THREE ESSAYS IN LABOUR ECONOMICS

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Three Essays In Labour Economics

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Abstract

This thesis extends the existing literature on the response of labour markets to different types of economic shocks. First, we examine the effects of sector-specific fluctuations in job separation and job finding rates on the overall unemployment, sectoral allocation of labour and wages by solving a two-sector search and matching model with heterogeneous workers. The simulated results show how sector-specific shocks spill over the rest of the economy, causing workers to relocate between sectors in search of jobs. Inter-sectoral reallocation depends on the distribution of worker productivity in the affected sector. When an adverse shock hits a sector that attracts workers with relatively low productivity, the most productive among displaced workers move to compete for jobs in the sector with higher productivity. This offsets some of the increase in unemployment, subject to the ability of unaffected sector to employ additional workers. Next, we conduct meta-analysis to explain discrepancies between estimated effects of immigration shocks on wages in the literature. The results show that wage impact of immigration tends to be small in magnitude and negative significant. Labour market conditions at the period of study play a significant role in explaining the differences in measured impact. The estimates vary across countries and are related to the choice of modelling approach and estimators. Finally, we use EU-LFS dataset to analyse unemployment and labour market flows in Europe between 2006 and 2016. We identify the relative impact of shocks to job finding and separation rates on unemployment and investigate the role of socio-demographics, urbanisation and immigration status in shaping worker flow patterns in Europe. We find that over the studied period job losses accounted for three quarters of the rise in unemployment. The analysis of socio-demographic characteristics of the unemployed shows that young and less educated workers contributed the most to employment losses. Recent and intermediate immigrants in cities contributed to employment losses.

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Abbreviations

BLS	Bureau of Labour Statistics
CES	Current Employment Survey
CEPR	Center for Economic Policy Research
CPS	Current Population Survey
DWS	Displaced Worker Survey
EU	Employment to Unemployment
EU-LFS	European Union Labour Force Survey
IV	Instrumental Variable
JOLTS	Job Openings and Labour Turnover Survey
MP	Mortensen and Pissarides
NELP	National Employment Law Project
OLS	Ordinary Least Squares
SDC	Socio-Demographic Characteristics
UE	Unemployment to Employment

Introduction

Labour market outcomes are very important for the welfare of any individual and are of fundamental importance for the formation of public policies. Policy making relies heavily on realistic characterisation and representation of labour markets over time. The three chapters of this thesis are self-contained and contribute to our understanding of how labour markets respond to sector-specific fluctuations in job separation and job finding rates, migration and changing socio-demographics over time. This section summarises each of the three chapters.

The first chapter is entitled *Multi-sectoral allocation of workers*. This chapter evaluates the effect of sector-specific shocks on the unemployment, allocation of labour across sectors and wages. It applies the two-sector equilibrium search model by Albrecht et al. (2009) to the US economy during 2006-2010, covering the period of Great Recession. The model is calibrated to the US construction and non-construction sectors. The motivation behind this chapter is that the 2008 recession caused the US national unemployment rate to increase from 5% in 2007 to about 10% in 2009. This increase in unemployment was linked to displacement of workers from sectors in which they were previously employed. The uneven distribution of job losses across industries caused structural imbalances in the economy that required substantial movements of workers between sectors (Phelps 2008).

The results of the simulations show that when adverse shocks to job finding and job separation rates that are specific to the construction sector hit the economy, the unemployment levels of low and medium productivity workers in this sector increase while unemployment among high productivity workers in non-construction sector remains unchanged. While low productivity workers remain in the construction sector, some medium productivity workers move to the non-construction sector. For example, when job separation rate in the construction sector increases by 20% and job finding rate decreases by 15%, employment in non-construction sector increases by approximately 1.6% as medium productivity workers move to this sector for work. In the meantime, employment in construction sector decreases by 11% and the total unemployment in the economy increases by

10%. The average wages decrease by only 0.9%, suggesting wage stickiness. The results in this chapter indicate that relocation of medium productivity workers to non-construction jobs helps in reducing some of the increase in total unemployment. It helps in understanding that while sector-specific fluctuations in job finding and job separation rates increases the total unemployment in the economy, the movement of workers between sectors can also possibly reduce total unemployment as some displaced workers get re-employed in growing sectors. The results of the counterfactual exercise show that in the absence of spill-over effects, the increase in unemployment is lower than the case when there are spillover effects. This is because for any shock resulting in labor reallocation across sectors, the economy will take much longer to respond due to imperfect mobility in addition to the standard search friction causing higher unemployment rate. In case of no spill over effects, the employment in construction sector is lower and employment in non-construction sector is high.

The second chapter is called *The wage effect of immigration: A meta-analysis.* Over the last three decades, there was a large body of literature assessing the wage effect of immigration. Yet existing evidence on whether immigration has a positive or negative effect on wages and if the impact is significant or not is still inconclusive. Therefore, this chapter aggregates 663 estimates of wage impact of immigration from 46 papers and evaluates the sign and significance of the effect of immigration through meta-analysis. The systematic differences in each study are classified in three categories: characteristics of the study, context of the study and labour market conditions. The estimation results show that the wage impact of immigration is generally small and negative significant. The results vary across countries and are related to the type of modelling approach and estimation specification used. Studies using skill-cell approach tend to find positive significant impact as compared to mixed approach. The labour market conditions in a country play a significant role in explaining why wage impact of immigration varies from study to study. Bad labour market conditions i.e. high unemployment rate in the host country decrease the probability of finding positive significant results by 35% and increase the probability of finding negative significant results by about 19%.

In meta-analysis literature, there is increasing concern that sample of studies suffer from researcher driven biases. It is also argued in recent research that selection bias is severe and prevalent in economics (Olken 2015, Broudeur et al. 2016, Christensen and Miguel 2018). The two widely recognised researcher driven biases are publication bias and p-hacking. Publication bias happens when authors, referees and editors prefer the publication of statistically significant results, while p-hacking occurs when authors influence their data and/or statistical analysis to produce significant results. In this chapter, the presence of publication bias is investigated using two tests suggested by Card and Krueger (1995) and Stanley et al. (2004). P-hacking is checked for by using a test suggested by Head et al. (2015). The results show that sample of studies collected for this meta-analysis do not suffer from researcher driven biases. The most important aspect of the meta-analysis in this chapter is that it takes into account the economic conditions of a country when assessing the wage impact of immigration. It also provides a critical discussion of the wage impact of immigration by classifying study differences into three categories based on context of the study, labour market conditions and study characteristics.

The third chapter is called *Unemployment and labour market mobility in Europe.* European Union is making progress to be viewed as a single economic area. A single labour market is one of the most flourishing policy areas of European Union's integration and enlargement. A defiant feature of this single European labour market is the substantial variation in its unemployment rate over the years. Labour market dynamics literature since 1970s argue that changes in the stock of unemployment are shaped by the flows of workers between employment and unemployment pools. Economic theory also highlights that different labour market groups play a significant role in contributing to unemployment variation through worker flows. Focusing on these three dimensions, this chapter evaluates the annual worker flows and socio-demographic composition of these flows in Europe to identify the contribution of job finding and job separation rates to the changes in the unemployment rate and to assess the importance of socio-demographics in shaping worker flow patterns in Europe. Using European Union labour force survey (EU-LFS), worker flows are calculated at the European level. The European unemployment variance is decomposed into parts accounted for by changes in unemployment inflow and outflow rates and lastly, the correlation between the socio-demographic characteristics, immigration status, degree of urbanisation and worker flows is evaluated.

The results are as follows. Transitions from unemployment to employment are found to be less frequent over the years for Europe compared to the flows from employment to unemployment. The latter have significantly changed over time since 2006 and have not adjusted back to their initial levels. Unemployment outflow rate accounts for around 24% of the rise in unemployment while unemployment inflow rate accounts for around 73%. The estimation results show that male workers, less educated workers and young workers are affected the most as they have higher probability of job losses than other socio-demographic groups. Worker from Southern European countries (Spain, Greece and Portugal) have higher probability of employment to unemployment transition and lower probability of unemployment to employment transition than other regions. Recent and intermediate immigrants are adversely effected as they increase the probability of job separation by 1.6% and 1.5%, respectively. For urbanisation groups, workers in town/suburbs and rural areas lower the job separation probability by 0.38% and 0.4%, respectively compared to workers in cities. The results also show that all three immigrant groups in towns and rural areas have lower job separation rates and higher job finding rates as compared to the workers in cities. The main contributions of this chapter are that it identifies the role of job finding and job separation rates in changing European unemployment rate. It also provides a structural analysis of unemployment and worker flows by using annual gross data for calculations. This chapter also highlights the correlation between socio-demographic characteristics, degree of urbanisation of workers, their immigration status and worker flows.

Chapter 1

The Multi-Sectoral Allocation of Workers

1.1 Introduction

The Great Recession has adversely affected the overall labour market and started problems in the housing and financial sectors. However, its impact was not the same across different sectors and industries. Because of the mortgage crisis and problems in the housing markets, the construction sector was among the most adversely affected. While the overall employment loss in the economy between December 2007 and January 2009 was 6%, construction went down by 13.7% over the same period. In contrast, employment in education and health services increased by almost 2.2%.[1]

In addition, job losses were unevenly distributed among industries with different average wages. About 60% of all job losses recorded during recession originated in industries that paid average hourly wages ranging from 14 and 21 dollars per hour, such as construction and retail trade. The industries that paid average hourly wage of 21.14 to 54.55 dollars (such as health and education, professional and business services) contributed 19 percent to the job losses. [2] Statistics from Displaced Workers Survey (DWS, 2010) show that about 1.1 million workers in the construction sector lost their jobs. This accounted for 16% of the total displaced workers in the US. The main reasons reported for employment losses were insufficient work, plant and vacancy closure. Only 44% of these workers were able to get re-employed, with 23% finding work in other sectors. The average wages in the economy generally remained rigid throughout the recession. Fallick et al. (2016) assessed wage rigidity in the US during the Great Recession and reported no evidence that the high degree of labour market distress reduced the amount of downward nominal wage rigidity. Average hourly wages for several sectors (such as construction, manufacturing, retail, education and health services) were rigid during this time period.

The statistics above indicate that during the Great Recession, workers were displaced from construction sector and were re-employed to different industries. One aspect of changing labour market dynamics of a particular sector during a recession is that it can have spillover effects on other sectors

[1]Source: The Recession of 2007-2009: Bureau of Labour Statistics (BLS) Spotlight on Statistics.
[2]Source: The Low-Wage Recovery and Growing Inequality, National Employment Law Project (2012).

or on the economy as a whole. These spillover effects due to intersectoral reallocation of workers in search of employment opportunities in one sector may contribute to unemployment changes in the economy. It is therefore important to understand whether the movement of workers between sectors explains the unemployment dynamics. In this paper, I examine the impact of sector-specific shock on the overall unemployment as well as unemployment dynamics for each worker type, employment levels in construction and non-construction sectors, distribution of workers across the sectors and average wages. I examine how the shocks experienced by a sector with low productivity propagate to other sectors of the economy, and evaluate the response of sector-specific and economy-wide employment levels and wages to these shocks. I also explain the role played by worker productivity in the sectoral allocation of workers.

In order to assess the spillover effects of an adverse shock in one sector on the labour market outcomes in the economy, I set up a two-sector equilibrium search and matching model which extends the canonical Mortensen and Pissarides (1994, MP) search and matching framework and is similar to the one developed by Albrecht, Navarro and Vroman (2009). I solve the model to derive the worker productivity thresholds that determine the distribution of workers between the two sectors and reservation productivity schedule of each worker type. These productivity thresholds are used to determine steady state employment in the two sectors and unemployment for each worker type and overall economy. The model is calibrated to pre-recession (2007) US construction and non-construction sectors to ensure that the baseline labour market matches the data.

After the baseline economy is set up, I treat the fluctuations in job separation and job finding rates in construction sector as indicators of adverse shock in this sector during a recession and run simulations to assess how these sector-specific shocks propagate to the rest of the economy. This is because job finding was low in construction sector due to low re-employment rates and job separation rates were high due to workers displacement in this sector. Taking various combinations of job finding and separation rates, I examine the effect of shocks on unemployment of each worker type and overall economy, employment in the two sectors and wages in the model economy.

I run three sets of simulations. In the first case, I increase job separation rate while keeping the job finding rate constant. In the second case, I change the job finding rate and keep job separation rate constant. In the third case, I change both of them simultaneously. As a result of the first case, the employment dynamics start to change in the construction sector as unemployment for low and medium productivity workers increases by 15% and 9% respectively. In the non-construction sector, while unemployment remains unchanged, employment starts to increase by 1% as medium productivity workers move to this sector to find work. The overall unemployment in the economy increases by 5% but it is not as severe as the unemployment levels of low and medium productivity workers. This is because some of the increase in the overall unemployment is offset by medium productivity workers finding work in the non-construction sector. When job finding rate starts to decrease, unemployment for low and medium productivity workers in construction sector increases by 20% and 10% respectively. The overall unemployment in the model economy increases by 6%. Employment in non-construction sector increase by 1.2%. In the final case, when job separation rate increases and job finding rate decreases, unemployment for low and medium productivity workers in construction sector increases by 30% and 15% while overall unemployment increases by 10%. Employment in construction sector decreases by 11% and it increases in non-construction sector by 1.6%. The results of the counterfactuals indicate that sector-specific shocks do have spillover effects on other sectors and the economy, as they tend to increase unemployment rate and causes workers to relocate to other sectors to find work. This reallocation of workers depends on the productivity levels of workers.

After the simulations, I run counterfactual exercise to quantify how much unemployment in the model will change in the absence of the spillover effects. The results show that incase of no spillover effects, unemployment in the model is lower, employment in construction sector is lower and employment in non-construction sector is high. Manufacturing sector is closer in terms of skills to construction sector, I assume the model economy has two sectors only; construction and manufacturing. The baseline and simulation results show that unemployment is higher for this hypothetical economy.

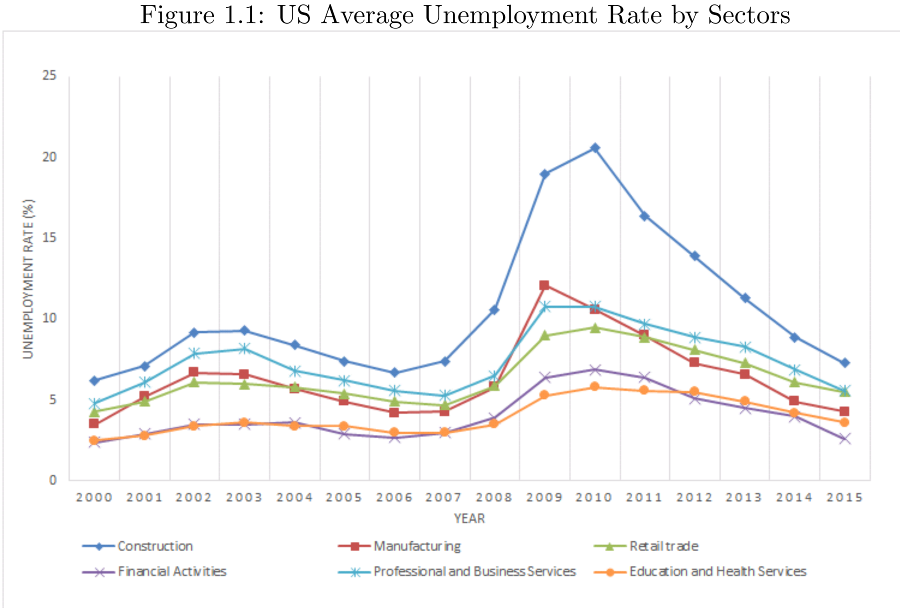
This paper contributes to the literature that examines the impact of inter-sectoral mobility of workers on the levels of unemployment in the economy, especially during the Great Recession, and tests the sectoral shift hypothesis of Lilien (1982). It was reported in this study that the structural changes in the US sectors in the 1970s caused the equilibrium unemployment rate to fluctuate by about 3%. Alvarez and Shimer (2011) analyse theoretical properties of the labour market equilibrium in an economy with a continuum of industries and rest unemployment, which allows unemployed workers to wait for better prospects in their own industry instead of automatically engaging in search activities. Chang (2011) and Pilossoph (2012) approach sectoral reallocation by using multi-sectoral models based on MP (1994) to estimate the effects of sectoral reallocation on aggregate unemployment and wages. Carilla-Tudela and Visschers (2013) create a multi-sectoral MP model and examine the interactions between rest, search and reallocation unemployment. I extend this literature further by examining the response of sector-specific shock on unemployment of worker types, employment in each sector and wages.

The paper is organised as follows. In the next section, data facts about the US labour market during 2007-2009 recession are reviewed. In section 1.3, I will set up and solve the two sector search and matching model. Section 1.4 explains the data and the calibration strategy of parameters of the model. Section 1.5 then explains the baseline case, while section 1.6 will present the simulations and counterfactuals of the model. Section 1.7 calibrates the model to US construction and manufacturing sector only. Section 1.8 provides the discussion and section 1.9 concludes.

1.2 Data Facts for the US labour market

In this section, I review the data facts for the US labour market to highlight the role played by different sectors in changing employment dynamics of the overall economy during the Great Recession. The US labour market has been deeply affected by the Great Recession of 2007-2009. Unemployment rate was one of the main indicators of 2008 crisis as it increased from 5% in 2007 to about 10% in 2009. Unemployment by industry is defined as the number of workers who are out of work and had held their last jobs in the specific industry. In order to understand the role played by each sector in changing labour market dynamics of the US economy, unemployment rate for different sectors is extracted from CPS data and is shown in Figure 1.1 below. Unemployment was generally the highest for goods producing industries as shown in Figure 1.1. Construction sector

Figure 1.1: US Average Unemployment Rate by Sectors



Data source: US Bureau of Labour Statistics (BLS): Labour Force Statistics from the Current Population Survey.

suffered from the largest increase in its unemployment rate as it increased from 10% in 2008 to about 18% in 2009. The job losses during this crisis were larger than in the previous recessions. Table 1.1 shows the percentage change in employment of six main industries in the US during the last four recessions.[3] Manufacturing sector experienced large employment losses during all four recessions. Barring the 2001 recession, the construction sector experienced high levels of employment losses in all others. The 2007-2009 recession was typical in this regard, with construction and manufacturing both experiencing their largest percentage declines in employment of 13.7% and 10.0% respectively. The employment losses in the US construction sector were the highest among all the

Table 1.1: Percent Change in Employment of Selected Sectors at Recent Recessions

		Recessionary Period		
Industry	Jul 1981 - Nov 1982	Jul 1990 - Mar 1991	Mar 2001 - Nov 2001	Dec 2007 - Jun 2009
Construction	-6.2	-11.0	-1.7	-13.7
Manufacturing	-8.4	-4.7	-9.7	-10.0
Retail Trade	-0.3	-2.6	-2.0	-4.5
Financial Activities	0.7	-0.6	0.9	-3.9
Professional and Business Services	0.5	-2.8	-5.7	-6.0
Education and Health Services	1.9	5.2	3.9	2.2

Data source: Current Employment Survey (CES)

sectors. Data extracted from Current Employment Survey (CES) Highlights (2007-2008) shows that during 2007-2008, construction sector lost 195,000 jobs, with the residential components accounting for the decline and reflecting the continuing difficulties in the housing market. Few industries attracted as much attention during the recent recession as financial activities, which experienced a 3.9% reduction in employment. Before 2007, the only recession since 1939 to see job losses in financial activities was that of 1990-1991. Employment increased in education and health services during the recent recession. In fact, employment in this sector has increased for more than 30 years at all stages of the business cycle. Employment in education and health services has decreased in only 1 of the 12 recessions that have occurred since 1945.[4] This suggests that workers were moving to other sectors after suffering from job losses in their initial sectors. These sector-specific job losses and limited employment opportunities led to displacement of workers from these sectors.

The Bureau of Labour Statistics defines a displaced worker as persons 20 years of age and older who lost or left job because their plant or company closed or moved, there was insufficient work for them to do, or their position or shift was abolished. Displaced worker survey (DWS 2010) reported that

[3] Since the recessions vary in length, the percentages are measured across different number of months for recession and then they are transformed to annual percentages.

[4] Bureau of Labour Statistics (BLS) Spotlight on Statistics:The Recession of 2007-2009.

around 6.8 million workers in the US were displaced from their jobs during the 2007-2009 recession. The number of displaced workers in construction sector were more than 1.1 million. In 2010, the re-employment rate of displaced workers in this sector was 44% with only 21% finding employment in the same sector. The other 23% were re-employed in other sectors.[5] Construction sector at the time made up about 7% of the US workforce. These figures indicate that with low re-employment rates and accounting for 16% of the total displaced worker group in the US, construction sector was one of the adversely effected sectors in terms of employment losses, with many workers finding employment in other sectors.

Table 1.2: Reasons for Displacement in the Last Two Recessions

	Year	
Reasons	2002	2010
Insufficient work	26%	43%
Plant or company closed/moved	47%	31%
Position or shift abolished	27%	26%

Data source: U.S. Bureau of Labour Statistics. 2010. News Release: Worker Displacement: 2007-2009.

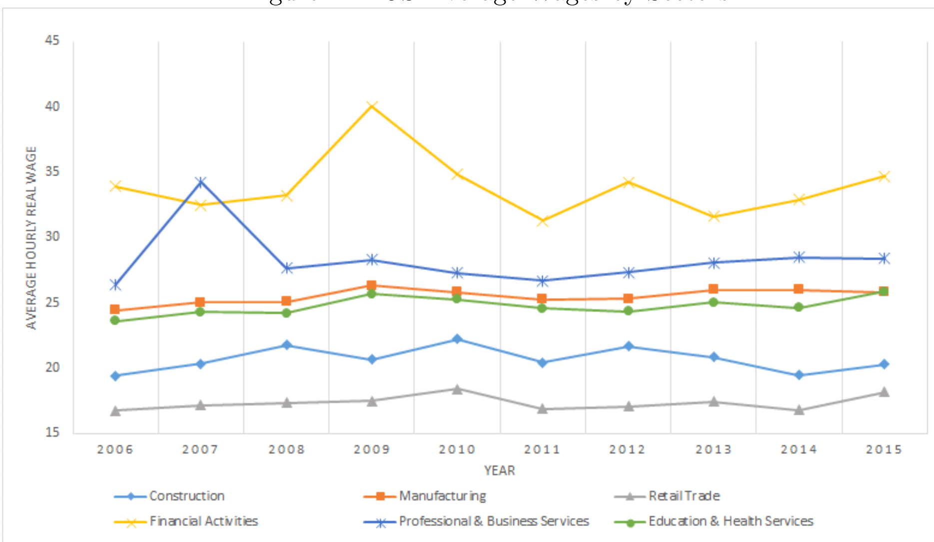
Reasons of displacement during the Last Two Recessions using data extracted from DWS are reported in Table 1.2. During the Great Recession, most workers lost their jobs due to the lack of full time job opportunities - 43% of the workers were displaced due to insufficient work. Job separation was also one of the main reasons for employment losses as about 31% of the workers lost their jobs due to plant or company closing and 26% were separated from their jobs because their posts were abolished. This highlights the fact that workers were becoming unemployed from their respective sectors due to low job finding rate in the form of low re-employment rates within the same sector and high job separation rate in the form of company closure, insufficient work and termination of jobs.

Elsby et al. (2013) report that real wages are procyclical but the degree of procyclicality varies

[5]Data Source: U.S. Bureau of Labor Statistics. 2010. News Release: Worker Displacement: 2007-2009. Calculations by CPWR Data Center.

across recessions. US distributions of year-to-year nominal wage change show many workers reporting zero change (suggesting wage stickiness) and many reporting nominal reductions (suggesting wage flexibility). The wage data for different industries have been collected from the CPS dataset

Figure 1.2: US Average Wages by Sectors



Data source: CPS.

for 2006-2015. The respondents were asked questions about their occupation and industries in which they are working currently and in which they have worked a year before. For the purpose of this study, the nominal wage variables for workers in each of the five industries were created. The wages were then converted into real wages by using annual CPI. Figure 1.2 shows the average real wage for each year between 2006 and 2015 for five different industries in the US. Reductions in the growth of wages and salaries typically began during recessions and continued afterwards as well. There has been a change in the average real wages of workers in professional and business services and the finance sectors over the years but on average, the wage growth slowed down during the Great Recession. Wages in the finance sector were more volatile, but showed no growth. Furthermore, even though there has been a decrease in employment in manufacturing and construction sectors in 2007-2009 recession, there is no significant change in the wages of these sectors.

These data facts from above show that during the Great Recession, some sectors (for example, construction) were adversely affected in terms of high unemployment and low re-employment rates due to high job separations and low job findings. The unemployed workers displaced from these sectors moved to other sectors to find work. On the other hand, there are some sectors where unemployment levels increased by small amount and/or are more or less the same before and after the Great Recession (for example, retail trade, professional and business services). In some sectors, unemployment has decreased during the great recession (for example, education and health services). The movement of displaced workers from construction sector to these sectors may have caused employment in these latter sectors to increase (for example, retail trade, education and health services). These data figures help to motivate the idea of worker reallocation between the sectors of economy in response to the shocks that originate in a specific sector which in turn may contribute to the changing unemployment rate in the whole economy.

1.3 Model

The model in this paper is based on the search and matching framework developed in MP (1994), which is extended to an economy with two sectors and heterogeneous workers. The two sectors of the economy differ in the work opportunities that they can offer and workers have different relative productivities in the two sectors. Similar approach has been previously developed and used in other two-sector settings, including formal versus informal and public versus private sectors (Albrecht et al. 2009, 2018). I use a simplified version of the model developed by Albrecht et al. (2009) without taxes, and apply it to the US construction and non-construction sectors.

In the model, the two sectors represent the US construction and non-construction. A shock to one particular sector takes place which spreads throughout the economy. Construction sector is chosen as an adversely affected sector because the empirical facts of the previous section show that this sector was hit harder than other sectors by the 2008 recession in terms of job loss and low re-employment levels. The increase in the housing prices through various mechanisms caused a sharp reduction in construction activity. This led to significant job losses in this sector and the need to absorb unemployed workers in other sectors (Valleta et al. 2008).

Time is continuous, and the labour market is populated by a unit mass of risk neutral, infinitely lived workers who discount the future at rate r. Workers can be either unemployed or employed in one of the two sectors. They can move between the states of employment in construction sector, employment in non-construction sector and unemployment. Immediate transitions between the jobs in two sectors are not allowed. Such transitions may only happen through the state of unemployment. Workers differ in the maximum productivity that they can achieve, denoted by y. Productivity is i.i.d. across the unit measure of workers and is described by a continuous probability density $f(y), 0 \leq y \leq 1$. Worker types are determined by dividing productivities y in three intervals, determined by two threshold levels. These thresholds are used to identify the distribution of workers across construction and non-construction sectors. The labour market frictions are modelled using a standard matching function. Workers and firms who meet form a match if and only if the joint surplus generated by the match is higher than the sum of the values of their respective outside options. Wages in non-construction sector are determined by Nash bargaining. Following the literature, I assume the free vacancy entry.

The two sectors in the model work in the following way. Workers employed in the construction sector receive flow income of y_0. They meet vacancies at the rate α, where α is the exogenous job finding rate in the construction sector. Construction jobs are destroyed at exogenous rate δ. This sector is assumed to be low skilled so the least productive workers in the economy do not find it profitable to work in non-construction sector. Employed workers in non-construction sector receive wage w which depends on worker's productivity level. The unemployed workers in non-construction sector find jobs at a rate $m(\theta)$, where m is the matching function and θ is the labour market tightness. When the matches are formed, all workers start non-construction jobs at their maximum potential productivity levels. Later matches receive exogenous productivity shocks that arrive at Poisson rate λ and change the actual productivity of workers in the match to y'. Productivity shocks are i.i.d. drawn from a continuous density $g(y')/G(y)$ for $0 \leq y' \leq y$, where $G(y)$ is a continuous distribution and $0 \leq y \leq 1$. The realised productivity y' is restricted to be less than or equal to y because we assume that worker's current productivity does not exceed his type.

If a series of productivity shocks pushes y' so low that the match surplus becomes less than the sum of the outside options, worker and firm will decide to end the match. The threshold value of productivity y' that determines the point of match destruction defines the reservation productivity of a worker of type y and is denoted by $R(y)$. The reservation productivity $R(y)$ is determined endogenously in the model for each worker type. If $y' \leq R(y)$, the match breaks with probability $G(R(y))/G(y)$. If $R(y) \leq y' \leq y$, the productivity changes to y' and the match survives with the probability $1 - G(R(y))/G(y)$. The reservation productivity also determines the lowest level of worker's productivity type that a firm would be willing to hire.

With all the model assumptions, I set up the value functions for unemployed and employed workers in the two sectors. These will then be used to derive wage schedule for non-construction sector, reservation productivity schedule, cut-off productivities that identify the sector in which each worker type works. The employment levels in the two sectors and unemployment level in the economy will be determined using the derived productivity levels and model's assumptions on the sectoral allocation of each worker type.

1.3.1 Workers

Unemployed workers receive a flow benefit b, and face a chance to meet vacancies in both construction and non-construction sectors. The value of unemployment for a worker of type y is denoted by $U(y)$ and is given by:

$$rU(y) = b + \alpha max[N_o(y) - U(y), 0] + m(\theta)max[N_1(y) - U(y), 0], \tag{1.1}$$

where α is the job finding rate in construction sector and $m(\theta)$ is the matching function. At the rate α, a worker receives an opportunity to work in the construction sector and, if the match is formed, gains the flow value of $N_o(y) - U(y)$, which is the difference between the values of employment and unemployment in construction, $U(y)$. Non-construction jobs arrive at the rate $m(\theta)$ and, if the match is formed, yield the difference between the values of employment and unemployment in non-construction sector, $N_1(y) - U(y)$. The value of employment in construction sector for a worker of type y is given by:

$$rN_o(y) = y_o + \delta[U(y) - N_o(y)]. \tag{1.2}$$

Equation (1.2) states that a worker employed in construction sector gets a flow income of y_0 while employment lasts, $y_0 \geq b$. At the rate δ, he loses his job and gets a capital gain of $U(y) - N_o(y)$. The value of employment in non-construction sector for a worker of type y with current productivity level y', $N_1(y', y)$ is given by:

$$\begin{aligned} rN_1(y', y) = w(y', y) &+ \lambda \frac{G[R(y)]}{G(y)}[U(y) - N_1(y', y)] \\ &+ \lambda \int_{R(y)}^{y} [N_1(x, y) - N_1(y', y)] \frac{g(x)}{G(y)} dx, \end{aligned} \tag{1.3}$$

Equation (1.3) states that a worker employed in non-construction sector gets a wage $w(y)$ from the match. At the rate λ, a shock that affects worker's realised productivity arrives. This shock either destroys the job with the probability $\dfrac{G[R(y)]}{G(y)}$ or shifts the productivity to a new level in the range $R(y) \leq y' \leq y$, in which case a worker stays employed but the value of employment changes to $N(x, y)$.

1.3.2 Firms

Let $J(y', y)$ be the value of a filled job for a firm that employs a worker of type y with current productivity level y' and it is given by:

$$\begin{aligned} rJ(y', y) = y' - w(y', y) + \lambda \frac{G[R(y)]}{G(y)}[V - J(y', y)] \\ +\lambda \int_{R(y)}^{y} [J(x, y) - J(y', y)] \frac{g(x)}{G(y)}.dx \end{aligned} \tag{1.4}$$

Equation (1.4) states that a firm receives a flow output of y' and pays a wage of $w(y', y)$. At the rate λ, a productivity shock arrives which causes the job to become vacant with the probability $\frac{G[R(y)]}{G(y)}$. If the new productivity level is in the range $R(y) \leq y' \leq y$, the match survives but firm's value changes to $J(x, y)$. Let V be the value of a vacancy and it is defined as:

$$rV = -c + \frac{m(\theta)}{\theta} max[J(y) - V, 0]; \tag{1.5}$$

Equation (1.5) states that the vacancy is advertised at a cost of c and if filled gives firm a capital gain of $J(y) - V$. One of the important and fundamental equilibrium assumptions in MP (1994) is that there is free entry of vacancies i.e. $V = 0$. This helps in determining the equilibrium value of θ.

