMPs using different approaches such as presented in this thesis.

7.4 Policy Implications

The empirical evidence obtained in this investigation and theoretical arguments developed in this thesis have potential useful policy implications for the design and implementation of ALMPs in European economies. The findings are specifically relevant to the economies aiming to increase the effectiveness of labour market policies in reducing unemployment.

As discussed in section 7.2, the findings in chapter 3 suggest that ALMPs are effective in increasing matching between unemployed and vacancies, but their effectiveness in economic terms is limited since only a very small number of unemployed participants transition to employment. The findings from chapter 3 also suggest that the labour markets in transition economies might exhibit multiple equilibria where the low-skilled are trapped in a bad-job equilibrium. Given that in transition economies the ALMPs are provided only on a small scale, they are insufficient to shift the labour market from a bad to a good-job equilibrium. In addition, as argued in chapter 2, when the demand for labour is low, as in many transition economies one of the main objectives of ALMPs should be to reduce employers' labour costs. As a consequence firms would be more likely to open more vacancies thus increasing demand for labour. Considering these arguments and noting that it is difficult to escape the bad-job equilibrium, following Snower's (1994) argument, only a 'big push' in the amount of expenditure/investment on ALMPs is likely to be effective in addressing unemployment in transition economies.

ALMPs in most European Transition economies are currently fairly small-scale policies, hence in order to maximise their effects then the targeting of the participants should be clearly defined and then carefully implemented. The ALMPs analysed in chapters 5 and 6 targeted the disadvantaged groups in the labour market such as the long-term unemployed (with at least 6 months unemployment spell), women, younger unemployed, minority groups etc. The descriptive statistics in chapter 5 suggest that more than half of participants reported that they had been unemployed for longer than 2 years before treatment, while the findings from the multinomial probit suggest that this group were less likely to be employed than those with shorter unemployment spells. This finding might indicate that those with longer unemployment spells might need more intensive and specific training. A potential policy implication in this case would be to group participants based on the unemployment spells and design the training based on their level of skills. Additionally, according to the findings in chapter 5, those belonging to a minority group and those who have two or more family members unemployed are also more likely to be unemployed post-treatment given that they lack the social network, connections and information about vacancies. As expected, young participants are also found less likely to be employed. Given that they are joining the labour market probably for the first time, they might benefit more from training focused on soft skills and counselling about job search activity. The target group of ALMPs in Kosovo are all disadvantaged groups; however they all differ from one another in a sense that they all require specific treatment. In order to improve their prospects in the labour market, policy should tailor ALMPs based on the specific needs of the targeted subgroups of the unemployed.

As chapter 1 emphasised, there has been an increase in the number of beneficiaries of ALMPs in recent years in Kosovo, however, there are still many challenges to overcome. According to MLSW (2017), there are limited interactions between the unemployed, the employment services and the active measures because a large number of the unemployed are not registered and a large part of working age population are inactive. Most of the unemployed in Kosovo are unaware of the services and opportunities provided by employment offices, hence there is an issue in attracting the right target group. A more general policy implication with regard to targeting would be to pro-actively promote the target groups in order to increase awareness of the advantages of employing more marginalised groups who might be threatened by social exclusion, such as women, the long-term unemployed and youths.

This thesis also found evidence to suggest that the active measures designed to divide the training between activities at the regional VTCs and firms may be ineffective. The training activities at the VTCs were intended to enhance a participant's employability skills, team-working skills, work readiness skills, information and communication technology and other non-vocational skills. However, the absence of information about the quality and content of the training within VTCs did not allow us to fully assess whether the skills and productivity were improved by each element of the training provided. In addition, there is a huge constraint in the small number of employment services officers where the ratio of officers to job-seekers is about 1:1,000 (MLSW, 2017). This reflects budget constraints since the ALMPs are mostly supported by international donors. These constraints may help to explain the finding in chapter 5, that whether or not participants held an individual employment/training plan had no impact on the probability of being employed. Given that the training at the VTC and counselling of the participants by the employment counsellors at the Employment Offices, are a crucial design element of ALMPs, a policy recommendation in this case would be to improve the level and quality of the employment services and VTCs allocate more time to participants and dedicate more effort to formulating employment/training plans. In addition, the employment/training plans should be upgraded to include not only a pre- but also post-training skill assessment of all the participants through a system of profiling each participants’ strengths and identifying their employment opportunities in the labour market.

According to the MLSW (2017), there is lack of effective monitoring and evaluation mechanisms to ensure that the full cycle of active measure is completed and that these policies provided by VTCs are of the quality required by the labour market. The findings from this thesis suggest that a considerable number of participants did not have a employment/training plan or the certificate of completion of the active measures and they stayed a longer or a shorter period in the training than anticipated. These findings question the effectiveness of the current active measures in Kosovo. Hence, the policy recommendation in this case would be to improve the existing system of monitoring and evaluating the implementation and effectiveness of these measures in promoting employment.

A possible drawback in the implementation process of ALMPs, is the lack of assessment of the needs of the labour market. Because of the unavailability of data about the labour demand, there is a challenge in providing well-designed training and other active measures in those professions required by the labour market. This is particularly challenging since there is insufficient cooperation between VTC, enterprises and the social partners (MLSW, 2017). In this case, the policy agenda should focus on increasing this cooperation at the regional level in order to design and adapt training and other active measures to region-specific opportunities rather than having a 'one size fits all' approach. This cooperation, however, should be coordinated centrally in order to avoid too large divergences between different regions.

As emphasised in chapter 4, an experimental design approach provides the most reliable evaluation of the active measures. In Kosovo, there is lack of systematic evaluation of ALMPs which would shed light on the impact of these policies in improving employment prospects of the various groups of unemployed. The policy recommendation in this case is that in order to conduct an experimental design evaluation, measures to ensure the collection of data about the beneficiaries and the control group should be incorporated into the design and implementation stages of any ALMP.

7.5 Limitations and Future Work

There are certain limitations in the research undertaken which could not be addressed in this thesis due to data unavailability.

A general limitation of the empirical analysis conducted in this thesis is straightforward. Given the problems experienced with the data in the empirical investigations, when designing ALMPs it is crucial to simultaneously design appropriate evaluation strategies and the data collection methods. With regard to the data at the national level, as discussed in chapter 3, the matching efficiency would have been captured better if more frequent data about ALMPs were available, such as monthly or quarterly data as pointed out in section 7.2. Currently only annual data is available for analysis. Additionally, the data necessary for this approach was restricted in terms of the time span (the data is available only for period 2010-2015) and country coverage (11 transition economies and 3 Western economies). Using the available data with the approach discussed in section 3.3.3, restricted the sample to only 49 observations. Due to the small sample for the matching function, it was also not possible to estimate the effectiveness of different ALMPs. Given that the current unemployment rate is partly determined by the previous unemployment rates, then ideally a dynamic panel analysis is required. However, due to a small sample size, dynamic panel estimators could not be used. . The second empirical approach to analysing the effectiveness of ALMPs did utilise a dynamic panel model, however it was not possible to divide the samples and estimate the effectiveness of ALMPs for the two sets of countries (transition and non-transition European economies).

The collection of the individual level data for the control group should be conducted at the same time as for those of the treatment group. This enables obtaining the necessary and relevant information for both groups, hence allowing for a more comprehensive comparison between participants and non-participants. Most importantly, this would avoid the potential measurement error issues such as those experienced in the empirical investigation presented in chapter 6. The main limitation of the individual level analysis is that it lacked an appropriate control group. Obtaining the data on the control group from the same source would have increased the number of factors to match the treatment and controls individuals hence improving the reliability of the estimated treatment effects. As argued in chapters 4 and 6, an evaluation analysis should ideally utilise a dataset with as much pre-treatment information as possible about the employment of both treated and control individuals. This information may have helped capture unobserved characteristics such as individuals' motivation, willingness to remain attached to the labour market, search intensity, interpersonal skills and employers' preference towards certain workers. The quality of variables such as employment history and the missing information about the incidence of nepotism in the selection process and on the probability of finding employment might have also influenced accuracy of the estimated results. A variable measuring the individuals' pre-treatment employment history was constructed from different questions asked of the treatment and control groups, hence imposing measurement errors in the analysis of chapter 6. Additionally, the inability to account for ALMP participation of the individuals in the control group due to the limitation of the data, increased the possibility of bias in the estimated results.

The evaluation of the treatment effects of the policies would have been more thorough if investigated both through cross-sectional analysis and over time. Apart from the data being collected at single point in time, the first approach used for investigation at the individual level was a multinomial probit model which did not address the selection bias issue. Additionally, after attempting to address the selection bias issue when using the IPWRA estimator, the sample for certain outcome models was reduced which created an imbalance between different treatment groups. This might have distorted the estimated results for this outcome model when analysing the relative effectiveness of the individual programmes. Also, the treatment group dataset provided no information about the quality or the content of the training and internships and the unavailability of such data restricted the interpretation of the estimated results. Another limitation of the data is that the participants were not surveyed at a fixed time after completing their treatment.

It is important to note that whilst ALMPs might increase both future employment prospects and lifetime earnings, their provision is costly. Hence, to be able to fully assess whether active measures have been worthwhile from the social perspective additional expenditure and earnings data should be collected and made available to researchers. There is currently no systematic data available about the costs of and monetary benefits to the participants, employers, government and society as a whole in Kosovo.

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The Effectiveness of Active Labour Market Policies in Reducing Unemployment in Transition Economies

Appendices

Albulena JAHJA LUBISHTANI

Appendix 2 – Chapter 2

Appendix A2.1 Snower's (1994) model of multiple equilibria in the labour market

Based on the theoretical model of Snower (1994), multiple equilibria can result in a 'low-skill, bad-job equilibrium' and a 'high-skill, good-job equilibrium'. Snower argues that labour market can fall into a 'low-skill, bad-job trap' which entails a preponderance of jobs that are associated with low wages, low productivity and little opportunity to acquire training or enhance human capital. In this context, firms do not provide a lot of skilled vacancies because there is not enough skilled labour and these vacancies would be difficult to fill. Snower refers to this as the 'vacancy supply externality'. Similarly, workers are not incentivised to acquire skills since there are few skilled vacancies and as such the skills would be likely to remain under-compensated. This is regarded as the 'training supply externality'. If firms provide skilled vacancies it raises the workers' returns to education and training, however firms do not pay for the workers' education. By the same argument, workers who acquire training and education increase firms' returns to opening vacancies for skilled jobs. Snower argues these two externalities reinforce one another and can induce an insufficient level of training.

Snower assumes that there is fixed number of workers who either are 'unskilled' and have a marginal product of α_u and can work only at the 'bad jobs' or are 'skilled' who have a marginal product of α_s which is higher than α_u. All workers live for two periods; during the first period every worker makes the decision to acquire the necessary education or training and to become skilled. Those who decide not to acquire education start working in the first period while those that start the education or training are able to provide work only in the second period. The barriers to entry which gives workers and employers a market power in the wage setting process make the market for 'good jobs' imperfectly competitive, while the market for 'bad jobs' remains perfectly competitive. In the market of unskilled workers, on account to perfect competition, the real wage is equal to the marginal product of the unskilled workers:

$$w_u = \alpha_u \qquad 2.14$$

Assuming that this wage is above the reservation wage of the unskilled workers, there is no unemployment. The real wage of the skilled workers w_s is determined by a Nash bargain between the employer and the high skilled workers. The skilled worker receives the wage w_s while the employer receives the return of $\alpha_s - w_s$. In case of disagreement, the high skilled worker will receive w_u while the vacancy of the employer will remain unfilled. The bargaining problem is to maximise the Nash product $(w_s - w_u)^{\mu}$. $(\alpha_s - w_s)^{1-\mu}$ with respect to w_s, where the μ is the bargaining power of the skilled worker relative to employer. The wage that solves this problem is:

$$w_s = \mu * \alpha_s + (1 - \mu) * \alpha_{\mu} \qquad 2.15$$

With regard to the education/training decision, workers are assumed to be heterogenous in terms of their ability to acquire education. The marginal skilled worker's cost of education increases with the aggregate number of the educated workers, $e * N_s^{\epsilon}$, where the e and ϵ are positive constants. After the worker acquires education, his/her probability of having a high skilled job is ρ and having a wage w_s, while the probability of having a low skilled job is *(1- ρ)* and having a bad job wage w_u. Thus the marginal skilled worker's net return from acquiring education is $\rho * w_s + (1 - \rho) * w_u - e * N_s^{\epsilon}$. The marginal worker in the equilibrium is indifferent whether to acquire education or remaining unskilled is $\rho * w_s + (1 - \rho) * w_u - e * N_s^{\epsilon} = 2w_u$ where $2w_u$is the income of unskilled worker during the two periods. This equation is equivalent to

$$\rho * w_s - (1 + \rho) * w_u = e * N_s^{\epsilon} \qquad 2.16$$

The matching process is given by the following expression:

$$X_s = A * \min(N_s, V_s) \qquad 2.17$$

Where X_s is the number of aggregate matches, N_s is the number of skilled job seekers, V_s is the aggregate number of skilled vacancies and the constant $A < 1$ because workers have imperfect information about the availability of skilled vacancies. Consequently, the probability of finding a good job is:

$$\rho = \frac{X_s}{N_s} = A * \min\left[\frac{V_s}{N_s}, 1\right] \qquad 2.18$$

Substituting the wage equation in 2.15 and 2.16 along with equation 2.18 into the marginal condition 2.15, will give the training function:

$$A * \mu * (\alpha_s - \alpha_u) * \frac{V_s}{N_s} - \alpha_u = e * N_s^{\epsilon} \qquad for\ V_s < N_s \qquad 2.19$$

$$A * \mu * (\alpha_s - \alpha_u) - \alpha_u = e * N_s^{\epsilon} \qquad for\ V_s \geq N_s \qquad 2.20$$

This training function is shown by the TF curve in Figure 2.5.

The model assumes that firms face free entry in the sector so the aggregate number of skilled vacancies may be determined by a zero-profit constraint. Each firm has a fixed cost of k_1 while beyond that, firms are assumed to be heterogenous in terms of the costs of supplying vacancies. So the marginal firm's total cost of supplying vacancies rises with the aggregate number of vacancies supplied. The vacancy induced part of the total costs is $k_2 * V_s^{\delta}$ where k_2 and δ are positive constants and δ>1; thus the average cost of marginal firm is $(k_1/ V_s) + k_2 * V_s^{\delta-1}$.

Because each firm has the same average return from creating a skilled vacancy, $\theta * (\alpha_s - w_s)$, where θ is the firm's probability of finding a skilled worker, so the zero profit condition of supplying vacancies is:

$$\theta * (\alpha_s - w_s) = \frac{k_1}{V_s} + k_2 * V_s^{\delta-1} \qquad 2.21$$

The probability that a firm will find a skilled worker is:

$$\theta = \frac{X_s}{V_s} = B * min\left[\frac{N_s}{V_s}, 1\right] \qquad 2.22$$

By substituting 2.22 into 2.21, the skilled vacancy function is obtained:

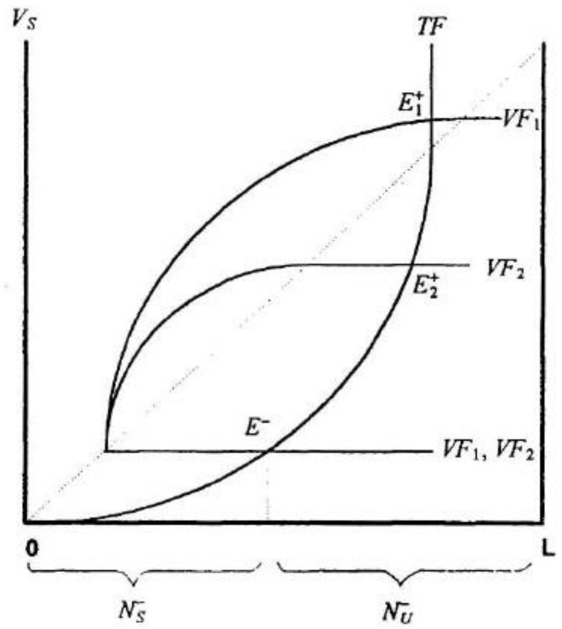
$$k_1 + k_2 * V_s^{\delta} = B * N_s * (1 - \mu) * (\alpha_s - \mathrm{a}_u) \qquad for\ V_s > N_s \qquad 2.23$$

$$k_1 + k_2 * V_s^{\delta} = B * V_s * (1 - \mu) * (\alpha_s - \alpha_u) \qquad for\ V_s \leq N_s \qquad 2.24$$

This is depicted by the vacancy function VF in Figure 2.5. Equation 2.24 represents the horizontal vacancy function lying beneath the 45^{o} line in Figure 2.5, while the equation 2.23 represents the vacancy function lying above the 45^{o}line which is concave.

Equilibria lie at the intersections of the training function and the vacancy function. Rising marginal cost of training makes the lower portion of the training function convex (equation 2.19), while the rising marginal costs of vacancies makes the vacancy function concave (equation 2.23). Thus there exist at least two equilibria. The low skilled equilibrium lies at the upward sloping portion of TF curve and horizontal VF function at point E^{-}. The good job equilibrium is either at the intersection of the upward sloping portion of the VF curve and vertical portion of TF curve at point E_1^{+} (the intersection of VF1 and TF in Figure 2.5), or at the intersection of the upper horizontal portion of the VF curve and the upward sloping portion of the TF curve at point E_2^{+} (the intersection of VF2 and TF in Figure 2.5).

Figure 2.5 Multiple equilibria – the low-skill, bad-job trap and the high-skill, good job equilibrium



Source: Snower (1994)

At the bad-job equilibrium, few workers acquire education since firms supply few skilled vacancies and similarly firms supply less skilled vacancies because there are not enough skilled workers who can fill these vacancies. Thus, skilled workers employment is N_s^- and because labour force is constant at L, the unskilled employment is $N_u^- = L - N_s^-$. Firms offer plenty of skilled vacancies at the good-job equilibrium since many workers acquire education.

Snower's model can be used to explain the different incidence of skilled employment opportunities in different countries and the emergence of multiple equilibria. Technological progress increased the demand for skilled workers in Western economies while increased international trade increased the demand for unskilled workers in Central and Eastern Europe. In this context, due to low demand for skilled labour in transition economies there is little incentive for labour to acquire skills through education and training because they will likely be under-compensated. In the same vein, because there are only a small proportion of skilled workers in transition economies, firms do not have sufficient incentives to open vacancies for high-skilled labour. As discussed in section 2.3, in transition countries highly-skilled labour is largely missing and these economies are not considered knowledge-based economies.

Appendix A2.2 Youth Unemployment

One of the aims of this thesis was to evaluate the effectiveness of ALMPs that are targeted specifically at youth unemployment. As Chapter 1 documented, youth unemployment rates are considerably high, reaching double-digit figures in most of the European transition economies. This section examines the causes of these high youth unemployment rates in European transition economies.

A common feature for every country with available statistics is that the youth unemployment rate is higher than the adult unemployment rate (O'Higgins, 2001). The gap between the youth and adult unemployment rates is typically wider in developing and transition countries compared to industrialised countries. In addition, it is observed that an increase in the adult unemployment rate is usually associated with a proportionate increase (Gaude, 1997) or more than proportionate increase in youth unemployment (O'Higgins, 2001). Thus, one of the objectives of this section is to discuss the causes of the disproportionate increase in youth unemployment rate compared to adult unemployment rate.

Economic growth is a precondition for improved employment opportunities for labour market entrants, though in recent years it was observed that many industrialised and developing economies have experienced jobless growth (O’Higgins, 2015). Despite relatively high economic growth in European transition economies in the last decade, youth unemployment remains high and it poses a continuing challenge to policymakers (Kovtun et al., 2014). The low youth employment rates in most ETEs may cause the human capital of the unemployed young people to rapidly depreciate, hence making it more difficult for them to find ‘good’ jobs in the future. Further, it will increase the dependence of young people on the social security system which in turn will diminish the countries’ growth potential. As observed in section 2.2.2, this may lead to a ‘hysteresis’ effect on overall unemployment and consequently the natural rate of unemployment will tend to increase.

The following sub-sections will identify what are the causes of youth unemployment in European transition economies with particular reference to youth unemployment in Kosovo. Section 2.2.1 analyses how aggregate demand impacts disproportionately on the youth unemployment rate and particularly analysing the peculiarities during the transitional restructuring. Section 2.2.2 will further discuss the causes of the extended school-to-work transition, particularly focusing on the relevance of education and the evidence of skill mismatch in transition economies.

2.2.1 Youth Labour Force Size and the Fluctuation in Aggregate Demand

Previous research suggests that there are a number of factors that contribute to persistently high youth unemployment levels, where some are specifically related to young people while others reflect the overall situation in the ETEs. One of the arguments underlying the cause of the youth unemployment is the demographic composition, particularly the size of youth cohort in the labour market (O’Higgins, 2001; Zimmermann et al., 2013). A high growth of the young population means that the job creation should also increase in order to absorb the new entrants in the labour market so that youth unemployment does not rise. According to some studies, youth population growth can explain to some extent the high youth unemployment in Romania, Moldova, Kosovo and FYR Macedonia (Kolev and Saget, 2005, Mojsoska-Blazevski, 2016). However, in the long run employment tends to grow at the same rate as the labour supply (Mojsoska-Blazevski, 2016).

Zimmermann et al. (2013) argues that even though the size of the labour force is an important determinant of the level of youth unemployment, labour demand and overall employment opportunities are a more important factor. Youth unemployment is affected by economic growth in a similar way as that of adults, but it is much more sensitive to fluctuations in the business cycle (O'Higgins, 2001). Young workers are less likely to be employed because they have less experience. Also, the argument behind the disproportionate impact on youth unemployment is that young workers tend to quit jobs more than adults for several reasons. Firstly, young workers have fewer job-specific skills and therefore are less likely to suffer a wage loss when moving between jobs. Secondly, young workers are more likely to quit trying to find a better match with their skills and aspirations. Thirdly, the opportunity cost of young people not being employed is lower than that of adults since they are less skilled, tend to have lower wages and are less likely to 'need' a job to support their families (O'Higgins, 2001). A contributing factor to this issue is that young people are more likely to be employed in temporary jobs or disproportionately working in the more cyclical-sensitive industries than adults (O'Higgins, 2015).

Since young people are disproportionately low-skilled and generally have acquired less training investment by firms, it is less costly to dismiss them rather than older employees. Furthermore, the employment protection legislation usually does not cover young people since such legislation usually requires a qualifying period or a certain level of experience which increases with tenure (O'Higgins, 2001; Kovtun et al., 2014). Moreover, during recession periods firms will primarily freeze the recruitments of new employees and afterwards they start layoffs typically on a 'last-in/first-out' (LIFO) basis. In cases of hiring freezes and layoffs, young people are more likely to be hit harder.

O'Higgins (2001) argues that in Central and Eastern Europe, as a consequence of the transition from central to market economy, youth unemployment has increased at a higher rate compared to industrialised countries. The outflow from the unemployment has been much lower compared to the flow of new entrants into the unemployment pool. The structural adjustments in the 1990s had a huge impact in the downsizing of employment in the public sector while the new job-openings have been insufficient to compensate the loss of jobs during the transition period. The extent of restructuring in transition economies has caused the large-scale job reallocation which affected youth unemployment. Countries that have had a slow restructuring may have temporarily preserved the jobs of senior workers at the expense of the young workers (Kolev and Saget, 2005; O'Higgins, 2015). This made it harder for young people to find employment, causing the disproportionate high youth unemployment rate. The development of the private sector was expected to reduce youth unemployment; however, no clear relation is evident between the job-creation in the private sector and youth unemployment. Kolev and Saget (2005) suggest that this is because the private sector is mostly comprised of former public enterprises which have been restructured to private enterprises as opposed to newly established private enterprises. It is the growth of service sectors, such as retail trade, hotels and restaurants and information technology that has created opportunities for young people.

The macroeconomic and fiscal policies that were introduced in Kosovo, such as the promotion of private sector development through offering low tax rates, liberalisation of trade, reduction of public employment and public subsidies and transfers, have not been fully successful in opening new job opportunities and reducing unemployment. Insufficient foreign and domestic investment and decreasing external income transfers together with rapid de-industrialisation have dampened aggregate demand and slowed down economic growth. Additionally, the predominance of micro-enterprises with low productivity and competitiveness seem to have been one of the main causes of the large trade deficits which in turn affect employment.

As recorded above, transition economies with high unemployment and poverty have developed large scale informal employment. For instance, in Kosovo young people mostly transit from school and unemployment to low paid jobs in the informal economy (Corbanese and Rosas, 2007). The causes of young people engaging in informal employment vary across countries but the main reason is that they cannot find jobs in the formal sector (Corbanese and Rosas, 2007; Shehu and Nilsson, 2014; Mojsoska-Blazevski, 2016).

As discussed in section 2.3, labour protection legislation is very limited in Kosovo and inadequately enforced. Corbanese and Rosas (2007) attribute the predominance of informal employment of youths in Kosovo to the low enforcement of employment regulation. Despite the lowest mandatory social security contributions in the South-East Europe (5% of the gross wage paid by each: employer and employee), the survey of Corbanese and Rosas found that 73% of enterprises in Kosovo responded that they preferred informal employment because of the avoidance of the cost of paying social security contributions for their workers. It is the limited capacity of public administration to ensure the enforcement of labour legislation that leads to high informal employment among young people. In other European transition economies, young people are typically not eligible to claim unemployment benefits because they lack employment experience, this provides another incentive for the young unemployed to take informal jobs (Marjanovic, 2016, Djuric, 2016).

2.2.2 School to work transition and the contribution of education

The school to work transition is characterised by different status episodes that can consist of: vocational education, higher education, military service, temporary jobs etc. with the final objective of becoming fully integrated into the formal labour market. These status episodes can be viewed as optimal job-search episodes where young people move in and out of the labour market before they get settled in a particular job that offers them a career or before they go back to full-time education. Some of the young workers enter the labour market through temporary jobs and afterwards move to more stable jobs while other young workers move to unemployment and inactivity. The most common risk faced by young workers is the mismatch of the level of education acquired and the level of skills required in the labour market. As the first chapter emphasised, the unemployment rate for more educated and skilled young people is lower than that of low-skilled youths. General education and training thus are one of the major factors determining the shape of school to work transition (Dietrich, 2012).

European transition economies show different patterns of school to work transition which in addition are heavily influenced by the educational policies and the education system. Zimmermann et al. (2013) suggests that when the formal education cannot translate into jobs the educational mismatch can cause youth unemployment and underemployment. General education (non-vocational primary and secondary school) aims to improve the cognitive skills required for successful integration into the formal labour market and it is usually observed that those who have completed high-quality general education have higher earnings compared to those who attended education of a lower quality. However, as opposed to individuals with vocational education, those who complete general secondary education have a higher risk of being weakly attached to the labour market because they are not specialised in a specific occupation (Zimmermann et al., 2013) and do not gain practical experience. Well-designed and targeted vocational education, on the other hand, can increase employment opportunities for youths. It aims to promote the direct entry of youths into the labour market and its success depends on the alignment of the skills acquired in school to skills required in the labour market.

Skill mismatches are an important factor contributing to youth unemployment and inactivity in European transition economies. According to the School to Work transition reports conducted by International Labour Organisation, the mismatch between the skills and labour demand is quite large in European transition economies (Corbanese and Rosas, 2007; Matsumoto and Elder, 2010; Shehu and Nielson, 2014; Djuric, 2016; Mojsoska-Blazevski, 2016; Marjanovic, 2016). This skill mismatch may prolong the school-to-work transition. In Serbia and FYR Macedonia, the over-education is more common than under-education (Marjanovic, 2016; Mojsoska-Blazevski, 2016). Since newly created jobs were mostly in lower skilled occupations, this made the overqualified young individuals to take the available jobs in the labour market. Consequently, they earn less than what they could have otherwise and their potential is not fully utilised.

The skill mismatch is a particularly important determinant of the slow school-to-work transition in Kosovo. The skill mismatch seems to have been a consequence of the education system from the 1990's. In Kosovo during this decade the access to education was limited and education was mostly informally obtained while vocational education was acquired mostly on the job (Corbanese and Rosas, 2007). In spite of significant improvement since after the conflict in Kosovo, the educational system still suffers from high drop-out rates and is poorly financed which triggers low educational outcomes. These gaps are predominantly evident for vocational education and trainings. According to Corbanese and Rosas (2007), vocational education in Kosovo does not attract students despite the fact that enterprises seem to require workers with vocational skills. Another important reason for young people in Kosovo not having completed the transition to work (e.g. are inactive) is that they do not believe that they can find employment. For young women in Kosovo not having completed the transition to work, a reason might be their household-related responsibilities and childcare. A possible explanation for this is that social services and childcare facilities are largely unavailable in Kosovo. The low inactivity of young women in Kosovo is also related to gender stereotypical factors which are engraved even in younger generation that some occupations are not unsuitable for women (Corbanese and Rosas, 2007).

As Chapter 1 identified, the percentage of NEETs (not in education, employment or training) can be as high as 35 percent of youths in Kosovo, 31 percent in FYR Macedonia and 28 percent in Montenegro (Mojsoska-Blazevski, 2016; Djuric, 2016). NEETs neither contribute to the economic production nor are they investing in their human capital through education and training. The concept of idleness or disconnected youth, closely related to the NEET, is related to the idea that young people do not have a strong network to support them in the labour market. Arulampalam (2001) also considers that there is a strong relationship between the initial experience of unemployment amongst young people and their future labour market success. The mechanisms behind this relationship can be explained through three different processes: deteriorating working skills and loss of experience; negative signalling effects to labour market and potential future earnings; and loss of social networks.

Studies provide evidence that the longer the unemployment spells in early working life, the larger the skill deterioration and the 'scarring' effect will prevail in the future labour market status and at the level of earnings (Ball and Mankiw, 2002; Luijkx and Wolbers, 2009; Dietrich, 2012). The shock that leads to unemployment leaves a permanent scar through diminishing human capital and signalling of low productivity to the labour market. This makes the unemployed less attractive to employers and by attaching the social stigma of long-term unemployment leading to a higher natural rate of unemployment. Studies found evidence that the early youth unemployment has high negative effect on employment prospects while the effect on earnings is slightly lower (Arulampalam, 2001; Gartell, 2009). When evaluating the scaring effects one should take into consideration the labour market condition at that period. Experiencing unemployment when overall unemployment is low, signals low productivity and loss of future earnings compared to being unemployed in periods when the aggregate unemployment is high.

The social capital and social network consist of both formal and informal job-related networks which can impact or facilitate reemployment success (McKee-Ryanet al., 2005). Fugate et al. (2004) argue that social capital and 'knowing-whom' competencies increases the employability perspective of the young unemployed and young people entering the labour market for the first time do not always have the right social network to get a job and the longer the young individual is unemployed it is more likely that social capital will be less utilised and developed.

Experiencing unemployment as a youth and social exclusion from the labour market may also influence mental health of the young unemployed, as various studies show (Fernandes and Gabe, 2009; Bell and Blanchflower, 2009). Unemployment spells when young can create permanent scars many years later through affecting happiness, job satisfaction and wellbeing (Bell and Blanchflower, 2009). Alvaro and Garrido (2003) show that the main cause of diminishing well-being of young unemployed are financial issues and lack of social inclusion.

In conclusion, youth unemployment rates in transition economies remain very high despite the relatively high economic growth in recent years. Youth unemployment rates were disproportionally impacted by the transition process compared to adult unemployment rates, mainly because during the restructuring process enterprises preserved the employment of existing workers at the expense of new ones, while the private sector was unable to create jobs at the rate required to match the inflow of entrants to the labour market. Additionally, the low enforcement of labour protection legislation and inadequate labour market policies have contributed to the emergence of significant informal employment. The transition of youths from school to formal work is fraught with difficulties, whilst the low quality of education in ETEs and large mismatch of skills have extended this transition.

Appendix 3 – Chapter 3

Table A3.1.1 Correlation Matrix

	lnUEflow	AL~plag1	ln~Tlag1	lnVaca~1	lnEUflow	lnIUflow	lnLFor	ShLongUn	ShYoun~n	ShWome~n	PLMPE~g1	Inform~1	GDPgro~h	LabFre~1
lnUEflow	1.0000													
ALMPExplag1	0.5578	1.0000												
lnUnemplST~1	0.6620	-0.0327	1.0000											
lnVacancie~1	0.7412	0.5262	0.2685	1.0000										
lnEUflow	0.9731	0.5489	0.6032	0.7317	1.0000									
lnIUflow	0.9044	0.4883	0.4424	0.7333	0.9082	1.0000								
lnLFor	0.8914	0.2887	0.6974	0.8160	0.8637	0.8612	1.0000							
ShLongUn	-0.4215	-0.6585	0.2847	-0.6392	-0.4326	-0.5502	-0.3451	1.0000						
ShYoungUn	0.4855	0.6752	-0.0971	0.7084	0.4632	0.5936	0.4624	-0.8000	1.0000					
ShWomenUn	0.1894	0.2511	-0.0789	0.1182	0.2215	0.0836	-0.0190	-0.0584	-0.0752	1.0000				
PLMPExplag1	0.3551	0.5176	-0.0139	0.3279	0.4263	0.3733	0.1886	-0.1629	0.2404	0.3060	1.0000			
Informalit~1	-0.4673	-0.6293	0.0649	-0.6920	-0.4492	-0.4454	-0.4126	0.4953	-0.5986	-0.5166	-0.4857	1.0000		
GDPgrowth	-0.2329	-0.1000	-0.0330	-0.3603	-0.3184	-0.2640	-0.2809	0.1344	-0.1485	-0.2556	-0.1979	0.2597	1.0000	
LabFreeInd~1	0.2900	-0.2478	0.5815	0.1270	0.2529	0.1524	0.3751	0.2688	-0.3702	0.0084	-0.2578	0.1091	0.0091	1.0000
EcoFreeInd~1	0.1215	0.4106	-0.1820	0.3788	0.0777	0.0537	0.0390	-0.4151	0.3359	0.2354	0.3193	-0.5060	0.2569	0.0175
EduTertiary	-0.2340	0.3976	-0.6349	-0.0165	-0.2109	-0.2014	-0.4254	-0.4649	0.2274	0.0156	0.1862	-0.0767	0.2767	-0.4317
EduSecondary	-0.0982	-0.4907	0.4662	-0.3514	-0.1507	-0.2910	-0.0207	0.6526	-0.5679	0.2063	-0.4664	0.2068	-0.0436	0.4865
PopDensity	0.5054	0.2531	0.2712	0.4855	0.5741	0.5031	0.4871	-0.0486	0.1222	0.3642	0.7950	-0.5142	-0.2946	0.1065

	EcoFre~1	EduTer~y	EduSec~y	PopDen~y
EcoFreeInd~1	1.0000			
EduTertiary	0.5224	1.0000		
EduSecondary	-0.3821	-0.7356	1.0000	
PopDensity	0.2886	-0.1212	-0.2356	1.0000

Table A3.1.2 Variance Inflation Factor

All Variables

Variable	VIF	1/VIF
lnLFor	117.79	0.008490
EduSecondary	51.71	0.019337
lnVacancie~1	43.20	0.023146
lnEUflow	42.26	0.023665
lnIUflow	41.86	0.023892
lnUnemplST~1	39.51	0.025307
PopDensity	25.33	0.039472
EduTertiary	21.57	0.046367
ShLongUn	18.86	0.053015
Informalit~1	16.11	0.062064
ShYoungUn	13.71	0.072933
PLMPExplag1	10.09	0.099082
ALMPExplag1	9.25	0.108091
EcoFreeInd~1	8.28	0.120725
ShWomenUn	7.40	0.135165
LabFreeInd~1	4.83	0.206904
GDPgrowth	2.64	0.378943
Mean VIF	27.91	

Without Shares

Variable	VIF	1/VIF
lnLFor	63.12	0.015843
lnEUflow	31.99	0.031261
lnVacancie~1	29.61	0.033776
lnIUflow	29.22	0.034221
EduSecondary	22.15	0.045140
lnUnemplST~1	18.02	0.055492
PopDensity	13.01	0.076883
Informalit~1	12.85	0.077819
EduTertiary	12.34	0.081053
ALMPExplag1	8.32	0.120192
PLMPExplag1	8.29	0.120686
EcoFreeInd~1	4.28	0.233718
LabFreeInd~1	2.66	0.376102
GDPgrowth	2.54	0.394042
Mean VIF	18.46	

Without EduSecondary

Variable	VIF	1/VIF
lnLFor	62.83	0.015916
lnVacancie~1	23.43	0.042673
lnEUflow	21.59	0.046312
lnIUflow	21.43	0.046670
lnUnemplST~1	16.44	0.060833
PopDensity	9.53	0.104898
PLMPExplag1	8.17	0.122350
ALMPExplag1	6.45	0.155083

```
 EduTertiary |      5.94    0.168420
Informalit~1 |      5.51    0.181638
EcoFreeInd~1 |      3.98    0.251149
   GDPgrowth |      2.37    0.422810
LabFreeInd~1 |      2.23    0.449058
-------------+----------------------
    Mean VIF |     14.61


Without EcoFreeIndlag1

    Variable |       VIF       1/VIF
-------------+----------------------
      lnLFor |     56.66    0.017649
    lnIUflow |     20.37    0.049101
    lnEUflow |     19.80    0.050512
lnVacancie~1 |     19.53    0.051207
lnUnemplST~1 |     14.52    0.068868
  PopDensity |      8.94    0.111806
 PLMPExplag1 |      8.09    0.123612
 ALMPExplag1 |      6.44    0.155202
 EduTertiary |      5.08    0.196992
Informalit~1 |      5.00    0.200001
   GDPgrowth |      2.10    0.476909
LabFreeInd~1 |      2.04    0.489056
-------------+----------------------
    Mean VIF |     14.05
```

Table A3.2.1 Model 1- Random effects estimated results

```
xtreg lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow lnLFor
ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1
EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, re
note: Y11 omitted because of collinearity
note: Y15 omitted because of collinearity

Random-effects GLS regression                   Number of obs     =         49
Group variable: CountryID                       Number of groups  =         14

R-sq:                                           Obs per group:
     within  = 0.6205                                         min =          1
     between = 0.9976                                         avg =        3.5
     overall = 0.9891                                         max =          4

                                                Wald chi2(19)     =    2623.44
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------------
       lnUEflow |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------------
    ALMPExplag1 |   .2103095   .1628138     1.29   0.196    -.1087997    .5294187
 lnUnemplSTlag1 |   .3639824   .0901802     4.04   0.000     .1872324    .5407323
lnVacancieslag1 |   .0662571   .0730406     0.91   0.364       -.0769    .2094141
       lnEUflow |   .3318623   .1077998     3.08   0.002     .1205786    .5431461
       lnIUflow |   .3332963   .1058643     3.15   0.002     .1258059    .5407866
         lnLFor |  -.1438179   .2124609    -0.68   0.498    -.5602336    .2725977
       ShLongUn |   -.002468   .0034364    -0.72   0.473    -.0092032    .0042672
      ShYoungUn |  -.0030278   .0098497    -0.31   0.759    -.0223328    .0162772
```

ShWomenUn	.0062877	.0118253	0.53	0.595	-.0168895	.0294649
PLMPExplag1	-.0638675	.1466339	-0.44	0.663	-.3512647	.2235297
Informalityl1	-.0121141	.0065005	-1.86	0.062	-.0248548	.0006265
GDPgrowth	-.003859	.0127516	-0.30	0.762	-.0288517	.0211337
LabFreeIndlag1	-.0005993	.0029596	-0.20	0.840	-.0063999	.0052014
EduTertiary	.011437	.0080847	1.41	0.157	-.0044087	.0272827
PopDensity	.0004987	.0027374	0.18	0.855	-.0048664	.0058639
PopDen2	-1.45e-06	4.60e-06	-0.32	0.752	-.0000105	7.56e-06
Y11	0	(omitted)				
Y12	.0123046	.0578129	0.21	0.831	-.1010066	.1256158
Y13	-.0003466	.0489755	-0.01	0.994	-.0963368	.0956436
Y14	-.0251891	.0455727	-0.55	0.580	-.1145098	.0641317
Y15	0	(omitted)				
_cons	.5270129	1.493766	0.35	0.724	-2.400715	3.454741
sigma_u	0					
sigma_e	.07176607					
rho	0	(fraction of variance due to u_i)				

Table A3.2.2 Model 1- Fixed effects estimated results

```
. xtreg lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, fe
note: Y11 omitted because of collinearity
note: Y15 omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =         49
Group variable: CountryID                       Number of groups  =         14

R-sq:                                           Obs per group:
     within  = 0.8535                                         min =          1
     between = 0.5840                                         avg =        3.5
     overall = 0.5876                                         max =          4

                                                F(19,16)          =       4.90
corr(u_i, Xb)  = -0.9936                        Prob > F          =     0.0012
```

lnUEflow	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ALMPExplag1	.3688273	.2250573	1.64	0.121	-.1082728	.8459275
lnUnemplSTlag1	.2268562	.2461955	0.92	0.371	-.2950549	.7487672
lnVacancieslag1	-.1122832	.1952238	-0.58	0.573	-.5261393	.3015729
lnEUflow	.0969108	.1218783	0.80	0.438	-.1614596	.3552813
lnIUflow	.4306739	.1351354	3.19	0.006	.1441996	.7171481
lnLFor	1.442781	2.521462	0.57	0.575	-3.902479	6.788042
ShLongUn	.0151545	.0077504	1.96	0.068	-.0012755	.0315845
ShYoungUn	.0087283	.0140387	0.62	0.543	-.0210325	.0384891
ShWomenUn	.0046092	.014068	0.33	0.747	-.0252137	.0344321
PLMPExplag1	.0673884	.2638013	0.26	0.802	-.4918453	.6266221
Informalityl1	-.1676947	.2030228	-0.83	0.421	-.5980838	.2626945
GDPgrowth	-.0164374	.0170993	-0.96	0.351	-.0526864	.0198116

LabFreeIndlag1	.0129254	.0048447	2.67	0.017	.0026552	.0231957
EduTertiary	.0134148	.0287974	0.47	0.648	-.0476328	.0744625
PopDensity	.0333606	.0651036	0.51	0.615	-.1046529	.1713741
PopDen2	-.0000235	.0000711	-0.33	0.745	-.0001742	.0001272
Y11	0	(omitted)				
Y12	.2114057	.2666313	0.79	0.439	-.3538273	.7766388
Y13	.1427422	.2090091	0.68	0.504	-.3003373	.5858217
Y14	.0671069	.122732	0.55	0.592	-.1930732	.327287
Y15	0	(omitted)				
_cons	-19.69832	35.06323	-0.56	0.582	-94.02904	54.63241
sigma_u	4.0123355					
sigma_e	.07176607					
rho	.99968018	(fraction of variance due to u_i)				

F test that all u_i=0: F(13, 16) = 2.84 Prob > F = 0.0255

Table A3.2.3 Model 1- Fixed versus Random effects

```
. hausman fixed random, sigmamore

Note: the rank of the differenced variance matrix (13) does not equal the number
of coefficients being tested (19); be sure this is what you
        expect, or there may be problems computing the test.  Examine the output
of your estimators for anything unexpected and possibly
        consider scaling your variables so that the coefficients are on a similar
scale.
```

	---- Coefficients ---- (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ALMPExplag1	.3688273	.2103095	.1585179	.2565864
lnUnemplST~1	.2268562	.3639824	-.1371262	.3199591
lnVacancie~1	-.1122832	.0662571	-.1785403	.2532791
lnEUflow	.0969108	.3318623	-.2349515	.1243428
lnIUflow	.4306739	.3332963	.0973776	.1486159
lnLFor	1.442781	-.1438179	1.586599	3.397962
ShLongUn	.0151545	-.002468	.0176226	.0098846
ShYoungUn	.0087283	-.0030278	.0117561	.0161958
ShWomenUn	.0046092	.0062877	-.0016785	.0148656
PLMPExplag1	.0673884	-.0638675	.1312559	.3246149
Informalit~1	-.1676947	-.0121141	-.1555805	.274054
GDPgrowth	-.0164374	-.003859	-.0125785	.0192476
LabFreeInd~1	.0129254	-.0005993	.0135247	.0058337
EduTertiary	.0134148	.011437	.0019778	.0380338
PopDensity	.0333606	.0004987	.0328619	.0878634
PopDen2	-.0000235	-1.45e-06	-.0000221	.0000959
Y12	.2114057	.0123046	.1991011	.355346
Y13	.1427422	-.0003466	.1430888	.2779319
Y14	.0671069	-.0251891	.092296	.1593291

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

```
    Test:  Ho:  difference in coefficients not systematic

                 chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       20.22
                Prob>chi2 =      0.0898
                (V_b-V_B is not positive definite)
```

Table A3.2.4 Model 1- Diagnostic tests

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (14)  =     139.46
Prob>chi2 =      0.0000


. xtserial lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15

Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation
    F(  1,      10) =      1.392
           Prob > F =      0.2653


. pantest2 lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15


Test for serial correlation in residuals
Null hypothesis is either that rho=0 if residuals are AR(1)
or that lamda=0 if residuals are MA(1)
Following tests only approximate for unbalanced panels
LM= .26778097
which is asy. distributed as chisq(1) under null, so:
Probability of value greater than LM is .60482422
LM5= .51747557
which is asy. distributed as N(0,1) under null, so:
Probability of value greater than abs(LM5) is .30241211


Test for significance of fixed effects
F= 2.8362991
Probability>F= .02553437


Test for normality of residuals
```

```
                    Skewness/Kurtosis tests for Normality
                                                          ------ joint ------
    Variable |        Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+---------------------------------------------------------------
    __00000B |         49      0.2923        0.9317        1.16         0.5585
```

Table A3.3.1 Model 2 - Random effects estimated results

```
. xtreg lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity
PopDen2 Y11 Y12 Y13 Y14 Y15, re
note: Y11 omitted because of collinearity
note: Y15 omitted because of collinearity

Random-effects GLS regression                   Number of obs      =        49
Group variable: CountryID                       Number of groups   =        14

R-sq:                                           Obs per group:
     within  = 0.6312                                          min =         1
     between = 0.9971                                          avg =       3.5
     overall = 0.9887                                          max =         4

                                                Wald chi2(16)      =   2803.39
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

--------------------------------------------------------------------------------
       lnUEflow |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+---------------------------------------------------------------
    ALMPExplag1 |   .2090653   .1473779     1.42   0.156       -.07979    .4979206
 lnUnemplSTlag1 |   .3574434   .0668219     5.35   0.000      .2264749    .4884119
lnVacancieslag1 |   .0790493   .0595936     1.33   0.185     -.0377519    .1958506
       lnEUflow |   .3632491   .0992787     3.66   0.000      .1686664    .5578318
       lnIUflow |   .3667876   .0847777     4.33   0.000      .2006265    .5329488
         lnLFor |  -.2094547   .1292363    -1.62   0.105     -.4627532    .0438437
    PLMPExplag1 |  -.1249271   .1156449    -1.08   0.280     -.3515869    .1017327
  Informalityl1 |  -.0134375   .0046894    -2.87   0.004     -.0226284   -.0042465
      GDPgrowth |  -.0053599   .0121389    -0.44   0.659     -.0291517    .0184318
 LabFreeIndlag1 |  -.0001254   .0016943    -0.07   0.941     -.0034461    .0031953
    EduTertiary |   .0154241   .0058656     2.63   0.009      .0039277    .0269206
     PopDensity |   .0016755   .0012723     1.32   0.188     -.0008181    .0041691
        PopDen2 |  -3.46e-06   2.16e-06    -1.60   0.110     -7.70e-06    7.83e-07
            Y11 |          0  (omitted)
            Y12 |     .02382   .0513156     0.46   0.643     -.0767567    .1243966
            Y13 |  -.0084442    .042042    -0.20   0.841     -.0908451    .0739566
            Y14 |  -.0306881    .041683    -0.74   0.462     -.1123853    .0510091
            Y15 |          0  (omitted)
          _cons |   .7382203   .6429947     1.15   0.251      -.522026    1.998467
----------------+---------------------------------------------------------------
        sigma_u |          0
        sigma_e |  .07381611
            rho |          0   (fraction of variance due to u_i)
--------------------------------------------------------------------------------
```

Table A3.3.2 Model 2- Fixed effects estimated results

```
. xtreg lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity
PopDen2 Y11 Y12 Y13 Y14 Y15, fe
note: Y11 omitted because of collinearity
note: Y15 omitted because of collinearity

Fixed-effects (within) regression               Number of obs      =        49
Group variable: CountryID                       Number of groups   =        14

R-sq:                                           Obs per group:
     within  = 0.8159                                         min =         1
     between = 0.3374                                         avg =       3.5
     overall = 0.3443                                         max =         4

                                                F(16,19)           =      5.26
corr(u_i, Xb)  = -0.9938                        Prob > F           =    0.0004

---------------------------------------------------------------------------------
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
    ALMPExplag1 |   .2690424    .217477     1.24   0.231    -.1861421     .724227
 lnUnemplSTlag1 |   .4761076   .1919659     2.48   0.023     .0743184    .8778967
lnVacancieslag1 |   -.159109   .1904059    -0.84   0.414     -.557633    .2394151
       lnEUflow |    .055846   .1134434     0.49   0.628    -.1815938    .2932857
       lnIUflow |   .4352632    .136523     3.19   0.005     .1495172    .7210091
         lnLFor |  -.2635231   2.425759    -0.11   0.915    -5.340695    4.813649
    PLMPExplag1 |  -.0401567   .2615544    -0.15   0.880    -.5875963    .5072829
  Informalityl1 |  -.1038271   .1932142    -0.54   0.597     -.508229    .3005748
      GDPgrowth |  -.0123861   .0171245    -0.72   0.478    -.0482281    .0234559
 LabFreeIndlag1 |    .012366   .0048525     2.55   0.020     .0022097    .0225223
    EduTertiary |   .0175104   .0282197     0.62   0.542    -.0415542    .0765749
     PopDensity |   .0788168   .0615362     1.28   0.216    -.0499798    .2076135
        PopDen2 |  -.0000757   .0000664    -1.14   0.269    -.0002146    .0000633
            Y11 |          0  (omitted)
            Y12 |   .1239867   .2518366     0.49   0.628    -.4031134    .6510869
            Y13 |   .1184844   .2047234     0.58   0.570    -.3100066    .5469753
            Y14 |   .0543626     .12139     0.45   0.659    -.1997096    .3084348
            Y15 |          0  (omitted)
          _cons |  -.1809657   34.31742    -0.01   0.996    -72.00816    71.64623
----------------+----------------------------------------------------------------
        sigma_u |   5.041739
        sigma_e |  .07381611
            rho |  .99978569   (fraction of variance due to u_i)
---------------------------------------------------------------------------------
F test that all u_i=0: F(13, 19) = 2.51                      Prob > F = 0.0337
```

Table A3.3.3 Model 2 - Fixed effects versus Random effects

```
. hausman fixed random, sigmamore

Note: the rank of the differenced variance matrix (13) does not equal the number
of coefficients being tested (16); be sure this is what you
        expect, or there may be problems computing the test.  Examine the output
of your estimators for anything unexpected and possibly
        consider scaling your variables so that the coefficients are on a similar
scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
 ALMPExplag1 |    .2690424     .2090653        .0599771        .2335095
lnUnemplST~1 |    .4761076     .3574434        .1186642        .2343985
lnVacancie~1 |    -.159109     .0790493       -.2381583        .2342964
    lnEUflow |     .055846     .3632491       -.3074031        .1043584
    lnIUflow |    .4352632     .3667876        .0684755        .1511958
      lnLFor |   -.2635231    -.2094547       -.0540683         3.07725
 PLMPExplag1 |   -.0401567    -.1249271        .0847704         .311307
Informalit~1 |   -.1038271    -.0134375       -.0903897        .2452773
   GDPgrowth |   -.0123861    -.0053599       -.0070262        .0180388
LabFreeInd~1 |     .012366    -.0001254        .0124914        .0059236
 EduTertiary |    .0175104     .0154241        .0020862        .0353469
  PopDensity |    .0788168     .0016755        .0771413        .0781215
     PopDen2 |   -.0000757    -3.46e-06       -.0000722        .0000843
         Y12 |    .1239867       .02382        .1001667          .31561
         Y13 |    .1184844    -.0084442        .1269286        .2565128
         Y14 |    .0543626    -.0306881        .0850507        .1483843
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       20.21
                Prob>chi2 =      0.0900
                (V_b-V_B is not positive definite)
```

Table A3.3.4 Model 2- Diagnostic tests

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (14)  =    2.0e+26
Prob>chi2 =      0.0000    -  presence of heteroscedasticity
```

```
. xtserial lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 Ed
> uTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15

Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation
    F(  1,       10) =      0.615
           Prob > F =      0.4509    - no serial correlation



. pantest2 lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 Ed
> uTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15


Test for serial correlation in residuals
Null hypothesis is either that rho=0 if residuals are AR(1)
or that lamda=0 if residuals are MA(1)
Following tests only approximate for unbalanced panels
LM= .14305331
which is asy. distributed as chisq(1) under null, so:
Probability of value greater than LM is .70526428
LM5= .37822389
which is asy. distributed as N(0,1) under null, so:
Probability of value greater than abs(LM5) is .35263214


Test for significance of fixed effects
F= 2.5067412
Probability>F= .03365295


Test for normality of residuals

                    Skewness/Kurtosis tests for Normality
                                                      ------ joint ------
    Variable |        Obs  Pr(Skewness)  Pr(Kurtosis) adj chi2(2)   Prob>chi2
-------------+---------------------------------------------------------------
     __00000B |         49      0.3764        0.7780        0.89         0.6393   -
there is normality in the residuals
```

Table A3.4.1 Model 1 - Fixed effects Driscoll Kraay standard errors

```
. xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        49
Method: Fixed-effects regression                 Number of groups  =        14
Group variable (i): CountryID                    F( 21,      3)    =      3.31
maximum lag: 1                                   Prob > F          =    0.1767
                                                 within R-squared  =    0.8535
```

```
------------------------------------------------------------------------------
                |             Drisc/Kraay
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
    ALMPExplag1 |   .3688273   .1176355     3.14   0.052    -.0055414    .7431961
   lnUnemplSTlag1 |   .2268562   .1354863     1.67   0.193    -.2043218    .6580341
 lnVacancieslag1 |  -.1122832   .1432888    -0.78   0.490    -.5682921    .3437257
       lnEUflow |   .0969108   .1009649     0.96   0.408    -.2244045    .4182262
       lnIUflow |   .4306739   .1890671     2.28   0.107    -.1710221     1.03237
         lnLFor |   1.442781   1.026804     1.41   0.255    -1.824968     4.71053
       ShLongUn |   .0151545   .0077352     1.96   0.145    -.0094623    .0397714
      ShYoungUn |   .0087283   .0073409     1.19   0.320    -.0146339    .0320904
      ShWomenUn |   .0046092   .0008516     5.41   0.012     .0018991    .0073193
    PLMPExplag1 |   .0673884   .1566408     0.43   0.696    -.4311124    .5658893
   Informalityl1 |  -.1676947   .1454643    -1.15   0.333     -.630627    .2952376
       GDPgrowth |  -.0164374   .0119613    -1.37   0.263    -.0545035    .0216286
  LabFreeIndlag1 |   .0129254   .0026244     4.93   0.016     .0045734    .0212774
     EduTertiary |   .0134148   .0128297     1.05   0.373    -.0274151    .0542448
     PopDensity |   .0333606   .0361021     0.92   0.424    -.0815324    .1482536
        PopDen2 |  -.0000235   .0000385    -0.61   0.584    -.0001461     .000099
            Y11 |          0  (omitted)
            Y12 |  -19.48691   17.04874    -1.14   0.336    -73.74362     34.7698
            Y13 |  -19.55557   17.03529    -1.15   0.334    -73.76946    34.65831
            Y14 |  -19.63121   16.98838    -1.16   0.332    -73.69582     34.4334
            Y15 |  -19.69832   16.92031    -1.16   0.329    -73.54629    34.14966
          _cons |          0  (omitted)
------------------------------------------------------------------------------
```

Table A3.4.2 Model 2 - Fixed effects Driscoll Kraay standard errors

```
. xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity
PopDen2 Y11 Y12 Y13 Y14 Y15, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        49
Method: Fixed-effects regression                 Number of groups  =        14
Group variable (i): CountryID                    F( 18,      3)    =      1.33
maximum lag: 1                                   Prob > F          =    0.4644
                                                 within R-squared  =    0.8159


------------------------------------------------------------------------------
                |             Drisc/Kraay
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
    ALMPExplag1 |   .2690424   .0867664     3.10   0.053    -.0070869    .5451717
   lnUnemplSTlag1 |   .4761076   .0784168     6.07   0.009     .2265503    .7256648
 lnVacancieslag1 |   -.159109   .1562102    -1.02   0.383    -.6562396    .3380217
       lnEUflow |    .055846   .1081853     0.52   0.641    -.2884479    .4001399
       lnIUflow |   .4352632   .1391011     3.13   0.052    -.0074187    .8779451
         lnLFor |  -.2635231   .9905391    -0.27   0.807    -3.415861    2.888814
    PLMPExplag1 |  -.0401567   .1484008    -0.27   0.804    -.5124342    .4321208
   Informalityl1 |  -.1038271   .1343679    -0.77   0.496    -.5314456    .3237914
       GDPgrowth |  -.0123861   .0090679    -1.37   0.265    -.0412443     .016472
```

```
   LabFreeIndlag1 |    .012366   .0026824     4.61   0.019     .0038292    .0209027
     EduTertiary |   .0175104   .0073643     2.38   0.098    -.0059262     .040947
      PopDensity |   .0788168   .0193167     4.08   0.027     .0173424    .1402913
         PopDen2 |  -.0000757   .0000108    -6.99   0.006    -.0001101   -.0000412
             Y11 |          0  (omitted)
             Y12 |  -.0569791   15.46727    -0.00   0.997    -49.28075    49.16679
             Y13 |  -.0624814     15.471    -0.00   0.997    -49.29811    49.17314
             Y14 |  -.1266032   15.47161    -0.01   0.994    -49.36416    49.11095
             Y15 |  -.1809658    15.4614    -0.01   0.991    -49.38603     49.0241
           _cons |          0  (omitted)
------------------------------------------------------------------------------------
```