1.3.3 Wage Determination

Wages in non-construction sector are determined through Nash bargaining. With worker's bargaining parameter β and the equilibrium condition of free entry $V = 0$, the joint surplus from a match can be written as:

$$max_{w(y',y)}[N_1(y, w) - U(y)]^{\beta} J(y, w)^{1-\beta}$$

I multiply firm's value function by β and worker's value function by $1-\beta$. After taking the difference of the two and simplifying it:

$$\begin{aligned} r[\beta J(y)-(1-\beta)N_1(y)] &= \beta y - w(y',y) - \lambda\frac{G[R(y)]}{G(y)}[\beta J(y)+(1-\beta)(U(y)-N_1(y))] \\ &\quad +\lambda\int_{R(y)}^{y}[\beta(J(x,y)-J(y))-(1-\beta)((U(y)-N_1(y))]\frac{g(x)}{G(y)}dx \end{aligned} \tag{1.6}$$

The surplus of a match is defined as the sum of the gain of the firm and worker being in a match relative to not being in a match. It is assumed that the wage is set such that the total match surplus is shared between the worker and firm according to the Nash-bargaining solution with share parameter β. The surplus sharing rule is as follows:

$$\begin{aligned} (1-\beta)N(y)-(1-\beta)U(y) &= \beta J(y) \\ -(1-\beta)U(y) &= \beta J(y)-(1-\beta)N(y) \end{aligned} \tag{1.7}$$

Putting (1.7) in the equation (1.6) and simplifying it:

$$w(y',y) = \beta y + r(1-\beta)U(y) \tag{1.8}$$

Equation (1.8) determines the wage paid to the workers in non-construction sector. It states that the wage is a weighted average of productivity and the flow value of unemployment with the weights being β and $1-\beta$, respectively.

1.3.4 Reservation Productivity

When a productivity shock is realised, workers and firms separate if worker's productivity level is less than reservation productivity $R(y)$. $R(y)$ is derived using zero surplus sharing rule which states that a match between the firm and a worker with current productivity level equal to $R(y)$ will generate zero profits and is given as:

$$N(R(y),y)-U(y)+J(R(y),y)=0$$

Worker with current productivity of $R(y)$ will equally value employment and unemployment i.e. $N(R(y),y) = U(y)$. So the surplus sharing rule is equal to:

$$J(R(y),y) = 0$$

The substitution of wage equation (1.8) in (1.4) which is the value function of a filled job for a firm and using the fundamental equilibrium condition is given by free entry of vacancies i.e. V=0 which gives:

$$(r+\lambda)J(y',y) = (1-\beta)y' - r(1-\beta)U(y) + \lambda\int_{R(y)}^{y} J(x,y)\frac{g(x)}{G(y)}dx \tag{1.9}$$

Evaluation of equation (1.9) at $y = R(y)$ i.e. when the current productivity of a worker equals his reservation productivity, and using the zero surplus sharing rule $J(R(y),y) = 0$ gives:

$$0 = (1-\beta)R(y) - r(1-\beta)U(y) + \lambda\int_{R(y)}^{y} J(x,y)\frac{g(x)}{G(y)}dx \tag{1.10}$$

Solving equation (1.9) and (1.10) simultaneously gives:

$$y - R(y) = \frac{(r+\lambda)}{(1-\beta)}J(y',y)$$

$$J(y',y) = \frac{(1-\beta)(y-R(y))}{(r+\lambda)} \tag{1.11}$$

Substitution of (1.11) in equation (1.9) and simplification gives:

$$(r+\lambda)J(y',y) = (1-\beta)y' - r(1-\beta)U(y) + \frac{\lambda(1-\beta)}{(r+\lambda)}(y-R(y)) - \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}\int_{R(y)}^{y} G(x)dx$$

Evaluating the equation above at y'=R(y) at J(R(y),y))=0: and solving for $R(y)$

$$R(y) = \frac{G(y)r(r+\lambda)U(y) - \lambda[\int_{R(y)}^{y}(1-G(x))dx - (1-G(y))y]}{\lambda + rG(y)} \tag{1.12}$$

For any value of y, there is a corresponding $R(y)$. A higher y will increase outside options of a worker, i.e. $U(y)$ is increasing in y. This causes $R(y)$ to increase but the final term in equation (1.12) is decreasing in y which suggests that $R(y)$ decreases. Hence which of these effects on $R(y)$ is higher depends on the parameter values.

1.3.5 Cut-Off Productivity Thresholds

The threshold of the productivity levels that identify whether the worker works in the construction or non-construction sector are such that a worker with productivity level $y \leq y^*$ will not be able to work in the non-construction sector. This is because non-construction sector consists of high skilled workers on average so low productivity workers do not possess the necessary skill set to work in this sector. Similarly, workers with $y \geq y^{**}$ will not find it worthwhile to work in the construction sector because becoming unemployed in non-construction sector yields them more benefit than moving to the construction sector to find work.

There are two threshold levels of worker types. Workers with $y < y^*$ are low productivity workers and will only work in construction sector. Workers with $y^* \leq y \leq y^{**}$ are medium productivity workers and they can work either in construction or non-construction sector depending on any job offer that comes along their way. Workers with $y > y^{**}$ are high productivity workers who will only work in non-construction sector. Using these characteristics of worker types, I derive the two cut-off productivity levels. First we consider worker's cut-off productivity level y^*. The worker of this type is indifferent to being unemployed or being employed in non-construction sector i.e. $U(y^*) = N_1(y^*)$. Hence his value functions can be written as:

$$rU(y^*) = b + \alpha[N_o(y^*) - U(y^*)]$$

$$rN_0(y^*) = y_o + \delta[U(y^*) - N_o(y^*)]$$

$$N_0(y^*) = \frac{y_0 + \delta U(y^*)}{r+\delta}$$

Substituting the value of $N_0(y^*)$ in $rU(y^*)$ and simplifying it:

$$rU(y^*) = \frac{b(r+\delta) + \alpha y_0}{r+\delta+\alpha} \tag{1.13}$$

Equation (1.13) is the unemployment value for all workers with $y \leq y^*$ and it depends on the job finding rate α and job separation rate δ. Next we substitute $N_1(x,y)$ out of the following surplus sharing rule:

$$N(x,y) = \frac{\beta}{1-\beta} J(x,y) + U(y)$$

and substitute it in equation (1.3):

$$rN_1(y^*) = w(y^*) + \lambda \frac{G[R(y^*)]}{G(y^*)}[U(y^*) - N_1(y^*)] + \lambda \int_{R(y^*)}^{y^*} [\frac{\beta}{1-\beta} J(x,y^*) + U(y^*) - N_1(y^*)] \frac{g(x)}{G(y^*)} dx$$

Now using $U(y^*) = N_1(y^*)$ and simplifying it using wage equation (1.8):

$$rN_1(y^*) = \beta y^* + r(1-\beta)U(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}[\int_{R(y*)}^{y*}(G(y^*) - G(x))dx]$$

Solving for y^* using $U(y^*) = N_1(y^*)$:

$$y^* = \frac{b(r+\delta) + \alpha y_0}{r+\delta+\alpha} - \frac{\lambda}{(r+\lambda)G(y)}[\int_{R(y*)}^{y*}(G(y^*) - G(x))dx] \tag{1.14}$$

Equation (1.14) shows that y^* depends on $rU(y^*)$ so $R(y^*)$ also depends on $rU(y^*)$. Next, a high productivity worker will only accept non-construction sector jobs and is indifferent between unemployment and construction sector job offers, so for him $U(y^{**}) = N_0(y^{**})$. Using this condition in the value function for unemployed worker:

$$rU(y^{**}) = b + \alpha[N_o(y^{**}) - U(y^{**})] + m(\theta)max[N_1(y^{**}) - U(y^{**})]$$

$$rU(y^{**}) = b + m(\theta)max[N_1(y^{**}) - U(y^{**})]$$

Since $U(y^{**}) = N_0(y^{**})$ so we know from $rN_0(y^{**})$:

$$rN_0(y^{**}) = y_0$$

and

$$rU(y^{**}) = rN_0(y^{**}) = y_0 \tag{1.15}$$

Equation (1.15) shows that unemployment value $U(y^{**})$ is equal to the flow income y_0 for all workers with $y \geq y^{**}$

So:

$$y_0 = b + m(\theta)max[N_1(y^{**}) - \frac{y_0}{r}]$$

$$N_1(y^{**}) = \frac{y_0(r + m(\theta)) - rb}{rm(\theta)} \tag{1.16}$$

Equation (1.16) shows that the value of employment for workers with $y \geq y^{**}$ depends on the matching function $m(\theta)$ and labour market tightness θ. Substituting $N_1(x, y^{**})$ from surplus sharing rule into equation (1.3) and simplifying it using wage equation (1.8), value of $N_1(y^{**})$ and using equation (1.11) to replace $J(x, y^{**})$:

$$(r+\lambda)\frac{y_0(r + m(\theta)) - rb}{m(\theta)} = \beta y^{**} + r(1-\beta)U(y^{**}) + \lambda U(y^{**}) + \frac{\lambda\beta}{(r+\lambda)G(y^{**})}[\int_{R(y^{**})}^{y^{**}}(G(y^{**}) - G(x))dx]$$

Simplifying in terms of y^{**}:

$$y^{**} = y_0 + (rG(y^{**}) + \lambda)\frac{(y_0 - b)}{\beta m(\theta)G(y^{**})} - \frac{\lambda}{(r+\lambda)G(y^{**})}[\int_{R(y^{**})}^{y^{**}}(G(y^{**}) - G(x))dx] \tag{1.17}$$

y^{**} depends on the $m(\theta)$, reservation productivity $R(y^{**})$ and model parameters.

1.3.6 Ins and Outs of Employment

In order to derive the employment rates for the two sectors and unemployment rates for different worker types and overall economy, the steady state conditions of the model are used. Let $u(y)$ be the fraction of time of unemployment for worker type y, $n_C(y)$ be the fraction of time of employment for workers in construction sector and $n_{NC}(y)$ be the fraction time of employment for workers in non-construction sector. The sum of these three equals one and can be written as:

$$u(y) + n_C(y) + n_{NC}(y) = 1 \tag{1.18}$$

The steady state condition for low productivity workers in construction sector is that flow into employment equals the flow into unemployment. So the steady state unemployment and employment for workers of type $y < y^*$ is equal to:

$$u(y) = \frac{\delta}{\delta + \alpha} \tag{1.19}$$

$$n_C(y) = \frac{\alpha}{\delta + \alpha} \tag{1.20}$$

$$n_{NC}(y) = 0 \tag{1.21}$$

$n_{NC}(y) = 0$ because a low productivity worker will not be able to work in non-construction sector. For workers of type $y^* \leq y \leq y^{**}$, the steady state conditions are such that the employment inflow in construction sector is equal to outflow into unemployment in the same sector:

$$\alpha u(y) = \delta n_C(y) \tag{1.22}$$

In non-construction sector, employment inflow is equal to the flow into unemployment i.e.:

$$m(\theta)u(y) = \lambda \frac{G[R(y)]}{G(y)} n_{NC}(y) \tag{1.23}$$

and

$$n_{NC}(y) = 1 - u(y) - n_C(y) \tag{1.24}$$

So from solving equation (1.22), (1.23) and (1.24) simultaneously, we get the employment and unemployment rates which are as follows:

$$n_C(y) = \frac{\alpha\lambda G[R(y)]}{\delta m(\theta)G(y) + \lambda(\delta+\alpha)G(R(y))} \tag{1.25}$$

$$u(y) = \frac{\delta\lambda G[R(y)]}{\delta m(\theta)G(y) + \lambda(\delta+\alpha)G(R(y))} \tag{1.26}$$

$$n_{NC}(y) = \frac{\delta m(\theta)G(y)}{\delta m(\theta)G(y) + \lambda(\delta+\alpha)G(R(y))} \tag{1.27}$$

For workers of type $y > y^{**}$, the steady state condition is such that the flow into employment in non-construction sector is equal to outflow into unemployment in the same sector:

$$m(\theta)u(y) = \lambda \frac{G[R(y)]}{G(y)} n_{NC}(y)$$

which can be rewritten as:

$$m(\theta)u(y) = \lambda \frac{G[R(y)]}{G(y)} [1 - u(y)] \tag{1.28}$$

and we know that such workers will not work in the construction sector so the employment rate for these workers in construction sector can be written as

$$n_C(y) = 0 \tag{1.29}$$

hence simplifying equations (1.24), (1.28) and (1.29) in terms of $u(y)$ and $n_{NC}(y)$:

$$u(y) = \frac{\lambda G[R(y)]}{m(\theta)G(y) + \lambda G(R(y))} \tag{1.30}$$

$$n_{NC}(y) = \frac{m(\theta)G(y)}{m(\theta)G(y) + \lambda G(R(y))} \tag{1.31}$$

The total unemployment in the economy will be derived by the following:

$$u = \int_0^{y^*} u(y)f(y)dy + \int_{y^*}^{y^{**}} u(y)f(y)dy + \int_{y^{**}}^{1} u(y)f(y)dy \tag{1.32}$$

Intuitively, in equilibrium, workers will be sorted in the two sectors based on their types, y. High productivity workers are more likely to take jobs in non-construction sector, while low productivity workers are more likely to take construction sector jobs, and medium productivity workers will take both. In addition to compositional effects, changes in model parameters affect the steady state distributions of workers among sectors, affecting also the distributions of wages across non-construction sector.

1.3.7 Equilibrium

The fundamental equilibrium condition is given by free entry of vacancies i.e. V=0. So:

$$c = \frac{m(\theta)}{\theta} max[J(y', y), 0] \tag{1.33}$$

We need to take into account that the density of types among the unemployed is contaminated in the sense that the distribution of types among the unemployed is affected by the different transition rates to and from unemployment by worker types. Let $f_u(y)$ be the density of types among unemployed workers. The can also be written as:

$$f_u(y) = u(y)f(y)/u$$

The eexpression above states that the distribution of types among the unemployed, $f_u(y)$, can be written as the type-specific unemployment rate, u(y), times the distribution function, $f(y)$ normalised by the overall unemployment rate in equation (1.32). Using the above expression and replacing the value of $J(y', y)$ from (1.11), equation (1.33) becomes:

$$c = \frac{m(\theta)}{\theta}(1-\beta)\int_{y^*}^{1} \frac{(y - R(y))}{(r+\lambda)} \frac{u(y)f(y)}{u} dy \tag{1.34}$$

Equation (1.34) takes into account the fact that $J(y) < 0$ for $y < y^*$, i.e., some contracts do not lead to a match. θ can be solved numerically given the assumed functional forms for the distribution functions, F(y), G(y) and for the matching function, $m(\theta)$ and values for exogenous parameter r and λ. Normalising the total labour force to unity, an equilibrium is labour allocations $u(y)$, $n_C(y)$, $n_{NC}(y)$, set of value functions $N_o(y)$,$N_1(y', y)$, $J(y', y)$ and $U(y)$, reservation productivity function $R(y)$, wages $w(y', y)$ such that:

1. free entry condition holds in the economy and satisfies equation (1.34).

2. matches are completed and dissolved if and only if it is in the mutual interest of the worker and firm to do so.

3. the steady state condition holds which implies that the evolution of employment for three worker types follows equations (1.20) (1.21) (1.25), (1.27) (1.29) and (1.31) in the two sectors while

4. evolution of unemployment for three worker types and overall economy follows equations (1.19), (1.26) and (1.30) and (1.32).

5. workers of type $y < y^*$ do not find work in non-construction sector with cut-off productivity threshold y^* satisfied by equation (1.14) and

6. workers of type $y > y^{**}$ do not work in construction sector with cut-off productivity threshold y^{**} satisfied by equation (1.17).

7. reservation productivity schedule follows equation (1.12) and differs for each worker type.

1.4 Parametrization

The model parameters, discount rate r, elasticity of the matching function η, unemployment benefits b, wage bargaining power parameter β, flow income y_0, vacancy creation cost c, Poisson rate at which productivity shock arrives λ, job finding rate α and job destruction rate δ need to be calibrated in order to solve for the productivity thresholds, reservation productivities, non-construction wage distribution, employment and unemployment values for each sector. In this section I calibrate the model to US construction and non-construction sectors before great recession (i.e. in year 2007) using data from multiple sources. In order to analyse the effects of job separation and job finding rates, I fix several model parameters according to their values used in the literature and from other sources. The model parameter values are summarised in Table 1.3 and discussed below.

The parameter values in the model are chosen to produce results for the baseline case of the model that are consistent with the US economy. First, I choose the discount rate of $r = 0.04$ and set the value of elasticity of matching function equal to $\eta = 0.5$. This value of $\eta = 0.5$ is chosen from Mortensen and Nagypal (2007) and Pilossoph (2014) since they use data on vacancies and unemployment levels from CPS data to estimate the elasticity of the Cobb-Douglas matching function.

The worker's bargaining power parameter β is set equal to the elasticity of matching function so that Hosios (1990) condition holds. This condition requires that the match surplus be divided between the workers and firms to properly compensate for their search decisions. More precisely, worker's (or firm's) share of the match surplus should be equal to their share of contribution in a match (Mangin and Julien 2018). A broad range of search models apply this condition (for example, Rogerson, Shimer, and Wright 2005; Pilossoph 2012; Wright, Kircher, Julien, and Guerrieri 2017). For this condition to hold, the elasticity of match function and Nash bargaining parameter are assumed to be equal to each other.

The value of the unemployment benefits is set as $b = 0.2$ and is taken from Hall and Milgrom (2008) who state that b is essentially a replacement rate, the fraction of normal earnings paid as the typical unemployment benefit and while some workers receive a substantial fraction of their earlier wages as benefits, many features of the system limit the effective rate. They estimate b=0.2 as a reasonable figure of unemployed benefits from the the lower (12%) and the upper bound (36%) of ratio of benefits paid to previous earnings that are calculated in the literature (Hall, 2006 and Anderson and Meyer, 1997).

I set the flow income to $y_0 = 0.4$, and vacancy creation cost to $c = 1$, $\lambda = 0.4$ and assume a Cobb-Douglas function of the form $m(\theta) = 4(\theta)^{\eta}$ from the search and matching literature so that the model economy is an approximate of the US data.

Table 1.3: Parameter Values

Parameters	Description	Values	Source
r	Discount Rate	0.04	Chang (2011)
η	Elasticity of the Matching Function	0.5	Mortensen and Nagypál (2007), Pilossoph (2014)
β	Worker's Bargaining Power	0.5	Hosios Condition (1994)
b	Unemployment Benefits	0.2	Hall and Milgrom (2008)
y_0	Flow income in Construction Sector	0.4	Albrecht et al. (2009)
c	Vacancy Creation Cost	1	Pilossoph (2012)
λ	Productivity Shock in Non-Construction Sector	0.4	Bureau of Labour Statistics (BLS) data
$m(\theta)$	Cobb-Douglas Matching Function	$4(\theta)^{\eta}$	Search and matching framework literature
δ	Job Separation Rate in Construction Sector	0.058	JOLTS/Own Calculations
α	Job Finding Rate in Construction Sector	0.64	CPS/Own Calculations

I extract the job separation rate in the construction sector δ from the Job Openings and Labour Turnover Survey (JOLTS) database. It is a monthly survey that has been developed to address the need for data on job openings, hires, and separations. From the JOLTS data, the 2007 pre-recession average monthly job separation rate in construction sector is 5.8%. Hence I use the value shown in Table 1.3 for job separation rate δ in the model. I calculate job finding rate α by using a measure used by Shimer (2005). I first calculate the job finding probability F_t using

$$F_t = 1 - \frac{(Un_{t+1} - Un^s_{t+1})}{Un_t}$$

where F_t is the job finding probability, Un_{t+1} is number of unemployed workers at date $t+1$ and Un^s_{t+1} is the number of short term unemployed workers, those who are unemployed at date $t+1$ but held a job at some point during period t. Un_t is the number of unemployed workers at time t. F_t is expressed as a function of unemployment and short term unemployment and is then mapped onto job finding rate α such that $\alpha = -log(1 - F_t)$. I derived F_t and α for construction sector using the monthly CPS unemployment series and the derived short term unemployment series from Center for Economic Policy Research (CEPR) dataset for construction sector from 2001-2010. I set α at 64% in 2007 for the baseline model economy.

Finally, I assume that the distribution of worker types is uniform over $[0, 1]$. Therefore $G(y)$ is a standard uniform distribution. With the functional forms and parameters of the model, the baseline case is reported which assesses the aggregate outcomes of the model: cut-off productivities, reservation productivities, unemployment rate of different worker types and of overall economy, employment in two sectors and average wages in the economy.

1.5 Baseline Case

The baseline labour market in this model is meant to approximate a composite of US labour market during the pre-recession period of 2007. Since the model is set up to assess the effects of sector-specific shocks on unemployment levels, construction sector employment and non-construction sector employment, a primary target of our calibration is to produce reasonable figures for these categories. With the job separation rate at 5.8% and job finding rate of 64%, the aggregate outcomes of the model are as follows.

The baseline model outcomes generated with the first set of job separation and job finding rates

Table 1.4: Baseline Model Variables

Aggregate Outcomes	Description	Model
y^*	Cut-off level for low productivity workers	0.373
$R(y^*)$	Reservation productivity for low productivity workers	0.373
y^{**}	Cut-off level for high productivity workers	0.464
$R(y^{**})$	Reservation productivity for high productivity workers	0.395
u_0	Unemployment rate for $y < y^*$	0.083
u_1	Unemployment rate for $y^* < y < y^{**}$	0.040
u_2	Unemployment rate for $y > y^{**}$	0.060
$\bar{y}$	Average productivity in non-construction sector	0.698
$\bar{w}$	Average Wages in non-construction sector	0.403

Table 1.5: Aggregate Model Outcomes vs US Data

Aggregate Outcomes	Description	Model	Data
θ	Labour market tightness	0.78	0.73
u	Total unemployment rate	0.056	0.052
n_C	Construction employment share	0.151	0.160
n_{NC}	Non-construction employment share	0.793	0.788

are shown in Tables 1.4 and 1.5. Table 1.4 shows that the distribution of labour force in the two sectors is such that around 37% of the labour force works in construction sector as $y^* = 0.373$ and about 50% of the labour force works in non-construction sector as $y^{**} = 0.464$ while the remaining 11% are those medium productivity workers who are willing to work in either sector.

The reservation productivity $R(y)$ for the worker type y^* who is just on the margin of working in the non-construction sector is the same as that worker's type i.e. $y^* = R(y^*) = 0.373$. This indicates that if a worker of this type is employed in non-construction sector then the match would end if worker's productivity goes below his maximum potential (Albrecht el al. 2017). The reservation productivity schedule of high productivity workers $R(y^{**})$ is higher than the reservation productivity of workers of y^* type. This is because the effect of y on $R(y)$ is two folds. Highly productive workers are more skilled and have great potential of keeping their jobs $[\int_{R(y)}^{y}(1 - G(x))dx - (1 - G(y))y]$ but at the same time, they have better outside options $G(y)r(r + \lambda)U(y)$.

Table 1.4 also shows the unemployment rates for different worker types. For low productivity workers ($y < y^*$) and for medium productivity workers $y^* < y < y^{**}$, the unemployment rate is about 8% and 4% while for high productivity workers $y > y^{**}$, the average unemployment rate is about 6%. The average unemployment rate for medium productivity workers is low because they are willing to work in both the construction and non-construction sectors.

The aggregate unemployment rate in the model economy is 5.6% which is slightly more than the average unemployment rate in US in 2007 as reported in Table 1.5. The labour market tightness generated in the model is 0.78. Data on US labour market tightness is extracted from Fred Economic data which calculates θ as total unfilled vacancies/total unemployment level/1000. In 2007, the average labour market tightness in US was about 0.73.

Table 1.5 also reports the model generated employment rates for the two sectors. In the model economy about 15% of the labour force is employed in the construction sector while about 79% is employed in the non-construction sector. The US data shows that around 16% of the labour force is employed in construction sector while 78% of the labour force is employed in the non-construction section. The average wages and average productivity in the non-construction sector of the model are also reported in Table 1.4. The average productivity in the non-construction sector is about 0.7 and the average wages paid in this sector are 0.403.

Now that the baseline economy is set up, I run simulations to assess if sector-specific shocks propagate to the rest of the economy and contribute to changing unemployment levels. Taking various combinations of job finding rates and separation rates in the construction sector, I simulate the effect of shocks on unemployment, employment levels and wages in the model economy.

1.6 Simulations and Counterfactuals

1.6.1 Simulations

Increase in the unemployment rate reflects variation in the growth of labour demand across sectors. When workers move from sectors with little or no job opportunities to other sectors to find employment, this leads to intervening spells of unemployment that may change the overall unemployment rate. Moreover, when workers relocate to expanding sectors, a mismatch can arise between job requirements and worker's skills. This may put little or no downward pressure on wages of this sector (Valleta et al. 2008). Hence, now with the functional forms and parameters of the model, I simulate the effects of construction sector's changing job separation rate and job finding rate on the unemployment rate for all three types of workers, total unemployment rate and employment rates in two sectors and the average wage in non-construction sector.

Construction sector was adversely affected by the 2008 economic downturn in the US because of the housing bubble. This led to 60% of the workers getting displaced from this sector, thus decreasing labour market activity. Phelps (2008) states that the persistent job losses in this sector due to higher job separations and lower job findings may change the economy's unemployment rate due to the need to absorb the displaced construction sector workers into other sectors. Therefore, increasing levels of job separation rate and decreasing levels of job finding rate in the construction sector are used as an indicator of an adverse labour demand shock in this sector. I first examine the effect of changing δ while keeping α fixed at 60%. I then change α and keep δ fixed at 5%. Finally, I change δ and α simultaneously and examine their effects.

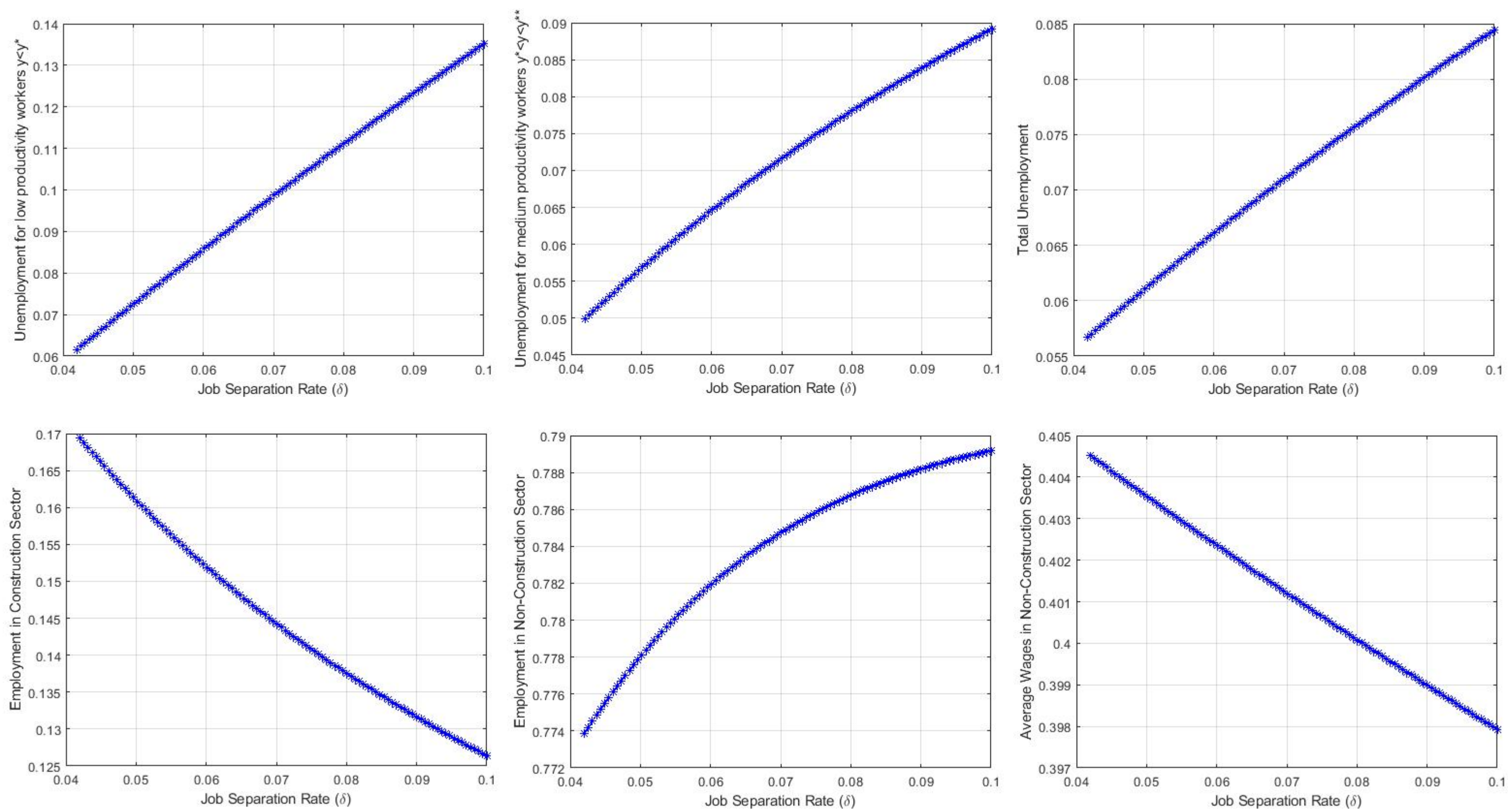
Consider the first case of changing δ only. The effects on the aggregate outcomes of the model are reported in Figure 1.3. As δ increases, unemployment for each worker type in this sector increases. Unemployment rate in the model for low productivity workers ($y < y^*$) and medium productivity workers ($y^* < y < y^{**}$) starts to increase as a result of high job separations. The increase in the unemployment rate for medium productivity workers is smaller than that of low productivity workers. This is explained by one of the assumptions of the model that medium productivity workers will accept any job opportunity that they get, be it in construction sector or in non-construction sector.

For some of these workers, it is profitable to move to non-construction sector to find employment. This leads to a smaller increase in the unemployment rate of medium productivity workers as compared to the low productivity workers. The unemployment of high productivity workers u_2 who only work in non-construction sector remains unchanged with changing δ. So there are no spillover effect of increase in δ on the unemployment levels of high productivity workers in non-construction sector. But the total unemployment in the model increases with increasing δ. The increasing unemployment rates for low and medium productivity workers contributes to higher total unemployment rate in the model however some of it is offset by medium productivity workers moving to non-construction sector to find jobs.

Figure 1.3 also shows the employment rate in the two sectors. The employment rate in construction sector n_C decreases when δ increases while employment in non-construction sector n_{NC} increases. Employment losses in the construction sector are partly because of the increase in the job separation rate and partly because of medium productivity workers moving to non-construction sector to find employment. In non-construction sector, employment levels increase because with more workers losing their jobs in construction sector, some medium productivity workers move to this sector and get employed here.

The average wages $\bar{w}$ for workers in non-construction sector start to decrease. As the job separation rate in construction sector starts to increase further, the labour market conditions become adverse with low and medium productivity workers facing higher unemployment levels.

Figure 1.3: Simulating the Impact of δ on Aggregate Model Outcomes.