Table A3.4.3 Model 3 - Fixed effects Vector Decomposition

```
. xtfevd lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShYoungUn ShLongUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Transition TransAlmp Y11 Y12 Y13 Y14
Y15 , invariant (ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShYoungUn ShLongUn  Informalityl1 LabFreeIndlag1 EduTertiary PopDensity
Transition TransAlmp Y11 Y12 Y13 Y14 Y15 )
note: Y11 dropped because of collinearity
note: Y12 dropped because of collinearity

panel fixed effects regression with vector decomposition

degrees of freedom fevd     =        14          number of obs       =        49
mean squared error          = .0012914           F( 23, 14)          = 69.61665
root mean squared error     = .0359362           Prob > F            = 9.57e-11
Residual Sum of Squares     = .0632792           R-squared           = .9974593
Total Sum of Squares        = 24.90641           adj. R-squared      = .9912891
Estimation Sum of Squares   = 24.84313

------------------------------------------------------------------------------------
                |               fevd
       lnUEflow |      Coef.   Std. Err.       t     P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------------
      ShWomenUn |  -.0058359   .0116968    -0.50   0.626    -.0309231    .0192513
    PLMPExplag1 |   .1403465   .2084367     0.67   0.512    -.3067057    .5873987
      GDPgrowth |  -.0175212   .0140616    -1.25   0.233    -.0476804    .0126379
        PopDen2 |  -8.37e-06   .0000178    -0.47   0.645    -.0000465    .0000298
    ALMPExplag1 |  -.0158621    .257772    -0.06   0.952    -.5687281     .537004
 lnUnemplSTlag1 |   .4191055   .1659405     2.53   0.024     .0631986    .7750124
lnVacancieslag1 |   .0098564   .1213886     0.08   0.936    -.2504962     .270209
       lnEUflow |   .2988957    .177792     1.68   0.115    -.0824303    .6802218
       lnIUflow |   .3525121   .1474683     2.39   0.031     .0362242    .6688001
         lnLFor |   -.232976   .3304523    -0.71   0.492    -.9417256    .4757736
      ShYoungUn |   .0163243    .017277     0.94   0.361    -.0207312    .0533797
       ShLongUn |  -.0051206   .0055562    -0.92   0.372    -.0170374    .0067963
  Informalityl1 |  -.0150511   .0187811    -0.80   0.436    -.0553326    .0252303
 LabFreeIndlag1 |   .0051965   .0066247     0.78   0.446    -.0090122    .0194051
    EduTertiary |   .0231657   .0133591     1.73   0.105    -.0054868    .0518182
     PopDensity |   .0041234   .0102543     0.40   0.694    -.0178698    .0261167
     Transition |   .0253691   .8496806     0.03   0.977    -1.797015    1.847753
      TransAlmp |   .2156918     .27136     0.79   0.440    -.3663175    .7977011
            Y13 |  -.0317285   .0464383    -0.68   0.506    -.1313287    .0678717
```

```
             Y14 |  -.0340524   .0509123    -0.67   0.514    -.1432484    .0751435
             Y15 |    .021637   .0590033     0.37   0.719    -.1049126    .1481865
             eta |   .9999999          .        .       .            .           .
           _cons |   1.229792   2.636751     0.47   0.648    -4.425476     6.88506
------------------------------------------------------------------------------
```

Table A3.4.4 Model 4 – Fixed effects Vector Decomposition

```
. xtfevd lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informality1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity
PopDen2 Transition TransAlmp Y11 Y12 Y13 Y14 Y15 , invariant (ALMPExplag1
lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow lnLFor Informality1
LabFreeIndlag1 EduTertiary PopDensity Transition TransAlmp Y11 Y12 Y13 Y14 Y15 )
note: Y11 dropped because of collinearity
note: Y12 dropped because of collinearity

panel fixed effects regression with vector decomposition

degrees of freedom fevd    =        17          number of obs        =       49
mean squared error         = .0018075           F( 20, 17)           = 22.45638
root mean squared error    = .0425151           Prob > F             = 1.88e-08
Residual Sum of Squares    = .0885691           R-squared            = .9964439
Total Sum of Squares       = 24.90641           adj. R-squared       = .9899593
Estimation Sum of Squares  = 24.81784

------------------------------------------------------------------------------
                 |                fevd
        lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
     PLMPExplag1 |   .0350401   .5739618     0.06   0.952    -1.175913    1.245994
       GDPgrowth |  -.0108214   .0259919    -0.42   0.682    -.0656594    .0440166
         PopDen2 |  -.0000545   .0000332    -1.64   0.119    -.0001245    .0000155
     ALMPExplag1 |   -.438968   .3977543    -1.10   0.285    -1.278156    .4002202
  lnUnemplSTlag1 |    .741545   .3209103     2.31   0.034     .0644834    1.418607
 lnVacancieslag1 |  -.1352387   .2291942    -0.59   0.563    -.6187962    .3483187
        lnEUflow |  -.0837976   .3860516    -0.22   0.831    -.8982952       .7307
        lnIUflow |   .7539002   .3600563     2.09   0.052    -.0057521    1.513553
          lnLFor |  -.6835512   .6375332    -1.07   0.299    -2.028629    .6615262
    Informality1 |   .0231103   .0362731     0.64   0.533    -.0534192    .0996399
  LabFreeIndlag1 |   .0120507   .0087954     1.37   0.188     -.006506    .0306075
     EduTertiary |   .0613646   .0232273     2.64   0.017     .0123593    .1103699
      PopDensity |   .0284794   .0192276     1.48   0.157    -.0120873    .0690461
      Transition |   -2.35014    1.93987    -1.21   0.242    -6.442908    1.742627
       TransAlmp |  -.5686798   .4616829    -1.23   0.235    -1.542746    .4053859
             Y13 |   .0076052   .0695641     0.11   0.914    -.1391621    .1543726
             Y14 |  -.0414401   .0850589    -0.49   0.632    -.2208986    .1380184
             Y15 |  -.1038633   .1160867    -0.89   0.383    -.3487847    .1410581
             eta |   .9999999          .        .       .            .           .
           _cons |    3.47707   4.922688     0.71   0.490    -6.908894    13.86303
------------------------------------------------------------------------------
```

Table A3.4.5 Models 1 and 2 Fixed Effects Driscoll Kraay including variable *ALMPExp2lag1*

```
. xtscc lnUEflow ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow
lnIUflow lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        49
Method: Fixed-effects regression                 Number of groups  =        14
Group variable (i): CountryID                    F( 22,      3)    =      3.94
maximum lag: 1                                   Prob > F          =    0.1420
                                                 within R-squared  =    0.8585

------------------------------------------------------------------------------
             |             Drisc/Kraay
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 ALMPExplag1 |   .7873498   .3370624     2.34   0.102    -.2853333    1.860033
ALMPExp2lag1 |  -.4487401   .4584658    -0.98   0.400    -1.907783    1.010303
lnUnemplSTlag1 | .2384307   .1863354     1.28   0.291    -.3545718    .8314332
lnVacancieslag1 | .0134431  .2487156     0.05   0.960    -.7780809    .8049672
    lnEUflow |   .0953937    .102901     0.93   0.422    -.2320833    .4228707
    lnIUflow |   .4695351   .1593043     2.95   0.060    -.0374424    .9765126
      lnLFor |   1.973188   1.059726     1.86   0.160    -1.399333    5.345709
    ShLongUn |   .0151473   .0079844     1.90   0.154    -.0102626    .0405572
   ShYoungUn |   .0122288   .0095327     1.28   0.290    -.0181085     .042566
   ShWomenUn |   .0032965   .0015315     2.15   0.120    -.0015773    .0081703
 PLMPExplag1 |   .0656843   .1094917     0.60   0.591    -.2827671    .4141357
Informalityl1 |   -.11949   .1260839    -0.95   0.413    -.5207452    .2817653
   GDPgrowth |  -.0179593   .0124625    -1.44   0.245    -.0576204    .0217019
LabFreeIndlag1 |  .0122958  .0027511     4.47   0.021     .0035406     .021051
 EduTertiary |   .0193682   .0116445     1.66   0.195    -.0176899    .0564263
  PopDensity |   .0510252   .0496425     1.03   0.380    -.1069595    .2090099
     PopDen2 |  -.0000449   .0000522    -0.86   0.453    -.0002111    .0001213
         Y11 |          0  (omitted)
         Y12 |  -31.71955   20.36695    -1.56   0.217    -96.53628    33.09717
         Y13 |  -31.79522    20.3563    -1.56   0.216    -96.57807    32.98762
         Y14 |   -31.8416    20.3106    -1.57   0.215    -96.47899     32.7958
         Y15 |  -31.88043   20.25141    -1.57   0.214    -96.32945     32.5686
       _cons |          0  (omitted)
------------------------------------------------------------------------------


. xtscc lnUEflow ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow
lnIUflow lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary
PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        49
Method: Fixed-effects regression                 Number of groups  =        14
Group variable (i): CountryID                    F( 19,      3)    =      2.61
maximum lag: 1                                   Prob > F          =    0.2338
```

```
                                                  within R-squared  =     0.8194

------------------------------------------------------------------------------
                |             Drisc/Kraay
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
    ALMPExplag1 |   .6077271   .3899977     1.56   0.217    -.6334197    1.848874
   ALMPExp2lag1 |  -.3537821   .4206666    -0.84   0.462    -1.692531    .9849667
  lnUnemplSTlag1 |   .4692318   .0901878     5.20   0.014     .1822139    .7562497
lnVacancieslag1 |   -.058317   .2611418    -0.22   0.838    -.8893867    .7727527
       lnEUflow |   .0562167   .1079838     0.52   0.639     -.287436    .3998695
       lnIUflow |   .4680013   .1033823     4.53   0.020     .1389926      .79701
         lnLFor |   .1189252   .8712911     0.14   0.900    -2.653912    2.891762
    PLMPExplag1 |  -.0333812   .1280158    -0.26   0.811    -.4407847    .3740223
   Informalityl1 |    -.05488   .0877199    -0.63   0.576    -.3340439    .2242839
      GDPgrowth |  -.0129878    .011126    -1.17   0.327    -.0483957      .02242
  LabFreeIndlag1 |   .0119602    .002625     4.56   0.020     .0036063    .0203141
    EduTertiary |   .0208572   .0047789     4.36   0.022     .0056487    .0360656
     PopDensity |   .0906636   .0365489     2.48   0.089    -.0256512    .2069784
        PopDen2 |  -.0000913   .0000313    -2.92   0.062    -.0001909    8.28e-06
            Y11 |          0  (omitted)
            Y12 |   -9.05307   16.37816    -0.55   0.619    -61.17567    43.06953
            Y13 |  -9.056876   16.40471    -0.55   0.619      -61.264    43.15025
            Y14 |  -9.096417   16.42043    -0.55   0.618    -61.35354    43.16071
            Y15 |  -9.126938   16.43499    -0.56   0.617    -61.43041    43.17654
          _cons |          0  (omitted)
------------------------------------------------------------------------------
```

Table A3.4.6 Models 3 and 4 Fixed Effects Vector Decomposition including variable *ALMPExp2lag1*

```
. xtfevd lnUEflow ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow
lnIUflow lnLFor ShYoungUn ShLongUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Transition TransAlmp Y11 Y12 Y13 Y14
Y15 , invariant (ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow
lnIUflow lnLFor ShYoungUn ShLongUn  Informalityl1 LabFreeIndlag1 EduTertiary
PopDensity Transition TransAlmp Y11 Y12 Y13 Y14 Y15 )
note: Y11 dropped because of collinearity
note: Y12 dropped because of collinearity

panel fixed effects regression with vector decomposition

degrees of freedom fevd     =        13         number of obs       =       49
mean squared error          = .0010851          F( 24, 13)          = 38.26931
root mean squared error     = .0329414          Prob > F            = 1.68e-08
Residual Sum of Squares     = .0531717          R-squared           = .9978651
Total Sum of Squares        = 24.90641          adj. R-squared      = .9921174
Estimation Sum of Squares   = 24.85324


------------------------------------------------------------------------------
                |                fevd
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
      ShWomenUn |  -.0108913   .0131917    -0.83   0.424    -.0393903    .0176077
```

```
    PLMPExplag1 |   .1540743   .3486001     0.44   0.666    -.5990305    .9071791
      GDPgrowth |  -.0207964   .0197345    -1.05   0.311    -.0634302    .0218375
        PopDen2 |  -.0000472   .0000404    -1.17   0.264    -.0001346    .0000402
    ALMPExplag1 |   1.790506   .9396866     1.91   0.079    -.2395636    3.820575
   ALMPExp2lag1 |  -2.127342   1.241152    -1.71   0.110    -4.808688     .554005
 lnUnemplSTlag1 |   .9426165   .4341394     2.17   0.049     .0047153    1.880518
lnVacancieslag1 |   -.037702   .1758484    -0.21   0.834    -.4175994    .3421954
       lnEUflow |  -.0928856   .3347186    -0.28   0.786    -.8160011    .6302298
       lnIUflow |   .6879981   .3395405     2.03   0.064    -.0455345    1.421531
         lnLFor |  -1.084635   .8691929    -1.25   0.234    -2.962412     .793142
      ShYoungUn |   .0571737   .0396419     1.44   0.173    -.0284675     .142815
       ShLongUn |  -.0173056   .0113277    -1.53   0.151    -.0417775    .0071664
  Informalityl1 |   .0189463   .0410171     0.46   0.652    -.0696658    .1075584
 LabFreeIndlag1 |   .0201829   .0149671     1.35   0.201    -.0121515    .0525172
    EduTertiary |   .0500081   .0250329     2.00   0.067    -.0040722    .1040884
     PopDensity |   .0256487   .0231261     1.11   0.287    -.0243123    .0756097
     Transition |  -.9791195   1.581596    -0.62   0.547     -4.39595    2.437711
      TransAlmp |  -.7150214   .6183255    -1.16   0.268    -2.050833    .6207896
            Y13 |   .0200127   .0644501     0.31   0.761    -.1192234    .1592487
            Y14 |    .085404   .0995331     0.86   0.406    -.1296242    .3004322
            Y15 |   .1089978   .1024187     1.06   0.307    -.1122643    .3302599
            eta |   .9999999          .        .       .            .           .
          _cons |   5.340617   5.482036     0.97   0.348    -6.502601    17.18384
------------------------------------------------------------------------------



. xtfevd lnUEflow ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow
lnIUflow lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFr
> eeIndlag1 EduTertiary PopDensity PopDen2 Transition TransAlmp Y11 Y12 Y13 Y14
Y15 , invariant (ALMPExplag1 ALMPExp2lag1 lnUnemplSTlag1 lnV
> acancieslag1 lnEUflow lnIUflow lnLFor  Informalityl1 LabFreeIndlag1 EduTertiary
PopDensity Transition TransAlmp Y11 Y12 Y13 Y14 Y15)
note: Y11 dropped because of collinearity
note: Y12 dropped because of collinearity

panel fixed effects regression with vector decomposition

degrees of freedom fevd    =       16          number of obs       =       49
mean squared error         = .0017237          F( 21, 16)          = 19.53196
root mean squared error    = .0415175          Prob > F            = 1.10e-07
Residual Sum of Squares    = .0844616          R-squared           = .9966088
Total Sum of Squares       = 24.90641          adj. R-squared      = .9898265
Estimation Sum of Squares  = 24.82195

------------------------------------------------------------------------------
                |                fevd
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
    PLMPExplag1 |   .0509783   .7971499     0.06   0.950    -1.638904    1.740861
      GDPgrowth |  -.0115687   .0298803    -0.39   0.704     -.074912    .0517746
        PopDen2 |  -.0000756   .0000489    -1.55   0.142    -.0001792    .0000281
    ALMPExplag1 |   1.347909    .902694     1.49   0.155    -.5657164    3.261535
   ALMPExp2lag1 |  -1.772241   1.074527    -1.65   0.119    -4.050137    .5056553
 lnUnemplSTlag1 |    1.01864   .5241696     1.94   0.070    -.0925502     2.12983
lnVacancieslag1 |  -.0726656   .2938228    -0.25   0.808    -.6955422     .550211
       lnEUflow |  -.2974786   .5234511    -0.57   0.578    -1.407145    .8121881
       lnIUflow |    1.04201   .5664403     1.84   0.084    -.1587902    2.242809
```

```
        lnLFor |  -1.146352   1.055432    -1.09   0.294    -3.383768    1.091063
 Informalityl1 |   .0412155   .0531294     0.78   0.449    -.0714138    .1538448
LabFreeIndlag1 |   .0160274   .0120378     1.33   0.202    -.0094915    .0415463
   EduTertiary |   .0777053    .030306     2.56   0.021     .0134595    .1419511
    PopDensity |   .0392475   .0280018     1.40   0.180    -.0201137    .0986087
    Transition |  -2.911803   2.682918    -1.09   0.294    -8.599335    2.775729
     TransAlmp |  -1.811259   .8934914    -2.03   0.060    -3.705376    .0828586
           Y13 |   .0566402   .0849011     0.67   0.514    -.1233421    .2366225
           Y14 |   .0363491   .1080994     0.34   0.741    -.1928114    .2655095
           Y15 |  -.1149681   .1441653    -0.80   0.437    -.4205849    .1906488
           eta |          1          .        .       .            .           .
         _cons |   4.172804    6.86928     0.61   0.552    -10.38942    18.73503
------------------------------------------------------------------------------
```

Table A3.5 Returns to Scale

Model 1

```
. xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth
LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15, fe


. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .6421577   .1653083     3.88   0.030     .1160728    1.168242
------------------------------------------------------------------------------
```

Model 2

```
. xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity
PopDen2 Y11 Y12 Y13 Y14 Y15, fe


. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .8081077   .1892566     4.27   0.024     .2058087    1.410407
------------------------------------------------------------------------------
```

Model 3

```
. xtfevd lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShYoungUn ShLongUn ShWomenUn PLMPExplag1 Informality
> l1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity PopDen2 Transition TransAlmp
Y11 Y12 Y13 Y14 Y15 , invariant (ALMPExplag1 lnUnemplSTlag
> 1 lnVacancieslag1 lnEUflow lnIUflow lnLFor ShYoungUn ShLongUn  Informalityl1
LabFreeIndlag1 EduTertiary PopDensity Transition TransAlmp Y1
> 1 Y12 Y13 Y14 Y15 )



. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |    1.08037   .2345406     4.61   0.000     .5773303    1.583409
------------------------------------------------------------------------------
```

Model 4

```
. xtfevd lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 Edu
> Tertiary PopDensity PopDen2 Transition TransAlmp Y11 Y12 Y13 Y14 Y15 , invariant
(ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIU
> flow lnLFor Informalityl1 LabFreeIndlag1 EduTertiary PopDensity Transition
TransAlmp Y11 Y12 Y13 Y14 Y15)


. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   1.276409   .4374473     2.92   0.010     .3534757    2.199342
------------------------------------------------------------------------------
```

Model 5

```
. . xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl
> 1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15 if
Transition==1, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        37
Method: Fixed-effects regression                 Number of groups  =        11
Group variable (i): CountryID                    F( 21,     3)     =     59.51
maximum lag: 1                                   Prob > F          =    0.0031
                                                 within R-squared  =    0.9254

--------------------------------------------------------------------------------
```

```
                |              Drisc/Kraay
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
    ALMPExplag1 |   .4413269   .1936163     2.28   0.107    -.1748465      1.0575
  lnUnemplSTlag1 |   .6316515   .2171559     2.91   0.062    -.0594354    1.322738
lnVacancieslag1 |  -.0457022   .0839903    -0.54   0.624    -.3129967    .2215924
       lnEUflow |   .2216063   .1051707     2.11   0.126    -.1130937    .5563064
       lnIUflow |   .5030952   .2157519     2.33   0.102    -.1835237    1.189714
         lnLFor |   1.156418   2.108172     0.55   0.622    -5.552726    7.865561
       ShLongUn |   .0202351   .0053119     3.81   0.032     .0033303    .0371399
      ShYoungUn |  -.0200766   .0212113    -0.95   0.414    -.0875803    .0474271
      ShWomenUn |  -.0110116   .0041788    -2.64   0.078    -.0243103     .002287
    PLMPExplag1 |  -.2921545    .250742    -1.17   0.328    -1.090128    .5058186
   Informalityl1 |   -.214972   .1116682    -1.93   0.150    -.5703501     .140406
      GDPgrowth |  -.0578897   .0195133    -2.97   0.059    -.1199896    .0042102
 LabFreeIndlag1 |   .0187806   .0033658     5.58   0.011     .0080692    .0294919
    EduTertiary |   .0375509   .0254929     1.47   0.237    -.0435788    .1186806
     PopDensity |  -.1337318   .0933328    -1.43   0.247    -.4307584    .1632947
        PopDen2 |    .001215   .0004007     3.03   0.056    -.0000601    .0024902
            Y11 |          0  (omitted)
            Y12 |          0  (omitted)
            Y13 |  -.2366143   .0568152    -4.16   0.025    -.4174256   -.0558031
            Y14 |  -.3754613   .0958131    -3.92   0.030    -.6803812   -.0705413
            Y15 |  -.4766822   .1275645    -3.74   0.033    -.8826495   -.0707149
          _cons |  -16.40543   28.79176    -0.57   0.609    -108.0336    75.22279
---------------------------------------------------------------------------------


. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   1.310651    .161662     8.11   0.004     .7961702    1.825132
------------------------------------------------------------------------------
```

Model 6

```
. . xtscc lnUEflow ALMPExplag1 lnUnemplSTlag1 lnVacancieslag1 lnEUflow lnIUflow
lnLFor PLMPExplag1 Informalityl1 GDPgrowth LabFreeIndlag1 Ed
> uTertiary PopDensity PopDen2 Y11 Y12 Y13 Y14 Y15 if Transition==1, fe

Regression with Driscoll-Kraay standard errors   Number of obs     =        37
Method: Fixed-effects regression                 Number of groups  =        11
Group variable (i): CountryID                    F( 18,     3)     =      6.53
maximum lag: 1                                   Prob > F          =    0.0737
                                                 within R-squared  =    0.8681

---------------------------------------------------------------------------------
                |              Drisc/Kraay
       lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
    ALMPExplag1 |   .4089648   .1481309     2.76   0.070     -.062454    .8803836
```

```
 lnUnemplSTlag1 |   .7502171   .2230092     3.36   0.044     .0405024    1.459932
lnVacancieslag1 |  -.1898325     .155245    -1.22   0.309    -.6838913    .3042263
       lnEUflow |   .0612245   .1426543     0.43   0.697    -.3927653    .5152143
       lnIUflow |   .5197556   .2080855     2.50   0.088    -.1424655    1.181977
         lnLFor |  -.0883273     2.3955    -0.04   0.973    -7.711877    7.535222
    PLMPExplag1 |  -.2753001   .2961312    -0.93   0.421    -1.217722    .6671215
   Informalityl1 |  -.1025874   .2097123    -0.49   0.658    -.7699857    .5648108
      GDPgrowth |  -.0330377   .0227174    -1.45   0.242    -.1053345    .0392591
 LabFreeIndlag1 |   .0140652   .0037735     3.73   0.034     .0020562    .0260742
    EduTertiary |   .0229731   .0073098     3.14   0.052    -.0002899    .0462361
     PopDensity |  -.1748834   .1880417    -0.93   0.421    -.7733159    .4235492
        PopDen2 |   .0017678   .0011113     1.59   0.210    -.0017689    .0053046
            Y11 |          0  (omitted)
            Y12 |          0  (omitted)
            Y13 |  -.0835755   .0728666    -1.15   0.335    -.3154697    .1483186
            Y14 |  -.1475639   .1397648    -1.06   0.369     -.592358    .2972302
            Y15 |  -.1934651   .2285959    -0.85   0.460    -.9209592     .534029
          _cons |   .1085458   33.86719     0.00   0.998     -107.672     107.889
--------------------------------------------------------------------------------


. lincom lnUnemplSTlag1+ lnVacancieslag1+ lnEUflow+ lnIUflow

 ( 1)  lnUnemplSTlag1 + lnVacancieslag1 + lnEUflow + lnIUflow = 0

------------------------------------------------------------------------------
    lnUEflow |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   1.141365   .2996006     3.81   0.032     .1879018    2.094827
------------------------------------------------------------------------------
```

Table A3.6 Correlation Matrix

```
. corr UnemPActPop ALMPExp_01 TrainSh EmpIncSh SupportSh DirectJobSh PLMPExp_01 Informality GDPgrowth LabFreeIndex EduTertiary PopDensity
(obs=245)
```

	UnemPA~p	ALMPE~01	TrainSh	EmpIncSh	Suppor~h	Direct~h	PLMPE~01	Inform~y	GDPgro~h	LabFre~x
UnemPActPop	1.0000									
ALMPExp_01	-0.0785	1.0000								
TrainSh	-0.0278	0.1433	1.0000							
EmpIncSh	-0.0820	-0.2723	-0.4638	1.0000						
SupportSh	-0.1881	0.3607	-0.3214	-0.1882	1.0000					
DirectJobSh	0.1519	-0.1663	-0.3246	-0.2443	-0.3720	1.0000				
PLMPExp_01	0.2432	0.6942	0.2855	-0.1971	0.1353	-0.2407	1.0000			
Informality	0.2855	-0.5581	-0.1752	0.1941	-0.3381	0.2988	-0.5061	1.0000		
GDPgrowth	-0.2017	-0.1459	-0.1259	0.0427	-0.0073	0.0865	-0.3134	0.1207	1.0000	
LabFreeIndex	-0.1567	0.1721	-0.2259	-0.1067	0.2731	0.1793	-0.0166	-0.0530	0.0467	1.0000
EduTertiary	0.0409	0.2838	0.1172	0.0103	0.0473	-0.1063	0.3594	-0.1895	-0.1070	-0.0138
PopDensity	-0.2462	0.1985	-0.2311	0.0886	0.5014	-0.2623	0.3074	-0.4321	-0.0702	0.0655

	EduTer~y	PopDen~y
EduTertiary	1.0000	
PopDensity	0.0733	1.0000

Table A3.6.1 VIF diagnostics

```
. reg UnemPActPop ALMPExp_01 TrainSh EmpIncSh SupportSh DirectJobSh PLMPExp_01
Informality GDPgrowth LabFreeIndex EduTertiary PopDensity

      Source |       SS           df       MS      Number of obs   =       245
-------------+----------------------------------   F(11, 233)      =     22.32
       Model |  1968.44168        11  178.949243   Prob > F        =    0.0000
    Residual |  1868.29009       233  8.01841239   R-squared       =    0.5131
-------------+----------------------------------   Adj R-squared   =    0.4901
       Total |  3836.73176       244  15.7243105   Root MSE        =    2.8317


------------------------------------------------------------------------------
 UnemPActPop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  ALMPExp_01 |  -4.593658    1.09539    -4.19   0.000    -6.751793   -2.435523
     TrainSh |  -.1601032   .0251768    -6.36   0.000    -.2097064     -.1105
    EmpIncSh |  -.1451453   .0260649    -5.57   0.000    -.1964983   -.0937923
   SupportSh |  -.1077022    .029418    -3.66   0.000    -.1656615   -.0497429
 DirectJobSh |  -.1089322   .0270249    -4.03   0.000    -.1621767   -.0556878
  PLMPExp_01 |   4.242314   .4482715     9.46   0.000      3.35913    5.125497
 Informality |   .1785261   .0341833     5.22   0.000     .1111783    .2458739
   GDPgrowth |  -.1114642   .0483535    -2.31   0.022      -.20673   -.0161983
LabFreeIndex |  -.0250062   .0138429    -1.81   0.072    -.0522794     .002267
 EduTertiary |   .0091814   .0248632     0.37   0.712    -.0398041    .0581668
  PopDensity |  -.0114019   .0023862    -4.78   0.000    -.0161031   -.0067006
       _cons |   19.21647   2.457935     7.82   0.000     14.37385    24.05909
------------------------------------------------------------------------------


. vif

    Variable |       VIF       1/VIF
-------------+----------------------
     TrainSh |      9.94    0.100554
   SupportSh |      9.42    0.106180
 DirectJobSh |      8.47    0.118106
    EmpIncSh |      7.97    0.125412
  PLMPExp_01 |      2.98    0.335200
  ALMPExp_01 |      2.94    0.340154
  PopDensity |      1.94    0.516439
 Informality |      1.87    0.534752
LabFreeIndex |      1.25    0.797896
 EduTertiary |      1.22    0.820811
   GDPgrowth |      1.13    0.884683
-------------+----------------------
    Mean VIF |      4.47
```

Table A3.7.1 Dynamic Panel Difference GMM estimation, 2004-2016 (dep. variable *UnemRate*)

```
xtabond2 UnemPActPop l.UnemPActPop ALMPExp_01 ALMPEx2 PLMPExp_01 Informality GDPgrowth
LabFreeIndex EduTertiary PopDensity Y5 Y6 Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16 , gmm
(l.UnemPActPop, lag(3 4) coll) gmm(ALMPExp_01, lag(2 4) coll) gmm(ALMPEx2, lag(2 4)
coll) gmm(PLMPExp_01, coll lag (3 4)) iv (Informalityl1 GDPgrowth  LabFreeIndlag1
EduTertiary PopDensity Y5 Y6 Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16) nolevel orthog
small two robust
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: CountryID                       Number of obs      =       211
Time variable : Year                            Number of groups   =        28
Number of instruments = 23                      Obs per group: min =         2
F(21, 28)     =    300.67                                      avg =      7.54
Prob > F      =     0.000                                      max =         8
------------------------------------------------------------------------------
             |              Corrected
 UnemPActPop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 UnemPActPop |
         L1. |   .8029835   .0897542     8.95   0.000     .6191303    .9868368
             |
  ALMPExp_01 |  -1.766425   4.304943    -0.41   0.685     -10.5847    7.051851
     ALMPEx2 |   .6537321   1.843726     0.35   0.726     -3.12297    4.430434
  PLMPExp_01 |   1.506833     1.0193     1.48   0.150    -.5811085    3.594774
 Informality |  -.2839615   .7307676    -0.39   0.701    -1.780871    1.212948
   GDPgrowth |  -.3197609   .0537135    -5.95   0.000     -.429788   -.2097338
LabFreeIndex |  -.0544686   .0260127    -2.09   0.045    -.1077532   -.001184
 EduTertiary |  -.0695874   .0640921    -1.09   0.287    -.2008742    .0616994
  PopDensity |   .0306049   .0297469     1.03   0.312    -.0303289    .0915388
          Y5 |          0  (omitted)
          Y6 |          0  (omitted)
          Y7 |          0  (omitted)
          Y8 |  -.3625466   .5431668    -0.67   0.510    -1.475173    .7500801
          Y9 |  -1.198688   .8866481    -1.35   0.187    -3.014905    .6175279
         Y10 |   -1.01152   .6609107    -1.53   0.137    -2.365334    .3422942
         Y11 |   .3692955   1.088361     0.34   0.737     -1.86011    2.598701
         Y12 |  -.6940559   1.205192    -0.58   0.569    -3.162779    1.774667
         Y13 |  -.7969428   1.376565    -0.58   0.567    -3.616709    2.022823
         Y14 |  -.7710867   1.754208    -0.44   0.664    -4.364418    2.822245
         Y15 |  -.8559475   1.777762    -0.48   0.634    -4.497529    2.785634
         Y16 |          0  (omitted)
------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
```

```
  Standard
    FOD.(Informalityl1 GDPgrowth LabFreeIndlag1 EduTertiary PopDensity Y5 Y6
    Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(3/4).PLMPExp_01 collapsed
    L(2/4).ALMPEx2 collapsed
    L(2/4).ALMPExp_01 collapsed
    L(3/4).L.UnemPActPop collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.67  Pr > z =  0.008
Arellano-Bond test for AR(2) in first differences: z =  -1.40  Pr > z =  0.163
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(2)    =   1.81  Prob > chi2 =  0.404
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(2)    =   2.34  Prob > chi2 =  0.310
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  gmm(L.UnemPActPop, collapse lag(3 4))
    Hansen test excluding group:     chi2(0)    =   1.06  Prob > chi2 =      .
    Difference (null H = exogenous): chi2(2)    =   1.28  Prob > chi2 =  0.527
  gmm(PLMPExp_01, collapse lag(3 4))
    Hansen test excluding group:     chi2(0)    =   1.82  Prob > chi2 =      .
    Difference (null H = exogenous): chi2(2)    =   0.52  Prob > chi2 =  0.770
```

Table A3.7.2 Dynamic Panel Difference GMM estimation, 2004-2016 (dep. variable *UnemRate*) including variables *TrainSh, EmpIncSh, SupportSh, DirectJobSh* and *StartupSh*

```
. xtabond2 UnemPActPop l.UnemPActPop ALMPExp_01 ALMPEx2 TrainSh EmpIncSh SupportSh
DirectJobSh PLMPExp_01 Informality GDPgrowth LabFreeIndex EduTertiary PopDensity Y5 Y6
Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16 , gmm (l.UnemPActPop, lag(2 2) coll)
gmm(ALMPExp_01, lag(1 4) coll) gmm(ALMPEx2, lag(1 4) coll) gmm(PLMPExp_01, coll lag (2
2)) iv (TrainSh EmpIncSh SupportSh DirectJobSh Informalityl1 GDPgrowth  LabFreeIndlag1
EduTertiary PopDensity Y5 Y6 Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16) nolevel orthog
small two robust
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimat
> ion.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: CountryID                       Number of obs      =       194
Time variable : Year                            Number of groups   =        27
```

```
Number of instruments = 27                      Obs per group: min =         2
F(25, 27)     =   1230.04                                      avg =      7.19
Prob > F      =     0.000                                      max =         8
------------------------------------------------------------------------------
             |              Corrected
  UnemPActPop |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 UnemPActPop |
        L1. |   .8108625   .1251556     6.48   0.000     .5540643    1.067661
             |
  ALMPExp_01 |  -2.653723   5.008279    -0.53   0.601    -12.92986    7.622417
     ALMPEx2 |   1.866048   1.944381     0.96   0.346    -2.123493    5.855588
     TrainSh |  -.0062418   .0294469    -0.21   0.834    -.0666618    .0541782
    EmpIncSh |   .0005877   .0285775     0.02   0.984    -.0580485    .0592239
   SupportSh |   .0227252   .0252127     0.90   0.375    -.0290069    .0744573
 DirectJobSh |   .0030111   .0377527     0.08   0.937     -.074451    .0804732
  PLMPExp_01 |   1.219703    1.10226     1.11   0.278    -1.041948    3.481354
 Informality |  -.0840336   .6553656    -0.13   0.899    -1.428733    1.260666
   GDPgrowth |  -.3404664   .0448648    -7.59   0.000    -.4325215   -.2484114
LabFreeIndex |  -.0243384   .0219517    -1.11   0.277    -.0693796    .0207027
 EduTertiary |  -.0090602    .057657    -0.16   0.876    -.1273625    .1092421
  PopDensity |   .0428234   .0324361     1.32   0.198      -.02373    .1093769
          Y5 |          0  (omitted)
          Y6 |          0  (omitted)
          Y7 |   .2404947   .4075819     0.59   0.560    -.5957942    1.076784
          Y8 |          0  (omitted)
          Y9 |  -.7772027   .4228337    -1.84   0.077    -1.644786    .0903804
         Y10 |  -.6702403   .4682324    -1.43   0.164    -1.630974    .2904933
         Y11 |   .9418979    .636306     1.48   0.150    -.3636942     2.24749
         Y12 |  -.3329215   .8490945    -0.39   0.698     -2.07512    1.409277
         Y13 |  -.5248557   .9922158    -0.53   0.601    -2.560714    1.511003
         Y14 |  -.5370858   1.386175    -0.39   0.701    -3.381282    2.307111
         Y15 |    -.74371    1.40572    -0.53   0.601     -3.62801    2.140589
         Y16 |          0  (omitted)
------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(TrainSh EmpIncSh SupportSh DirectJobSh Informalityl1 GDPgrowth
    LabFreeIndlag1 EduTertiary PopDensity Y5 Y6 Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14
    Y15 Y16)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L2.PLMPExp_01 collapsed
    L(1/4).ALMPEx2 collapsed
    L(1/4).ALMPExp_01 collapsed
    L2.L.UnemPActPop collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.42  Pr > z =  0.016
Arellano-Bond test for AR(2) in first differences: z =  -1.33  Pr > z =  0.182
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(2)    =   1.18  Prob > chi2 =  0.553
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(2)    =   1.98  Prob > chi2 =  0.371
  (Robust, but weakened by many instruments.)
```

```
Difference-in-Hansen tests of exogeneity of instrument subsets:
  gmm(L.UnemPActPop, collapse lag(2 2))
    Hansen test excluding group:     chi2(1)    =   1.83  Prob > chi2 =  0.176
    Difference (null H = exogenous): chi2(1)    =   0.15  Prob > chi2 =  0.700
  gmm(PLMPExp_01, collapse lag(2 2))
    Hansen test excluding group:     chi2(1)    =   1.93  Prob > chi2 =  0.165
    Difference (null H = exogenous): chi2(1)    =   0.05  Prob > chi2 =  0.823
```

Table A3.8.1 Instrumental Variable Approach for the Matching Function specification; Instrument: *ALMPExplag1*

```
. xtivreg2 lnUEflow  lnUnemploymentSTlag1 lnVacancieslag1 lnEUflow lnIUflow lnLFor
ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth EcoFreeIndex
EduTertiary Y11 Y12 Y13 Y14 Y15  (ALMPExp ALMPExp2= ALMPExplag1 ALMPExp2lag1), fe
endog (ALMPExp)
Warning - singleton groups detected.  1 observation(s) not used.
Warning - collinearities detected
Vars dropped:       Y11 Y15

FIXED EFFECTS ESTIMATION
------------------------
Number of groups =        13                    Obs per group: min =         2
                                                               avg =       3.7
                                                               max =         4
Warning - collinearities detected
Vars dropped:  Y11 Y15
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only
                                                      Number of obs =       48
                                                      F( 18,     17) =     0.43
                                                      Prob > F      =   0.9595
Total (centered) SS     =   .5623271776               Centered R2   =  -0.8691
Total (uncentered) SS   =   .5623271776               Uncentered R2 =  -0.8691
Residual SS             =   1.051048527               Root MSE      =    .1733

------------------------------------------------------------------------------
            lnUEflow |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------
             ALMPExp |   36.62942   72.82149     0.50   0.615    -106.0981    179.3569
            ALMPExp2 |  -3320.165   6842.135    -0.49   0.627     -16730.5    10090.17
lnUnemploymentSTlag1 |  -1.430722   2.454789    -0.58   0.560     -6.24202    3.380576
     lnVacancieslag1 |  -.1072928   .4610507    -0.23   0.816    -1.010936    .7963499
            lnEUflow |   .4057029   .5990795     0.68   0.498    -.7684714    1.579877
            lnIUflow |  -.6549891    1.50119    -0.44   0.663    -3.597267    2.287289
              lnLFor |    8.62242   10.28435     0.84   0.402    -11.53453    28.77937
            ShLongUn |   .0194153   .0223759     0.87   0.386    -.0244406    .0632713
           ShYoungUn |  -.0921094   .1561642    -0.59   0.555    -.3981857    .2139669
           ShWomenUn |   .0158908   .0369706     0.43   0.667    -.0565703    .0883518
         PLMPExplag1 |   1.931171   3.148014     0.61   0.540    -4.238824    8.101165
       Informalityl1 |   -1.14282   1.954934    -0.58   0.559     -4.97442     2.68878
           GDPgrowth |   .0753888   .1683375     0.45   0.654    -.2545467    .4053243
        EcoFreeIndex |  -.0869994   .0717081    -1.21   0.225    -.2275448    .0535459
```

```
        EduTertiary |  -.1144043   .1691777    -0.68   0.499    -.4459865    .2171779
                Y11 |          0  (omitted)
                Y12 |   1.318679   2.456291     0.54   0.591    -3.495564    6.132922
                Y13 |   1.179178   2.336734     0.50   0.614    -3.400737    5.759092
                Y14 |   .5659593   1.168634     0.48   0.628    -1.724521     2.85644
                Y15 |          0  (omitted)
------------------------------------------------------------------------------------
Underidentification test (Anderson canon. corr. LM statistic):            0.500
                                                   Chi-sq(1) P-val =    0.4797
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):                 0.123
Stock-Yogo weak ID test critical values: 10% maximal IV size               7.03
                                         15% maximal IV size               4.58
                                         20% maximal IV size               3.95
                                         25% maximal IV size               3.63
Source: Stock-Yogo (2005).  Reproduced by permission.
------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):            0.000
                                                 (equation exactly identified)
-endog- option:
Endogeneity test of endogenous regressors:                                5.436
                                                   Chi-sq(1) P-val =    0.0197
Regressors tested:    ALMPExp
------------------------------------------------------------------------------
Instrumented:         ALMPExp ALMPExp2
Included instruments: lnUnemploymentSTlag1 lnVacancieslag1 lnEUflow lnIUflow
                      lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1
                      Informalityl1 GDPgrowth EcoFreeIndex EduTertiary Y12 Y13
                      Y14
Excluded instruments: ALMPExplag1 ALMPExp2lag1
Dropped collinear:    Y11 Y15
------------------------------------------------------------------------------
```

Table A3.8.2 Instrumental Variable Approach for the Matching Function specification; Instrument: *CompGov*

```
. xtivreg2 lnUEflow  lnUnemploymentSTlag1 lnVacancieslag1 lnEUflow lnIUflow lnLFor
ShLongUn ShYoungUn ShWomenUn PLMPExplag1 Informalityl1 GDPgrowth EcoFreeIndex
EduTertiary Y11 Y12 Y13 Y14 Y15  (ALMPExp = CompGov), fe endog (ALMPExp)
Warning - singleton groups detected.  1 observation(s) not used.
Warning - collinearities detected
Vars dropped:       Y11 Y15

FIXED EFFECTS ESTIMATION
------------------------
Number of groups =        13                    Obs per group: min =         2
                                                               avg =       3.5
                                                               max =         4

Warning - collinearities detected
Vars dropped:  Y11 Y15
IV (2SLS) estimation
--------------------
Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only
                                                      Number of obs =       46
                                                      F( 17,    16) =     3.67
```

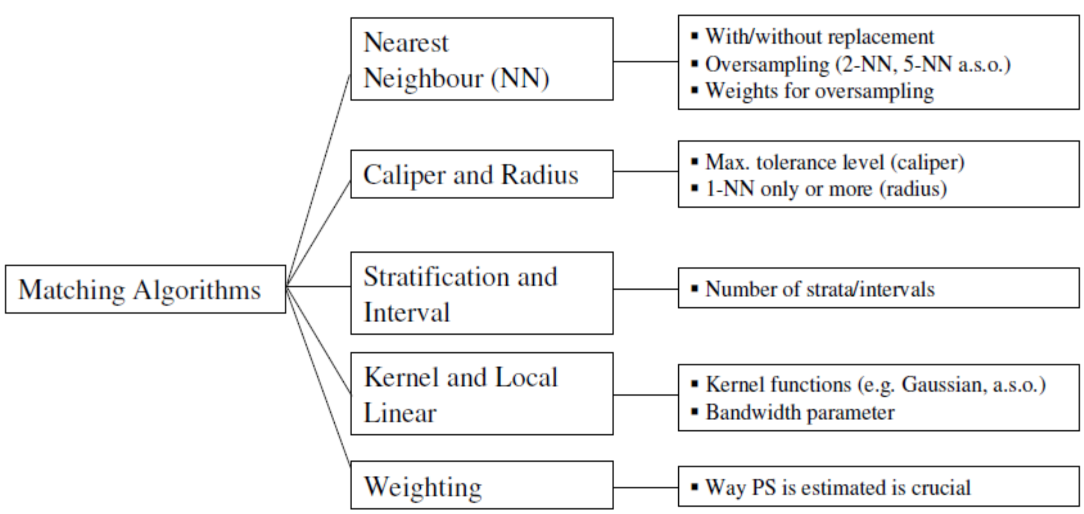
```
                                                      Prob > F      =   0.0063
Total (centered) SS     =  .4604319025                Centered R2   =   0.7765
Total (uncentered) SS   =  .4604319025                Uncentered R2 =   0.7765
Residual SS             =  .1029111646                Root MSE      =   .05584
------------------------------------------------------------------------------------
           lnUEflow |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
            ALMPExp |    .991117   .8501442     1.17   0.244     -.675135    2.657369
lnUnemploymentSTlag1 |  -.3590063   .3386942    -1.06   0.289    -1.022835    .3048222
     lnVacancieslag1 |  -.2441166   .1568904    -1.56   0.120    -.5516161    .0633829
           lnEUflow |   .1834128   .1022803     1.79   0.073    -.0170529    .3838786
           lnIUflow |   .0173152   .2206178     0.08   0.937    -.4150877    .4497181
             lnLFor |   .7252567   2.595003     0.28   0.780    -4.360855    5.811368
           ShLongUn |   .0087909   .0058639     1.50   0.134    -.0027022     .020284
          ShYoungUn |  -.0152553   .0246109    -0.62   0.535    -.0634919    .0329812
          ShWomenUn |   .0104089   .0131803     0.79   0.430    -.0154241    .0362418
        PLMPExplag1 |   .6516695   .3576061     1.82   0.068    -.0492256    1.352565
       Informalityl1 |  -.2330759   .1833585    -1.27   0.204    -.5924519    .1263001
          GDPgrowth |   .0257738   .0173248     1.49   0.137    -.0081822    .0597299
        EcoFreeIndex |  -.0183485   .0338955    -0.54   0.588    -.0847825    .0480854
        EduTertiary |   .0132404   .0382611     0.35   0.729    -.0617499    .0882306
                Y11 |          0  (omitted)
                Y12 |   .3228151   .2315507     1.39   0.163    -.1310158    .7766461
                Y13 |   .3386977   .1958829     1.73   0.084    -.0452257    .7226212
                Y14 |   .1605702   .1060527     1.51   0.130    -.0472893    .3684298
                Y15 |          0  (omitted)
------------------------------------------------------------------------------------
Underidentification test (Anderson canon. corr. LM statistic):          2.606
                                                   Chi-sq(1) P-val =    0.1065
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):               1.372
Stock-Yogo weak ID test critical values: 10% maximal IV size            16.38
                                         15% maximal IV size             8.96
                                         20% maximal IV size             6.66
                                         25% maximal IV size             5.53
Source: Stock-Yogo (2005).  Reproduced by permission.
------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):          0.000
                                                 (equation exactly identified)
-endog- option:
Endogeneity test of endogenous regressors:                              1.822
                                                   Chi-sq(1) P-val =    0.1770
Regressors tested:    ALMPExp
------------------------------------------------------------------------------
Instrumented:         ALMPExp
Included instruments: lnUnemploymentSTlag1 lnVacancieslag1 lnEUflow lnIUflow
                      lnLFor ShLongUn ShYoungUn ShWomenUn PLMPExplag1
                      Informalityl1 GDPgrowth EcoFreeIndex EduTertiary Y12 Y13
                      Y14
Excluded instruments: CompGov
Dropped collinear:    Y11 Y15
```

Appendix 4.1 – Chapter 4 - Matching methods

There are different matching estimators using a weighting scheme which determines the weights when comparing the two groups (Dehejia and Wahba, 2002). The closer the matched control to the treated individual in terms of propensity score value, the higher the quality of the matching. However, choosing parameters that maximise the quality may induce lower variability, as the number of matched individuals from the control group will be reduced. Therefore, matching methods are subject to a trade-off between bias and variance which is crucial when using small samples (Caliendo and Kopeinig, 2008). In addition, issues with low common support tend to distort the performance of the algorithms and hence should be accounted for (Busso et al., 2014).

There is a large group of methods used for balancing of covariates or propensity scores (Heckman et al. 1999; Dehejia and Wahba, 2002). Figure 4.1 offers an overview of the methods used. The most commonly applied matching algorithms and trade-offs faced when using different algorithms are presented and explained below.

Figure 4.1 Different Matching Algorithms



Source: Caliendo and Kopeinig, 2008

The Nearest Neighbour matching algorithm is commonly used in the evaluations of the effectiveness of ALMPs (Bonin and Rinne, 2014). The criteria to form match sets of propensity scores based on this algorithm is to assign the closest propensity score of the un-treated subject to that of a treated one. There are two primary methods to form the matches with this algorithm: the nearest neighbour matching without replacement and the nearest neighbour matching with replacement (Rosenbaum and Rubin, 1985). Nearest neighbour without replacement – also called 'greedy matching' - assigns a weight to the nearest control observations and zero to all the others. This method does not impose any common support condition because it dedicates one control observation $\mathrm{D} = 0$ to match at most one treated observation $\mathrm{D} = 1$. In the case where multiple untreated have equally close proximity to the treated propensity scores, the propensity score is selected randomly. An important note to this method is that there is no restriction on the approximate distance between the propensity scores (Austin, 2011). Thus, there is a risk that in the case when there are a limited number of control units, the matched control and treated units will not be similar in terms of propensity scores and there will not be quality matched pairs. Nearest neighbour matching with replacement is used in particular to minimize the distance between the matched control and treatment units, since it allows the comparison unit to be matched more than once. This is likely to be beneficial since it reduces bias by ensuring that each treated observation is matched to the closest available control, however, it may reduce efficiency since the total sample of matched controls contains a smaller number of controls than the full sample (Deheija and Wahba, 2002; Caliendo and Kopeinig, 2008). Ming and Rosenbaum (2000) found evidence of reduction in bias when varying number of control subjects was used in matching. Another method that can be used to match treated and untreated individuals is 'oversampling' matching. When using 'oversampling' matching, one should decide on a random number of partners to be matched based on distance or weights, where one treated can be matched with more than one control. At the same time, it may also assign different weights when matching the propensity scores. The difference of this method to matching with replacement is that the former dedicates a number of neighbours to be matched while in the later replacement may or may not happen depending on the number of the control propensity scores within the allowed distance or weights. Caliendo and Kopeinig (2008) suggest 'oversampling' with more than one nearest neighbour using distance-based weights rather than uniform weights to aggregate the observations mitigates the trade-off between bias and variance (Schmidl, 2014). However, since oversampling matching selects ad-hoc a number of neighbours and as such is not protected from outlier values, this method is outperformed by most other methods.

If the propensity scores are far from each other, nearest neighbour matching is not an appropriate choice since it will not form quality matches. This issue could be overcome by imposing a maximum distance to allow creating matching pairs. **Caliper and Radius matching** uses all the control units within a radius (caliper) for a maximum threshold allowed and rules out matches beyond that particular threshold (Austin, 2011). When using Caliper matching, for a given treated subject, one can identify a set of untreated subjects whose propensity score lie within the caliper; the closest propensity score from this restricted set will be chosen for matching with treated. If within the caliper there is no untreated subject, the treated propensity score will not be matched and consequently will be excluded from the matched sample (Austin, 2011). The advantage of this type of matching is that it allows good matching within the caliper when good control units are available and vice versa (Dehejia and Wahba, 2002). According to Dehejia and Wahba, Radius matching may be a more appropriate choice than Caliper. This method allows forming more than one matching pair within the specified caliper if there are available quality matches. When using caliper matching there is no consensus agreed among researchers as to what constitutes an optimal distance. A wide range of caliper widths have been used in the ALMP evaluations. After examining the reduction in bias, Cochran and Rubin (1973) suggest that choosing a caliper of 0.2 of the standard deviation of the logarithm of the propensity score, will remove 98% of the bias.

The idea behind **Stratification/Interval Matching** is to separate the common support into different strata (intervals) and treatment effects are calculated through simple averaging within each strata (Caliendo and Kopeinig, 2008; Todd, 2006). This variant of matching is also referred in the literature as blocking and sub-classification (Rosenbaum and Rubin, 1983). To implement this method one should make a choice of the number of intervals and how wide they should be (Caliendo and Kopeinig, 2008; Todd, 2010). Partitioning propensity scores into five intervals will often remove 95% of the bias

(Imbens, 2004). Caliendo and Kopeinig (2008) suggest that propensity scores need to be balanced within the intervals meaning that mean values of the propensity scores of both groups are not statistically different from each other. If they are not balanced then the interval is too large and need to be partitioned again.

The matching methods discussed above use one or more untreated subjects to construct the counterfactuals for a treated subject. In contrast, the **Kernel and Local-Linear methods** compare each treated unit to a weighted average of the outcomes of all control units. Control units with closer propensity scores to the treated unit being matched are given a higher weight. Since this method uses more information to create matching, it increases the efficiency, while the drawback of this method is that it includes information from poor matches. Kernel matching can use different weighting schemes: weighted average (kernel matching) or weighted regression on an intercept and a linear term of the propensity score (local linear matching). Gausian and Epanechnikov are kernel methods mostly used. Epanechnikov, similar to caliper method, drops matches that are out of pre-assigned distance. This method is more likely to be performed when there is a risk in using distant matches. However, Gaussian is recommended since it uses more information therefore produces higher efficiency. In comparison to nearest neighbour method, kernel produces much less bias, since kernel weights reduce the variability of the estimator (Blundell and Costa-Dias, 2009). A disadvantage of the kernel method is that it produces bias at the ends of the distribution of propensity scores; in this case the Local Linear matching method would be more suitable. Local linear matching is different from kernel matching since it includes a linear term which is helpful when the observations in the control group are asymmetrically distributed around the participants' observations. This asymmetry is more likely to be present at the boundary points.

When implementing a social experiment to assess the effectiveness of ALMPs, the propensity scores are known and can be directly used as weights to obtain balance between two groups. This is known as **Weighting on Propensity Score** and is mostly used in experimental settings (Imbens, 2004).

The propensity score can be used to construct matched pairs by also applying **Mahalanobis metric matching** (Stuart, 2010). Mahalanobis metric matching can also impose a specified caliper to form matching pairs. This method defines distance between the treated and untreated observations within a caliper and uses the estimated propensity scores and also the set of 'key variables' to create matching pairs (Stuart, 2010). The set of key variables used may be the pre-treatment measures which affect the outcome. This form of matching has been regarded as being very efficient in balancing the covariates between the two groups and is superior to the Nearest Neighbour matching (Feng et al., 2006; Stuart, 2010). This method works quite well when fewer than 8 covariates are used for matching but it does not perform well when there is no normal distribution among the covariates (Rubin, 1974).

When selecting among the matching algorithms one should consider the trade-off between bias and efficiency. In general, if there is sufficient data on control and treated units and there is considerable overlapping between the control and treated groups all these matching methods will yield similar results. In contrast, if there are only a handful of comparison units that can be good matches to the treated units choosing only the nearest match in terms of propensity scores will minimize the bias but it will ignore a great deal of information providing less efficient results. When assessing cross-programme effectiveness the number of potential matches is typically low and as consequence only a small share of the treatment group might be in the common support (Stephan and Pahnke, 2008). In such cases when using nearest neighbour matching without replacement the evaluator is likely to end up with only a few observations. Matching methods are not mutually exclusive; these methods may be combined in order to produce more quality matches (such as combining Nearest Neighbour with Caliper method or with Stratification). The existing literature is inconclusive regarding the most preferred matching method, however Kernel and Mahalanobis matching methods seem to be more appropriate in case of small samples since these methods utilise more information provided in the sample.