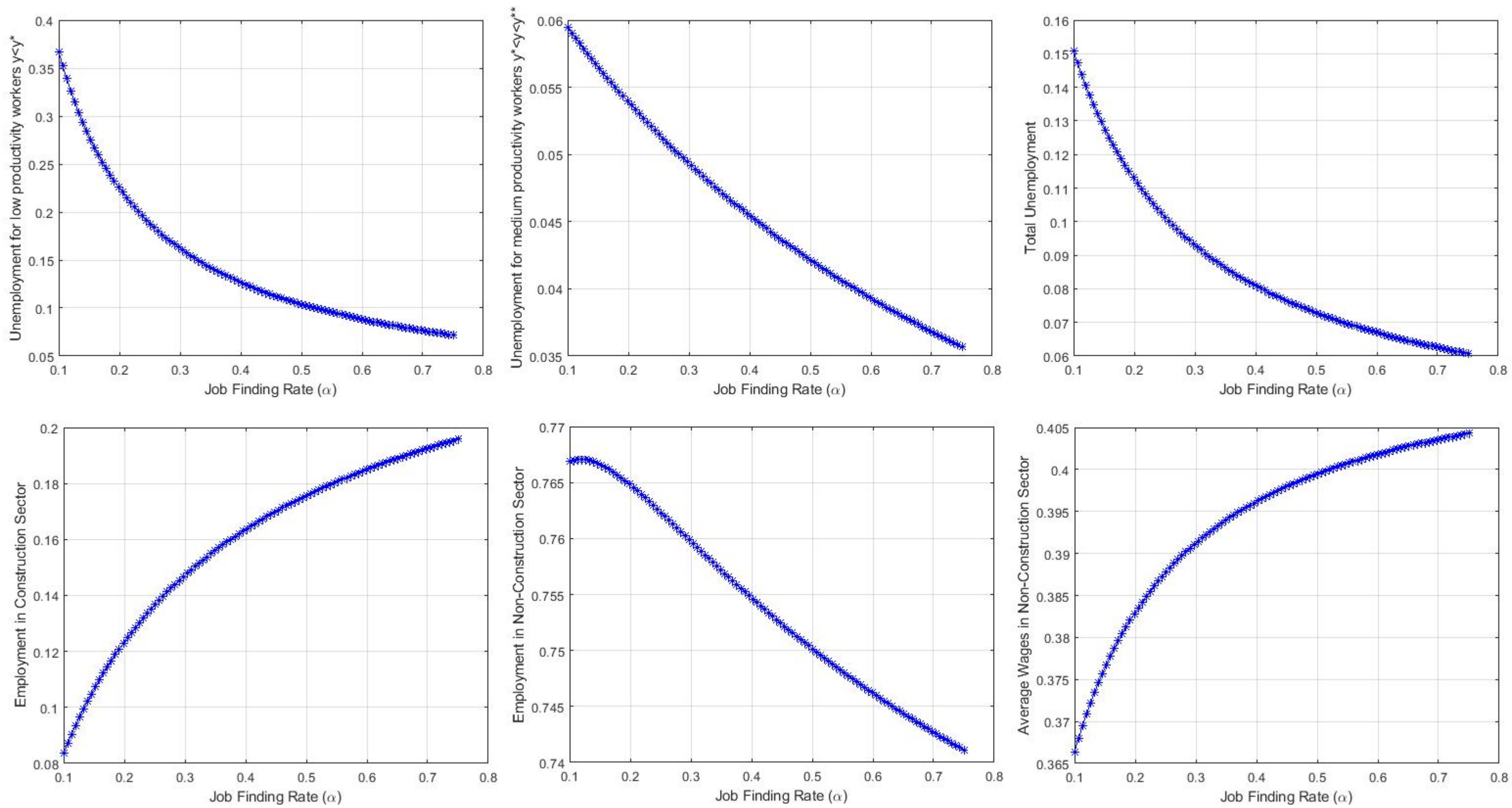


Consider the second case of changing α only in Figure 1.4. A decrease in α causes the labour market dynamics to change in the following way. In construction sector, medium productivity workers would want to leave this sector as the prospects of them finding employment decreases but in non-construction sector, they have better prospects of finding jobs. With lower job finding rate in construction sector, unemployment rate for low productivity workers (u_0) increases significantly because it will be harder for these workers to find jobs in construction sector. Unemployment for medium productivity workers also increases in the model as a result of lower job finding rate in construction sector but, it is not as severe as that of low productivity workers. In this case, a large amount of medium productivity workers move to non-construction sector to find employment.

The unemployment rate for high productivity workers remains unchanged while unemployment in the model economy increases. Initially in non-construction sector, medium productivity workers are able to find jobs. But as the job finding prospects in construction sector becomes smaller, it increases the pool of unemployed workers in the economy. So the increased unemployment for low and medium productivity workers dominates the total unemployment in the model. A decrease in α causes employment rate in construction sector to decrease significantly while employment in non-construction sector increases as medium productivity workers move there.

One interesting pattern seen in Figure 1.4 is that as the job finding rate in construction sector becomes significantly lower, it starts to have a negative impact on the employment levels in not just the construction sector, but also in non-construction sector. When α is extremely low, a large amount of medium productivity workers move to non-construction sector to find employment.

Figure 1.4: Simulating the Impact of α on Aggregate Model Outcomes.

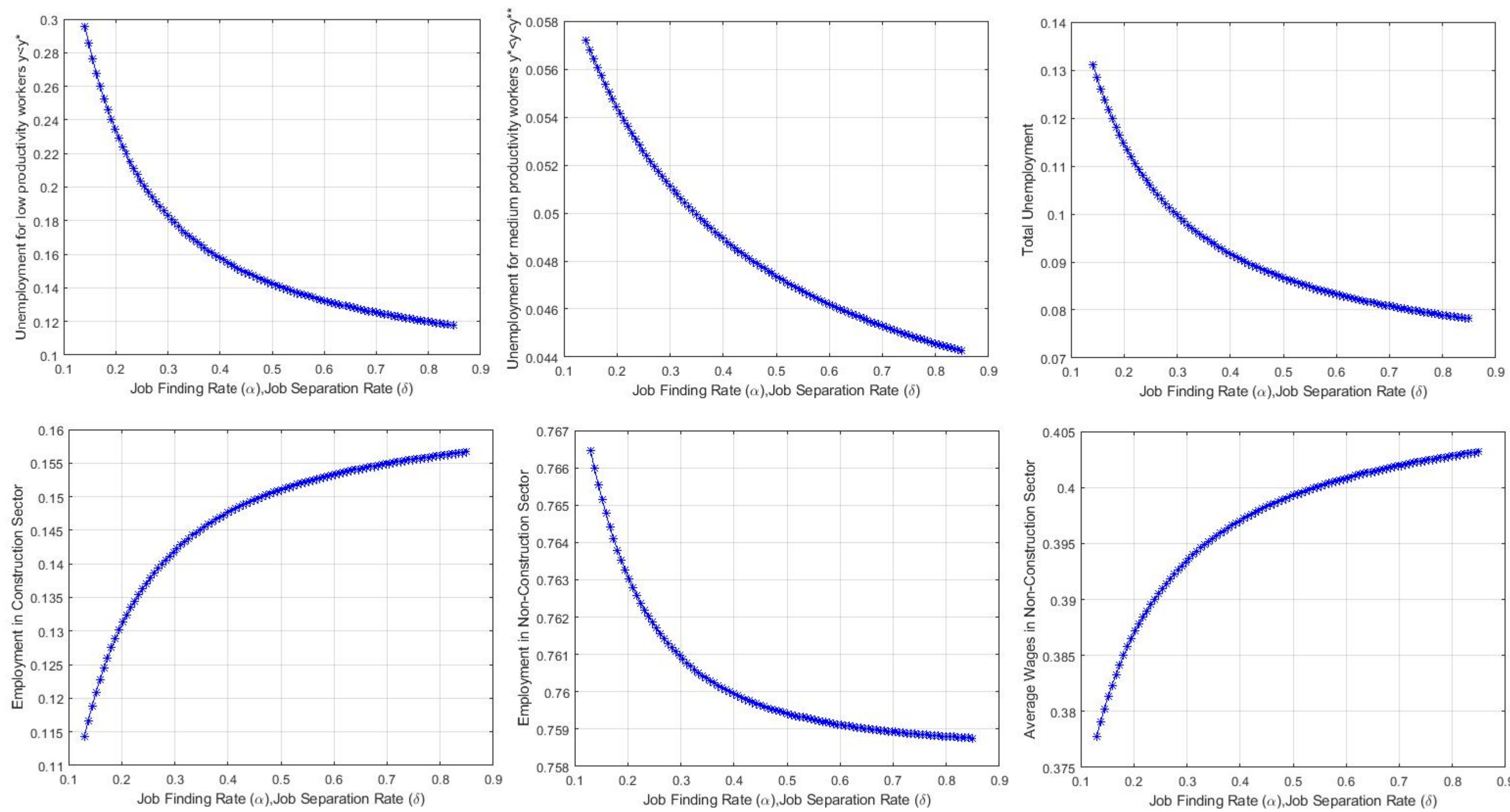


However the number of vacancies in non-construction sector are now low as compared a higher pool of workers searching for jobs in this sector. This indicates that when job finding rate in construction sector becomes significantly low, it starts to have adverse spillover effects on not just the total unemployment in the model and employment levels in construction sector but also on the employment levels in non-construction sector.

The average wage in non-construction sector decreases as firms know that with less employment prospects in the other sector, existing employed workers in non-construction sector would not want to risk losing their jobs and would be willing to work for lower wages. Because of lower job finding prospects in construction sector and more people moving to non-construction sector, for high productivity workers, the benefit of keeping the existing jobs in this sector is higher than finding high paying employment. Hence even when average wages decrease, unemployment for high skilled workers does not change.

Consider the third case of changing both δ and α together in Figure 1.5. A decrease in α and an increase in δ leads to a large increase in the unemployment rate for low productivity workers (u_0) and medium productivity workers (u_1). For high productivity workers, unemployment remains unchanged as again the effect of keeping existing jobs dominates the impact of finding high paying jobs in non-construction sector. However, the increased unemployment for low and medium productivity workers have the higher impact on the total unemployment in the model economy as it increases. The employment in the construction sector decreases while in non-construction sector, it increases for various combinations of δ and α. Compared to the previous two cases, average wages in the non-construction sector start to decrease significantly with lower α and higher δ indicating that now there is a large pool of workers looking for jobs in this sector. Simulations of changing combinations of α and δ on the aggregate model outcomes in Figure 1.5 show that the effect of variations in α is higher than δ on all the model outcomes, indicating that α dominates in measuring the impact.

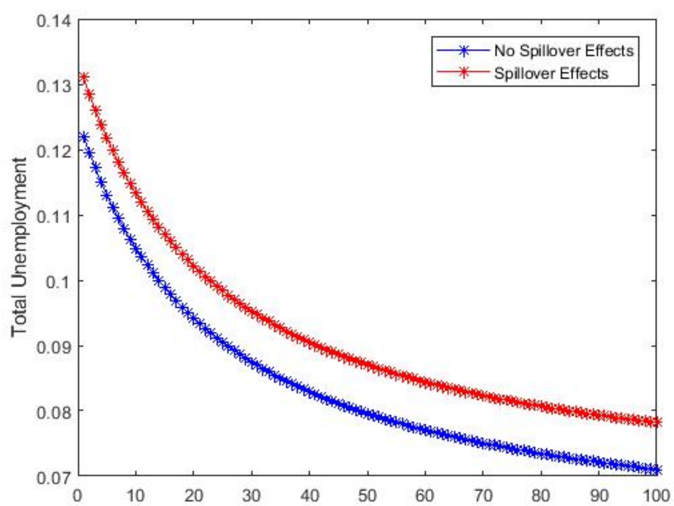
Figure 1.5: Simulating the Impact of δ and α on Aggregate Model Outcomes.



1.6.2 Counterfactuals

The results from the previous section show that sector-specific shocks in construction sector causes spill over effects i.e. there is movement of labor across sectors. This movement of workers between sectors take place because of low job finding rate and high job separation rate in the construction sector. In this section, I run counterfactual exercise to quantify how overall unemployment in the model and employment in two sectors of the model behave in the absence of the spill over effects i.e. there is no movement of workers between the sectors. In order to do so, I keep the productivity levels of the workers fixed. I also assume that there is now only one productivity threshold level (y^{**}) in the model and only two type of workers; low productivity workers and high productivity workers. Low productivity workers are those with productivity level of $y < y^{**}$ and they only work in construction sector. High productivity workers are those with productivity levels of $y > y^{**}$ and they only work in non-construction sector.

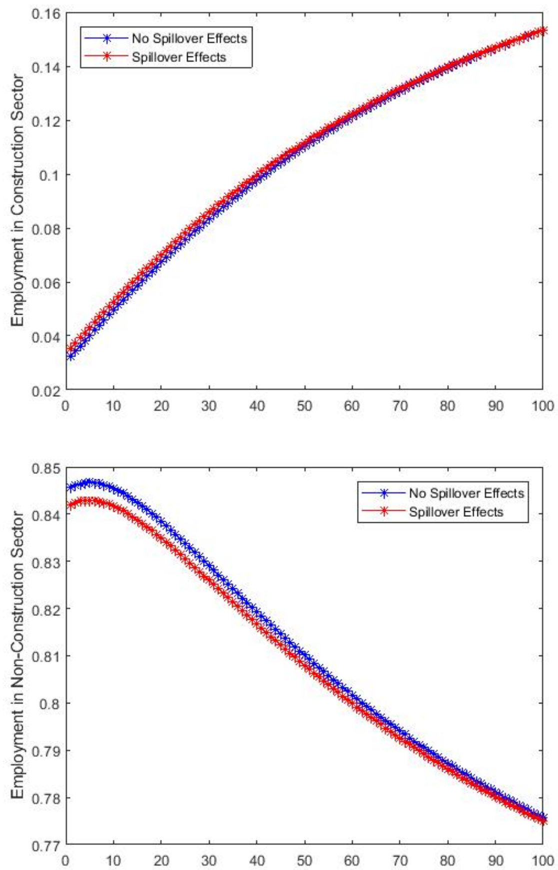
Figure 1.6: Counterfactuals: Spillover Vs No Spillover Unemployment



With no movement of workers between the sectors, figure 1.6 shows the overall level of unemployment in the hypothetical economy. Overall unemployment in the model when there are no spill over effects is always lower as compared to when there is movement of workers across sectors. On average, the unemployment in "no spill over case" is 5% lower then the unemployment in spill over case. There are two possible reasons for this. First, in the absence of sectoral reallocation of workers, there is a balance between the labour demand and labour supply in non-construction sector. So there is lower probability of a mismatch between worker skills and requirements of the employers. Secondly, as highlighted in the literature on the sectoral shift hypothesis, for any shock resulting in labor reallocation across sectors, the economy will take much longer to respond due to imperfect mobility in addition to the standard search friction causing higher unemployment rate (For example: Lillien, 1982; Chang, 2011 and Pilossoph, 2012). Therefore in the absence of spill over effects, the unemployment rate in the economy will be relatively lower.

Figure 1.7 compares the employment levels in the construction and non-construction sectors when there is no labour reallocation across sectors and when there are spillover effects. The employment levels in the construction sector when there are no spill over effects is lower than the case when sectoral movement of workers is allowed in the model. On average, the no spill over employment in construction sector is approximately about 1.5% lower than the spill over case employment. This is because in the latter case, some of the pressure on employment level in this sector is taken off by the movement of medium productivity workers to non-construction sector to find work. In non-construction sector, employment is high when there is no movement of workers from construction sector to this sector as the labour demand relative to the labour supply is balanced and there is no mismatch between workers and firms in this sector.

Figure 1.7: Counterfactuals: Spillover Vs No Spillover Employment in Construction and Non-Construction Sector



1.7 Two-Sector Economy: Manufacturing and Construction

The US manufacturings sector is closer to the construction sector in terms of the skill set of workers. So it is likely that when workers are displaced from the construction sector, they move to manufacturing sector to find work. Keeping this idea in mind, I assume that in the hypothetical economy of the model, there are only two sectors; construction and manufacturing. I calibrate the model to these two sectors from the US data in pre-recessionary time period to assess the changes in the total unemployment level and employment levels in the two sectors of the model. Table 1.6 reports the changes in the calibration of some model parameters while taking into account the manufacturing sector.

Table 1.6: Parameter Values for Manufacturing Sector

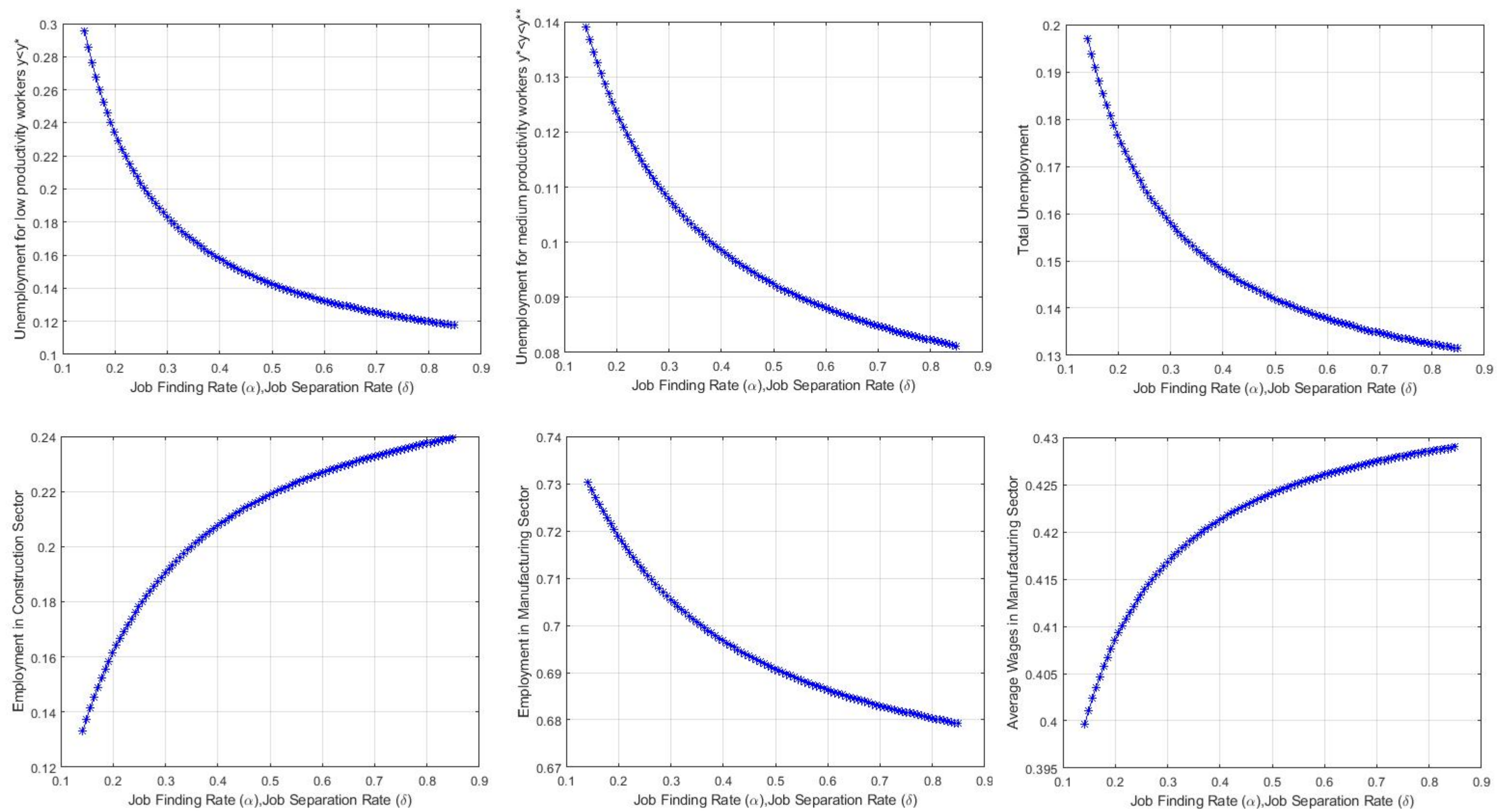
Parameters	Description	Values	Source
r	Discount Rate	0.04	Chang (2011)
η	Elasticity of the Matching Function	0.7	Warren (1996), Petrongolo and Pissarides (2001)
β	Worker's Bargaining Power	0.7	Hosios Condition (1994)
λ	Productivity Shock in Manufacturing Sector	0.7	Bureau of Labour Statistics (BLS) data

Table 1.7: Baseline Model Variables of Two Sectors Model Economy

Aggregate Outcomes	Description	Model
y^*	Cut-off level for low productivity workers	0.373
$R(y^*)$	Reservation productivity for low productivity workers	0.373
y^{**}	Cut-off level for high productivity workers	0.528
$R(y^{**})$	Reservation productivity for high productivity workers	0.381
u_0	Unemployment rate for $y < y^*$	0.083
u_1	Unemployment rate for $y^* < y < y^{**}$	0.047
u_2	Unemployment rate for $y > y^{**}$	0.078
$\bar{y}$	Average productivity in non-construction sector	0.690
$\bar{w}$	Average Wages in non-construction sector	0.4315
θ	Labour market tightness	0.6
u	Total unemployment rate	0.093
n_C	Construction employment share	0.175
n_M	Manufacturing employment share	0.732

With the calibration of the parameters, the baseline model outcomes for pre-recessionary time period of 2007 are reported in Table 1.7. Assuming that there are two sectors in the hypothetical economy, 35% of the workers are low productivity workers and work in construction sector ($y^* = 0.373$) and 50% of the workers are high skilled and work in manufacturing sector. The remaining 15% are medium productivity workers who work move between the two sectors. Unemployment rates for low and high productivity workers are about 8.3% and 7.8% respectively while for medium productivity workers, unemployment rate is relatively low compared to the other two worker groups and is about 5%. This is because these type of workers move between sectors and get employed while the former two groups remain in their respective sectors and stay unemployed while waiting for new job opportunities.

Figure 1.8: Simulating the Impact of δ and α on Two-Sector Economy.



The total unemployment in the model economy is 9.3% and the employment share in the two sectors are 17.5% and 73.24% respectively. The employment share of manufacturing sector is higher than the employment share of construction sector because there are many sub-divisions of industries in the manufacturing sector such as mining, durable manufacturing, non-durable manufacturing and industrial manufacturing among others. So with only two sectors in the economy, manufacturing sector tends have a higher employment share based on different variety of industries in this sector.

Figure 1.8 shows the impact of the sector-specific shock in construction sector on the aggregate outcomes of the two-sector economy. A decrease in α and an increase in δ leads to a large increase in the unemployment rate for low productivity workers (u_0) and medium productivity workers (u_1). This causes the overall unemployment in the hypothetical economy to increase. The employment in the construction sector decreases while in manufacturing sector, it increases for various combinations of δ and α. Compared to the economy that takes into account all the the sectors, this hypothetical economy has higher unemployment levels suggesting that when construction sector is struggling in terms of generating more employment opportunities then only a small amount of workers are able to find work in the manufacturing sector while most of the displaced workers remain unemployed. Compared to the non-construction sector (that includes all the other sectors), manufacturing sector has limited work opportunities so it employees a relatively small of displaced workers as compared to the non-construction sector case.

1.8 Discussion

The simulations and counterfactuals of the model give a qualitative sense for the properties of the model as well as a quantitative sense for the impact of sector-specific labour demand shocks on the economy. Adverse sector-specific labour demand shock causes an increase of 10% in the total unemployment that is caused by increasing unemployment levels of low and medium productivity workers in construction sector.[6] Some of the increase in total unemployment is offset by workers

[6] The results of the third case of simulations.

moving to non-construction sector to find jobs. The sector-specific shock in the construction sector allows for sectoral reallocation of workers through reservation productivity of workers. As indicated in section 1.3, the reservation productivity varies with different productivity levels. So changes in the worker's outside options cause these sector-specific shocks to spill over to other sectors in the form of changing employment levels. These shocks also propagate across the economy as the increasing unemployment levels of worker types in one sector lead to increased overall unemployment level even though some of it is partially offset by the movement of workers across sectors.

The results of the simulations also show that when a sector experiences a negative sector-specific shock, the labour flows away from this sector. Employment in non-construction sector increased by approximately 1.5-2% while it decreased in the construction sector by 11%. A negative sector-specific shock in the model results in slack labour market i.e. a decrease in the employment opportunities for workers in construction sector. This is because medium productivity workers can move to non-construction sector to find employment, but low skilled workers have no option but to remain unemployed in the construction sector and wait for employment opportunities to rise when economic conditions improve. During the 2007-2009 recession, the construction sector witnessed a decrease of 13.7% in employment levels and there was persistent decrease in hiring of workers in this sector. This led to slow employment recovery in construction sector which contributed to total employment losses in the US (Phelps et al. 2008). Wages in the non-construction sector are downward rigid and decrease by less than 1% when there is adverse labour demand shock in the construction sector.

The simulation results show that the responses to changes in job separation rate are small as compared to changes in job finding rate. This is because in the former case, the unemployment rate for medium productivity workers decreases by a smaller amount, indicating that these types of workers will still be able to get employed in the construction sector - a small percentage of these workers lose their jobs. When they move to the non-construction sector, they are not a threat to the existing high productivity workers in that sector. Employment in this sector increases. In the latter case, with lower job finding prospects in construction sector, more workers would want to move to non-construction sector. However, both the shocks are important in explaining the distinctions for the sectoral and skill composition of productivity, unemployment, employment and wages. The sector-specific shocks of increased job separation and decreased job finding that result in displacement of workers may have persistent effects on the overall unemployment rate. This is because workers who are separated from their regular jobs may have relatively low job finding rates after displacement due to the greater specificity of their human capital; if they are displaced from long term jobs then they also have a higher risk of termination at their new jobs (Dickens and Triest 2012). This potential decrease in job finding rate and increase in job separation rate increase the unemployment rate of the economy due to increase in the unemployment levels of low and medium productivity workers. However some of the increase in total unemployment is offset by the movement of medium productivity workers to non-construction sector.

1.9 Conclusion

In this paper, I set up and solve a two sector search and matching model to investigate the effect of changing job separation rate and job finding rate on the employment, unemployment and average wages in the model economy. The model is the simplified version of the model developed by Albrecht et al. (2009) without taxes. It is the extension of Mortensen and Pissarides (1994) to two sectors. In light of evidence on declining employment in construction sector during the recessionary years of 2007-2009 in the US, I limit the implementation of the model to US construction and non-construction sectors. The construction sector is assumed to be lower in terms of skills than the non-construction sector. This is because the non-construction sector comprises various types of sectors e.g. finance, manufacturing, education and health services and professional and business services. There are various types of skills in demand in this sector as compared to the construction sector.

Workers are sorted into the two sectors depending on their productivity levels and then the unemployment rates, employment rates are derived for the two sectors. Different combinations of job separation rate and derived job finding rate from CPS and JOLTS data are used while other parameters of the model are calibrated to values from previous literature to examine the unemployment rates, employment rates, distribution of total labour force and wages in the model economy.

Overall unemployment changes with each combination of job finding and job separation rates but the unemployment for high productivity workers remains unchanged. The employment rates in the two sectors change. Employment in construction sector responds to changes in job separation and job finding rates. Changes in employment in non-construction are explained by the assumption of the model that medium productivity workers are indifferent to working in either of the sectors. Thus with declining work opportunities in construction sector, they look for work in non-construction sector. Wages in the model economy change by small amount, supporting the wage rigidity literature.

This paper contributes to the existing literature by using an extension of search and matching framework to examine the distributional question of how the changes in the labour market formation of one sector affects the employment, unemployment and distribution of labour force and wages in all the sectors or in the overall economy. It also analyses whether there are any spillover effects of changing labour market dynamics of one sector on another sector. The business cycle literature highlights that in a recession, wages in ongoing jobs are relatively sticky whereas employment drops, which just like in our case is mostly accounted for by reduced hiring and not by increased separations (e.g., Hall 2005; Shimer 2005; Rogerson and Shimer 2011; Shimer 2012). This suggests that the findings of this study can generally help us better understand how labour markets respond to shocks.

1.10 Appendices

Derivation of Wages

Surplus sharing rule:

$$max_{w(y',y)}[N_1(y,w) - U(y)]^{\beta} J(y,w)^{1-\beta}$$

Multiply firm's value function by β and worker's value function by $1-\beta$, take the difference of the two and simplifying it:

$$\begin{aligned} r[\beta J(y) - (1-\beta)N_1(y)] = \beta y - w(y',y) - \lambda \frac{G[R(y)]}{G(y)}[\beta J(y) + (1-\beta)(U(y) - N_1(y))] \\ +\lambda \int_{R(y)}^{y} [\beta(J(x,y) - J(y)) - (1-\beta)((U(y) - N_1(y))] \frac{g(x)}{G(y)} dx \end{aligned} \tag{1.35}$$

The two surplus sharing rules for the first and the remaining time periods:

$$N_1(y) - U(y) = \beta(J(y) + N_1(y) - U(y)$$

$$N_1(y',y) - U(y) = \beta(J(y) + N_1(y',y) - U(y)$$

They give the following expressions to substitute into equation (1.35):

$$(1-\beta)N(y) - (1-\beta)U(y) = \beta J(y) : \tag{1.36}$$

$$-(1-\beta)U(y) = \beta J(y) - (1-\beta)N(y) \tag{1.37}$$

Substitution of (1.36) and (1.37) into (1.35)

$$-r(1-\beta)U(y) = \beta y - w(y',y) - \lambda \frac{G[R(y)]}{G(y)}[(1-\beta)U(y) + (1-\beta)U(y)] + \lambda \int_{R(y)}^{y} [(1-\beta)U(y) - (1-\beta)U(y)] \frac{g(x)}{G(y)}.dx$$

$$-r(1-\beta)U(y) = \beta y - w(y', y)$$

$$w(y', y) = \beta y + r(1-\beta)U(y) \tag{1.38}$$

Derivation of Reservation Productivity

Zero surplus sharing rule:

$$N(R(y), y) - U(y) + J(R(y), y) = 0$$

which is equal to:

$$J(R(y), y) = 0$$

Substituting the wage in the value of a filled job for a firm:

$$rJ(y', y) = (1-\beta)y' - r(1-\beta)U(y) - \lambda \frac{G[R(y)]}{G(y)}[J(y', y)] + \lambda \int_{R(y)}^{y} [J(x, y) - J(y', y)] \frac{g(x)}{G(y)}.dx,$$

and simplifying it:

$$(r+\lambda)J(y', y) = (1-\beta)y' - r(1-\beta)U(y) + \lambda \int_{R(y)}^{y} J(x, y) \frac{g(x)}{G(y)}.dx \tag{1.39}$$

Evaluating (1.39) with y'=R(y) using the condition J(R(y),y)=0:

$$0 = (1-\beta)R(y) - r(1-\beta)U(y) + \lambda \int_{R(y)}^{y} J(x, y) \frac{g(x)}{G(y)}.dx \tag{1.40}$$

Bringing equation (1.39) and (1.40) in terms of y and R(y) and taking their difference:

$$y - R(y) = \frac{(r+\lambda)}{(1-\beta)} J(y', y)$$

Solving for $J(y', y)$

$$J(y', y) = \frac{(1-\beta)(y - R(y))}{(r+\lambda)} \tag{1.41}$$

Substitute (1.41) in (1.39) :

$$(r+\lambda)J(y', y) = (1-\beta)y' - r(1-\beta)U(y) + \lambda\int_{R(y)}^{y}[\frac{(1-\beta)(x - R(y)}{(r+\lambda)}]\frac{g(x)}{G(y)}.dx \tag{1.42}$$

Simplifying the Integral term in (1.42):

$$= \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}\int_{R(y)}^{y} xdG(x) - \frac{\lambda(1-\beta)R(y)}{(r+\lambda)G(y)}\int_{R(y)}^{y} dG(x)$$

$$= \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}[xG(x)\Big|_{R(y)}^{y} - \int_{R(y)}^{y} G(x).dx] - \frac{\lambda(1-\beta)R(y)}{(r+\lambda)G(y)}(G(y) - G(R(y))$$

$$= \frac{\lambda(1-\beta)}{(r+\lambda)}(y - R(y)) - \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}\int_{R(y)}^{y} G(x)dx$$

and replace it in the original expression:

$$(r+\lambda)J(y', y) = (1-\beta)y' - r(1-\beta)U(y) + \frac{\lambda(1-\beta)}{(r+\lambda)}(y - R(y)) - \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}\int_{R(y)}^{y} G(x)dx$$

Evaluating the equation above at y'=R(y) and solving for $R(y)$:

$$0 = (1-\beta)R(y) - r(1-\beta)U(y) + \frac{\lambda(1-\beta)}{(r+\lambda)}(y - R(y)) - \frac{\lambda(1-\beta)}{(r+\lambda)G(y)}\int_{R(y)}^{y} G(x)dx$$

$$0 = R(y)\frac{r}{(r+\lambda)} - rU(y) + \frac{r}{(r+\lambda)}y - \frac{\lambda}{(r+\lambda)G(y)}\int_{R(y)}^{y} G(x)dx$$

$$0 = R(y)\frac{r}{r+\lambda} - rU(y) + \frac{r}{r+\lambda}y - \frac{\lambda}{(r+\lambda)G(y)}[\int_{R(y)}^{y}(1-G(x))dx - (1-G(y))y + R(y)]$$

Solve for R(y):

$$R(y)\frac{(\lambda + rG(y))}{(r+\lambda)G(y)} = rU(y) - \frac{\lambda}{(r+\lambda)G(y)}[\int_{R(y)}^{y}(1-G(x))dx - (1-G(y))y]$$

$$R(y) = \frac{G(y)r(r+\lambda)U(y) - \lambda\int_{R(y)}^{y}(1-G(x))dx - (1-G(y))y}{\lambda + rG(y)} \tag{1.43}$$