Appendix 5 – Chapter 5

Table A5.1 Hausman test

```
. *Multinomial Logit – omitting category 2

. . mlogit LABSTATE OJT IS Amduration AM2009 AM2010 Cert Emplan Age Agesq Male Disability
Minority Socialassist Twounempl Remittance Primaryeduc Secondaryeduc  Undur6 Undur12 Undur24 FER
GJAK GJIL MIT PEJ PRZ

Iteration 0:   log likelihood =  -664.9741
Iteration 1:   log likelihood = -548.43968
Iteration 2:   log likelihood =  -537.0644
Iteration 3:   log likelihood = -536.72965
Iteration 4:   log likelihood = -536.72674
Iteration 5:   log likelihood = -536.72673

Multinomial logistic regression                   Number of obs   =        751
                                                  LR chi2(52)     =     256.49
                                                  Prob > chi2     =     0.0000
Log likelihood = -536.72673                       Pseudo R2       =     0.1929

------------------------------------------------------------------------------
    LABSTATE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0            |  (base outcome)
-------------+----------------------------------------------------------------
1            |
         OJT |   .4597266   .2917661     1.58   0.115    -.1121243    1.031578
          IS |   .5103823   .3244463     1.57   0.116    -.1255208    1.146285
  Amduration |  -.0157657   .0857393    -0.18   0.854    -.1838117    .1522802
      AM2009 |  -.1949788   .2744215    -0.71   0.477    -.7328351    .3428774
      AM2010 |   -.798991   .2663633    -3.00   0.003    -1.321053   -.2769286
        Cert |   .5498937   .2305077     2.39   0.017      .098107     1.00168
      Emplan |   .1473124   .2264484     0.65   0.515    -.2965184    .5911432
         Age |   .2222954   .1660162     1.34   0.181    -.1030903    .5476811
       Agesq |  -.0027416   .0027363    -1.00   0.316    -.0081047    .0026216
        Male |   .3659762   .1978192     1.85   0.064    -.0217422    .7536946
  Disability |  -1.655212   1.072373    -1.54   0.123    -3.757024    .4466009
    Minority |   -.984669   .4876099    -2.02   0.043    -1.940367   -.0289712
Socialassist |  -.8496233   .4073139    -2.09   0.037    -1.647944   -.0513028
   Twounempl |  -.5390388   .2219733    -2.43   0.015    -.9740986   -.1039791
  Remittance |  -.3516946   .3625584    -0.97   0.332    -1.062296    .3589069
 Primaryeduc |  -.8467976   .3175506    -2.67   0.008    -1.469185   -.2244098
Secondaryeduc |  -.9813312   .2373486    -4.13   0.000    -1.446526   -.5161365
      Undur6 |   1.349181   .3500525     3.85   0.000     .6630904    2.035271
     Undur12 |    .154713   .2794858     0.55   0.580     -.393069    .7024951
     Undur24 |   .5172292   .3306467     1.56   0.118    -.1308265    1.165285
         FER |  -.4050338   .3644336    -1.11   0.266     -1.11931    .3092429
        GJAK |  -.7839924   .3797028    -2.06   0.039    -1.528196   -.0397886
        GJIL |  -.4159494   .3232929    -1.29   0.198    -1.049592    .2176932
         MIT |  -2.342225   .4656797    -5.03   0.000     -3.25494   -1.429509
         PEJ |  -.4183847   .3846836    -1.09   0.277    -1.172351    .3355813
         PRZ |  -1.106432   .3789633    -2.92   0.004    -1.849186   -.3636774
       _cons |  -3.967431   2.591582    -1.53   0.126    -9.046839    1.111976
-------------+----------------------------------------------------------------
2            |
         OJT |   1.094729   .4269262     2.56   0.010     .2579689    1.931489
          IS |   .6127019   .4870321     1.26   0.208    -.3418635    1.567267
  Amduration |   .3606224   .1306877     2.76   0.006     .1044792    .6167655
      AM2009 |  -.4541542   .4223747    -1.08   0.282    -1.281993     .373685
      AM2010 |  -.5149485   .3829009    -1.34   0.179     -1.26542    .2355233
        Cert |  -.7380894   .3129407    -2.36   0.018    -1.351442   -.1247369
      Emplan |   .1968594   .3419847     0.58   0.565    -.4734183     .867137
         Age |   .5827392   .2770131     2.10   0.035     .0398035    1.125675
       Agesq |  -.0092678    .004771    -1.94   0.052    -.0186188    .0000833
```

```
         Male |   1.484491   .3247421     4.57   0.000     .8480082    2.120974
   Disability |  -1.035347   1.171001    -0.88   0.377    -3.330466    1.259772
     Minority |  -1.815683    .680237    -2.67   0.008    -3.148923   -.4824432
 Socialassist |  -.2684868   .5620885    -0.48   0.633     -1.37016    .8331864
    Twounempl |   .0634986    .323416     0.20   0.844    -.5703851    .6973823
   Remittance |   .1541961   .4972226     0.31   0.756    -.8203422    1.128734
  Primaryeduc |   1.369059   .4970307     2.75   0.006     .3948968    2.343221
Secondaryeduc |   1.781445    .416228     4.28   0.000     .9656527    2.597236
       Undur6 |   1.556241   .4434997     3.51   0.000     .6869977    2.425485
      Undur12 |     .00767   .3978933     0.02   0.985    -.7721866    .7875266
      Undur24 |   .8443963   .4618276     1.83   0.067    -.0607692    1.749562
          FER |  -1.318202   .5346858    -2.47   0.014    -2.366167   -.2702375
         GJAK |  -1.306474   .5584836    -2.34   0.019    -2.401082   -.2118661
         GJIL |  -1.115373     .44656    -2.50   0.013    -1.990614   -.2401313
          MIT |  -1.369892   .4806071    -2.85   0.004    -2.311865   -.4279195
          PEJ |  -2.172006   .8320165    -2.61   0.009    -3.802728   -.5412833
          PRZ |  -1.313306   .5031249    -2.61   0.009    -2.299413   -.3271996
        _cons |  -13.32806   4.182931    -3.19   0.001    -21.52646   -5.129668
------------------------------------------------------------------------------

. . estimates store allcats

. . hausman . allcats, alleqs constant
the two models need to be different
r(198);

.  . mlogit  LABSTATE  OJT  IS  Amduration  AM2009  AM2010  Cert  Emplan  Age  Agesq  Male  Disability
Minority Socialassist Twounempl Remittance Pri
> maryeduc Secondaryeduc  Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ if LABSTATE!= 2

Iteration 0:   log likelihood = -414.52635
Iteration 1:   log likelihood = -338.34147
Iteration 2:   log likelihood = -334.54489
Iteration 3:   log likelihood =  -334.5016
Iteration 4:   log likelihood = -334.50134
Iteration 5:   log likelihood = -334.50134

Multinomial logistic regression                   Number of obs   =        673
                                                  LR chi2(26)     =     160.05
                                                  Prob > chi2     =     0.0000
Log likelihood = -334.50134                       Pseudo R2       =     0.1931

------------------------------------------------------------------------------
     LABSTATE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0             |  (base outcome)
-------------+----------------------------------------------------------------
1             |
          OJT |   .4633314   .2965452     1.56   0.118    -.1178864    1.044549
           IS |   .5249883   .3303649     1.59   0.112    -.1225149    1.172492
   Amduration |   .0052355   .0866417     0.06   0.952     -.164579    .1750501
       AM2009 |  -.2820691   .2796365    -1.01   0.313    -.8301466    .2660083
       AM2010 |  -.9072117   .2721565    -3.33   0.001    -1.440629   -.3737948
         Cert |   .5838014   .2349768     2.48   0.013     .1232553    1.044347
       Emplan |    .124732   .2283894     0.55   0.585    -.3229031     .572367
          Age |   .2050731   .1619691     1.27   0.205    -.1123805    .5225266
        Agesq |  -.0024886   .0026613    -0.94   0.350    -.0077046    .0027274
         Male |   .3134485   .2007348     1.56   0.118    -.0799844    .7068815
   Disability |  -1.612346   1.078726    -1.49   0.135     -3.72661    .5019185
     Minority |  -.9469323   .4892818    -1.94   0.053    -1.905907    .0120425
 Socialassist |   -.898881   .4156091    -2.16   0.031     -1.71346   -.0843021
    Twounempl |  -.6054384    .224338    -2.70   0.007    -1.045133   -.1657441
   Remittance |  -.4004109   .3676038    -1.09   0.276    -1.120901    .3200793
  Primaryeduc |  -.8586244   .3197078    -2.69   0.007     -1.48524   -.2320087
Secondaryeduc |  -.9550832   .2385986    -4.00   0.000    -1.422728   -.4874385
       Undur6 |    1.58059   .3678728     4.30   0.000     .8595724    2.301607
      Undur12 |    .158366   .2853416     0.56   0.579    -.4008932    .7176252
      Undur24 |    .548747   .3366296     1.63   0.103    -.1110348    1.208529
```

```
         FER |  -.4355245   .3732842    -1.17   0.243    -1.167148     .296099
        GJAK |  -.7534865   .3874847    -1.94   0.052    -1.512943    .0059696
        GJIL |  -.4272716   .3303703    -1.29   0.196    -1.074785    .2202422
         MIT |   -2.37131    .477567    -4.97   0.000    -3.307324   -1.435296
         PEJ |  -.4358382   .3913001    -1.11   0.265    -1.202772    .3310959
         PRZ |  -1.176137   .3919322    -3.00   0.003     -1.94431    -.407964
       _cons |  -3.669244   2.539658    -1.44   0.149    -8.646883    1.308394
------------------------------------------------------------------------------

. . hausman . allcats, alleqs constant

Note: the rank of the differenced variance matrix (26) does not equal the number of coefficients
being tested (27); be sure this is what
        you expect, or there may be problems computing the test.  Examine the output of your
estimators for anything unexpected and
        possibly consider scaling your variables so that the coefficients are on a similar
scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       .         allcats       Difference          S.E.
-------------+----------------------------------------------------------------
         OJT |    .4633314     .4597266        .0036048        .0530246
          IS |    .5249883     .5103823         .014606        .0622536
  Amduration |    .0052355    -.0157657        .0210013        .0124719
      AM2009 |   -.2820691    -.1949788       -.0870903        .0537531
      AM2010 |   -.9072117     -.798991       -.1082206        .0558548
        Cert |    .5838014     .5498937        .0339076        .0456106
      Emplan |     .124732     .1473124       -.0225804        .0297126
         Age |    .2050731     .2222954       -.0172223               .
       Agesq |   -.0024886    -.0027416         .000253               .
        Male |    .3134485     .3659762       -.0525277        .0340886
  Disability |   -1.612346    -1.655212        .0428659        .1169019
    Minority |   -.9469323     -.984669        .0377367        .0404147
Socialassist |    -.898881    -.8496233       -.0492577        .0826217
   Twounempl |   -.6054384    -.5390388       -.0663996        .0324864
  Remittance |   -.4004109    -.3516946       -.0487163        .0606952
 Primaryeduc |   -.8586244    -.8467976       -.0118268        .0370762
Secondarye~c |   -.9550832    -.9813312         .026248        .0243918
      Undur6 |     1.58059     1.349181        .2314092        .1131091
     Undur12 |     .158366      .154713         .003653        .0575111
     Undur24 |     .548747     .5172292        .0315178         .063184
         FER |   -.4355245    -.4050338       -.0304907        .0808038
        GJAK |   -.7534865    -.7839924        .0305059        .0772672
        GJIL |   -.4272716    -.4159494       -.0113222        .0680161
         MIT |    -2.37131    -2.342225        -.029085        .1058897
         PEJ |   -.4358382    -.4183847       -.0174535         .071654
         PRZ |   -1.176137    -1.106432       -.0697053        .0999886
       _cons |   -3.669244    -3.967431        .2981869               .
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from mlogit
           B = inconsistent under Ha, efficient under Ho; obtained from mlogit

    Test:  Ho:  difference in coefficients not systematic

                 chi2(26) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        3.26
                Prob>chi2 =      1.0000
                (V_b-V_B is not positive definite)


. *Multinomial Logit – omitting category 1

. . mlogit LABSTATE OJT IS Amduration AM2009 AM2010 Cert Emplan Age Agesq Male Disability
Minority Socialassist Twounempl Remittance Pri
> maryeduc Secondaryeduc  Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ, baseoutcome (1)

Iteration 0:   log likelihood =  -664.9741
Iteration 1:   log likelihood = -548.43968
```

```
Iteration 2:   log likelihood =  -537.0644
Iteration 3:   log likelihood = -536.72965
Iteration 4:   log likelihood = -536.72674
Iteration 5:   log likelihood = -536.72673

Multinomial logistic regression                   Number of obs   =        751
                                                  LR chi2(52)     =     256.49
                                                  Prob > chi2     =     0.0000
Log likelihood = -536.72673                       Pseudo R2       =     0.1929

------------------------------------------------------------------------------
     LABSTATE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0            |
         OJT |  -.4597266   .2917661    -1.58   0.115    -1.031578    .1121243
          IS |  -.5103823   .3244463    -1.57   0.116    -1.146285    .1255208
   Amduration |   .0157657   .0857393     0.18   0.854    -.1522802    .1838117
       AM2009 |   .1949788   .2744215     0.71   0.477    -.3428774    .7328351
       AM2010 |    .798991   .2663633     3.00   0.003     .2769286    1.321053
         Cert |  -.5498937   .2305077    -2.39   0.017     -1.00168    -.098107
       Emplan |  -.1473124   .2264484    -0.65   0.515    -.5911432    .2965184
          Age |  -.2222954   .1660162    -1.34   0.181    -.5476811    .1030903
        Agesq |   .0027416   .0027363     1.00   0.316    -.0026216    .0081047
         Male |  -.3659762   .1978192    -1.85   0.064    -.7536946    .0217422
   Disability |   1.655212   1.072373     1.54   0.123    -.4466009    3.757024
     Minority |    .984669   .4876099     2.02   0.043     .0289712    1.940367
 Socialassist |   .8496233   .4073139     2.09   0.037     .0513028    1.647944
    Twounempl |   .5390388   .2219733     2.43   0.015     .1039791    .9740986
   Remittance |   .3516946   .3625584     0.97   0.332    -.3589069    1.062296
  Primaryeduc |   .8467976   .3175506     2.67   0.008     .2244098    1.469185
Secondaryeduc |   .9813312   .2373486     4.13   0.000     .5161365    1.446526
       Undur6 |  -1.349181   .3500525    -3.85   0.000    -2.035271   -.6630904
      Undur12 |   -.154713   .2794858    -0.55   0.580    -.7024951     .393069
      Undur24 |  -.5172292   .3306467    -1.56   0.118    -1.165285    .1308265
          FER |   .4050338   .3644336     1.11   0.266    -.3092429     1.11931
         GJAK |   .7839924   .3797028     2.06   0.039     .0397886    1.528196
         GJIL |   .4159494   .3232929     1.29   0.198    -.2176932    1.049592
          MIT |   2.342225   .4656797     5.03   0.000     1.429509     3.25494
          PEJ |   .4183847   .3846836     1.09   0.277    -.3355813    1.172351
          PRZ |   1.106432   .3789633     2.92   0.004     .3636774    1.849186
        _cons |   3.967431   2.591582     1.53   0.126    -1.111976    9.046839
-------------+----------------------------------------------------------------
1            |  (base outcome)
-------------+----------------------------------------------------------------
2            |
         OJT |   .6350022   .4737188     1.34   0.180    -.2934697    1.563474
          IS |   .1023196   .5373253     0.19   0.849    -.9508186    1.155458
   Amduration |   .3763881   .1422335     2.65   0.008     .0976156    .6551606
       AM2009 |  -.2591754   .4471344    -0.58   0.562    -1.135543    .6171919
       AM2010 |   .2840425   .4115321     0.69   0.490    -.5225457    1.090631
         Cert |  -1.287983   .3504318    -3.68   0.000    -1.974817   -.6011495
       Emplan |    .049547   .3733776     0.13   0.894    -.6822597    .7813536
          Age |   .3604439   .3031939     1.19   0.235    -.2338053     .954693
        Agesq |  -.0065262    .005187    -1.26   0.208    -.0166926    .0036402
         Male |   1.118515   .3516377     3.18   0.001     .4293177    1.807712
   Disability |   .6198646   1.534446     0.40   0.686    -2.387594    3.627323
     Minority |  -.8310143   .7896506    -1.05   0.293    -2.378701    .7166725
 Socialassist |   .5811364   .6298056     0.92   0.356    -.6532599    1.815533
    Twounempl |   .6025374   .3517561     1.71   0.087    -.0868918    1.291967
   Remittance |   .5058907   .5526644     0.92   0.360    -.5773116    1.589093
  Primaryeduc |   2.215857   .5389817     4.11   0.000     1.159472    3.272241
Secondaryeduc |   2.762776   .4408597     6.27   0.000     1.898707    3.626845
       Undur6 |   .2070604   .4709984     0.44   0.660    -.7160796      1.1302
      Undur12 |   -.147043   .4417662    -0.33   0.739    -1.012889    .7188029
      Undur24 |   .3271671   .5066823     0.65   0.518    -.6659119    1.320246
          FER |  -.9131686   .5838935    -1.56   0.118    -2.057579    .2312417
         GJAK |  -.5224815   .5932143    -0.88   0.378     -1.68516    .6401972
         GJIL |  -.6994234   .4863514    -1.44   0.150    -1.652655    .2538077
          MIT |   .9723326   .5965839     1.63   0.103    -.1969504    2.141616
```

```
         PEJ |  -1.753621   .8552865    -2.05   0.040    -3.429952   -.0772902
         PRZ |  -.2068746   .5484497    -0.38   0.706    -1.281816    .8680671
       _cons |   -9.36063   4.602088    -2.03   0.042    -18.38056   -.3407034
------------------------------------------------------------------------------

. . estimates store allcats

. . hausman . allcats, alleqs constant
the two models need to be different
r(198);

. . mlogit LABSTATE OJT IS Amduration AM2009 AM2010 Cert Emplan Age Agesq Male Disability
Minority Socialassist Twounempl Remittance Pri
> maryeduc Secondaryeduc  Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ if  LABSTATE != 1

Iteration 0:   log likelihood = -223.76921
Iteration 1:   log likelihood = -183.59836
Iteration 2:   log likelihood = -175.51166
Iteration 3:   log likelihood = -175.21807
Iteration 4:   log likelihood = -175.21531
Iteration 5:   log likelihood = -175.21531

Multinomial logistic regression                   Number of obs   =        545
                                                  LR chi2(26)     =      97.11
                                                  Prob > chi2     =     0.0000
Log likelihood = -175.21531                       Pseudo R2       =     0.2170

------------------------------------------------------------------------------
     LABSTATE |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0            |  (base outcome)
-------------+----------------------------------------------------------------
2            |
         OJT |   1.076963   .4425022     2.43   0.015     .2096751    1.944252
          IS |   .6694552   .5034822     1.33   0.184    -.3173519    1.656262
  Amduration |   .3335893   .1397581     2.39   0.017     .0596684    .6075102
      AM2009 |  -.4188908   .4399431    -0.95   0.341    -1.281163    .4433818
      AM2010 |  -.4637839    .402037    -1.15   0.249    -1.251762    .3241941
        Cert |  -.8007494   .3226123    -2.48   0.013    -1.433058    -.168441
      Emplan |   .3778588   .3615245     1.05   0.296    -.3307161    1.086434
         Age |   .5331342   .2741219     1.94   0.052    -.0041348    1.070403
       Agesq |  -.0083947   .0046633    -1.80   0.072    -.0175346    .0007453
        Male |   1.548984   .3291945     4.71   0.000     .9037741    2.194193
  Disability |  -1.044292   1.170088    -0.89   0.372    -3.337623    1.249038
    Minority |  -1.751292   .6888179    -2.54   0.011     -3.10135   -.4012341
Socialassist |  -.3053427   .5708567    -0.53   0.593    -1.424201    .8135158
   Twounempl |   .0695731   .3417902     0.20   0.839    -.6003233    .7394696
  Remittance |   .1092955   .5150997     0.21   0.832    -.9002813    1.118872
 Primaryeduc |   1.400195   .5264263     2.66   0.008     .3684186    2.431972
Secondaryeduc |     1.7761   .4347528     4.09   0.000     .9240006      2.6282
      Undur6 |   1.543768   .4577152     3.37   0.001     .6466623    2.440873
     Undur12 |  -.1805326   .4018381    -0.45   0.653    -.9681208    .6070556
     Undur24 |   .7411883    .476862     1.55   0.120    -.1934439    1.675821
         FER |  -1.310509     .55292    -2.37   0.018    -2.394213   -.2268062
        GJAK |  -1.141076   .5754469    -1.98   0.047    -2.268931   -.0132207
        GJIL |   -1.14778   .4668586    -2.46   0.014    -2.062806   -.2327536
         MIT |  -1.354635   .4882264    -2.77   0.006    -2.311541   -.3977289
         PEJ |  -1.944116   .8670739    -2.24   0.025     -3.64355   -.2446828
         PRZ |  -1.172205   .5171251    -2.27   0.023    -2.185752   -.1586588
       _cons |  -12.71889     4.2037    -3.03   0.002    -20.95799   -4.479784
------------------------------------------------------------------------------

. . hausman . allcats, alleqs constant

Note: the rank of the differenced variance matrix (26) does not equal the number of coefficients
being tested (27); be sure this is what
        you expect, or there may be problems computing the test.  Examine the output of your
estimators for anything unexpected and
```

```
        possibly  consider  scaling  your  variables  so  that  the  coefficients  are  on  a  similar
scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       .          allcats       Difference          S.E.
-------------+----------------------------------------------------------------
         OJT |    1.076963     .6350022        .4419612               .
          IS |    .6694552     .1023196        .5671357               .
  Amduration |    .3335893     .3763881       -.0427988               .
      AM2009 |   -.4188908    -.2591754       -.1597154               .
      AM2010 |   -.4637839     .2840425       -.7478264               .
        Cert |   -.8007494    -1.287983        .4872337               .
      Emplan |    .3778588      .049547        .3283119               .
         Age |    .5331342     .3604439        .1726903               .
       Agesq |   -.0083947    -.0065262       -.0018685               .
        Male |    1.548984     1.118515        .4304687               .
  Disability |   -1.044292     .6198646       -1.664157               .
    Minority |   -1.751292    -.8310143        -.920278               .
Socialassist |   -.3053427     .5811364       -.8864792               .
   Twounempl |    .0695731     .6025374       -.5329643               .
  Remittance |    .1092955     .5058907       -.3965952               .
 Primaryeduc |    1.400195     2.215857       -.8156615               .
Secondarye~c |      1.7761     2.762776       -.9866754               .
      Undur6 |    1.543768     .2070604        1.336707               .
     Undur12 |   -.1805326     -.147043       -.0334896               .
     Undur24 |    .7411883     .3271671        .4140213               .
         FER |   -1.310509    -.9131686       -.3973409               .
        GJAK |   -1.141076    -.5224815       -.6185944               .
        GJIL |    -1.14778    -.6994234       -.4483562               .
         MIT |   -1.354635     .9723326       -2.326968               .
         PEJ |   -1.944116    -1.753621       -.1904955        .1424858
         PRZ |   -1.172205    -.2068746       -.9653306               .
       _cons |   -12.71889     -9.36063       -3.358255               .
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from mlogit
           B = inconsistent under Ha, efficient under Ho; obtained from mlogit

    Test:  Ho:  difference in coefficients not systematic

                 chi2(26) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      210.06
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Table A5.2 Multinomial probit model and marginal effects of the final model using dependent variable LABSTATE

```
. . mprobit LABSTATE OJT IS Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability
Minority Socialassist Twounempl Remittance Primaryeduc Secondaryeduc Undur6 Undur12 Undur24 FER
GJAK GJIL MIT PEJ PRZ

Iteration 0:   log likelihood =   -539.105
Iteration 1:   log likelihood = -537.12037
Iteration 2:   log likelihood =  -537.0904
Iteration 3:   log likelihood = -537.09039

Multinomial probit regression                     Number of obs   =        751
                                                  Wald chi2(52)   =     199.55
Log likelihood = -537.09039                       Prob > chi2     =     0.0000
```

LABSTATE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
0	(base outcome)					
1						
OJT	.3917622	.2289026	1.71	0.087	-.0568786	.8404031
IS	.4314454	.2565022	1.68	0.093	-.0712896	.9341805
Amduration	-.0124474	.069435	-0.18	0.858	-.1485375	.1236426
AM2008	.6600419	.2131802	3.10	0.002	.2422164	1.077867
AM2009	.4675774	.1854235	2.52	0.012	.104154	.8310009
Cert	.4040996	.1815747	2.23	0.026	.0482197	.7599795
Emplan	.1274878	.1813859	0.70	0.482	-.2280219	.4829976
Age	.1790627	.1349573	1.33	0.185	-.0854488	.4435742
Agesq	-.0022631	.0022426	-1.01	0.313	-.0066585	.0021323
Male	.3230189	.1586846	2.04	0.042	.0120028	.634035
Disability	-1.291635	.7512435	-1.72	0.086	-2.764045	.1807747
Minority	-.8267022	.3653888	-2.26	0.024	-1.542851	-.1105534
Socialassist	-.7721515	.3222473	-2.40	0.017	-1.403745	-.1405585
Twounempl	-.4591886	.1767584	-2.60	0.009	-.8056287	-.1127486
Remittance	-.3074324	.292005	-1.05	0.292	-.8797518	.2648869
Primaryeduc	-.6990088	.2527711	-2.77	0.006	-1.194431	-.2035866
Secondaryeduc	-.738497	.1903087	-3.88	0.000	-1.111495	-.3654989
Undur6	1.126386	.2785105	4.04	0.000	.5805155	1.672257
Undur12	.1098213	.226483	0.48	0.628	-.3340772	.5537197
Undur24	.4295659	.2675983	1.61	0.108	-.0949171	.954049
FER	-.3732822	.2917459	-1.28	0.201	-.9450937	.1985292
GJAK	-.6890372	.3077592	-2.24	0.025	-1.292234	-.0858402
GJIL	-.3700658	.2572416	-1.44	0.150	-.8742501	.1341185
MIT	-1.869331	.3462665	-5.40	0.000	-2.548001	-1.190661
PEJ	-.3674074	.3133319	-1.17	0.241	-.9815266	.2467119
PRZ	-.9669882	.3032506	-3.19	0.001	-1.561348	-.3726279
_cons	-3.768876	2.063958	-1.83	0.068	-7.814159	.2764075
2						
OJT	.7628254	.2940522	2.59	0.009	.1864937	1.339157
IS	.393991	.3379471	1.17	0.244	-.2683732	1.056355
Amduration	.2493871	.094475	2.64	0.008	.0642196	.4345547
AM2008	.4168909	.2778403	1.50	0.133	-.127666	.9614478
AM2009	.1063493	.2388008	0.45	0.656	-.3616918	.5743904
Cert	-.4473866	.2213226	-2.02	0.043	-.8811708	-.0136023
Emplan	.199591	.2430901	0.82	0.412	-.2768568	.6760388
Age	.44342	.1962733	2.26	0.024	.0587313	.8281087
Agesq	-.0069977	.0033605	-2.08	0.037	-.0135841	-.0004113
Male	1.024555	.2181042	4.70	0.000	.5970781	1.452031
Disability	-.8918562	.8712783	-1.02	0.306	-2.59953	.8158178
Minority	-1.311852	.4630656	-2.83	0.005	-2.219444	-.4042604
Socialassist	-.2101106	.3907467	-0.54	0.591	-.97596	.5557388
Twounempl	.0007493	.2322625	0.00	0.997	-.4544767	.4559754
Remittance	.1009049	.3524518	0.29	0.775	-.589888	.7916977
Primaryeduc	.8146505	.3421494	2.38	0.017	.1440499	1.485251
Secondaryeduc	1.105831	.2796901	3.95	0.000	.557648	1.654013
Undur6	1.238188	.3177207	3.90	0.000	.6154667	1.860909
Undur12	-.0119304	.2861954	-0.04	0.967	-.5728632	.5490023
Undur24	.5867474	.3358453	1.75	0.081	-.0714972	1.244992
FER	-.9169577	.3771587	-2.43	0.015	-1.656175	-.1777402
GJAK	-.8569173	.3981051	-2.15	0.031	-1.637189	-.0766457
GJIL	-.7457064	.3195222	-2.33	0.020	-1.371958	-.1194545
MIT	-1.066837	.3567498	-2.99	0.003	-1.766053	-.3676198
PEJ	-1.39678	.5241895	-2.66	0.008	-2.424173	-.3693875
PRZ	-.9335005	.3651058	-2.56	0.011	-1.649095	-.2179062
_cons	-10.29498	2.947795	-3.49	0.000	-16.07256	-4.517413

```
. . margins, dydx(*) predict(pr outcome(0))

Average marginal effects                        Number of obs   =        751
Model VCE    : OIM
```

```
Expression   : Pr(LABSTATE==0), predict(pr outcome(0))
dy/dx w.r.t. : OJT IS Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability Minority
Socialassist Twounempl Remittance
               Primaryeduc Secondaryeduc Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ

------------------------------------------------------------------------------
              |            Delta-method
              |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
          OJT |  -.1209935    .047696    -2.54   0.011    -.2144759    -.027511
           IS |  -.0999437   .0541527    -1.85   0.065     -.206081    .0061937
   Amduration |  -.0165842   .0149075    -1.11   0.266    -.0458023    .0126338
       AM2008 |  -.1390221   .0449949    -3.09   0.002    -.2272105   -.0508338
       AM2009 |  -.0843751   .0388958    -2.17   0.030    -.1606095   -.0081408
         Cert |  -.0326569   .0378044    -0.86   0.388    -.1067522    .0414383
       Emplan |  -.0357418   .0387676    -0.92   0.357    -.1117249    .0402413
          Age |  -.0623768   .0288951    -2.16   0.031    -.1190101   -.0057435
        Agesq |   .0008924   .0004848     1.84   0.066    -.0000579    .0018427
         Male |  -.1292964   .0330837    -3.91   0.000    -.1941393   -.0644535
   Disability |   .2777296   .1468617     1.89   0.059     -.010114    .5655732
     Minority |   .2330832   .0744048     3.13   0.002     .0872525    .3789139
 Socialassist |   .1419107    .066246     2.14   0.032      .012071    .2717505
    Twounempl |   .0750079   .0375356     2.00   0.046     .0014395    .1485763
   Remittance |   .0427227   .0608123     0.70   0.482    -.0764672    .1619126
  Primaryeduc |   .0534463   .0536921     1.00   0.320    -.0517883     .158681
Secondaryeduc |   .0381623   .0410567     0.93   0.353    -.0423074    .1186319
       Undur6 |   -.276573   .0564184    -4.90   0.000    -.3871511   -.1659949
      Undur12 |  -.0170618   .0473619    -0.36   0.719    -.1098894    .0757657
      Undur24 |  -.1140274   .0562307    -2.03   0.043    -.2242375   -.0038173
          FER |   .1294799   .0616056     2.10   0.036     .0087352    .2502246
         GJAK |    .176614   .0653298     2.70   0.007       .04857    .3046579
         GJIL |   .1161686   .0542014     2.14   0.032     .0099358    .2224014
          MIT |   .3852297    .065498     5.88   0.000      .256856    .5136035
          PEJ |   .1643426   .0716926     2.29   0.022     .0238278    .3048575
          PRZ |   .2277684   .0624652     3.65   0.000     .1053389     .350198
------------------------------------------------------------------------------

. margins, dydx(*) predict(pr outcome(1))

Average marginal effects                          Number of obs   =        751
Model VCE    : OIM

Expression   : Pr(LABSTATE==1), predict(pr outcome(1))
dy/dx w.r.t. : OJT IS Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability Minority
Socialassist Twounempl Remittance
               Primaryeduc Secondaryeduc Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ

------------------------------------------------------------------------------
              |            Delta-method
              |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
          OJT |   .0502385   .0438837     1.14   0.252    -.0357719    .1362488
           IS |   .0719219   .0493342     1.46   0.145    -.0247714    .1686152
   Amduration |  -.0117748   .0132898    -0.89   0.376    -.0378223    .0142727
       AM2008 |   .1169424   .0400223     2.92   0.003     .0385002    .1953846
       AM2009 |   .0898725    .035366     2.54   0.011     .0205564    .1591886
         Cert |   .0977328   .0343696     2.84   0.004     .0303696     .165096
       Emplan |   .0181584    .034936     0.52   0.603     -.050315    .0866317
          Age |   .0194377   .0261911     0.74   0.458    -.0318959    .0707712
        Agesq |  -.0001938   .0004368    -0.44   0.657    -.0010499    .0006622
         Male |   .0267077    .030117     0.89   0.375    -.0323205    .0857359
   Disability |  -.2260158   .1485043    -1.52   0.128    -.5170789    .0650472
     Minority |  -.1170944   .0705121    -1.66   0.097    -.2552957    .0211068
 Socialassist |  -.1471314   .0614546    -2.39   0.017    -.2675802   -.0266827
    Twounempl |  -.0921731   .0333756    -2.76   0.006     -.157588   -.0267581
   Remittance |  -.0654459   .0560129    -1.17   0.243    -.1752291    .0443373
  Primaryeduc |   -.170574   .0473014    -3.61   0.000    -.2632829    -.077865
Secondaryeduc |  -.1893296   .0343317    -5.51   0.000    -.2566186   -.1220407
       Undur6 |   .1799721   .0508242     3.54   0.000     .0803585    .2795858
```

```
      Undur12 |   .0224816   .0438406     0.51   0.608    -.0634444    .1084076
      Undur24 |   .0643744   .0510487     1.26   0.207    -.0356793    .1644281
          FER |  -.0407965   .0556763    -0.73   0.464    -.1499201    .0683271
         GJAK |  -.1063924   .0580531    -1.83   0.067    -.2201743    .0073895
         GJIL |  -.0465214   .0488351    -0.95   0.341    -.1422365    .0491937
          MIT |  -.3354327   .0638271    -5.26   0.000    -.4605315   -.2103338
          PEJ |  -.0217687   .0602588    -0.36   0.718    -.1398739    .0963364
          PRZ |  -.1593199   .0566606    -2.81   0.005    -.2703726   -.0482671
------------------------------------------------------------------------------

. . margins, dydx(*) predict(pr outcome(2))

Average marginal effects                          Number of obs    =        751
Model VCE    : OIM

Expression   : Pr(LABSTATE==2), predict(pr outcome(2))
dy/dx w.r.t. : OJT IS Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability Minority
Socialassist Twounempl Remittance
               Primaryeduc Secondaryeduc Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ

------------------------------------------------------------------------------
              |            Delta-method
              |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
          OJT |    .070755   .0315136     2.25   0.025     .0089896    .1325204
           IS |   .0280217    .036328     0.77   0.440    -.0431799    .0992234
   Amduration |    .028359   .0100862     2.81   0.005     .0085904    .0481276
       AM2008 |   .0220797   .0293189     0.75   0.451    -.0353842    .0795436
       AM2009 |  -.0054974   .0255026    -0.22   0.829    -.0554816    .0444869
         Cert |  -.0650759   .0234657    -2.77   0.006    -.1110679   -.0190839
       Emplan |   .0175834   .0260968     0.67   0.500    -.0335653    .0687322
          Age |   .0429391   .0212665     2.02   0.043     .0012576    .0846206
        Agesq |  -.0006986    .000365    -1.91   0.056     -.001414    .0000169
         Male |   .1025887    .023258     4.41   0.000     .0570038    .1481736
   Disability |  -.0517138   .0967032    -0.53   0.593    -.2412486     .137821
     Minority |  -.1159888   .0499839    -2.32   0.020    -.2139555    -.018022
 Socialassist |   .0052207   .0417256     0.13   0.900      -.07656    .0870013
    Twounempl |   .0171652   .0246564     0.70   0.486    -.0311605    .0654908
   Remittance |   .0227232   .0376575     0.60   0.546    -.0510842    .0965306
  Primaryeduc |   .1171276    .036235     3.23   0.001     .0461083     .188147
Secondaryeduc |   .1511674   .0291913     5.18   0.000     .0939534    .2083813
       Undur6 |   .0966009   .0320659     3.01   0.003     .0337529    .1594488
      Undur12 |  -.0054198   .0308658    -0.18   0.861    -.0659156    .0550761
      Undur24 |    .049653   .0357437     1.39   0.165    -.0204035    .1197095
          FER |  -.0886834   .0401473    -2.21   0.027    -.1673706   -.0099961
         GJAK |  -.0702216   .0419906    -1.67   0.094    -.1525217    .0120785
         GJIL |  -.0696472   .0337756    -2.06   0.039    -.1358462   -.0034482
          MIT |  -.0497971   .0365503    -1.36   0.173    -.1214344    .0218403
          PEJ |  -.1425739   .0565762    -2.52   0.012    -.2534612   -.0316866
          PRZ |  -.0684486   .0381302    -1.80   0.073    -.1431824    .0062852
------------------------------------------------------------------------------
```

Table A5.3 Estimated results from Inverse probability weighting – Regression Adjustment - EMP Outcome Model

```
**EMP Outcome Model
* including all variables

. . teffects ipwra (EMP Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability Minority
Socialassist Twounempl Remittance Primaryeduc Secondaryeduc Undur6 Undur12 Undur24 FER GJAK GJIL
MIT PEJ PRZ, logit) (AMTYPE Amduration AM2008 AM2009 Cert Emplan Age Agesq Male Disability
Minority Socialassist Twounempl Remittance Primaryeduc Secondaryeduc Jobsearchbt Undur6 Undur12
Undur24 FER GJAK GJIL MIT PEJ PRZ Vtcmncp), atet aequ
```

```
Iteration 0:   EE criterion =   .0028074
Iteration 1:   EE criterion =  .00084465
Iteration 2:   EE criterion =  .00032005
Iteration 3:   EE criterion =  .00004341
Iteration 4:   EE criterion =  4.304e-06
Iteration 5:   EE criterion =  3.276e-07
Iteration 6:   EE criterion =  1.832e-08
Iteration 7:   EE criterion =  1.932e-09

Treatment-effects estimation                    Number of obs      =       775
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
             |               Robust
         EMP |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
      AMTYPE |
    (2 vs 1) |  -.0439966   .0411158    -1.07   0.285    -.1245821    .0365889
    (3 vs 1) |  -.2306781   .0472774    -4.88   0.000    -.3233401   -.1380162
-------------+----------------------------------------------------------------
POmean       |
      AMTYPE |
           1 |   .4207408   .0305375    13.78   0.000     .3608884    .4805932
-------------+----------------------------------------------------------------
OME1         |
   Amduration |  -.0627644   .1303158    -0.48   0.630    -.3181786    .1926498
      AM2008 |   .5885721    .438524     1.34   0.180    -.2709191    1.448063
      AM2009 |   .3764315   .3755101     1.00   0.316    -.3595549    1.112418
        Cert |   -.108387   .3388105    -0.32   0.749    -.7724433    .5556693
      Emplan |  -.0460054   .3620198    -0.13   0.899    -.7555512    .6635403
         Age |   .5386367   .2722076     1.98   0.048     .0051196    1.072154
       Agesq |  -.0083705   .0045713    -1.83   0.067    -.0173301     .000589
        Male |   1.160854   .2903829     4.00   0.000     .5917135    1.729994
  Disability |  -2.515615     1.1588    -2.17   0.030    -4.786822   -.2444086
    Minority |   -2.76118   .7085929    -3.90   0.000    -4.149996   -1.372363
 Socialassist |   .3444823   .5696708     0.60   0.545     -.772052    1.461016
   Twounempl |   -.271202   .3384137    -0.80   0.423    -.9344806    .3920767
  Remittance |  -.3015599   .5125612    -0.59   0.556    -1.306161    .7030416
 Primaryeduc |  -.9373679   .4560413    -2.06   0.040    -1.831192   -.0435434
Secondaryeduc |  -.3071879   .3476105    -0.88   0.377     -.988492    .3741162
      Undur6 |   1.554599   .5943598     2.62   0.009     .3896753    2.719523
     Undur12 |  -.5105077   .4606861    -1.11   0.268    -1.413436    .3924205
     Undur24 |   .4740173   .5287411     0.90   0.370    -.5622963    1.510331
         FER |  -.3391754   .5876229    -0.58   0.564    -1.490895    .8125443
        GJAK |  -.1144167     .63751    -0.18   0.858    -1.363913     1.13508
        GJIL |  -.2202198   .5427857    -0.41   0.685     -1.28406    .8436207
         MIT |  -2.111176   .7391942    -2.86   0.004     -3.55997   -.6623822
         PEJ |   .9000074   .6956095     1.29   0.196    -.4633622    2.263377
         PRZ |   .4902991   .6264216     0.78   0.434    -.7374646    1.718063
       _cons |  -8.341024   4.000653    -2.08   0.037    -16.18216   -.4998876
-------------+----------------------------------------------------------------
OME2         |
   Amduration |  -.0528849   .1626507    -0.33   0.745    -.3716744    .2659046
      AM2008 |   .9601598   .4628436     2.07   0.038      .053003    1.867317
      AM2009 |   .8849673   .4409396     2.01   0.045     .0207417    1.749193
        Cert |   .6859635   .3750789     1.83   0.067    -.0491775    1.421105
      Emplan |  -.0964195   .3765648    -0.26   0.798    -.8344729    .6416339
         Age |   .3300517   .4286507     0.77   0.441    -.5100883    1.170192
       Agesq |  -.0052958   .0073758    -0.72   0.473    -.0197521    .0091604
        Male |   .8151041   .3640748     2.24   0.025     .1015307    1.528678
  Disability |  -8.219612   .9235115    -8.90   0.000    -10.02966   -6.409563
    Minority |  -1.210774   .8045656    -1.50   0.132    -2.787693    .3661458
 Socialassist |  -.5206427   .6292882    -0.83   0.408    -1.754025    .7127395
   Twounempl |  -.2773804   .4233309    -0.66   0.512    -1.107094     .552333
  Remittance |  -.2559838   .6344453    -0.40   0.687    -1.499474    .9875062
 Primaryeduc |   .4713746   .5492713     0.86   0.391    -.6051775    1.547927
```

Secondaryeduc	-.6405328	.3792625	-1.69	0.091	-1.383874	.1028081
Undur6	2.138261	.6996729	3.06	0.002	.7669272	3.509595
Undur12	.4738089	.4918827	0.96	0.335	-.4902635	1.437881
Undur24	.9988515	.8858621	1.13	0.260	-.7374064	2.735109
FER	-1.110155	.635524	-1.75	0.081	-2.355759	.1354489
GJAK	-2.365871	.7502384	-3.15	0.002	-3.836311	-.8954304
GJIL	-1.156276	.6167073	-1.87	0.061	-2.365	.0524484
MIT	-2.413818	.6655569	-3.63	0.000	-3.718286	-1.109351
PEJ	-1.901809	.8040223	-2.37	0.018	-3.477664	-.3259546
PRZ	-1.549686	.7409136	-2.09	0.036	-3.00185	-.0975217
_cons	-4.855077	5.951074	-0.82	0.415	-16.51897	6.808813
OME3						
Amduration	.5901876	.3973585	1.49	0.137	-.1886207	1.368996
AM2008	.5749502	.8729531	0.66	0.510	-1.136006	2.285907
AM2009	-1.90357	.889983	-2.14	0.032	-3.647905	-.1592353
Cert	.3093716	.7776974	0.40	0.691	-1.214887	1.83363
Emplan	.7193027	.769889	0.93	0.350	-.789652	2.228257
Age	-.5588032	.502037	-1.11	0.266	-1.542778	.4251712
Agesq	.0099583	.0075848	1.31	0.189	-.0049077	.0248242
Male	1.130225	.6832662	1.65	0.098	-.2089524	2.469402
Disability	6.942585	2.835869	2.45	0.014	1.384385	12.50079
Minority	2.02076	1.828067	1.11	0.269	-1.562186	5.603707
Socialassist	-8.274242	2.516683	-3.29	0.001	-13.20685	-3.341633
Twounempl	-3.340542	.8764125	-3.81	0.000	-5.058279	-1.622805
Remittance	-1.170883	1.041103	-1.12	0.261	-3.211409	.8696421
Primaryeduc	-4.003694	2.009059	-1.99	0.046	-7.941377	-.0660114
Secondaryeduc	2.135157	.9667549	2.21	0.027	.2403519	4.029961
Undur6	3.132367	1.831742	1.71	0.087	-.4577812	6.722514
Undur12	2.496569	1.263554	1.98	0.048	.0200484	4.97309
Undur24	6.385734	2.338571	2.73	0.006	1.802219	10.96925
FER	.4291426	1.595427	0.27	0.788	-2.697837	3.556122
GJAK	-4.655251	1.853636	-2.51	0.012	-8.288312	-1.022191
GJIL	-.3609159	.9061367	-0.40	0.690	-2.136911	1.415079
MIT	-16.34204	3.567898	-4.58	0.000	-23.335	-9.349093
PEJ	-6.566865	2.281503	-2.88	0.004	-11.03853	-2.095202
PRZ	-2.476982	1.424689	-1.74	0.082	-5.269321	.3153575
_cons	4.050914	7.508062	0.54	0.590	-10.66462	18.76644
TME2						
Amduration	.2329991	.0838307	2.78	0.005	.0686938	.3973043
AM2008	1.234078	.2462185	5.01	0.000	.7514989	1.716658
AM2009	.1470328	.2220062	0.66	0.508	-.2880914	.582157
Cert	.0172119	.2252752	0.08	0.939	-.4243194	.4587432
Emplan	.2091462	.2196086	0.95	0.341	-.2212787	.6395712
Age	.1598413	.1340997	1.19	0.233	-.1029892	.4226719
Agesq	-.0030997	.0021689	-1.43	0.153	-.0073507	.0011513
Male	-.0440999	.1899546	-0.23	0.816	-.4164041	.3282043
Disability	-.3981354	.6460456	-0.62	0.538	-1.664361	.8680907
Minority	-.0685822	.3791509	-0.18	0.856	-.8117043	.6745398
Socialassist	.6226882	.3631565	1.71	0.086	-.0890855	1.334462
Twounempl	.4005677	.2140876	1.87	0.061	-.0190363	.8201716
Remittance	.2351421	.3290873	0.71	0.475	-.4098572	.8801413
Primaryeduc	-.1364308	.3109532	-0.44	0.661	-.7458878	.4730262
Secondaryeduc	.1207818	.2360897	0.51	0.609	-.3419456	.5835092
Jobsearchbt	.4425851	.2522755	1.75	0.079	-.0518658	.937036
Undur6	-1.274316	.3646765	-3.49	0.000	-1.989069	-.5595632
Undur12	-.5470632	.2724658	-2.01	0.045	-1.081086	-.0130402
Undur24	-.8556659	.3146513	-2.72	0.007	-1.472371	-.2389607
FER	1.068962	.3774749	2.83	0.005	.3291246	1.808799
GJAK	1.051089	.3935209	2.67	0.008	.2798026	1.822376
GJIL	.6588806	.3462634	1.90	0.057	-.0197832	1.337544
MIT	1.110043	.3813545	2.91	0.004	.3626017	1.857484
PEJ	1.046338	.3992684	2.62	0.009	.2637862	1.82889
PRZ	.5137491	.4041379	1.27	0.204	-.2783467	1.305845
Vtcmncp	-.781792	.1891974	-4.13	0.000	-1.152612	-.4109718
_cons	-4.833665	2.122526	-2.28	0.023	-8.99374	-.6735905
TME3						

```
   Amduration |   .0699453   .1026532     0.68   0.496    -.1312512    .2711419
       AM2008 |   .3738966   .3009637     1.24   0.214    -.2159814    .9637746
       AM2009 |  -.7006541   .2928764    -2.39   0.017    -1.274681   -.1266269
         Cert |  -.3147974   .2505141    -1.26   0.209     -.805796    .1762011
       Emplan |   .7616696   .2905456     2.62   0.009     .1922107    1.331128
          Age |   .1582482   .1943625     0.81   0.416    -.2226953    .5391917
        Agesq |  -.0023262   .0032816    -0.71   0.478    -.0087581    .0041056
         Male |  -.1965395    .224941    -0.87   0.382    -.6374157    .2443368
   Disability |   .2362288   .7070531     0.33   0.738     -1.14957    1.622027
     Minority |  -.0211426   .4437801    -0.05   0.962    -.8909357    .8486504
 Socialassist |  -.1434028   .4926486    -0.29   0.771    -1.108976    .8221706
    Twounempl |   .7158547   .2658317     2.69   0.007     .1948341    1.236875
   Remittance |   .1740182   .4339583     0.40   0.688    -.6765244    1.024561
  Primaryeduc |   .3734437   .3727712     1.00   0.316    -.3571744    1.104062
Secondaryeduc |   .5329797   .2998281     1.78   0.075    -.0546725    1.120632
  Jobsearchbt |   .8118546   .3396121     2.39   0.017     .1462271    1.477482
       Undur6 |  -.0187538   .4246984    -0.04   0.965    -.8511474    .8136397
      Undur12 |   .3849114   .3013072     1.28   0.201    -.2056397    .9754626
      Undur24 |   .3669331   .3769147     0.97   0.330    -.3718062    1.105672
          FER |  -.5393957   .3657813    -1.47   0.140    -1.256314    .1775224
         GJAK |  -1.576471    .574202    -2.75   0.006    -2.701887   -.4510561
         GJIL |  -.5222018   .3428936    -1.52   0.128    -1.194261    .1498572
          MIT |  -1.590113   .5036984    -3.16   0.002    -2.577344   -.6028823
          PEJ |  -.7224363   .4894672    -1.48   0.140    -1.681774    .2369018
          PRZ |  -.2941617   .3988018    -0.74   0.461    -1.075799    .4874756
      Vtcmncp |   .1647272   .2480323     0.66   0.507    -.3214072    .6508616
        _cons |  -5.180945   2.945028    -1.76   0.079    -10.95309    .5912033
------------------------------------------------------------------------------
```

*Final Model for EMP; OJT defined as the control group

```
. teffects ipwra (EMP Age Agesq Male Minority Disability Socialassist Twounempl Remittance
Secondaryeduc Tertiaryeduc Amduration AM2009 AM2010 Cert Emplan Undur6 Undur12 Undur24  Regunmp,
logit) (AMTYPE Age Male Minority Disability Socialassist Twounempl Remittance Secondaryeduc
Tertiaryeduc  AM2008 AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ
Vtcmncp), atet aequ

Iteration 0:   EE criterion =  .00013777
Iteration 1:   EE criterion =  5.368e-06
Iteration 2:   EE criterion =  4.777e-07
Iteration 3:   EE criterion =  1.633e-08
Iteration 4:   EE criterion =  1.310e-09

Treatment-effects estimation                   Number of obs     =        775
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
             |               Robust
         EMP |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
      AMTYPE |
    (2 vs 1) |  -.0548059   .0432557    -1.27   0.205    -.1395855    .0299737
    (3 vs 1) |  -.1874647   .0514709    -3.64   0.000    -.2883458   -.0865835
-------------+----------------------------------------------------------------
POmean       |
      AMTYPE |
           1 |   .4315867   .0332301    12.99   0.000     .3664569    .4967165
-------------+----------------------------------------------------------------
OME1         |
         Age |    .564068   .2197993     2.57   0.010     .1332692    .9948668
```

Agesq	-.008986	.0034663	-2.59	0.010	-.0157799	-.0021921
Male	1.077326	.3052461	3.53	0.000	.479055	1.675598
Minority	-2.131653	.6789061	-3.14	0.002	-3.462285	-.8010217
Disability	-1.759941	1.026867	-1.71	0.087	-3.772563	.2526803
Socialassist	-.4438142	.5832432	-0.76	0.447	-1.58695	.6993215
Twounempl	-.2522157	.3207956	-0.79	0.432	-.8809636	.3765322
Remittance	-.1205627	.4233139	-0.28	0.776	-.9502426	.7091173
Secondaryeduc	.5924487	.4915488	1.21	0.228	-.3709693	1.555867
Tertiaryeduc	1.147507	.5019215	2.29	0.022	.163759	2.131255
Amduration	.0008367	.1337267	0.01	0.995	-.2612629	.2629362
AM2009	-.3331047	.4215384	-0.79	0.429	-1.159305	.4930955
AM2010	-.5841415	.4209084	-1.39	0.165	-1.409107	.2408239
Cert	-.278692	.3239883	-0.86	0.390	-.9136973	.3563134
Emplan	-.2239667	.3016824	-0.74	0.458	-.8152533	.3673199
Undur6	.9511897	.4445372	2.14	0.032	.0799127	1.822467
Undur12	-.5641854	.4364019	-1.29	0.196	-1.419517	.2911467
Undur24	.4275026	.3972222	1.08	0.282	-.3510386	1.206044
Regunmp	.0193867	.0142039	1.36	0.172	-.0084525	.0472259
_cons	-9.735501	3.580699	-2.72	0.007	-16.75354	-2.71746
OME2						
Age	.3290636	.4356758	0.76	0.450	-.5248454	1.182973
Agesq	-.0054928	.0075501	-0.73	0.467	-.0202908	.0093052
Male	.7691322	.3391117	2.27	0.023	.1044854	1.433779
Minority	-.9707207	.7340795	-1.32	0.186	-2.40949	.4680486
Disability	-6.461809	.9453664	-6.84	0.000	-8.314693	-4.608925
Socialassist	-.3667602	.5957894	-0.62	0.538	-1.534486	.8009656
Twounempl	-.3107361	.3846959	-0.81	0.419	-1.064726	.443254
Remittance	-.434276	.5704788	-0.76	0.447	-1.552394	.683842
Secondaryeduc	-1.169853	.4802645	-2.44	0.015	-2.111154	-.2285517
Tertiaryeduc	-.5243086	.4952637	-1.06	0.290	-1.495008	.4463905
Amduration	-.0431157	.1491718	-0.29	0.773	-.335487	.2492556
AM2009	-.0183602	.3964591	-0.05	0.963	-.7954058	.7586854
AM2010	-.9108668	.4256333	-2.14	0.032	-1.745093	-.0766409
Cert	.3899731	.373649	1.04	0.297	-.3423654	1.122312
Emplan	-.0710129	.361261	-0.20	0.844	-.7790715	.6370456
Undur6	1.548749	.6600847	2.35	0.019	.2550068	2.842491
Undur12	.4375261	.4840877	0.90	0.366	-.5112684	1.386321
Undur24	.3784083	.7547346	0.50	0.616	-1.100844	1.857661
Regunmp	-.025802	.017712	-1.46	0.145	-.060517	.0089129
_cons	-3.780572	6.112092	-0.62	0.536	-15.76005	8.198908
OME3						
Age	-.4753036	.5929791	-0.80	0.423	-1.637521	.6869142
Agesq	.0080286	.0092375	0.87	0.385	-.0100766	.0261338
Male	.8265213	.5732131	1.44	0.149	-.2969558	1.949998
Minority	1.39971	1.839669	0.76	0.447	-2.205975	5.005394
Disability	5.858273	2.261611	2.59	0.010	1.425598	10.29095
Socialassist	-7.628091	2.096519	-3.64	0.000	-11.73719	-3.518989
Twounempl	-3.128161	.7312034	-4.28	0.000	-4.561294	-1.695029
Remittance	-2.850865	1.431468	-1.99	0.046	-5.656491	-.0452389
Secondaryeduc	5.124749	1.620706	3.16	0.002	1.948223	8.301276
Tertiaryeduc	4.752533	1.642633	2.89	0.004	1.533032	7.972034
Amduration	-.0737341	.2859281	-0.26	0.797	-.6341429	.4866747
AM2009	-2.241873	.9776115	-2.29	0.022	-4.157956	-.3257894
AM2010	-1.046779	.9059241	-1.16	0.248	-2.822358	.7287996
Cert	-.8625012	.7444766	-1.16	0.247	-2.321648	.5966461
Emplan	1.379132	.6936569	1.99	0.047	.019589	2.738674
Undur6	1.738822	.8813282	1.97	0.049	.0114503	3.466193
Undur12	2.007601	.815216	2.46	0.014	.4098071	3.605395

```
      Undur24 |   2.161926    1.23921     1.74   0.081    -.2668821    4.590733
      Regunmp |  -.1055114   .0412353    -2.56   0.011    -.1863311   -.0246917
        _cons |   5.449672   9.669776     0.56   0.573    -13.50274    24.40208
--------------+----------------------------------------------------------------
TME2          |
          Age |  -.0230224   .0211147    -1.09   0.276    -.0644065    .0183617
         Male |  -.0461145   .1867698    -0.25   0.805    -.4121766    .3199477
     Minority |   .0272558   .3661039     0.07   0.941    -.6902948    .7448063
   Disability |   -.428773   .6256488    -0.69   0.493    -1.655022     .797476
 Socialassist |   .5597349   .3544127     1.58   0.114    -.1349013    1.254371
    Twounempl |   .3931691   .2118415     1.86   0.063    -.0220327    .8083709
   Remittance |   .2418132   .3253031     0.74   0.457    -.3957692    .8793956
Secondaryeduc |   .2617961   .2758849     0.95   0.343    -.2789283    .8025206
 Tertiaryeduc |   .4270143   .2938807     1.45   0.146    -.1489814     1.00301
       AM2008 |   1.110861   .2385366     4.66   0.000     .6433375    1.578384
       AM2009 |    .032839    .215568     0.15   0.879    -.3896665    .4553446
       Emplan |    .273116   .2148994     1.27   0.204     -.148079    .6943111
  Jobsearchbt |   .4865343   .2493387     1.95   0.051    -.0021607    .9752293
       Undur6 |  -1.229632   .3484286    -3.53   0.000     -1.91254   -.5467245
      Undur12 |  -.5288263   .2760252    -1.92   0.055    -1.069826    .0121731
      Undur24 |  -.9240161   .3143914    -2.94   0.003    -1.540212   -.3078202
          FER |   .9365803   .3632649     2.58   0.010     .2245943    1.648566
         GJAK |   1.063305   .3793692     2.80   0.005     .3197549    1.806855
         GJIL |   .6252092   .3420067     1.83   0.068    -.0451115     1.29553
          MIT |   1.049897   .3716283     2.83   0.005     .3215184    1.778275
          PEJ |   1.096769   .3985844     2.75   0.006     .3155582     1.87798
          PRZ |   .5635947   .4008738     1.41   0.160    -.2221034    1.349293
      Vtcmncp |  -.7920202    .185652    -4.27   0.000    -1.155891   -.4281488
        _cons |   -1.53445   .7677026    -2.00   0.046     -3.03912   -.0297811
--------------+----------------------------------------------------------------
TME3          |
          Age |   .0095294   .0240766     0.40   0.692    -.0376599    .0567188
         Male |  -.1728018   .2247162    -0.77   0.442    -.6132373    .2676338
     Minority |    .073275   .4223298     0.17   0.862    -.7544762    .9010261
   Disability |    .117096   .7091327     0.17   0.869    -1.272779    1.506971
 Socialassist |  -.1774981    .491178    -0.36   0.718    -1.140189    .7851931
    Twounempl |   .7069163   .2685615     2.63   0.008     .1805455    1.233287
   Remittance |   .1390156   .4267626     0.33   0.745    -.6974236    .9754549
Secondaryeduc |   .1273452   .3300205     0.39   0.700    -.5194832    .7741735
 Tertiaryeduc |  -.3026011    .336995    -0.90   0.369    -.9630991     .357897
       AM2008 |   .3318749   .2876811     1.15   0.249    -.2319697    .8957195
       AM2009 |  -.7350617   .2848813    -2.58   0.010    -1.293419   -.1767046
       Emplan |   .7865257   .2914136     2.70   0.007     .2153655    1.357686
  Jobsearchbt |   .8000072   .3485275     2.30   0.022     .1169059    1.483109
       Undur6 |   .0009203   .4247558     0.00   0.998    -.8315858    .8334265
      Undur12 |   .3828117   .3023662     1.27   0.205    -.2098152    .9754386
      Undur24 |   .3530662   .3738044     0.94   0.345    -.3795768    1.085709
          FER |  -.5227817   .3621072    -1.44   0.149    -1.232499    .1869355
         GJAK |  -1.695781   .5737932    -2.96   0.003    -2.820394   -.5711666
         GJIL |  -.5104089   .3389441    -1.51   0.132    -1.174727    .1539094
          MIT |  -1.689925   .5029444    -3.36   0.001    -2.675678   -.7041722
          PEJ |  -.7374181   .4909741    -1.50   0.133     -1.69971    .2248734
          PRZ |    -.31525   .3929581    -0.80   0.422    -1.085434    .4549338
      Vtcmncp |   .1120576   .2431995     0.46   0.645    -.3646046    .5887199
        _cons |  -2.431239   .8687185    -2.80   0.005    -4.133896   -.7285821
-------------------------------------------------------------------------------


. tebalance sum

  Covariate balance summary
```

Treatment	Observations Raw	Observations Weighted
1bn.AMTYPE =	434	266.8
2.AMTYPE =	215	260.1
3.AMTYPE =	126	248.0
Total =	775	775.0

	Standardized differences Raw	Standardized differences Weighted	Variance ratio Raw	Variance ratio Weighted
2.AMTYPE				
Age	-.0678291	-.0018754	.5369847	.7090128
Male	-.0132747	.0471284	1.004152	.9966165
Minority	.0458827	.0136406	1.159304	1.042683
Disability	-.0459175	.0263776	.7408577	1.220008
Socialassist	.1072386	-.0373641	1.3155	.9218237
Twounempl	.1581292	-.0316135	1.054328	.9960882
Remittance	.0267562	.0027943	1.080152	1.007737
Secondaryeduc	.0124827	.074304	1.006664	1.030859
Tertiaryeduc	.026563	-.0285668	1.011413	.9920741
AM2008	.4176771	-.101535	1.737583	.9358358
AM2009	-.1748149	-.0001514	.8442664	.999914
Emplan	.1672003	-.0670688	.8822599	1.072764
Jobsearchbt	.1248105	.0480782	.82352	.9215799
Undur6	-.1918028	.0203489	.5470082	1.084407
Undur12	-.1510318	.0265457	.7264488	1.06986
Undur24	-.150218	.0830826	.6250328	1.40823
FER	.0967362	.0293226	1.224914	1.058445
GJAK	-.0026116	.0914655	.9972103	1.219827
GJIL	.0048082	-.0458883	1.009151	.9408615
MIT	.1844576	-.0184909	1.439318	.9711882
PEJ	.0259385	.0134178	1.072776	1.035376
PRZ	-.1775181	-.0363147	.6685847	.9094665
Vtcmncp	-.3764772	-.041915	1.056687	.9920788
3.AMTYPE				
Age	.0024615	-.014137	.6569841	.5916758
Male	-.1212737	.2389363	1.008882	.9384594
Minority	.0299832	.0966511	1.107869	1.311958
Disability	.0383374	.0867318	1.251365	1.805588
Socialassist	-.106935	.1485006	.714682	1.309968
Twounempl	.400877	.0624914	1.037655	1.002314
Remittance	-.0675719	-.0308559	.8155747	.9168337
Secondaryeduc	.0804742	.2297438	1.028082	1.05904
Tertiaryeduc	-.108869	-.2023614	.9544092	.9109877
AM2008	.1543468	-.0266902	1.310053	.9851328
AM2009	-.3846312	-.2308287	.6168735	.6979702
Emplan	.4312289	.1184841	.6277311	.8578052
Jobsearchbt	.365399	.1723042	.4722596	.7162723
Undur6	-.1288816	-.0108593	.6907432	.956348
Undur12	.0082529	-.0786436	1.0208	.7999073
Undur24	.0314918	.179775	1.090249	1.950019
FER	.0540492	-.1419401	1.130358	.7206681
GJAK	-.3820654	.038094	.3009627	1.091374
GJIL	.0623979	.1986769	1.092133	1.221178
MIT	-.2623877	-.1867469	.4324768	.70229
PEJ	-.1302014	.1379881	.6699214	1.371341

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           PRZ |   -.016284   -.0371711      .9746405   .9075171
       Vtcmncp |  -.0482927   -.1599332      1.028956   .9515728
  ----------------------------------------------------------------
```

*Final Model for EMP; IS defined as the control group

```
.  . teffects ipwra (EMP Age Agesq Male Minority Disability Socialassist Twounempl Remittance
Secondaryeduc Tertiaryeduc Amduration AM2009 AM2010 Cert Emplan Undur6 Undur12 Undur24  Regunmp,
logit) (AMTYPE Age Male Minority Disability Socialassist Twounempl Remittance Secondaryeduc
Tertiaryeduc  AM2008 AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ
Vtcmncp), control(2) atet aequ

Iteration 0:   EE criterion =  .00048362
Iteration 1:   EE criterion =   .0000189
Iteration 2:   EE criterion =  2.219e-06
Iteration 3:   EE criterion =  1.265e-07
Iteration 4:   EE criterion =  1.139e-08
Iteration 5:   EE criterion =  7.640e-10

Treatment-effects estimation                    Number of obs     =        775
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
              |               Robust
          EMP |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET          |
       AMTYPE |
    (1 vs 2)  |   .0132943   .0493514     0.27   0.788    -.0834326    .1100213
    (3 vs 2)  |  -.1615823   .0557652    -2.90   0.004    -.2708801   -.0522845
-------------+----------------------------------------------------------------
POmean        |
       AMTYPE |
            2 |   .4221895   .0450768     9.37   0.000     .3338406    .5105385
-------------+----------------------------------------------------------------
OME1          |
          Age |   .3555378   .1599303     2.22   0.026     .0420802    .6689954
        Agesq |  -.0047716   .0025722    -1.86   0.064     -.009813    .0002698
         Male |   .6272575   .2151691     2.92   0.004     .2055339    1.048981
     Minority |  -1.062448   .4922263    -2.16   0.031    -2.027193   -.0977018
   Disability |  -.7002416   .7995441    -0.88   0.381    -2.267319    .8668361
 Socialassist |  -.9621916   .4325418    -2.22   0.026    -1.809958   -.1144252
    Twounempl |  -.3550106    .250606    -1.42   0.157    -.8461894    .1361681
   Remittance |  -.5315613   .3776834    -1.41   0.159    -1.271807    .2086845
Secondaryeduc |    .408088    .339943     1.20   0.230     -.258188    1.074364
 Tertiaryeduc |   .9511209   .3610006     2.63   0.008     .2435726    1.658669
   Amduration |   .0677976   .0920094     0.74   0.461    -.1125375    .2481327
       AM2009 |  -.3039122    .329441    -0.92   0.356    -.9496046    .3417802
       AM2010 |  -.5634386   .3193848    -1.76   0.078    -1.189421    .0625441
         Cert |  -.2398386   .2622122    -0.91   0.360    -.7537651     .274088
       Emplan |   .2390566   .2359918     1.01   0.311    -.2234789    .7015921
       Undur6 |   .8193721   .3540247     2.31   0.021     .1254965    1.513248
      Undur12 |   -.446396   .3288358    -1.36   0.175    -1.090902    .1981103
```

Undur24	.0048597	.3442055	0.01	0.989	-.6697706	.67949
Regunmp	.0218089	.0111575	1.95	0.051	-.0000594	.0436772
_cons	-7.357804	2.542043	-2.89	0.004	-12.34012	-2.375492
OME2						
Age	.7615354	.5099778	1.49	0.135	-.2380027	1.761073
Agesq	-.012766	.0090131	-1.42	0.157	-.0304312	.0048993
Male	1.195647	.3915337	3.05	0.002	.4282555	1.963039
Minority	-.3391327	1.140973	-0.30	0.766	-2.575399	1.897134
Disability	-8.153542	1.426372	-5.72	0.000	-10.94918	-5.357904
Socialassist	-1.020312	.7201723	-1.42	0.157	-2.431823	.3912001
Twounempl	-.2178595	.4368585	-0.50	0.618	-1.074086	.6383674
Remittance	-.741187	.6449859	-1.15	0.250	-2.005336	.5229622
Secondaryeduc	-1.452402	.538278	-2.70	0.007	-2.507408	-.3973969
Tertiaryeduc	-.7624754	.5641786	-1.35	0.177	-1.868245	.3432943
Amduration	-.2353584	.165339	-1.42	0.155	-.5594168	.0887
AM2009	-.204226	.4171904	-0.49	0.624	-1.021904	.6134522
AM2010	-.7458789	.4596267	-1.62	0.105	-1.646731	.1549729
Cert	.6266007	.4030011	1.55	0.120	-.1632669	1.416468
Emplan	.1962163	.4219629	0.47	0.642	-.6308157	1.023248
Undur6	.8622146	.5673309	1.52	0.129	-.2497336	1.974163
Undur12	.3543984	.6307943	0.56	0.574	-.8819357	1.590733
Undur24	.7979761	.9120326	0.87	0.382	-.989575	2.585527
Regunmp	-.0245198	.019497	-1.26	0.209	-.0627332	.0136936
_cons	-9.521713	7.069237	-1.35	0.178	-23.37716	4.333738
OME3						
Age	-.2186589	.4498074	-0.49	0.627	-1.100265	.6629474
Agesq	.003462	.0066684	0.52	0.604	-.0096079	.0165318
Male	.8357335	.5236569	1.60	0.110	-.1906152	1.862082
Minority	-1.243846	1.726844	-0.72	0.471	-4.628398	2.140707
Disability	2.494899	1.027847	2.43	0.015	.4803557	4.509443
Socialassist	-3.900294	1.487789	-2.62	0.009	-6.816306	-.9842812
Twounempl	-2.28188	.558867	-4.08	0.000	-3.377239	-1.186521
Remittance	-2.468048	1.132103	-2.18	0.029	-4.68693	-.2491661
Secondaryeduc	2.067616	1.046027	1.98	0.048	.0174413	4.117791
Tertiaryeduc	2.663065	.9968961	2.67	0.008	.7091844	4.616945
Amduration	-.2908568	.24037	-1.21	0.226	-.7619732	.1802597
AM2009	-1.434142	.8174757	-1.75	0.079	-3.036365	.1680809
AM2010	-.2140462	.7878155	-0.27	0.786	-1.758136	1.330044
Cert	-.0363909	.5660568	-0.06	0.949	-1.145842	1.07306
Emplan	.9753456	.5803867	1.68	0.093	-.1621913	2.112883
Undur6	.7258337	.8339626	0.87	0.384	-.908703	2.36037
Undur12	1.722254	.6675755	2.58	0.010	.41383	3.030678
Undur24	2.228145	.8650997	2.58	0.010	.5325807	3.923709
Regunmp	-.1207516	.0359788	-3.36	0.001	-.1912688	-.0502345
_cons	4.703475	7.113951	0.66	0.509	-9.239613	18.64656
TME1						
Age	.0230224	.0211147	1.09	0.276	-.0183617	.0644065
Male	.0461145	.1867698	0.25	0.805	-.3199477	.4121766
Minority	-.0272558	.3661039	-0.07	0.941	-.7448063	.6902948
Disability	.428773	.6256488	0.69	0.493	-.797476	1.655022
Socialassist	-.5597349	.3544127	-1.58	0.114	-1.254371	.1349013
Twounempl	-.3931691	.2118415	-1.86	0.063	-.8083709	.0220327
Remittance	-.2418132	.3253031	-0.74	0.457	-.8793956	.3957692
Secondaryeduc	-.2617961	.2758849	-0.95	0.343	-.8025206	.2789283
Tertiaryeduc	-.4270143	.2938807	-1.45	0.146	-1.00301	.1489814
AM2008	-1.110861	.2385366	-4.66	0.000	-1.578384	-.6433375
AM2009	-.032839	.215568	-0.15	0.879	-.4553446	.3896665

```
       Emplan |   -.273116   .2148994    -1.27   0.204    -.6943111     .148079
  Jobsearchbt |  -.4865343   .2493387    -1.95   0.051    -.9752293    .0021607
       Undur6 |   1.229632   .3484286     3.53   0.000     .5467245     1.91254
      Undur12 |   .5288263   .2760252     1.92   0.055    -.0121731    1.069826
      Undur24 |   .9240161   .3143914     2.94   0.003     .3078202    1.540212
          FER |  -.9365803   .3632649    -2.58   0.010    -1.648566   -.2245943
         GJAK |  -1.063305   .3793692    -2.80   0.005    -1.806855   -.3197549
         GJIL |  -.6252092   .3420067    -1.83   0.068     -1.29553    .0451115
          MIT |  -1.049897   .3716283    -2.83   0.005    -1.778275   -.3215184
          PEJ |  -1.096769   .3985844    -2.75   0.006     -1.87798   -.3155582
          PRZ |  -.5635947   .4008738    -1.41   0.160    -1.349293    .2221034
      Vtcmncp |   .7920202    .185652     4.27   0.000     .4281488    1.155891
        _cons |    1.53445   .7677026     2.00   0.046     .0297811     3.03912
-------------+----------------------------------------------------------------
TME3         |
          Age |   .0325518   .0280539     1.16   0.246    -.0224327    .0875364
         Male |  -.1266873   .2503674    -0.51   0.613    -.6173984    .3640239
     Minority |   .0460192   .4873019     0.09   0.925    -.9090749    1.001113
   Disability |    .545869    .835418     0.65   0.513     -1.09152    2.183258
  Socialassist |   -.737233   .5527755    -1.33   0.182    -1.820653    .3461872
    Twounempl |   .3137472   .2951957     1.06   0.288    -.2648257    .8923202
   Remittance |  -.1027976   .4828955    -0.21   0.831    -1.049255    .8436602
Secondaryeduc |  -.1344509   .3767758    -0.36   0.721     -.872918    .6040161
 Tertiaryeduc |  -.7296153   .3913419    -1.86   0.062    -1.496631    .0374008
       AM2008 |  -.7789858   .2998533    -2.60   0.009    -1.366688   -.1912841
       AM2009 |  -.7679007   .3201505    -2.40   0.016    -1.395384   -.1404173
       Emplan |   .5134096   .3270476     1.57   0.116    -.1275919    1.154411
  Jobsearchbt |   .3134729    .391893     0.80   0.424    -.4546233    1.081569
       Undur6 |   1.230552    .504891     2.44   0.015     .2409843    2.220121
      Undur12 |   .9116381    .368618     2.47   0.013       .18916    1.634116
      Undur24 |   1.277082   .4312697     2.96   0.003     .4318091    2.122355
          FER |  -1.459362   .4286079    -3.40   0.001    -2.299418    -.619306
         GJAK |  -2.759085   .6454695    -4.27   0.000    -4.024183   -1.493988
         GJIL |  -1.135618   .3996894    -2.84   0.004    -1.918995   -.3522413
          MIT |  -2.739822   .5609588    -4.88   0.000    -3.839281   -1.640363
          PEJ |  -1.834187   .5650037    -3.25   0.001    -2.941574   -.7268004
          PRZ |  -.8788447   .4791612    -1.83   0.067    -1.817983     .060294
      Vtcmncp |   .9040778   .2660051     3.40   0.001     .3827174    1.425438
        _cons |  -.8967887   1.020752    -0.88   0.380    -2.897426    1.103849
------------------------------------------------------------------------------

. tebalance sum

  Covariate balance summary
                                                 Observations
                               Treatment           Raw     Weighted
                          ----------------------------------------
                            1bn.AMTYPE =           434        275.4
                            2.AMTYPE   =           215        261.1
                            3.AMTYPE   =           126        238.5
                            Total      =           775        775.0
                          ----------------------------------------


  ----------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |        Raw    Weighted           Raw   Weighted
  ---------------+------------------------------------------------
  1.AMTYPE       |
             Age |   .0678291       .0602       1.86225   1.972814
            Male |   .0132747    .0213407      .9958648   .9971013
```

```
          Minority |  -.0458827    .0125859      .8625864   1.043287
        Disability |   .0459175    .0229909      1.349787    1.15563
      Socialassist |  -.1072386    -.032924      .7601673   .9138627
         Twounempl |  -.1581292   -.0648614      .9484715   .9731745
        Remittance |  -.0267562   -.0247555       .925796   .9328523
     Secondaryeduc |  -.0124827    .0487914      .9933797   1.019859
      Tertiaryeduc |   -.026563   -.0226891      .9887159   .9920579
            AM2008 |  -.4176771   -.0601096       .575512   .8931296
            AM2009 |   .1748149    -.082829       1.18446   .9452037
            Emplan |  -.1672003   -.0682123      1.133453   1.045229
       Jobsearchbt |  -.1248105    .0984191        1.2143   .8850456
            Undur6 |   .1918028    .0501703      1.828126   1.142705
           Undur12 |   .1510318    .0542696      1.376559   1.109925
           Undur24 |    .150218    .1550883      1.599916   1.633426
               FER |  -.0967362    .0543424       .816384   1.139787
              GJAK |   .0026116    .1312138      1.002798    1.34387
              GJIL |  -.0048082   -.1472809      .9909323    .837401
               MIT |  -.1844576   -.0426374      .6947735   .9084236
               PEJ |  -.0259385    .0194836      .9321606   1.054722
               PRZ |   .1775181   -.0109066      1.495697   .9795942
           Vtcmncp |   .3764772    .0531773      .9463541   .9752052
---------------+------------------------------------------------
3.AMTYPE           |
               Age |   .0798579    .1174111      1.223469   1.531705
              Male |  -.1079032    .0738068       1.00471   .9871909
          Minority |  -.0158672    .1235349      .9556325   1.451093
        Disability |   .0836776    .0690918      1.689075   1.500922
      Socialassist |  -.2128018    .0337177      .5432779   1.090079
         Twounempl |   .2389379    .0331421      .9841861   1.010847
        Remittance |  -.0941555   -.0512798      .7550558   .8628922
     Secondaryeduc |    .067946    .1495471      1.021276   1.046757
      Tertiaryeduc |  -.1354217   -.1531382      .9436395   .9296092
            AM2008 |  -.2614834    .0788847      .7539509   1.137736
            AM2009 |  -.2082087   -.2109584      .7306621   .8405048
            Emplan |   .2610492    .1011247      .7115037   .9183888
       Jobsearchbt |   .2414269    .3092292      .5734647   .6154978
            Undur6 |    .063799    .0326308      1.262766   1.092897
           Undur12 |   .1590057    .0046304      1.405192   1.009778
           Undur24 |   .1809766     .203182      1.744307   1.848489
               FER |  -.0426173    .0097031      .9228061    1.02515
              GJAK |  -.3792364   -.0181466      .3018047   .9540108
              GJIL |   .0575603    .0209381       1.08223   1.021163
               MIT |  -.4401124   -.1468737      .3004735   .6912175
               PEJ |  -.1557422   -.0848431      .6244744   .7702631
               PRZ |    .161032    .0353862      1.457767   1.065677
           Vtcmncp |   .3262228   -.0574194      .9737566   1.020832
----------------------------------------------------------------
```

Table A5.4 Estimated results from Inverse probability weighting – Regression Adjustment - ACTSRCAT Outcome Model

```
**ACTSRCAT Outcome Model
* including all variables


. teffects ipwra (ACTSRCAT Age Agesq Male Minority Disability Secondaryeduc Tertiaryeduc
Socialassist Amduration AM2008 AM2009 Emplan Undur6 Undur12 Undur24 Regunemp, logit) (AMTYPE Age
```

```
Male Minority Disability Socialassist Twounempl Remittance Secondaryeduc Tertiaryeduc AM2008
AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ Vtcmncp), control(1)
atet aequ

Iteration 0:   EE criterion =  .01638724
Iteration 1:   EE criterion =  .01006662
Iteration 2:   EE criterion =  .00847948
Iteration 3:   EE criterion =  .00062315
Iteration 4:   EE criterion =  .00003246
Iteration 5:   EE criterion =  1.686e-06
Iteration 6:   EE criterion =  1.300e-07
Iteration 7:   EE criterion =  3.741e-09
Iteration 8:   EE criterion =  9.645e-10

Treatment-effects estimation                    Number of obs     =        385
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
              |               Robust
     ACTSRCAT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
       AMTYPE |
    (2 vs 1)  |   .1921274   .0642331     2.99   0.003     .0662329     .318022
    (3 vs 1)  |   .1054037   .0689658     1.53   0.126    -.0297668    .2405741
--------------+----------------------------------------------------------------
POmean        |
       AMTYPE |
           1  |   .6474952   .0541566    11.96   0.000     .5413502    .7536402
--------------+----------------------------------------------------------------
OME1          |
          Age |   .7855234   .3305322     2.38   0.017     .1376921    1.433355
        Agesq |  -.0131236   .0053049    -2.47   0.013    -.0235211   -.0027262
         Male |   .9209845   .4581127     2.01   0.044        .0231    1.818869
     Minority |   1.178178   1.126998     1.05   0.296    -1.030698    3.387053
   Disability |   1.958913   1.358724     1.44   0.149    -.7041378    4.621963
Secondaryeduc |  -.3781189   .7702736    -0.49   0.624    -1.887827     1.13159
 Tertiaryeduc |   .6546435   .8086952     0.81   0.418    -.9303699    2.239657
 Socialassist |  -.1283874   .9438567    -0.14   0.892    -1.978313    1.721538
   Amduration |   .1745178    .247074     0.71   0.480    -.3097383    .6587739
       AM2008 |   .5782775   .7065633     0.82   0.413    -.8065611    1.963116
       AM2009 |   .4253178    .509013     0.84   0.403    -.5723294    1.422965
       Emplan |   .3363128   .6293192     0.53   0.593    -.8971301    1.569756
       Undur6 |   .1944928   .8136496     0.24   0.811    -1.400231    1.789217
      Undur12 |   .9896838   .7311165     1.35   0.176    -.4432782    2.422646
      Undur24 |   .6338765   .9148453     0.69   0.488    -1.159187     2.42694
     Regunemp |   .0346191    .030677     1.13   0.259    -.0255066    .0947449
        _cons |  -13.64592   5.354346    -2.55   0.011    -24.14025   -3.151598
--------------+----------------------------------------------------------------
OME2          |
          Age |   -1.26435   .8890177    -1.42   0.155    -3.006792     .478093
        Agesq |    .018973   .0142685     1.33   0.184    -.0089928    .0469388
         Male |   -.348881   .7102232    -0.49   0.623    -1.740893    1.043131
     Minority |   .0989111   1.165032     0.08   0.932    -2.184509    2.382331
   Disability |  -2.907915   1.289745    -2.25   0.024    -5.435768   -.3800618
Secondaryeduc |   .2816064   .9344415     0.30   0.763    -1.549865    2.113078
 Tertiaryeduc |   1.101218    1.27291     0.87   0.387     -1.39364    3.596076
 Socialassist |   .3290989   .8126935     0.40   0.686    -1.263751    1.921949
   Amduration |    .990741   .3812899     2.60   0.009     .2434266    1.738055
```

AM2008	-.609777	.9201519	-0.66	0.508	-2.413242	1.193688
AM2009	-1.042218	.9379028	-1.11	0.266	-2.880474	.7960374
Emplan	-1.988228	.8890076	-2.24	0.025	-3.730651	-.2458048
Undur6	-4.996561	1.422994	-3.51	0.000	-7.785578	-2.207544
Undur12	-1.976822	1.254593	-1.58	0.115	-4.43578	.4821365
Undur24	-2.16246	1.197947	-1.81	0.071	-4.510393	.1854734
Regunemp	-.0283003	.0470194	-0.60	0.547	-.1204566	.0638559
_cons	21.76476	12.78821	1.70	0.089	-3.299671	46.82919
OME3						
Age	.6639564	1.250694	0.53	0.596	-1.78736	3.115272
Agesq	-.013077	.0181811	-0.72	0.472	-.0487113	.0225574
Male	4.649181	1.594984	2.91	0.004	1.52307	7.775291
Minority	15.48883	3.550417	4.36	0.000	8.530138	22.44752
Disability	-6.84905	1.993739	-3.44	0.001	-10.75671	-2.941393
Secondaryeduc	1.228815	1.286932	0.95	0.340	-1.293525	3.751156
Tertiaryeduc	4.209563	2.888558	1.46	0.145	-1.451908	9.871033
Socialassist	-6.913187	2.858857	-2.42	0.016	-12.51644	-1.30993
Amduration	-.9779994	.8239995	-1.19	0.235	-2.593009	.6370099
AM2008	-1.517675	1.648279	-0.92	0.357	-4.748242	1.712892
AM2009	3.081588	1.790679	1.72	0.085	-.428078	6.591254
Emplan	-1.465409	1.705103	-0.86	0.390	-4.80735	1.876531
Undur6	-4.689655	1.513316	-3.10	0.002	-7.655699	-1.723611
Undur12	-3.201606	1.299426	-2.46	0.014	-5.748434	-.6547785
Undur24	-6.210585	1.942114	-3.20	0.001	-10.01706	-2.404112
Regunemp	.2244805	.0981028	2.29	0.022	.0322026	.4167584
_cons	-9.28485	21.76238	-0.43	0.670	-51.93833	33.36863
TME2						
Age	-.0107182	.0301458	-0.36	0.722	-.0698028	.0483665
Male	-.0145628	.2928872	-0.05	0.960	-.5886112	.5594856
Minority	.5183788	.4725444	1.10	0.273	-.4077912	1.444549
Disability	-.24759	.7675267	-0.32	0.747	-1.751915	1.256735
Socialassist	.6917754	.5241023	1.32	0.187	-.3354461	1.718997
Twounempl	.4810493	.3228976	1.49	0.136	-.1518184	1.113917
Remittance	.5892035	.4846377	1.22	0.224	-.360669	1.539076
Secondaryeduc	.7108797	.3644914	1.95	0.051	-.0035105	1.42527
Tertiaryeduc	.5889222	.4149555	1.42	0.156	-.2243757	1.40222
AM2008	1.198901	.3747809	3.20	0.001	.4643434	1.933458
AM2009	-.2354281	.3479118	-0.68	0.499	-.9173226	.4464664
Emplan	.4894523	.3400249	1.44	0.150	-.1769844	1.155889
Jobsearchbt	.9085695	.3747099	2.42	0.015	.1741516	1.642987
Undur6	-1.203228	.6725296	-1.79	0.074	-2.521361	.1149062
Undur12	-.7441301	.422225	-1.76	0.078	-1.571676	.0834157
Undur24	-1.227016	.4865824	-2.52	0.012	-2.1807	-.2733315
FER	1.351682	.5873415	2.30	0.021	.2005142	2.502851
GJAK	1.490546	.6188091	2.41	0.016	.277703	2.70339
GJIL	.0833482	.6307585	0.13	0.895	-1.152916	1.319612
MIT	.8992903	.5857786	1.54	0.125	-.2488146	2.047395
PEJ	2.379415	.7201428	3.30	0.001	.9679614	3.790869
PRZ	.5260253	.6516298	0.81	0.420	-.7511456	1.803196
Vtcmncp	-1.22444	.2836089	-4.32	0.000	-1.780303	-.6685763
_cons	-2.502794	1.177249	-2.13	0.034	-4.810159	-.1954287
TME3						
Age	.0055744	.0327451	0.17	0.865	-.0586049	.0697537
Male	.3828976	.3331292	1.15	0.250	-.2700237	1.035819
Minority	-.0209445	.5453514	-0.04	0.969	-1.089814	1.047925
Disability	-.6334026	.9198573	-0.69	0.491	-2.43629	1.169485
Socialassist	.362595	.6041698	0.60	0.548	-.8215561	1.546746

```
   Twounempl |   1.395816   .4146874     3.37   0.001     .5830436    2.208588
  Remittance |   .3777435   .6364503     0.59   0.553    -.8696762    1.625163
Secondaryeduc |   .1742506    .433992     0.40   0.688    -.6763581    1.024859
 Tertiaryeduc |  -.1356057   .4379488    -0.31   0.757    -.9939696    .7227581
       AM2008 |   .5498323   .4880917     1.13   0.260    -.4068099    1.506475
       AM2009 |   -.421889   .3781891    -1.12   0.265    -1.163126    .3193479
       Emplan |   1.395946   .4112312     3.39   0.001     .5899479    2.201944
  Jobsearchbt |   .8051559   .4278951     1.88   0.060     -.033503    1.643815
       Undur6 |  -.0305311   .6315204    -0.05   0.961    -1.268288    1.207226
      Undur12 |  -.4555178   .4327111    -1.05   0.292    -1.303616    .3925805
      Undur24 |  -.5648889   .5551786    -1.02   0.309    -1.653019    .5232411
          FER |   -.380537   .5503666    -0.69   0.489    -1.459236    .6981616
         GJAK |  -1.356918   .6936049    -1.96   0.050    -2.716359    .0025224
         GJIL |  -.9156303   .5531677    -1.66   0.098    -1.999819    .1685584
          MIT |  -2.150158    .647901    -3.32   0.001     -3.42002    -.880295
          PEJ |   .8573721   .7078696     1.21   0.226    -.5300269    2.244771
          PRZ |   .2243124   .6074618     0.37   0.712    -.9662909    1.414916
      Vtcmncp |  -.0192191   .3203944    -0.06   0.952    -.6471806    .6087423
        _cons |  -2.938529   1.270639    -2.31   0.021    -5.428934   -.4481228
------------------------------------------------------------------------------

. tebalance sum

  Covariate balance summary
                                                 Observations
                             Treatment           Raw     Weighted
                          ----------------------------------------
                            1bn.AMTYPE =           198        127.6
                            2.AMTYPE   =           106        135.2
                            3.AMTYPE   =            81        122.3
                            Total      =           385        385.0
                          ----------------------------------------


  ----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+-----------------------------------------------
  2.AMTYPE        |
              Age |   .0469178   -.1176441      .6697239   .4930499
             Male |   .0228163    .0666434      1.006693    1.00914
         Minority |    .130576    .0284658       1.39318   1.065543
       Disability |  -.0400379    .0192032      .8099595   1.119374
     Socialassist |   .1173884   -.1151869      1.254727   .8416362
        Twounempl |   .1586626    .0441835      1.055684   1.008288
       Remittance |   .0734337    .0220473      1.220114    1.05637
    Secondaryeduc |   .1169856    .0733064      1.004898   .9966409
     Tertiaryeduc |  -.0120731   -.0169054      .9935561   .9845396
           AM2008 |   .4462825   -.1384233      2.024386    .900612
           AM2009 |  -.2650759   -.1286476      .7418974   .8425819
           Emplan |   .2459716   -.1422474      .8399412    1.18709
      Jobsearchbt |   .2145967     .171024      .7404639   .7752592
           Undur6 |  -.1825743    .0183309      .4910266   1.095554
          Undur12 |  -.2528701   -.0101925      .6357149   .9765382
          Undur24 |  -.1586015    .1033995      .6272406   1.513257
              FER |   .2020129    .1698698       1.49761   1.382373
             GJAK |   .0496555     .062013       1.10144   1.123216
             GJIL |  -.2071617   -.0277422      .7217675   .9481301
              MIT |   .1468002   -.2045398      1.211077   .8445723
              PEJ |   .1918449     .187964      1.977895    1.93371
              PRZ |  -.2406805     .018363      .5451572   1.061895
```

```
        Vtcmncp |  -.5956623   -.0501914      .9392673   .9665852
  ----------------+---------------------------------------------
  3.AMTYPE        |
            Age |   .0610288   -.1824096      .5611763   .2705367
           Male |  -.0504876    .1871295      .9986175    1.00447
       Minority |  -.0157253    .0395087       .962368    1.09212
     Disability |  -.0622575    .0405248       .711348   1.260678
   Socialassist |  -.1586101   -.0429769      .6753459   .9426918
       Twounempl |   .4780627   -.0294926       1.00627   .9923483
     Remittance |  -.0609651    .2677074       .836034   1.700987
  Secondaryeduc |  -.0011195    .1472895      1.007248   .9836359
   Tertiaryeduc |   .0230942   -.1275994      1.027585   .8767174
         AM2008 |   .1280804    -.224049      1.322035   .8261523
         AM2009 |   -.330247   -.2959073      .6696204   .6227825
         Emplan |   .4933111     .064386      .6060147   .9075907
    Jobsearchbt |   .4226874    .3922785      .4689016   .4719845
         Undur6 |  -.0250875     .062998      .9302026   1.346306
        Undur12 |  -.1115962   -.0377317      .8471476   .9153915
        Undur24 |  -.1275203    .2756192      .6995739   2.532545
            FER |   .0589499   -.0194497      1.151546   .9566218
           GJAK |  -.3435652   -.0827095      .3678549   .8354458
           GJIL |  -.0240006    .2737024      .9762657    1.47047
            MIT |   -.376092   -.3607303      .4285997   .6929506
            PEJ |   .1648216      .35033      1.833082   2.875119
            PRZ |   .0896691    .0754917      1.182391   1.264106
        Vtcmncp |  -.1227302   -.0575387      1.051715   .9621428
  ----------------------------------------------------------------


*ACTSRCAT


. . teffects ipwra (ACTSRCAT Age Agesq Male Minority Disability Secondaryeduc Tertiaryeduc
Socialassist Amduration AM2008 AM2009 Emplan Undur6 Undur12 Undur24 Regunemp, logit) (AMTYPE Age
Male Minority Disability Socialassist Twounempl Remittance Secondaryeduc Tertiaryeduc AM2008
AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL MIT PEJ PRZ Vtcmncp), control(2)
atet aequ

Iteration 0:   EE criterion =  .01592071
Iteration 1:   EE criterion =  .01166808
Iteration 2:   EE criterion =  .00093145
Iteration 3:   EE criterion =   .0001571
Iteration 4:   EE criterion =  9.368e-06
Iteration 5:   EE criterion =  7.510e-06
Iteration 6:   EE criterion =  2.879e-06
Iteration 7:   EE criterion =  1.587e-07
Iteration 8:   EE criterion =  3.983e-09
Iteration 9:   EE criterion =  2.411e-09

Treatment-effects estimation                    Number of obs     =        385
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
              |               Robust
     ACTSRCAT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
ATET          |
       AMTYPE |
    (1 vs 2)  |  -.1920193   .0415693    -4.62   0.000    -.2734936    -.110545
```

(3 vs 2)	-.0886878	.0388308	-2.28	0.022	-.1647947	-.0125809
POmean						
AMTYPE						
2	.8637365	.0262012	32.97	0.000	.8123832	.9150898
OME1						
Age	.5278033	.2427499	2.17	0.030	.0520223	1.003584
Agesq	-.0094776	.0040586	-2.34	0.020	-.0174323	-.0015228
Male	.2355423	.3310657	0.71	0.477	-.4133345	.8844191
Minority	1.606358	.8089989	1.99	0.047	.0207498	3.191967
Disability	1.510059	1.182681	1.28	0.202	-.8079539	3.828072
Secondaryeduc	-.3784887	.4564943	-0.83	0.407	-1.273201	.5162238
Tertiaryeduc	.0547136	.5274265	0.10	0.917	-.9790233	1.088451
Socialassist	-.3859264	.5939675	-0.65	0.516	-1.550081	.7782284
Amduration	.2676195	.1799104	1.49	0.137	-.0849984	.6202373
AM2008	.5012953	.5872473	0.85	0.393	-.6496882	1.652279
AM2009	.1660366	.3802438	0.44	0.662	-.5792275	.9113006
Emplan	-1.026109	.4005349	-2.56	0.010	-1.811143	-.2410748
Undur6	-.1188785	.5967711	-0.20	0.842	-1.288528	1.050771
Undur12	.7633018	.4251614	1.80	0.073	-.0699993	1.596603
Undur24	.9534763	.6155676	1.55	0.121	-.2530142	2.159967
Regunemp	-.0151766	.0201283	-0.75	0.451	-.0546275	.0242742
_cons	-6.647015	3.730022	-1.78	0.075	-13.95772	.6636939
OME2						
Age	-1.702706	1.20255	-1.42	0.157	-4.05966	.6542483
Agesq	.0239457	.0189859	1.26	0.207	-.0132659	.0611573
Male	.2616281	1.127252	0.23	0.816	-1.947745	2.471001
Minority	.5560734	1.336804	0.42	0.677	-2.064015	3.176161
Disability	-6.450657	3.181505	-2.03	0.043	-12.68629	-.2150218
Secondaryeduc	-.4575954	1.079094	-0.42	0.672	-2.572581	1.65739
Tertiaryeduc	-.0416049	1.848478	-0.02	0.982	-3.664555	3.581345
Socialassist	-.5028637	.9755297	-0.52	0.606	-2.414867	1.409139
Amduration	1.039097	.5992965	1.73	0.083	-.135503	2.213696
AM2008	-.2919937	1.836497	-0.16	0.874	-3.891462	3.307474
AM2009	-1.299163	.9690926	-1.34	0.180	-3.198549	.6002239
Emplan	-2.900869	1.030958	-2.81	0.005	-4.92151	-.8802284
Undur6	-4.684602	1.547021	-3.03	0.002	-7.716707	-1.652496
Undur12	-.0854218	1.014419	-0.08	0.933	-2.073647	1.902803
Undur24	-1.278675	1.358028	-0.94	0.346	-3.94036	1.383011
Regunemp	-.1399308	.0716475	-1.95	0.051	-.2803574	.0004957
_cons	34.86274	18.03677	1.93	0.053	-.4886715	70.21416
OME3						
Age	-.9192463	1.382563	-0.66	0.506	-3.62902	1.790527
Agesq	.0090623	.0189473	0.48	0.632	-.0280738	.0461984
Male	6.747202	2.432296	2.77	0.006	1.979988	11.51442
Minority	25.01594	7.829698	3.20	0.001	9.670016	40.36187
Disability	-6.284884	2.104192	-2.99	0.003	-10.40902	-2.160744
Secondaryeduc	3.426887	1.953232	1.75	0.079	-.4013775	7.255151
Tertiaryeduc	10.50046	6.058336	1.73	0.083	-1.373658	22.37458
Socialassist	-17.17769	6.184165	-2.78	0.005	-29.29843	-5.056948
Amduration	-2.962514	1.642176	-1.80	0.071	-6.18112	.2560918
AM2008	-1.354023	1.339307	-1.01	0.312	-3.979016	1.270971
AM2009	6.973179	3.339297	2.09	0.037	.4282767	13.51808
Emplan	2.308827	2.702151	0.85	0.393	-2.987291	7.604945
Undur6	-6.769747	1.777209	-3.81	0.000	-10.25301	-3.286481
Undur12	-1.536215	1.280427	-1.20	0.230	-4.045806	.9733759
Undur24	-5.365509	1.51606	-3.54	0.000	-8.336932	-2.394086

```
     Regunemp |   .2624056   .0846091     3.10   0.002     .0965747    .4282365
        _cons |   18.63529   24.66947     0.76   0.450    -29.71599    66.98657
--------------+----------------------------------------------------------------
TME1          |
          Age |   .0107182   .0301458     0.36   0.722    -.0483665    .0698028
         Male |   .0145628   .2928872     0.05   0.960    -.5594856    .5886112
     Minority |  -.5183788   .4725444    -1.10   0.273    -1.444549    .4077912
   Disability |     .24759   .7675267     0.32   0.747    -1.256735    1.751915
  Socialassist |  -.6917754   .5241023    -1.32   0.187    -1.718997    .3354461
    Twounempl |  -.4810493   .3228976    -1.49   0.136    -1.113917    .1518184
   Remittance |  -.5892035   .4846377    -1.22   0.224    -1.539076     .360669
Secondaryeduc |  -.7108797   .3644914    -1.95   0.051     -1.42527    .0035105
 Tertiaryeduc |  -.5889222   .4149555    -1.42   0.156     -1.40222    .2243757
       AM2008 |  -1.198901   .3747809    -3.20   0.001    -1.933458   -.4643434
       AM2009 |   .2354281   .3479118     0.68   0.499    -.4464664    .9173226
       Emplan |  -.4894523   .3400249    -1.44   0.150    -1.155889    .1769844
  Jobsearchbt |  -.9085695   .3747099    -2.42   0.015    -1.642987   -.1741516
       Undur6 |   1.203228   .6725296     1.79   0.074    -.1149062    2.521361
      Undur12 |   .7441301    .422225     1.76   0.078    -.0834157    1.571676
      Undur24 |   1.227016   .4865824     2.52   0.012     .2733315      2.1807
          FER |  -1.351682   .5873415    -2.30   0.021    -2.502851   -.2005142
         GJAK |  -1.490546   .6188091    -2.41   0.016     -2.70339    -.277703
         GJIL |  -.0833482   .6307585    -0.13   0.895    -1.319612    1.152916
          MIT |  -.8992903   .5857786    -1.54   0.125    -2.047395    .2488146
          PEJ |  -2.379415   .7201428    -3.30   0.001    -3.790869   -.9679614
          PRZ |  -.5260253   .6516298    -0.81   0.420    -1.803196    .7511456
      Vtcmncp |    1.22444   .2836089     4.32   0.000     .6685763    1.780303
        _cons |   2.502794   1.177249     2.13   0.034     .1954287    4.810159
--------------+----------------------------------------------------------------
TME3          |
          Age |   .0162926   .0337335     0.48   0.629    -.0498239     .082409
         Male |   .3974604   .3645366     1.09   0.276    -.3170182    1.111939
     Minority |  -.5393232   .5906892    -0.91   0.361    -1.697053    .6184063
   Disability |  -.3858126   1.025519    -0.38   0.707    -2.395792    1.624167
  Socialassist |  -.3291805   .7089888    -0.46   0.642    -1.718773    1.060412
    Twounempl |   .9147666   .4367696     2.09   0.036     .0587139    1.770819
   Remittance |    -.21146   .7135111    -0.30   0.767    -1.609916    1.186996
Secondaryeduc |   -.536629   .5047437    -1.06   0.288    -1.525908    .4526504
 Tertiaryeduc |   -.724528    .530147    -1.37   0.172    -1.763597    .3145411
       AM2008 |  -.6490683   .4572438    -1.42   0.156     -1.54525    .2471132
       AM2009 |  -.1864609   .4249025    -0.44   0.661    -1.019255    .6463327
       Emplan |   .9064938   .4528083     2.00   0.045     .0190059    1.793982
  Jobsearchbt |  -.1034135    .492785    -0.21   0.834    -1.069254    .8624274
       Undur6 |   1.172696   .7958985     1.47   0.141    -.3872359    2.732629
      Undur12 |   .2886123   .5063369     0.57   0.569    -.7037898    1.281014
      Undur24 |   .6621266   .6453526     1.03   0.305    -.6027413    1.926995
          FER |  -1.732219   .6391062    -2.71   0.007    -2.984845   -.4795944
         GJAK |  -2.847465    .765895    -3.72   0.000    -4.348591   -1.346338
         GJIL |  -.9989786   .6655394    -1.50   0.133    -2.303412    .3054547
          MIT |  -3.049448   .7306176    -4.17   0.000    -4.481432   -1.617464
          PEJ |  -1.522043   .8180163    -1.86   0.063    -3.125326    .0812393
          PRZ |  -.3017129   .7408984    -0.41   0.684    -1.753847    1.150421
      Vtcmncp |    1.20522   .3576987     3.37   0.001      .504144    1.906297
        _cons |  -.4357348   1.456346    -0.30   0.765    -3.290121    2.418651
-------------------------------------------------------------------------------


. tebalance sum

  Covariate balance summary
                                                Observations
```

Treatment		Raw	Weighted
1bn.AMTYPE	=	198	124.4
2.AMTYPE	=	106	144.3
3.AMTYPE	=	81	116.3
Total	=	385	385.0

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
1.AMTYPE				
Age	-.0469178	.0537635	1.493153	2.890789
Male	-.0228163	.3116836	.9933519	1.148539
Minority	-.130576	.0996957	.7177825	1.377608
Disability	.0400379	.0330115	1.23463	1.193099
Socialassist	-.1173884	-.3086257	.7969861	.6155944
Twounempl	-.1586626	.1758147	.9472535	1.126547
Remittance	-.0734337	.0633585	.8195957	1.215718
Secondaryeduc	-.1169856	-.1314029	.9951257	1.002496
Tertiaryeduc	.0120731	-.0468204	1.006486	.9629164
AM2008	-.4462825	.036214	.4939769	1.095858
AM2009	.2650759	-.4535307	1.347895	.8649161
Emplan	-.2459716	.1151906	1.19056	.9629924
Jobsearchbt	-.2145967	.3496678	1.350505	.78525
Undur6	.1825743	-.0179602	2.036549	.9481264
Undur12	.2528701	-.1441152	1.573032	.8451491
Undur24	.1586015	.2235563	1.594285	2.067697
FER	-.2020129	.2470047	.6677305	2.226414
GJAK	-.0496555	.221716	.9079023	1.735648
GJIL	.2071617	-.5190951	1.385488	.7162455
MIT	-.1468002	-.1184387	.8257112	.8568192
PEJ	-.1918449	.0514234	.5055881	1.275628
PRZ	.2406805	.2663825	1.834333	2.015142
Vtcmncp	.5956623	-.1516683	1.06466	1.103908
3.AMTYPE				
Age	.0140858	.1455162	.8379218	1.22289
Male	-.0732274	.2065342	.9919786	1.122496
Minority	-.1459679	.2283169	.6907709	1.909743
Disability	-.0223603	.0274183	.8782512	1.160196
Socialassist	-.2746511	-.3120877	.5382414	.6113503
Twounempl	.3131423	.0541008	.9531932	1.046551
Remittance	-.1339151	.213049	.6852098	1.761333
Secondaryeduc	-.1178929	.0022497	1.002338	1.001353
Tertiaryeduc	.0351215	-.2022647	1.034249	.8144936
AM2008	-.3175752	.2175756	.6530546	1.581343
AM2009	-.0647055	-.392656	.9025781	.903673
Emplan	.2424322	.1927289	.7214966	.9242017
Jobsearchbt	.2083997	.64816	.6332538	.5030829
Undur6	.1577672	-.0738311	1.894404	.7891293
Undur12	.1410316	-.24876	1.33259	.7201211
Undur24	.031316	.2266712	1.11532	2.085542
FER	-.143024	.1592348	.7689223	1.756056
GJAK	-.3908774	-.0825605	.3339763	.7561397
GJIL	.1827122	-.1405034	1.352604	.9670858
MIT	-.5215216	-.2598305	.3538996	.6715809
PEJ	-.0274744	-.0463111	.9267843	.7786548
PRZ	.3284055	.1797991	2.168899	1.671262

```
        Vtcmncp |   .4632873   -.1564898      1.119718   1.107055
  -----------------------------------------------------------------
```

Table A5.5 Estimated results from Inverse probability weighting – Regression Adjustment - CONTRACT Outcome Model

```
**CONTRACT Outcome Model
*Final IPWRA model for CONTRACT; OJT is defined as the control group


. . teffects ipwra (CONTRACT Age Agesq Male Minority Secondaryeduc Tertiaryeduc Amduration
AM2008 AM2009 Cert Regunemp, logit) (AMTYPE Age Male Minority Twounempl Remittance Socialassist
Secondaryeduc Tertiaryedu AM2008 AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL
MIT PEJ PRZ Vtcmncp), control(1) atet aequ

Iteration 0:   EE criterion =   .0015559
Iteration 1:   EE criterion =  .00013411
Iteration 2:   EE criterion =  .00001898
Iteration 3:   EE criterion =  1.140e-06
Iteration 4:   EE criterion =  1.222e-07  (not concave)
Iteration 5:   EE criterion =  1.039e-07

Treatment-effects estimation                    Number of obs     =        284
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
             |               Robust
    CONTRACT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
      AMTYPE |
    (2 vs 1) |   .0594402   .0603879     0.98   0.325    -.0589178    .1777983
    (3 vs 1) |   .1893358   .0706651     2.68   0.007     .0508347     .327837
-------------+----------------------------------------------------------------
POmean       |
      AMTYPE |
          1  |   .7168694   .0513943    13.95   0.000     .6161384    .8176004
-------------+----------------------------------------------------------------
OME1         |
         Age |  -1.570828   1.195468    -1.31   0.189    -3.913903    .7722462
       Agesq |   .0291066   .0215583     1.35   0.177    -.0131469    .0713601
        Male |  -2.246234   .8922786    -2.52   0.012    -3.995067   -.4973997
    Minority |  -.2418361   1.292622    -0.19   0.852    -2.775329    2.291657
Secondaryeduc |  -1.328795   .8430968    -1.58   0.115    -2.981234    .3236446
 Tertiaryeduc |   2.063662   .7855583     2.63   0.009     .5239959    3.603328
   Amduration |  -.3312716    .278012    -1.19   0.233     -.876165    .2136218
      AM2008 |   1.376503   .8159476     1.69   0.092    -.2227244    2.975731
      AM2009 |   .1662639   .5757278     0.29   0.773     -.962142     1.29467
        Cert |   1.524838   .6779907     2.25   0.025     .1960009    2.853675
    Regunemp |   .0387214   .0285997     1.35   0.176     -.017333    .0947758
       _cons |   21.74803   16.82114     1.29   0.196    -11.22079    54.71685
-------------+----------------------------------------------------------------
OME2         |
         Age |  -.2658279   1.089792    -0.24   0.807    -2.401781    1.870125
       Agesq |   .0008018   .0198097     0.04   0.968    -.0380245     .039628
        Male |  -1.276675   .9490504    -1.35   0.179     -3.13678    .5834293
    Minority |  -.0970382   1.366984    -0.07   0.943    -2.776278    2.582202
Secondaryeduc |  -1.884402   .9329271    -2.02   0.043    -3.712906   -.0558988
 Tertiaryeduc |    1.29451   1.130685     1.14   0.252    -.9215908    3.510611
   Amduration |  -.3054533   .3348809    -0.91   0.362    -.9618077    .3509012
      AM2008 |   .3508733   .8814225     0.40   0.691    -1.376683     2.07843
```

AM2009	1.743472	.9377163	1.86	0.063	-.0944181	3.581362
Cert	-.4357196	.8257698	-0.53	0.598	-2.054199	1.18276
Regunemp	-.0526567	.0361213	-1.46	0.145	-.1234533	.0181398
_cons	11.8787	15.01367	0.79	0.429	-17.54756	41.30495
OME3						
Age	.4321133	1.877156	0.23	0.818	-3.247045	4.111272
Agesq	-.012179	.0310651	-0.39	0.695	-.0730654	.0487074
Male	1.261803	1.818907	0.69	0.488	-2.303188	4.826795
Minority	.6319239	2.992577	0.21	0.833	-5.233419	6.497266
Secondaryeduc	-1.25577	2.622665	-0.48	0.632	-6.396099	3.884559
Tertiaryeduc	2.917971	2.352839	1.24	0.215	-1.693509	7.529452
Amduration	-.5168567	.7711814	-0.67	0.503	-2.028345	.9946311
AM2008	6.806376	1.997931	3.41	0.001	2.890504	10.72225
AM2009	6.871649	1.503253	4.57	0.000	3.925328	9.817969
Cert	1.348271	1.598652	0.84	0.399	-1.785029	4.481572
Regunemp	-.0432261	.1461427	-0.30	0.767	-.3296604	.2432083
_cons	-.4308561	26.6373	-0.02	0.987	-52.63901	51.7773
TME2						
Age	-.0321092	.0417511	-0.77	0.442	-.1139398	.0497215
Male	-.0555829	.345719	-0.16	0.872	-.7331797	.6220139
Minority	-.2253931	.7113321	-0.32	0.751	-1.619578	1.168792
Twounempl	.3327355	.3640496	0.91	0.361	-.3807886	1.04626
Remittance	.3154091	.585174	0.54	0.590	-.8315108	1.462329
Socialassist	.1349841	.6048854	0.22	0.823	-1.05057	1.320538
Secondaryeduc	-.76215	.5109524	-1.49	0.136	-1.763598	.2392983
Tertiaryeduc	-.4896404	.5133815	-0.95	0.340	-1.49585	.5165687
AM2008	1.490915	.4018534	3.71	0.000	.7032967	2.278533
AM2009	.5394315	.3739309	1.44	0.149	-.1934596	1.272323
Emplan	.2139617	.388943	0.55	0.582	-.5483525	.9762759
Jobsearchbt	.3669636	.4561027	0.80	0.421	-.5269813	1.260908
Undur6	-1.178853	.4847572	-2.43	0.015	-2.12896	-.2287465
Undur12	-.3330404	.4500222	-0.74	0.459	-1.215068	.5489868
Undur24	-.9803232	.5865138	-1.67	0.095	-2.129869	.1692226
FER	.9047341	.587994	1.54	0.124	-.247713	2.057181
GJAK	.5578453	.6605465	0.84	0.398	-.7368022	1.852493
GJIL	.6900692	.5125764	1.35	0.178	-.3145622	1.694701
MIT	1.286926	.6385944	2.02	0.044	.035304	2.538548
PEJ	.1052606	.6556827	0.16	0.872	-1.179854	1.390375
PRZ	-.1027597	.6497056	-0.16	0.874	-1.376159	1.17064
Vtcmncp	-.7542088	.3478689	-2.17	0.030	-1.436019	-.0723983
_cons	-.3773053	1.339358	-0.28	0.778	-3.0024	2.247789
TME3						
Age	.0190426	.0600367	0.32	0.751	-.0986271	.1367123
Male	-.6835441	.4488813	-1.52	0.128	-1.563335	.1962471
Minority	.0452239	1.077308	0.04	0.967	-2.066261	2.156709
Twounempl	-.1540059	.4753825	-0.32	0.746	-1.085738	.7777266
Remittance	.9346604	.8024783	1.16	0.244	-.6381682	2.507489
Socialassist	-12.42394	.6835657	-18.18	0.000	-13.7637	-11.08417
Secondaryeduc	.2733795	.7331014	0.37	0.709	-1.163473	1.710232
Tertiaryeduc	-.4544521	.8008147	-0.57	0.570	-2.02402	1.115116
AM2008	.2484433	.5110058	0.49	0.627	-.7531097	1.249996
AM2009	-1.136448	.618007	-1.84	0.066	-2.34772	.074823
Emplan	.9537092	.6181927	1.54	0.123	-.2579263	2.165345
Jobsearchbt	1.696085	.933726	1.82	0.069	-.1339838	3.526155
Undur6	-.3548364	.7780781	-0.46	0.648	-1.879841	1.170169
Undur12	.6772807	.5729837	1.18	0.237	-.4457467	1.800308
Undur24	1.238775	.6874923	1.80	0.072	-.1086847	2.586236
FER	.155961	.609641	0.26	0.798	-1.038913	1.350835
GJAK	-2.582432	1.159891	-2.23	0.026	-4.855776	-.3090877
GJIL	-.0767641	.6261877	-0.12	0.902	-1.304069	1.150541
MIT	-11.99773	.7019423	-17.09	0.000	-13.37352	-10.62195
PEJ	-2.406719	1.274765	-1.89	0.059	-4.905211	.0917737
PRZ	-1.235042	.753814	-1.64	0.101	-2.712491	.2424058
Vtcmncp	.406721	.5838408	0.70	0.486	-.7375859	1.551028
_cons	-3.463821	1.944484	-1.78	0.075	-7.274939	.3472978

```
. tebalance sum

  Covariate balance summary
                                                 Observations
                           Treatment          Raw     Weighted
                      -----------------------------------------
                        1bn.AMTYPE =          171        120.4
                        2.AMTYPE   =           76        114.5
                        3.AMTYPE   =           37         49.1
                        Total      =          284        284.0
                      -----------------------------------------

  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw    Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  2.AMTYPE        |
              Age |  -.0594412     .070625      .7816163   .9266607
             Male |   .0360304    -.039862      .9890909   1.024291
         Minority |   .0559252    .1127639      1.345663   1.913613
        Twounempl |   .2359867   -.1249337      1.107521   .9963255
       Remittance |   .0152592    .0026797      1.052692   1.008075
     Socialassist |   .1030645    .0286481      1.399602   1.087794
    Secondaryeduc |  -.0582697    .0079244       .969076   1.006315
     Tertiaryeduc |  -.0757699    -.030478      1.013264   1.001367
           AM2008 |   .4950311   -.0704007      1.599483   .9792844
           AM2009 |  -.1147192    .0076706      .9265127   1.007144
           Emplan |   .1067222   -.0571073      .9244431   1.059437
      Jobsearchbt |   .0314618   -.0379047      .9511413   1.077511
           Undur6 |  -.2021795    .0339182      .6558865   1.095538
          Undur12 |  -.0365508    .1134711      .9378858   1.296097
          Undur24 |  -.1594276    .0790126      .6269044   1.360027
              FER |   .1198741    .0009534      1.357258   1.002521
             GJAK |  -.1515404    .0560614      .7567446   1.139317
             GJIL |   .2130829   -.0757362      1.379446   .9232308
              MIT |   .2636853    .1488059      2.071875   1.424037
              PEJ |  -.1668189   -.0320652      .6748767   .9162914
              PRZ |   -.214791    -.104038      .6152098   .7673325
          Vtcmncp |  -.3324751    .0341398      1.086712   1.005236
  ----------------+------------------------------------------------
  3.AMTYPE        |
              Age |  -.0495102    .0189432      .6867129   .6148146
             Male |  -.2563443    .1161219      1.077045   .9257834
         Minority |  -.0132737    .0356315      .9465972   1.274061
        Twounempl |   .2875319   -.2817954      1.129528   .9591612
       Remittance |  -.0236874   -.1544714      .9513167   .5950157
     Socialassist |  -.3697241   -.4263498             0          0
    Secondaryeduc |   .1540443    .1531235      1.092842   1.106302
     Tertiaryeduc |  -.1562826   -.1507679      1.020951   .9985018
           AM2008 |   .1356457   -.3659149       1.23645   .8073939
           AM2009 |  -.5289898   -.0254639      .5204012   .9889955
           Emplan |   .5736149    .1573697        .43955    .825431
      Jobsearchbt |   .4908913     .422618      .1907906   .2212138
           Undur6 |  -.2831584     .002422      .5262603   1.019133
          Undur12 |   .0819851    .0836183      1.178783   1.232708
          Undur24 |   .2842129     .615492      1.753201   4.329271
              FER |   .2045328   -.1030863      1.636824    .786326
             GJAK |  -.5336367   -.0252988      .1766357   .9496481
             GJIL |   .1966349     .130581      1.373559   1.125183
              MIT |  -.3697241   -.4595307             0          0
              PEJ |  -.4314507   -.1634096      .2152536   .5988853
              PRZ |  -.2525193    .0169182      .5559643   1.051621
          Vtcmncp |   .1380455    .1895535      .9236101   1.009127
  -----------------------------------------------------------------
```