Derivation of Unemployment Values and Cut Off Productivities

The worker of this type is indifferent to being unemployed or being employed in formal sector i.e. $U(y^*) = N_1(y^*)$. Hence his value functions can be written as:

$$rU(y^*) = b + \alpha[N_o(y^*) - U(y^*)] + m(\theta)max[N_1(y^*) - U(y^*)]$$

$$rU(y^*) = b + \alpha[N_o(y^*) - U(y^*)]$$

Finding the value for $N_0(y^*)$:

$$rN_0(y) = y_o + \delta[U(y) - N_o(y)]$$

$$N_0(y^*) = \frac{y_0 + \delta U(y^*)}{r+\delta}$$

Substituting it in $rU(y^*)$ and simplifying it:

$$rU(y^*) = \frac{b(r+\delta) + \alpha y_0}{r+\delta+\alpha} \tag{1.44}$$

Substitute $N_1(x,y)$ out of the following surplus sharing rule:

$$N(x,y) = \frac{\beta}{1-\beta}J(x,y) + U(y)$$

so that:

$$rN_1(y^*) = w(y^*) + \lambda\frac{G[R(y^*)]}{G(y^*)}[U(y^*) - N_1(y^*)] + \lambda\int_{R(y^*)}^{y^*}[\frac{\beta}{1-\beta}J(x,y^*) + U(y^*) - N_1(y^*)]\frac{g(x)}{G(y^*)}.dx$$

Now using $U(y^*) = N_1(y^*)$:

$$rN_1(y^*) = w(y^*) + \frac{\lambda\beta}{(1-\beta)G(y^*)}\int_{R(y^*)}^{y^*} J(x,y^*)dG(x)$$

Substituting equation 39 in the expression above:

$$rN_1(y^*) = w(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}\int_{R(y^*)}^{y^*} (y^* - R(y^*))dG(x)$$

$$rN_1(y^*) = w(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}[(y^* - R(y^*))G(y^*) - \int_{R(y^*)}^{y^*} G(x)dx]$$

$$rN_1(y^*) = w(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}[G(y^*)\int_{R(y^*)}^{y^*} dx - \int_{R(y^*)}^{y^*} G(x)dx]$$

$$rN_1(y^*) = w(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}[\int_{R(y^*)}^{y^*} (G(y^*) - G(x)dx]$$

Substituting the value of $w(y^*)$ in the expression above:

$$rN_1(y^*) = \beta y^* + r(1-\beta)U(y^*) + \frac{\lambda\beta}{(r+\lambda)G(y)}[\int_{R(y^*)}^{y^*} (G(y^*) - G(x)dx]$$

Now solving for y^* using $U(y^*) = N_1(y^*)$:

$$y^* = \frac{b(r+\delta)+\alpha y_0}{r+\delta+\alpha} - \frac{\lambda}{(r+\lambda)G(y)}[\int_{R(y^*)}^{y^*}(G(y^*)-G(x)dx] \tag{1.45}$$

A high productivity worker will only accept non-construction sector jobs and is indifferent between unemployment and construction sector job offer so for him $U(y^{**}) = N_0(y^{**})$.

$$rU(y^{**}) = b + \alpha[N_o(y^{**}) - U(y^{**})] + m(\theta)max[N_1(y^{**}) - U(y^{**})]$$

$$rU(y^{**}) = b + m(\theta)max[N_1(y^{**}) - U(y^{**})]$$

Since $U(y^{**}) = N_0(y^{**})$ so we know from $rN_0(y^{**})$:

$$rN_0(y^{**}) = y_0$$

and

$$rU(y^{**}) = rN_0(y^{**}) = y_0$$

So:

$$y_0 = b + m(\theta)max[N_1(y^{**}) - \frac{y_0}{r}]$$

$$N_1(y^{**}) = \frac{y_0(r+m(\theta)) - rb}{rm(\theta)} \tag{1.46}$$

Substitute $N_1(x, y^{**})$ out of the following surplus sharing rule:

$$N(x, y^{**}) = \frac{\beta}{1-\beta}J(x, y^{**}) + U(y^{**})$$

into the value function for employed worker in non-construction sector:

$$(r+\lambda)N_1(y^{**}) = w(y^{**}) + \lambda U(y^{**}) + \frac{\lambda\beta}{(1-\beta)G(y^{**})}\int_{R(y^{**})}^{y^{**}} J(x, y^{**})dG(x)$$

then evaluate at y^{**} using value of $N_1(y^{**})$ and equation (1.41) to replace $J(x, y^{**})$:

$$(r+\lambda)\frac{y_0(r+m(\theta))-rb}{m(\theta)} = \beta y^{**}+r(1-\beta)U(y^{**})+\lambda U(y^{**})+\frac{\lambda\beta}{(r+\lambda)G(y^{**})}[\int_{R(y^{**})}^{y^{**}}(G(y^{**})-G(x))dx]$$

Simplifying in terms of y^{**}:

$$y^{**} = y_0 + (rG(y^{**})+\lambda)\frac{(y_0-b)}{\beta m(\theta)G(y^{**})} - \frac{\lambda}{(r+\lambda)G(y^{**})}[\int_{R(y^{**})}^{y^{**}}(G(y^{**})-G(x))dx] \qquad (1.47)$$

Chapter 2

The Wage Effect of Immigration: A Meta-Analysis

2.1 Introduction

Migration continues to increase around the globe. For example, the US foreign-born population relative to the total population increased from 7.9% in 1990 to 14% in 2018.[1] Similarly, in 2018, 13.8% of the resident population of UK were born outside the UK, compared to 6.7% in 1990.[2] Hence estimating the economic impact of immigration has become a centre of public debate in recent decades. The large influx of people affects the labour market of the host country. The impact of immigration on employment opportunities for the existing workers or immigrants competing with the native workers in bidding down their wages has been widely researched by economists and policy makers (Longhi et al. 2005). But the general consensus on the magnitude and direction of the wage effect of immigration cannot be reached.

The effect of immigration on wages in the host country is one of the highly contested research topics. Many studies have examined the effect of immigration on wages and other labour market outcomes, for example, Glitz (2012); Aydemir and Borjas (2011); Gonzalez and Ortega (2011); Borjas (2003); Dustmann, Fabbri and Preston (2013); Smith (2012); Friedberg (2001); Cohen-Goldner and Paserman (2001) and many more. Contrary to expectations, there is no consensus among economists on whether immigration has significant impact on wages, and if it does, how large the effect may be. Since the effect of immigration on wages has become a policy issue, papers evaluating it have a number of different characteristics that make it challenging to draw general conclusions.

Differences in the study characteristics measuring the wage impact of immigration has led to a lot of contradictory empirical results. Borjas (2003) states that the measured impact of immigration on the wages of workers in the host country differs widely from study to study and sometimes within the same study. There could be multiple reasons as to why the results are not similar as studies analyse datasets of different countries and time periods. Papers differ in the approaches they use to estimate the wage impact of immigration and while some assess the wage impact for spe-

[1] Pew's analysis and American Community Survey 2010-2018
[2] Office of National Statistics (ONS)

cific groups, there are others that estimate the effect on the representative population of a country. [3]

Because the literature on the wage impact of immigration is inconclusive, in this chapter I attempt to reconcile the results by performing meta-analytic assessment on 663 comparable estimates of wage impact of immigration derived from 46 primary studies. Meta-analysis is a statistical procedure that uses the information from a wide range of diverse literature in order to identify a common effect (Haidich 2010). Meta-analysis was originally developed in medicine to aggregate the results of costly clinical trials, and it has been widely used in economics to investigate the heterogeneity in reported results since first been used by Stanley and Jarrell (1989). Recent applications of meta-analysis in economics include, among others, Rusnak et al. (2013) on the effect of monetary policy on prices, and Babecky and Campos (2011) on the relation between structural reforms and economic growth in transition countries. It is a well-established concept in sciences but is also now rapidly growing in labour economics.

I classify the differences in empirical literature into three categories: (i) *study characteristics*; (ii) *context of each study* and (iii) *labour market conditions over the sample.* The first category focuses on the systematic differences across each study. For example, there are alternative theories that contradict the findings of the neo-classical model of labour supply and demand. This might be because the empirical specifications used to test the theory differ in various ways. While most papers published in the 1990s exploit variation in immigrant flows across the regions in order to estimate the wage impact of immigration (Altonji and Card, 1991), others since early 2000s use the variation in the immigrant inflows across education-experience groups to measure the wage impact (Borjas 2003). Additionally, there are studies that use the variation across the regions as well as education-experience cells. Research papers also differ in the type of data they use or the target group they study.

[3] Specific groups can be gender based, skills based or whether the reference group is natives or immigrants.

The second category focuses on the country and time period of the study. The wage impact of immigration differs by country. This might be because either the host country under study is big and hence can easily adjust to the immigrant influx or it is small and therefore react more to the increased immigration. The size of a country under study does contribute to the impact of immigration. The third category relates to how the labour market conditions of a country under study can affect the wage impact of immigration. The economic conditions during the time period under evaluation might also have something to do with the variations in the results of different papers. Labour market conditions in the host country may influence individuals' decision on when and where to migrate. Under a simple demand and supply model, less advantaged groups such as immigrants, less educated or young workers are particularly sensitive to economic slowdowns. When economic conditions are adverse, immigrants are likely to get laid off because immigrants frequently lack extensive social networks and are typically unfamiliar with local social norms and culture (Wang and Sakamoto 2016). These workers are not just directly affected by the slow economic activity during recessions but are also indirectly replaced by high skilled workers who move down the skill chain (Devereux 2004). Low skilled immigrants are affected more than the low skilled natives during rough times because they face additional difficulties such as language barriers, tend to have less social capital and are relatively ill-informed about the labour markets. For each country and time period under study, a variable using the unemployment series from the World Bank Database is used as one of the indicators of labour market conditions and is included in the estimation in order to better understand the variation in the results. The average immigrant share in working population for each country from World Bank Database for the time period under study is also created and included in the estimation in order to examine whether the size of immigrant stock in total population in a country matters.

To my knowledge there have been two meta-analyses of the wage impact of immigration. Longhi et al. (2005) evaluate the impact of immigration on the wages of natives using meta-analytic assessment. This study specifically focuses on evaluating the impact on the wages of the natives and uses least square estimation to evaluate a common effect of immigration on wages. The second paper, Longhi et al. (2008) measures the combined impact of immigration on wages, employment and labour force participation of natives in the host country and only assesses the relationship between the observed impact and key study characteristics such as country, methodology, year of publication and type of migrant. Okkerse (2008) and Dustmann et al. (2016) do not quantitatively assess the labour market impacts of immigration; instead they classify the studies into the broad categories of empirical approaches identified in the literature.

Compared to the previous meta-analysis and existing literature, the findings of this paper contribute in three ways. Most importantly, this paper takes into account the economic conditions of a country when assessing the wage impact. To my knowledge, use of the economy-wide data on labour market conditions in order to understand the variations in the results of different empirical studies has not been done before. In addition, it provides a critical discussion of methods previously employed by researchers in examining the wage impact of immigration. This paper evaluates the ambiguity in the wage impact of immigration by classifying the estimation approaches into three categories. Finally, the data set I created only takes those papers as primary studies which were published during the time period of 2000-2017. Published papers, relevant working papers and unpublished papers written during this time period of 2000-2017 and available on the web are also included in the list of primary studies. The main reason for focusing on this time period is that contemporary studies during this time period contribute to our understanding of the problem of ambiguity in the wage effect of immigration, while those published in the 1990s were not analysed in this way.

In order to meta-analyse the effect of immigration on wages, I created a categorical variable in the data set on the sign and significance of each wage estimate in the primary studies. This is done using the point estimates, standard errors and sample sizes reported in each primary study. The derived categorical variable is then used as a dependent variable in ordered probit model estimation. The dummy variables that capture study characteristics, study context and labour market conditions are used as regressors. The findings suggest that the wage impact of immigration is small and negative. The results show that the context and economic conditions do matter when explaining the variations in the effects of immigrations on wages. Studies that use skill-cell and spatial approach tend to find positive wage impact on average as compared to those that use mixed approach. Studies that employ IV estimation techniques tend to find larger negative impact as compared to those who rely on OLS estimation techniques.[4] Low skilled workers tend to suffer more as the wage estimate for them is more negative and significant. Moreover, the labour market conditions of the host country at the time of study play a crucial part in explaining why the wage impact vary from study to study.

I then revisit the issue of publication bias and p-hacking in the literature. Publication bias is tested for using tests suggested by Card and Krueger (1995) and Stanely (2005;2008) that estimate the link between the immigration coefficient to their standard errors. The results show that publication bias is not an issue in the data. P-hacking is tested for using the binomial test suggested by Head et al. (2015). It is a two part test. The first part tests for the evidential value i.e. if the true effect is non-zero and the second part compares the number of p-values in two adjacent bins. The results show no signs of p-hacking in the sample.

This chapter is organised as follows. In the next section, I explain the factors that cause the wage estimates to differ across studies. Section 2.3 discusses the process of selecting the primary studies and the type of data collected for the analysis. Section 2.4 explains the meta-analysis methodologies and discusses estimated results. Section 2.5 tests for publication bias and p-hacking in the literature. Section 2.6 reports robustness checks and Section 2.7 provides the discussion and policy implications. Finally section 2.8 concludes.

[4]This supports the findings of Longhi et al. (2005).

2.2 Why do Estimates Differ?

There are many possible reasons for lack of consensus on the wage effect of immigration. In a simple demand-supply framework, the labour market impact of immigration is described by using a neo-classical competitive model of supply and demand in the market for workers (Chiswick 1982; Greenwood and McDowell 1994). This theoretical model suggests that when immigration increases, the labour supply in host country also increases. This would lower the wages of natives if immigrants and natives are perfect substitutes because increase in labour supply exerts a downward pressure on wages. If, instead, the newly migrated workers complement the skills of natives in the host country, wages increase. Nevertheless, the impact of immigration on labour market remains theoretically uncertain.

This theoretical uncertainty created a need for empirical results and stimulated empirical work. The empirical literature assessing the wage impact of immigration finds inconclusive results. Some of the empirical literature agrees with the findings of the standard neo-classical theory with perfect substitutes (for example, Card 2007; Foged and Peri 2016; Bouston, Fishback and Kantor 2010). Some of the literature contradicts these findings and indicates that the negative wage impact of immigration is rather small, insignificant and sometimes of the opposite sign (Orrenius and Zavodeny, 2007; Dustmann, Fabbri and Preston, 2013). There are multiple explanations for these differing results: it may be that immigrant influx increase the prices of those factors with which they are perfect complements or there are some external institutional factors (for example, the economic conditions of the host country) that offset the downward effect on wages. Studies analyse different data sets over time periods using non-identical techniques. This can also lead to different results.

The empirical literature can be grouped into three common approaches. These are derived from the same canonical model, but variation in immigration shock used in them as a regressor are non-identical. All the empirical studies in general are categorised as one of three types of approaches: *spatial*, *skill-cell* and *mixed* approach. Papers that adopt the *spatial* approach use variation in the immigrant share across locations as main regressor in the estimations. This approach was first adopted by Altonji and Card (1991) who used the following specification to measure the wage impact of immigration:

$$\Delta log(w_{gart}) = \theta_{ga}^{spatial} \Delta p_{rt} + s_{ga} \Delta \pi_t + \Delta \varphi_{rt} \tag{2.1}$$

Equation (2.1) uses the spatial variation in immigration shock in measuring the wage change of natives. w_{gart} measures the wage change in education group g, experience group a in region r related to the total region-specific immigration shock in time period t which is given by Δp_{rt}. $\theta_{ga}^{spatial}$ estimates the wage change due to immigration shock by taking differences over time and across regions and it identifies total effect of immigration on wages of a particular skill group. $s_{ga}\Delta\pi_t$ controls for nation-wide education-experience specific time trends where π_t is time fixed effects and s_{ga} represents education-experience fixed effects and φ_{rt} is the error term. This approach exploits the geographic clustering of immigrants and uses differences across local labour markets to identify the wage effect of immigration. Among the empirical papers that use this approach, some find a sizeable effect of immigration on wages of native workers, while others do not. For example, Altonji and Card (1991) report total wage impact of immigration for white male high school drop-outs is about -1.1 while Card (2007) finds small positive total wage effects of 0.06 for native workers. This approach is not built from the theoretical framework. A common criticism of this approach is that immigrants move relatively freely within a country which leads to labour market outcomes across regions to be washed out through market forces (Tumen, 2015).

Borjas (2003) argues that the spatial framework has been troublesome because it ignores the strong currents that tend to equalise economic conditions across cities and regions. Therefore the measured impact of immigration on the wage of native workers fluctuates widely from study to study. Borjas (2003) uses an empirical approach focusing on the characteristics of workers that define a skill group. He used the insight that both schooling and work experience play a role in defining a skill group. This framework is called *skill-cell* approach in which the variation in the immigrant share across education-experience cells is used in the estimation. It has the following specification:

$$\Delta log(w_{gat}) = \theta^{skill}\Delta p_{gat} + \Delta\pi_t + s_g\Delta\pi_t + x_a\Delta\pi_t + \Delta\varphi_{gat} \tag{2.2}$$

Equation (2.2) identifies the wage effect of immigration by categorising workers into education-experience cells. w_{gat} measures the wage of native workers in education group g and experience group a at time t. Δp_{gat} is the education-experience specific immigration shock and θ^{skill} measures the the effect of immigration by experience. s_g, x_a and π_t control for education, experience, and time fixed effects and φ_{gat} is the error term. $s_g\Delta\pi_t$ controls for education specific time trends and $x_a\Delta\pi_t$ controls for experience specific time trends. Borjas (2003) finds that typical wage estimates of immigration for native men are around -0.5. Llull (2014) finds the wage estimates for natives to be around -0.166. This approach has a strong theoretical background but is criticised for its dependency on the degree of substitutability between natives and immigrants and on labour demand conditions.

Some authors adopt *mixed* approach, that is, using the variation across both education groups and across regions for estimation. This approach is a mixture of skill-cell and spatial approaches. Studies using the mixed approach (for example, Card 2001) use the following specification:

$$\Delta log(w_{grt}) = \theta^{mixed}\Delta p_{grt} + s_g\Delta\pi_t + s_r\Delta\pi_t + \Delta\varphi_{grt} \tag{2.3}$$

In equation (2.3), w_{grt} measures the wage change of education group g and region r to education specific immigration shock Δp_{grt} in that region at time t. $s_g\Delta\pi_t$ and $s_r\Delta\pi_t$ controls for education and region specific time trends. θ^{mixed} is the estimate of the wage effect of immigration. φ_{grt} is the error term. Borjas (2006) finds the wage estimates to be -0.06 for natives in the US while Glitz (2015) finds the wage impact of immigration to be around -0.26 for native workers in Germany. Dustmann et al. (2016) point out that mixed approach identifies the relative effect of immigration by measuring its impact on low skilled workers wages relative to high skilled workers wages. Therefore because the effects of immigration common to all education-experience groups are differenced out, this approach is criticised for measuring the distributional effects of immigration between education groups, but not its absolute effects.

There are also some papers that use a *structural* approach, i.e. using theoretical models and simulate these models. The simulated wage estimates on strong theoretical assumptions are far more stringent than those imposed by empirical literature (Dustmann et al. 2016). For example, Ottaviano and Peri (2012) use a flexible nested CES model with worker heterogeneity to simulate the wage impact of immigration. However, for the multivariate analysis in this paper, I focus only on studies that are data driven and use reduced form empirical specifications.

2.3 Selection of Studies and Construction of Dataset

The selection of the primary studies for the analysis was done mainly through extensive search in five journals; Journal of Labour Economics, Quarterly Journal of Economics, American Economic Review, Journal of Political Economy and Journal of European Economic Association. The keywords for search in these journal were *immigrants*, *immigration*, *wages* and *earnings*. Further studies were collected from the literature reviews and references of the papers from these journals. The search was limited to finding the studies that were published during 2000-2017. A total of 46 empirical studies and 663 observations were collected and reported in Table 2.1. There are several observations collected from each paper because some studies report results from multiple estimations. Some of them estimate the impact for different groups (natives, immigrants, male, female, low skilled, high skilled) and others use both IV and OLS estimation to get results.

The main variable of interest in each study is the estimate of the effect of immigration on wages. The estimate is collected along with other study features from each primary study. From now, the wage coefficient is denoted as effect size. The descriptive statistics of the effect sizes corresponding to each study feature is reported in Table 2.2. Figure 2.1 shows the histogram and kernel density of the effect sizes collected from primary studies. The average effect size is about 0.03 with standard deviation of 0.56. The average effect size varies with the study characteristics.

The primary studies collected for the analysis differ in multiple ways and this could matter for the results. They use data from a number of countries and for different time periods to assess the wage impact. For example, some papers studied the US labour market and others examined the impact of immigrant share in U.K, Germany, Norway, Malaysia among others. Table 2.2 shows that the average effect size is negative and small for papers using US data while those evaluating European countries tend to have positive average effect sizes of 0.04 and other countries find a bigger average negative effect of -0.038. Longhi et al. (2008) argues that the wage impact of immigration tends to be more negative in the countries where internal mobility is low (other countries) as compared to those countries with higher internal mobility (US).

Among the regression techniques used by the empirical papers, some primary studies use ordinary least squares (OLS) estimation (for example, Borjas 2006, Peri and Yasenov 2016, Aydemir and Borjas 2007) while others use instrumental variable (IV) estimation (Llull (2014), Dustmann, Fabbri, and Preston 2005, Card 2001). The average effect size for studies using IV estimation is 0.116, while for OLS estimations, it is small and negative at about -0.017. The average effect size for skill-cell approach and mixture approach is negative and about -0.168 and -0.012 respectively, while for spatial approach it is about 0.143. Dustmann et al. (2016) states that the average impact for skill-cell and mixed approaches are generally negative because they rely on the assumption that labour supply is homogenous across different groups and hence natives and immigrants are substitutes of each other. The results of spatial approach vary widely depending on which skill group is studied because this approach recovers the total wage impact of immigration on a particular native skill group that takes into account complementarities across skill-cells and across labour and capital. Studies applying the skill-cell approach tend to find larger wage effect of immigration than those applying spatial approach because analysing changes over time for various skills group within a region gives negative impact of immigration which increase in magnitude when the area covered becomes wider. Secondly, spatial approach does not take into account the fact that natives respond to immigration increase in their region by migrating out. This tends to understate the depressing effect of immigration on wages (Borjas et al., 1996).

Among the different characteristics of worker, the average wage impact of immigration is negative for studies that focus on male workers or female workers while those that do not focus on the gender of the target group find positive impact of immigration. The negative average wage estimate for male workers is bigger than female workers. Borjas (1996) states that the labour force participation rates of female workers seem to react more to changes in wages and unemployment rates than the labour force participation rate of male workers. As a result, the effect of immigration on male workers is probably more clearly estimated than for women therefore the impact of immigration on wages of male workers is more negative. The average wage impact of immigration for low skilled and medium skilled workers is negative at -0.015 and -0.118 respectively. In many countries, immigrants have significantly lower skills than natives on average and they are likely to compete with low skilled natives in the host country thus causing more negative impact on the wages of these types of workers. The average wage estimate of immigration in the sample of studies for natives is smaller (0.03) than the wage impact for earlier immigrants (0.04). Welch (1979) highlights that new immigrants in the host country are likely to be close substitutes for somewhat earlier cohorts and are more in competition with each other and less likely to compete with native workers. Certain characteristics of immigrants such as language, skills, education obtained in the home country and their culture are not close substitutes for natives thus causing a smaller impact on the labour market outcomes of native workers.

In order to derive the labour market conditions, unemployment rate and immigrant inflow rate are used for the host country under study. Both the unemployment rate and immigrant inflow rate are taken from the World Bank's development indicator series. Research papers estimate the wage effect of immigration for different time durations. For example, some studies focus on yearly changes, others estimate the impact for three or five years. For each study, the immigrant inflow rate and unemployment series is taken for the entire time period. These series are used to calculate the average inflow rate and unemployment rate. The average effect size corresponding to these variables on labour market conditions of the host country are reported in Table 2.2. When the immigrant inflow rate is low (less than 7%), the average effect size among studies is 0.41. When it is medium (between 7 and 10%) and high (more than 10%), the mean wage effect of immigration is negative and about -0.018 and -0.043. When unemployment rate of the host country is low (less than 5%), the average effect size is -0.13. It is also negative (-0.08) when unemployment rates are high (more than 10%). When unemployment rates are between 5% and 10%, the average effect size is positive at 0.04 but is very small. The average effect sizes corresponding to the indicators of labour market conditions in the host country suggest that when labour market conditions are adverse i.e. when unemployment in the host country is high or when the immigrant share in the total population of the host country is high then an increase in immigration tends to have a negative impact on average on the wages of natives and earlier immigrants.

The summary statistics in this section provides the group averages, standard deviations, minimum and maximum values of the estimated wage impact of immigration corresponding to different study features and data characteristics. They do not assess the statistical significance of the variation in the estimated wage impact across different groups and do not take into account the heterogeneity across different studies and the fact that specific features interact with other study characteristics. So it is preferable to assess the impact of different features by means of meta-analytic estimation techniques.

2.4 Meta-Regression Methodology and Results

Meta-regression analysis is used to examine the relationships between the research design and the empirical findings. The purpose of meta-analysis in this paper is to determine the possible relationships between empirical findings and study characteristics, context of the study and the labour market conditions of a country under study. There is heterogeneity among the estimated coefficients in the literature because of the differences in the study characteristics as we can see from Table 2.2. The estimation strategy used for the meta-regressions makes use of the t-statistics associated with each effect size. A categorical variable on the sign and significance of each of the estimated wage coefficient is created and used as a dependent variable. The three values of this variable are *insignificant*, *negative and significant* and *positive and significant*. Figure 2.2 shows box plots for effect sizes in each of these three categories. The wage estimates associated with negative significance are between 0 and -2%. They are also closer to each other as compared to wage estimates associated with insignificance and positive significance. For positive significance effect, wage estimates are on average dispersed and are between 0-4%. This approach of using the sign and significance of the wage estimate as a dependent variable helps in pointing out the direction of the wage impact of immigration that most of the previous empirical studies agree on and the extent to which this explains the differences between these studies.

I use an ordered probit model to identify the common effect of the immigration on wages in the literature. The idea behind this estimation method is that there is a latent continuous metric underlying the ordinal responses. Thresholds partition the real line into a series of regions corresponding to the various ordinal categories (Greene, 2011). The latent continuous variable y^*, is a linear function of different characteristics x_i where i represents one of the regressors, plus a disturbance term, $\kappa \sim N(0,1)$ that has a standard normal distribution. It is written as:

$$y_i^* = x_i'\beta + \kappa_i, \tag{2.4}$$

From y_i^* in equation (2.4), we observe only three possible outcomes related to the t-statistic (denoted as t) of each wage estimate. We observe a variable y such that:

$$y = \begin{cases} 0 & \text{if } \alpha_1 < y_i^* < \alpha_2 \\ 1 & \text{if } y_i^* \leq \alpha_1 \\ 2 & \text{if } y_i^* \geq \alpha_2 \end{cases} \tag{2.5}$$

The categorical variable y takes three values i.e. $y = 0$ if the immigration has insignificant impact on the wages ($-1.65 < t < +1.65$) and it coincides $\alpha_1 < y_i^* < \alpha_2$, $y = 1$ if it has a negative significant effect on wages (when $t \leq -1.65$) and is the case when $y_i^* \leq \alpha_1$ and $y = 2$ if immigration has a positive significant impact on wages (when $t \geq +1.65$) and it coincides with $y_i^* \geq \alpha_2$.
The ordered probit estimator allows for flexible correlation structures across alternatives and does not rely on the restrictive assumption that the unobserved attributes of all the alternatives are perceived as equally similar (Independence of Irrelevant Alternatives assumption). The probabilities of the three outcomes p_{ij} where j is one of the three alternatives, are as follows:

$$p_{ij} = \begin{cases} p(y=0|x_i) = p(\alpha_1 < y_i^* \leq \alpha_2) = \Phi(\alpha_2 - x_i'\beta) - \Phi(\alpha_1 - x_i'\beta) \\ p(y=1|x_i) = p(y_i^* \leq \alpha_1) = -\Phi(x_i'\beta) \\ p(y=2|x_i) = p(y_i^* \geq \alpha_2) = 1 - \Phi(\alpha_2 - x_i'\beta) \end{cases} \tag{2.6}$$

Where Φ is the standard normal CDF. Equation (2.6) represents the probability that one of the three alternatives on the sign and significance of the wage estimate is selected (Greene, 2011). The marginal effects m_{ij} of changes in independent variables x_i on the three probabilities are written as:

$$m_{ij} = \begin{cases} \frac{\partial p(y=0|x_i)}{\partial x_i} = [\phi(-x_i'\beta_i) - \phi(\alpha_1 - x_i'\beta_i)]\beta_i \\ \frac{\partial p(y=1|x_i)}{\partial x_i} = -\phi(x_i'\beta_)\beta_i \\ \frac{\partial p(y=2|x_i)}{\partial x_i} = \phi(\alpha_2 - x_i'\beta_i)\beta_i \end{cases} \tag{2.7}$$

Where ϕ is the standard normal PDF. The marginal effects represent the change in probability of selecting alternative j in response to a unit change in a respective regressor x_i, To facilitate the interpretation of the role of labour market conditions, context of the study, study and data characteristics, the results are reported in Table 2.3. Marginal effects in this meta-regression represent the change by which different characteristics change the probabilities of all three categories of the dependant variable. The standard errors are clustered at the study level and the estimations are weighted by the inverse of the standard error associated with effect sizes in the sample in order to take into account the precision of the estimates in the individual studies, giving larger weights to the most accurate or least variable ones. This choice of weight minimises the imprecision (uncertainty) of the pooled effect estimate and focuses on the quality of the estimates collected from studies.

Labour Market Conditions

The labour market conditions are characterised into two categories. The first category is the immigration inflow rate and the second category is the variation in the unemployment rate. The marginal effects associated with these two categories are reported in Table 2.3. The marginal effect of the unemployment rate on the sign and significance of the effect sizes shows that increase in unemployment rate is associated with primary studies finding negative impact on average. The results show that a unit increase in unemployment rate for the time period under study decreases the probability of finding positive significant wage effect of immigration by 35% and increases the probability of finding negative significant wage impact by 12.4%. The results support the findings of the theoretical labour demand and supply models that when the pool of workers looking for jobs is large, firms employ those workers who are willing to accept lower wages (Chiswick 1982). The ordered probit model estimates show that when the labour market conditions of a country are adverse, primary studies tend to find negative impact of immigration on wages. The marginal effects associated with immigrant inflow rate are insignificant. These results suggest that when the stock of immigrants in the working population of the host country is already high, further increase in immigration does not have significant impact on the wages of already employed workers.

Literature evaluating the effects of macroeconomic conditions on immigrant assimilation argues that employers have little information about the skills of immigrants, resulting in more job mismatches. This may cause immigrants to suffer from employment losses during recessions and can also lead to little or no firm specific training among them (Chiswick, Cohen and Zach 1997). As years of residence in the host country increases, immigrants are expected to not be adversely affected by economic crisis. Aslund and Rooth (2007) state that difficult labour market conditions can have a significant effect on the exposed immigrants. They report that early wages assimilation can only take place if the labour market conditions are favourable.

Context of the Study

Keeping US as a reference category, Table 2.3 also reports the marginal effects of a region under study. The dataset comprises studies estimating the wage impact of immigration in multiple countries such as the US, United Kingdom, Germany, Norway and Malaysia among others. These countries are categorised as European countries and other countries (i.e. non-Europe and non-US). The results show that compared to the US, researchers assessing the wage effect of immigration in European and non-European countries tend to find negative significant results. For European countries, the marginal effects for positive significance are -0.305 and for non-European and non-US regions, marginal effects are -0.669. These estimated marginal effects for different regions show that the probability of finding positive wage impact is the smallest for non-European regions compared to Europe and US. Longhi et al. (2006) point out that countries which have high internal mobility are expected to have stronger adjustment effects which results in smaller impact of immigration on the wages in those countries. Compared to the US and Europe, non-European countries see a larger decline in their wages when immigration increases because the internal mobility within the country is relatively low. The negative wage impact for other countries compared to US and Europe is plausible given that there is relatively high geographical labour mobility, capital mobility, greater flexibility and competitiveness of US and European labour markets.