*Final IPWRA model for CONTRACT; IS is defined as the control group

```
 . teffects ipwra (CONTRACT Age Agesq Male Minority Secondaryeduc Tertiaryeduc Amduration AM2008
AM2009 Cert Regunemp, logit) (AMTYPE Age Male Minority Twounempl Remittance Socialassist
Secondaryeduc Tertiaryedu AM2008 AM2009 Emplan Jobsearchbt Undur6 Undur12 Undur24 FER GJAK GJIL
MIT PEJ PRZ Vtcmncp), control(2) atet aequ

Iteration 0:   EE criterion =  .00586947
Iteration 1:   EE criterion =  .00058801
Iteration 2:   EE criterion =  9.171e-06
Iteration 3:   EE criterion =  2.949e-06
Iteration 4:   EE criterion =  6.657e-07  (not concave)
Iteration 5:   EE criterion =  6.640e-07

Treatment-effects estimation                    Number of obs     =        284
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
             |               Robust
    CONTRACT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
      AMTYPE |
   (1 vs 2)  |  -.1035414   .0521981    -1.98   0.047    -.2058477   -.0012351
   (3 vs 2)  |   .0727087   .0616882     1.18   0.239     -.048198    .1936153
-------------+----------------------------------------------------------------
POmean       |
      AMTYPE |
          2  |   .7994478   .0426138    18.76   0.000     .7159263    .8829693
-------------+----------------------------------------------------------------
OME1         |
         Age |  -1.248272   .9997846    -1.25   0.212    -3.207814    .7112699
       Agesq |   .0229369   .0183953     1.25   0.212    -.0131173    .0589911
        Male |  -1.327431   .5262206    -2.52   0.012    -2.358804   -.2960574
    Minority |   1.250961   1.300732     0.96   0.336    -1.298426    3.800349
Secondaryeduc |  -.3041944   .6170931    -0.49   0.622    -1.513675    .9052858
Tertiaryeduc |   2.420622   .7478692     3.24   0.001     .9548248    3.886418
  Amduration |  -.2839854   .1898289    -1.50   0.135    -.6560431    .0880724
      AM2008 |  -.1717216   .6047537    -0.28   0.776    -1.357017    1.013574
      AM2009 |  -.3598976   .4598987    -0.78   0.434    -1.261282    .5414873
        Cert |   1.377256   .4834783     2.85   0.004     .4296564    2.324857
    Regunemp |    .059871   .0219963     2.72   0.006      .016759     .102983
       _cons |   16.08565   13.49414     1.19   0.233    -10.36237    42.53367
-------------+----------------------------------------------------------------
OME2         |
         Age |   .1068924   1.039525     0.10   0.918    -1.930539    2.144324
       Agesq |  -.0046417   .0186729    -0.25   0.804    -.0412399    .0319565
        Male |    -1.2793   1.013344    -1.26   0.207    -3.265417    .7068181
    Minority |   .0138729   2.309163     0.01   0.995    -4.512003    4.539749
Secondaryeduc |  -3.385988   1.087702    -3.11   0.002    -5.517843   -1.254132
Tertiaryeduc |   .1527821    1.22911     0.12   0.901    -2.256229    2.561793
  Amduration |  -.3476181   .3840903    -0.91   0.365    -1.100421    .4051851
      AM2008 |    .477221   1.331504     0.36   0.720    -2.132478     3.08692
      AM2009 |   2.368121   1.041274     2.27   0.023     .3272616     4.40898
        Cert |  -.3440903    .802113    -0.43   0.668    -1.916203    1.228022
    Regunemp |  -.0603549   .0352103    -1.71   0.087    -.1293659     .008656
       _cons |   7.520743   14.83491     0.51   0.612    -21.55515    36.59664
-------------+----------------------------------------------------------------
OME3         |
         Age |   .2124117   1.708186     0.12   0.901    -3.135571    3.560394
       Agesq |  -.0081298   .0276568    -0.29   0.769    -.0623362    .0460766
        Male |  -.2812231   1.569249    -0.18   0.858    -3.356895    2.794449
    Minority |  -.3809191   3.131774    -0.12   0.903    -6.519083    5.757245
Secondaryeduc |   1.162634   2.340185     0.50   0.619    -3.424045    5.749313
Tertiaryeduc |   3.682896   1.910331     1.93   0.054    -.0612844    7.427077
  Amduration |  -.9890902   .6484963    -1.53   0.127     -2.26012    .2819392
```

```
       AM2008 |   6.007305   2.046504     2.94   0.003      1.99623    10.01838
       AM2009 |   6.126339   1.403316     4.37   0.000      3.37589    8.876789
         Cert |   1.291372   1.770329     0.73   0.466    -2.178409    4.761154
     Regunemp |   .0963573   .1224774     0.79   0.431    -.1436939    .3364086
        _cons |   .0175405   24.44519     0.00   0.999    -47.89415    47.92923
--------------+----------------------------------------------------------------
TME1          |
          Age |   .0321092   .0417511     0.77   0.442    -.0497215    .1139398
         Male |   .0555829    .345719     0.16   0.872    -.6220139    .7331797
     Minority |   .2253931   .7113313     0.32   0.751    -1.168791    1.619577
    Twounempl |  -.3327359   .3640496    -0.91   0.361     -1.04626    .3807882
   Remittance |  -.3154093   .5851742    -0.54   0.590     -1.46233    .8315111
  Socialassist |  -.1349841   .6048851    -0.22   0.823    -1.320537    1.050569
Secondaryeduc |   .7621496   .5109523     1.49   0.136    -.2392985    1.763598
 Tertiaryeduc |   .4896407   .5133814     0.95   0.340    -.5165684     1.49585
       AM2008 |  -1.490915   .4018534    -3.71   0.000    -2.278533   -.7032967
       AM2009 |  -.5394314   .3739309    -1.44   0.149    -1.272323    .1934597
       Emplan |  -.2139618    .388943    -0.55   0.582     -.976276    .5483524
  Jobsearchbt |  -.3669635   .4561028    -0.80   0.421    -1.260909    .5269815
       Undur6 |   1.178853   .4847569     2.43   0.015     .2287465    2.128959
      Undur12 |   .3330405   .4500221     0.74   0.459    -.5489866    1.215068
      Undur24 |   .9803252   .5865146     1.67   0.095    -.1692223    2.129873
          FER |  -.9047361   .5879935    -1.54   0.124    -2.057182      .24771
         GJAK |  -.5578452   .6605465    -0.84   0.398    -1.852493    .7368021
         GJIL |  -.6900689   .5125764    -1.35   0.178      -1.6947    .3145623
          MIT |  -1.286926   .6385946    -2.02   0.044    -2.538548   -.0353035
          PEJ |  -.1052594   .6556831    -0.16   0.872    -1.390375    1.179856
          PRZ |   .1027597   .6497055     0.16   0.874     -1.17064    1.376159
      Vtcmncp |   .7542088   .3478689     2.17   0.030     .0723983    1.436019
        _cons |   .3773053   1.339358     0.28   0.778    -2.247789      3.0024
--------------+----------------------------------------------------------------
TME3          |
          Age |   .0511517   .0678593     0.75   0.451    -.0818501    .1841536
         Male |  -.6279613   .5006648    -1.25   0.210    -1.609246    .3533236
     Minority |   .2706169   1.151258     0.24   0.814    -1.985808    2.527042
    Twounempl |  -.4867426   .5214663    -0.93   0.351    -1.508798    .5353125
   Remittance |    .619251   .8905398     0.70   0.487    -1.126175    2.364677
  Socialassist |   -15.3879   .6950939   -22.14   0.000    -16.75026   -14.02554
Secondaryeduc |   1.035528   .7944133     1.30   0.192    -.5214931     2.59255
 Tertiaryeduc |   .0351891   .8603897     0.04   0.967    -1.651144    1.721522
       AM2008 |  -1.242472     .56669    -2.19   0.028    -2.353164   -.1317796
       AM2009 |   -1.67588   .6760086    -2.48   0.013    -3.000832   -.3509274
       Emplan |   .7397474   .6622417     1.12   0.264    -.5582224    2.037717
  Jobsearchbt |   1.329122   .9804046     1.36   0.175    -.5924358     3.25068
       Undur6 |   .8240139   .8448844     0.98   0.329    -.8319292    2.479957
      Undur12 |   1.010321    .664597     1.52   0.128    -.2922648    2.312907
      Undur24 |   2.219102   .7590951     2.92   0.003     .7313033    3.706901
          FER |  -.7487797   .7237458    -1.03   0.301    -2.167295    .6697359
         GJAK |  -3.140277   1.285695    -2.44   0.015    -5.660193     -.62036
         GJIL |  -.7668321   .6650865    -1.15   0.249    -2.070378    .5367134
          MIT |  -12.92957   .8044269   -16.07   0.000    -14.50622   -11.35293
          PEJ |  -2.511956   1.319023    -1.90   0.057    -5.097194    .0732819
          PRZ |  -1.132283   .8778469    -1.29   0.197    -2.852831    .5882655
      Vtcmncp |    1.16093   .5977694     1.94   0.052    -.0106767    2.332536
        _cons |  -3.086515   2.163127    -1.43   0.154    -7.326167    1.153136
-------------------------------------------------------------------------------

. tebalance sum

  Covariate balance summary
                                              Observations
                             Treatment          Raw     Weighted
                          ----------------------------------------
                           1bn.AMTYPE =          171        106.4
                           2.AMTYPE   =           76         98.1
                           3.AMTYPE   =           37         79.5
                           Total      =          284        284.0
                          ----------------------------------------
```

	Standardized differences Raw	Standardized differences Weighted	Variance ratio Raw	Variance ratio Weighted
1.AMTYPE				
Age	.0594412	.0340956	1.2794	1.277449
Male	-.0360304	-.0995189	1.011029	1.058372
Minority	-.0559252	.1048286	.7431283	2.061955
Twounempl	-.2359867	-.0991135	.9029173	.9465268
Remittance	-.0152592	-.0041699	.9499452	.9871157
Socialassist	-.1030645	.002227	.7144887	1.007187
Secondaryeduc	.0582697	.0092989	1.031911	1.004889
Tertiaryeduc	.0757699	.023615	.98691	.9961463
AM2008	-.4950311	-.0576343	.6252021	.9154157
AM2009	.1147192	-.0985306	1.079316	.9516876
Emplan	-.1067222	-.0247015	1.081732	1.016888
Jobsearchbt	-.0314618	.0549605	1.051368	.9113584
Undur6	.2021795	.0194067	1.524654	1.033696
Undur12	.0365508	.0611573	1.066228	1.129668
Undur24	.1594276	.0758768	1.595139	1.226066
FER	-.1198741	.029855	.7367796	1.089455
GJAK	.1515404	.0999352	1.32145	1.194703
GJIL	-.2130829	-.0351566	.7249289	.9391437
MIT	-.2636853	.0330902	.4826546	1.129897
PEJ	.1668189	.0450042	1.481752	1.098568
PRZ	.214791	-.0839615	1.625462	.8678166
Vtcmncp	.3324751	.250539	.920207	.9244295
3.AMTYPE				
Age	.0124118	-.1545446	.8785806	.7581899
Male	-.2923724	-.1056007	1.088924	1.06483
Minority	-.0688049	-.0878776	.7034432	.386044
Twounempl	.051484	-.3560358	1.01987	.7437724
Remittance	-.0388174	-.2170771	.9036987	.4333304
Socialassist	-.4474694	-.3672328	0	0
Secondaryeduc	.2121379	.0314612	1.127716	1.02112
Tertiaryeduc	-.0803936	.0679031	1.007587	.9906179
AM2008	-.3534865	-.2273836	.7730311	.6618851
AM2009	-.4098836	-.2697245	.5616773	.8338597
Emplan	.4625227	-.2048462	.4754755	1.113508
Jobsearchbt	.4601577	.5609997	.2005912	.1463
Undur6	-.0824566	.203515	.8023649	1.347573
Undur12	.1181524	.1763607	1.256851	1.375989
Undur24	.4374878	.4020809	2.796599	2.232682
FER	.0855782	-.1569431	1.205979	.5664245
GJAK	-.3912531	-.2717778	.2334152	.4835543
GJIL	-.0155176	.0235399	.9957326	1.042411
MIT	-.5779343	-.3440102	0	0
PEJ	-.2752961	-.0622915	.3189525	.8658297
PRZ	-.0388174	.4194878	.9036987	1.503117
Vtcmncp	.4737685	-.056139	.8499124	1.002388

Appendix 6 – Chapter 6

Table 6.1 Outcome variable: *employed* – Model 1

Table A6.1.1 PSM

```
. teffects psmatch (employed) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani
mitrovica peja prizren ), atet vce(robust)
```

```
Treatment-effects estimation                   Number of obs      =      7,753
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =          9
------------------------------------------------------------------------------
             |              AI Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
bintreatment |
   (1 vs 0)  |   .0730028   .0253384     2.88   0.004     .0233404    .1226652
------------------------------------------------------------------------------


*** Balancing diagnostics

. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                                         Raw      Matched
                          -----------------------------------------
                          Number of obs =          7,753        1,694
                          Treated obs   =            847          847
                          Control obs   =          6,906          847
                          -----------------------------------------

  -----------------------------------------------------------------
                |Standardized differences          Variance ratio
                |        Raw     Matched           Raw    Matched
  ----------------+------------------------------------------------
              age |  -.6060234   -.076445      .3243216   .9326923
            agesq |  -.6665971  -.0780366      .2800718   .9368594
             male |  -.4618398   .0472512      1.323737   .9960958
         minority |   .0377737    .099327       1.14086   1.450887
      socialassist |   .3709548   .1608743       7.49496   1.734988
     secondaryeduc |  -.4394493     .07248      1.036461   1.031882
      tertiaryeduc |   .5968176   -.085886      1.880529   .9758825
           emp2011 |  -.5101395   .0226697      .9074829   1.017066
           emphist |  -.0797406  -.0575831      1.032292   1.021107
            hhsize |   -.453916  -.0571991      .3536742   .9977826
         hhsizegen |  -.5622479   .0271119      .5529141   1.068583
           ferizaj |   .0111471  -.0416516      1.026757    .913981
           gjakova |   .0257213   .1493787       1.06098   1.471432
           gjilani |   .4442438  -.0704341      2.838404   .9122407
         mitrovica |   .1091392   .0652934      1.308213   1.165055
              peja |  -.0639643  -.0607731      .8656221    .870611
          prizreni |  -.0658709   .0598134      .8802186   1.141693
  -----------------------------------------------------------------
```

Table A6.1.2 IPW

```
*** Binary treatment model

.  teffects  ipw  (employed)  (bintreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc  emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani
mitrovica peja prizren ), atet vce(robust) aequ

Iteration 0:   EE criterion =  1.527e-16
```

```
Iteration 1:   EE criterion =  3.351e-30

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
  bintreatment |
     (1 vs 0)  |   .0786837   .0206062     3.82   0.000     .0382962    .1190711
---------------+----------------------------------------------------------------
POmean         |
  bintreatment |
            0  |   .3309976   .0196182    16.87   0.000     .2925465    .3694486
---------------+----------------------------------------------------------------
TME1           |
           age |   1.451319    .152215     9.53   0.000     1.152983    1.749655
         agesq |  -.0282003   .0028461    -9.91   0.000    -.0337786   -.0226221
          male |  -.9374553   .2214396    -4.23   0.000    -1.371469   -.5034416
      minority |  -.0999522   .1994632    -0.50   0.616    -.4908928    .2909885
  socialassist |   2.932207   .2344679    12.51   0.000     2.472658    3.391755
 secondaryeduc |  -.3021237   .1255887    -2.41   0.016    -.5482729   -.0559744
  tertiaryeduc |   .8970667   .1349911     6.65   0.000     .6324891    1.161644
       emp2011 |  -2.518161   .1463909   -17.20   0.000    -2.805082   -2.231241
       emphist |   2.190087   .1425687    15.36   0.000     1.910658    2.469517
        hhsize |  -.1693141    .024119    -7.02   0.000    -.2165865   -.1220417
     hhsizegen |   .0336501   .0320513     1.05   0.294    -.0291693    .0964696
       ferizaj |   .9545303   .1645074     5.80   0.000     .6321016    1.276959
       gjakova |   .9650004   .1586301     6.08   0.000      .654091     1.27591
       gjilani |   1.903647   .1596132    11.93   0.000     1.590811    2.216483
     mitrovica |   1.237659   .1651726     7.49   0.000     .9139271    1.561392
          peja |   .5909044   .1643426     3.60   0.000     .2687989    .9130099
      prizreni |   .8850921   .1538299     5.75   0.000      .583591    1.186593
         _cons |  -19.57279   2.002432    -9.77   0.000    -23.49748   -15.64809
--------------------------------------------------------------------------------


*** Multinomial probit treatment model


.  teffects  ipw  (employed)  (multitreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc   emp2011 employment0811 hhsize hhsizegen ferizaj gjakova
gjilani mitrovica peja prizren ), atet vce(robust) aequ

Iteration 0:   EE criterion =  3.811e-17
Iteration 1:   EE criterion =  3.182e-26

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .1024067     .02652     3.86   0.000     .0504284    .1543849
```

(2 vs 0)	.0937236	.03319	2.82	0.005	.0286723	.1587749
(3 vs 0)	-.0666286	.042343	-1.57	0.116	-.1496192	.0163621
POmean						
multitreatment						
0	.3444019	.0241336	14.27	0.000	.2971009	.3917028
TME1						
age	1.413724	.1781519	7.94	0.000	1.064552	1.762895
agesq	-.0276842	.003336	-8.30	0.000	-.0342226	-.0211457
male	-.717694	.2689107	-2.67	0.008	-1.244749	-.1906388
minority	-.1919382	.2398957	-0.80	0.424	-.6621252	.2782488
socialassist	2.882324	.2669839	10.80	0.000	2.359045	3.405602
secondaryeduc	-.3460953	.1535257	-2.25	0.024	-.6470002	-.0451904
tertiaryeduc	.9204818	.1595055	5.77	0.000	.6078568	1.233107
emp2011	-2.447462	.1698918	-14.41	0.000	-2.780443	-2.11448
emphist	2.151887	.1626965	13.23	0.000	1.833008	2.470766
hhsize	-.1398375	.0290449	-4.81	0.000	-.1967645	-.0829104
hhsizegen	.001012	.038801	0.03	0.979	-.0750366	.0770607
ferizaj	.9347286	.2068503	4.52	0.000	.5293095	1.340148
gjakova	1.153686	.195793	5.89	0.000	.7699389	1.537433
gjilani	1.999726	.1949397	10.26	0.000	1.617651	2.381801
mitrovica	1.353333	.203549	6.65	0.000	.9543842	1.752282
peja	.6318902	.2083549	3.03	0.002	.2235222	1.040258
prizreni	1.126131	.1917063	5.87	0.000	.7503936	1.501869
_cons	-19.81157	2.347503	-8.44	0.000	-24.41259	-15.21055
TME2						
age	1.346897	.2628578	5.12	0.000	.831705	1.862089
agesq	-.0259819	.0049166	-5.28	0.000	-.0356183	-.0163455
male	-.7979321	.3745817	-2.13	0.033	-1.532099	-.0637655
minority	.0446592	.3027216	0.15	0.883	-.5486643	.6379826
socialassist	3.195568	.3042002	10.50	0.000	2.599346	3.791789
secondaryeduc	-.0119571	.2216409	-0.05	0.957	-.4463652	.422451
tertiaryeduc	1.202353	.2365829	5.08	0.000	.7386587	1.666047
emp2011	-2.432426	.226858	-10.72	0.000	-2.877059	-1.987792
emphist	1.909995	.2100973	9.09	0.000	1.498212	2.321778
hhsize	-.1776654	.0366943	-4.84	0.000	-.249585	-.1057459
hhsizegen	.0266939	.056103	0.48	0.634	-.0832659	.1366538
ferizaj	1.682184	.3010803	5.59	0.000	1.092078	2.272291
gjakova	1.638374	.3010562	5.44	0.000	1.048315	2.228434
gjilani	2.377816	.2959141	8.04	0.000	1.797835	2.957797
mitrovica	1.999283	.2964681	6.74	0.000	1.418217	2.58035
peja	1.407159	.2923936	4.81	0.000	.8340779	1.98024
prizreni	1.208193	.317206	3.81	0.000	.586481	1.829906
_cons	-20.36672	3.454223	-5.90	0.000	-27.13687	-13.59656
TME3						
age	1.845249	.3940853	4.68	0.000	1.072856	2.617642
agesq	-.0354639	.0073317	-4.84	0.000	-.0498338	-.021094
male	-2.077053	.4621661	-4.49	0.000	-2.982882	-1.171224
minority	-.0372633	.3519049	-0.11	0.916	-.7269842	.6524576
socialassist	2.460318	.4081779	6.03	0.000	1.660304	3.260332
secondaryeduc	-.6603757	.2685839	-2.46	0.014	-1.18679	-.1339609
tertiaryeduc	.2656454	.2724921	0.97	0.330	-.2684293	.7997201
emp2011	-2.816691	.2412737	-11.67	0.000	-3.289579	-2.343803
emphist	2.751174	.2544869	10.81	0.000	2.252389	3.249959
hhsize	-.2744273	.0558694	-4.91	0.000	-.3839293	-.1649252
hhsizegen	.1802097	.069577	2.59	0.010	.0438413	.3165781
ferizaj	.2731118	.3064866	0.89	0.373	-.327591	.8738146
gjakova	-.6912424	.4154098	-1.66	0.096	-1.505431	.1229458

```
      gjilani |   1.306612   .2641516     4.95   0.000     .7888841    1.824339
    mitrovica |  -.2686435   .4071526    -0.66   0.509    -1.066648     .529361
         peja |  -.6522711   .4023617    -1.62   0.105    -1.440885    .1363434
     prizreni |  -.0450278   .3066457    -0.15   0.883    -.6460424    .5559868
        _cons |  -24.98753   5.233495    -4.77   0.000    -35.24499   -14.73007
------------------------------------------------------------------------------------

*** Balancing diagnostics

. tebalance sum

  Covariate balance summary
                                                Observations
                               Treatment          Raw     Weighted
                          -----------------------------------------
                          0bn.multitr~t =        6,906      1,937.6
                          1.multitrea~t =          470      1,962.2
                          2.multitrea~t =          241      1,951.5
                          3.multitrea~t =          136      1,901.7
                          Total         =        7,753      7,753.0
                          -----------------------------------------


  -----------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |        Raw    Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.6269269   -.0768009      .3221864   .9668094
            agesq |  -.6869872   -.0765679      .2738164    .982205
             male |  -.4450008    .0386108      1.321906   .9952384
         minority |   .0052393    .0184935      1.021027   1.069807
      socialassist |   .3428648    .1603264      6.827683   1.808988
     secondaryeduc |  -.4696964    .0583174       1.02591   1.028303
      tertiaryeduc |   .6244724   -.0756302      1.899256   .9818704
          emp2011 |  -.4831847    .0041387      .9244103   1.002763
          emphist |  -.0721193   -.0236421      1.030833   1.008142
           hhsize |  -.4328879   -.0341622      .3461522   .8928136
        hhsizegen |  -.5568747    .0215153      .5330855    .969723
          ferizaj |  -.0306483   -.0071066      .9316378   .9828628
          gjakova |   .0687207    .0569443       1.16296   1.129645
          gjilani |   .4292703   -.0708377      2.780606   .9090178
        mitrovica |   .1178972    .0379924      1.334737   1.088544
             peja |  -.0830119   -.0207665      .8265375   .9500848
         prizreni |  -.0032518    .0522388      .9960333   1.106533
  ----------------+------------------------------------------------
  2.multitreatm~t |
              age |  -.5756687   -.0624487      .3526933   .9005252
            agesq |  -.6322685    -.066895      .3161966   .9323647
             male |  -.4294723    .0508539      1.321162   .9931169
         minority |    .078628    .0138854       1.30295   1.052258
      socialassist |   .4499272    .1834829      9.517168   1.939953
     secondaryeduc |  -.4066554    .0711956      1.050123   1.033665
      tertiaryeduc |   .6102409   -.0949887      1.895007   .9754653
          emp2011 |   -.573383    .0311655      .8684703   1.020092
          emphist |   -.218392   -.0325065      1.059018   1.010917
           hhsize |  -.4703471    -.071082      .3897204   1.011424
        hhsizegen |  -.5477794    .0211668      .5800314   1.048448
          ferizaj |   .0779458   -.0344939      1.185588   .9173304
          gjakova |   .0702349    .0726757      1.168982    1.16558
          gjilani |   .4113551   -.0365455      2.713313   .9537108
        mitrovica |   .2067901    .0480908      1.594995   1.112192
```

```
            peja |   .0507065    -.000676      1.112635   .9983651
        prizreni |  -.1745717    .0021834      .6845422   1.004453
-----------------+------------------------------------------------
 3.multitreatm~t |
             age |  -.5874766   -.0012217      .2839457   .9544984
           agesq |  -.6574538   -.0041206      .2399639   1.031749
            male |  -.5770215    .1282286      1.335005   .9729907
        minority |   .0709291   -.0401744       1.27692   .8542379
    socialassist |   .3115719     .173463       6.14469   1.882948
   secondaryeduc |  -.3928189    .1159143      1.057358   1.049694
    tertiaryeduc |   .4754033   -.1376762      1.788427   .9588983
         emp2011 |  -.4921984    -.047144      .9235891   .9663668
         emphist |   .1462006    .0421045      .9189746   .9828377
          hhsize |  -.4971539   -.0499302      .3182613   .8294375
      hhsizegen  |   -.605161    .0967708      .5796272    .981256
         ferizaj |   .0290471   -.0238964      1.074949    .942605
         gjakova |  -.2503322    .0713566      .4612281   1.162584
         gjilani |   .5480294   -.0699444      3.261717   .9102099
       mitrovica |  -.1407073      .01267      .6399687   1.029453
            peja |  -.2319707    .0030906      .5307899   1.007473
        prizreni |  -.1079457    .0048408      .8079007    1.00989
------------------------------------------------------------------
```

Table A6.1.3 RA

```
*** Binary treatment model

. teffects ra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizreni, logit) (bintreatment), atet vce(robust)aequ

Iteration 0:   EE criterion =  1.286e-23
Iteration 1:   EE criterion =  1.666e-33

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
------------------------------------------------------------------------------
             |               Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |    .069562   .0170429     4.08   0.000     .0361586    .1029655
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .3401192   .0162374    20.95   0.000     .3082946    .3719438
-------------+----------------------------------------------------------------
OME0         |
         age |   .1808925   .1380061     1.31   0.190    -.0895945    .4513794
       agesq |  -.0018676   .0023268    -0.80   0.422    -.0064281    .0026929
        male |   .4311122    .327872     1.31   0.189    -.2115051    1.073729
    minority |   .0855887   .3472056     0.25   0.805    -.5949217    .7660992
 socialassist |   1.182815   .5900737     2.00   0.045     .0262914    2.339338
secondaryeduc |   .5530994   .1964932     2.81   0.005     .1679798    .9382189
 tertiaryeduc |    .994315   .2897802     3.43   0.001     .4263562    1.562274
```

```
      emp2011 |   6.753188   .3304302    20.44   0.000     6.105557     7.40082
      emphist |   .9124589   .3502011     2.61   0.009     .2260774     1.59884
       hhsize |   .0549228   .0278171     1.97   0.048     .0004023    .1094433
    hhsizegen |  -.0610614   .0342143    -1.78   0.074    -.1281201    .0059973
      ferizaj |   -.808614    .295916    -2.73   0.006    -1.388599   -.2286292
      gjakova |  -.5492257   .2154132    -2.55   0.011    -.9714278   -.1270235
      gjilani |  -.3347647   .3226504    -1.04   0.299    -.9671478    .2976185
    mitrovica |   .0805916   .2882117     0.28   0.780     -.484293    .6454763
         peja |  -.9308065   .2856165    -3.26   0.001    -1.490604   -.3710085
     prizreni |  -.3631649   .2625625    -1.38   0.167     -.877778    .1514482
        _cons |  -8.326984   1.991491    -4.18   0.000    -12.23023   -4.423734
-------------+----------------------------------------------------------------
OME1          |
          age |   .4888125   .2598077     1.88   0.060    -.0204011    .9980262
        agesq |  -.0080254   .0047377    -1.69   0.090    -.0173111    .0012602
         male |   -.218195   .4571157    -0.48   0.633    -1.114125    .6777353
     minority |  -.5892953   .3331128    -1.77   0.077    -1.242184    .0635938
 socialassist |  -.5339743   .3671626    -1.45   0.146      -1.2536    .1856511
secondaryeduc |  -.1018293   .2585159    -0.39   0.694    -.6085113    .4048526
 tertiaryeduc |   .6767813   .2629518     2.57   0.010     .1614052    1.192157
      emp2011 |   2.140557   .2229235     9.60   0.000     1.703635    2.577479
      emphist |   .7164347   .2483117     2.89   0.004     .2297527    1.203117
       hhsize |  -.0863489   .0585863    -1.47   0.141     -.201176    .0284782
    hhsizegen |    .114222   .0708649     1.61   0.107    -.0246706    .2531145
      ferizaj |  -.6452049   .3473382    -1.86   0.063    -1.325975    .0355654
      gjakova |  -.3286613   .2936638    -1.12   0.263    -.9042318    .2469092
      gjilani |  -.2569687    .270016    -0.95   0.341    -.7861903    .2722528
    mitrovica |  -.9280101   .3656768    -2.54   0.011    -1.644723   -.2112967
         peja |   .8872465   .3282573     2.70   0.007      .243874    1.530619
     prizreni |   -.473688   .3364302    -1.41   0.159    -1.133079    .1857032
        _cons |  -8.443024   3.542638    -2.38   0.017    -15.38647   -1.499582



*** Multinomial probit treatment model

. teffects ra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 emphist hhsize hhsiz
> egen ferizaj gjakova gjilani mitrovica peja prizreni, logit) (multitreatment), atet
vce(robust) aequ

Iteration 0:   EE criterion =  1.253e-22
Iteration 1:   EE criterion =  6.712e-34

Treatment-effects estimation                   Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
---------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+-----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .0953583   .0240248     3.97   0.000     .0482706     .142446
     (2 vs 0)  |   .0869834   .0302539     2.88   0.004     .0276869    .1462798
     (3 vs 0)  |  -.0430681   .0393597    -1.09   0.274    -.1202116    .0340754
---------------+-----------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .3514502   .0213164    16.49   0.000     .3096708    .3932297
```

OME0						
age	.1808925	.1380061	1.31	0.190	-.0895945	.4513794
agesq	-.0018676	.0023268	-0.80	0.422	-.0064281	.0026929
male	.4311122	.327872	1.31	0.189	-.2115051	1.073729
minority	.0855887	.3472056	0.25	0.805	-.5949217	.7660992
socialassist	1.182815	.5900737	2.00	0.045	.0262914	2.339338
secondaryeduc	.5530994	.1964932	2.81	0.005	.1679798	.9382189
tertiaryeduc	.994315	.2897802	3.43	0.001	.4263562	1.562274
emp2011	6.753188	.3304302	20.44	0.000	6.105557	7.40082
emphist	.9124589	.3502011	2.61	0.009	.2260774	1.59884
hhsize	.0549228	.0278171	1.97	0.048	.0004023	.1094433
hhsizegen	-.0610614	.0342143	-1.78	0.074	-.1281201	.0059973
ferizaj	-.808614	.295916	-2.73	0.006	-1.388599	-.2286292
gjakova	-.5492257	.2154132	-2.55	0.011	-.9714278	-.1270235
gjilani	-.3347647	.3226504	-1.04	0.299	-.9671478	.2976185
mitrovica	.0805916	.2882117	0.28	0.780	-.484293	.6454763
peja	-.9308065	.2856165	-3.26	0.001	-1.490604	-.3710085
prizreni	-.3631649	.2625625	-1.38	0.167	-.877778	.1514482
_cons	-8.326984	1.991491	-4.18	0.000	-12.23023	-4.423734
OME1						
age	.8781218	.3576114	2.46	0.014	.1772162	1.579027
agesq	-.0148516	.0065542	-2.27	0.023	-.0276976	-.0020056
male	-.7646896	.6402417	-1.19	0.232	-2.01954	.490161
minority	-.5772255	.4981694	-1.16	0.247	-1.55362	.3991685
socialassist	-.6689897	.5311511	-1.26	0.208	-1.710027	.3720472
secondaryeduc	.0939106	.3546871	0.26	0.791	-.6012634	.7890845
tertiaryeduc	.8924367	.3606946	2.47	0.013	.1854883	1.599385
emp2011	1.867267	.2972801	6.28	0.000	1.284609	2.449925
emphist	.6932728	.3336896	2.08	0.038	.0392533	1.347292
hhsize	-.0873919	.0774409	-1.13	0.259	-.2391732	.0643895
hhsizegen	.1837764	.0988439	1.86	0.063	-.0099541	.3775069
ferizaj	-.870921	.4984884	-1.75	0.081	-1.84794	.1060982
gjakova	-.2300903	.3889685	-0.59	0.554	-.9924545	.5322738
gjilani	-.4720055	.3950961	-1.19	0.232	-1.24638	.3023687
mitrovica	-.9234312	.4893246	-1.89	0.059	-1.88249	.0356273
peja	1.246366	.4892611	2.55	0.011	.287432	2.2053
prizreni	-.5611171	.4199471	-1.34	0.181	-1.384198	.2619641
_cons	-13.68027	4.878485	-2.80	0.005	-23.24192	-4.118611
OME2						
age	.2174579	.427506	0.51	0.611	-.6204384	1.055354
agesq	-.0044487	.0073458	-0.61	0.545	-.0188461	.0099488
male	.4865273	.8504345	0.57	0.567	-1.180294	2.153348
minority	-.983394	.7627025	-1.29	0.197	-2.478263	.5114754
socialassist	-.4155856	.5695115	-0.73	0.466	-1.531808	.7006364
secondaryeduc	-1.308013	.5301429	-2.47	0.014	-2.347074	-.2689517
tertiaryeduc	-.2254472	.4920602	-0.46	0.647	-1.189867	.738973
emp2011	2.000179	.4502903	4.44	0.000	1.117626	2.882731
emphist	1.605919	.5258016	3.05	0.002	.5753672	2.636472
hhsize	-.096349	.1089791	-0.88	0.377	-.3099441	.1172461
hhsizegen	.0956543	.126824	0.75	0.451	-.1529161	.3442247
ferizaj	-1.228609	.8022271	-1.53	0.126	-2.800946	.3437268
gjakova	-1.676685	.7325251	-2.29	0.022	-3.112407	-.2409617
gjilani	-1.129984	.6617085	-1.71	0.088	-2.426909	.1669405
mitrovica	-1.769147	.7465952	-2.37	0.018	-3.232447	-.3058474
peja	-.2260909	.6836617	-0.33	0.741	-1.566043	1.113861
prizreni	-1.172745	.8476881	-1.38	0.167	-2.834183	.4886937
_cons	-2.780253	6.173858	-0.45	0.652	-14.88079	9.320286

```
OME3          |
          age |   -.41594   1.002928    -0.41   0.678    -2.381643    1.549763
        agesq |  .0094703   .0188905     0.50   0.616    -.0275545     .046495
         male |  -1.69968   1.881086    -0.90   0.366    -5.386541    1.987181
     minority | -1.724112   1.659226    -1.04   0.299    -4.976136    1.527912
  socialassist | -1.148109   4.292848    -0.27   0.789    -9.561937    7.265719
 secondaryeduc |  1.258236   .7785581     1.62   0.106      -.26771    2.784181
  tertiaryeduc |  1.209672   .8380442     1.44   0.149    -.4328642    2.852209
      emp2011 |  4.459772   1.196606     3.73   0.000     2.114468    6.805076
      emphist |  .3789327    .853587     0.44   0.657    -1.294067    2.051932
       hhsize | -.3260869    .197547    -1.65   0.099     -.713272    .0610981
    hhsizegen |  .1646882   .3036852     0.54   0.588    -.4305238    .7599002
      ferizaj | -.4170348   .7885456    -0.53   0.597    -1.962556    1.128486
      gjakova |  1.072785   1.132719     0.95   0.344    -1.147303    3.292873
      gjilani |  .7914437   .8721782     0.91   0.364    -.9179942    2.500882
    mitrovica | -2.863647    1.05063    -2.73   0.006    -4.922843   -.8044508
         peja |  -1.54128   1.252629    -1.23   0.219    -3.996389     .913828
     prizreni |  .5834345   1.667557     0.35   0.726    -2.684916    3.851785
        _cons |  2.417672   13.06953     0.18   0.853    -23.19814    28.03348
--------------------------------------------------------------------------------
```

Table A6.1.4 IPWRA

```
*** Binary treatment model

. teffects ipwra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 emphist  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizreni, logit) (bintreatment age agesq male minority socialassist secondaryeduc
tertiaryeduc  emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ), atet vce(robust) aequ

Iteration 0:   EE criterion =  1.527e-16
Iteration 1:   EE criterion =  2.390e-30

Treatment-effects estimation                 Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
--------------------------------------------------------------------------------
              |               Robust
     employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+-----------------------------------------------------------------
ATET          |
  bintreatment |
      (1 vs 0) |  .0724515   .0177001     4.09   0.000       .03776    .1071431
--------------+-----------------------------------------------------------------
POmean        |
  bintreatment |
            0 |  .3372297   .0167379    20.15   0.000     .3044241    .3700353
--------------+-----------------------------------------------------------------
OME0          |
          age | -.7118113   .4517788    -1.58   0.115    -1.597281    .1736588
        agesq |  .0130895   .0084505     1.55   0.121    -.0034731    .0296522
         male |  .6283904   .6700931     0.94   0.348     -.684968    1.941749
     minority |   .141273     .56156     0.25   0.801    -.9593644     1.24191
  socialassist |  .9968692    .807604     1.23   0.217    -.5860055    2.579744
 secondaryeduc | -.0889005     .73791    -0.12   0.904    -1.535178    1.357377
  tertiaryeduc | -.0284332   .9497138    -0.03   0.976    -1.889838    1.832972
```

```
     emp2011 |   6.83069   .4426385    15.43   0.000     5.963134    7.698245
     emphist |  1.589349   .6860297     2.32   0.021     .2447557    2.933943
      hhsize |  .1676132   .0749671     2.24   0.025     .0206803     .314546
   hhsizegen | -.0873391   .0878019    -0.99   0.320    -.2594276    .0847494
     ferizaj |  .5130356   1.072509     0.48   0.632    -1.589044    2.615115
     gjakova |  -.333446    .468361    -0.71   0.477    -1.251417    .5845247
     gjilani | -.0707092   .4651375    -0.15   0.879    -.9823619    .8409435
   mitrovica |  .8006694   .5094594     1.57   0.116    -.1978526    1.799191
        peja |  .9435543   1.043219     0.90   0.366    -1.101118    2.988226
    prizreni | -.3613945   .4945576    -0.73   0.465     -1.33071    .6079205
       _cons |  3.422022   5.345466     0.64   0.522      -7.0549    13.89894
-------------+----------------------------------------------------------------
OME1         |
         age |  .4888125   .2598077     1.88   0.060    -.0204011    .9980262
       agesq | -.0080254   .0047377    -1.69   0.090    -.0173111    .0012602
        male |  -.218195   .4571157    -0.48   0.633    -1.114125    .6777353
    minority | -.5892953   .3331128    -1.77   0.077    -1.242184    .0635938
socialassist | -.5339743   .3671626    -1.45   0.146      -1.2536    .1856511
secondaryeduc | -.1018293  .2585159    -0.39   0.694    -.6085113    .4048526
tertiaryeduc |  .6767813   .2629518     2.57   0.010     .1614052    1.192157
     emp2011 |  2.140557   .2229235     9.60   0.000     1.703635    2.577479
     emphist |  .7164347   .2483117     2.89   0.004     .2297527    1.203117
      hhsize | -.0863489   .0585863    -1.47   0.141     -.201176    .0284782
   hhsizegen |   .114222   .0708649     1.61   0.107    -.0246706    .2531145
     ferizaj | -.6452049   .3473382    -1.86   0.063    -1.325975    .0355654
     gjakova | -.3286613   .2936638    -1.12   0.263    -.9042318    .2469092
     gjilani | -.2569687    .270016    -0.95   0.341    -.7861903    .2722528
   mitrovica | -.9280101   .3656768    -2.54   0.011    -1.644723   -.2112967
        peja |  .8872465   .3282573     2.70   0.007      .243874    1.530619
    prizreni |  -.473688   .3364302    -1.41   0.159    -1.133079    .1857032
       _cons | -8.443024   3.542638    -2.38   0.017    -15.38647   -1.499582
-------------+----------------------------------------------------------------
TME1         |
         age |  1.451319    .152215     9.53   0.000     1.152983    1.749655
       agesq | -.0282003   .0028461    -9.91   0.000    -.0337786   -.0226221
        male | -.9374553   .2214396    -4.23   0.000    -1.371469   -.5034416
    minority | -.0999522   .1994632    -0.50   0.616    -.4908928    .2909885
socialassist |  2.932207   .2344679    12.51   0.000     2.472658    3.391755
secondaryeduc | -.3021237  .1255887    -2.41   0.016    -.5482729   -.0559744
tertiaryeduc |  .8970667   .1349911     6.65   0.000     .6324891    1.161644
     emp2011 | -2.518161   .1463909   -17.20   0.000    -2.805082   -2.231241
     emphist |  2.190087   .1425687    15.36   0.000     1.910658    2.469517
      hhsize | -.1693141    .024119    -7.02   0.000    -.2165865   -.1220417
   hhsizegen |  .0336501   .0320513     1.05   0.294    -.0291693    .0964696
     ferizaj |  .9545303   .1645074     5.80   0.000     .6321016    1.276959
     gjakova |  .9650004   .1586301     6.08   0.000      .654091     1.27591
     gjilani |  1.903647   .1596132    11.93   0.000     1.590811    2.216483
   mitrovica |  1.237659   .1651726     7.49   0.000     .9139271    1.561392
        peja |  .5909044   .1643426     3.60   0.000     .2687989    .9130099
    prizreni |  .8850921   .1538299     5.75   0.000      .583591    1.186593
       _cons | -19.57279   2.002432    -9.77   0.000    -23.49748   -15.64809
------------------------------------------------------------------------------



*** Multinomial probit treatment model

. teffects ipwra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 emphist  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizreni, logit) (multitreatment age agesq  male minority socialassist secondaryeduc
tertiaryeduc  emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ), atet vce(robust)  aequations
```

```
Iteration 0:   EE criterion =  3.811e-17
Iteration 1:   EE criterion =  1.731e-26

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .0991218   .0244461     4.05   0.000     .0512083    .1470353
     (2 vs 0)  |   .0879362   .0305271     2.88   0.004     .0281042    .1477681
     (3 vs 0)  |   -.053061   .0409642    -1.30   0.195    -.1333494    .0272274
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .3476867   .0215506    16.13   0.000     .3054483    .3899251
---------------+----------------------------------------------------------------
OME0           |
           age |  -.6677465   .4478029    -1.49   0.136    -1.545424    .2099309
         agesq |   .0124019   .0083481     1.49   0.137    -.0039602    .0287639
          male |   .4794327   .6788999     0.71   0.480    -.8511866    1.810052
      minority |   .1307871   .5747539     0.23   0.820    -.9957098    1.257284
  socialassist |   1.023982   .7943787     1.29   0.197    -.5329718    2.580936
 secondaryeduc |   .0726845   .6986675     0.10   0.917    -1.296679    1.442048
  tertiaryeduc |    .125271   .9093575     0.14   0.890    -1.657037    1.907579
       emp2011 |   6.804093   .4501296    15.12   0.000     5.921855    7.686331
       emphist |    1.65305   .6776125     2.44   0.015     .3249537    2.981146
        hhsize |   .1455636   .0756676     1.92   0.054    -.0027423    .2938694
     hhsizegen |  -.0671963   .0902719    -0.74   0.457    -.2441261    .1097334
       ferizaj |   .5367144   1.138176     0.47   0.637    -1.694069    2.767498
       gjakova |  -.2804227    .460167    -0.61   0.542    -1.182333    .6214879
       gjilani |  -.1633164   .4570627    -0.36   0.721    -1.059143    .7325099
     mitrovica |   .8001392    .510842     1.57   0.117    -.2010928    1.801371
          peja |   1.021226   1.011514     1.01   0.313    -.9613059    3.003757
      prizreni |  -.3738089   .5051459    -0.74   0.459    -1.363877    .6162589
         _cons |   2.733365   5.340782     0.51   0.609    -7.734375     13.2011
---------------+----------------------------------------------------------------
OME1           |
           age |   .8781218   .3576114     2.46   0.014     .1772162    1.579027
         agesq |  -.0148516   .0065542    -2.27   0.023    -.0276976   -.0020056
          male |  -.7646896   .6402417    -1.19   0.232     -2.01954     .490161
      minority |  -.5772255   .4981694    -1.16   0.247     -1.55362    .3991685
  socialassist |  -.6689897   .5311511    -1.26   0.208    -1.710027    .3720472
 secondaryeduc |   .0939106   .3546871     0.26   0.791    -.6012634    .7890845
  tertiaryeduc |   .8924367   .3606946     2.47   0.013     .1854883    1.599385
       emp2011 |   1.867267   .2972801     6.28   0.000     1.284609    2.449925
       emphist |   .6932728   .3336896     2.08   0.038     .0392533    1.347292
        hhsize |  -.0873919   .0774409    -1.13   0.259    -.2391732    .0643895
     hhsizegen |   .1837764   .0988439     1.86   0.063    -.0099541    .3775069
       ferizaj |   -.870921   .4984884    -1.75   0.081     -1.84794    .1060982
       gjakova |  -.2300903   .3889685    -0.59   0.554    -.9924545    .5322738
       gjilani |  -.4720055   .3950961    -1.19   0.232     -1.24638    .3023687
     mitrovica |  -.9234312   .4893246    -1.89   0.059     -1.88249    .0356273
          peja |   1.246366   .4892611     2.55   0.011      .287432      2.2053
      prizreni |  -.5611171   .4199471    -1.34   0.181    -1.384198    .2619641
         _cons |  -13.68027   4.878485    -2.80   0.005    -23.24192   -4.118611
```

OME2						
age	.136024	.4809697	0.28	0.777	-.8066594	1.078707
agesq	-.0027331	.0085085	-0.32	0.748	-.0194096	.0139433
male	.7981886	.8943002	0.89	0.372	-.9546075	2.550985
minority	-.974543	.8667033	-1.12	0.261	-2.67325	.7241643
socialassist	-.4927547	.5228051	-0.94	0.346	-1.517434	.5319244
secondaryeduc	-1.501587	.557957	-2.69	0.007	-2.595162	-.4080114
tertiaryeduc	-.3254069	.5345709	-0.61	0.543	-1.373146	.7223328
emp2011	1.968352	.4713379	4.18	0.000	1.044546	2.892157
emphist	1.588437	.5209449	3.05	0.002	.567404	2.609471
hhsize	-.0870363	.1094399	-0.80	0.426	-.3015345	.1274619
hhsizegen	.0764527	.128024	0.60	0.550	-.1744697	.3273751
ferizaj	-1.078196	.7796379	-1.38	0.167	-2.606259	.4498659
gjakova	-1.598505	.7513452	-2.13	0.033	-3.071114	-.1258952
gjilani	-.9448311	.6686614	-1.41	0.158	-2.255383	.365721
mitrovica	-1.660417	.7641433	-2.17	0.030	-3.15811	-.1627235
peja	-.1053805	.6918786	-0.15	0.879	-1.461438	1.250677
prizreni	-1.175091	.830445	-1.42	0.157	-2.802734	.452551
_cons	-1.976327	6.689965	-0.30	0.768	-15.08842	11.13576
OME3						
age	-.1638573	.9690795	-0.17	0.866	-2.063218	1.735504
agesq	.006548	.0180793	0.36	0.717	-.0288869	.0419828
male	-1.365352	2.186413	-0.62	0.532	-5.650641	2.919938
minority	-2.448472	1.288977	-1.90	0.057	-4.974821	.0778771
socialassist	-3.010292	4.312833	-0.70	0.485	-11.46329	5.442706
secondaryeduc	1.675777	.8040307	2.08	0.037	.0999058	3.251648
tertiaryeduc	1.332617	.8585433	1.55	0.121	-.3500971	3.015331
emp2011	3.970016	1.210366	3.28	0.001	1.597744	6.342289
emphist	1.156213	.7996599	1.45	0.148	-.4110919	2.723517
hhsize	-.4893157	.2561319	-1.91	0.056	-.9913249	.0126935
hhsizegen	.0879398	.3519665	0.25	0.803	-.6019018	.7777814
ferizaj	-.2868893	.9552357	-0.30	0.764	-2.159117	1.585338
gjakova	1.115135	1.109826	1.00	0.315	-1.060084	3.290354
gjilani	1.001144	.8825521	1.13	0.257	-.7286266	2.730914
mitrovica	-3.356343	1.073165	-3.13	0.002	-5.459708	-1.252977
peja	-1.058001	1.095014	-0.97	0.334	-3.204189	1.088186
prizreni	.0768549	1.877923	0.04	0.967	-3.603806	3.757516
_cons	-1.70247	12.64516	-0.13	0.893	-26.48653	23.08159
TME1						
age	1.413724	.1781519	7.94	0.000	1.064552	1.762895
agesq	-.0276842	.003336	-8.30	0.000	-.0342226	-.0211457
male	-.717694	.2689107	-2.67	0.008	-1.244749	-.1906388
minority	-.1919382	.2398957	-0.80	0.424	-.6621252	.2782488
socialassist	2.882324	.2669839	10.80	0.000	2.359045	3.405602
secondaryeduc	-.3460953	.1535257	-2.25	0.024	-.6470002	-.0451904
tertiaryeduc	.9204818	.1595055	5.77	0.000	.6078568	1.233107
emp2011	-2.447462	.1698918	-14.41	0.000	-2.780443	-2.11448
emphist	2.151887	.1626965	13.23	0.000	1.833008	2.470766
hhsize	-.1398375	.0290449	-4.81	0.000	-.1967645	-.0829104
hhsizegen	.001012	.038801	0.03	0.979	-.0750366	.0770607
ferizaj	.9347286	.2068503	4.52	0.000	.5293095	1.340148
gjakova	1.153686	.195793	5.89	0.000	.7699389	1.537433
gjilani	1.999726	.1949397	10.26	0.000	1.617651	2.381801
mitrovica	1.353333	.203549	6.65	0.000	.9543842	1.752282
peja	.6318902	.2083549	3.03	0.002	.2235222	1.040258
prizreni	1.126131	.1917063	5.87	0.000	.7503936	1.501869
_cons	-19.81157	2.347503	-8.44	0.000	-24.41259	-15.21055

```
TME2          |
          age |   1.346897   .2628578     5.12   0.000      .831705    1.862089
        agesq |  -.0259819   .0049166    -5.28   0.000    -.0356183   -.0163455
         male |  -.7979321   .3745817    -2.13   0.033    -1.532099   -.0637655
     minority |   .0446592   .3027216     0.15   0.883    -.5486643    .6379826
 socialassist |   3.195568   .3042002    10.50   0.000     2.599346    3.791789
secondaryeduc |  -.0119571   .2216409    -0.05   0.957    -.4463652     .422451
 tertiaryeduc |   1.202353   .2365829     5.08   0.000     .7386587    1.666047
      emp2011 |  -2.432426    .226858   -10.72   0.000    -2.877059   -1.987792
      emphist |   1.909995   .2100973     9.09   0.000     1.498212    2.321778
       hhsize |  -.1776654   .0366943    -4.84   0.000     -.249585   -.1057459
    hhsizegen |   .0266939    .056103     0.48   0.634    -.0832659    .1366538
      ferizaj |   1.682184   .3010803     5.59   0.000     1.092078    2.272291
      gjakova |   1.638374   .3010562     5.44   0.000     1.048315    2.228434
      gjilani |   2.377816   .2959141     8.04   0.000     1.797835    2.957797
    mitrovica |   1.999283   .2964681     6.74   0.000     1.418217     2.58035
         peja |   1.407159   .2923936     4.81   0.000     .8340779     1.98024
      prizreni |   1.208193    .317206     3.81   0.000      .586481    1.829906
        _cons |  -20.36672   3.454223    -5.90   0.000    -27.13687   -13.59656
--------------+----------------------------------------------------------------
TME3          |
          age |   1.845249   .3940853     4.68   0.000     1.072856    2.617642
        agesq |  -.0354639   .0073317    -4.84   0.000    -.0498338    -.021094
         male |  -2.077053   .4621661    -4.49   0.000    -2.982882   -1.171224
     minority |  -.0372633   .3519049    -0.11   0.916    -.7269842    .6524576
 socialassist |   2.460318   .4081779     6.03   0.000     1.660304    3.260332
secondaryeduc |  -.6603757   .2685839    -2.46   0.014     -1.18679   -.1339609
 tertiaryeduc |   .2656454   .2724921     0.97   0.330    -.2684293    .7997201
      emp2011 |  -2.816691   .2412737   -11.67   0.000    -3.289579   -2.343803
      emphist |   2.751174   .2544869    10.81   0.000     2.252389    3.249959
       hhsize |  -.2744273   .0558694    -4.91   0.000    -.3839293   -.1649252
    hhsizegen |   .1802097    .069577     2.59   0.010     .0438413    .3165781
      ferizaj |   .2731118   .3064866     0.89   0.373     -.327591    .8738146
      gjakova |  -.6912424   .4154098    -1.66   0.096    -1.505431    .1229458
      gjilani |   1.306612   .2641516     4.95   0.000     .7888841    1.824339
    mitrovica |  -.2686435   .4071526    -0.66   0.509    -1.066648     .529361
         peja |  -.6522711   .4023617    -1.62   0.105    -1.440885    .1363434
     prizreni |  -.0450278   .3066457    -0.15   0.883    -.6460424    .5559868
        _cons |  -24.98753   5.233495    -4.77   0.000    -35.24499   -14.73007
-------------------------------------------------------------------------------
```