Study Characteristics

Study characteristics include estimation technique, approach of choosing the variation in immigration as a regressor, gender and skills of the target group and whether the target group is natives or immigrants. Marginal effects associated with different approaches suggest the use of skill-cell and spatial approach increase the probability of finding positive significant wage impact by 42.5% and 32.5% when mixed approach is used as a reference category. For studies using skill-cell approach, the positive significant estimated impact is bigger than those that use spatial approach. As pointed out by Borjas et al. (1996), it is possible that the wage effect of immigration using spatial approach is smaller in magnitude as compared to skill-cell approach because of the diluting effect of native migration flows across regions. This may cause the estimation results from spatial approach to be understated. The marginal effects associated with spatial approach align with the summary statistics of the previous section but for skill-cell approach, average effect size was negative while estimated marginal effects suggest that wage impact of immigration tends to be positive. There are a few reasons for the heterogeneity in the results for skill-cell approach. First, the marginal effects are estimated while using mixture approach as the reference category. So the marginal effects associated with skill-cell approach are produced in comparison to mixture approach and because the former approach identify the wage impact of one experience group versus another group within an education group and the latter approach estimates the relative wage impact of immigration of one education group versus another. Hence it is possible that the estimated relative wage impact of education groups is negative as compared to the estimated wage impact of experience groups within an education group. Secondly, skill-cell approach rely on the assumption that the elasticity of labour supply is homogenous across different groups of natives. This assumption ignores the response of immigration on employment and only focus on wage impact. If employment of natives indeed respond to immigration then part of its overall impact is absorbed by employment causing the the wage impact of immigration estimated using skill-cell approach to be rather positive. Furthermore, it is also possible that studies that use the skill-cell approach have specific features that interact with study characteristics causing the wage impact estimates to be positive in different studies.

Primary studies also differ in terms of skill-set of the target group. Since immigrants are more in competition with low skilled workers, wage effect estimated for low skilled workers is likely to be more negative significant as compared to high-skilled workers. The low skilled workers decrease the probability of getting positive significant results by 33% as compared to high skilled workers who decrease it by about 20%. The marginal effects associated with these skill sets are statistically significant. The reference category in this case are those studies that focus on all skill sets of the target group. Literature on migration highlights that immigrants are more in competition with with low skilled native workers and therefore have a bigger depressing impact on the labour market outcomes of low skilled natives (Borjas 2003). However, Ottaviano and Peri (2005) state that the degree of substitutability between natives and immigrants when assessing the impact of immigration on natives is likely to differ across education groups. So in studies that assess the impact of immigration on the wages of high skilled or low skilled natives, there is no differentiation of immigrants by education groups. Furthermore, there are also studies that compute the proportion of immigrants by skills groups to estimate the impact of this immigrant group on the natives of that same skill group. So the resulting estimates average out the skill group specific impact.

Marginal effects associated with other study characteristics are statistically insignificant. Keeping OLS as the reference category, the marginal effects show that studies that use IV estimation technique increases the probability of insignificance and negative significance by 3.5% and 6.5% respectively while it decreases the probability of positive significance by about 10%. While assessing the impact of the characteristics of the affected group, the marginal effects reported in Table 2.3 show that being a male increases the probability of negative significance by 1.8% and decreases the probability of positive significance by 5%; being a female worker tends to find positive significant wage effect. Primary studies estimating the impact of immigration on earlier immigrants tend to confirm positive wage impacts as compared to those estimating the impact of immigration on both groups, while the reverse happens for those studies that consider natives only.

Data Characteristics

The data characteristics collected from each primary study includes information on the type of data used and level of wage in the estimations. The marginal effects reported in Table 2.3 show that keeping yearly data as a reference category, studies estimating the wage impact of immigration using decadal data seem to confirm insignificant wage impact more often than those estimated using cross-section data. The marginal effects for decadal data are -0.375 for positive significance, 0.131 for negative significance and 0.243 for insignificance. Longhi et al. (2008) highlights that the impact estimated using cross-section data might underestimate the impact of immigration and first-differences should be used to capture the short-run effects of immigration, since they would be less affected by city-specific unobserved characteristics that might influence immigrant density or natives' outcomes. However, most studies use census data and therefore compute first-differences over rather long periods. So the assumption of time-invariant location effects become unreasonable. The wage level used in each study as a dependent variable is also categorised under the data characteristics. Our sample includes primary studies that use annual, monthly, weekly, daily, hourly wages and/or give no detail on the level of the wages used. For the ordered probit model estimations, weekly wage level is used as a reference category. Table 2.3 shows that the marginal effects for a monthly wage dummy is 0.999 for positive significance. It is large and rather questionable. The definition of the wage in studies is quite heterogeneous so it is suspected that the dummy variable on the level of the wage might capture effects different than the ones they intend to measure. Secondly, the definition of the wage reported or imputed, is often problematic and such a problem may be responsible for the implausible results obtained for monthly wage.

2.5 Publication Bias and P-hacking

In meta-analysis literature, there is increasing concern that journals especially those with higher impact factor, disproportionately publish statistically significant results. This gives the authors of research papers an incentive to publish statistically significant results (Dwan et al. 2008, Fanelli, 2012 and Song et al. 2000). The selectivity of statistically significant results leads to two types of researcher driven biases: publication bias and inflation bias or p-hacking. Each of these biases is explained and tested below.

Publication bias is defined as a tendency of authors, referees and editors to favour the publication of statistically significant results (Stanley et al 2004). Publication bias has two potential sources. First, researchers may treat statistically significant results more favourably, as seems to be the case in many areas of empirical economics (Card and Krueger 1995). Second, researchers may prefer a particular direction of the estimate of a particular hypothesis. For example, some researchers may be tempted to report "good news" (positive estimates) for developing countries in contrast to doubtful results. The presence of publication selection would probably not just affect the selection of studies in our sample but it could bias the ordered probit model results of the previous section.

In order to reduce the impact of publication bias on the estimates, the sample of research papers in this study includes unpublished, discussion papers and working papers in addition to published papers. These were collected from the references and citations in published papers. All the estimates of wage effect of immigration (whether significant or insignificant and positive or negative) from all the papers are included in the dataset. The presence of publication bias is usually tested graphically and analytically. The graphical test uses so-called funnel plot (Egger et al. 1997; Stanley and Doucouliagos 2010), a scatter plot of the estimates of the wage effect of immigration on horizontal axis against their precision (the inverse of the standard error) on the vertical axis. In the absence of publication bias, the funnel plot is symmetrical - the most precise estimates are close to each other while the imprecise estimates are dispersed widely. In consequence, the scatter plot should resemble an inverted funnel. If some estimates of wage effect of immigration were discarded because of their unintuitive sign, the funnel will become asymmetrical. If insignificant estimates are not reported, the funnel becomes hollow meaning results yielding small coefficients with large standard errors were discarded. The funnel plot for our sample of effect sizes is reported in Figure 2.3. The funnel seems to be full and symmetrical in general, although the left portion of the funnel might be a little heavier than the right one. This means that publication bias is not an issue in the data.

Because the interpretation of the funnel plot is rather subjective, more formal methods are needed to assess the presence of publication bias in the wage effect of immigration literature. In order to test if publication bias exists in the studies, I used the funnel asymmetry test (FAT) suggested by Card and Krueger (1995). The idea behind this test for publication bias reformulates the funnel plot as a regression relationship. If we switch the axes in the funnel plot and invert the values on the new horizontal axis, we get a relation between the estimate of wage effect and its standard error. In the absence of publication bias, the estimated size of the coefficient should not be correlated with its standard error. But if estimates are selected on the basis of their significance level, the relationship will become significant. The following regression model, suggested by Card and Krueger (1995), is used to formally test for publication bias:

$$b_i = \beta_0 + \beta_1 S(b_i) + \epsilon_i, \tag{2.8}$$

where b_i denotes the effect sizes, β_0 is the average underlying effect, $S(b_i)$ is the standard error of b_i, ϵ_i is the error term and β_1 measures the magnitude of publication bias. Stanley (2005, 2008) criticises FAT by arguing that it is likely to be heteroskedastic as the explanatory variable is a sample estimate of the standard deviation of the response variable. In order to ensure efficiency, he suggests that specification (2.8) be divided by the standard error and then estimated using Ordinary Least Squares (OLS):

$$t_i = \frac{\beta_0}{S(b_i)} + \beta_1 + e_i. \tag{2.9}$$

In equation (2.9), the inverted value of the standard error estimates the precision of the effect. β_0 detects whether the estimates are biased due to publication selectivity. This test is called the precision effect testing (PET) suggested by Stanley and Doucouliagos (2012). Since studies differ in their characteristics, we add explanatory variables on study features in the estimations to correct for omitted variable bias and cluster the standard errors at the study level. The results for FAT and PET tests are reported in Table 2.4 and they confirm the intuition based on the funnel plot, i.e. the estimates for publication bias are small and insignificant. In a quantitative survey of economic meta-analyses, Doucouliagos and Stanley (2012) state that values of the coefficient for publication bias in the funnel asymmetry test are important if they are statistically significant and larger than one in absolute value. The coefficients for publication bias reported in Table 2.4 are around -0.003 for FAT test and 0.033 for PET test and are statistically insignificant. I can safely conclude that publication bias in this sample of studies is negligible.

The second researcher driven bias is called p-hacking and it occurs when authors influence the data collection process or statistical analyses performed in order to produce statistically significant results. Authors p-hack their results by conducting analysis midway through experiments to decide whether to continue collecting data, stopping data exploration if analysis yields statistically significant p-value and deciding whether to include all the response variables, outliers, covariates and treatment groups post-analysis (Head et al. 2015). Testing for p-hacking is important because statistically significant estimates attract more attention and can lead to fruitless research programs if these estimates are p-hacked. The estimates collected for this meta-analysis are tested for p-hacking using p-curve and binomial test suggested by Head et al. (2015).

A p-curve is defined as the distribution of p-values for a set of estimates. It is used to identify p-hacking by looking at the significant estimates and evaluating the reliability of published papers. The evidence of p-hacking is indicated by the shape of the p-curve. If authors p-hack their findings by turning non-significant results into significant, the p-curve will be altered close to a particular significance threshold level. I set the significance threshold level to be p-value= 0.05. The p-curve for the sample of statistically significant estimates measuring the wage effect of immigration is shown in Figure 2.4. If authors are p-hacking, there will be an over representation of p-values in the tail of distribution around p-value= 0.05. Based on the shape of the p-curve in Figure 2.4, there is no strong evidence of p-hacking in the papers from which the wage estimates are collected.

While the p-curve gives a rough estimate of whether there is evidence of p-hacking, it does not formally test the presence of p-hacking. In order to formally test if p-hacking exists in the studies, I use the binomial test suggested by Head et al. (2015). The test for p-hacking is divided into two parts. The first part examines whether the sample of studies used for meta-analysis contains evidential value. Evidential value refers to when the results for a specific hypothesis suggest a non-zero effect size. A two-tailed binomial test is used to test for evidential value which compares the number of p-values under two threshold levels. The null hypothesis is that the expected number of p-values in each of the two bins is equal, or there is no evidential value. A lower bin is defined as $0 \leq \text{p} < 0.025$ and the upper bin is defined as $0.025 \leq \text{p} < 0.05$.

A binomial test is a probability test that compares the relative frequencies of the two categories of a dichotomous variable to the expected frequencies under a binomial distribution with specified probability. With n trials (sample size), number of successes k defined as number of statistically significant p-values in the upper bin of $0.025 \leq \text{p} < 0.05$ and q as the observed proportion of p-values in this upper bin, the estimated binomial proportion of p-values in the upper bin is given as:

$$\pi = \binom{n}{k} q^k (1-q)^{n-k}, \tag{2.10}$$

where $\binom{n}{k} = \frac{n!}{k!(n-k)!}$.

More p-values in the upper bin is consistent with p-hacking and more p-values in the lower bin coincides with non-zero effect size. Table 2.5 reports the test for the evidential value. Results show that the probability of success is 0.1 with p-value of less than 0.001. Hence, we reject the null hypothesis of no evidential value as the wage effect of immigration is non-zero.

The first step of this test is only able to measure severe form of p-hacking. The second part of the test involves evaluating the increase in relative frequency of p-values just below p-value

=0.05. This helps in measuring the modest levels of p-hacking. Using the binomial test, p-hacking is assessed by comparing the number of p-values in the adjacent lower bin below p=0.05. The criteria for setting the bin thresholds is similar to Head et al. (2015). They argue that this test is more likely to determine p-hacking if one uses smaller bins because p-values are rightly skewed to p=0.05 if there is evidence of p-hacking. The lower bin is defined as $0.04 \leq \mathrm{p} < 0.045$ and the upper bin is defined as $0.045 \leq \mathrm{p} < 0.05$. Using the binomial test, number of successes k now is defined as number of statistically significant p-values in upper bin of $0.045 \leq \mathrm{p} < 0.05$ and q is the observed proportion of p-values in this bin. The results are reported in Table 2.5 as a measure of the strength of p-hacking. The probability of success is 0.583. The p-value associated with the binomial test for p-hacking is 0.3872. This indicates there is no strong evidence of p-hacking in this meta-analysis. Tables 2.6 and 2.7 report the results of binomial tests for p-hacking at 1% and 10% threshold levels as robustness checks. The results do not provide evidence of p-hacking.

The results in this section test for publication bias and p-hacking (inflation bias) due to selectivity of published results. The funnel plots, funnel asymmetry test, p-curves and binomial test show that the sample of studies collected for this meta-analysis do not suffer from publication bias and p-hacking.

2.6 Robustness Check

For sensitivity analysis, the model is re-estimated using Ordinary Least Squares (OLS) using the specification:

$$b_i = \beta_0 + x_i'\beta + \epsilon_i \tag{2.11}$$

where b_i is the effect size (estimated coefficient of the wage effect of immigration) collected from each study, x_i' is a vector of study, data characteristics and labour market conditions and ϵ_i is the disturbance term. The estimation is weighted by the inverse of the standard errors. The second specification uses the t-statistics associated with each wage estimate as a dependent variable in the following OLS estimation:

$$t_i = \beta_0 + x_i'\beta + u_i \tag{2.12}$$

where t_i is the t-statistics associated with the estimate of the wage effect of immigration and u_i is the disturbance term. The results for these two estimations are reported in Table 2.8. The regression results are qualitatively similar to the estimation results of section 2.4, with a few exceptions. The immigrant inflow rate has a negative and statistically significant impact on the wage effect of immigration. When the immigrant inflow rate is high, increase in immigration causes wage to decrease. This is different from the ordered probit model estimations in section 2.4 which showed that the magnitude of immigrant inflow rate doesn't have a significant impact on the behaviour of wages in the host country when there is an increase in immigration. The magnitude of the unemployment rate also plays a vital role in shaping the wage effect of immigration as higher the unemployment rate, the negative is the impact of immigration on wages. The arrival of new immigrants has a bigger impact on wages of other immigrants than on wages of natives (Manacorda et al. 2012). The effect of immigration is similar and insignificant for both genders. These robustness checks confirm the results of the ordered probit model that low-skilled workers seem to be more negatively affected by immigration than high skilled workers. There is a high substitutability between low skilled native and immigrant workers.

Robustness checks also confirm that the effects sizes calculated for European countries and other countries are negative as compared to the US. Papers in which effect sizes are estimated by means of skill-cell approach are closer to zero as compared to the mixed approach while those using the spatial approach tend to find positive wage effects. Table 2.8 also support the findings of meta-regressions of section 2.4 that papers that estimated the effect sizes using IV estimations are closer to zero as compared to those that use OLS estimations. When assessing the data characteristics, studies that use cross-section and/or decadal data estimate effect sizes that are negative as compared to those that use yearly data and compared to the weekly wages, effect sizes calculated using hourly and monthly data are positive.

The exceptions are that the effect on immigrant inflow on the wage estimates are statistically significant in the OLS estimations while marginal effects of immigrant inflow in ordered probit estimations are insignificant. Similarly, the OLS estimates for affected groups are significant while their marginal effects are not. The problem with evaluating the direct relationship between the wage estimates and the study characteristics in meta-analysis is that there is no common metric of the effect sizes collected from the wide rage of studies. Therefore, there is inconsistency in the comparison between the results of different studies. The quantitative comparison becomes possible if there is a single metric of all the effect sizes - which is why the use of sign and statistical significance as the dependant variable in the estimations and the associated results are preferred.

2.7 Discussion

Given the increase in migration in the recent years, it is no secret there is large scientific literature that has attempted to document and quantify ways in which immigrants affect the lives of people in the host country and these impacts are wide ranging across cultural, social, economic and several other areas. The size and the composition of immigration that maximises the wellbeing of population in host country is an important policy question (Hanson, 2008). The results from the previous sections explain that labour market conditions, study characteristics and context of the study play a significant role in explaining the direction in which the wage effect of immigration goes and its statistical significance. The objective of this section is to first discuss the possible explanatory factors that complement results derived in the previous sections and then look for policy recommendations. This meta-analysis aggregates the the data from the literature on wage impact of immigration and evaluates it to identify a common effect. The results of this meta-analysis indicate that on average, the wage impact of immigration is small, negative and can either be significant or insignificant. Study, data characteristics, context of the study and labour market conditions play a significant role in identifying the common wage effect. Three factors that could possibly explain the negative significant and insignificant wage effect of immigration are the country characteristics, level of unionisation in the labour market and the role played by sectors/industries in absorbing the influx of immigration.

Economic theory suggests that in the short run, the impact of immigration on the existing workforce depends on the extent to which immigrant labour is either a substitute for, or a complement to existing workers. But in the long run, impacts are more positive as the economy has time to adjust to the expansion in the number of workers. Demand for goods and services among immigrants is likely to increase hiring and investment in the sectors which produce these items. This increase in demand for labour then translates into increased employment and wages in these sectors (McGuinness and Hawkins 2016). However, the impact of immigration on employment and wages will likely be affected by current economic conditions. During an economic downturn when demand is constrained, there is more risk of displacement of existing workers. Firms are less likely to expand production despite the increase in labour supply, so migrant workers will be in greater competition for jobs with the existing workforce.

The role that labour and trade unions can play in assessing the wage impact of immigration is significant and depends upon the activity undertaken by the unions. For example, the role of union bargaining in enhancing the conditions and pay of workers, including migrants can lead to higher wages for natives and earlier immigrants in time when new migrants enter the country. These practices work across a collective body of organised workers and consequently affect workers involved in that bargaining unit, whether migrant or not (Connolly et al. 2012). On paper, union membership appears to deliver a modest wage premium of a relatively similar magnitude to both natives and immigrant workers. Wage inequality tends to be higher among all non-union workers including immigrant workers compared to unionised natives and earlier immigrants (Turner et al. 2015).

Dustmann et al. (2008) state that economies are characterised by a multitude of different sectors, producing goods that differ in their capital intensity and in their relative use of skilled versus unskilled labour. They argue that if there is an economy with two sectors (low skilled and high skilled), each produces goods which are traded in the world market with fixed prices. Immigration influx will increase the labour supply of unskilled workers which will initially decrease the wages of these workers. However, this change in relative wages now leads to a relatively larger decrease in unit production costs for the low skilled industry as compared to high skilled industry. One other important aspect that leads to small wage effect of immigration is that immigration could impact the other indicators of labour markets more than it affects the wages. For example, there is a possibility that entry of new migrants affects the hours worked by currently employed workers. It can also possibly affect the unemployment durations of unemployed workers, capital flows, sectoral change, economies of scale and technological change.

Even with the small negative wage impact of immigration, the distributional impacts on various kind of workers and capital owners may be larger and will depend on the skill mix of immigrant inflow in the labour force of host country, the changes in the composition of demand, sectoral and location choices of immigrants and change in non-wage income (Longhi et al. 2008). These factors will change over time. Furthermore, economic and broader impacts in the host country such as economic integration and demographic imbalances can be potential causes of concern as well. Focusing on these economic and labour market impacts of immigration in the host country, the public policy should be designed accordingly to respond to labour market needs and demographic objectives of the host country. The objective should be to manage the volume, origin, direction and composition of immigration inflows. One of the main results of the meta-analysis of the previous sections show that the impact of immigration on wages is smaller in more flexible economies as compared to those which more institutional rigidity. So reformation of labour markets policies to be less rigid may be help to increase immigrant economic integration by larger internal mobility of immigrants.

The immigration impact also differs by regions. Other things being equal, the largest short-term impact will be felt in areas that see the largest growth in immigrant numbers, as local labour markets need time to adjust. Immigration into an area may also lead to some existing workers moving to new areas. However, while immigration flows can drive changes to wages and employment, the reverse is also true: immigrants are often drawn to areas experiencing economic growth and strong demand for labour, in which case the results for the local economy would be more positive (McGuinness and Hawkins 2016). Hence creating employment opportunities and improving infrastructure, housing and education systems in rural or underdeveloped regions of the host country will attract immigrants to these areas causing them to spread evenly across the entire country while reducing the downward pressure on the wages of workers.

Immigrants affect the local labour market outcomes in the host country by changing the relative supply of labour in the skill group. But it is a fact that immigrant population is geographically concentrated. Immigrants tend to locate to areas with better amenities or where there is already a large immigrant population. The information on the location choices of immigrants can help the policy makers predict which locations can expect to receive immigrants in the future and can help in tackling the endogenous sorting of immigrants. Recently, a growing number of countries are now directing their attention towards the regional distribution of immigrants (Dustmann et al. 2008). This facilitates immigrants' integration in the host country. This policy involves giving bigger role to local authority in managing migration flows in accordance to labour market needs. One way to overcome the overcrowding of immigrants in specific regions is to introduce a system for allocating a particular group of immigrants exogenously with regard to their skill levels to different localities while ensuring compliance with these allocation decisions (Glitz, 2012). For example, the Assigned Place of Residence Act was introduced in Germany in 1989 in the aftermath of the large immigrant influx at the time. This influx of immigrants was concentrated in specific regions in Germany creating shortages in the housing and other facilities in those regions. Meanwhile, other regions were relatively empty. The authorities implemented this law to ensure that there was an even distribution of ethnic immigrants across Germany and no specific regions were overcrowded. Such an approach not just solves the problem of uneven distribution of immigrants across the country but also ensures that immigrants are competing with natives who have the same set of skills as them in terms of their labour market outcomes.

The estimation results also show that the the entry of immigrants tend to decrease the wages of low skilled workers in the host country as immigrants are considered close substitutes of low skilled natives. One key policy recommendation to tackle the negative wage impact of immigration for low skilled workers is to manage the need for temporary low-skilled immigration. Low skilled immigration is expected to serve the purpose of filling temporary labour shortages. Hence well-designed temporary migration programs should be created to facilitate the entry of low skilled immigrants. Along with handling the negative effect of immigration on low skilled native workers, these temporary migration programs are also an effective measure to fill labour shortages.

2.8 Conclusion

In this paper, I estimate the relationship between immigration and wages through the means of meta-analysis. It was conducted because previous empirical literature assessing the wage impact of immigration arrived to inconclusive results. As already noted by Borjas (2003), the estimation results vary from study to study and sometimes even within the same study. For the purpose of this meta-analysis, 663 estimates were collected from the sample of 46 studies that examine the impact of a percentage change in immigration on the wages of workers in the host country.[5] The simple descriptive summary statistics show that the overall effect is very small and the mean wage effect of immigration is 0.03. However, in order to examine the statistical significance of the variation in the collected estimates across different categories for each study characteristics, ordered probit model is used.

Ordered probit model is used to estimate the marginal effects of different characteristics on the sign and significance of wage effect of immigration. The results from this estimation show that

[5]Here workers include not just native workers but also previous/old immigrants.

there is negative impact of immigration on wages when countries are going through adverse labour market conditions (such as high unemployment rates). The negative wage impact of immigration is significant for non-US and non-European countries. Primary studies using IV estimation tends to find negative significant impact as compared to OLS estimation. Other things being equal, immigrants are more in competition with low skilled workers and hence they tend to decrease the wages of low skilled workers. Studies using monthly wages compared to weekly wages tend to find positive results.

I also test for publication bias and p-hacking which can result from the tendency of the journals to favour the publication of statistically significant results. In order to test for publication bias, FAT test of Card and Krueger (1995) and PET test of Stanley and Doucouliagos (2012) are used. The idea behind these tests is to look at the relationship between the effect sizes and their standard errors. The results show that publication bias is not an issue in our sample. P-hacking is tested using the binomial test suggested by Head et al. (2015). The tests show no signs of p-hacking. Results from robustness checks show that compared to the effect sizes that are calculated using mixed approach, studies using spatial approach find positive wage impact. Furthermore, when the labour market conditions are adverse, the wage impact of immigration is negative and significant. In other words, when unemployment rate in the host country is high, immigrant influx into the labour market decreases the wages of existing employed workers.

The estimation results in this study show that the empirical literature on the wage effects of immigration find different results because each study has different characteristics such as approach, estimation specification and different types of data. The context in the empirical papers is also different from one another when the impact for different countries is estimated. Finally, studies find different results from one another because the economic conditions in the targeted country at a specific time period are different and play an important role in shaping the wage effect of immigration. The general conclusion from the meta-analysis estimations of this study is that the wage impact of immigration is on average small, negative and can be statistically significant or insignificant. Hence the results of this study not only contribute to the existing literature but also help in understanding factors that cause the estimated results to be different from one another.

2.9 Appendices

2.9.1 Tables

Table 2.1: Sample of Studies

Study's ID	Author(s)	Approach	Country	Time period	No.of Obs.
1	Glitz (2012)	Mixed	Germany	1996-2001	24
2	Boustan, Fishback and Kantor (2010)	Spatial	US	1935-1940	6
3	Smith (2012)	Spatial	US	1980-2007	6
4	Aydemir and Borjas (2011)	Skill-cell	US, Canada	1971-2001, 1960-2000	26
5	Dustmann and Glitz (2015)	Mixed	Germany	1985-1995	6
6	Ortega and Verdugo (2014)	Skill-cell	France	1968-1999	20
7	Gonzalez and Ortega (2011)	Spatial	Spain	2001-2006	6
8	Bodvarsson, Van den Berg and Lewer (2008)	Skill-Cell	US	1975-1980	2
9	Orrenius and Zavodeny (2007)	Mixed	US	1994-2000	18
10	Bratsberg, Raaum and Roed (2014)	Spatial	Norway	1972-2012	34
11	Borjas (2003)	Skill-Cell	US	1960-2001	26
12	Friedberg (2001)	Mixed	Israel	1990-1995	14
13	Cohen-Goldner and Paserman (2001)	Mixed	Israel	1989-1999	10
14	Dustmann, Fabbri and Preston (2013)	Spatial	U.K	1997-2005	70
15	Borjas (2015)	Spatial	US	1977-1992	12
16	Foged and Peri (2016)	Spatial	Denmark	1991-2008	22
17	Reed and Latorre (2009)	Spatial	UK	2004-2007	5
18	Dustmann, Frattini and Preston (2008)	Mixed	UK	1997-2005	20
19	Carrasco, Jimeno and Ortega (2008)	Mixed	Spain	1991-2001	2
20	Barrett, Bergin and Kelly (2009)	Skill-Cell	Ireland	1999-2007	22
21	Addison and Worswick (2002)	Spatial	Australia	1982-1996	11
22	Easton (2001)	Spatial	US	1985-1990	20
23	Hofer and Huber (2003)	Spatial	Austria	1991-1994	2
24	Aydemir and Borjas (2007)	Skill-cell	US, Canada	1971-2001	4
25	Card and Peri (2016)	Skill-cell	US	1960-2011	3
26	Peri and Yasenov (2016)	Spatial	US	1997-1992	12
27	Borjas (2006)	Mixed	US	1960-2000	20
28	Card and Lewis (2007)	Mixed	US	1990-2006	6
29	Lewis (2011)	Mixed	US	1960-2006	6
30	Ozden and Wagner (2015)	Mixed	Malaysia	2007-2010	16
31	Bratsberg, Ragan and Nasir (2002)	Skill-cell	US	1979-1998	25
32	Prantl and Spitz-Oener (2011)	Mixed	Germany	1986-1999	2
33	Steinhardht (2011)	Skill-cell	Germany	1975-2001	2
34	Dustmann, Schonberg and Stuhler (2016)	Spatial	Germany	1986-1996	6
35	Ottaviano and Peri (2005)	Mixed	US	1970-2000	8
36	Bonin (2005)	Skill-cell	Germany	1975-1997	20
37	Kugler and Yuksel (2008)	Spatial	US	1980-2005	48
38	Card (2001)	Mixed	US	1985-1990	16
39	Dustmann, Fabbri and Preston (2005)	Spatial	UK	1992-2000	6
40	Card (2005)	Mixed	US	1965-2000	2
41	Card (2009)	Mixed	US	1980-2006	15
42	Borjas (2005)	Skill-cell	US	1968-2000	6
43	Lemos (2011)	Spatial	UK	1978-2007	3
44	Barrett and Mccarthy (2007)	Mixed	Ireland	2004	9
45	Borjas (2001)	Spatial	US	1950-1990	24
46	Card (2007)	Spatial	US	1980-2000	6

Table 2.2: Summary statistics of effect size corresponding to study features.

	Variable	Obs	Mean	Std. Dev.	Min	Max
	Coefficient	663	0.0307798	0.5578093	-2.225	3.798
Country	US#	324	-0.0297269	0.5081758	-2.225	3.557
	Europe	270	0.120913	0.6108897	-3.642	3.798
	Others	69	-0.0377961	0.8958133	-1.54	2.638
Immigrant Inflow Rate	Immigrant Inflow Rate $<$ 7%	84	0.413	1.01755	-0.674	3.642
	7% $\leq$ Immigrant Inflow Rate $<$ 10%	340	-0.0118	0.5768199	-2.225	3.798
	Immigrant Inflow Rate $\geq$ 10%	239	-0.0431901	.558344	-1.775	2.638
L M Conditions	Low Unemployment Rate ($<$ 5%)	103	-0.132699	0.3783284	-1.775	1.104
	Moderate Unemployment Rate (5% $\leq$ u $<$ 10%)	512	0.0432684	0.541812	-2.225	3.798
	High Unemployment Rate ($\geq$ 10%)	48	-0.0820924	1.257191	-1.54	3.642
Approach	Mixed#	200	-0.0117	0.4853223	-1.54	3.672
	Skill-cell	137	-0.1684978	0.5552823	-2.225	1.134
	Spatial	326	0.1438218	0.5740912	−1.169	3.798
Estimator	IV	227	0.1157696	0.5533191	-1.775	3.798
	OLS#	436	-0.0134693	0.5556319	-2.225	3.642
Gender	Both#	328	0.1797588	0.6841247	-1.775	3.798
	Male	261	-0.1241059	0.3616354	-2.225	1.134
	Female	74	-0.083273	0.2463661	-1.289	0.63
Skill Level	All#	439	0.0446733	0.5833517	-1.775	3.642
	High Skill	61	0.1286934	0.5030237	-1.096	2.316
	low Skill	119	-0.0146314	0.4978281	-1.416	3.798
	Medium Skill	45	-0.1184067	0.4963093	-2.225	0.23
Affected Group	All#	123	0.0138415	.6820143	-1.289	3.557
	Immigrants	70	0.0408271	0.2267254	-0.947	0.771
	Natives	470	0.0337163	0.5572574	-2.225	3.798
Frequency of Data	3 year Diff#	58	-0.1126552	0.1424824	-0.458	0.114
	cross-section	48	-0.0009792	0.2287651	-0.948	0.63
	decadal	186	-0.0701366	0.6475012	-2.225	3.557
	yearly	371	-0.701336	0.5682113	-1.775	3.798
Wage Level	Annual	103	0.0516777	0.9008629	-2.225	3.642
	Daily	64	-0.1593156	0.2549528	-1.289	0.283
	Hourly	343	0.1264299	0.49634	-1.775	3.798
	Monthly	22	0.2339091	0.1953195	-0.237	0.58
	No Details	5	-0.2094	0.1939299	-0.392	0.078
	Weekly#	126	-0.1760635	0.4178165	-2.074	2.638

Reference Category denoted with #

Table 2.3: Marginal Effects

Response Variable:		Insignificant	Negative Significant	Positive Significant
Labour Market Conditions				
1. Immigrant Inflow Rate		-0.192	-0.105	0.297
		(0.527)	(0.306)	(0.831)
2.Variation in Unemployment Rate		0.229***	0.124*	-0.354***
		(0.086)	(0.069)	0.128)
Context of the Study				
1. Country Under Study [US]	European	0.197**	0.107*	-0.305***
		(0.098)	(0.065)	(0.144)
	Others	0.434***	0.236*	-0.669***
		(0.114)	(0.125)	(0.184)
Data Characteristics				
1. Frequency of the Data [Yearly]	3 Year Difference	0.076	0.041	-0.117
		(0.113)	(0.066)	(0.177)
	Cross-Section	0.176**	0.096*	-0.272**
		(0.075)	(0.051)	(0.107)
	Decadal	0.243***	0.131*	-0.375***
		(0.076)	(0.069)	(0.113)
2. Level of the Wage [Weekly]	Annual	-0.074	-0.040	0.114
		(0.108)	(0.062)	(0.167)
	Daily	0.063	0.034	-0.097
		(0.103)	(0.060)	(0.161)
	Hourly	-0.138*	-0.075	0.214*
		(0.077)	(0.048)	(0.112)
	Monthly	-0.998**	-0.566*	0.999***
		(0.389)	(0.304)	(0.565)
	No Details	0.232**	0.126*	-0.358**
		(0.098)	(0.065)	(0.144)
Study Characteristics				
1. Estimation Technique [OLS]	IV	0.065	0.035	-0.099
		(0.046)	(0.024)	(0.065)
2. Approach [Mixed]	Skill-Cell	-0.275***	-0.150**	0.425***
		(0.087)	(0.076)	(0.125)
	Spatial	-0.211***	-0.115**	0.325***
		(0.057)	(0.056)	(0.08)
3. Gender [Both]	Male	0.003	0.018	-0.05
		(0.066)	(0.037)	(0.101)
	Female	-0.165	-0.089	0.254
		(0.081)	(0.058)	(0.174)
4. Affected Group [All]	Immigrants	-0.118	-0.064	0.182
		(0.081)	(0.058)	(0.132)
	Natives	0.028	0.016	-0.044
		(0.06)	(0.035)	(0.094)
Skills Level [All Skills]	High Skilled	0.140*	0.076*	-0.216**
		(0.077)	(0.042)	(0.104)
	Low Skilled	0.214***	0.116**	-0.331***
		(0.069)	(0.056)	(0.095)
	Medium Skilled	0.104	0.056	-0.160
		(0.075)	(0.052)	(0.121)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference categories in brackets

Table 2.4: Test for Publication Bias

Dependent Variable: Effect size		
	FAT Univariate	FAT Multivariate
	(1)	(2)
Standard Error (Publication Bias)	-0.0015	-0.0034
	(0.005)	(0.004)
Dependent Variable: t-statistics		
	PET Univariate	PET Multivariate
	(1)	(2)
1/Standard Error (Publication Bias)	0.037	0.033
	(0.041)	(0.031)
Observations	663	663

In Specification 2, moderator variables on study features are added as controls in the estimation.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Tests for Evidential Value and p-hacking for published significant estimates at 5%.

Test for Evidential Value	
No. of p-values between 0 and 0.025	369
No. of p-values between 0.025 and 0.05	41
Estimated Probability of Success	0.1
Binomial test for Evidential Value	$p - value < 0.001$
Test for p-hacking	
No. of p-values between 0.04 and 0.045	5
No. of p-values between 0.045 and 0.05	7
Estimated Probability of Success	0.583
Binomial test for p-hacking	$p - value = 0.3872$

Table 2.6: Tests for Evidential Value and p-hacking for published significant estimates at 1%.

Test for Evidential Value	
No. of p-values between 0 and 0.005	283
No. of p-values between 0.005 and 0.01	32
Estimated Probability of Success	0.1013
Binomial test for Evidential Value	$p - value < 0.001$
Test for p-hacking	
No. of p-values between 0.009 and 0.0095	1
No. of p-values between 0.0095 and 0.01	2
Estimated Probability of Success	0.666
Binomial test for p-hacking	$p - value = 0.5$

Table 2.7: Tests for Evidential Value and p-hacking for published significant estimates at 10%.

Test for Evidential Value	
No. of p-values between 0 and 0.05	410
Estimated Probability of Success	0.124
Binomial test for Evidential Value	$p - value < 0.001$
Test for p-hacking	
No. of p-values between 0.09 and 0.095	5
No. of p-values between 0.095 and 0.1	2
Estimated Probability of Success	0.285
Binomial test for p-hacking	$p - value = 0.9375$

Table 2.8: Robustness Checks

		Dependant variable (1) Effect Sizes	Dependant variable (2) t-statistics
Study Features:			
Immigrant Infows		-0.822**	-35.6**
		(0.323)	(13.5)
Variation in Unemployment Rate		-0.157***	-4.85*
		(0.061)	(2.74)
Region	Europe	-0.009	-12.9***
[US]		(0.093)	(3.79)
	Others	0.124*	0.607
		(0.074)	(2.84)
Approach	Skill-Cell	0.023	6.55***
[Mixed]		(0.044)	(2.24)
	Spatial	0.116***	4.05**
		(0.037)	(1.66)
Specification	IV	0.001	-0.768
[OLS]		(0.015)	(0.741)
Frequency	3 year Difference	-0.025	-2.02
[Yearly]		(0.042)	(2.81)
	Cross-section	-0.139***	-7.44**
		(0.039)	(3.33)
	Decadal	-0.112***	-6.34**
		(0.032)	(2.96)
Gender	Male	-0.013	-1.176
[Both]		(0.033)	(2.13)
	Female	0.007	0.130
		(0.038)	(1.94)
Affected Group	Immigrants	0.072**	4.89*
[Immigrants and Natives]		(0.031)	(2.98)
	Natives	0.057**	1.37
		(0.026)	(2.06)
Skills Level	High Skills	-0.097***	-4.47**
[All Skills]		(0.034)	(1.79)
	Low Skills	-0.099***	-5.89***
		(0.033)	(1.70)
	Medium Skills	-0.104***	-5.35***
		(0.034)	(1.95)
Level of Wage	Annual	-0.028	-2.49
[Weekly]		(0.068)	(2.27)
	Daily	0.092	10.8***
		(0.074)	(2.84)
	Hourly	0.201***	7.44***
		(0.025)	(1.80)
	Monthly	0.959***	28.5**
		(0.247)	(11.5)
	No Details	-0.081	-4.89
		(0.208)	(5.99)
Observations		663	663

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Reference categories in brackets

2.9.2 Figures

Figure 2.1: Total Effect Sizes From All Primary Studies

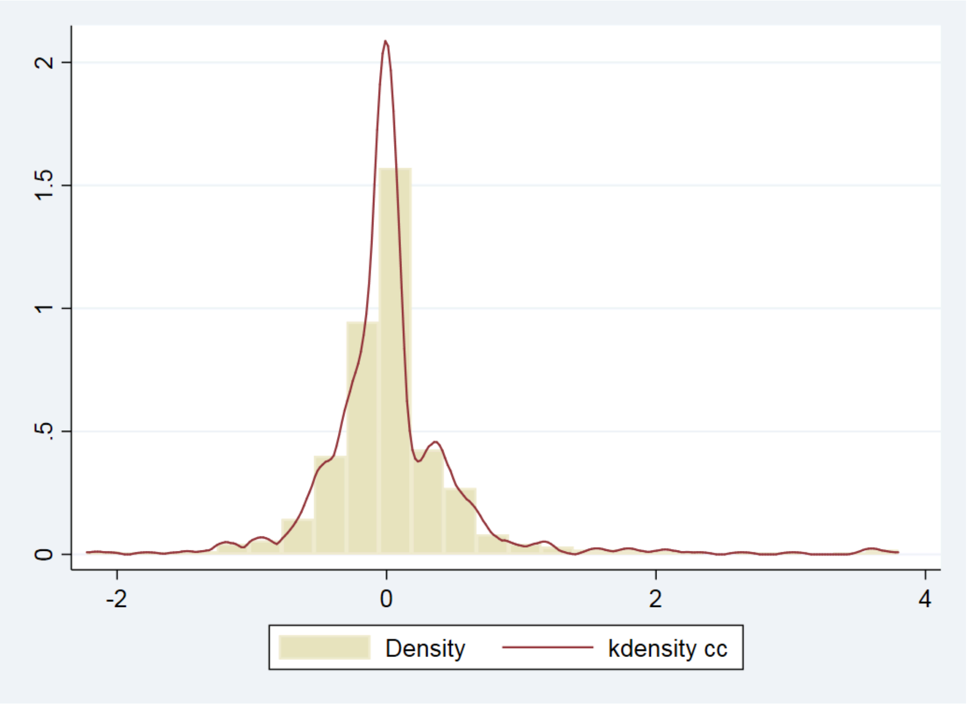


Figure 2.2: Sign and Significance of the Effect Sizes

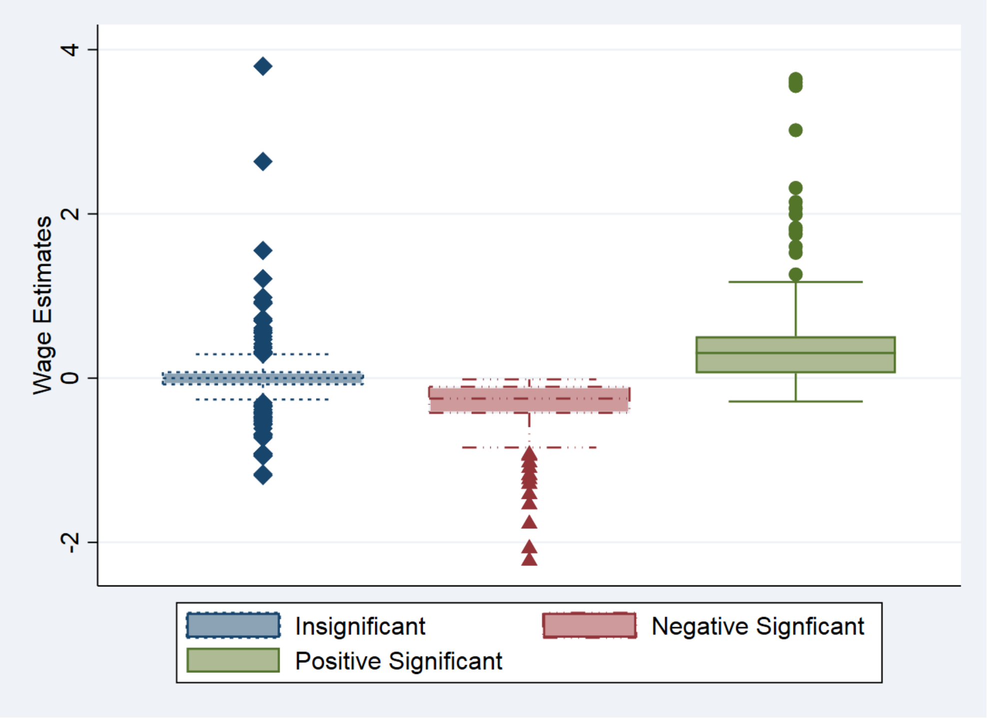


Figure 2.3: Funnel Plot For Publication Bias

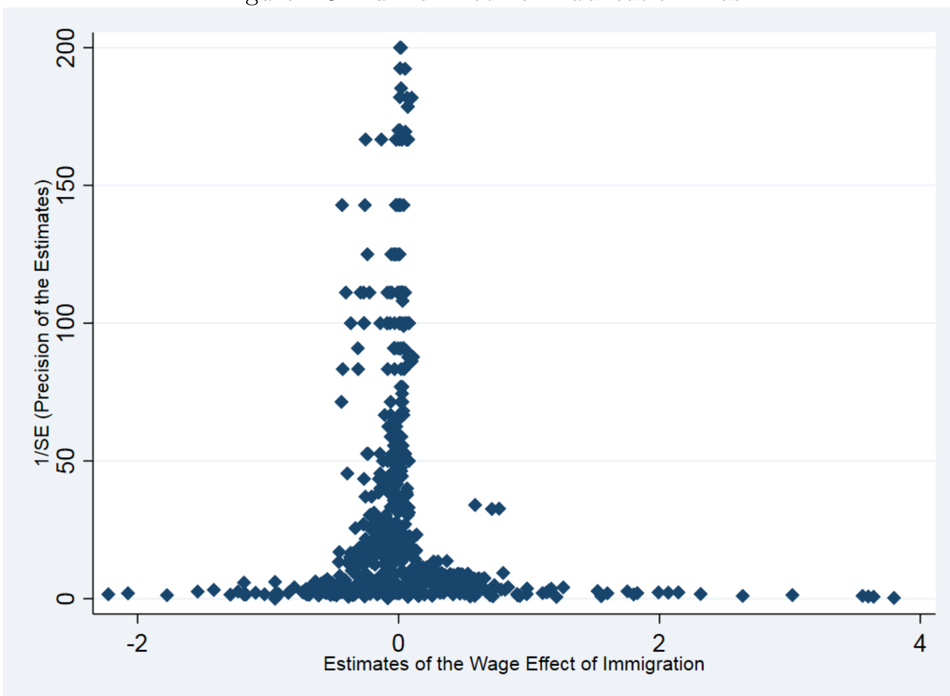
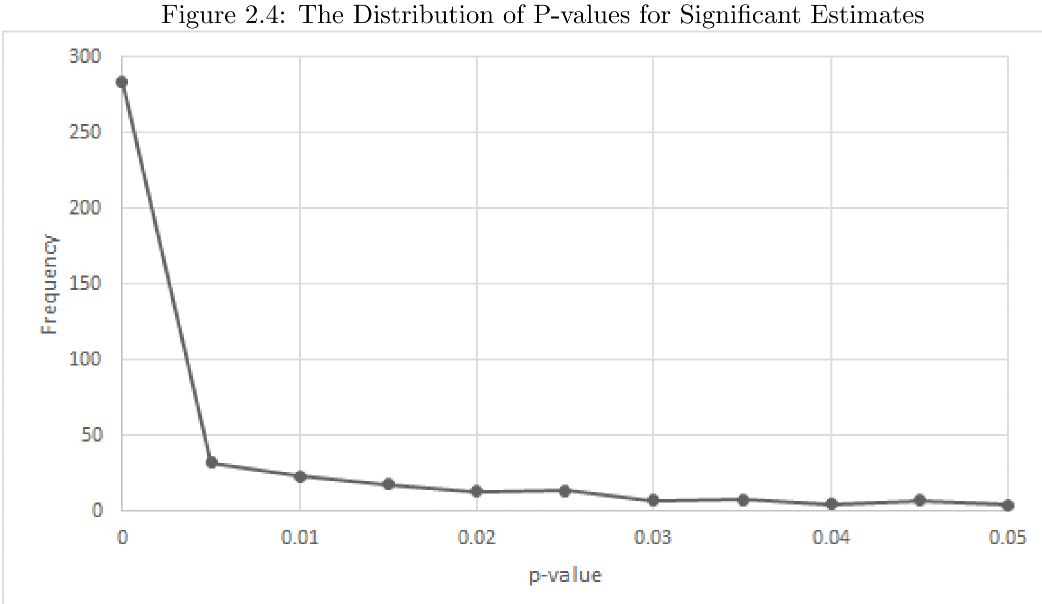


Figure 2.4: The Distribution of P-values for Significant Estimates



Chapter 3

Unemployment and Labour Market Mobility in Europe

3.1 Introduction

Since early 2000, the dynamics of unemployment in Europe varied widely between countries and various worker groups (Eurostat Statistics). In some countries for example, Belgium, Austria and Germany, unemployment has barely changed over the years and on average remains the same. In others, most notably, Greece, Portugal and Spain, the unemployment rate surged to higher levels than that of the high unemployment period of the early 1980s (European Central Bank reports 2012, 2014). In Greece and Spain, unemployment increased from about 9% in 2006 to 10% and 18% in 2009, respectively and increased further to approximately 25% in 2012. Unemployment also varies significantly across different labour market groups such as socio-demographic groups, Immigrant groups and urbanisation groups. For example, youth unemployment in both developed and emerging parts of Europe remains persistently high since 2008. In France, young workers still face high levels of unemployment hovering around 23%. Unemployment rates for females were higher than that of males till 2008 but the gender gap in unemployment converged in the recent years. Changing demographics significantly impact unemployment through channels of labour supply, labour productivity, and labour demand.

The 2007 enlargement of European Union was unprecedented in terms of the post enlargement migration flows between European countries. Unemployment rates for immigrants remain persistently high since 2008. Among the immigrant groups, new immigrants suffer more in terms of high unemployment as compared to earlier immigrants. The degree of urbanisation also seems to be one of the determinants of changing unemployment in Europe. In denser populated areas such as the cities, individuals have more contacts and are more likely to have bigger networks than workers in less densely populatd areas (Sato and Zenou, 2014). In cities, the unemployed workers have access to better supply or work opportunities when it comes job search (for example, local news paper advertisements, public service offices and easy commuting access to big firms). This helps them in finding job faster than worker in rural areas. However, there is a large supply of workers relative to labour demand in the cities which causes unemployment in these areas to increase.This can effect the unemployment rates, directly or not.

These statistics and facts show that the unemployment levels in European countries have behaved differently over the years and this can lead to greater divergences in labour market across Europe as a whole. The role played by flows into and out of employment is one of the possible determinants behind the variations in European unemployment rate. Labour markets are in a constant state of flux, and the same stocks and structures at the aggregate level can be linked to diverse patterns of employment transitions. I analyse annual worker flows and the composition of these flows for different worker groups over Europe and across various European countries for over a period of 2006-2016. My analysis answers the following two questions. The first question is whether high unemployment in Europe is a result of high job separation or low job finding. The second question is how important are socio-demographics, immigration status and degree of urbanisation in shaping worker flow patterns in Europe? Using the yearly data from European Union Labour Force Survey (EU-LFS), I compute European worker flows to better understand the differences in unemployment rates over time and most importantly to what extent does the change in aggregate unemployment rates are attributed to each of these flows. I then evaluate the correlation between various socio-demographic characteristics (SDCs), immigration status and degree of urbanisation on employment transitions to demonstrate that in addition to basic economic factors that affect the labour demand, changing demographic characteristics of workforce may also influence on European unemployment.

The same level of unemployment over the years can have very different implications depending on whether contributions to it are made by employment changes of the whole population or of specific labour market groups. Labour market flows at the individual level can change employment dynamics across regions and over time. This can lead to important policy concerns. For example, the changing age distribution of workers affects the labour force growth, participation and the long-run natural rate of unemployment at the same time. This has implications for long-run economic growth because one of the key determinants of the economy's longer-run growth rate are labour force growth and how effectively the economy combines its labour and capital inputs to create output (Mester 2017).

Over the years, there have been many studies assessing the ins and outs of unemployment (Hall, 2005; Fujita and Ramey, 2009; Shimer, 2012; Elsby et al. 2009). There is ample research on worker flows in the US, but there is no consensus on the relative empirical importance of job finding and separation rates over the years. Hall (2005) suggests that the separation rate is roughly acyclical, whereas there is high variability in job finding rate at low and business cycle frequencies. Shimer (2012) supports these findings and adds that the job finding probability accounts for 77% of the US unemployment changes and job separation accounts for only 24% for the period from 1948 to 2010, being relatively insignificant during the last two decades. Elsby et al. (2009) show that transition from employment to unemployment plays an important role in driving unemployment dynamics, especially during recessionary periods. Portugal and Rua (2017) reviewed research on US worker flows and reported conflicting results in previous literature. They argue that job separation rate is equally important as the job finding rate in explaining overall unemployment changes especially during recessions. In recent years, there has been some research done on European worker flows. Petrongolo and Pissarides (2008) study unemployment in three European countries: the United Kingdom, France, and Spain. Smith (2011) also focuses on the UK case, whereas more recently Elsby et al. (2013) and Kilponen and Vanhala (2009) provide a set of comparable estimates for the flow rates to and from unemployment for fourteen OECD economies. The results of their analysis show that variations in both unemployment inflow and outflow rates contribute substantially to unemployment variability within countries compared to the US where job finding rate is relatively more important than job separation rate in explaining the unemployment changes.

The main contributions of this study that sets it apart from the existing literature on worker flows in Europe are as follows: first, this study evaluates the impact of migration, urbanisation level and combined impact of the degree of urbanisation of different types of international migrants in shaping the worker flow patterns in Europe. To my knowledge, this has not been done previously. Second, calculation and evaluation of yearly worker flows is provided collectively for Europe as a whole and for specific countries. This provides a wider comparison of Europe with individual European countries. Worker flows are also calculated for each labour force group. This provides an insight into how changing unemployment dynamics of labour force groups and countries over time reflect on Europe as a whole. I use annual gross data from the EU-LFS for the computation of worker flows as compared to these previous studies which use quarterly and monthly data. Caroleo and Pastore (2010) argue that as short-term spells are often related to various institutional factors such as the unemployment benefit system, the annual flows are preferable for international comparisons. They also claim that only permanent moves affect permanent employment, hence annual flows are more suitable for a structural analysis. Finally, this chapter analyses the correlation between labour market characteristics and worker flows in addition to computing separate worker flows (as done previously) for each labour market group.[1]

Socio-demographic characteristics are measured in groups of age, gender and educational level. The age groups are categorised into *young workers* (aged between 15-29), *middle aged workers* (aged between 30-49) and *old age workers* (aged between 50-65). Educational level in the EU labour force survey is measured by the the highest level of education and is categorised into three levels of *Low: lower secondary, ISCED 0-2*, *medium: upper secondary, ISCED 3-4* and *high: third level, ISCED 5-8*. The degree of urbanisation is categorised into three groups of *cities* (densely populated), *towns and suburbs* (intermediate) and *rural areas* (thinly populated). The variable on years of residence in the data is used as indicator of immigration status with four categories of *born in the country*, *recent immigrants* (moved to this country in the last 5 years (0-5 years)), *intermediate immigrants* (moved to this country longer than 5 years go but less than 10 years (6-10 years)) and *earlier immigrants* (been in the country for more than 10 years ago ($\geq$ 11 years)).

[1]Elsby et al. (2009) compute the ratio of the rise in unemployment for individual socio-demographic groups to the rise in overall unemployment. They computed individual hazard rate for each group.

The result of the analysis reveals that employment to unemployment flows significantly varied over the years for Europe, while flows from unemployment to employment were less frequent over time. The decomposition of unemployment variation into parts accounted for by changes in rates of job loss and job finding show that about two-thirds of the volatility of unemployment in Europe over 2006-2016 can be traced to rises in rates of job loss while one-third accounts for job finding rates. The estimation results suggest that among all the socio-demographic groups, male workers, young workers and less educated workers are the most adversely affected group over the time period of 2006-2016. The job loss probability for these groups is higher. More specifically, young and less educated workers from Southern European countries (such as Spain, Greece and Portugal) have high probability of employment to unemployment transitions and low probability of unemployment to employment transitions. From the immigrants groups, recent and intermediate immigrants are adversely effected as they increase the probability of job separation by 1.6% and 1.5% respectively. The marginal effects associated with the urbanisation groups show that workers in town and suburbs (intermediate) and rural areas lower the job separation probability by 0.38% and 0.4%, respectively compared to workers in cities. Furthermore, all three immigrant groups in towns (intermediate populated) and rural areas have lower job separation rates and higher job finding rates as compared to the workers in cities.

The importance of socio-demographics, immigration status and degree of urbanisation when assessing the variations in unemployment can be highlighted through economic theory. It rationalises the empirical analysis by indicating that one of the factors that determine relative unemployment is relative labour supply which is determined by demographic evolutions (Jimeno and Rodriguez-Palenzuela, 2002). Theory predicts that those with higher levels of education suffer the least in terms of job losses and have a better chance of getting high paying job opportunities. Less educated workers are predicted by theory to be relatively unskilled and are likely to become unemployed during times of crisis. Two factors that contribute to their job losses are that firms are likely to sack their least productive workers and highly educated workers occupy their jobs as they move down the skill chain instead of getting laid off during times of crisis. Theory also provides an insight behind the differences in the unemployment levels. Young workers tend to face higher unemployment due to the economic conditions, education and training systems, labour market and employment policies and the stratification and distribution of opportunities in society (Dietrich 2012). Analysing the impact of socio-demographics on worker flows is important because there are significant differences in employment transitions across different segments of society. Elsby et al. (2011) argue that unemployment flows for various socio-demographic groups are an important determinant of disparate trends in unemployment across these groups.

The importance of urbanisation can be highlighted through the fact that there are high paying employment opportunities in cities compared to small areas which is one of the main pull factors for individuals to move there. Many industries are located in cities and offer opportunities of high urban wages. There are also more educational institutions providing courses and training in a wide range of subjects and skills. People are attracted to an urban lifestyle and the 'bright lights' of city life. All of these factors result in both temporary and permanent movement of workers to urban areas. The degree of urbanisation has positive as well as negative economic impact. The pros include economic development, and education. However, urbanisation places stresses on existing social services and infrastructure thus impacting unemployment rate.

Economic theory also highlights the importance of immigration when evaluating the changing unemployment dynamics. There are two theoretical frameworks (*Competition and Discrimination*; *Human capitalization and local labour markets*) on the impact of immigration on unemployment levels. Theoretical models on competition and discrimination (Harrison 1984, Tigges and Tootle 1993, Spalter-Roth and Lowenth 2005 among others) argue that immigrants' employment prospects depend on degree of competition with native workers and discrimination against immigrants in the host country. Due to immigrant influx, when labour supply in the host country increases immigrants are likely to experience relatively high unemployment due to competition and discrimination from the workers already established in the local labor markets (Harrison 1984). The theoretical models of Chiswick (1978) and Borjas (1990, 1999) emphasise the importance of human capital distribution and local labour market conditions in the host country. There is a possibility that the unemployment levels in host country can change with the influence of immigrants on the human capital distribution of workforce in the host country. If the concentration of migrants in the local labour markets tend to increase the local human capital, then unemployment rates are likely to decline (Oh et al. 2011).

The next section provides the data description and summary statistics. Section 3.3 provides the derivation of worker flows along with the results. Section 3.4 evaluates the importance of socio-demographics, immigration status and urbanisation level in assessing worker flows. Section 3.5 provides the discussion and section 3.6 concludes.

3.2 Data Description and Summary Statistics

The European Union Labour Force Survey (EU-LFS) is a large household survey and is conducted quarterly in twenty eight member states of the European Union, two candidate countries and three countries of the European Free Trade Association (EFTA) since 1983. It provides information on both quarterly and annual labour market statistics of individuals aged 15 and over, demographic information of respondents (gender, nationality, marital status, number of children among others), job characteristics (full time/part time work, duration of job, hours worked, etc.), wage decile groups, search for employment, education and training, labour market status of individuals a year before. It provides information on several dimensions of economic activity of individuals and of households such as industry and occupation of work. The EU-LFS sample size is 1.3 million (EU-28 1.2 million) people aged 15-74 years every quarter, covering 33 participating countries. This makes the EU-LFS the largest household survey in Europe.

The sample time period for this study is 2006-2016. The definition of labour market status and the definition of all demographic variables are identical across all countries in EU-LFS data. European Commission (Eurostat) relies heavily on high degree of harmonisation of concepts, definitions, classifications and methodologies. Its regulations define a common coding scheme, ensuring that all member states use same variable definitions, classifications and that the measurement of the labour market statistics are harmonised across all countries.

The main variables used to calculate the worker flows are an individual's current labour market status and their labour market status a year ago. The sample of countries included in this study for analysis are: Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Lithuania, Luxembourg, Latvia, Norway, Poland, Portugal, Romania, Sweden, Spain, Slovakia, Slovenia and United Kingdom. For the remaining European countries in EU-LFS data, there is an issue of missing information. For example, Bulgaria, Ireland, Iceland, Switzerland and Netherlands are deleted because data on labour market status of individual a year before is missing for some years. Malta is removed from the sample because there is no information available prior to 2008.

Individuals are classified in three categories as employed, unemployed or economically inactive. The definition of three categories of labour market status in EU-LFS are fully compatible with the International Labour Organisation's (ILO) guidelines and are defined as follows: *Employed* individuals comprise persons aged 15 years and more who, during the reference week, worked for at least one hour for pay, profit or family gain and those who were not at work during the reference week but had a job or business from which they were temporarily absent. *Unemployed* comprise persons aged 15 years and more who are not employed but are available for paid employment or self-employment before the end of the two weeks following the reference week and are actively seeking work by taking specific steps in the four-week period ending with the reference week to seek paid employment or self-employment. It also includes those who found a job to start later within a period of at most three months from the end of the reference week. *Inactive* persons are those who are neither employed nor unemployed. They can include children, students, pensioners and anybody provided that they are not working at all and not available or looking for work either; some of these may be of working-age.[2]

ILO measures the unemployment rate by expressing the number of unemployed persons as a percentage of the total number of persons in the labour force (ILO Geneva, 2015). The labour force (formerly known as the economically active population) is the sum of the number of persons employed and the number of persons unemployed. Unemployment rate reflects the inability of a country to generate jobs for those who are willing and actively seeking work. Yearly unemployment rate in this chapter is calculated using the ILO's measure in the following way: Using the ILO definition of unemployment, the number of unemployed for each country in each year are totalled using the weighting factor. Once these unemployment numbers for each country are derived, they are added together. Similarly, the total labour force for each country in each year are calculated and are added together. Using the sum of unemployment numbers and of labour force of each country, the combined unemployment rate for European countries specified earlier is calculated using the ILO measure. The dataset contains a variable named ILOSTAT which is the labour market status of an individual. I use it to calculate the combined European unemployment rate for 2006-2016. Unemployment rates for some European countries are also calculated. Results are shown in Figure 3.1. [3]

In Europe, GDP went up to about 3% in 2006-2007 from 1.8% in 2005.[4] Unemployment rate in Europe during this time was about 8% as shown in Figure 3.1. During 2008-2013, Europe went through two recessions and unemployment rate in Europe fluctuated during this time period. The global economic and financial crisis of 2007 which began in the US and rapidly spread to Europe from the second quarter of 2008 to 2009 lasted for about 15 months. The decrease in output led to deterioration of European labour market. Unemployment increased from 7.1% in 2008 to 9%

[2]Source for the official definition of labour market statuses: Eurostat Statistics explained.
[3]Calculations are based on Eurostat EU-LFS data.
[4]GDP figures from European Commission report 2007.

in 2009. Unemployment then continued to increase while output stayed unchanged till 2013. It was after 2013 that the European unemployment started to decrease gradually. However European countries such as Greece, Croatia, Italy and Spain had increasing unemployment rates after 2013.

During 2006-2016, changes in unemployment were not uniform across these countries. Figure 3.1 shows the unemployment rates for some of the European countries in the sample over the years. Some of these countries were adversely affected. For example, Figure 3.1 shows that in 2009, unemployment rate was around 18% in Spain, 10% in Greece, 9% in Italy and 17% in Latvia. There were severe fluctuations in unemployment in these countries during and after 2009-2010. In Greece, unemployment increased to about 20% during 2012-2016. In some countries, unemployment barely increased and from 2008 up till 2016, it has been more or less at the same level. For example, unemployment in Austria has been around 4-6% over these years. Some countries were hit by the 2008-2009 recession but quickly recovered in terms of their unemployment levels after the recession was over (e.g., United Kingdom, France). It is therefore important to evaluate the role played by each of these countries in explaining the unemployment.

Table 3.1 reports the summary statistics for worker's characteristics. There are slightly more females in the sample than males. There are more middle aged workers in the sample as compared to young and old aged workers. The percentage of highly educated workers is low on average in Europe with only about 18% of the sample with high education levels relative to other two levels of education. Most of the workers are less educated (38%) or have medium levels of education (43%). In Europe, 33% of the workers live in cities, 29% live in suburbs and 37% live in rural areas. The degree of urbanisation of workers vary from country to country. The summary statistics on immigrant status shows that most of the workers in the sample are native born (92%), approximately 1% and 2% of the workers are new immigrants and intermediate immigrants, respectively. 5% of the workers are earlier immigrants who moved to the host country more than 10 years ago. The average unemployment rate is 9% while inactivity rate is 45%. [5]

3.3 Worker Flows

EU-LFS data contains information on the labour market status of individuals a year before the survey date and their current labour market status. Individuals are classified in three categories as employed, unemployed or economically inactive. In order to construct labour market transitions, I use the information available in the variable ILOSTAT (labour market status in the current year according to the ILO definition), as well as the variable WSTAT1Y (self-declared labour market status in the year prior to the survey).