Table 6.2 Outcome Variable: *employed* – Model 2, excluding *emphist*

Table A6.2.1 PSM

```
. teffects psmatch (employed) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica
peja prizren ) if insampm==1, atet vce(robust)

Treatment-effects estimation                   Number of obs      =      7,753
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =          9
------------------------------------------------------------------------------
             |              AI Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
ATET           |
bintreatment |
   (1 vs 0)  |    .0670012   .0246546     2.72   0.007     .0186791    .1153233
------------------------------------------------------------------------------


*** Balancing diagnostics

. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                                  Raw      Matched
                          -----------------------------------------
                          Number of obs =        7,753        1,694
                          Treated obs   =          847          847
                          Control obs   =        6,906          847
                          -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Matched           Raw    Matched
  ----------------+------------------------------------------------
              age |  -.6060234  -.0272963       .3243216   .9542477
            agesq |  -.6665971   -.029148       .2800718   .9545983
             male |  -.4618398   .0378049       1.323737   .9965182
         minority |   .0377737   .1103094        1.14086   1.521516
     socialassist |   .3709548   .1106018        7.49496    1.42536
    secondaryeduc |  -.4394493   .0578811       1.036461   1.024474
     tertiaryeduc |   .5968176  -.0953859       1.880529   .9741495
          emp2011 |  -.5101395  -.0125136       .9074829   .9911969
           hhsize |   -.453916  -.0180904       .3536742   .8421255
        hhsizegen |  -.5622479   .0253108       .5529141   .9879471
          ferizaj |   .0111471   .0741576       1.026757    1.19752
          gjakova |   .0257213   .0141508        1.06098   1.032134
          gjilani |   .4442438   -.005757       2.838404   .9919855
        mitrovica |   .1091392  -.0576464       1.308213   .8876912
             peja |  -.0639643  -.0880067       .8656221   .8224986
         prizreni |  -.0658709   .0206687       .8802186   1.044971
  -----------------------------------------------------------------
```

Table A6.2.2 IPW

```
*** Binary treatment model

.  teffects  ipw  (employed)  (bintreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc  emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica
peja prizren ) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  1.061e-23
Iteration 1:   EE criterion =  8.893e-32

Treatment-effects estimation                   Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
```

```
 bintreatment |
    (1 vs 0)  |   .0793523   .0177834     4.46   0.000     .0444975    .1142071
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
           0  |   .3303289   .0169624    19.47   0.000     .2970832    .3635746
--------------+----------------------------------------------------------------
TME1          |
          age |   1.529679   .1520654    10.06   0.000     1.231637    1.827722
        agesq |  -.0293802   .0028491   -10.31   0.000    -.0349643   -.0237961
         male |  -.8143384   .2115076    -3.85   0.000    -1.228886    -.399791
     minority |   -.117641   .1887696    -0.62   0.533    -.4876227    .2523406
 socialassist |   2.898167   .2258356    12.83   0.000     2.455537    3.340797
secondaryeduc |  -.2218473   .1213679    -1.83   0.068    -.4597239    .0160294
 tertiaryeduc |    .967574   .1272537     7.60   0.000     .7181613    1.216987
      emp2011 |   -.815216   .0962615    -8.47   0.000    -1.003885   -.6265469
       hhsize |  -.1566946    .023219    -6.75   0.000    -.2022031   -.1111862
    hhsizegen |   .0261437   .0305012     0.86   0.391    -.0336375    .0859249
      ferizaj |   .8376426   .1531923     5.47   0.000     .5373912    1.137894
      gjakova |   .8286225    .153645     5.39   0.000     .5274839    1.129761
      gjilani |   1.826747   .1465489    12.47   0.000     1.539517    2.113978
    mitrovica |   1.021507   .1600413     6.38   0.000     .7078318    1.335182
         peja |   .2845783   .1530052     1.86   0.063    -.0153063     .584463
     prizreni |   .9107659   .1476721     6.17   0.000     .6213338    1.200198
        _cons |  -20.44219   2.004136   -10.20   0.000    -24.37022   -16.51416
-------------------------------------------------------------------------------

*** Balancing diagnostics

. tebalance sum

  Covariate balance summary
                                               Raw     Weighted
                          ----------------------------------------
                          Number of obs =        7,753      7,753.0
                          Treated obs   =          847      3,937.0
                          Control obs   =        6,906      3,816.0
                          ----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+------------------------------------------------
              age |  -.6060234   -.0399176      .3243216   .9571953
            agesq |  -.6665971     -.04135      .2800718   .9836777
             male |  -.4618398    .0048963      1.323737   .9993789
         minority |   .0377737    .0018411       1.14086    1.00612
     socialassist |   .3709548    .1339313       7.49496   1.555801
    secondaryeduc |  -.4394493    .0123786      1.036461   1.004586
     tertiaryeduc |   .5968176   -.0299941      1.880529   .9898049
          emp2011 |  -.5101395   -.0027371      .9074829   .9980306
           hhsize |   -.453916   -.0149439      .3536742   .9519562
        hhsizegen |  -.5622479   -.0079745      .5529141   .9926433
          ferizaj |   .0111471    .0203222      1.026757   1.047771
          gjakova |   .0257213    -.020305       1.06098   .9571171
          gjilani |   .4442438    .0212731      2.838404    1.03105
```

```
       mitrovica |   .1091392   -.0231879      1.308213   .9516492
            peja |  -.0639643   -.0058137      .8656221   .9860955
        prizreni |  -.0658709    .0076986      .8802186   1.016287
  -----------------------------------------------------------------
```

```
*** Multinomial treatment model


. teffects ipw (employed) (multitreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica
peja prizren ) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  1.415e-25
Iteration 1:   EE criterion =  1.365e-30

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .1048446   .0243483     4.31   0.000     .0571229    .1525664
     (2 vs 0)  |   .0886774   .0314554     2.82   0.005      .027026    .1503289
     (3 vs 0)  |  -.0619315   .0412751    -1.50   0.133    -.1428292    .0189661
---------------+--------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .3419639   .0219641    15.57   0.000     .2989149    .3850128
---------------+--------------------------------------------------------------
TME1           |
           age |   1.488677   .1806225     8.24   0.000     1.134663     1.84269
         agesq |  -.0288241   .0033858    -8.51   0.000    -.0354602    -.022188
          male |  -.5852999   .2593222    -2.26   0.024    -1.093562   -.0770378
      minority |  -.2005106   .2352003    -0.85   0.394    -.6614948    .2604736
  socialassist |   2.858397   .2596356    11.01   0.000      2.34952    3.367273
 secondaryeduc |  -.2658465   .1522796    -1.75   0.081     -.564309    .0326161
  tertiaryeduc |   .9955244    .155405     6.41   0.000     .6909361    1.300113
       emp2011 |  -.7686188   .1200859    -6.40   0.000    -1.003983   -.5332547
        hhsize |  -.1273163   .0280696    -4.54   0.000    -.1823317   -.0723008
     hhsizegen |  -.0075608     .03714    -0.20   0.839    -.0803539    .0652323
       ferizaj |   .8305248   .2003134     4.15   0.000     .4379177    1.223132
       gjakova |   1.036952   .1953685     5.31   0.000     .6540371    1.419868
       gjilani |   1.927927    .186489    10.34   0.000     1.562415    2.293438
     mitrovica |    1.15678   .2026307     5.71   0.000      .759631    1.553929
          peja |   .3477453   .2019948     1.72   0.085    -.0481572    .7436478
      prizreni |   1.157398   .1882848     6.15   0.000     .7883668     1.52643
         _cons |    -20.647   2.384039    -8.66   0.000    -25.31963   -15.97437
---------------+--------------------------------------------------------------
TME2           |
           age |   1.398609   .2665012     5.25   0.000     .8762767    1.920942
         agesq |  -.0267274   .0049928    -5.35   0.000    -.0365131   -.0169417
          male |  -.7163576   .3709546    -1.93   0.053    -1.443415       .0107
      minority |   .0143413   .2935359     0.05   0.961    -.5609785    .5896612
  socialassist |   3.159174   .2977953    10.61   0.000     2.575506    3.742842
 secondaryeduc |   .0464099   .2216867     0.21   0.834     -.388088    .4809078
```

```
  tertiaryeduc |   1.264522   .2337751     5.41   0.000     .8063315    1.722713
       emp2011 |  -.8877192   .1677239    -5.29   0.000    -1.216452   -.5589864
        hhsize |  -.1671686   .0365646    -4.57   0.000    -.2388339   -.0955034
     hhsizegen |   .0217715   .0555829     0.39   0.695    -.0871689    .1307119
       ferizaj |   1.579255   .2946838     5.36   0.000     1.001686    2.156825
       gjakova |   1.529028   .2976047     5.14   0.000     .9457336    2.112323
       gjilani |   2.320191    .289253     8.02   0.000     1.753265    2.887116
     mitrovica |   1.828277   .2904867     6.29   0.000     1.258933     2.39762
          peja |   1.163869   .2864361     4.06   0.000     .6024641    1.725273
      prizreni |   1.235643   .3145016     3.93   0.000     .6192306    1.852054
         _cons |  -20.92444   3.506563    -5.97   0.000    -27.79718    -14.0517
---------------+----------------------------------------------------------------
TME3           |
           age |   1.979701   .4019656     4.93   0.000     1.191863    2.767539
         agesq |  -.0374467    .007472    -5.01   0.000    -.0520915    -.022802
          male |  -1.824051   .4473795    -4.08   0.000    -2.700898    -.947203
      minority |  -.0890958   .3342492    -0.27   0.790    -.7442123    .5660206
  socialassist |    2.49236    .394361     6.32   0.000     1.719427    3.265294
 secondaryeduc |  -.4864627   .2748068    -1.77   0.077    -1.025074    .0521488
  tertiaryeduc |    .393309    .273296     1.44   0.150    -.1423414    .9289594
       emp2011 |  -.8624769   .2057616    -4.19   0.000    -1.265762   -.4591917
        hhsize |  -.2534561   .0544834    -4.65   0.000    -.3602417   -.1466705
     hhsizegen |   .1634357   .0677831     2.41   0.016     .0305832    .2962882
       ferizaj |    .148274   .2914652     0.51   0.611    -.4229873    .7195353
       gjakova |  -.8398084   .4075449    -2.06   0.039    -1.638582    -.041035
       gjilani |   1.220565   .2435454     5.01   0.000     .7432244    1.697905
     mitrovica |  -.5330993   .3927957    -1.36   0.175    -1.302965    .2367662
          peja |  -1.063046   .3837402    -2.77   0.006    -1.815163    -.310929
      prizreni |   .0140902   .3109107     0.05   0.964    -.5952835     .623464
         _cons |  -26.63742   5.360814    -4.97   0.000    -37.14442   -16.13042
--------------------------------------------------------------------------------
*** Balancing diagnostics

. tebalance sum
  Covariate balance summary
                                                   Observations
                                    Treatment          Raw     Weighted
                               ---------------------------------------
                               0bn.multitr~t =       6,906      1,901.9
                               1.multitrea~t =         470      1,959.0
                               2.multitrea~t =         241      1,951.1
                               3.multitrea~t =         136      1,940.9
                               Total         =       7,753      7,753.0
                               ---------------------------------------
  -------------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+--------------------------------------------------
  1.multitreatm~t |
              age |  -.6269269   -.0389111      .3221864   .9565371
            agesq |  -.6869872   -.0404997      .2738164   .9746485
             male |  -.4450008    .0051839      1.321906   .9991708
         minority |   .0052393    .0013714      1.021027     1.0049
     socialassist |   .3428648     .124423      6.827683   1.548222
    secondaryeduc |  -.4696964    .0094012       1.02591   1.004009
     tertiaryeduc |   .6244724   -.0264873      1.899256   .9922846
          emp2011 |  -.4831847    -.004493      .9244103   .9970294
           hhsize |  -.4328879   -.0170643      .3461522   .8874219
        hhsizegen |  -.5568747   -.0079624      .5330855   .9636638
          ferizaj |  -.0306483    .0180038      .9316378   1.045925
          gjakova |   .0687207   -.0175528       1.16296   .9657325
```

```
       gjilani |   .4292703    .0205999      2.780606   1.031008
     mitrovica |   .1178972   -.0261339      1.334737   .9467408
          peja |  -.0830119   -.0036363      .8265375   .9909039
      prizreni |  -.0032518    .0084815      .9960333   1.015833
---------------+--------------------------------------------------
2.multitreatm~t |
           age |  -.5756687   -.0302419      .3526933   .8810271
         agesq |  -.6322685   -.0371779      .3161966   .9099084
          male |  -.4294723    .0230807      1.321162   .9959539
      minority |    .078628    .0018004       1.30295   1.006441
   socialassist |   .4499272    .1460166      9.517168    1.65164
  secondaryeduc |  -.4066554    .0066291      1.050123   1.002842
   tertiaryeduc |   .6102409   -.0348289      1.895007     .98958
        emp2011 |   -.573383    .0112631      .8684703   1.007236
         hhsize |  -.4703471   -.0625769      .3897204   .9827943
      hhsizegen |  -.5477794    -.008632      .5800314   1.026098
        ferizaj |   .0779458   -.0040152      1.185588   .9897935
        gjakova |   .0702349   -.0061039      1.168982   .9880772
        gjilani |   .4113551    .0474671      2.713313    1.07084
      mitrovica |   .2067901   -.0223583      1.594995   .9544265
           peja |   .0507065    .0238161      1.112635    1.05981
       prizreni |  -.1745717    -.035644      .6845422   .9332364
---------------+--------------------------------------------------
3.multitreatm~t |
           age |  -.5874766   -.0296457      .2839457   1.005488
         agesq |  -.6574538   -.0280253      .2399639   1.067238
          male |  -.5770215    .1272245      1.335005   .9649316
      minority |   .0709291   -.0288807       1.27692   .8984358
   socialassist |   .3115719    .1221867       6.14469   1.537644
  secondaryeduc |  -.3928189    .0399179      1.057358   1.015899
   tertiaryeduc |   .4754033    -.106945      1.788427   .9607291
        emp2011 |  -.4921984   -.0572278      .9235891   .9597447
         hhsize |  -.4971539   -.0202623      .3182613   .8647128
      hhsizegen |   -.605161    .1097637      .5796272   1.020864
        ferizaj |   .0290471    .0216465      1.074949    1.05527
        gjakova |  -.2503322    .0075024      .4612281   1.014623
        gjilani |   .5480294    .0069959      3.261717   1.010569
      mitrovica |  -.1407073   -.0923244      .6399687   .8130044
           peja |  -.2319707    .0323926      .5307899    1.08149
       prizreni |  -.1079457     .017153      .8079007   1.032017
------------------------------------------------------------------
```

Table A6.2.3 RA

```
*** Binary treatment model

. teffects ra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni,
logit) (bintreatment) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  7.882e-24
Iteration 1:   EE criterion =  1.455e-33

Treatment-effects estimation                   Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
------------------------------------------------------------------------------
             |               Robust
```

```
     employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
 bintreatment |
   (1 vs 0)   |   .0754428   .0165533     4.56   0.000     .0429989    .1078867
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
           0  |   .3342384   .0157554    21.21   0.000     .3033585    .3651183
--------------+----------------------------------------------------------------
OME0          |
          age |   .1739483   .1384529     1.26   0.209    -.0974144    .4453109
        agesq |  -.0016824   .0023459    -0.72   0.473    -.0062803    .0029154
         male |   .4312049   .3242473     1.33   0.184    -.2043081    1.066718
     minority |   .0725496    .341229     0.21   0.832     -.596247    .7413461
 socialassist |   1.101173   .5870512     1.88   0.061    -.0494262    2.251772
secondaryeduc |    .565752   .1956808     2.89   0.004     .1822246    .9492794
 tertiaryeduc |   1.002006   .2889504     3.47   0.001     .4356737    1.568339
      emp2011 |   7.507091   .1921049    39.08   0.000     7.130573     7.88361
       hhsize |   .0548388   .0272224     2.01   0.044     .0014839    .1081937
    hhsizegen |  -.0604394   .0338882    -1.78   0.075    -.1268591    .0059804
      ferizaj |  -.8505879   .2939916    -2.89   0.004    -1.426801   -.2743749
      gjakova |  -.5909916   .2156204    -2.74   0.006      -1.0136   -.1683834
      gjilani |  -.3466467   .3338538    -1.04   0.299    -1.000988    .3076948
    mitrovica |   .0003534   .2824008     0.00   0.999     -.553142    .5538488
         peja |  -.9984065   .2782186    -3.59   0.000    -1.543705   -.4531081
     prizreni |  -.3955839   .2642355    -1.50   0.134     -.913476    .1223081
        _cons |  -8.104945   1.983933    -4.09   0.000    -11.99338   -4.216507
--------------+----------------------------------------------------------------
OME1          |
          age |   .5014897    .270826     1.85   0.064    -.0293195    1.032299
        agesq |  -.0081754   .0049658    -1.65   0.100    -.0179082    .0015575
         male |  -.1344847   .4492491    -0.30   0.765    -1.014997    .7460273
     minority |  -.5419511   .3303748    -1.64   0.101    -1.189474    .1055715
 socialassist |  -.4340609    .368882    -1.18   0.239    -1.157056    .2889345
secondaryeduc |  -.0305491   .2538747    -0.12   0.904    -.5281342    .4670361
 tertiaryeduc |   .6810658   .2561136     2.66   0.008     .1790924    1.183039
      emp2011 |   2.520389   .1906286    13.22   0.000     2.146764    2.894014
       hhsize |  -.0771316   .0577986    -1.33   0.182    -.1904148    .0361515
    hhsizegen |   .1069022   .0701897     1.52   0.128    -.0306671    .2444716
      ferizaj |  -.6781667   .3489586    -1.94   0.052    -1.362113    .0057796
      gjakova |  -.2724553   .2991633    -0.91   0.362    -.8588047    .3138941
      gjilani |  -.3299047   .2685538    -1.23   0.219    -.8562605    .1964511
    mitrovica |  -.9772652   .3645494    -2.68   0.007    -1.691769   -.2627615
         peja |   .6604484   .3134478     2.11   0.035     .0461019    1.274795
     prizreni |  -.3979773   .3296818    -1.21   0.227    -1.044142    .2481871
        _cons |  -8.453706   3.674403    -2.30   0.021     -15.6554   -1.252007
-------------------------------------------------------------------------------


*** Multinomial probit probit treatment model
```

```
. teffects ra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni,
logit) (multitreatment) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  1.196e-22
Iteration 1:   EE criterion =  1.463e-33

Treatment-effects estimation                   Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .1013386   .0237429     4.27   0.000     .0548033    .1478739
     (2 vs 0)  |   .0811349   .0297426     2.73   0.006     .0228404    .1394294
     (3 vs 0)  |  -.0345264   .0370209    -0.93   0.351     -.107086    .0380332
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .3454699   .0210372    16.42   0.000     .3042378     .386702
---------------+----------------------------------------------------------------
OME0           |
           age |   .1739483   .1384529     1.26   0.209    -.0974144    .4453109
         agesq |  -.0016824   .0023459    -0.72   0.473    -.0062803    .0029154
          male |   .4312049   .3242473     1.33   0.184    -.2043081    1.066718
      minority |   .0725496    .341229     0.21   0.832     -.596247    .7413461
  socialassist |   1.101173   .5870512     1.88   0.061    -.0494262    2.251772
 secondaryeduc |    .565752   .1956808     2.89   0.004     .1822246    .9492794
  tertiaryeduc |   1.002006   .2889504     3.47   0.001     .4356737    1.568339
       emp2011 |   7.507091   .1921049    39.08   0.000     7.130573     7.88361
        hhsize |   .0548388   .0272224     2.01   0.044     .0014839    .1081937
     hhsizegen |  -.0604394   .0338882    -1.78   0.075    -.1268591    .0059804
       ferizaj |  -.8505879   .2939916    -2.89   0.004    -1.426801   -.2743749
       gjakova |  -.5909916   .2156204    -2.74   0.006      -1.0136   -.1683834
       gjilani |  -.3466467   .3338538    -1.04   0.299    -1.000988    .3076948
     mitrovica |   .0003534   .2824008     0.00   0.999     -.553142    .5538488
          peja |  -.9984065   .2782186    -3.59   0.000    -1.543705   -.4531081
      prizreni |  -.3955839   .2642355    -1.50   0.134     -.913476    .1223081
         _cons |  -8.104945   1.983933    -4.09   0.000    -11.99338   -4.216507
---------------+----------------------------------------------------------------
OME1           |
           age |   .9045607   .3653916     2.48   0.013     .1884064    1.620715
         agesq |  -.0152479   .0067114    -2.27   0.023    -.0284021   -.0020938
          male |  -.5726078   .6330777    -0.90   0.366    -1.813417    .6682017
      minority |    -.50035   .5095082    -0.98   0.326    -1.498968    .4982676
  socialassist |  -.5613401    .547356    -1.03   0.305    -1.634138    .5114579
 secondaryeduc |    .151391   .3519244     0.43   0.667    -.5383681    .8411501
  tertiaryeduc |   .9169005   .3540227     2.59   0.010     .2230288    1.610772
       emp2011 |   2.222583   .2565311     8.66   0.000     1.719791    2.725375
```

hhsize	-.0710066	.076656	-0.93	0.354	-.2212496	.0792364
hhsizegen	.1610572	.0988294	1.63	0.103	-.032645	.3547593
ferizaj	-.9482069	.4926257	-1.92	0.054	-1.913736	.0173217
gjakova	-.1875847	.3944766	-0.48	0.634	-.9607446	.5855752
gjilani	-.6400604	.3812018	-1.68	0.093	-1.387202	.1070813
mitrovica	-1.010493	.4877512	-2.07	0.038	-1.966468	-.0545181
peja	.9499454	.4528238	2.10	0.036	.0624271	1.837464
prizreni	-.5466719	.4146967	-1.32	0.187	-1.359463	.2661187
_cons	-13.89721	4.983012	-2.79	0.005	-23.66373	-4.130684
OME2						
age	.3050504	.4251022	0.72	0.473	-.5281347	1.138235
agesq	-.0055252	.0074743	-0.74	0.460	-.0201746	.0091242
male	.4715506	.8520853	0.55	0.580	-1.198506	2.141607
minority	-.7893973	.6900379	-1.14	0.253	-2.141847	.563052
socialassist	-.2693546	.5309975	-0.51	0.612	-1.310091	.7713813
secondaryeduc	-.8728817	.4568688	-1.91	0.056	-1.768328	.0225647
tertiaryeduc	-.1017518	.460685	-0.22	0.825	-1.004678	.8011741
emp2011	2.871955	.3951667	7.27	0.000	2.097442	3.646467
hhsize	-.080814	.1143602	-0.71	0.480	-.3049559	.1433279
hhsizegen	.0955063	.1337495	0.71	0.475	-.1666379	.3576505
ferizaj	-1.307936	.8520808	-1.53	0.125	-2.977983	.3621121
gjakova	-1.629053	.7910716	-2.06	0.039	-3.179525	-.0785814
gjilani	-1.105803	.7261535	-1.52	0.128	-2.529038	.3174316
mitrovica	-1.75528	.8068848	-2.18	0.030	-3.336745	-.1738143
peja	-.59098	.7615134	-0.78	0.438	-2.083519	.9015589
prizreni	-1.174985	.8712466	-1.35	0.177	-2.882597	.5326273
_cons	-3.999873	5.960206	-0.67	0.502	-15.68166	7.681916
OME3						
age	-.4811639	1.006041	-0.48	0.632	-2.452968	1.490641
agesq	.0104985	.0189708	0.55	0.580	-.0266835	.0476806
male	-1.729743	1.863676	-0.93	0.353	-5.382481	1.922995
minority	-1.619945	1.63731	-0.99	0.322	-4.829014	1.589125
socialassist	-1.223795	4.182051	-0.29	0.770	-9.420465	6.972875
secondaryeduc	1.243717	.7898034	1.57	0.115	-.304269	2.791703
tertiaryeduc	1.185714	.8366557	1.42	0.156	-.4541012	2.825529
emp2011	4.666074	.9318401	5.01	0.000	2.839701	6.492447
hhsize	-.3329732	.1886001	-1.77	0.077	-.7026225	.0366761
hhsizegen	.1765113	.2987702	0.59	0.555	-.4090675	.7620902
ferizaj	-.3879032	.7821124	-0.50	0.620	-1.920815	1.145009
gjakova	1.069933	1.129233	0.95	0.343	-1.143323	3.283189
gjilani	.8194994	.8319558	0.99	0.325	-.8111041	2.450103
mitrovica	-2.852956	1.052288	-2.71	0.007	-4.915404	-.7905091
peja	-1.517402	1.247406	-1.22	0.224	-3.962272	.9274685
prizreni	.7599637	1.538918	0.49	0.621	-2.25626	3.776187
_cons	3.603758	13.04108	0.28	0.782	-21.95629	29.1638

Table A6.2.4 IPWRA

```
*** Binary treatment model
```

```
. teffects ipwra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni,
logit) (bintreatment age agesq male minority socialassist secondaryeduc tertiaryeduc
emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if
insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  1.153e-23
Iteration 1:   EE criterion =  8.681e-32

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |   .0805836   .0164736     4.89   0.000     .0482959    .1128712
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .3290976   .0157353    20.91   0.000     .2982571    .3599382
-------------+----------------------------------------------------------------
OME0         |
         age |  -.2262621   .4341884    -0.52   0.602    -1.077256    .6247315
       agesq |   .0055272   .0081847     0.68   0.499    -.0105145     .021569
        male |   .5588442   .6182347     0.90   0.366    -.6528736    1.770562
    minority |  -.2106421   .4040391    -0.52   0.602    -1.002544    .5812599
 socialassist |   .8294192   .9685587     0.86   0.392    -1.068921    2.727759
secondaryeduc |   .6463209   .4631962     1.40   0.163     -.261527    1.554169
 tertiaryeduc |   .8491812   .5496118     1.55   0.122    -.2280382      1.9264
     emp2011 |   7.810324   .3298494    23.68   0.000     7.163831    8.456817
      hhsize |   .0590892   .0715206     0.83   0.409    -.0810886     .199267
   hhsizegen |  -.0153849   .0808653    -0.19   0.849     -.173878    .1431082
     ferizaj |  -1.268089   .7435662    -1.71   0.088    -2.725452    .1892736
     gjakova |  -1.287125   .5570029    -2.31   0.021    -2.378831   -.1954195
     gjilani |  -.6878748   .4624748    -1.49   0.137    -1.594309    .2185591
   mitrovica |   -.320406   .4421026    -0.72   0.469    -1.186911    .5460991
        peja |  -.3413098   .8454592    -0.40   0.686    -1.998379     1.31576
    prizreni |   -1.05728   .5670165    -1.86   0.062    -2.168612    .0540522
       _cons |  -2.893375   5.214786    -0.55   0.579    -13.11417    7.327417
-------------+----------------------------------------------------------------
OME1         |
         age |   .5014897    .270826     1.85   0.064    -.0293195    1.032299
       agesq |  -.0081754   .0049658    -1.65   0.100    -.0179082    .0015575
        male |  -.1344847   .4492491    -0.30   0.765    -1.014997    .7460273
    minority |  -.5419511   .3303748    -1.64   0.101    -1.189474    .1055715
 socialassist |  -.4340609    .368882    -1.18   0.239    -1.157056    .2889345
secondaryeduc |  -.0305491   .2538747    -0.12   0.904    -.5281342    .4670361
 tertiaryeduc |   .6810658   .2561136     2.66   0.008     .1790924    1.183039
```

```
      emp2011 |   2.520389   .1906286    13.22   0.000     2.146764    2.894014
       hhsize |  -.0771316   .0577986    -1.33   0.182    -.1904148    .0361515
    hhsizegen |   .1069022   .0701897     1.52   0.128    -.0306671    .2444716
      ferizaj |  -.6781667   .3489586    -1.94   0.052    -1.362113    .0057796
      gjakova |  -.2724553   .2991633    -0.91   0.362    -.8588047    .3138941
      gjilani |  -.3299047   .2685538    -1.23   0.219    -.8562605    .1964511
    mitrovica |  -.9772652   .3645494    -2.68   0.007    -1.691769   -.2627615
         peja |   .6604484   .3134478     2.11   0.035     .0461019    1.274795
     prizreni |  -.3979773   .3296818    -1.21   0.227    -1.044142    .2481871
        _cons |  -8.453706   3.674403    -2.30   0.021     -15.6554   -1.252007
--------------+----------------------------------------------------------------
TME1          |
          age |   1.529679   .1520654    10.06   0.000     1.231637    1.827722
        agesq |  -.0293802   .0028491   -10.31   0.000    -.0349643   -.0237961
         male |  -.8143384   .2115076    -3.85   0.000    -1.228886    -.399791
     minority |   -.117641   .1887696    -0.62   0.533    -.4876227    .2523406
 socialassist |   2.898167   .2258356    12.83   0.000     2.455537    3.340797
secondaryeduc |  -.2218473   .1213679    -1.83   0.068    -.4597239    .0160294
 tertiaryeduc |    .967574   .1272537     7.60   0.000     .7181613    1.216987
      emp2011 |   -.815216   .0962615    -8.47   0.000    -1.003885   -.6265469
       hhsize |  -.1566946    .023219    -6.75   0.000    -.2022031   -.1111862
    hhsizegen |   .0261437   .0305012     0.86   0.391    -.0336375    .0859249
      ferizaj |   .8376426   .1531923     5.47   0.000     .5373912    1.137894
      gjakova |   .8286225    .153645     5.39   0.000     .5274839    1.129761
      gjilani |   1.826747   .1465489    12.47   0.000     1.539517    2.113978
    mitrovica |   1.021507   .1600413     6.38   0.000     .7078318    1.335182
         peja |   .2845783   .1530052     1.86   0.063    -.0153063     .584463
     prizreni |   .9107659   .1476721     6.17   0.000     .6213338    1.200198
        _cons |  -20.44219   2.004136   -10.20   0.000    -24.37022   -16.51416
-------------------------------------------------------------------------------



*** Multinomial probit treatment model

. teffects ipwra ( employed age agesq male minority socialassist secondaryeduc
tertiaryeduc emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni,
logit) (multitreatment age agesq male minority socialassist secondaryeduc tertiaryeduc
emp2011 hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if
insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  6.376e-24
Iteration 1:   EE criterion =  1.872e-31
Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .1063634   .0236892     4.49   0.000     .0599334    .1527935
```

(2 vs 0)	.0830785	.0292299	2.84	0.004	.025789	.140368
(3 vs 0)	-.0442443	.0345548	-1.28	0.200	-.1119704	.0234819
POmean						
multitreatment						
0	.3404451	.0210635	16.16	0.000	.2991613	.3817288
OME0						
age	-.2904645	.3972418	-0.73	0.465	-1.069044	.4881151
agesq	.0068103	.007504	0.91	0.364	-.0078974	.021518
male	.4819534	.6193396	0.78	0.436	-.7319299	1.695837
minority	-.2310351	.4025864	-0.57	0.566	-1.02009	.5580197
socialassist	.756079	.9807899	0.77	0.441	-1.166234	2.678392
secondaryeduc	.740045	.4250841	1.74	0.082	-.0931045	1.573195
tertiaryeduc	.9320518	.5306001	1.76	0.079	-.1079053	1.972009
emp2011	7.877888	.3341251	23.58	0.000	7.223015	8.532762
hhsize	.0565099	.0659018	0.86	0.391	-.0726553	.1856751
hhsizegen	-.0103306	.0776207	-0.13	0.894	-.1624645	.1418033
ferizaj	-1.336282	.7586819	-1.76	0.078	-2.823271	.150707
gjakova	-1.223612	.5595416	-2.19	0.029	-2.320293	-.1269307
gjilani	-.7280765	.4769634	-1.53	0.127	-1.662908	.2067545
mitrovica	-.3177137	.4614019	-0.69	0.491	-1.222045	.5866174
peja	-.2405535	.8501725	-0.28	0.777	-1.906861	1.425754
prizreni	-1.087353	.5825042	-1.87	0.062	-2.22904	.0543347
_cons	-2.168215	4.761691	-0.46	0.649	-11.50096	7.164528
OME1						
age	.9045607	.3653916	2.48	0.013	.1884064	1.620715
agesq	-.0152479	.0067114	-2.27	0.023	-.0284021	-.0020938
male	-.5726078	.6330777	-0.90	0.366	-1.813417	.6682017
minority	-.50035	.5095082	-0.98	0.326	-1.498968	.4982676
socialassist	-.5613401	.547356	-1.03	0.305	-1.634138	.5114579
secondaryeduc	.151391	.3519244	0.43	0.667	-.5383681	.8411501
tertiaryeduc	.9169005	.3540227	2.59	0.010	.2230288	1.610772
emp2011	2.222583	.2565311	8.66	0.000	1.719791	2.725375
hhsize	-.0710066	.076656	-0.93	0.354	-.2212496	.0792364
hhsizegen	.1610572	.0988294	1.63	0.103	-.032645	.3547593
ferizaj	-.9482069	.4926257	-1.92	0.054	-1.913736	.0173217
gjakova	-.1875847	.3944766	-0.48	0.634	-.9607446	.5855752
gjilani	-.6400604	.3812018	-1.68	0.093	-1.387202	.1070813
mitrovica	-1.010493	.4877512	-2.07	0.038	-1.966468	-.0545181
peja	.9499454	.4528238	2.10	0.036	.0624271	1.837464
prizreni	-.5466719	.4146967	-1.32	0.187	-1.359463	.2661187
_cons	-13.89721	4.983012	-2.79	0.005	-23.66373	-4.130684
OME2						
age	.2776937	.4982021	0.56	0.577	-.6987645	1.254152
agesq	-.0048634	.0090429	-0.54	0.591	-.0225871	.0128604
male	.826246	.8859974	0.93	0.351	-.910277	2.562769
minority	-.647995	.7979432	-0.81	0.417	-2.211935	.915945
socialassist	-.302681	.5308647	-0.57	0.569	-1.343157	.7377947
secondaryeduc	-.9862897	.4627274	-2.13	0.033	-1.893219	-.0793607
tertiaryeduc	-.2368137	.4777363	-0.50	0.620	-1.17316	.6995321

emp2011	2.856388	.4201064	6.80	0.000	2.032995	3.679782
hhsize	-.0790102	.1118083	-0.71	0.480	-.2981505	.1401301
hhsizegen	.0791055	.1338036	0.59	0.554	-.1831446	.3413557
ferizaj	-1.00536	.8289143	-1.21	0.225	-2.630002	.6192819
gjakova	-1.397607	.7781177	-1.80	0.072	-2.922689	.1274757
gjilani	-.7843113	.7119811	-1.10	0.271	-2.179769	.611146
mitrovica	-1.489404	.7969223	-1.87	0.062	-3.051343	.0725352
peja	-.3405993	.7440961	-0.46	0.647	-1.799001	1.117802
prizreni	-.8852856	.8457887	-1.05	0.295	-2.543001	.7724298
_cons	-4.060629	6.749413	-0.60	0.547	-17.28923	9.167976
OME3						
age	-.6159187	.9352814	-0.66	0.510	-2.449036	1.217199
agesq	.0143873	.0176043	0.82	0.414	-.0201165	.0488912
male	-1.4357	2.102815	-0.68	0.495	-5.557142	2.685742
minority	-1.650699	1.076011	-1.53	0.125	-3.759642	.4582449
socialassist	-4.203331	4.541444	-0.93	0.355	-13.1044	4.697735
secondaryeduc	1.245403	.7597816	1.64	0.101	-.2437411	2.734548
tertiaryeduc	1.409617	.8831028	1.60	0.110	-.3212325	3.140467
emp2011	4.501698	1.111401	4.05	0.000	2.323393	6.680003
hhsize	-.4748813	.2199765	-2.16	0.031	-.9060274	-.0437353
hhsizegen	.167488	.3268997	0.51	0.608	-.4732236	.8081997
ferizaj	-.1171851	.9449948	-0.12	0.901	-1.969341	1.734971
gjakova	.680064	1.181365	0.58	0.565	-1.635368	2.995496
gjilani	.7284944	.889441	0.82	0.413	-1.014778	2.471767
mitrovica	-3.240155	1.047393	-3.09	0.002	-5.293006	-1.187303
peja	-1.199277	1.039999	-1.15	0.249	-3.237637	.8390831
prizreni	.5166203	1.970444	0.26	0.793	-3.345379	4.37862
_cons	5.202919	11.74923	0.44	0.658	-17.82514	28.23098
TME1						
age	1.488677	.1806225	8.24	0.000	1.134663	1.84269
agesq	-.0288241	.0033858	-8.51	0.000	-.0354602	-.022188
male	-.5852999	.2593222	-2.26	0.024	-1.093562	-.0770378
minority	-.2005106	.2352003	-0.85	0.394	-.6614948	.2604736
socialassist	2.858397	.2596356	11.01	0.000	2.34952	3.367273
secondaryeduc	-.2658465	.1522796	-1.75	0.081	-.564309	.0326161
tertiaryeduc	.9955244	.155405	6.41	0.000	.6909361	1.300113
emp2011	-.7686188	.1200859	-6.40	0.000	-1.003983	-.5332547
hhsize	-.1273163	.0280696	-4.54	0.000	-.1823317	-.0723008
hhsizegen	-.0075608	.03714	-0.20	0.839	-.0803539	.0652323
ferizaj	.8305248	.2003134	4.15	0.000	.4379177	1.223132
gjakova	1.036952	.1953685	5.31	0.000	.6540371	1.419868
gjilani	1.927927	.186489	10.34	0.000	1.562415	2.293438
mitrovica	1.15678	.2026307	5.71	0.000	.759631	1.553929
peja	.3477453	.2019948	1.72	0.085	-.0481572	.7436478
prizreni	1.157398	.1882848	6.15	0.000	.7883668	1.52643
_cons	-20.647	2.384039	-8.66	0.000	-25.31963	-15.97437
TME2						
age	1.398609	.2665012	5.25	0.000	.8762767	1.920942
agesq	-.0267274	.0049928	-5.35	0.000	-.0365131	-.0169417
male	-.7163576	.3709546	-1.93	0.053	-1.443415	.0107

```
     minority |   .0143413   .2935359     0.05   0.961    -.5609785    .5896612
  socialassist |   3.159174   .2977953    10.61   0.000     2.575506    3.742842
 secondaryeduc |   .0464099   .2216867     0.21   0.834     -.388088    .4809078
  tertiaryeduc |   1.264522   .2337751     5.41   0.000     .8063315    1.722713
       emp2011 |  -.8877192   .1677239    -5.29   0.000    -1.216452   -.5589864
        hhsize |  -.1671686   .0365646    -4.57   0.000    -.2388339   -.0955034
     hhsizegen |   .0217715   .0555829     0.39   0.695    -.0871689    .1307119
       ferizaj |   1.579255   .2946838     5.36   0.000     1.001686    2.156825
       gjakova |   1.529028   .2976047     5.14   0.000     .9457336    2.112323
       gjilani |   2.320191    .289253     8.02   0.000     1.753265    2.887116
     mitrovica |   1.828277   .2904867     6.29   0.000     1.258933     2.39762
          peja |   1.163869   .2864361     4.06   0.000     .6024641    1.725273
      prizreni |   1.235643   .3145016     3.93   0.000     .6192306    1.852054
         _cons |  -20.92444   3.506563    -5.97   0.000    -27.79718    -14.0517
---------------+----------------------------------------------------------------
TME3           |
           age |   1.979701   .4019656     4.93   0.000     1.191863    2.767539
         agesq |  -.0374467    .007472    -5.01   0.000    -.0520915    -.022802
          male |  -1.824051   .4473795    -4.08   0.000    -2.700898    -.947203
      minority |  -.0890958   .3342492    -0.27   0.790    -.7442123    .5660206
  socialassist |    2.49236    .394361     6.32   0.000     1.719427    3.265294
 secondaryeduc |  -.4864627   .2748068    -1.77   0.077    -1.025074    .0521488
  tertiaryeduc |    .393309    .273296     1.44   0.150    -.1423414    .9289594
       emp2011 |  -.8624769   .2057616    -4.19   0.000    -1.265762   -.4591917
        hhsize |  -.2534561   .0544834    -4.65   0.000    -.3602417   -.1466705
     hhsizegen |   .1634357   .0677831     2.41   0.016     .0305832    .2962882
       ferizaj |    .148274   .2914652     0.51   0.611    -.4229873    .7195353
       gjakova |  -.8398084   .4075449    -2.06   0.039    -1.638582    -.041035
       gjilani |   1.220565   .2435454     5.01   0.000     .7432244    1.697905
     mitrovica |  -.5330993   .3927957    -1.36   0.175    -1.302965    .2367662
          peja |  -1.063046   .3837402    -2.77   0.006    -1.815163    -.310929
      prizreni |   .0140902   .3109107     0.05   0.964    -.5952835     .623464
         _cons |  -26.63742   5.360814    -4.97   0.000    -37.14442   -16.13042
--------------------------------------------------------------------------------
```

Table 6.3 Outcome Variable: *employed* – Model 3, excluding *emphist* and *emp2011*

Table A6.3.1 PSM

```
*** Binary treatment model


. teffects psmatch (employed) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ) if insampm==1, atet vce(robust)

Treatment-effects estimation                   Number of obs      =      7,753
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =         16
------------------------------------------------------------------------------
             |              AI Robust
```

```
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
bintreatment |
   (1 vs 0)  |  -.1201402   .0274427    -4.38   0.000    -.1739269   -.0663535
------------------------------------------------------------------------------

.
. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                               Raw      Matched
                          -----------------------------------------
                          Number of obs =        7,753        1,694
                          Treated obs   =          847          847
                          Control obs   =        6,906          847
                          -----------------------------------------

  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Matched           Raw    Matched
  ----------------+------------------------------------------------
              age |  -.6060234   -.0560202      .3243216   1.032325
            agesq |  -.6665971   -.0516844      .2800718   1.027513
             male |  -.4618398    .0590598      1.323737   .9958181
         minority |   .0377737    .0625463       1.14086   1.250156
      socialassist |   .3709548    .2393765       7.49496   2.528539
     secondaryeduc |  -.4394493    .0192129      1.036461   1.007279
      tertiaryeduc |   .5968176   -.1547271      1.880529   .9673542
           hhsize |   -.453916    .0715541      .3536742   .8875756
        hhsizegen |  -.5622479    .0385221      .5529141   .9956847
          ferizaj |   .0111471    .0399729      1.026757   1.098258
          gjakova |   .0257213    .0431534       1.06098   1.104466
          gjilani |   .4442438   -.0370242      2.838404   .9511813
        mitrovica |   .1091392    .0035033      1.308213   1.007722
             peja |  -.0639643   -.0255434      .8656221   .9414794
         prizreni |  -.0658709   -.0367838      .8802186   .9287426
  -----------------------------------------------------------------
```

Table A6.3.2 IPW

```
. *** Binary treatment model

.  teffects  ipw  (employed)  (bintreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc  hhsize hhs
>  izegen  ferizaj  gjakova  gjilani  mitrovica  peja  prizren  )  if  insampm==1,  atet
vce(robust) aequ

Iteration 0:   EE criterion =  1.009e-23
Iteration 1:   EE criterion =  3.061e-32

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
-------------------------------------------------------------------------------
              |               Robust
```

```
     employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
 bintreatment |
    (1 vs 0)  |  -.0791602   .0212052    -3.73   0.000    -.1207216   -.0375987
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
           0  |   .4888414   .0142626    34.27   0.000     .4608871    .5167956
--------------+----------------------------------------------------------------
TME1          |
          age |   1.489746   .1510649     9.86   0.000     1.193664    1.785828
        agesq |  -.0290606   .0028341   -10.25   0.000    -.0346153   -.0235059
         male |  -.9042557    .209688    -4.31   0.000    -1.315237   -.4932748
     minority |  -.0438336   .1833028    -0.24   0.811    -.4031005    .3154332
 socialassist |   3.109302   .2212496    14.05   0.000      2.67566    3.542943
secondaryeduc |  -.3147433    .118473    -2.66   0.008    -.5469462   -.0825404
 tertiaryeduc |   .8323472   .1235364     6.74   0.000     .5902204    1.074474
       hhsize |  -.1567485   .0230038    -6.81   0.000    -.2018351    -.111662
    hhsizegen |   .0265874   .0301634     0.88   0.378    -.0325317    .0857065
      ferizaj |   .8335969   .1508638     5.53   0.000     .5379093    1.129285
      gjakova |   .9042148   .1490287     6.07   0.000      .612124    1.196306
      gjilani |   1.832649   .1431117    12.81   0.000     1.552155    2.113142
    mitrovica |   1.113014    .158378     7.03   0.000     .8025985    1.423429
         peja |    .511612   .1512205     3.38   0.001     .2152254    .8079987
     prizreni |   .8182876   .1460099     5.60   0.000     .5321135    1.104462
        _cons |  -19.86672   1.987935    -9.99   0.000      -23.763   -15.97044
-------------------------------------------------------------------------------

*** Balancing diagnostics


. tebalance sum

  Covariate balance summary
                                             Raw     Weighted
                         ----------------------------------------
                         Number of obs =       7,753      7,753.0
                         Treated obs   =         847      3,946.7
                         Control obs   =       6,906      3,806.3
                         ----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+------------------------------------------------
              age |  -.6060234   -.0475656      .3243216   .9581938
            agesq |  -.6665971   -.0487129      .2800718   .9868389
             male |  -.4618398     .002955      1.323737   .9996149
         minority |   .0377737     .020367       1.14086    1.07147
     socialassist |   .3709548    .1592337       7.49496   1.722564
    secondaryeduc |  -.4394493    .0089127      1.036461   1.003264
     tertiaryeduc |   .5968176   -.0343847      1.880529   .9884746
           hhsize |   -.453916   -.0079835      .3536742   .9402526
        hhsizegen |  -.5622479   -.0072016      .5529141   .9931567
          ferizaj |   .0111471    .0257461      1.026757   1.061253
          gjakova |   .0257213   -.0029112       1.06098   .9936182
          gjilani |   .4442438    .0212012      2.838404    1.03094
        mitrovica |   .1091392   -.0225392      1.308213   .9529385
             peja |  -.0639643   -.0171653      .8656221   .9599668
         prizreni |  -.0658709   -.0128522      .8802186   .9739011
```

```
  ------------------------------------------------------------------

*** Multinomial probit treatment model


. teffects ipw (    employed) (multitreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  2.160e-25
Iteration 1:   EE criterion =  3.282e-31

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.0457259   .0263508    -1.74   0.083    -.0973724    .0059207
     (2 vs 0)  |   -.076272   .0353308    -2.16   0.031    -.1455191   -.0070249
     (3 vs 0)  |  -.2228705   .0451723    -4.93   0.000    -.3114067   -.1343343
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
             0 |   .4925344   .0153671    32.05   0.000     .4624154    .5226533
---------------+----------------------------------------------------------------
TME1           |
           age |   1.452835   .1796828     8.09   0.000     1.100663    1.805007
         agesq |  -.0285565   .0033743    -8.46   0.000      -.03517    -.021943
          male |  -.6717092   .2580573    -2.60   0.009    -1.177492   -.1659261
      minority |  -.1324891    .231146    -0.57   0.567    -.5855269    .3205486
  socialassist |   3.067042   .2537005    12.09   0.000     2.569798    3.564286
 secondaryeduc |  -.3466381   .1509441    -2.30   0.022    -.6424831   -.0507931
  tertiaryeduc |   .8748281   .1537469     5.69   0.000     .5734897    1.176166
        hhsize |  -.1274079   .0279889    -4.55   0.000    -.1822651   -.0725507
     hhsizegen |  -.0067229   .0368747    -0.18   0.855     -.078996    .0655502
       ferizaj |   .8270523   .1986786     4.16   0.000     .4376494    1.216455
       gjakova |   1.108157    .191103     5.80   0.000     .7336015    1.482712
       gjilani |   1.934041    .184201    10.50   0.000     1.573013    2.295068
     mitrovica |   1.243574   .2015755     6.17   0.000     .8484936    1.638655
          peja |   .5639601   .2007041     2.81   0.005     .1705872     .957333
      prizreni |   1.069853   .1865271     5.74   0.000     .7042669     1.43544
         _cons |  -20.13843   2.367687    -8.51   0.000    -24.77901   -15.49785
---------------+----------------------------------------------------------------
TME2           |
           age |   1.360546   .2673669     5.09   0.000     .8365163    1.884575
         agesq |  -.0264873   .0050132    -5.28   0.000    -.0363131   -.0166615
          male |  -.8044124    .369694    -2.18   0.030    -1.528999   -.0798254
      minority |   .0870677   .2874638     0.30   0.762     -.476351    .6504864
  socialassist |   3.380726   .2945283    11.48   0.000     2.803462    3.957991
 secondaryeduc |  -.0570558   .2159371    -0.26   0.792    -.4802847    .3661731
  tertiaryeduc |   1.108868   .2257367     4.91   0.000     .6664318    1.551303
        hhsize |  -.1674929   .0365388    -4.58   0.000    -.2391076   -.0958782
     hhsizegen |   .0219234   .0553486     0.40   0.692    -.0865579    .1304047
       ferizaj |   1.565415   .2914305     5.37   0.000     .9942216    2.136608
       gjakova |   1.608339   .2940545     5.47   0.000     1.032002    2.184675
       gjilani |   2.324789   .2845205     8.17   0.000     1.767139    2.882439
```

```
    mitrovica |   1.920447   .2892411     6.64   0.000     1.353545    2.487349
         peja |   1.408167   .2860544     4.92   0.000     .8475103    1.968823
     prizreni |   1.137828   .3102009     3.67   0.000     .5298456    1.745811
        _cons |  -20.35176   3.514834    -5.79   0.000     -27.2407   -13.46281
--------------+----------------------------------------------------------------
TME3          |
          age |   1.914787   .3967772     4.83   0.000     1.137118    2.692456
        agesq |  -.0366737    .007375    -4.97   0.000    -.0511284   -.0222189
         male |   -1.91522   .4409584    -4.34   0.000    -2.779483   -1.050958
     minority |   .0075032   .3308248     0.02   0.982    -.6409015     .655908
  socialassist |   2.702783   .3957607     6.83   0.000     1.927106    3.478459
 secondaryeduc |  -.6107306   .2664775    -2.29   0.022    -1.133017   -.0884443
  tertiaryeduc |    .240355   .2659369     0.90   0.366    -.2808719    .7615818
        hhsize |  -.2508386   .0533032    -4.71   0.000     -.355311   -.1463662
     hhsizegen |   .1607539    .066522     2.42   0.016     .0303731    .2911347
       ferizaj |   .1565877   .2890636     0.54   0.588    -.4099665    .7231419
       gjakova |  -.7563943   .4065169    -1.86   0.063    -1.553153    .0403642
       gjilani |   1.227501   .2417102     5.08   0.000     .7537573    1.701244
     mitrovica |  -.4284341   .3908317    -1.10   0.273     -1.19445    .3375821
          peja |  -.8302177   .3820004    -2.17   0.030    -1.578925   -.0815106
      prizreni |   -.086036   .3056564    -0.28   0.778    -.6851115    .5130396
         _cons |  -25.72966   5.288687    -4.87   0.000     -36.0953   -15.36402
-------------------------------------------------------------------------------

*** Balancing diagnostics


. tebalance sum

  Covariate balance summary
                                                    Observations
                                     Treatment           Raw      Weighted
                                -----------------------------------------
                                0bn.multitr~t =        6,906       1,896.0
                                1.multitrea~t =          470       1,960.1
                                2.multitrea~t =          241       1,948.6
                                3.multitrea~t =          136       1,948.2
                                Total         =        7,753       7,753.0
                                -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences         Variance ratio
                  |         Raw    Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.6269269   -.0462105      .3221864   .9580967
            agesq |  -.6869872   -.0474977      .2738164   .9782737
             male |  -.4450008    .0028551      1.321906   .9995277
         minority |   .0052393    .0177392      1.021027   1.066792
     socialassist |   .3428648    .1476677      6.827683    1.70901
    secondaryeduc |  -.4696964    .0073878       1.02591   1.003128
     tertiaryeduc |   .6244724   -.0308911      1.899256   .9911459
           hhsize |  -.4328879   -.0097892      .3461522   .8800767
        hhsizegen |  -.5568747   -.0071883      .5330855    .965112
          ferizaj |  -.0306483    .0224416      .9316378   1.057842
          gjakova |   .0687207   -.0002716       1.16296   .9994342
          gjilani |   .4292703    .0220984      2.780606   1.033354
        mitrovica |   .1178972   -.0252817      1.334737   .9483873
             peja |  -.0830119   -.0134813      .8265375   .9670548
         prizreni |  -.0032518   -.0128668      .9960333   .9769054
  ----------------+------------------------------------------------
```

```
  2.multitreatm~t |
              age |  -.5756687   -.0272215      .3526933    .886999
            agesq |  -.6322685   -.0338573      .3161966   .9219734
             male |  -.4294723    .0190387      1.321162   .9966462
         minority |    .078628     .018009       1.30295   1.067823
      socialassist |   .4499272    .1682574      9.517168   1.818464
     secondaryeduc |  -.4066554    .0050543      1.050123   1.002149
      tertiaryeduc |   .6102409   -.0286358      1.895007   .9918568
            hhsize |  -.4703471   -.0504451      .3897204    .985924
         hhsizegen |  -.5477794   -.0074872      .5800314   1.034602
           ferizaj |   .0779458    .0060072      1.185588   1.015414
           gjakova |   .0702349    .0057401      1.168982   1.011579
           gjilani |   .4113551    .0422679      2.713313   1.063398
         mitrovica |   .2067901   -.0181121      1.594995   .9630094
              peja |   .0507065    .0136519      1.112635   1.033515
          prizreni |  -.1745717   -.0439517      .6845422   .9209734
  ----------------+---------------------------------------------------
  3.multitreatm~t |
              age |  -.5874766   -.0331906      .2839457   1.004342
            agesq |  -.6574538   -.0315444      .2399639   1.066691
             male |  -.5770215    .1266538      1.335005   .9645727
         minority |   .0709291   -.0126459       1.27692   .9533034
      socialassist |   .3115719    .1480874       6.14469   1.711224
     secondaryeduc |  -.3928189    .0507329      1.057358   1.019453
      tertiaryeduc |   .4754033   -.1121614      1.788427   .9592518
            hhsize |  -.4971539   -.0105451      .3182613   .8636918
         hhsizegen |   -.605161    .1136171      .5796272   1.029173
           ferizaj |   .0290471    .0097819      1.074949   1.025132
           gjakova |  -.2503322    .0209289      .4612281   1.042249
           gjilani |   .5480294    .0117647      3.261717   1.017808
         mitrovica |  -.1407073   -.0966607      .6399687   .8040265
              peja |  -.2319707    .0250584      .5307899   1.061657
          prizreni |  -.1079457     .014166      .8079007   1.025317
  --------------------------------------------------------------------
```