No information is available on labour market mobility within a particular year. The measure of worker transition rates in this study is an annual measure. Annual workers transition rates are constructed from the declared employment status of an individual in previous year ($t-1$) and in the survey year (t). The annual transition rates do not take into account short-term changes in labour market status within a year. This means that the seasonality of flows with a higher temporal frequency can be avoided (Merikull, 2011). The two worker transition rates are defined and constructed as share of workers who move from employment to unemployment (EU) and from unemployment to employment (UE) in a year. The other transition rates such as flows to and from inactivity contribute much less to unemployment changes and are relatively constant.[6] Such transition rates are omitted from the analysis.

Worker mobility can be specified by several measures with transition rates among them. A worker may leave unemployment and enter employment (UE or job finding) or leave employment and enter unemployment (EU or job separation). The worker transition rates are then defined as change in labour market state between year t-1 and t. The methodology I use is similar to Elsby et al. (2011) and Fujita et al. (2016) to calculate the transition rates. These studies argue that worker

[5]Unemployment numbers for Europe and some countries are also reported in Table 3.2
[6]Inactivity Rates are shown in Figure 3.2

flows between labour market states and associated transition rates are closely related concepts. For example, EU flow is movement of workers from employment to unemployment and the associated transition probability is given by the number of workers making that transition over a given period, divided by the stock of individuals in the original state. Hence Elsby et al. (2011) argue that this is one of the main approaches of measuring worker flows. Using their methodology, the EU transition probability s is as follows:

$$s_t = \frac{(EU)_t}{E_{t-1}} \tag{3.1}$$

EU_t is the number of workers who transitioned from employment in period t-1 to unemployment in period t and E_{t-1} is the stock of employed workers one year ago. Equation (3.1) shows the share of employed individuals at time t-1 that transitioned into unemployment at time period t. The UE transition probability f is as follows:

$$f_t = \frac{(UE)_t}{U_{t-1}} \tag{3.2}$$

UE_t is the number of worker who transitioned from unemployment in period t-1 to employment in period t and U_{t-1} is the stock of unemployed workers one year ago. Equation (3.2) shows the share of unemployed individuals at time t-1 that transitioned into employment at time period t. Job separation and job finding rates are measured using the transitions among labour market status from one year to the next.

Table 3.3 reports the EU and UE worker transition rates for Europe. Before 2008, EU transition rate was small and less than 2%. During 2008-2009 which also happened to be the time of great recession, s_t increased to about 3% before dropping back to less that 2.7% in 2011. EU transition rate in Europe increased slightly in mid 2011 before starting to decrease. Europe's UE transition rate is decreasing over the years. Before 2008, f_t increased and went up to about 32% before dropping to about 26% in 2009. It kept on decreasing on average until 2013 to about 23%. European unemployment rate during the course of this period was on rise from mid 2008 until 2013.[7]

[7]Unemployment rate, job separation rate and job finding rate for Europe are also shown in Figure 3.3.

The European unemployment rate increased during 2006-2016 and the results above show that at the same time, EU transition rate increased and UE transition rate decreased on average. It is therefore important to check if the increased unemployment can be traced to increased EU transitions as well as reduced UE transitions. In order to formally assess the relative roles of these transitions in shaping unemployment variation, I calculate the fraction of the overall variance in the unemployment rate across time that is attributed to each of the transitions using the *two state approach* used in the recent literature (see, among others, Elsby et al., 2009; Elsby et al., 2011; Fujita and Ramey, 2009; Shimer, 2007). The conventional variance decomposition of unemployment assumes that the actual unemployment rate moves closely to the steady state unemployment rate. Thus, the actual unemployment rate u_t is approximated by:

$$u_t \approx u_t^* \equiv \frac{s_t}{s_t + f_t} \tag{3.3}$$

where $*$ indicates the steady state value. The idea behind this assumption is that transitions s_t and f_t do move over time and so does the steady state unemployment levels. Therefore, the actual unemployment rate that we observe in the data u_t is in fact continually converging toward a moving target u_t^*. The steady-state unemployment rate provides a link from variation in the transitions s_t and f_t to variation in the unemployment rate. Using simple log differentiation suggested by Elsby et al. (2009) implies that a Taylor series approximation to changes in the steady-state unemployment rate can be broken down as follows:

$$\Delta ln(u_t^*) \approx \alpha[\Delta ln s_t - \Delta ln f_t], \tag{3.4}$$

where $\alpha = (1 - u_{t-1}^*)$. Equation (3.4) traces out the cumulative log rise in unemployment inflow, and the cumulative log decline in the unemployment outflow while analysing the changing unemployment rate over time. Figure 3.4 displays the logarithmic variation in the transition rates s_t and f_t. The results show that both job separations and job findings play significant role in causing the European unemployment to change over time. While evaluating the quantitative contribution of each transition, Figure 3.4 shows that in 2009, EU flows had a bigger part to play in driving up the European unemployment rate. In order to also formally assess the role played by each of these two in changing unemployment rate, Fujita and Ramey (2009) demonstrate that Equation 3.4 can be used to derive the decomposition of variance of unemployment rate. The relative contribution of each transition rate is summarised by:

$$\beta_s = \frac{cov(\alpha \Delta lns_t, \Delta lnu_t^*)}{var(\Delta lnu_t^*)} \tag{3.5}$$

and

$$\beta_f = \frac{cov(-\alpha \Delta lnf_t, \Delta lnu_t^*)}{var(\Delta lnu_t^*)} \tag{3.6}$$

This decomposition of variance shows summary measures of the contributions of the two flows to changes in the unemployment rate, namely the ratio of their variance contribution to the total variance of the log change in unemployment rate. Equations (3.5) and (3.6) hold approximately for discrete changes in unemployment rate, so β_s and β_f will approximately sum to unity. Table 3.4 summarises the results of this decomposition of variance. The results are in line with what is displayed in Figure 3.4. Job separations account for 73.5% of the changes in unemployment rate and job findings account for 24.3% of the changes. The results for Europe are similar to those found in the US. Elsby et al. (2012) decomposed the US unemployment rate during a recession into unemployment inflow and outflow rates. They state that unemployment inflows account for a substantial fraction of unemployment variation early on in the downturn, and then subside in the latter stages of the recession while the contribution of unemployment outflow rate becomes more dominant as each recession progresses.

EU and UE transition rates are calculated separately for some European countries in Tables 3.5 and 3.6 to make it possible to identify three different pairs of countries that affect Europe on the basis of the fluidity of their labour markets. United Kingdom and Austria show similar patterns in their unemployment and worker flows. The labour markets seem to be fluid in both the countries with smaller s_t and higher f_t. Mobility patterns between Spain, Greece, Latvia and Portugal are similar to one another with increasing s_t and decreasing f_t on average during 2008-2009. EU transition rate s_t in these countries was increasing by large amounts during this time. UE transition rate f_t was the lowest for Greece and Croatia. For Greece, f_t started to decrease from 2008 and stayed low throughout the remaining time period after 2008. In Croatia, f_t decreased until 2010 and then started to gradually recover. France belongs to a third group of countries with comparatively less mobile labour markets. One thing common in all the countries was that for none of them, the UE transition rates went back to their 2008 pre-recession levels.

3.4 Worker Flows by Socio-Demographic Groups

The evaluation of European unemployment and worker flows cannot be fully explained unless the socio-demographic composition of the labour force is accounted for. Figure 3.5 shows the unemployment rate in Europe across different worker groups focusing on the following dimensions of heterogeneity: gender, age and education level, immigration status and urbanisation level. The unemployment rate for young workers is the highest among all the groups with unemployment rate increasing from 2008 till 2013 where it was higher than 20% as compared to middle aged workers and old workers. Table 3.7 shows that the employment to unemployment transitions for young workers were the highest especially during 2008-2009. The job separation rate for young workers jumped from 4.29% in 2008 to 6.51% in 2009 which means that young workers were laid off from their jobs more than other groups. Job separation rate gradually decreased afterwards but it was consistently high for young workers compared to other groups and stayed between 5-6%. Table 3.8 shows the changes in job finding rate for this group were as dramatic as their job separation rate. Table 3.11 shows the contribution of job separation and job finding rates to the unemployment rates of the socio-demographic groups. The results show that job separation accounted for 64% of the changes in youth unemployment while job findings accounted for 32%.

In 2008-2009, workers with low education levels faced high unemployment that showed no sign of slowing down as the unemployment rate kept on increasing till 2013 and went up to about 17%.

They had higher employment outflow on average as it stayed around 4% after the crisis time period of 2008-2009. Table 3.11 shows that employment losses for low education group and medium education group accounted for 70% of the changes in their unemployment levels. For high education groups, job separation accounted for 56% and job finding for 33% of the unemployment changes, respectively. The contribution of job finding to changing unemployment levels for this group is the highest.

The two gender groups, male and females had almost similar unemployment rates over the years. Female workers had slightly higher levels of unemployment as compared to male workers. Unemployment for male workers increased from about 5-6% in 2006-2008 to 9% in 2009. Female workers had unemployment rates of approximately 8% during 2006-2008 and increased to approximately 9.5% during 2009-2010. Table 3.7 suggests the job separation rate for male workers increased by significant amount in 2008-2009. For female workers, it remained unchanged on average. Similarly, both the gender groups experienced the decrease in their respective job finding rates over the years. Table 3.8 shows that the job finding rate for male workers were higher than that of females. However, job finding rate for male workers decreased by a bigger amount as compared to females over the years. These figures tend to suggest that male workers in the European labour market suffered more from the recession as compared to female workers. Table 3.11 shows that job separation rate accounted for 70% of the unemployment changes for male workers and 66% for female workers. Worker flows derived for Europe above suggest that young workers and workers with low levels of education were the most adversely affected labour force groups. The increase in their unemployment levels was a result of increase in their job separation rate and decrease in job finding rate. Unemployment and job loss for male workers were bigger as compared to females.

The level of unemployment for workers in cities (densely populated areas) is the highest among all the group of degree of urbanisation with increasing unemployment from 2009 to 2013 where it was the highest at 11.2%. The EU transitions for workers in cities was higher than 3% during this period and UE transitions decreased from 31% in 2008 to 22% in 2013. Workers from suburbs and towns faced a similar pattern with a decrease in their UE transitions and an increase in their EU transitions between 2008-2013 while for workers in rural areas, the changes in their employment transitions were not as dramatic as the former two groups with their unemployment rate and job separation and finding rates going back to their initial levels once the 2008-2009 recession was over. The contribution of job separation and job finding rates to the changing unemployment rates for the degree or urbanisation groups show that it was job separation rates that mostly accounted for the changing unemployment levels.

The unemployment rates, job separations and job finding rates for worker groups of different immigration status show that native born workers suffered the least in terms of changing unemployment levels over the years. Their unemployment rate remained below 10% throughout the time period of 2006-2016. Their job separation rate increased to about 3.1% in 2009 but started to decreased immediately in the years to follow. Their job finding rate followed an inconsistent pattern over the years i.e. it decreased until 2009 and increased to about 27% in the next two years until 2011 only to decrease to 23% in 2013. This suggest that native workers faced a difficulty in finding work after the 2008-2009 recession was over. Among all three immigrants groups, earlier migrants had the lowest unemployment rates and job separation rates over the years. Their job finding rates were also higher than the recent migrants and intermediate migrants. The latter two groups saw high unemployment rates reaching to about 20% in 2013. These figures indicate that because earlier migrants were in the host country for longer time periods so they know their way through the labour markets in the country as compared to recent migrants who have limited knowledge of employment opportunities and have specific skills set.

It can be seen that there were substantial differences in the unemployment rates across demographic groups, urbanisation group and immigration status in various time periods. In particular, young workers, less educated groups, workers from cities (densely populated areas), recent and intermediate immigrants were the most affected groups in Europe over the years with significant variations in the unemployment and employment transitions for both males and females. There is also a stark contrast across countries and over the years in this regard which leads to further exploring the role of how these socio-demographics affects the worker flows. In order to look into this heterogeneity across some socio-demographic groups, immigration status and urbanisation levels in different regions and over the years, I evaluate the variation in labour market transitions across these groups. I use logit regression to determine the change in probability of labour market transition given that the individual belongs to one of the groups. Along with the all these characteristics, the estimations will also include region dummies to examine the impact on the labour market transitions in Europe.

3.4.1 Estimation Methodology

In order to determine the relative risk of a particular transition, logit model is used. The dependent variable $y_i \in [0, 1]$ represents whether a worker's employment status changes. Given the regressors x_i, we want to describe the probability of a worker transitioning between employment and unemployment (in two separate estimations) given by $Pr(y_i = 1|x_i)$. The model to be estimated is:

$$y_i^* = x_i'\beta + \eta_i \tag{3.7}$$

where η_i has a logistic distribution and:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

For then the probability of worker transitioning is given as:

$$\begin{aligned} Pr(y_i = 1|x_i) &= Pr(y_i^* > 0|x_i) \\ &= Pr(x_i'\beta + \eta_i|x_i) \\ &= Pr(\eta_i > -x_i'\beta|x_i) \end{aligned}$$

$$= 1 - F(-x_i'\beta)$$
$$= F(x_i'\beta)$$

where F(u) is a known CDF, typically assumed to be symmetric about zero so that $F(u) = 1 - F(-u)$. $F(x_i'\beta)$ has the following logistic form:

$$F(x_i'\beta) = (1 + e^{x_i'\beta})^{-1} \tag{3.9}$$

x_i is a vector of exogenous variables of age and dummy variables that identify whether the individual belongs to any of the demographic groups that i.e. gender groups, education attainment levels, immigrant group, urbanisation level groups, regions and year dummies D_t (t= 2006...2016). β are the regression coefficients associated with the reference groups and η_i is error term of observation i. The dependent variable y_i denotes one of two different outcomes in two separate regressions. In the first specification, flow from employment to unemployment y_i^{EU} is a binary variable that takes the value 1 if an employed worker becomes unemployed and 0 otherwise. In the second specification, flow from unemployment to employment y_i^{UE} is a binary variable that takes the value 1 if an unemployed worker becomes employed and 0 otherwise. The marginal effects recovered from the corresponding coefficients (β) are interpreted as a relative risk of a particular transition. They represent the probability of job loss and job finding for each group. What follows is a presentation and discussion of the evolution of labour market transitions for each group of workers.

3.4.2 Results

Table 3.12 reports the marginal effects of the socio-demographic characteristics on EU and UE transitions. It highlights the the probability of losing or finding a job for each socio-demographic group over 2006-2016. Year dummy variables are also added in the estimations. When it comes to EU and UE transitions, Table 3.12 shows that the less educated workers contribute the most to these worker flows. The probability of job loss for less educated workers is 2% higher than that of highly educated workers and their probability of finding a job is 14% lower than highly educated workers. The probability of job loss for a worker with medium level of educational attainment is also higher and the probability of job finding is lower than highly educated workers who are used as a reference category. Job finding probability for female workers is 2.8% lower than that of male workers who are used as a reference category. The marginal effects associated with age show that the older the person is, the lower his chance is of losing employment and job finding. This suggests that young workers are more at risk of losing jobs while old workers have a small chance of moving into employment from unemployment. Table 3.12 also reports the marginal effects of different regions on EU and UE transitions. The probability of finding employment for workers in Southern Europe is 8.3% lower than workers from Western Europe. This indicates that over this time period, flows from unemployment to employment were small for countries such as Spain, Greece and Portugal among others during times when unemployment in these countries were large. For Northern region, the marginal effects associated with UE transitions are positive and about 10%.

The marginal effects associated with degree of urbanisation on EU transitions in Table 3.12 show that the probabilities of job loss for workers in suburbs and rural areas are 0.38% and 0.4% lower than that of workers in densely populated areas (cities). The probability of finding job for these groups is 2.2% and 3.1% higher than workers in densely populated areas. The marginal effect of migration indicator on the worker transitions show that probability of job loss for recent immigrants and intermediate immigrants is 1.6% higher than that of native workers while the probability of job loss of earlier immigrants is only 1.12% higher than the native workers. The probability of job loss for this group is lower than that of recent and intermediate immigrants. This is because after the native born workers, earlier immigrants are less likely to suffer in terms of employment losses. The probability of job finding for these groups is such that compared to the native workers, recent immigrants and intermediate immigrants are 4% and 3.2% more likely to find work. This is due to the fact that these workers are willing to take any type of jobs: part time work, low wage job or temporary work. For earlier immigrants, probability of finding job is almost the same as that of natives as the marginal effects associated with earlier immigrants are 0.5% lower than the former group. This is because just like natives, these workers have been in the host country's labour market for a while so they look for either high paying full time jobs or jobs that are more suited to their skills.

While Table 3.12 gives an idea on the job finding and job loss probabilities for each worker group in different time periods of longer durations, it tends to absorb the effects of different crisis countries face that take place over shorter course of time (for example within a year). It does not provide an insight into how each worker group's labour market transitions are impacted over smaller time durations when economies are going through different circumstances (e.g. 2009 recession and its aftermath). Therefore, I run the estimations with interacting socio-demographic characteristics, immigration status and urbanisation levels with all the year dummies. Tables 3.13 and and 3.14 only report the marginal effects for three specific year 2007, 2009 and 2012.

Table 3.13 reports the marginal effects on EU transitions for each group in 2007, 2009 and 2012. Keeping male workers as reference categories, the marginal effects associated with female workers for EU transitions are small and positive during 2007. In 2009, the probability of job loss for female workers was 0.4% lower than that of male workers. Another relevant personal characteristic affecting the risk of losing a job is an individual's educational attainment. Keeping workers with high levels of educational attainments as reference category, the results in Table 3.13 shows that the job loss probability of less educated workers increases in all the years. The job loss probability of less educated workers increases by 3% in 2009 indicating that workers with lower levels of educational attainment suffered in terms of employment loss. Workers with medium levels of education also suffered in terms employment loss during and after 2009 as the marginal effects associated with this group of workers were 1.5% and 1.1% respectively. These results highlight a particularly strong role played by higher education in protecting workers from downward mobility over the years. Table 3.13 also reports the marginal effects of age on the probability of EU transitions. The marginal effects are negative and small in all three years. During 2007, one year increase in age is associated with the marginal effects of -0.7% for employment loss while in 2009 and 2012, the marginal effects are -0.12%. These results again indicate that the older the worker is, the smaller is the chance of him losing his job. The marginal effects of different European regions show that during 2009, workers in Northern and Eastern Europe had a higher risk of losing employment but in 2012, workers from Southern Europe suffered while adjusting to the aftermath of the recession as their associated marginal effects on EU transition are positive and higher than other regions of Europe.

The marginal effects associated with degree of urbanisation on EU transitions in Table 3.13 show that the probabilities of job loss for workers in suburbs and rural areas is lower than that of city workers in all three years; 2007, 2009 and 2012. The probability of job loss for recent, intermediate and earlier immigrants is higher than that of natives in all three years. In 2008, the the job loss probability is highest for all three groups among all the three years suggesting that immigrants suffered during the recession time period of 2008-2009. In 2019, the probability of job loss for intermediate and earlier immigrants started to decrease while for recent immigrants, the job loss probability kept increasing. This indicates that new immigrants were suffering from the aftermath of the 2008-2009 recession in terms of staying employed at their jobs.

Table 3.14 reports the marginal effects of the same groups in 2007, 2009 and 2012 on UE transitions. The results show that female workers have a low probability of finding job in all three years. This suggests that during and after the recession, male workers suffered less in terms of job finding as compared to female workers. Compared to highly educated workers, workers with lower and medium levels of education had lower probability of finding employment in all three years. This suggest that highly educated workers did not have a problem finding employment as compared to other groups. The marginal effects of age on UE transitions are small and negative for all the years but they are significant, indicating that regardless of the economic situation, old age workers have a lower chance of finding employment as compared to young workers. The marginal effects of European regions show that workers in Southern Europe found it problematic to find employment and this worsened in 2009 and afterwards.

The marginal effects associated with degree of urbanisation on UE transitions in Table 3.14 show that the job finding probabilities for workers in suburbs and rural areas is higher than that of city workers in all three years; 2007, 2009 and 2012. For workers from suburbs, the marginal effects start to decrease in 2009 and 2012. This shows that workers from this area too suffered from the effects of 2008-2009 crisis due to lack of jobs in this area. Compared to the native workers, recent and intermediate immigrants had high probability of finding work during all three years as they were willing to take up any job in order to remain in the host country. Earlier immigrants had a lower probability of finding work compared to natives but the gap between their job finding probability and natives' job finding probability started closing up in the years to follow from 2009. This indicates that for immigrants, as their years in the host country increase, they face the same labour market obstacles as natives and they adopt the same job search behaviour as the latter group.

The results from these estimation show a straightforward pattern in the labour market transitions for some groups over the years while for others, there are no common patterns detected. For example, higher education is a shield against employment loss in Europe during and after the recession. On the other hand, less educated workers tend to suffer the most in terms of employment losses. Among the two gender groups, no common patterns in employment losses and job finding can be detected for females. For age, the older a worker is, the lower the impact they have on employment loss and job finding prospects over the years. Patterns of employment mobility across different regions in Europe are dissimilar. Workers from Southern European countries tend to suffer more in terms of high EU and low UE transitions. Employment transition patterns for immigrant groups and urbanisation groups are dissimilar over the years.

To provide more insight into how the labour market transitions between employment and unemployment for each group shaped up over the years, it is important to evaluate the effects of covariates identifying the different groups that arise as a result of interacting gender, age, educational attainment, region in each year on the two types of labour market transitions. I run the estimations using most affected socio-demographic groups based on the estimation results in 3.13 and 3.14 while interacting them with the region dummies to examine how worker groups in different regions in Europe were affected in terms of labour market transitions. I also interact immigrant groups to urbanisation level groups to understand location choices of immigrants. I interact group dummy variables of gender, educational attainment, age, region and year dummies. I also interact dummy variables for degrees of urbanisation, immigration status and year dummies. The marginal effects are estimated for less educated and medium educated workers (male and female) in Southern and Northern Europe at average age of 21 and 39 for young (16-29) and middle aged (30-49) workers and for all three types of immigrants in intermediate populated area and rural area. The marginal effects for years 2007, 2009 and 2012 are reported in Tables 3.15, 3.16, 3.17 and 3.18.

Table 3.15 reports the marginal effects for EU transitions. The estimates show that less educated male workers in Southern European countries were adversely affected in terms of job losses. The job loss probability of less educated male workers in Southern region was high in all the years. Being a worker from the same group in Northern Europe also had a high probability of employment losses in 2009 only but they started to recover gradually afterwards. Marginal effects of female workers on EU transitions were also positive but they are smaller in 2012 compared to 2009. The results also show that young workers suffered more as compared to middle aged workers regardless of the gender and educational attainment level. The marginal effects in Table 3.16 show that the marginal effects of all three immigrant groups in suburbs and rural areas on EU transitions are negative in all three years as compared to the workers in cities. Recent immigrants in suburbs and rural areas have a higher probability of job loss during in 2009 suggesting that they suffered from the 2009 recession. Table 3.17 reports the marginal effects for the UE transitions. The estimated marginal effects are negative across all the specified groups and indicate that workers in Southern and Northern European region had lower job finding prospects. Table 3.18 shows the marginal effects of all three immigrant groups in suburbs and rural areas on UE transitions. The job finding probability for Earlier immigrants in rural area in 2009 is the lowest among all the groups. This shows that the type of jobs in which earlier immigrants were employed previously were lacking in rural areas which caused troubled earlier immigrants who were unemployed in finding similar jobs. The job finding probability for all the immigrant groups in these areas started to decrease in the aftermath of 2008-2009 recession.

Finally, I conduct robustness checks to test for potential endogeneity between immigration and worker flows. The potential source of endogeneity might be related to the short run impact of recent immigrant arrivals into the host country. For robustness checks, marginal effects are estimated while excluding the recent immigrant category (i.e. those who moved to the host country between 0-5 years) and are reported in Tables 3.19, 3.20 and 3.21. The marginal effects do not suffer from endogeneity. Overall the results from these estimations indicate that among the socio-demographic groups, male workers, less educated workers and young workers were among the adversely affected group. From the immigrants groups, the recent and intermediate migrants that are adversely effected. The marginal effects associated with the urbanisation groups show that workers in suburbs and rural areas have lower job separation probability and higher job finding probability than workers in cities. The increase in the job losses of these groups even after the 2009 recession was over indicate that it was difficult for these workers to be able to keep their jobs relative to 2006. The results also indicate that while all the regions suffered with increased EU transitions and decreased UE transitions in 2009, Southern European countries were still struggling in years to follow with high EU transitions and low UE transitions.

3.5 Discussion

The calculation of worker flows between employment and unemployment provide a picture of how labour market flows have heterogenous patterns over time. The comparisons of patterns of mobility between employment and unemployment in Europe by means of transitions sheds light on the effect that socio-demographic characteristics (gender, educational attainment and age), migration level and degree of urbanisation in different times and regions can have on the probability of losing and finding employment. In particular, the results show that the economic crisis in 2009 affected the relative importance of these characteristics in explaining mobility patterns across dissimilar socio-economic models. Moreover, the decomposition of employment variance into job separation and job finding shows that employment outflow contributes more to the increasing unemployment in Europe as compared to job finding.

The variation in the transition between employment and unemployment over time and across different worker groups in Europe as a single labour market are significant and play a crucial role in explaining the changing patterns in the unemployment dynamics. The results of the previous section in particular shed a light on the relative importance of these groups in explaining the mobility patterns in Europe. Among the two gender groups, the unemployment rate and job separation rate for women were initially higher than that of men but over the years, these indicators increased for the latter group. The decomposition of unemployment variance shows that high rate of unemployment inflow for men tend to account for much of the higher unemployment rate faced by them. The unemployment, job separation rate and job finding rate for females remained the same on average. Elsby et al. (2011) state that female unemployment dynamics accords well with the observation that women are more likely to move in and out of the labour force with the demands of childcare responsibilities, an activity more than proportionately allocated to women. This makes it important to understand the participation decisions that women face. There is a broad range of polices that can foster gender equality in labour markets. Working policies are needed to further accompany the reconciliation of working and family life. For example, paid parental leave, access to good quality and affordable childcare, workplace family measures and promoting the equal sharing of unpaid work responsibilities helps to encourage female workers to go start working after they become mothers. Policies such as free education and training should also continue to focus on low skilled women with children, to ensure increased female labour force participation.

The results of the previous sections show that there are substantial differences in unemployment rates, job separation and job finding rates across workers of different age groups. The unemployment rate faced by young workers is substantially higher than that of older age groups. Moreover, job separation rate for young workers is higher than the other two groups. The decomposition of the youth unemployment show that reduced level of job finding contributes more to their higher unemployment level as compared to the other two age groups. One reason for why young workers and less educated workers have higher incidence of job losses in the estimations is that they are assumed to be low skilled by employers. When the crisis hit and as a result the firms decide to downsize their number of employees to cut their costs, these workers are generally among the first group of people to lose employment. They have the highest probability of job loss over the years as compared to other groups. Bertola (2006) highlights that expenditure on active labour market policies (ALMPs) tends to increase the job finding especially among the young less educated workers as this group generally seeks help from public offices in finding employment. The strictness of Employment Protection Legislation (EPL) tends to decrease the transitions from employment to unemployment for young workers. Hence provision of Public Employment Services (PES), such as job search assistance and Vocational Education and Training (VET), including apprenticeships can be a key to lowering youth unemployment and facilitating youth job finding rates. Policy-makers should enhance VET programs in order to provide an attractive alternative to general upper-secondary and tertiary education and in order to better meet the skill requirements of the labour market. This could play an increasingly crucial role in the policy response to youth unemployment, in particular in the longer term.

The unemployment, job separation and job finding rates vary considerably by educational attainment level. Less educated workers have higher unemployment rate and job separation rate among all three education groups. Their job finding rate was also substantially lower than the other two education groups. The results show that less educated workers bear the brunt of unemployment. Elsby et al. (2011) suggest that less educated workers not only face significantly higher rates of entry into unemployment, they also experience substantially longer jobless spells relative to their more educated counterparts. So increased incidence and long unemployment duration leads to higher unemployment among less educated workers. The contribution of job finding and job separation rates in the decomposition of employment variance is the same for low and medium educational level groups. It is no secret that education significantly increases the re-employment rates of the unemployed (Riddell and Song, 2011). Therefore in order to reduce the employment to unemployment transitions for less educate workers, policies enhancing their skill sets should be implemented. For example, training programmes for low skilled unemployed people, including those that offer subsidies for trainees who attend courses, VET or apprenticeships, and for companies that take on people who combine work with relevant training, will act as a shield against unemployment for these type of workers.

The results from the previous section on the urbanisation levels of workers show that workers who live the cities tend to face higher job separation rates and lower job finding rates as compared workers who live in suburbs and rural areas. The main reason for this outcome is that the supply of labour in cities is higher than the demand of labour. The idea of living in a big city in hopes of gaining a better standard of living, better employment opportunities, higher wages, more educational institutions providing courses and training in a wide range of subjects and skills, urban lifestyle and bright lights of city life act as pull factors to attract people to cities and as push factors that drive people away from rural areas. The increased supply of workers in cities causes the unemployment in these areas to increase. Moreover, in order to stay in the cities, workers are willing take jobs that are below their skills and pay low wages in hopes to finding better jobs by staying the city. So in times for crisis (for example during recessions), workers in cities face higher job separations and lower job finding rates. Hence benefits of urban life do not apply to all. Rapid population increases and unplanned growth create an urban sprawl with negative economic and social consequences. In order to cope with the negative labour market consequences, policy makers should focus on rural development so that people are attracted to living in rural areas thus reducing the overload of workers in cities. The authorities should work on employment-intensive investment policies, improve the education and training systems and should encourages companies (especially big companies) to start their operations in rural areas which will not only create more employment opportunities but will also encourage workers who want to work for big firms to move to rural areas. Other recommendations that the governments can use are improving social activities, housing, roads, sewage and water systems in rural areas to attract people to move there.

The results from the previous sections also show that different types of immigrants also have an impact on worker flow patterns in Europe. Compared to the native workers, immigrants are adversely affected in terms of increased employment loss and reduced job finding. Among the immigrant groups, recent and intermediate migrants tend to suffer more as compared to earlier migrants who moved to the host country more than 10 years ago. This is because, earlier immigrant workers have had more time to settle in the host country and learn about the labour markets there. Therefore they compete with native born workers for high paying jobs as they acquire the necessary education, training and skills to work in high paying permanent jobs. Recent and intermediate immigrants tend to face high job separations because they are unaware of proper job opportunities and training programs. One of the most important determinants of immigrant's unemployment is the economy's rate of growth. When the aggregate level of economic activity and the level of adult employment are high, immigrants can easily find jobs and become employed. So their unemployment rates appears to be one of the most sensitive variables in the labor market, increasing during boom periods and falling substantially during less active periods. This might be caused by insufficient skill sets of immigrants. Another reason is the decline in the demand for labor in general due to low aggregate demand. In this case, immigrants who are assumed to be low skilled are likely to become unemployed first as firms look to downsize their least productive workers. Native or earlier immigrants are unlikely to get laid off from work, instead if need be, they are moved down the chain to take lower level jobs in times of crisis hence cause recent immigrants to become unemployed. So in order to reduce the unemployment of immigrants, policy makers should design policies that create more awareness about public services offices that help immigrants in finding jobs that suit their skill sets. The policies designed should also support immigrant's access to entrepreneurship development programs and provide training programs to improve the skills and human capital of immigrants.

From the previous section, the estimation results on the degree of urbanisation of different types of immigrants show that immigrants are willing to live in small areas of the growing host countries. This is because generally low skilled immigrants are willing to take any work that comes their way regardless of the location of that work. Another reason is that for them, the living standards in the small areas of the host country are better than their home countries. Once they have settled in the host country and are aware of how the labour markets operate, then they move to the cities to look for work. Policies designed to improve the employment opportunities, incomes and infrastructure in rural areas can also help in encouraging immigrants to stay in these areas permanently which will eventually reduce the burden that cities (densely populated areas) face in terms of high unemployment, job separation and low job finding rates.

3.6 Conclusion

This study provides an in depth analysis of the European unemployment rate and labour market flows between 2006-2016 using EU-LFS data. The first part of this chapter derives the worker flows for Europe as a whole and for some of European countries. Transitions from unemployment to employment are found to be less frequent over the years for Europe while flows from employment to unemployment has significantly changed over time and have not adjusted back to their pre-recessionary levels. The unemployment variance is decomposed into unemployment inflow and outflow rate. The results show that unemployment inflow rate contributed about 73.5% to unemployment changes.