Table 6.3.3 RA

Table A6.3.4 IPWRA

```
.
. *** Binary treatment model
.
. teffects ipwra (employed age agesq male minority socialassist secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni, logit)
(bintreatment age agesq male minority socialassist secondaryeduc tertiaryeduc hhsize
hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if insampm==1, atet
vce(robust) aequ

Iteration 0:   EE criterion =  5.313e-15
Iteration 1:   EE criterion =  2.623e-26

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
--------------+----------------------------------------------------------------
ATET          |
 bintreatment |
   (1 vs 0)   |  -.0567178   .0207371    -2.74   0.006    -.0973618   -.0160737
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
          0   |    .466399   .0139171    33.51   0.000     .4391219    .4936761
--------------+----------------------------------------------------------------
OME0          |
          age |   .1523512   .1379542     1.10   0.269    -.1180342    .4227366
        agesq |   .0003626   .0025336     0.14   0.886    -.0046031    .0053283
         male |   .5089198   .3131192     1.63   0.104    -.1047826    1.122622
     minority |  -.8922428   .2565743    -3.48   0.001    -1.395119   -.3893664
 socialassist |  -2.792914    .577729    -4.83   0.000    -3.925242   -1.660586
secondaryeduc |   .9020205   .1343009     6.72   0.000     .6387955    1.165246
 tertiaryeduc |   1.083888   .1528397     7.09   0.000      .784328    1.383448
       hhsize |  -.0196155   .0394375    -0.50   0.619    -.0969116    .0576806
    hhsizegen |   .0127255   .0430549     0.30   0.768    -.0716604    .0971115
      ferizaj |  -.2071083   .1608543    -1.29   0.198    -.5223769    .1081603
      gjakova |  -.5806185   .1578682    -3.68   0.000    -.8900346   -.2712025
      gjilani |  -.0105097   .2097396    -0.05   0.960    -.4215917    .4005723
    mitrovica |  -.5025315   .1711469    -2.94   0.003    -.8379732   -.1670898
         peja |  -1.146402   .1801384    -6.36   0.000    -1.499466   -.7933368
     prizreni |   .7430386   .1604076     4.63   0.000     .4286455    1.057432
        _cons |  -5.012248   1.844008    -2.72   0.007    -8.626437   -1.398059
--------------+----------------------------------------------------------------
OME1          |
          age |   .5119307   .2112997     2.42   0.015     .0977909    .9260706
        agesq |  -.0083758   .0038008    -2.20   0.028    -.0158252   -.0009265
         male |  -.0227869   .4110149    -0.06   0.956    -.8283613    .7827876
     minority |  -.8287694   .3539911    -2.34   0.019    -1.522579   -.1349596
 socialassist |  -.4309245   .2887258    -1.49   0.136    -.9968168    .1349678
secondaryeduc |   .1135012   .2172495     0.52   0.601       -.3123    .5393024
 tertiaryeduc |   .6347905   .2199569     2.89   0.004     .2036829    1.065898
       hhsize |  -.0747009   .0507704    -1.47   0.141    -.1742091    .0248073
    hhsizegen |   .1097048   .0633041     1.73   0.083    -.0143689    .2337785
      ferizaj |  -.5178538   .2832156    -1.83   0.067    -1.072946    .0372384
      gjakova |  -.2611117   .2760369    -0.95   0.344    -.8021341    .2799108
      gjilani |   -.445238   .2531556    -1.76   0.079    -.9414139    .0509378
    mitrovica |  -1.161152   .2956017    -3.93   0.000    -1.740521   -.5817837
         peja |  -.1824993   .2869199    -0.64   0.525    -.7448521    .3798534
     prizreni |  -.5232536   .2703597    -1.94   0.053    -1.053149    .0066417
        _cons |  -7.652244   2.936347    -2.61   0.009    -13.40738    -1.89711
--------------+----------------------------------------------------------------
TME1          |
          age |   1.489746   .1510649     9.86   0.000     1.193664    1.785828
        agesq |  -.0290606   .0028341   -10.25   0.000    -.0346153   -.0235059
         male |  -.9042557    .209688    -4.31   0.000    -1.315237   -.4932748
     minority |  -.0438336   .1833028    -0.24   0.811    -.4031005    .3154332
 socialassist |   3.109302   .2212496    14.05   0.000      2.67566    3.542943
secondaryeduc |  -.3147433    .118473    -2.66   0.008    -.5469462   -.0825404
 tertiaryeduc |   .8323472   .1235364     6.74   0.000     .5902204    1.074474
```

```
       hhsize |  -.1567485   .0230038    -6.81   0.000    -.2018351    -.111662
    hhsizegen |   .0265874   .0301634     0.88   0.378    -.0325317    .0857065
      ferizaj |   .8335969   .1508638     5.53   0.000     .5379093    1.129285
      gjakova |   .9042148   .1490287     6.07   0.000      .612124    1.196306
      gjilani |   1.832649   .1431117    12.81   0.000     1.552155    2.113142
    mitrovica |   1.113014    .158378     7.03   0.000     .8025985    1.423429
         peja |    .511612   .1512205     3.38   0.001     .2152254    .8079987
     prizreni |   .8182876   .1460099     5.60   0.000     .5321135    1.104462
        _cons |  -19.86672   1.987935    -9.99   0.000      -23.763   -15.97044
------------------------------------------------------------------------------


.
. *** Multinomial probit treatment model


.
.  teffects  ipwra  (employed  age  agesq  male  minority  socialassist  secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni, logit)
(multitreatment  age  agesq  male  minority  socialassist  secondaryeduc  tertiaryeduc
hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if insampm==1, atet
vce(robust) aequ

Iteration 0:   EE criterion =  2.245e-20
Iteration 1:   EE criterion =  1.363e-31

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
-------------------------------------------------------------------------------
               |               Robust
      employed |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+---------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.0254893   .0259382    -0.98   0.326    -.0763273    .0253486
     (2 vs 0)  |  -.0602018   .0352423    -1.71   0.088    -.1292755    .0088719
     (3 vs 0)  |   -.198256   .0415232    -4.77   0.000      -.27964   -.1168721
---------------+---------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .4722978   .0154288    30.61   0.000     .4420579    .5025378
---------------+---------------------------------------------------------------
OME0           |
           age |   .1400378   .1380287     1.01   0.310    -.1304935     .410569
         agesq |   .0005487   .0025438     0.22   0.829    -.0044371    .0055345
          male |   .5357812   .3044452     1.76   0.078    -.0609205    1.132483
      minority |  -.8654024   .2600023    -3.33   0.001    -1.374998   -.3558072
  socialassist |  -2.910951   .5801124    -5.02   0.000     -4.04795   -1.773951
 secondaryeduc |   .8270565   .1362491     6.07   0.000     .5600132      1.0941
  tertiaryeduc |   1.017111   .1564595     6.50   0.000     .7104564    1.323766
        hhsize |  -.0170668   .0361488    -0.47   0.637    -.0879171    .0537835
     hhsizegen |   .0057499   .0402538     0.14   0.886    -.0731462    .0846459
       ferizaj |  -.1898509   .1604717    -1.18   0.237    -.5043697    .1246679
```

```
       gjakova |  -.5661943   .1590917    -3.56   0.000    -.8780082   -.2543803
       gjilani |  -.0258231   .2111879    -0.12   0.903    -.4397437    .3880975
     mitrovica |  -.4916423   .1706602    -2.88   0.004    -.8261301   -.1571545
          peja |   -1.14343   .1829398    -6.25   0.000    -1.501985   -.7848741
      prizreni |   .7478287   .1615893     4.63   0.000     .4311195    1.064538
         _cons |  -4.768192   1.845776    -2.58   0.010    -8.385846   -1.150538
---------------+----------------------------------------------------------------
OME1           |
           age |    .771614   .3050696     2.53   0.011     .1736886    1.369539
         agesq |  -.0129968   .0055079    -2.36   0.018     -.023792   -.0022016
          male |  -.3697689   .5519637    -0.67   0.503    -1.451598      .71206
      minority |  -.8981239   .5662227    -1.59   0.113      -2.0079    .2116523
  socialassist |  -.3497898   .4116745    -0.85   0.396    -1.156657    .4570773
 secondaryeduc |   .3289861   .3159554     1.04   0.298     -.290275    .9482473
  tertiaryeduc |   .8978944    .312165     2.88   0.004     .2860622    1.509727
        hhsize |  -.0543442   .0618897    -0.88   0.380    -.1756457    .0669574
     hhsizegen |   .1502849    .085277     1.76   0.078    -.0168549    .3174248
       ferizaj |  -.6979258   .4031789    -1.73   0.083    -1.488142    .0922904
       gjakova |   -.109384   .3800496    -0.29   0.773    -.8542675    .6354995
       gjilani |  -.7085552   .3732224    -1.90   0.058    -1.440058    .0229473
     mitrovica |  -1.233911   .4173416    -2.96   0.003    -2.051885   -.4159363
          peja |   .2738405   .4217283     0.65   0.516    -.5527318    1.100413
      prizreni |  -.4016541   .3733499    -1.08   0.282    -1.133406    .3300983
         _cons |  -11.36656   4.230742    -2.69   0.007    -19.65866    -3.07446
---------------+----------------------------------------------------------------
OME2           |
           age |   .1473416   .4137805     0.36   0.722    -.6636533    .9583364
         agesq |  -.0022723   .0074223    -0.31   0.759    -.0168197    .0122751
          male |   .4105205   .8363128     0.49   0.624    -1.228622    2.049663
      minority |  -.5964027   .6304277    -0.95   0.344    -1.832018    .6392129
  socialassist |  -.6062209   .5272215    -1.15   0.250    -1.639556    .4271142
 secondaryeduc |  -.7850725   .4177642    -1.88   0.060    -1.603875    .0337302
  tertiaryeduc |  -.2420901   .4233125    -0.57   0.567    -1.071767     .587587
        hhsize |  -.1046332   .1173059    -0.89   0.372    -.3345485    .1252821
     hhsizegen |   .1158886   .1312362     0.88   0.377    -.1413296    .3731068
       ferizaj |   -1.05825   .6453475    -1.64   0.101    -2.323108    .2066079
       gjakova |  -1.244594   .6525026    -1.91   0.056    -2.523475    .0342879
       gjilani |  -.7773096   .6087851    -1.28   0.202    -1.970507    .4158873
     mitrovica |  -1.636243   .6496147    -2.52   0.012    -2.909464   -.3630213
          peja |  -1.349373   .6544219    -2.06   0.039    -2.632016   -.0667294
      prizreni |  -1.227955   .6352079    -1.93   0.053    -2.472939    .0170299
         _cons |  -1.113319   5.739615    -0.19   0.846    -12.36276    10.13612
---------------+----------------------------------------------------------------
OME3           |
           age |   .3302282   .5771315     0.57   0.567    -.8009288    1.461385
         agesq |  -.0025658    .010544    -0.24   0.808    -.0232316    .0181001
          male |   .0662248   1.498513     0.04   0.965    -2.870806    3.003256
      minority |  -1.881336   1.351211    -1.39   0.164     -4.52966    .7669889
  socialassist |  -2.668093   2.013468    -1.33   0.185    -6.614418    1.278231
 secondaryeduc |   .6582037   .7685032     0.86   0.392     -.848035    2.164442
  tertiaryeduc |   1.229319   .8633618     1.42   0.154    -.4628395    2.921477
        hhsize |  -.3201979   .1986378    -1.61   0.107    -.7095207     .069125
     hhsizegen |   .1016827   .2358462     0.43   0.666    -.3605674    .5639328
```

```
      ferizaj |   1.040806   .7905504     1.32   0.188    -.5086447    2.590256
      gjakova |  -.4668876   1.018065    -0.46   0.647    -2.462259    1.528484
      gjilani |   .2599474   .6247903     0.42   0.677    -.9646191    1.484514
    mitrovica |  -1.662454   .8875603    -1.87   0.061     -3.40204     .077132
         peja |   -1.70144    1.20846    -1.41   0.159    -4.069977    .6670974
     prizreni |  -.8299097   .8301331    -1.00   0.317    -2.456941    .7971212
        _cons |  -6.723661   7.853104    -0.86   0.392    -22.11546     8.66814
--------------+----------------------------------------------------------------
TME1          |
          age |   1.452835   .1796828     8.09   0.000     1.100663    1.805007
        agesq |  -.0285565   .0033743    -8.46   0.000      -.03517    -.021943
         male |  -.6717092   .2580573    -2.60   0.009    -1.177492   -.1659261
     minority |  -.1324891    .231146    -0.57   0.567    -.5855269    .3205486
 socialassist |   3.067042   .2537005    12.09   0.000     2.569798    3.564286
secondaryeduc |  -.3466381   .1509441    -2.30   0.022    -.6424831   -.0507931
 tertiaryeduc |   .8748281   .1537469     5.69   0.000     .5734897    1.176166
       hhsize |  -.1274079   .0279889    -4.55   0.000    -.1822651   -.0725507
    hhsizegen |  -.0067229   .0368747    -0.18   0.855     -.078996    .0655502
      ferizaj |   .8270523   .1986786     4.16   0.000     .4376494    1.216455
      gjakova |   1.108157    .191103     5.80   0.000     .7336015    1.482712
      gjilani |   1.934041    .184201    10.50   0.000     1.573013    2.295068
    mitrovica |   1.243574   .2015755     6.17   0.000     .8484936    1.638655
         peja |   .5639601   .2007041     2.81   0.005     .1705872     .957333
     prizreni |   1.069853   .1865271     5.74   0.000     .7042669     1.43544
        _cons |  -20.13843   2.367687    -8.51   0.000    -24.77901   -15.49785
--------------+----------------------------------------------------------------
TME2          |
          age |   1.360546   .2673669     5.09   0.000     .8365163    1.884575
        agesq |  -.0264873   .0050132    -5.28   0.000    -.0363131   -.0166615
         male |  -.8044124    .369694    -2.18   0.030    -1.528999   -.0798254
     minority |   .0870677   .2874638     0.30   0.762     -.476351    .6504864
 socialassist |   3.380726   .2945283    11.48   0.000     2.803462    3.957991
secondaryeduc |  -.0570558   .2159371    -0.26   0.792    -.4802847    .3661731
 tertiaryeduc |   1.108868   .2257367     4.91   0.000     .6664318    1.551303
       hhsize |  -.1674929   .0365388    -4.58   0.000    -.2391076   -.0958782
    hhsizegen |   .0219234   .0553486     0.40   0.692    -.0865579    .1304047
      ferizaj |   1.565415   .2914305     5.37   0.000     .9942216    2.136608
      gjakova |   1.608339   .2940545     5.47   0.000     1.032002    2.184675
      gjilani |   2.324789   .2845205     8.17   0.000     1.767139    2.882439
    mitrovica |   1.920447   .2892411     6.64   0.000     1.353545    2.487349
         peja |   1.408167   .2860544     4.92   0.000     .8475103    1.968823
     prizreni |   1.137828   .3102009     3.67   0.000     .5298456    1.745811
        _cons |  -20.35176   3.514834    -5.79   0.000     -27.2407   -13.46281
--------------+----------------------------------------------------------------
TME3          |
          age |   1.914787   .3967772     4.83   0.000     1.137118    2.692456
        agesq |  -.0366737    .007375    -4.97   0.000    -.0511284   -.0222189
         male |   -1.91522   .4409584    -4.34   0.000    -2.779483   -1.050958
     minority |   .0075032   .3308248     0.02   0.982    -.6409015     .655908
 socialassist |   2.702783   .3957607     6.83   0.000     1.927106    3.478459
secondaryeduc |  -.6107306   .2664775    -2.29   0.022    -1.133017   -.0884443
 tertiaryeduc |    .240355   .2659369     0.90   0.366    -.2808719    .7615818
       hhsize |  -.2508386   .0533032    -4.71   0.000     -.355311   -.1463662
```

```
    hhsizegen |   .1607539    .066522     2.42   0.016     .0303731    .2911347
      ferizaj |   .1565877   .2890636     0.54   0.588    -.4099665    .7231419
      gjakova |  -.7563943   .4065169    -1.86   0.063    -1.553153    .0403642
      gjilani |   1.227501   .2417102     5.08   0.000     .7537573    1.701244
    mitrovica |  -.4284341   .3908317    -1.10   0.273     -1.19445    .3375821
         peja |  -.8302177   .3820004    -2.17   0.030    -1.578925   -.0815106
     prizreni |   -.086036   .3056564    -0.28   0.778    -.6851115    .5130396
        _cons |  -25.72966   5.288687    -4.87   0.000     -36.0953   -15.36402
------------------------------------------------------------------------------
```

Table 6.4 Outcome Variable: *emp1112* – Model 4

Table A6.4.1 PSM

```
. teffects psmatch (empl1112) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ) if insampm==1, atet vce(robust)

Treatment-effects estimation                   Number of obs      =      7,753
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =         16
------------------------------------------------------------------------------
             |              AI Robust
    empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
bintreatment |
   (1 vs 0)  |  -.0539964   .0274526    -1.97   0.049    -.1078024   -.0001904
------------------------------------------------------------------------------

. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                               Raw      Matched
                          -----------------------------------------
                          Number of obs =        7,753        1,694
                          Treated obs   =          847          847
                          Control obs   =        6,906          847
                          -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Matched           Raw    Matched
  ----------------+------------------------------------------------
              age |  -.6060234   -.0560202      .3243216   1.032325
            agesq |  -.6665971   -.0516844      .2800718   1.027513
             male |  -.4618398    .0590598      1.323737   .9958181
         minority |   .0377737    .0625463       1.14086   1.250156
     socialassist |   .3709548    .2393765       7.49496   2.528539
    secondaryeduc |  -.4394493    .0192129      1.036461   1.007279
     tertiaryeduc |   .5968176   -.1547271      1.880529   .9673542
           hhsize |   -.453916    .0715541      .3536742   .8875756
        hhsizegen |  -.5622479    .0385221      .5529141   .9956847
          ferizaj |   .0111471    .0399729      1.026757   1.098258
          gjakova |   .0257213    .0431534       1.06098   1.104466
          gjilani |   .4442438   -.0370242      2.838404   .9511813
```

```
       mitrovica |   .1091392     .0035033      1.308213   1.007722
            peja |  -.0639643    -.0255434      .8656221   .9414794
         prizreni |  -.0658709    -.0367838      .8802186   .9287426
  -----------------------------------------------------------------
```

Table A6.4.2 IPW

```
***Binary treatment model

. teffects ipw (empl1112) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  1.009e-23
Iteration 1:   EE criterion =  3.230e-32

Treatment-effects estimation                   Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |  -.0180082   .0212248    -0.85   0.396     -.059608    .0235916
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .5067921   .0142967    35.45   0.000     .4787711    .5348132
-------------+----------------------------------------------------------------
TME1         |
         age |   1.489746   .1510649     9.86   0.000     1.193664    1.785828
       agesq |  -.0290606   .0028341   -10.25   0.000    -.0346153   -.0235059
        male |  -.9042557    .209688    -4.31   0.000    -1.315237   -.4932748
    minority |  -.0438336   .1833028    -0.24   0.811    -.4031005    .3154332
 socialassist |   3.109302   .2212496    14.05   0.000      2.67566    3.542943
secondaryeduc |  -.3147433    .118473    -2.66   0.008    -.5469462   -.0825404
 tertiaryeduc |   .8323472   .1235364     6.74   0.000     .5902204    1.074474
      hhsize |  -.1567485   .0230038    -6.81   0.000    -.2018351    -.111662
   hhsizegen |   .0265874   .0301634     0.88   0.378    -.0325317    .0857065
     ferizaj |   .8335969   .1508638     5.53   0.000     .5379093    1.129285
     gjakova |   .9042148   .1490287     6.07   0.000      .612124    1.196306
     gjilani |   1.832649   .1431117    12.81   0.000     1.552155    2.113142
   mitrovica |   1.113014    .158378     7.03   0.000     .8025985    1.423429
        peja |    .511612   .1512205     3.38   0.001     .2152254    .8079987
    prizreni |   .8182876   .1460099     5.60   0.000     .5321135    1.104462
       _cons |  -19.86672   1.987935    -9.99   0.000      -23.763   -15.97044
------------------------------------------------------------------------------
```

```
*** Balancing diagnostics

. tebalance sum

  Covariate balance summary
                                                     Raw     Weighted
                           -----------------------------------------
                           Number of obs =         7,753      7,753.0
                           Treated obs   =           847      3,946.7
                           Control obs   =         6,906      3,806.3
                           -----------------------------------------

  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+------------------------------------------------
              age |  -.6060234   -.0475656      .3243216   .9581938
            agesq |  -.6665971   -.0487129      .2800718   .9868389
             male |  -.4618398     .002955      1.323737   .9996149
         minority |   .0377737     .020367       1.14086    1.07147
     socialassist |   .3709548    .1592337       7.49496   1.722564
    secondaryeduc |  -.4394493    .0089127      1.036461   1.003264
     tertiaryeduc |   .5968176   -.0343847      1.880529   .9884746
           hhsize |   -.453916   -.0079835      .3536742   .9402526
        hhsizegen |  -.5622479   -.0072016      .5529141   .9931567
          ferizaj |   .0111471    .0257461      1.026757   1.061253
          gjakova |   .0257213   -.0029112       1.06098   .9936182
          gjilani |   .4442438    .0212012      2.838404    1.03094
        mitrovica |   .1091392   -.0225392      1.308213   .9529385
             peja |  -.0639643   -.0171653      .8656221   .9599668
         prizreni |  -.0658709   -.0128522      .8802186   .9739011
  -----------------------------------------------------------------



*** Multinomial probit model

. teffects ipw (empl1112) (multitreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc  hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja
prizren ) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  2.160e-25
Iteration 1:   EE criterion =  1.373e-31

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
```

(1 vs 0)	.025506	.0262566	0.97	0.331	-.025956	.076968
(2 vs 0)	-.0311061	.0354972	-0.88	0.381	-.1006793	.0384671
(3 vs 0)	-.1539268	.0492953	-3.12	0.002	-.2505438	-.0573098
POmean						
multitreatment						
0	.5106642	.0154777	32.99	0.000	.4803285	.5409998
TME1						
age	1.452835	.1796828	8.09	0.000	1.100663	1.805007
agesq	-.0285565	.0033743	-8.46	0.000	-.03517	-.021943
male	-.6717092	.2580573	-2.60	0.009	-1.177492	-.1659261
minority	-.1324891	.231146	-0.57	0.567	-.5855269	.3205486
socialassist	3.067042	.2537005	12.09	0.000	2.569798	3.564286
secondaryeduc	-.3466381	.1509441	-2.30	0.022	-.6424831	-.0507931
tertiaryeduc	.8748281	.1537469	5.69	0.000	.5734897	1.176166
hhsize	-.1274079	.0279889	-4.55	0.000	-.1822651	-.0725507
hhsizegen	-.0067229	.0368747	-0.18	0.855	-.078996	.0655502
ferizaj	.8270523	.1986786	4.16	0.000	.4376494	1.216455
gjakova	1.108157	.191103	5.80	0.000	.7336015	1.482712
gjilani	1.934041	.184201	10.50	0.000	1.573013	2.295068
mitrovica	1.243574	.2015755	6.17	0.000	.8484936	1.638655
peja	.5639601	.2007041	2.81	0.005	.1705872	.957333
prizreni	1.069853	.1865271	5.74	0.000	.7042669	1.43544
_cons	-20.13843	2.367687	-8.51	0.000	-24.77901	-15.49785
TME2						
age	1.360546	.2673669	5.09	0.000	.8365163	1.884575
agesq	-.0264873	.0050132	-5.28	0.000	-.0363131	-.0166615
male	-.8044124	.369694	-2.18	0.030	-1.528999	-.0798254
minority	.0870677	.2874638	0.30	0.762	-.476351	.6504864
socialassist	3.380726	.2945283	11.48	0.000	2.803462	3.957991
secondaryeduc	-.0570558	.2159371	-0.26	0.792	-.4802847	.3661731
tertiaryeduc	1.108868	.2257367	4.91	0.000	.6664318	1.551303
hhsize	-.1674929	.0365388	-4.58	0.000	-.2391076	-.0958782
hhsizegen	.0219234	.0553486	0.40	0.692	-.0865579	.1304047
ferizaj	1.565415	.2914305	5.37	0.000	.9942216	2.136608
gjakova	1.608339	.2940545	5.47	0.000	1.032002	2.184675
gjilani	2.324789	.2845205	8.17	0.000	1.767139	2.882439
mitrovica	1.920447	.2892411	6.64	0.000	1.353545	2.487349
peja	1.408167	.2860544	4.92	0.000	.8475103	1.968823
prizreni	1.137828	.3102009	3.67	0.000	.5298456	1.745811
_cons	-20.35176	3.514834	-5.79	0.000	-27.2407	-13.46281
TME3						
age	1.914787	.3967772	4.83	0.000	1.137118	2.692456
agesq	-.0366737	.007375	-4.97	0.000	-.0511284	-.0222189
male	-1.91522	.4409584	-4.34	0.000	-2.779483	-1.050958
minority	.0075032	.3308248	0.02	0.982	-.6409015	.655908
socialassist	2.702783	.3957607	6.83	0.000	1.927106	3.478459
secondaryeduc	-.6107306	.2664775	-2.29	0.022	-1.133017	-.0884443
tertiaryeduc	.240355	.2659369	0.90	0.366	-.2808719	.7615818
hhsize	-.2508386	.0533032	-4.71	0.000	-.355311	-.1463662

```
    hhsizegen |   .1607539    .066522     2.42   0.016     .0303731    .2911347
      ferizaj |   .1565877   .2890636     0.54   0.588    -.4099665    .7231419
      gjakova |  -.7563943   .4065169    -1.86   0.063    -1.553153    .0403642
      gjilani |   1.227501   .2417102     5.08   0.000     .7537573    1.701244
    mitrovica |  -.4284341   .3908317    -1.10   0.273     -1.19445    .3375821
         peja |  -.8302177   .3820004    -2.17   0.030    -1.578925   -.0815106
     prizreni |   -.086036   .3056564    -0.28   0.778    -.6851115    .5130396
        _cons |  -25.72966   5.288687    -4.87   0.000     -36.0953   -15.36402
--------------------------------------------------------------------------------

*** Balancing diagnostics


. tebalance sum

  Covariate balance summary
                                               Observations
                             Treatment          Raw     Weighted
                        ----------------------------------------
                        0bn.multitr~t =        6,906      1,896.0
                        1.multitrea~t =          470      1,960.1
                        2.multitrea~t =          241      1,948.6
                        3.multitrea~t =          136      1,948.2
                        Total         =        7,753      7,753.0
                        ----------------------------------------


  ----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw    Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.6269269   -.0462105      .3221864   .9580967
            agesq |  -.6869872   -.0474977      .2738164   .9782737
             male |  -.4450008    .0028551      1.321906   .9995277
         minority |   .0052393    .0177392      1.021027   1.066792
     socialassist |   .3428648    .1476677      6.827683    1.70901
   secondaryeduc  |  -.4696964    .0073878       1.02591   1.003128
     tertiaryeduc |   .6244724   -.0308911      1.899256   .9911459
           hhsize |  -.4328879   -.0097892      .3461522   .8800767
        hhsizegen |  -.5568747   -.0071883      .5330855    .965112
          ferizaj |  -.0306483    .0224416      .9316378   1.057842
          gjakova |   .0687207   -.0002716       1.16296   .9994342
          gjilani |   .4292703    .0220984      2.780606   1.033354
        mitrovica |   .1178972   -.0252817      1.334737   .9483873
             peja |  -.0830119   -.0134813      .8265375   .9670548
         prizreni |  -.0032518   -.0128668      .9960333   .9769054
  ----------------+------------------------------------------------
  2.multitreatm~t |
              age |  -.5756687   -.0272215      .3526933    .886999
            agesq |  -.6322685   -.0338573      .3161966   .9219734
             male |  -.4294723    .0190387      1.321162   .9966462
         minority |    .078628     .018009       1.30295   1.067823
     socialassist |   .4499272    .1682574      9.517168   1.818464
```

```
    secondaryeduc |  -.4066554    .0050543      1.050123   1.002149
     tertiaryeduc |   .6102409   -.0286358      1.895007   .9918568
           hhsize |  -.4703471   -.0504451      .3897204    .985924
        hhsizegen |  -.5477794   -.0074872      .5800314   1.034602
          ferizaj |   .0779458    .0060072      1.185588   1.015414
          gjakova |   .0702349    .0057401      1.168982   1.011579
          gjilani |   .4113551    .0422679      2.713313   1.063398
        mitrovica |   .2067901   -.0181121      1.594995   .9630094
             peja |   .0507065    .0136519      1.112635   1.033515
         prizreni |  -.1745717   -.0439517      .6845422   .9209734
  ----------------+-----------------------------------------------
  3.multitreatm~t |
              age |  -.5874766   -.0331906      .2839457   1.004342
            agesq |  -.6574538   -.0315444      .2399639   1.066691
             male |  -.5770215    .1266538      1.335005   .9645727
         minority |   .0709291   -.0126459       1.27692   .9533034
     socialassist |   .3115719    .1480874       6.14469   1.711224
    secondaryeduc |  -.3928189    .0507329      1.057358   1.019453
     tertiaryeduc |   .4754033   -.1121614      1.788427   .9592518
           hhsize |  -.4971539   -.0105451      .3182613   .8636918
        hhsizegen |   -.605161    .1136171      .5796272   1.029173
          ferizaj |   .0290471    .0097819      1.074949   1.025132
          gjakova |  -.2503322    .0209289      .4612281   1.042249
          gjilani |   .5480294    .0117647      3.261717   1.017808
        mitrovica |  -.1407073   -.0966607      .6399687   .8040265
             peja |  -.2319707    .0250584      .5307899   1.061657
         prizreni |  -.1079457     .014166      .8079007   1.025317
  ----------------------------------------------------------------
```

Table A6.4.3 RA

```
*** Binary treatment model

.  teffects  ra  (empl1112  age  agesq  male  minority  socialassist  secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni, logit)
(multitreatment) if insampm==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  7.788e-17
Iteration 1:   EE criterion =  2.843e-27

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
--------------------------------------------------------------------------------
               |               Robust
      empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .0225809   .0252208     0.90   0.371    -.0268511    .0720128
     (2 vs 0)  |  -.0314998   .0345424    -0.91   0.362    -.0992016     .036202
     (3 vs 0)  |  -.1619296   .0456342    -3.55   0.000     -.251371   -.0724883
---------------+----------------------------------------------------------------
POmean         |
```

multitreatment						
0	.5135893	.0140706	36.50	0.000	.4860115	.5411671
OME0						
age	.4218355	.0492325	8.57	0.000	.3253415	.5183294
agesq	-.0053135	.0008252	-6.44	0.000	-.0069308	-.0036962
male	.6953048	.1367735	5.08	0.000	.4272338	.9633759
minority	.0540327	.1106093	0.49	0.625	-.1627575	.2708229
socialassist	-1.669971	.2750154	-6.07	0.000	-2.208992	-1.130951
secondaryeduc	.5943007	.0718422	8.27	0.000	.4534925	.7351089
tertiaryeduc	1.210722	.0947223	12.78	0.000	1.02507	1.396374
hhsize	.0101914	.0137174	0.74	0.458	-.0166942	.037077
hhsizegen	-.0013489	.0158066	-0.09	0.932	-.0323293	.0296315
ferizaj	-.0133214	.0899299	-0.15	0.882	-.1895809	.162938
gjakova	-.6499175	.0951831	-6.83	0.000	-.836473	-.4633621
gjilani	.0107498	.1186282	0.09	0.928	-.2217572	.2432569
mitrovica	-.3425645	.0927862	-3.69	0.000	-.524422	-.160707
peja	-1.431714	.0917698	-15.60	0.000	-1.61158	-1.251849
prizreni	.7294603	.0932899	7.82	0.000	.5466154	.9123052
_cons	-8.165179	.7301844	-11.18	0.000	-9.596314	-6.734044
OME1						
age	.6792348	.2967876	2.29	0.022	.0975419	1.260928
agesq	-.0112742	.0053536	-2.11	0.035	-.021767	-.0007814
male	-.1062614	.5455349	-0.19	0.846	-1.17549	.9629674
minority	-1.305959	.5432352	-2.40	0.016	-2.37068	-.2412374
socialassist	.2111297	.3870835	0.55	0.585	-.5475401	.9697994
secondaryeduc	.4389903	.2970251	1.48	0.139	-.1431682	1.021149
tertiaryeduc	.7105868	.3003635	2.37	0.018	.1218851	1.299288
hhsize	-.061795	.0588051	-1.05	0.293	-.1770509	.0534608
hhsizegen	.1136662	.0828352	1.37	0.170	-.0486879	.2760203
ferizaj	-.1672238	.395912	-0.42	0.673	-.943197	.6087494
gjakova	.1102961	.3884224	0.28	0.776	-.6509978	.87159
gjilani	-.6744633	.3593402	-1.88	0.061	-1.378757	.0298305
mitrovica	-.8125503	.3931781	-2.07	0.039	-1.583165	-.0419354
peja	.2596473	.4106387	0.63	0.527	-.5451899	1.064484
prizreni	.0589143	.3800356	0.16	0.877	-.6859418	.8037705
_cons	-9.923026	4.09973	-2.42	0.016	-17.95835	-1.887703
OME2						
age	-.1128602	.3830579	-0.29	0.768	-.8636398	.6379194
agesq	.0026772	.0068576	0.39	0.696	-.0107634	.0161178
male	.304864	.7275617	0.42	0.675	-1.121131	1.730859
minority	-.8498043	.5712328	-1.49	0.137	-1.9694	.2697914
socialassist	-.6574525	.4679755	-1.40	0.160	-1.574668	.2597626
secondaryeduc	-.4811004	.4036198	-1.19	0.233	-1.272181	.3099799
tertiaryeduc	-.0865895	.4132696	-0.21	0.834	-.8965832	.7234041
hhsize	-.0872666	.0925523	-0.94	0.346	-.2686657	.0941326
hhsizegen	.086008	.1105473	0.78	0.437	-.1306606	.3026767
ferizaj	-1.121272	.6137825	-1.83	0.068	-2.324264	.0817197
gjakova	-1.186881	.6329124	-1.88	0.061	-2.427367	.0536046
gjilani	-1.053826	.5982276	-1.76	0.078	-2.226331	.1186782
mitrovica	-1.685266	.6220251	-2.71	0.007	-2.904413	-.4661194
peja	-1.693098	.6390675	-2.65	0.008	-2.945647	-.4405486
prizreni	-.9423325	.6414572	-1.47	0.142	-2.199566	.3149006
_cons	2.51059	5.35139	0.47	0.639	-7.977941	12.99912
OME3						
age	.4641524	.5694996	0.82	0.415	-.6520463	1.580351
agesq	-.0060196	.0102927	-0.58	0.559	-.0261929	.0141538
male	.1276887	1.165306	0.11	0.913	-2.156269	2.411646

```
     minority |  -2.259389   1.454987    -1.55   0.120    -5.111111     .592333
 socialassist |  -1.080894   1.157489    -0.93   0.350    -3.349531    1.187743
secondaryeduc |    .552582   .5857586     0.94   0.345    -.5954838    1.700648
 tertiaryeduc |   .6563583   .6459736     1.02   0.310    -.6097267    1.922443
       hhsize |  -.0915123   .1539948    -0.59   0.552    -.3933365     .210312
    hhsizegen |   .1409588   .1820127     0.77   0.439    -.2157795    .4976971
      ferizaj |   .6829105   .6542256     1.04   0.297     -.599348    1.965169
      gjakova |  -.9671729   .9841802    -0.98   0.326    -2.896131    .9617849
      gjilani |   .2796782   .5672048     0.49   0.622    -.8320228    1.391379
    mitrovica |  -.2773383   .7611357    -0.36   0.716    -1.769137     1.21446
         peja |  -1.348642   .8456574    -1.59   0.111      -3.0061    .3088161
     prizreni |  -1.325335   .8412332    -1.58   0.115    -2.974122    .3234514
        _cons |  -8.592283   7.897945    -1.09   0.277    -24.07197    6.887404
--------------------------------------------------------------------------------



***Multinomial probit treatment model


.  teffects  ra  (empl1112  age  agesq  male  minority  socialassist  secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjako
>  va  gjilani  mitrovica  peja  prizreni,  logit)  (bintreatment)  if  insampm==1,  atet
vce(robust) aequ

Iteration 0:   EE criterion =  1.040e-22
Iteration 1:   EE criterion =  9.901e-33

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
-------------------------------------------------------------------------------
              |               Robust
     empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
 bintreatment |
   (1 vs 0)   |  -.0203787   .0199001    -1.02   0.306    -.0593821    .0186248
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
          0   |   .5091626   .0124222    40.99   0.000     .4848156    .5335096
--------------+----------------------------------------------------------------
OME0          |
          age |   .4218355   .0492325     8.57   0.000     .3253415    .5183294
        agesq |  -.0053135   .0008252    -6.44   0.000    -.0069308   -.0036962
         male |   .6953048   .1367735     5.08   0.000     .4272338    .9633759
     minority |   .0540327   .1106093     0.49   0.625    -.1627575    .2708229
 socialassist |  -1.669971   .2750154    -6.07   0.000    -2.208992   -1.130951
secondaryeduc |   .5943007   .0718422     8.27   0.000     .4534925    .7351089
 tertiaryeduc |   1.210722   .0947223    12.78   0.000      1.02507    1.396374
       hhsize |   .0101914   .0137174     0.74   0.458    -.0166942     .037077
    hhsizegen |  -.0013489   .0158066    -0.09   0.932    -.0323293    .0296315
      ferizaj |  -.0133214   .0899299    -0.15   0.882    -.1895809     .162938
      gjakova |  -.6499175   .0951831    -6.83   0.000     -.836473   -.4633621
      gjilani |   .0107498   .1186282     0.09   0.928    -.2217572    .2432569
    mitrovica |  -.3425645   .0927862    -3.69   0.000     -.524422    -.160707
         peja |  -1.431714   .0917698   -15.60   0.000     -1.61158   -1.251849
     prizreni |   .7294603   .0932899     7.82   0.000     .5466154    .9123052
        _cons |  -8.165179   .7301844   -11.18   0.000    -9.596314   -6.734044
-------------+----------------------------------------------------------------
```

```
OME1         |
         age |   .3305926   .2184138     1.51   0.130    -.0974905    .7586758
       agesq |  -.0048342   .0039498    -1.22   0.221    -.0125757    .0029072
        male |   .1709132   .3987284     0.43   0.668    -.6105802    .9524065
    minority |  -1.170302    .343686    -3.41   0.001    -1.843914     -.49669
 socialassist |  -.1999319   .2669771    -0.75   0.454    -.7231974    .3233337
secondaryeduc |   .2368948   .2084322     1.14   0.256    -.1716248    .6454144
 tertiaryeduc |   .5403934   .2165122     2.50   0.013     .1160373    .9647494
      hhsize |  -.0685269   .0468878    -1.46   0.144    -.1604252    .0233714
   hhsizegen |   .0855868   .0607878     1.41   0.159     -.033555    .2047286
     ferizaj |  -.1591271   .2777483    -0.57   0.567    -.7035036    .3852495
     gjakova |  -.1249758   .2782001    -0.45   0.653    -.6702379    .4202863
     gjilani |  -.4762569   .2481513    -1.92   0.055    -.9626246    .0101108
   mitrovica |  -.8189919   .2787783    -2.94   0.003    -1.365387   -.2725965
        peja |  -.2692949   .2831428    -0.95   0.342    -.8242445    .2856547
    prizreni |  -.1805978   .2740146    -0.66   0.510    -.7176566     .356461
       _cons |  -5.228399    3.00209    -1.74   0.082    -11.11239    .6555888
------------------------------------------------------------------------------
```

Table A6.4.4 IPWRA

```
*** Binary treatment model

. teffects ipwra (empl1112 age agesq male minority socialassist secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni, logit)
(bintreatment age agesq male minority socialassist secondaryeduc tertiaryeduc  hhsize
hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if insampm==1, atet
vce(robust) aequ

Iteration 0:   EE criterion =  5.414e-15
Iteration 1:   EE criterion =  2.721e-26

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |   .0055448   .0208449     0.27   0.790    -.0353105    .0464001
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
           0 |   .4832391   .0140324    34.44   0.000      .455736    .5107422
-------------+----------------------------------------------------------------
OME0         |
         age |   .1813934   .1368893     1.33   0.185    -.0869047    .4496914
       agesq |  -.0002334   .0025172    -0.09   0.926    -.0051669    .0047002
        male |   .5118456   .3101503     1.65   0.099    -.0960378    1.119729
    minority |  -.9294639   .2581721    -3.60   0.000    -1.435472    -.423456
 socialassist |  -2.858017   .5812323    -4.92   0.000    -3.997212   -1.718823
secondaryeduc |   .8383777   .1335969     6.28   0.000     .5765325    1.100223
```

```
 tertiaryeduc |   .9977612   .1523835     6.55   0.000      .699095    1.296428
       hhsize |  -.0190644      .0388    -0.49   0.623    -.095111    .0569823
    hhsizegen |   .0103909   .0424914     0.24   0.807    -.0728907    .0936724
      ferizaj |   -.058146   .1640144    -0.35   0.723    -.3796082    .2633162
      gjakova |  -.6045963   .1574492    -3.84   0.000    -.9131911   -.2960016
      gjilani |  -.0017457   .2110771    -0.01   0.993    -.4154491    .4119578
    mitrovica |  -.5568174   .1712103    -3.25   0.001    -.8923834   -.2212514
         peja |  -1.168458   .1773605    -6.59   0.000    -1.516079   -.8208382
     prizreni |   .8802752   .1631405     5.40   0.000     .5605258    1.200025
        _cons |  -5.223139    1.82486    -2.86   0.004    -8.799798   -1.646479
-------------+----------------------------------------------------------------
OME1         |
          age |   .3305926   .2184138     1.51   0.130    -.0974905    .7586758
        agesq |  -.0048342   .0039498    -1.22   0.221    -.0125757    .0029072
         male |   .1709132   .3987284     0.43   0.668    -.6105802    .9524065
     minority |  -1.170302    .343686    -3.41   0.001    -1.843914     -.49669
 socialassist |  -.1999319   .2669771    -0.75   0.454    -.7231974    .3233337
secondaryeduc |   .2368948   .2084322     1.14   0.256    -.1716248    .6454144
 tertiaryeduc |   .5403934   .2165122     2.50   0.013     .1160373    .9647494
       hhsize |  -.0685269   .0468878    -1.46   0.144    -.1604252    .0233714
    hhsizegen |   .0855868   .0607878     1.41   0.159     -.033555    .2047286
      ferizaj |  -.1591271   .2777483    -0.57   0.567    -.7035036    .3852495
      gjakova |  -.1249758   .2782001    -0.45   0.653    -.6702379    .4202863
      gjilani |  -.4762569   .2481513    -1.92   0.055    -.9626246    .0101108
    mitrovica |  -.8189919   .2787783    -2.94   0.003    -1.365387   -.2725965
         peja |  -.2692949   .2831428    -0.95   0.342    -.8242445    .2856547
     prizreni |  -.1805978   .2740146    -0.66   0.510    -.7176566     .356461
        _cons |  -5.228399    3.00209    -1.74   0.082    -11.11239    .6555888
-------------+----------------------------------------------------------------
TME1         |
          age |   1.489746   .1510649     9.86   0.000     1.193664    1.785828
        agesq |  -.0290606   .0028341   -10.25   0.000    -.0346153   -.0235059
         male |  -.9042557    .209688    -4.31   0.000    -1.315237   -.4932748
     minority |  -.0438336   .1833028    -0.24   0.811    -.4031005    .3154332
 socialassist |   3.109302   .2212496    14.05   0.000      2.67566    3.542943
secondaryeduc |  -.3147433    .118473    -2.66   0.008    -.5469462   -.0825404
 tertiaryeduc |   .8323472   .1235364     6.74   0.000     .5902204    1.074474
       hhsize |  -.1567485   .0230038    -6.81   0.000    -.2018351    -.111662
    hhsizegen |   .0265874   .0301634     0.88   0.378    -.0325317    .0857065
      ferizaj |   .8335969   .1508638     5.53   0.000     .5379093    1.129285
      gjakova |   .9042148   .1490287     6.07   0.000      .612124    1.196306
      gjilani |   1.832649   .1431117    12.81   0.000     1.552155    2.113142
    mitrovica |   1.113014    .158378     7.03   0.000     .8025985    1.423429
         peja |    .511612   .1512205     3.38   0.001     .2152254    .8079987
     prizreni |   .8182876   .1460099     5.60   0.000     .5321135    1.104462
        _cons |  -19.86672   1.987935    -9.99   0.000      -23.763   -15.97044
------------------------------------------------------------------------------



*** Multinomial probit model
```

```
. teffects ipwra (empl1112 age agesq male minority socialassist secondaryeduc
tertiaryeduc hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizreni, logit)
(multitreatment age agesq male minority socialassist secondaryeduc tertiaryeduc
hhsize hhsizegen ferizaj gjakova gjilani mitrovica peja prizren ) if insampm==1, atet
vce(robust) aequ

Iteration 0:   EE criterion =  5.169e-24
Iteration 1:   EE criterion =  1.178e-31

Treatment-effects estimation                    Number of obs     =      7,753
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      empl1112 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |   .0468789   .0259494     1.81   0.071     -.003981    .0977387
     (2 vs 0)  |  -.0096058   .0353888    -0.27   0.786    -.0789666     .059755
     (3 vs 0)  |  -.1318541   .0449612    -2.93   0.003    -.2199764   -.0437318
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .4892913   .0156023    31.36   0.000     .4587115    .5198712
---------------+----------------------------------------------------------------
OME0           |
           age |   .1747972   .1368043     1.28   0.201    -.0933344    .4429287
         agesq |  -.0001479   .0025245    -0.06   0.953    -.0050959       .0048
          male |   .5426173    .302843     1.79   0.073    -.0509441    1.136179
      minority |  -.8978346   .2619882    -3.43   0.001    -1.411322   -.3843472
  socialassist |  -2.981883     .58361    -5.11   0.000    -4.125738   -1.838029
 secondaryeduc |   .7528368   .1362856     5.52   0.000     .4857219    1.019952
  tertiaryeduc |   .9278286   .1564167     5.93   0.000     .6212576      1.2344
        hhsize |  -.0177029   .0357547    -0.50   0.621    -.0877809    .0523751
     hhsizegen |   .0044896   .0399185     0.11   0.910    -.0737492    .0827284
       ferizaj |  -.0408549   .1638213    -0.25   0.803    -.3619389     .280229
       gjakova |   -.597973   .1587051    -3.77   0.000    -.9090293   -.2869166
       gjilani |  -.0204982   .2129989    -0.10   0.923    -.4379684     .396972
     mitrovica |  -.5476132   .1708405    -3.21   0.001    -.8824545    -.212772
          peja |  -1.169302   .1802516    -6.49   0.000    -1.522588   -.8160152
      prizreni |   .8850417   .1640825     5.39   0.000     .5634459    1.206637
         _cons |  -5.049253    1.82372    -2.77   0.006    -8.623679   -1.474827
---------------+----------------------------------------------------------------
OME1           |
           age |   .6792348   .2967876     2.29   0.022     .0975419    1.260928
         agesq |  -.0112742   .0053536    -2.11   0.035     -.021767   -.0007814
          male |  -.1062614   .5455349    -0.19   0.846     -1.17549    .9629674
      minority |  -1.305959   .5432352    -2.40   0.016     -2.37068   -.2412374
  socialassist |   .2111297   .3870835     0.55   0.585    -.5475401    .9697994
 secondaryeduc |   .4389903   .2970251     1.48   0.139    -.1431682    1.021149
  tertiaryeduc |   .7105868   .3003635     2.37   0.018     .1218851    1.299288
```

hhsize	-.061795	.0588051	-1.05	0.293	-.1770509	.0534608
hhsizegen	.1136662	.0828352	1.37	0.170	-.0486879	.2760203
ferizaj	-.1672238	.395912	-0.42	0.673	-.943197	.6087494
gjakova	.1102961	.3884224	0.28	0.776	-.6509978	.87159
gjilani	-.6744633	.3593402	-1.88	0.061	-1.378757	.0298305
mitrovica	-.8125503	.3931781	-2.07	0.039	-1.583165	-.0419354
peja	.2596473	.4106387	0.63	0.527	-.5451899	1.064484
prizreni	.0589143	.3800356	0.16	0.877	-.6859418	.8037705
_cons	-9.923026	4.09973	-2.42	0.016	-17.95835	-1.887703
OME2						
age	-.2708713	.4760537	-0.57	0.569	-1.203919	.6621768
agesq	.005918	.0087167	0.68	0.497	-.0111664	.0230024
male	.2602801	.7468733	0.35	0.727	-1.203565	1.724125
minority	-.78222	.6193928	-1.26	0.207	-1.996208	.4317676
socialassist	-.8487386	.5067341	-1.67	0.094	-1.841919	.1444421
secondaryeduc	-.5799618	.430704	-1.35	0.178	-1.424126	.2642026
tertiaryeduc	-.2179208	.4386981	-0.50	0.619	-1.077753	.6419116
hhsize	-.1094553	.0958173	-1.14	0.253	-.2972539	.0783432
hhsizegen	.1062815	.1131365	0.94	0.348	-.115462	.328025
ferizaj	-.9485797	.6583913	-1.44	0.150	-2.239003	.3418435
gjakova	-1.100652	.6602612	-1.67	0.096	-2.39474	.1934359
gjilani	-.942762	.6254498	-1.51	0.132	-2.168621	.2830971
mitrovica	-1.528071	.6580075	-2.32	0.020	-2.817742	-.2384
peja	-1.62864	.6724134	-2.42	0.015	-2.946546	-.3107341
prizreni	-.9487918	.656736	-1.44	0.149	-2.235971	.3383871
_cons	4.490317	6.479971	0.69	0.488	-8.210193	17.19083
OME3						
age	.2609986	.4822458	0.54	0.588	-.6841859	1.206183
agesq	-.0014034	.0085829	-0.16	0.870	-.0182256	.0154188
male	.3095447	1.301042	0.24	0.812	-2.240451	2.859541
minority	-2.786682	1.423009	-1.96	0.050	-5.575729	.002365
socialassist	-1.271493	1.183893	-1.07	0.283	-3.591881	1.048895
secondaryeduc	.7815913	.6895376	1.13	0.257	-.5698776	2.13306
tertiaryeduc	1.112657	.7914902	1.41	0.160	-.4386352	2.66395
hhsize	-.1692422	.147936	-1.14	0.253	-.4591915	.120707
hhsizegen	.1432245	.1927477	0.74	0.457	-.234554	.5210031
ferizaj	1.16948	.698987	1.67	0.094	-.200509	2.53947
gjakova	-1.042794	1.000341	-1.04	0.297	-3.003426	.9178394
gjilani	.0934563	.6177404	0.15	0.880	-1.117293	1.304205
mitrovica	-.1266804	.7783693	-0.16	0.871	-1.652256	1.398895
peja	-1.422819	.9443763	-1.51	0.132	-3.273762	.4281244
prizreni	-1.025527	.9272289	-1.11	0.269	-2.842862	.7918083
_cons	-6.462511	6.855552	-0.94	0.346	-19.89915	6.974123
TME1						
age	1.452835	.1796828	8.09	0.000	1.100663	1.805007
agesq	-.0285565	.0033743	-8.46	0.000	-.03517	-.021943
male	-.6717092	.2580573	-2.60	0.009	-1.177492	-.1659261
minority	-.1324891	.231146	-0.57	0.567	-.5855269	.3205486
socialassist	3.067042	.2537005	12.09	0.000	2.569798	3.564286
secondaryeduc	-.3466381	.1509441	-2.30	0.022	-.6424831	-.0507931

tertiaryeduc	.8748281	.1537469	5.69	0.000	.5734897	1.176166
hhsize	-.1274079	.0279889	-4.55	0.000	-.1822651	-.0725507
hhsizegen	-.0067229	.0368747	-0.18	0.855	-.078996	.0655502
ferizaj	.8270523	.1986786	4.16	0.000	.4376494	1.216455
gjakova	1.108157	.191103	5.80	0.000	.7336015	1.482712
gjilani	1.934041	.184201	10.50	0.000	1.573013	2.295068
mitrovica	1.243574	.2015755	6.17	0.000	.8484936	1.638655
peja	.5639601	.2007041	2.81	0.005	.1705872	.957333
prizreni	1.069853	.1865271	5.74	0.000	.7042669	1.43544
_cons	-20.13843	2.367687	-8.51	0.000	-24.77901	-15.49785
TME2						
age	1.360546	.2673669	5.09	0.000	.8365163	1.884575
agesq	-.0264873	.0050132	-5.28	0.000	-.0363131	-.0166615
male	-.8044124	.369694	-2.18	0.030	-1.528999	-.0798254
minority	.0870677	.2874638	0.30	0.762	-.476351	.6504864
socialassist	3.380726	.2945283	11.48	0.000	2.803462	3.957991
secondaryeduc	-.0570558	.2159371	-0.26	0.792	-.4802847	.3661731
tertiaryeduc	1.108868	.2257367	4.91	0.000	.6664318	1.551303
hhsize	-.1674929	.0365388	-4.58	0.000	-.2391076	-.0958782
hhsizegen	.0219234	.0553486	0.40	0.692	-.0865579	.1304047
ferizaj	1.565415	.2914305	5.37	0.000	.9942216	2.136608
gjakova	1.608339	.2940545	5.47	0.000	1.032002	2.184675
gjilani	2.324789	.2845205	8.17	0.000	1.767139	2.882439
mitrovica	1.920447	.2892411	6.64	0.000	1.353545	2.487349
peja	1.408167	.2860544	4.92	0.000	.8475103	1.968823
prizreni	1.137828	.3102009	3.67	0.000	.5298456	1.745811
_cons	-20.35176	3.514834	-5.79	0.000	-27.2407	-13.46281
TME3						
age	1.914787	.3967772	4.83	0.000	1.137118	2.692456
agesq	-.0366737	.007375	-4.97	0.000	-.0511284	-.0222189
male	-1.91522	.4409584	-4.34	0.000	-2.779483	-1.050958
minority	.0075032	.3308248	0.02	0.982	-.6409015	.655908
socialassist	2.702783	.3957607	6.83	0.000	1.927106	3.478459
secondaryeduc	-.6107306	.2664775	-2.29	0.022	-1.133017	-.0884443
tertiaryeduc	.240355	.2659369	0.90	0.366	-.2808719	.7615818
hhsize	-.2508386	.0533032	-4.71	0.000	-.355311	-.1463662
hhsizegen	.1607539	.066522	2.42	0.016	.0303731	.2911347
ferizaj	.1565877	.2890636	0.54	0.588	-.4099665	.7231419
gjakova	-.7563943	.4065169	-1.86	0.063	-1.553153	.0403642
gjilani	1.227501	.2417102	5.08	0.000	.7537573	1.701244
mitrovica	-.4284341	.3908317	-1.10	0.273	-1.19445	.3375821
peja	-.8302177	.3820004	-2.17	0.030	-1.578925	-.0815106
prizreni	-.086036	.3056564	-0.28	0.778	-.6851115	.5130396
_cons	-25.72966	5.288687	-4.87	0.000	-36.0953	-15.36402

Table 6.5 Outcome variable: *contract* – Model 1

Table A6.5.1 Balancing diagnostics for full model specification

```
. *** Multinomial probit treatment model

.
.  teffects  ipw  (contract)  (multitreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc emp2011 emphist hhsize hhsizegen ferizaj gjakova gjilani
mitrovica peja prizren), atet vce(robust) aequ

*** Balancing diagnostics

. tebalance sum

  Covariate balance summary
                                                Observations
                           Treatment              Raw      Weighted
                      -----------------------------------------
                      0bn.multitr~t =        3,030        981.3
                      1.multitrea~t =          192        805.6
                      2.multitrea~t =           85        817.8
                      3.multitrea~t =           41        743.3
                      Total         =        3,348      3,348.0
                      -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw     Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.8541074     .1985329      .3211038   1.011826
            agesq |  -.9042022     .1939183      .2602484   1.048803
             male |  -.3350564    -.0321589      1.300651     1.0144
         minority |  -.1939599     .0499512      .4096266   1.385678
     socialassist |    .318195    -.1924937      16.49953   .5499166
    secondaryeduc |  -.5828769     .1492713      .9783695   1.127637
     tertiaryeduc |   .6902729     .2977356      1.390499    1.02651
          emp2011 |  -1.061003     .2780044      17.92027   .9553397
          emphist |  -.6408278     .0459344       14.8085   .9359292
           hhsize |  -.4313253    -.0517238       .340526   1.521414
        hhsizegen |  -.4544393      -.05962      .5452324   1.091934
          ferizaj |  -.1755376     .1360573      .6441975   1.623591
          gjakova |   .2596445     .2515405      1.742028   1.694551
          gjilani |    .242738     .1137196      1.942823   1.303381
        mitrovica |  -.0767595     .1176713       .804163   1.533829
             peja |   .2896076    -.4374641      2.148954   .5867448
         prizreni |  -.0659324     .1643801      .9052136    1.39153
  ----------------+------------------------------------------------
  2.multitreatm~t |
              age |  -.8206716      .234506      .3880385   .9673091
            agesq |  -.8688701     .2284668      .3077882   .9740608
```

```
            male |  -.2089692    .0464143      1.225166    .976314
        minority |  -.0322535    .0244565       .900063   1.181404
    socialassist |   .4291552   -.1728828      26.21908   .5925965
  secondaryeduc |  -.5729057    .0867995      .9900074   1.079246
    tertiaryeduc |   .5118697     .379239      1.410183   1.003156
         emp2011 |  -.9178498    .2532006      16.74044   .9652274
         emphist |   -.504344       .0114      11.38537    .984434
          hhsize |  -.4823514   -.0935517      .3923256    1.81289
       hhsizegen |  -.3935506   -.0173187      .5850512   1.200256
         ferizaj |  -.0259818    .1704414      .9564168     1.7973
         gjakova |   .1679657    .3082595      1.491215   1.846884
         gjilani |   .4536141    .0773054      2.808791   1.205164
       mitrovica |   .0920838    .0987764      1.266311    1.44252
            peja |    .213936   -.4999056      1.848637    .518054
        prizreni |   -.349434    .2287288       .472546    1.54132
-----------------+------------------------------------------------
 3.multitreatm~t |
             age |  -.7769607    .5690412      .2918462    1.83106
           agesq |  -.8300852    .5606674       .261426   2.417672
            male |  -.5140741    .1470868       1.37947   .9117922
        minority |  -.2031288    -.069451      .3918567    .559816
    socialassist |  -.0813654   -.4980214             0          0
   secondaryeduc |  -.4888091    .3427804      1.044886   1.224401
    tertiaryeduc |   .4948223    .2058703      1.425718   1.037678
         emp2011 |  -.4369979     .196124      8.219791   .9839879
         emphist |  -.1018025    .4338279      2.263379   .3751892
          hhsize |  -.6049662   -.0900813      .2959158   .9724069
       hhsizegen |  -.6203855    .0872319      .5012403   .9334936
         ferizaj |   .0229168    .0493114      1.074228   1.213258
         gjakova |  -.1866564    .0880038        .54102   1.240396
         gjilani |   .5543133    .2320697       3.21803   1.622259
       mitrovica |  -.3161127    -.154569      .2709133   .4377105
            peja |  -.2006215   -.5278004      .3954956   .4874217
        prizreni |  -.3816488    .5462008       .429547   2.145062
------------------------------------------------------------------
```

Table A6.5.2 PSM

```
. ***Binary treatment model

.
. teffects psmatch (contract) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp),  nneighbor(1) atet
vce(robust)

Treatment-effects estimation                   Number of obs      =      4,023
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =          8
------------------------------------------------------------------------------
             |              AI Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
ATET          |
bintreatment |
   (1 vs 0)  |  -.0813941   .0337876    -2.41   0.016    -.1476166   -.0151717
------------------------------------------------------------------------------

. *** Balancing diagnostics

. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                               Raw      Matched
                          -----------------------------------------
                          Number of obs =        4,023          636
                          Treated obs   =          318          318
                          Control obs   =        3,705          318
                          -----------------------------------------

  -----------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |         Raw     Matched           Raw    Matched
  ----------------+------------------------------------------------
              age |  -.6687634    .0689689      .3058151   .9148338
            agesq |  -.7321206    .0616005      .2567381    .910696
             male |  -.3082088    .0319953      1.268022   .9875495
         minority |  -.1413025   -.0779213       .548575   .6988825
     socialassist |   .3160415    .0271762      12.33553   1.110221
    secondaryeduc |  -.5695604    .0462669      .9849315   1.030838
     tertiaryeduc |   .6534658    .0376899      1.464296    .998576
          emp2011 |  -.3353843    .0656348      1.442703   .9610169
           hhsize |  -.4669681    .0400817      .3434917   1.412011
        hhsizegen |   -.445257    .0699095      .5424293    1.19541
          regunmp |   .2064665   -.0534836      1.718873   1.029532
  -----------------------------------------------------------------

.
```

Table A6.5.3 IPW

```
. ***Binary treatment model

.
.  teffects  ipw  (contract)  (bintreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp), atet vce(robust) aequ

Iteration 0:   EE criterion =  1.495e-24
Iteration 1:   EE criterion =  6.230e-32

Treatment-effects estimation                    Number of obs     =      4,023
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
-------------------------------------------------------------------------------
             |               Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+-----------------------------------------------------------------
ATET         |
 bintreatment |
    (1 vs 0)  |  -.0531552   .0295037    -1.80   0.072    -.1109814    .0046711
-------------+-----------------------------------------------------------------
POmean       |
 bintreatment |
```

```
           0  |   .7795703   .0206726    37.71   0.000     .7390528    .8200877
--------------+----------------------------------------------------------------
TME1          |
          age |   1.787138   .2308881     7.74   0.000     1.334606    2.239671
        agesq |  -.0343107   .0042514    -8.07   0.000    -.0426433   -.0259781
         male |   -.989517   .3603567    -2.75   0.006    -1.695803   -.2832309
     minority |   -.413426   .3689081    -1.12   0.262    -1.136473    .3096206
  socialassist |   3.544421   .4672553     7.59   0.000     2.628618    4.460225
secondaryeduc |  -.5413661   .2171526    -2.49   0.013    -.9669775   -.1157547
 tertiaryeduc |   .5932904   .2221933     2.67   0.008     .1577995    1.028781
      emp2011 |  -.5266228    .146149    -3.60   0.000    -.8130696   -.2401759
       hhsize |  -.2203855   .0473569    -4.65   0.000    -.3132033   -.1275677
    hhsizegen |   .1038605   .0554772     1.87   0.061    -.0048728    .2125937
      regunmp |    .015951   .0067856     2.35   0.019     .0026514    .0292507
        _cons |  -23.34299   3.071429    -7.60   0.000    -29.36288    -17.3231
-------------------------------------------------------------------------------

.
.
.
. ***Balancing diagnostics

.
. tebalance sum

  Covariate balance summary
                                                   Raw     Weighted
                          ----------------------------------------
                          Number of obs =        4,023      4,023.0
                          Treated obs   =          318      2,031.7
                          Control obs   =        3,705      1,991.3
                          ----------------------------------------

  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |        Raw    Weighted           Raw   Weighted
  ----------------+------------------------------------------------
              age |  -.6687634   -.0101709      .3058151   .9922146
            agesq |  -.7321206   -.0104416      .2567381   1.008397
             male |  -.3082088   -.0566228      1.268022   1.027775
         minority |  -.1413025    .0105815       .548575   1.056288
     socialassist |   .3160415      .01832      12.33553   1.072081
    secondaryeduc |  -.5695604    .0033879      .9849315   1.002053
     tertiaryeduc |   .6534658    .0655545      1.464296   .9993383
          emp2011 |  -.3353843     .026965      1.442703   .9826809
           hhsize |  -.4669681   -.0266543      .3434917   1.151019
        hhsizegen |   -.445257   -.0498187      .5424293   1.051337
          regunmp |   .2064665    .0377149      1.718873   1.232486
  -----------------------------------------------------------------

.
.
.
. *** Multinomial probit treatment model

.
.  teffects  ipw  (contract)  (multitreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp), atet vce(robust) aequ

Iteration 0:   EE criterion =  7.102e-13
Iteration 1:   EE criterion =  1.004e-17
```

```
convergence not achieved
    The  Gauss-Newton  stopping  criterion  has  been  met  but  missing  standard  errors
indicate some of the parameters are
    not identified.

Treatment-effects estimation                    Number of obs     =      4,023
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
               |               Robust
      contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.0889677   .0358217    -2.48   0.013     -.159177   -.0187584
     (2 vs 0)  |   .0367267   .0420389     0.87   0.382     -.045668    .1191214
     (3 vs 0)  |  -.0442655   .1281331    -0.35   0.730    -.2954018    .2068709
---------------+--------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .7868844   .0229639    34.27   0.000      .741876    .8318927
---------------+--------------------------------------------------------------
TME1           |
           age |    1.83568   .2897825     6.33   0.000     1.267717    2.403644
         agesq |  -.0352208   .0053346    -6.60   0.000    -.0456764   -.0247653
          male |  -.7631337   .4220943    -1.81   0.071    -1.590423    .0641558
      minority |  -.6129588   .5288955    -1.16   0.246    -1.649575    .4236573
   socialassist |    3.53812   .4913523     7.20   0.000     2.575087    4.501153
  secondaryeduc |  -.2788955   .2901324    -0.96   0.336    -.8475447    .2897536
   tertiaryeduc |   .9085453   .2890925     3.14   0.002     .3419345    1.475156
       emp2011 |  -.7336788   .1753622    -4.18   0.000    -1.077382   -.3899752
        hhsize |   -.173284   .0548441    -3.16   0.002    -.2807764   -.0657916
     hhsizegen |   .0711857   .0638124     1.12   0.265    -.0538844    .1962558
       regunmp |   .0251459    .007902     3.18   0.001     .0096582    .0406337
         _cons |  -25.20534   3.881139    -6.49   0.000    -32.81223   -17.59844
---------------+--------------------------------------------------------------
TME2           |
           age |   1.507212   .3312607     4.55   0.000     .8579531    2.156471
         agesq |   -.029378   .0060251    -4.88   0.000    -.0411869    -.017569
          male |  -.8360754   .6654798    -1.26   0.209    -2.140392    .4682411
      minority |   .0408404   .4922064     0.08   0.934    -.9238664    1.005547
   socialassist |   3.925611   .5632369     6.97   0.000     2.821687    5.029535
  secondaryeduc |  -.7885371   .3534703    -2.23   0.026    -1.481326   -.0957481
   tertiaryeduc |   .3625745   .3605925     1.01   0.315    -.3441738    1.069323
       emp2011 |  -.4472538   .2575516    -1.74   0.082    -.9520457     .057538
        hhsize |  -.2509303   .0838872    -2.99   0.003    -.4153462   -.0865144
     hhsizegen |   .1175312   .1045144     1.12   0.261    -.0873132    .3223757
       regunmp |   .0164741   .0123149     1.34   0.181    -.0076626    .0406107
         _cons |  -20.64357    4.42078    -4.67   0.000    -29.30814     -11.979
---------------+--------------------------------------------------------------
TME3           |
           age |   2.302579   .9654508     2.38   0.017     .4103298    4.194827
         agesq |  -.0431406   .0180003    -2.40   0.017    -.0784205   -.0078607
          male |  -2.026273   .9184989    -2.21   0.027    -3.826498   -.2260485
      minority |  -.7855342   1.000049    -0.79   0.432    -2.745595    1.174526
   socialassist |  -12.59514   .5067366   -24.86   0.000    -13.58833   -11.60195
  secondaryeduc |   -.902355   .5215018    -1.73   0.084     -1.92448    .1197698
   tertiaryeduc |  -.0747231   .5343684    -0.14   0.889    -1.122066    .9726196
       emp2011 |   .5515534   .5077857     1.09   0.277    -.4436883    1.546795
        hhsize |  -.3513137   .1202542    -2.92   0.003    -.5870075   -.1156199
```

```
     hhsizegen |   .2030183   .1510145     1.34   0.179    -.0929646    .4990012
       regunmp |  -.0483703    .026105    -1.85   0.064    -.0995351    .0027946
         _cons |  -30.23574   13.01587    -2.32   0.020    -55.74638   -4.725104
--------------------------------------------------------------------------------
Warning: convergence not achieved

.
.
. *** Balancing diagnostics

.
. tebalance sum

  Covariate balance summary
                                                     Observations
                             Treatment           Raw     Weighted
                        -----------------------------------------
                        0bn.multitr~t =        3,705        998.1
                        1.multitrea~t =          192      1,029.7
                        2.multitrea~t =           85      1,038.9
                        3.multitrea~t =           41        956.4
                        Total         =        4,023      4,023.0
                        -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
                  |         Raw     Weighted           Raw   Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.6857613    .0009526       .294323   .9883095
            agesq |  -.7495821    .0002474      .2458971    1.00425
             male |  -.3180552   -.0536444      1.275838   1.024964
         minority |  -.1887856   -.0043507      .4175114   .9745746
      socialassist |   .3072133    .0402706      11.88382   1.175286
     secondaryeduc |  -.5837315   -.0050938      .9788369   .9967731
      tertiaryeduc |   .7274203    .0691563      1.453482   .9903449
          emp2011 |  -.4439931    .0042727      1.534379   .9980736
           hhsize |  -.4313584   -.0269137      .3356183    1.03329
        hhsizegen |  -.4406238   -.0471646       .537843   .9962539
          regunmp |   .3088582    .0468255      1.875375   1.192052
  ----------------+------------------------------------------------
  2.multitreatm~t |
              age |  -.6578699    .0261223      .3556752   1.057265
            agesq |  -.7180838    .0291261      .2908153   1.050132
             male |  -.1922079   -.0702873      1.201792   1.031568
         minority |  -.0268375   -.0304171      .9173881   .8283963
      socialassist |    .420082    .0276942      18.88434    1.11935
     secondaryeduc |  -.5737564   -.0555737      .9904803   .9626369
      tertiaryeduc |   .5472105    .1190416      1.474056   .9775959
          emp2011 |  -.3125861   -.0515535      1.433359   1.020049
           hhsize |  -.4821607    .0066335      .3866713   1.428475
        hhsizegen |  -.3801953   -.0347226      .5771221   1.277959
          regunmp |    .189243    .0635752      1.725023   1.151698
  ----------------+------------------------------------------------
  3.multitreatm~t |
              age |  -.6091167    .1958112      .2675056   1.377136
            agesq |  -.6772006    .2010263      .2470098   1.732563
             male |  -.4966504    .1967056      1.353153    .865665
         minority |  -.1979924   -.1732274      .3993995   .1957617
      socialassist |  -.0960031   -.3183801             0          0
     secondaryeduc |  -.4896376   -.0778948      1.045385   .9462672
```

```
     tertiaryeduc |   .5298783    .2181423       1.490295   .9387354
          emp2011 |   .1956196    .2140998       .7037994   .8663008
           hhsize |  -.6039881   -.1060098        .291651   .6602269
        hhsizegen |  -.6055871    .0877931        .494447   .7545209
          regunmp |  -.3595329   -.0348564       .6350091   1.110573
  ------------------------------------------------------------------

.
```

Table A6.5.4 RA

```
***Binary treatment model


. teffects ra (contract age agesq male minority secondaryeduc tertiaryeduc emp2011
hhsize hhsizegen regunmp, logit) (bintreatment), atet vce(robust) aequ

Iteration 0:   EE criterion =  2.394e-23
Iteration 1:   EE criterion =  8.661e-34

Treatment-effects estimation                   Number of obs     =      4,023
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
------------------------------------------------------------------------------
             |               Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |  -.1036555   .0255562    -4.06   0.000    -.1537448   -.0535663
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .8300706    .012748    65.11   0.000     .8050849    .8550563
-------------+----------------------------------------------------------------
OME0         |
         age |   -.019906   .0825943    -0.24   0.810     -.181788    .1419759
       agesq |   .0009741   .0014081     0.69   0.489    -.0017856    .0037339
        male |  -1.397117   .2572819    -5.43   0.000     -1.90138   -.8928536
    minority |   .4338751   .2101851     2.06   0.039     .0219199    .8458303
secondaryeduc |   .9506443   .1091263     8.71   0.000     .7367607    1.164528
 tertiaryeduc |   3.008406   .2328904    12.92   0.000      2.55195    3.464863
     emp2011 |   1.617769   .1039142    15.57   0.000     1.414101    1.821437
      hhsize |  -.0529813   .0248429    -2.13   0.033    -.1016725     -.00429
   hhsizegen |   .0464073    .027145     1.71   0.087    -.0067959    .0996105
     regunmp |  -.0129036   .0048244    -2.67   0.007    -.0223592    -.003448
       _cons |   .4794648   1.189622     0.40   0.687    -1.852151     2.81108
-------------+----------------------------------------------------------------
OME1         |
         age |  -.3100284    .478725    -0.65   0.517    -1.248312    .6282553
       agesq |   .0049427   .0086465     0.57   0.568    -.0120042    .0218897
        male |  -1.512794   .8843458    -1.71   0.087    -3.246079    .2204922
    minority |   .1456986   .6401009     0.23   0.820    -1.108876    1.400273
secondaryeduc |  -.2178101   .3739005    -0.58   0.560    -.9506417    .5150215
 tertiaryeduc |   1.991002   .4548181     4.38   0.000     1.099575    2.882429
     emp2011 |  -.2222226   .3391423    -0.66   0.512    -.8869293     .442484
      hhsize |  -.1741016   .1189143    -1.46   0.143    -.4071694    .0589662
   hhsizegen |   .1428746   .1328593     1.08   0.282    -.1175249    .4032742
     regunmp |   .0385752   .0153333     2.52   0.012     .0085224    .0686279
```

```
       _cons |   5.498698   6.755251     0.81   0.416    -7.741351    18.73875
------------------------------------------------------------------------------


.
.
.
. ***Multinomial probit treatment model

.
.
. teffects ra (contract age agesq male minority secondaryeduc tertiaryeduc emp2011
hhsize hhsizegen regunmp, logit) (m
> ultitreatment), atet vce(robust) aequ

Iteration 0:   EE criterion =  8.985e-08
Iteration 1:   EE criterion =  1.571e-09

Treatment-effects estimation                   Number of obs     =      4,023
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
-------------------------------------------------------------------------------
              |               Robust
     contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
multitreatment |
     (1 vs 0)  |   -.134498   .0332475    -4.05   0.000    -.1996618   -.0693342
     (2 vs 0)  |  -.0247958   .0448081    -0.55   0.580    -.1126181    .0630265
     (3 vs 0)  |  -.1135615   .0840305    -1.35   0.177    -.2782584    .0511353
--------------+----------------------------------------------------------------
POmean        |
multitreatment |
            0  |   .8324147   .0153225    54.33   0.000     .8023831    .8624462
--------------+----------------------------------------------------------------
OME0          |
          age |   -.019906   .0825943    -0.24   0.810     -.181788    .1419759
        agesq |   .0009741   .0014081     0.69   0.489    -.0017856    .0037339
         male |  -1.397117   .2572819    -5.43   0.000     -1.90138   -.8928536
     minority |   .4338751   .2101851     2.06   0.039     .0219199    .8458303
 secondaryeduc |   .9506443   .1091263     8.71   0.000     .7367607    1.164528
  tertiaryeduc |   3.008406   .2328904    12.92   0.000      2.55195    3.464863
      emp2011 |   1.617769   .1039142    15.57   0.000     1.414101    1.821437
       hhsize |  -.0529813   .0248429    -2.13   0.033    -.1016725    -.00429
    hhsizegen |   .0464073    .027145     1.71   0.087    -.0067959    .0996105
      regunmp |  -.0129036   .0048244    -2.67   0.007    -.0223592   -.003448
        _cons |   .4794648   1.189622     0.40   0.687    -1.852151     2.81108
--------------+----------------------------------------------------------------
OME1          |
          age |  -.8460147   .9887881    -0.86   0.392    -2.784004    1.091974
        agesq |   .0160004   .0182369     0.88   0.380    -.0197432     .051744
         male |  -1.063684   1.230949    -0.86   0.388      -3.4763    1.348933
     minority |   .0393711   1.344069     0.03   0.977    -2.594956    2.673698
 secondaryeduc |  -.0885031   .5206252    -0.17   0.865     -1.10891    .9319035
  tertiaryeduc |   2.255794   .6350693     3.55   0.000     1.011081    3.500507
      emp2011 |  -.2505181   .4336732    -0.58   0.563    -1.100502    .5994658
       hhsize |  -.0587541   .1454687    -0.40   0.686    -.3438676    .2263593
    hhsizegen |   .0715809   .1724455     0.42   0.678    -.2664061     .409568
      regunmp |   .0663749   .0202058     3.28   0.001     .0267723    .1059774
        _cons |   9.852523    13.3482     0.74   0.460    -16.30948    36.01452
--------------+----------------------------------------------------------------
```

```
OME2         |
         age |  -.3017703    1.00923    -0.30   0.765    -2.279825    1.676284
       agesq |   .0018968   .0185297     0.10   0.918    -.0344208    .0382144
        male |   -.965941   1.558284    -0.62   0.535    -4.020122     2.08824
    minority |  -.2374131   .9844084    -0.24   0.809    -2.166818    1.691992
secondaryeduc |  -1.163633   .7580274   -1.54   0.125    -2.649339    .3220736
 tertiaryeduc |   1.672863   .9902008    1.69   0.091    -.2678953     3.61362
     emp2011 |  -.5460076    .732963    -0.74   0.456    -1.982589    .8905736
      hhsize |  -.0100316   .2159048    -0.05   0.963    -.4331972    .4131341
   hhsizegen |  -.0230368   .2551221    -0.09   0.928    -.5230671    .4769934
     regunmp |  -.0187081   .0307634    -0.61   0.543    -.0790032     .041587
       _cons |   9.970235   13.84832     0.72   0.472    -17.17197    37.11244
-------------+----------------------------------------------------------------
OME3         |
         age |   .2384848   1.159651     0.21   0.837     -2.03439    2.511359
       agesq |  -.0066156   .0191827    -0.34   0.730     -.044213    .0309819
        male |  -2.786613   3.645735    -0.76   0.445    -9.932121    4.358896
    minority |   1.251966   2.320986     0.54   0.590    -3.297082    5.801014
secondaryeduc |   .5300096   1.164119     0.46   0.649    -1.751621     2.81164
 tertiaryeduc |   2.548267   1.367172     1.86   0.062    -.1313407    5.227875
     emp2011 |   .1117718   1.209827     0.09   0.926    -2.259445    2.482989
      hhsize |  -.4779169   .5049383    -0.95   0.344    -1.467578     .511744
   hhsizegen |   .4880868   .6084775     0.80   0.422    -.7045071    1.680681
     regunmp |  -.0261873   .0512062    -0.51   0.609    -.1265495     .074175
       _cons |   1.586871   18.43861     0.09   0.931    -34.55214    37.72588
------------------------------------------------------------------------------
```

Table A6.5.5 IPWRA

```
. *** Binary treatment model

.
. teffects ipwra (contract age agesq male minority secondaryeduc tertiaryeduc emp2011
hhsize hhsizegen regunmp, logit)  (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp), atet vce(robust) aequ

Iteration 0:   EE criterion =  1.945e-23
Iteration 1:   EE criterion =  6.302e-32

Treatment-effects estimation                   Number of obs     =      4,023
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |  -.0917676   .0257825    -3.56   0.000    -.1423004   -.0412347
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .8181827   .0138309    59.16   0.000     .7910747    .8452906
-------------+----------------------------------------------------------------
OME0         |
```

```
          age |  -.3948837   .1830529    -2.16   0.031    -.7536608   -.0361066
        agesq |   .0075974    .003376     2.25   0.024     .0009805    .0142143
         male |  -1.173328   .6182617    -1.90   0.058    -2.385098    .0384429
     minority |   1.045111   .4014246     2.60   0.009     .2583332    1.831889
secondaryeduc |   1.298832    .178498     7.28   0.000     .9489823    1.648682
 tertiaryeduc |   3.475867   .3279171    10.60   0.000     2.833161    4.118573
      emp2011 |   1.571532   .1725883     9.11   0.000     1.233266    1.909799
       hhsize |  -.0098002    .080823    -0.12   0.903    -.1682104      .14861
    hhsizegen |   -.000643    .083786    -0.01   0.994    -.1648606    .1635745
      regunmp |  -.0131503   .0083096    -1.58   0.114    -.0294368    .0031362
        _cons |   5.072553   2.421922     2.09   0.036     .3256719    9.819433
--------------+----------------------------------------------------------------
OME1          |
          age |  -.3100284    .478725    -0.65   0.517    -1.248312    .6282553
        agesq |   .0049427   .0086465     0.57   0.568    -.0120042    .0218897
         male |  -1.512794   .8843458    -1.71   0.087    -3.246079    .2204922
     minority |   .1456986   .6401009     0.23   0.820    -1.108876    1.400273
secondaryeduc |  -.2178101   .3739005    -0.58   0.560    -.9506417    .5150215
 tertiaryeduc |   1.991002   .4548181     4.38   0.000     1.099575    2.882429
      emp2011 |  -.2222226   .3391423    -0.66   0.512    -.8869293     .442484
       hhsize |  -.1741016   .1189143    -1.46   0.143    -.4071694    .0589662
    hhsizegen |   .1428746   .1328593     1.08   0.282    -.1175249    .4032742
      regunmp |   .0385752   .0153333     2.52   0.012     .0085224    .0686279
        _cons |   5.498698   6.755251     0.81   0.416    -7.741351    18.73875
--------------+----------------------------------------------------------------
TME1          |
          age |   1.787138   .2308881     7.74   0.000     1.334606    2.239671
        agesq |  -.0343107   .0042514    -8.07   0.000    -.0426433   -.0259781
         male |   -.989517   .3603567    -2.75   0.006    -1.695803   -.2832309
     minority |   -.413426   .3689081    -1.12   0.262    -1.136473    .3096206
 socialassist |   3.544421   .4672553     7.59   0.000     2.628618    4.460225
secondaryeduc |  -.5413661   .2171526    -2.49   0.013    -.9669775   -.1157547
 tertiaryeduc |   .5932904   .2221933     2.67   0.008     .1577995    1.028781
      emp2011 |  -.5266228    .146149    -3.60   0.000    -.8130696   -.2401759
       hhsize |  -.2203855   .0473569    -4.65   0.000    -.3132033   -.1275677
    hhsizegen |   .1038605   .0554772     1.87   0.061    -.0048728    .2125937
      regunmp |    .015951   .0067856     2.35   0.019     .0026514    .0292507
        _cons |  -23.34299   3.071429    -7.60   0.000    -29.36288    -17.3231
-------------------------------------------------------------------------------

. ***Multinomial probit treatment model

. teffects ipwra (contract age agesq male minority secondaryeduc tertiaryeduc emp2011
hhsize hhsizegen regunmp, logit) (multitreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp), atet vce(robust) aequ

Iteration 0:   EE criterion =  1.773e-07
Iteration 1:   EE criterion =  4.322e-09
Iteration 2:   EE criterion =  1.790e-09  (not concave)
Iteration 3:   EE criterion =  4.122e-10  (not concave)
Iteration 4:   EE criterion =  3.292e-10
convergence not achieved
```

```
    The  Gauss-Newton  stopping  criterion  has  been  met  but  missing  standard  errors
indicate some of the parameters are
    not identified.

Treatment-effects estimation                    Number of obs     =      4,023
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
------------------------------------------------------------------------------
               |               Robust
      contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.1254563   .0329997    -3.80   0.000    -.1901344   -.0607781
     (2 vs 0)  |  -.0097316    .042872    -0.23   0.820    -.0937592     .074296
     (3 vs 0)  |  -.0586955   .0555669    -1.06   0.291    -.1676046    .0502136
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
            0  |   .8233547   .0164465    50.06   0.000       .79112    .8555893
---------------+----------------------------------------------------------------
OME0           |
           age |  -.3845057   .1909874    -2.01   0.044     -.758834   -.0101773
         agesq |   .0075053   .0035191     2.13   0.033      .000608    .0144026
          male |   -1.21692   .5895516    -2.06   0.039     -2.37242   -.0614204
      minority |   1.130275   .4071697     2.78   0.006     .3322369    1.928313
 secondaryeduc |   1.312264   .2025688     6.48   0.000     .9152367    1.709292
  tertiaryeduc |   3.592639   .3526157    10.19   0.000     2.901525    4.283753
       emp2011 |   1.514393   .1788322     8.47   0.000     1.163888    1.864898
        hhsize |  -.0146814   .0744079    -0.20   0.844    -.1605183    .1311555
     hhsizegen |   .0001983   .0774412     0.00   0.998    -.1515836    .1519802
       regunmp |  -.0123379    .009066    -1.36   0.174     -.030107    .0054312
         _cons |    4.89783    2.54936     1.92   0.055    -.0988233    9.894484
---------------+----------------------------------------------------------------
OME1           |
           age |  -.8460147   .9887859    -0.86   0.392    -2.783999     1.09197
         agesq |   .0160004   .0182368     0.88   0.380    -.0197431    .0517439
          male |  -1.063684   1.230948    -0.86   0.388    -3.476298     1.34893
      minority |   .0393694   1.344071     0.03   0.977    -2.594961      2.6737
 secondaryeduc |   -.088504   .5206255    -0.17   0.865    -1.108911    .9319032
  tertiaryeduc |   2.255794   .6350687     3.55   0.000     1.011082    3.500506
       emp2011 |  -.2505188   .4336729    -0.58   0.563    -1.100502    .5994644
        hhsize |  -.0587542   .1454687    -0.40   0.686    -.3438676    .2263591
     hhsizegen |   .0715808   .1724454     0.42   0.678     -.266406    .4095677
       regunmp |   .0663748   .0202057     3.28   0.001     .0267723    .1059774
         _cons |   9.852523   13.34818     0.74   0.460    -16.30943    36.01447
---------------+----------------------------------------------------------------
OME2           |
           age |    .038327   .9934928     0.04   0.969    -1.908883    1.985537
         agesq |  -.0036796   .0182128    -0.20   0.840     -.039376    .0320168
          male |  -.5615904   1.383975    -0.41   0.685    -3.274132    2.150951
      minority |   .0786396   .9613683     0.08   0.935    -1.805608    1.962887
```

secondaryeduc	-.9512698	.8003593	-1.19	0.235	-2.519945	.6174055
tertiaryeduc	1.567525	1.003617	1.56	0.118	-.3995295	3.534579
emp2011	-.7392993	.7239441	-1.02	0.307	-2.158204	.6796051
hhsize	.1042546	.1858189	0.56	0.575	-.2599439	.468453
hhsizegen	-.0811694	.2268486	-0.36	0.720	-.5257844	.3634456
regunmp	-.0112761	.0316631	-0.36	0.722	-.0733346	.0507823
_cons	3.991379	13.8049	0.29	0.772	-23.06573	31.04849
OME3						
age	.9253214	1.221767	0.76	0.449	-1.469297	3.31994
agesq	-.0218975	.0209477	-1.05	0.296	-.0629543	.0191593
male	-5.765252	4.051101	-1.42	0.155	-13.70526	2.174761
minority	2.36218	2.379711	0.99	0.321	-2.301967	7.026327
secondaryeduc	.5367164	1.314153	0.41	0.683	-2.038975	3.112408
tertiaryeduc	2.982151	1.586117	1.88	0.060	-.1265812	6.090884
emp2011	-1.508574	1.19464	-1.26	0.207	-3.850027	.8328781
hhsize	-.9145722	.6076637	-1.51	0.132	-2.105571	.2764268
hhsizegen	.9735966	.6708974	1.45	0.147	-.3413381	2.288531
regunmp	.0124613	.0592105	0.21	0.833	-.1035891	.1285116
_cons	-2.752929	18.38747	-0.15	0.881	-38.7917	33.28584
TME1						
age	1.83568	.2897815	6.33	0.000	1.267719	2.403642
agesq	-.0352208	.0053346	-6.60	0.000	-.0456764	-.0247653
male	-.7631325	.4220953	-1.81	0.071	-1.590424	.064159
minority	-.6129801	.5289027	-1.16	0.246	-1.64961	.4236502
socialassist	3.538121	.491353	7.20	0.000	2.575087	4.501155
secondaryeduc	-.2788772	.2901332	-0.96	0.336	-.8475277	.2897733
tertiaryeduc	.9085496	.2890938	3.14	0.002	.3419362	1.475163
emp2011	-.7337022	.1753612	-4.18	0.000	-1.077404	-.3900005
hhsize	-.1732843	.0548445	-3.16	0.002	-.2807775	-.0657912
hhsizegen	.071187	.0638126	1.12	0.265	-.0538834	.1962574
regunmp	.0251459	.007902	3.18	0.001	.0096581	.0406336
_cons	-25.20534	3.881125	-6.49	0.000	-32.8122	-17.59847
TME2						
age	1.507212	.3312599	4.55	0.000	.8579547	2.15647
agesq	-.029378	.0060251	-4.88	0.000	-.0411869	-.017569
male	-.8360743	.6654799	-1.26	0.209	-2.140391	.4682424
minority	.0408385	.4922064	0.08	0.934	-.9238682	1.005545
socialassist	3.925612	.5632367	6.97	0.000	2.821688	5.029535
secondaryeduc	-.7885339	.3534696	-2.23	0.026	-1.481321	-.0957462
tertiaryeduc	.362573	.3605922	1.01	0.315	-.3441747	1.069321
emp2011	-.4472578	.257551	-1.74	0.082	-.9520485	.0575329
hhsize	-.2509302	.0838874	-2.99	0.003	-.4153465	-.0865139
hhsizegen	.1175317	.1045143	1.12	0.261	-.0873127	.322376
regunmp	.0164741	.0123148	1.34	0.181	-.0076626	.0406107
_cons	-20.64357	4.420769	-4.67	0.000	-29.30812	-11.97902
TME3						
age	2.302577	.9655172	2.38	0.017	.4101979	4.194956
agesq	-.0431407	.0180015	-2.40	0.017	-.078423	-.0078584
male	-2.026316	.9185344	-2.21	0.027	-3.82661	-.2260216

```
     minority |  -.7851754   .9998204    -0.79   0.432    -2.744787    1.174436
  socialassist |  -1.57e+25          .        .       .            .           .
 secondaryeduc |  -.9025561   .5215195    -1.73   0.084    -1.924716    .1196035
  tertiaryeduc |  -.0747617   .5343678    -0.14   0.889    -1.122103      .97258
       emp2011 |   .5517549   .5078745     1.09   0.277    -.4436607    1.547171
        hhsize |  -.3513113   .1202511    -2.92   0.003    -.5869992   -.1156235
     hhsizegen |   .2030071   .1510193     1.34   0.179    -.0929852    .4989995
       regunmp |  -.0483687   .0261055    -1.85   0.064    -.0995346    .0027972
         _cons |  -30.23575   13.01677    -2.32   0.020    -55.74815   -4.723346
--------------------------------------------------------------------------------
Warning: convergence not achieved
```

Table 6.6 Outcome variable: *contract* – Model 2, excluding *emp2011*

Table A6.6.1 PSM

```
*** Binary treatment model

. teffects psmatch (contract) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc hhsize hhsizegen regunmp), nneighbor(1) atet vce(robust)

Treatment-effects estimation                   Number of obs      =      4,034
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =         10
------------------------------------------------------------------------------
             |              AI Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
bintreatment |
   (1 vs 0)  |  -.0897799   .0330325    -2.72   0.007    -.1545224   -.0250373
------------------------------------------------------------------------------


*** Balancing diagnostics



. tebalance sum
note: refitting the model using the generate() option

  Covariate balance summary
                                               Raw      Matched
                          -----------------------------------------
                          Number of obs =       4,034          636
                          Treated obs   =         318          318
                          Control obs   =       3,716          318
                          -----------------------------------------

  -------------------------------------------------------------------
                 |Standardized differences          Variance ratio
                 |        Raw     Matched           Raw     Matched
  ---------------+---------------------------------------------------
```

```
            age |  -.6683655   -.0652905      .3059298   .9740904
          agesq |  -.7316696   -.0653543      .2568255   .9619142
           male |  -.3074472     -.05818      1.266947   1.028703
       minority |  -.1416016    .0974457      .5479843   1.803953
    socialassist |   .3139258    .0558519      11.68782   1.249945
   secondaryeduc |   -.567801    .0730582      .9840757   1.051425
    tertiaryeduc |   .6537529   -.0314459      1.464826   1.003378
          hhsize |  -.4663061    .0313226      .3440954   1.220738
       hhsizegen |  -.4445942   -.0094706      .5429146   1.182609
         regunmp |   .2053474   -.0394231      1.714623   1.138531
  -----------------------------------------------------------------
```

Table A6.6.2 IPW

```
. ***Binary treatment model

.
.
.  teffects  ipw  (contract)  (bintreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc hhsize hhsizegen regunmp) if insampm2==1, atet vce(robust)

Iteration 0:   EE criterion =  1.128e-24
Iteration 1:   EE criterion =  1.820e-31

Treatment-effects estimation                   Number of obs     =      4,034
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: logit
-------------------------------------------------------------------------------
              |               Robust
     contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
ATET          |
 bintreatment |
   (1 vs 0)   |  -.0795846   .0270803    -2.94   0.003    -.1326611   -.0265082
--------------+----------------------------------------------------------------
POmean        |
 bintreatment |
          0   |   .8059997   .0166957    48.28   0.000     .7732767    .8387227
-------------------------------------------------------------------------------


.
. *** Balancing diagnostics

.
. tebalance sum

  Covariate balance summary
                                               Raw      Weighted
                          -----------------------------------------
                          Number of obs =        4,034      4,034.0
                          Treated obs   =          318      2,045.6
                          Control obs   =        3,716      1,988.4
                          -----------------------------------------


  -----------------------------------------------------------------
                  |Standardized differences          Variance ratio
```

```
                 |        Raw    Weighted          Raw   Weighted
  ---------------+-----------------------------------------------
             age |  -.6683655    -.006593     .3059298   .9905808
           agesq |  -.7316696   -.0070228     .2568255   1.003412
            male |  -.3074472    -.044584     1.266947    1.02122
        minority |  -.1416016    .0055177     .5479843   1.028734
    socialassist |   .3139258    .0825861     11.68782   1.407681
   secondaryeduc |   -.567801   -.0039861     .9840757   .9975961
    tertiaryeduc |   .6537529    .0413855     1.464826   .9985752
          hhsize |  -.4663061   -.0185211     .3440954   1.125238
       hhsizegen |  -.4445942   -.0391478     .5429146   1.044958
         regunmp |   .2053474    .0163749     1.714623   1.201666
  ---------------------------------------------------------------


.
.
.
. ***Multivalued treatment model

.
.  teffects  ipw  (contract)  (multitreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc hhsize hhsizegen regunmp) if insampm2==1, atet vce(robust)

Iteration 0:   EE criterion =  4.151e-11
Iteration 1:   EE criterion =  2.627e-18
convergence not achieved
    The  Gauss-Newton  stopping  criterion  has  been  met  but  missing  standard  errors
indicate some of the parameters are
    not identified.

Treatment-effects estimation                    Number of obs     =      4,034
Estimator      : inverse-probability weights
Outcome model  : weighted mean
Treatment model: (multinomial) logit
--------------------------------------------------------------------------------
               |               Robust
      contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.1212863   .0330934    -3.66   0.000    -.1861481   -.0564245
     (2 vs 0)  |   .0008112   .0406699     0.02   0.984    -.0789002    .0805227
     (3 vs 0)  |  -.0420783   .0860356    -0.49   0.625    -.2107049    .1265483
---------------+----------------------------------------------------------------
POmean         |
multitreatment |
            0  |    .819203   .0178698    45.84   0.000     .7841788    .8542271
--------------------------------------------------------------------------------
Warning: convergence not achieved

.
. *** Balancing diagnostics

.
. tebalance sum

  Covariate balance summary
                                                   Observations
                             Treatment           Raw     Weighted
                          -----------------------------------------
                          0bn.multitr~t =        3,716        975.3
```

```
                         1.multitrea~t =          192      1,011.2
                         2.multitrea~t =           85      1,012.4
                         3.multitrea~t =           41      1,035.0
                         Total         =        4,034      4,034.0
                         -----------------------------------------


  -----------------------------------------------------------------
                |Standardized differences          Variance ratio
                |        Raw     Weighted           Raw    Weighted
  ----------------+------------------------------------------------
  1.multitreatm~t |
              age |  -.6853646    .0006308     .2944334    .9909685
            agesq |   -.749132    .0000898     .2459809    1.003484
             male |  -.3172932   -.0427811     1.274756    1.019348
         minority |  -.1890778   -.0032868     .4170619    .9806851
     socialassist |   .3050684    .1197272     11.25983    1.716186
    secondaryeduc |  -.5819661   -.0070876     .9779864    .9955346
     tertiaryeduc |   .7277135    .0391452     1.454008    .9933294
           hhsize |  -.4306719   -.0174493     .3362081    1.009848
        hhsizegen |  -.4399588   -.0369529     .5383242     .991684
          regunmp |   .3077284    .0162281     1.870737    1.162522
  ----------------+------------------------------------------------
  2.multitreatm~t |
              age |  -.6574762   -.0077818     .3558087    1.039286
            agesq |  -.7176357   -.0053773     .2909144    1.021221
             male |  -.1914564   -.0696512     1.200773    1.029694
         minority |   -.027143   -.0114377     .9164003    .9335883
     socialassist |   .4183005    .1216673     17.89277    1.729156
    secondaryeduc |  -.5719987   -.0421551     .9896197    .9723164
     tertiaryeduc |   .5474891     .067965      1.47459    .9865208
           hhsize |   -.481514    .0170899     .3873509    1.399928
        hhsizegen |  -.3795199    -.029527     .5776384    1.277966
          regunmp |   .1881332    .0152758     1.720757    1.100384
  ----------------+------------------------------------------------
  3.multitreatm~t |
              age |  -.6087055   -.0341952     .2676059    .7487333
            agesq |  -.6767408   -.0478777      .247094    .8549602
             male |  -.4958697    .1844547     1.352005    .8796062
         minority |  -.1982826   -.1593651     .3989694    .2438254
     socialassist |  -.0986528   -.2591778            0           0
    secondaryeduc |  -.4879232   -.2440004     1.044477    .8029359
     tertiaryeduc |   .5301546    .3063669     1.490834     .873212
           hhsize |  -.6034122     -.22448     .2921636    .6309171
        hhsizegen |  -.6049638   -.0132029     .4948894    .6579276
          regunmp |   -.360582    .2120915     .6334388    1.274302
  -----------------------------------------------------------------


.
```

Table A6.6.3 RA

```
*** Binary treatment model

. teffects ra (contract age agesq male minority secondaryeduc tertiaryeduc hhsize
hhsizegen regunmp, logit) (bintreatment) if insampm2==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  2.472e-20
Iteration 1:   EE criterion =  2.141e-33

Treatment-effects estimation                   Number of obs     =      4,034
```

```
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
------------------------------------------------------------------------------
             |               Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
   (1 vs 0)  |  -.1155597   .0244018    -4.74   0.000    -.1633863   -.0677331
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
          0  |   .8419748   .0109942    76.58   0.000     .8204265    .8635231
-------------+----------------------------------------------------------------
OME0         |
         age |   .1509179   .0760053     1.99   0.047     .0019503    .2998854
       agesq |  -.0014991   .0012969    -1.16   0.248    -.0040409    .0010428
        male |  -1.119548   .2352938    -4.76   0.000    -1.580715   -.6583806
    minority |   .4620416   .2029913     2.28   0.023     .0641861    .8598972
secondaryeduc |   1.010762   .1056509     9.57   0.000     .8036898    1.217834
 tertiaryeduc |   2.988407   .2196649    13.60   0.000     2.557871    3.418942
      hhsize |  -.0469601   .0222715    -2.11   0.035    -.0906115   -.0033087
   hhsizegen |   .0392287   .0247578     1.58   0.113    -.0092956    .0877531
     regunmp |  -.0122432   .0046459    -2.64   0.008     -.021349   -.0031374
       _cons |  -1.424089   1.092765    -1.30   0.193    -3.565869     .717691
-------------+----------------------------------------------------------------
OME1         |
         age |  -.3297062   .4786149    -0.69   0.491    -1.267774    .6083617
       agesq |    .005416    .008662     0.63   0.532    -.0115613    .0223933
        male |  -1.487412     .89927    -1.65   0.098    -3.249949    .2751249
    minority |   .1079531   .6478203     0.17   0.868    -1.161751    1.377658
secondaryeduc |  -.2079764   .3746633    -0.56   0.579     -.942303    .5263501
 tertiaryeduc |   2.004656   .4553119     4.40   0.000     1.112261    2.897051
      hhsize |  -.1737133   .1218414    -1.43   0.154    -.4125181    .0650915
   hhsizegen |   .1389784   .1355916     1.02   0.305    -.1267763    .4047331
     regunmp |   .0410547   .0147819     2.78   0.005     .0120828    .0700266
       _cons |   5.438624   6.717985     0.81   0.418    -7.728385    18.60563
------------------------------------------------------------------------------

. ***Multivalued treatment model

. teffects ra (contract age agesq male minority secondaryeduc tertiaryeduc hhsize
hhsizegen regunmp, logit) (multitreatment) if insampm2==1, atet vce(robust) aequ

Iteration 0:   EE criterion =  9.201e-08
Iteration 1:   EE criterion =  1.557e-09

Treatment-effects estimation                    Number of obs     =      4,034
Estimator      : regression adjustment
Outcome model  : logit
Treatment model: none
-------------------------------------------------------------------------------
```

contract	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
multitreatment						
(1 vs 0)	-.1536416	.0310279	-4.95	0.000	-.2144552	-.092828
(2 vs 0)	-.0462612	.0451839	-1.02	0.306	-.13482	.0422977
(3 vs 0)	-.1277609	.0718879	-1.78	0.076	-.2686585	.0131367
POmean						
multitreatment						
0	.8515583	.0127352	66.87	0.000	.8265977	.8765188
OME0						
age	.1509179	.0760053	1.99	0.047	.0019503	.2998854
agesq	-.0014991	.0012969	-1.16	0.248	-.0040409	.0010428
male	-1.119548	.2352938	-4.76	0.000	-1.580715	-.6583806
minority	.4620416	.2029913	2.28	0.023	.0641861	.8598972
secondaryeduc	1.010762	.1056509	9.57	0.000	.8036898	1.217834
tertiaryeduc	2.988407	.2196649	13.60	0.000	2.557871	3.418942
hhsize	-.0469601	.0222715	-2.11	0.035	-.0906115	-.0033087
hhsizegen	.0392287	.0247578	1.58	0.113	-.0092956	.0877531
regunmp	-.0122432	.0046459	-2.64	0.008	-.021349	-.0031374
_cons	-1.424089	1.092765	-1.30	0.193	-3.565869	.717691
OME1						
age	-.816214	.9952297	-0.82	0.412	-2.766828	1.1344
agesq	.0155984	.0184517	0.85	0.398	-.0205664	.0517632
male	-1.065753	1.253671	-0.85	0.395	-3.522903	1.391397
minority	.0286073	1.389039	0.02	0.984	-2.693859	2.751073
secondaryeduc	-.0919015	.5221325	-0.18	0.860	-1.115262	.9314594
tertiaryeduc	2.252352	.6304068	3.57	0.000	1.016777	3.487926
hhsize	-.0617598	.1493416	-0.41	0.679	-.354464	.2309443
hhsizegen	.0710117	.1762196	0.40	0.687	-.2743724	.4163957
regunmp	.0693664	.0203803	3.40	0.001	.0294217	.1093111
_cons	9.117835	13.3014	0.69	0.493	-16.95242	35.18809
OME2						
age	-.5053123	.9575999	-0.53	0.598	-2.382174	1.371549
agesq	.0058938	.017436	0.34	0.735	-.0282802	.0400679
male	-.7932958	1.560302	-0.51	0.611	-3.851431	2.26484
minority	-.382802	.981652	-0.39	0.697	-2.306805	1.541201
secondaryeduc	-1.132552	.7404314	-1.53	0.126	-2.583771	.318667
tertiaryeduc	1.748164	.9586256	1.82	0.068	-.1307072	3.627036
hhsize	-.0038068	.2140206	-0.02	0.986	-.4232794	.4156658
hhsizegen	-.0434369	.2515896	-0.17	0.863	-.5365435	.4496697
regunmp	-.0144334	.0282511	-0.51	0.609	-.0698045	.0409377
_cons	11.8829	13.32835	0.89	0.373	-14.24018	38.00599
OME3						
age	.262944	1.096424	0.24	0.810	-1.886007	2.411895
agesq	-.0071313	.0177355	-0.40	0.688	-.0418922	.0276296
male	-2.790956	3.628883	-0.77	0.442	-9.903435	4.321524

```
     minority |   1.253479   2.297178     0.55   0.585    -3.248907    5.755864
secondaryeduc |   .5137475   1.150719     0.45   0.655     -1.74162    2.769115
 tertiaryeduc |   2.538786   1.361588     1.86   0.062    -.1298767    5.207448
       hhsize |  -.4808211   .5027216    -0.96   0.339    -1.466137    .5044951
    hhsizegen |   .4901745   .6083491     0.81   0.420    -.7021679    1.682517
      regunmp |  -.0250085   .0508912    -0.49   0.623    -.1247535    .0747364
        _cons |    1.39812   18.10044     0.08   0.938    -34.07809    36.87433
------------------------------------------------------------------------------


.
```

Table A6.6.4 IPWRA

```
*** Binary treatment model

. teffects ipwra (contract age agesq male minority secondaryeduc tertiaryeduc hhsize
hhsizegen regunmp, logit) (bintreatment age agesq male minority socialassist
secondaryeduc tertiaryeduc emp2011 hhsize hhsizegen regunmp) if insampm2==1, atet
vce(robust) aequ

Iteration 0:   EE criterion =  4.291e-24
Iteration 1:   EE criterion =  9.033e-32

Treatment-effects estimation                    Number of obs     =      4,023
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: logit
------------------------------------------------------------------------------
             |               Robust
    contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
 bintreatment |
    (1 vs 0) |  -.0781049   .0256902    -3.04   0.002    -.1284567   -.0277531
-------------+----------------------------------------------------------------
POmean       |
 bintreatment |
           0 |     .80452   .0144908    55.52   0.000     .7761186    .8329214
-------------+----------------------------------------------------------------
OME0         |
         age |  -.2213412   .1783175    -1.24   0.215     -.570837    .1281546
       agesq |    .004747   .0032516     1.46   0.144    -.0016259    .0111199
        male |   -1.18453   .5210096    -2.27   0.023    -2.205689   -.1633696
    minority |   .9736999   .3917071     2.49   0.013     .2059681    1.741432
secondaryeduc |    1.53916   .2220761     6.93   0.000     1.103899    1.974421
 tertiaryeduc |   3.595352   .3326008    10.81   0.000     2.943467    4.247238
      hhsize |  -.0334602   .0667151    -0.50   0.616    -.1642194     .097299
   hhsizegen |   .0287724   .0703799     0.41   0.683    -.1091696    .1667144
     regunmp |  -.0110411   .0079914    -1.38   0.167    -.0267039    .0046217
       _cons |   3.180737   2.349005     1.35   0.176    -1.423228    7.784701
-------------+----------------------------------------------------------------
OME1         |
         age |  -.3297062   .4786149    -0.69   0.491    -1.267774    .6083617
```

```
       agesq |   .005416    .008662     0.63   0.532    -.0115613    .0223933
        male | -1.487412     .89927    -1.65   0.098    -3.249949    .2751249
    minority |  .1079531   .6478203     0.17   0.868    -1.161751    1.377658
secondaryeduc | -.2079764   .3746633    -0.56   0.579     -.942303    .5263501
 tertiaryeduc |  2.004656   .4553119     4.40   0.000     1.112261    2.897051
       hhsize | -.1737133   .1218414    -1.43   0.154    -.4125181    .0650915
    hhsizegen |  .1389784   .1355916     1.02   0.305    -.1267763    .4047331
      regunmp |  .0410547   .0147819     2.78   0.005     .0120828    .0700266
        _cons |  5.438624   6.717985     0.81   0.418    -7.728385    18.60563
-------------+----------------------------------------------------------------
TME1         |
          age |  1.787138   .2308881     7.74   0.000     1.334606    2.239671
        agesq | -.0343107   .0042514    -8.07   0.000    -.0426433   -.0259781
         male |  -.989517   .3603567    -2.75   0.006    -1.695803   -.2832309
     minority |  -.413426   .3689081    -1.12   0.262    -1.136473    .3096206
 socialassist |  3.544421   .4672553     7.59   0.000     2.628618    4.460225
secondaryeduc | -.5413661   .2171526    -2.49   0.013    -.9669775   -.1157547
 tertiaryeduc |  .5932904   .2221933     2.67   0.008     .1577995    1.028781
      emp2011 | -.5266228    .146149    -3.60   0.000    -.8130696   -.2401759
       hhsize | -.2203855   .0473569    -4.65   0.000    -.3132033   -.1275677
    hhsizegen |  .1038605   .0554772     1.87   0.061    -.0048728    .2125937
      regunmp |   .015951   .0067856     2.35   0.019     .0026514    .0292507
        _cons | -23.34299   3.071429    -7.60   0.000    -29.36288    -17.3231
------------------------------------------------------------------------------


.
. ***Multivalued treatment model

.
. teffects ipwra (contract age agesq male minority secondaryeduc tertiaryeduc  hhsize
hhsizegen  regunmp,  logit)  (multitreatment  age  agesq  male  minority  socialassist
secondaryeduc tertiaryeduc hhsize hhsizegen regunmp) if insampm2==1, atet vce(robust)
aequ

Iteration 0:   EE criterion =  2.187e-07
Iteration 1:   EE criterion =  3.446e-10
Iteration 2:   EE criterion =  9.884e-11
convergence not achieved
    The  Gauss-Newton  stopping  criterion  has  been  met  but  missing  standard  errors
indicate some of the parameters are
    not identified.

Treatment-effects estimation                    Number of obs     =      4,034
Estimator      : IPW regression adjustment
Outcome model  : logit
Treatment model: (multinomial) logit
-------------------------------------------------------------------------------
               |               Robust
      contract |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+---------------------------------------------------------------
ATET           |
multitreatment |
     (1 vs 0)  |  -.1342829   .0316864    -4.24   0.000    -.1963871   -.0721787
```

(2 vs 0)	-.0223395	.0433742	-0.52	0.607	-.1073514	.0626725
(3 vs 0)	-.1111155	.0695782	-1.60	0.110	-.2474864	.0252553
POmean						
multitreatment						
0	.8321996	.0149664	55.60	0.000	.8028659	.8615333
OME0						
age	-.2721033	.1814601	-1.50	0.134	-.6277586	.083552
agesq	.0059646	.003324	1.79	0.073	-.0005503	.0124795
male	-1.184218	.5403033	-2.19	0.028	-2.243193	-.1252434
minority	.8540586	.4248918	2.01	0.044	.0212859	1.686831
secondaryeduc	1.430745	.2309481	6.20	0.000	.9780949	1.883395
tertiaryeduc	3.207037	.3268682	9.81	0.000	2.566387	3.847687
hhsize	-.0171822	.0621049	-0.28	0.782	-.1389056	.1045412
hhsizegen	.0145005	.0673594	0.22	0.830	-.1175215	.1465225
regunmp	-.0142443	.008678	-1.64	0.101	-.0312529	.0027643
_cons	4.005356	2.369792	1.69	0.091	-.6393508	8.650063
OME1						
age	-.816214	.9952297	-0.82	0.412	-2.766828	1.1344
agesq	.0155984	.0184517	0.85	0.398	-.0205664	.0517632
male	-1.065753	1.253671	-0.85	0.395	-3.522903	1.391397
minority	.0286073	1.389039	0.02	0.984	-2.693859	2.751073
secondaryeduc	-.0919015	.5221325	-0.18	0.860	-1.115262	.9314594
tertiaryeduc	2.252352	.6304068	3.57	0.000	1.016777	3.487926
hhsize	-.0617598	.1493416	-0.41	0.679	-.354464	.2309443
hhsizegen	.0710117	.1762196	0.40	0.687	-.2743724	.4163957
regunmp	.0693664	.0203803	3.40	0.001	.0294217	.1093111
_cons	9.117835	13.3014	0.69	0.493	-16.95242	35.18809
OME2						
age	-.4008049	.9087165	-0.44	0.659	-2.181857	1.380247
agesq	.0047686	.016508	0.29	0.773	-.0275865	.0371236
male	-.3087912	1.322937	-0.23	0.815	-2.901699	2.284117
minority	-.1051537	.9575459	-0.11	0.913	-1.981909	1.771602
secondaryeduc	-.8943782	.7643829	-1.17	0.242	-2.392541	.6037847
tertiaryeduc	1.607709	.9624972	1.67	0.095	-.2787508	3.494169
hhsize	.099376	.1774577	0.56	0.575	-.2484348	.4471868
hhsizegen	-.1037994	.2139058	-0.49	0.627	-.5230469	.3154482
regunmp	-.0059434	.0273337	-0.22	0.828	-.0595164	.0476295
_cons	8.79672	12.73684	0.69	0.490	-16.16704	33.76048
OME3						
age	.3816243	1.083634	0.35	0.725	-1.74226	2.505509
agesq	-.0087275	.018378	-0.47	0.635	-.0447478	.0272927
male	-8.130264	5.777888	-1.41	0.159	-19.45472	3.194188
minority	1.506297	3.44271	0.44	0.662	-5.241289	8.253884
secondaryeduc	1.055591	1.445295	0.73	0.465	-1.777135	3.888318
tertiaryeduc	3.01527	1.597167	1.89	0.059	-.1151199	6.145661
hhsize	-1.245441	.8237584	-1.51	0.131	-2.859978	.3690959
hhsizegen	1.132854	.8469339	1.34	0.181	-.5271064	2.792814
regunmp	.0306643	.0547067	0.56	0.575	-.0765589	.1378875

_cons	3.152773	15.48246	0.20	0.839	-27.19229	33.49783
TME1						
age	1.747354	.2817436	6.20	0.000	1.195147	2.299561
agesq	-.0339454	.0052062	-6.52	0.000	-.0441494	-.0237414
male	-.7344126	.4155233	-1.77	0.077	-1.548823	.079998
minority	-.6291995	.5317115	-1.18	0.237	-1.671335	.412936
socialassist	3.617107	.4685271	7.72	0.000	2.698811	4.535403
secondaryeduc	-.3055899	.282592	-1.08	0.280	-.8594601	.2482803
tertiaryeduc	.8989405	.2824734	3.18	0.001	.3453029	1.452578
hhsize	-.1672484	.0526473	-3.18	0.001	-.2704353	-.0640615
hhsizegen	.0632256	.0621255	1.02	0.309	-.0585382	.1849894
regunmp	.0289595	.0080931	3.58	0.000	.0130973	.0448216
_cons	-24.41935	3.781561	-6.46	0.000	-31.83108	-17.00763
TME2						
age	1.457357	.3349016	4.35	0.000	.8009621	2.113752
agesq	-.0286626	.0061042	-4.70	0.000	-.0406265	-.0166987
male	-.7573875	.6619038	-1.14	0.253	-2.054695	.5399201
minority	-.0020738	.5049319	-0.00	0.997	-.9917222	.9875746
socialassist	3.941553	.5473745	7.20	0.000	2.868719	5.014387
secondaryeduc	-.7964917	.3493081	-2.28	0.023	-1.481123	-.1118604
tertiaryeduc	.363226	.3568313	1.02	0.309	-.3361506	1.062603
hhsize	-.2387306	.0812043	-2.94	0.003	-.3978881	-.0795731
hhsizegen	.1033364	.1029335	1.00	0.315	-.0984096	.3050824
regunmp	.0182749	.0124787	1.46	0.143	-.0061829	.0427326
_cons	-20.28296	4.458232	-4.55	0.000	-29.02094	-11.54499
TME3						
age	2.372024	.9986721	2.38	0.018	.4146623	4.329385
agesq	-.0442698	.0186045	-2.38	0.017	-.080734	-.0078056
male	-2.079666	.9191793	-2.26	0.024	-3.881224	-.2781076
minority	-.8449368	.9976037	-0.85	0.397	-2.800204	1.110331
socialassist	-13.51197	.4909363	-27.52	0.000	-14.47419	-12.54976
secondaryeduc	-.8778545	.5180509	-1.69	0.090	-1.893216	.1375066
tertiaryeduc	-.0566182	.5325123	-0.11	0.915	-1.100323	.9870868
hhsize	-.3615299	.1230742	-2.94	0.003	-.6027508	-.1203089
hhsizegen	.213772	.1515059	1.41	0.158	-.083174	.5107181
regunmp	-.051403	.0249489	-2.06	0.039	-.1003021	-.002504
_cons	-30.69931	13.28566	-2.31	0.021	-56.73872	-4.659898

Warning: convergence not achieved