The second part of the study evaluates the probability of labour market transitions in Europe for socio-demographic groups, immigration status and urbanisation level using logit model. The results show that both gender groups, less educated workers and young workers suffered from the Great Recession. But the interaction of these groups show that young and less educated male workers have significantly lower chances of finding a job in 2009. The results show that being a worker from Southern European region (such as Spain, Greece and Portugal) face high probability of employment to unemployment transitions and low probability of unemployment to employment transitions. Among the immigrants groups, recent and intermediate immigrants are adversely effected. The marginal effects associated with the urbanisation groups show that workers in suburbs and rural areas have lower job separation probability and higher job finding probability than workers in cities. The interaction of these two groups show that three immigrant groups in suburbs and rural areas have lower job separation rates and higher job finding rates as compared to the workers in cities.

This chapter contributes to the existing literature by evaluating the role played by immigration status and urbanisation level in shaping worker flows in Europe. Calculation and evaluation of annual worker flows for Europe provides a wider comparison. Annual gross data from the EU-LFS is used for the computation of worker flows as compared to the previous studies that use data with a relatively short time horizon such as quarter and months. Since only long term worker flows affect long term unemployment dynamics so annual flows are more suitable for structural analysis. Finally, this study analyses the correlation between workers characteristics and labour market flows instead of computing separate worker flows (as done previously) for each group and for each European country.

The results of this study show that labour market flows between employment and unemployment have contributed significantly to the widespread increase in the European unemployment rate in recent years and especially during the crisis. In addition to this, the contributions of several demographic groups and European regions to the changes in each of the flows are substantial and also differ over time. The divergences across European regions also plays a vital role to understand the subsequent variation in unemployment. This along with the identification of the role of worker flows and their socio-demographic composition, immigration status and degree of urbanisation in driving the rise in the unemployment rate should be a first step to designing better employment policies to reduce unemployment.

3.7 Appendices

3.7.1 Tables

Table 3.1: Summary Statistics

		Countries												
Variables		Europe	AT	BE	HY	FR	DE	GR	IT	LV	PT	SE*	ES	UK
Gender(%)	*Male*	48.08	48.5	49.6	47.7	47.9	48.5	48.7	47.6	44.8	47.4	49.8	48.2	48.1
	Female	51.92	51.5	50.4	52.3	52.1	51.5	51.3	52.4	55.2	52.6	50.2	51.8	51.9
Age Band (%)	$15-29$	26.19	25.5	27.2	26.9	27.4	25.1	24.1	23.0	27.3	25.2	26.3	24.9	26.8
	$30-49$	41.07	44.1	41.8	36.9	40.4	40.9	43.1	43.8	39.7	40.9	41.4	44.3	42.8
	50 *and above*	32.74	30.4	31	36.2	32.2	34.0	32.8	33.2	33.0	33.9	32.3	30.9	30.4
Education Level (%)	*Low*	38.78	27.5	36.8	35.5	39.3	21.4	53.0	57.7	23.2	74.2	23.9	57.6	27.8
	Medium	43.42	55.6	34.8	51.0	38.5	55.7	31.2	32.0	56.7	14.7	46.8	18.6	41.9
	High	17.80	16.9	28.4	13.5	22.2	23.0	15.8	10.3	20.1	11.1	29.4	23.8	30.3
Type of Employment (%)	*Full time*	80.3	74.0	75.4	91.1	81.3	72.4	92.7	83.9	91.6	86.3	73.3	86.1	73.1
	Part time	19.7	26.0	24.6	8.90	18.7	27.6	7.34	16.1	8.40	13.7	26.7	13.9	26.9
Urbanisation Level (%)	*Cities*	33.43	26.92	40.92	39.44	43.89	36.52	39.30	30.72	29.95	32.95	44.47	28.67	62.10
	Town and Suburbs	29	29.23	45.24	40.94	29.40	41.25	20.63	41.77	13.71	32.23	23.64	22.51	22.34
	Rural Areas	37.57	43.85	13.84	19.62	26.71	22.24	40.06	27.51	56.94	34.82	31.64	48.82	15.56
Sector (%)	*Agriculture*	5.64	5.4	1.72	15.3	3.4	1.80	17.2	5.0	11.6	13.5	2.3	5.5	1.70
	Industry	24.8	27.4	22.9	29.1	23.0	28.9	19.3	29.2	25.5	24.9	20.7	24.5	20.7
	Services	69.6	67.2	75.3	55.6	73.6	69.3	63.5	65.8	65.9	61.6	77.0	70.0	77.6
Immigration Status (%)	*Native Born*	92.83	87.23	85.87	90.05	89.55	86.18	94	92.81	87.68	94.45	93.38	86.09	89.25
	Recent Immigrants	1.10	2.25	3.34	0.15	1.04	1.66	0.95	1.20	0.31	0.76	1.38	2.30	3.02
	Intermediate Immigrants	1.15	1.81	2.53	0.47	1.17	1.04	1.42	1.97	0.15	0.90	2.12	2.23	2.03
	Earlier Immigrants	4.91	8.70	8.25	9.33	8.24	11.12	3.63	4.02	11.86	3.89	3.13	9.37	5.70
Unemployment Rate (%)		9.19	6.05	10.8	20.4	12.8	4.98	17.7	17.4	13.4	16.4	7.81	18.3	5.93
Inactivity Rate (%)		45.6	43.3	43.2	50.9	46.8	41.2	51.5	52.3	37.6	45.5	28.5	45.2	40.6

Country Codes: AT-Austria, BE-Belgium, HY-Croatia, FR-France, DE-Germany, GR-Greece, IT-Italy, LV-Latvia, PT-Portugal, SE-Sweden, ES-Spain and UK-United Kingdom.
Sample Period: 2006-2016.
Own Calculations.

Table 3.2: Unemployment Rate (%)

Year	Europe	AT	BE	HR	DE	FR	GR	IT	LV	PT	ES	UK
2006	8.32	5.24	8.25	11.1	10.2	8.63	9.01	6.77	7.03	7.65	8.45	5.35
2007	7.25	4.85	7.46	9.90	8.61	7.73	8.40	6.08	6.05	8.0	8.23	5.22
2008	7.10	4.12	6.98	8.53	7.42	7.23	7.76	6.72	7.74	7.55	11.3	5.65
2009	9.08	5.30	7.70	9.20	7.81	9.12	9.62	7.75	17.5	9.43	17.9	7.58
2010	9.60	4.82	8.29	11.6	6.98	8.81	12.7	8.36	19.5	10.8	19.9	7.84
2011	9.66	4.56	7.14	13.7	5.89	8.96	17.8	8.36	16.2	12.7	21.4	8.08
2012	10.4	4.87	7.54	15.9	5.32	9.47	24.4	10.7	15.0	15.3	24.5	7.94
2013	10.8	5.33	8.43	17.3	5.27	9.91	27.5	12.1	11.9	16.2	26.1	7.57
2014	10.2	5.62	8.52	17.3	4.94	10.3	26.5	12.7	10.8	13.9	24.4	6.15
2015	9.40	5.72	8.48	16.2	4.58	10.4	26.5	11.9	9.87	12.4	22.1	5.35
2016	8.59	6.01	7.83	13.1	4.09	10.1	23.5	11.6	9.64	11.1	19.6	4.85

Table 3.3: European s_t and f_t

Year	Employment to Unemployment flows	Unemployment to Employment flows
2006	2.01	29.9
2007	1.77	32.2
2008	1.91	31.5
2009	3.3	26.9
2010	3.05	27.9
2011	2.77	27.4
2012	2.89	24.8
2013	2.97	23.4
2014	2.45	25.0
2015	2.26	25.4
2016	2.03	26.0

Table 3.4: Role of inflows and outflows in European unemployment.

Contribution to unemployment variance of changes in:	
Unemployment Inflow rate s_t	73.5%
Unemployment Outflow Rate f_t	24.3%

Note: The table shows the proportion of the variance of steady state unemployment accounted for by changes in the relevant transition rate, using the log decomposition described in the text. Components might not sum to 100% due to approximation error.

Table 3.5: s_t by Countries

Year	AT	BE	HR	FR	DE	GR	IT	LV	PT	ES	UK
2006	1.97	2.21	2.18	2.88	2.63	1.47	1.29	2.26	2.18	2.87	1.99
2007	1.76	2.08	2.01	2.61	2.34	1.39	1.19	2.54	2.36	2.65	1.69
2008	1.67	2.07	1.45	2.66	2.11	1.37	1.5	3.63	2.3	4.35	1.94
2009	2.35	2.51	2.34	3.91	2.69	2.5	1.94	9.34	3.52	7.06	3.49
2010	1.19	2.53	3.56	3.49	2.31	3.19	1.88	7.5	3.22	5.81	2.78
2011	1.17	1.97	3.08	3.21	1.69	4.32	1.8	4.33	4.17	5.54	2.56
2012	1.83	2.39	3.76	3.49	1.75	5.03	2.42	4.57	5.39	6.98	2.41
2013	2.12	2.72	3.98	3.81	1.65	4.51	2.62	3.5	4.44	6.11	2.2
2014	2.15	2.51	4.42	3.69	1.58	3.45	2.29	3.65	3.34	4.84	1.77
2015	2.01	2.47	3.04	3.63	1.39	3.27	2.11	3.35	3.07	3.92	1.63
2016	1.91	2.17	2.93	3.25	1.19	2.86	1.99	3.59	2.72	3.64	1.58

Table 3.6: f_t by Countries

Year	AT	BE	HR	FR	DE	GR	IT	LV	PT	ES	UK
2006	41.5	19.2	19.3	32.4	26.6	23.9	29.4	43.5	36.9	39.5	47
2007	43.3	19.7	22.5	34.7	31	22.9	29.8	43.6	39.5	41.2	49.6
2008	42.5	20.1	24.3	34.3	29.4	24.6	27.6	43	37.8	36.7	43.8
2009	39.4	16.2	19.3	29.1	26.9	21.7	23.3	28.6	33.4	27.1	38.3
2010	41.7	20.6	14.9	32.6	28.2	17.3	23.7	37.3	31.5	25.4	39.9
2011	41.9	21.8	17.5	33.3	26.9	11.6	24.4	38.6	25.2	23.5	38.8
2012	39.6	21.1	15.4	31.3	25.9	8.9	21.5	36.9	21.3	19.3	40.3
2013	38.4	19.8	14.9	30.5	25.1	9.91	18.7	40.7	21.9	18.1	41.1
2014	37.3	20.4	16.8	27.2	24.8	12.4	18.9	43.7	27.3	19.9	44.6
2015	38.9	20.3	18.3	26.7	24.3	12.5	20.9	44.2	28.9	21.9	45.6
2016	38.1	22.4	22.9	26.7	23.9	12	22.2	43.5	29.6	23.8	45.9

Table 3.7: European s_t by Socio-demographic Groups

Year	Male	Female	Young Workers	Middle Aged Workers	Old Workers	Low Education	Medium Education	High Education
2006	1.79	2.17	4.14	1.78	1.08	2.25	1.98	1.36
2007	1.68	1.95	3.89	1.64	1.01	2.2	1.78	1.22
2008	1.94	2.03	4.29	1.79	1.16	2.59	1.92	1.22
2009	3.32	2.84	6.51	2.9	1.87	3.95	3.13	1.95
2010	2.98	2.74	6.01	2.7	1.83	3.62	2.88	1.94
2011	2.85	2.72	5.86	2.67	1.75	3.7	2.69	1.89
2012	3.17	2.87	5.87	3.0	1.99	4.56	2.89	1.87
2013	3.07	2.75	5.88	2.89	1.91	4.26	2.87	1.87
2014	2.79	2.54	5.56	2.64	1.75	3.74	2.69	1.82
2015	2.58	2.36	5.13	2.49	1.62	3.42	2.51	1.73
2016	2.29	2.19	4.78	2.26	1.44	3.09	2.31	1.53

Table 3.8: European f_t by Socio-demographic Groups

Year	Male	Female	Young Workers	Middle Aged Workers	Old Workers	Low Education	Medium Education	High Education
2006	32.3	27.5	35.8	30.5	18.1	24.3	32.3	41.2
2007	34.2	30.2	38.9	32.9	20.5	25.8	35.2	44.4
2008	32.9	30.1	38.2	32.6	20.0	24.9	35.0	43.7
2009	27.4	26.4	31.9	28.3	17.5	21.3	29.5	38.0
2010	29.0	26.7	33.0	29.2	18.8	22.0	30.4	37.9
2011	28.9	25.6	32.1	29.1	18.6	21.4	30.0	37.0
2012	25.5	24.0	29.7	26.2	17.2	19.1	27.1	33.9
2013	23.8	22.8	28.2	24.4	16.5	17.7	25.6	31.8
2014	25.6	24.4	30.5	26.3	17.6	19.2	27.4	33.8
2015	26.1	24.5	31.5	26.7	17.8	20.1	27.3	33.5
2016	27.0	25.0	32.9	27.7	17.9	20.2	28.2	34.6

Table 3.9: European s_t by Urbanisation Level and Immigrant Groups

Year	Cities	Suburbs	Rural Area	Native Born	New Immigrants	Intermediate Immigrants	Earlier Immigrants
2006	2.29	1.90	2.04	1.91	4.43	4.17	2.85
2007	2.06	1.68	1.76	1.67	4.07	4.21	2.73
2008	2.21	1.75	1.97	1.80	4.50	4.34	2.73
2009	3.60	2.98	3.29	3.12	7.07	6.54	4.7
2010	3.38	2.75	2.94	2.89	6.25	5.69	4.31
2011	3.02	2.57	2.66	2.60	5.86	5.59	4.02
2012	3.16	2.86	2.68	2.71	6.71	6.16	4.09
2013	3.04	2.76	2.60	2.61	6.63	6.21	4.08
2014	2.72	2.45	2.23	2.28	6.13	5.45	3.76
2015	2.43	2.29	2.09	2.1	5.29	5.29	3.48
2016	2.22	2.0	1.88	1.88	4.90	4.29	3.08

Table 3.10: European f_t by Urbanisation Level and Immigrant Groups

Year	Cities	Suburbs	Rural Area	Native Born	New Immigrants	Intermediate Immigrants	Earlier Immigrants
2006	29.3	31	31.1	29.7	41	37.2	27.3
2007	31.4	32.3	33.4	32	42.5	38	30.4
2008	31.2	31	32.6	31.3	42.6	36.1	28.9
2009	26.0	26.3	28	26.7	36.3	32.2	24.1
2010	26.5	28.1	29	27.8	34.6	31.3	26
2011	26.2	27.8	28.1	27.3	32.8	31.6	25.3
2012	24.3	24	26.1	24.7	31.5	27.7	22.9
2013	22.6	22.6	24.6	23.3	30.8	25.3	21.5
2014	23.4	23.9	27.5	25.2	30.6	26.5	21.5
2015	23.8	24.2	27.8	25.5	31	27.2	22.4
2016	24.9	24.8	28.1	26.2	31	28.4	22.7

Table 3.11: Contribution to Worker groups' unemployment variance of changes in:

	Male	Female		
Unemployment Inflow rate s_t	69.0%	66.7%		
Unemployment Outflow Rate f_t	27.9%	32.0%		
	Young Workers	Middle Aged Workers	Old Workers	
Unemployment Inflow rate s_t	64.1%	71.1%	71.5%	
Unemployment Outflow Rate f_t	32.3%	27.2%	26.6%	
	Low Education	Medium Education	High Education	
Unemployment Inflow rate s_t	69.5%	69.5%	65.8%	
Unemployment Outflow Rate f_t	28.1%	28.7%	33.3%	
	Cities	Suburbs	Rural Area	
Unemployment Inflow rate s_t	77.08%	78.22%	84.23%	
Unemployment Outflow Rate f_t	22.9%	21.66%	15.76%	
	Native Born	New Immigrants	Intermediate Immigrants	Earlier Immigrants
Unemployment Inflow rate s_t	82.208%	76.84%	66.24%	80.14%
Unemployment Outflow Rate f_t	17.79%	23.15%	33.75%	19.88%

Note: The table shows the proportion of the variance of steady state unemployment accounted for by changes in the relevant transition rate, using the log decomposition described in the text. Components might not sum to 100% due to approximation error.

Table 3.12: Marginal Effects: Benchmark Case

Groups		EU Transitions	UE Transitions
Gender[1]	Female	-0.0003***	-0.028***
		(0.0001)	(0.001)
Educational Level[2]	Less Educated Workers	0.019***	-0.139***
		(0.0001)	(0.001)
	Medium Educated Workers	0.009***	-0.078***
		(0.0001)	(0.001)
Age	Age	-0.001***	-0.005***
		(2.74e-06)	(0.00002)
European Region[3]	Southern Europe	0.0003***	-0.083***
		(0.0001)	(0.001)
	Northern Europe	0.0022***	0.099***
		(0.0001)	(0.0012)
	Eastern Europe	0.001***	-0.026***
		(0.0001)	(0.001)
Degree of Urbanisation[4]	Suburbs	-0.0038***	0.022***
		(0.0001)	(0.0007)
	Rural Area (thinly populated)	-0.004***	0.031***
		(0.0001)	(0.001)
Immigration Status[5]	Recent Immigrant	0.016***	0.040***
		(0.0003)	(0.0023)
	Intermediate Immigrant	0.015***	0.032***
		(0.0003)	(0.0022)
	Earlier Immigrant	0.012***	-0.005***
		(0.0002)	(0.001)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.Cities (densely populated) and 5.Born in this country

Table 3.13: Marginal Effects: EU Transitions

Groups		2007	2009	2012
Gender[1]	Females	0.002**	-0.004***	-0.001***
		(0.0002)	(0.0002)	(0.0003)
Educational Level[2]	Less Educated Workers	0.017***	0.030***	0.026***
		(0.0004)	(0.0005)	(0.0004)
	Medium Educated Workers	0.0062***	0.015***	0.012***
		(0.0002)	(0.0003)	(0.0003)
Age	Age	-0.0007***	-0.0012***	-0.0011***
		(0.00001)	(0.00001)	(0.00001)
European Region[3]	Southern Europe	-0.007***	-0.05***	0.012***
		(0.0003)	(0.004)	(0.0004)
	Northern Europe	-0.0029***	0.019***	0.0021***
		(0.0004)	(0.0005)	(0.0004)
	Eastern Europe	0.002***	0.005***	0.005***
		(0.0004)	(0.0005)	(0.0004)
Degree of Urbanisation[4]	Suburbs	-0.0039***	-0.006***	-0.005***
		(0.0002)	(0.0003)	(0.0004)
	Rural Area (thinly populated)	-0.004***	-0.006***	-0.007***
		(0.0003)	(0.0003)	(0.0003)
Immigration Status[5]	Recent Immigrant	0.012***	0.02***	0.023***
		(0.001)	(0.002)	(0.002)
	Intermediate Immigrant	0.016***	0.029***	0.017***
		(0.001)	(0.001)	(0.001)
	Earlier Immigrant ($\geq$ 11 years)	0.01***	0.017***	0.014***
		(0.0006)	(0.001)	(0.001)

Robust standard errors in parentheses. Statistical Significance $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.cities (densely populated) and 5.Born in this country

Table 3.14: Marginal Effects: UE Transitions

Groups		2007	2009	2012
Gender	Females	-0.05***	-0.017***	-0.019***
		(0.002)	(0.002)	(0.002)
Educational Level	Less Educated Workers	-0.159***	-0.152***	-0.128***
		(0.004)	(0.004)	(0.003)
	Medium Educated Workers	-0.081***	-0.084***	-0.072***
		(0.004)	(0.004)	(0.003)
Age	Age	-0.006***	-0.004****	-0.004***
		(0.0001)	(0.0001)	(0.0001)
European Region	Southern Europe	-0.048***	-0.053***	-0.121***
		(0.003)	(0.003)	(0.002)
	Northern Europe	0.136***	0.054***	0.068***
		(0.009)	(0.009)	(0.007)
	Eastern Europe	-0.043***	-0.024***	-0.047***
		(0.004)	(0.004)	(0.003)
Degree of Urbanisation[4]	Suburbs	0.026***	0.021***	0.015***
		(0.003)	(0.003)	(0.002)
	Rural Area (thinly populated)	0.023***	0.028***	0.031***
		(0.003)	(0.003)	(0.002)
Immigration Status[5]	Recent Immigrants	0.066***	0.073***	0.039***
		(0.009)	(0.008)	(0.0039)
	Intermediate Immigrant	0.034***	0.053***	0.033***
		(0.009)	(0.008)	(0.006)
	Earlier Immigrant	-0.011***	-0.008***	-0.003***
		(0.005)	(0.005)	(0.003)

Robust standard errors in parentheses. Statistical Significance $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.cities (densely populated) and 5.Born in this country

Table 3.15: Marginal Effects of Interactions: EU Transitions I

Groups	2007	2009	2012
Less Educated and Young Male Workers in Southern Europe	0.033***	0.084***	0.007***
	(0.003)	(0.004)	(0.0032)
Less Educated and Young Male Workers in Northern Europe	0.022***	0.052***	0.039***
	(0.002)	(0.0028)	(0.0031)
Less Educated and Middle Aged Male Workers in Southern Europe	0.011***	0.046***	0.042***
	(0.0017)	(0.003)	(0.002)
Less Educated and Middle Aged Male Workers in Northern Europe	0.011***	0.036***	0.024***
	(0.002)	(0.003)	(0.003)
Less Educated and Young Female Workers in Southern Europe	0.044***	0.066***	0.063***
	(0.003)	(0.004)	(0.003)
Less Educated and Young Female Workers in Northern Europe	0.023***	0.039***	0.032***
	(0.002)	(0.003)	(0.003)
Less Educated and Middle Aged Female Workers in Southern Europe	0.019***	0.029***	0.029***
	(0.002)	(0.003)	(0.003)
Less Educated and Middle Aged Female Workers in Northern Europe	0.012***	0.020***	0.015***
	(0.002)	(0.002)	(0.003)
Medium Educated and Young Male Workers in Southern Europe	0.006***	0.017***	0.013***
	(0.002)	(0.003)	(0.003)
Medium Educated and Young Male Workers in Northern Europe	0.008***	0.026***	0.018***
	(0.001)	(0.002)	(0.002)
Medium Educated and Middle Aged Male Workers in Southern Europe	0.001	0.006***	0.003***
	(0.002)	(0.003)	(0.002)
Medium Educated and Middle Aged Male Workers in Northern Europe	0.005***	0.024***	0.014***
	(0.0014)	(0.002)	(0.002)
Medium Educated and Young Female Workers in Southern Europe	0.0013***	0.018***	0.018***
	(0.002)	(0.003)	(0.003)
Medium Educated and Young Female Workers in Northern Europe	0.009***	0.020***	0.013***
	(0.001)	(0.002)	(0.0002)
Medium Educated and Middle Aged Female Workers in Southern Europe	0.005***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)
Medium Educated and Middle Aged Female Workers in Northern Europe	0.007***	0.014***	0.008***
	(0.001)	(0.002)	(0.002)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $*\!*\!*\ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included along with the interactions in the regressions.

Marginal effects estimated at average $age = 21$ of Young Workers (16-29) and average $age = 39$ of middle aged workers (30-49).

Table 3.16: Marginal Effects of Interactions: EU Transitions II

Groups	2007	2009	2012
New Immigrants (0-5 years) in Suburbs	-0.005**	-0.006*	-0.007*
	(0.003)	(0.004)	(0.004)
Intermediate Immigrants (6-10 years) in Suburbs	-0.016***	-0.011***	-0.007**
	(0.002)	(0.003)	(0.003)
Earlier Immigrants ($\geq$ 11 years) in Suburbs	-0.008***	-0.009***	-0.009***
	(0.0014)	(0.002)	(0.001)
New Immigrants (0-5 years) in Rural Area	-0.006*	-0.008**	0.017***
	(0.003)	(0.004)	(0.004)
Intermediate Immigrants (6-10 years) in Rural Area	-0.003	-0.014***	-0.013***
	(0.004)	(0.003)	(0.0031)
Earlier Immigrants ($\geq$ 11 years) in Rural Area	-0.01***	-0.009***	-0.008***
	(0.0015)	(0.002)	(0.002)

Robust standard errors in parentheses. Statistical Significance $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included along with the interactions in the regressions.

Table 3.17: Marginal Effects of Interactions: UE Transitions I

Groups	2007	2009	2012
Less Educated and Young Male Workers in Southern Europe	-0.246***	-0.240***	-0.237***
	(0.011)	(0.014)	(0.011)
Less Educated and Young Male Workers in Northern Europe	-0.318***	-0.338***	-0.29***
	(0.013)	(0.017)	(0.015)
Less Educated and Middle Aged Male Workers in Southern Europe	-0.088***	-0.083***	-0.088***
	(0.020)	(0.022)	(0.015)
Less Educated and Middle Aged Male Workers in Northern Europe	-0.273***	-0.267***	-0.187***
	(0.027)	(0.033)	(0.028)
Less Educated and Young Female Workers in Southern Europe	-0.270***	-0.244***	-0.217***
	(0.01)	(0.009)	(0.013)
Less Educated and Young Female Workers in Northern Europe	-0.313***	-0.297***	-0.348***
	(0.014)	(0.017)	(0.015)
Less Educated and Middle Aged Female Workers in Southern Europe	-0.128***	-0.101***	-0.074***
	(0.017)	(0.016)	(0.011)
Less Educated and Middle Aged Female Workers in Northern Europe	-0.262***	-0.186***	-0.280***
	(0.026)	(0.032)	(0.027)
Medium Educated and Young Male Workers in Southern Europe	-0.161***	-0.145***	-0.152***
	(0.012)	(0.015)	(0.012)
Medium Educated and Young Male Workers in Northern Europe	-0.155***	-0.216***	-0.161***
	(0.012)	(0.016)	(0.006)
Medium Educated and Middle Aged Male Workers in Southern Europe	-0.082***	-0.048***	-0.061***
	(0.022)	(0.024)	(0.016)
Medium Educated and Middle Aged Male Workers in Northern Europe	-0.128***	-0.203***	-0.090***
	(0.025)	(0.032)	(0.026)
Medium Educated and Young Female Workers in Southern Europe	-0.171***	-0.155***	-0.134***
	(0.01)	(0.011)	(0.009)
Medium Educated and Young Female Workers in Northern Europe	-0.134***	-0.168***	-0.154***
	(0.009)	(0.012)	(0.016)
Medium Educated and Middle Aged Female Workers in Southern Europe	-0.091***	-0.068***	-0.041***
	(0.017)	(0.017)	(0.012)
Medium Educated and Middle Aged Female Workers in Northern Europe	-0.148***	-0.080***	-0.146***
	(0.024)	(0.03)	(0.024)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included along with the interactions in the regressions.

Marginal effects estimated at average $age = 21$ of Young Workers (16-29) and average $age = 39$ of middle aged workers (30-49).

Table 3.18: Marginal Effects of Interactions: UE Transitions II

Groups	2007	2009	2012
New Immigrants (0-5 years) in Suburbs	0.056**	0.02	0.034**
	(0.021)	(0.02)	(0.015)
Intermediate Immigrants (6-10 years) in Suburbs	0.145***	0.018	0.038***
	(0.023)	(0.019)	(0.014)
Earlier Immigrants ($\geq$ 11 years) in Suburbs	0.04***	0.034***	0.005***
	(0.023)	(0.011)	(0.007)
New Immigrants (0-5 years) in Rural Area	0.058**	0.036*	0.045**
	(0.03)	(0.021)	(0.018)
Intermediate Immigrants (6-10 years) in Rural Area	0.012	0.032	0.03*
	(0.024)	(0.021)	(0.016)
Earlier Immigrants ($\geq$ 11 years) in Rural Area	0.034***	-0.009	0.023***
	(0.012)	(0.011)	(0.009)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included along with the interactions in the regressions.

Table 3.19: Marginal Effects: Benchmark Case (Robustness Checks)

Groups		EU Transitions	UE Transitions
Gender[1]	Female	-0.0003***	-0.029***
		(0.0001)	(0.001)
Educational Level[2]	Less Educated Workers	0.019***	-0.139***
		(0.0001)	(0.001)
	Medium Educated Workers	0.009***	-0.078***
		(0.0001)	(0.001)
Age	Age	-0.001***	-0.005***
		(2.74e-06)	(0.00002)
European Region[3]	Southern Europe	0.0002***	-0.083***
		(0.0001)	(0.001)
	Northern Europe	0.0021***	0.099***
		(0.0001)	(0.0013)
	Eastern Europe	0.001***	-0.027***
		(0.0001)	(0.001)
Degree of Urbanisation[4]	Suburbs	-0.004***	0.022***
		(0.0001)	(0.0008)
	Rural Area (thinly populated)	-0.004***	0.030***
		(0.0001)	(0.0007)
Immigration Status[5]	Intermediate Immigrants	0.011***	0.030***
		(0.0002)	(0.002)
	Earlier Immigrants	0.009***	-0.006***
		(0.0001)	(0.001)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.Cities (densely populated) and 5.Born in this country

Table 3.20: Marginal Effects: EU Transitions (Robustness Checks)

Groups		2007	2009	2012
Gender[1]	Females	0.002**	-0.004***	-0.001***
		(0.0002)	(0.0002)	(0.0003)
Educational Level[2]	Less Educated Workers	0.017***	0.031***	0.027***
		(0.0004)	(0.0004)	(0.0004)
	Medium Educated Workers	0.0062***	0.015***	0.012***
		(0.0002)	(0.0003)	(0.0003)
Age	Age	-0.0007***	-0.0012***	-0.0011***
		(0.00001)	(0.00001)	(0.00001)
European Region[3]	Southern Europe	-0.007***	-0.05***	0.012***
		(0.0003)	(0.004)	(0.0004)
	Northern Europe	-0.003***	0.019***	0.002***
		(0.0004)	(0.0005)	(0.0004)
	Eastern Europe	0.002***	0.005***	0.004***
		(0.0004)	(0.0045)	(0.0003)
Degree of Urbanisation[4]	Suburbs	-0.004***	-0.006***	-0.005***
		(0.0002)	(0.0003)	(0.0004)
	Rural Area (thinly populated)	-0.004***	-0.006***	-0.008***
		(0.0003)	(0.0003)	(0.0003)
Immigration Status[5]	Intermediate Immigrants	0.016***	0.023***	0.017***
		(0.001)	(0.001)	(0.001)
	Earlier Immigrants	0.01***	0.017***	0.013***
		(0.0006)	(0.0008)	(0.0007)

Robust standard errors in parentheses. Statistical Significance $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.cities (densely populated) and 5.Born in this country

Table 3.21: Marginal Effects: UE Transitions (Robustness Checks)

Groups		2007	2009	2012
Gender	Females	-0.05***	-0.017***	-0.019***
		(0.002)	(0.002)	(0.002)
Educational Level	Less Educated Workers	-0.160***	-0.152***	-0.129***
		(0.004)	(0.004)	(0.003)
	Medium Educated Workers	-0.081***	-0.085***	-0.073***
		(0.004)	(0.004)	(0.003)
Age	Age	-0.006***	-0.004****	-0.004***
		(0.0001)	(0.0001)	(0.0001)
European Region	Southern Europe	-0.049***	-0.053***	-0.122***
		(0.003)	(0.003)	(0.002)
	Northern Europe	0.135***	0.054***	0.068***
		(0.009)	(0.009)	(0.007)
	Eastern Europe	-0.046***	-0.027***	-0.049***
		(0.004)	(0.004)	(0.003)
Degree of Urbanisation[4]	Suburbs	0.026***	0.02***	0.014***
		(0.003)	(0.003)	(0.002)
	Rural Area (thinly populated)	0.023***	0.027***	0.031***
		(0.003)	(0.003)	(0.002)
Immigration Status[5]	Intermediate Immigrant	0.032***	0.05***	0.032***
		(0.009)	(0.008)	(0.006)
	Earlier Immigrants	-0.012***	-0.01***	-0.004***
		(0.005)	(0.005)	(0.003)

Robust standard errors in parentheses. Statistical Significance $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Individual Categorical Variables and Year Dummy Variables were also included in the regressions.

Reference Categories: 1.Male, 2.Highly Educated Workers, 3.Western Europe, 4.cities (densely populated) and 5.Born in this country

3.7.2 Figures

Figure 3.1: Unemployment Rate (2006-2016)

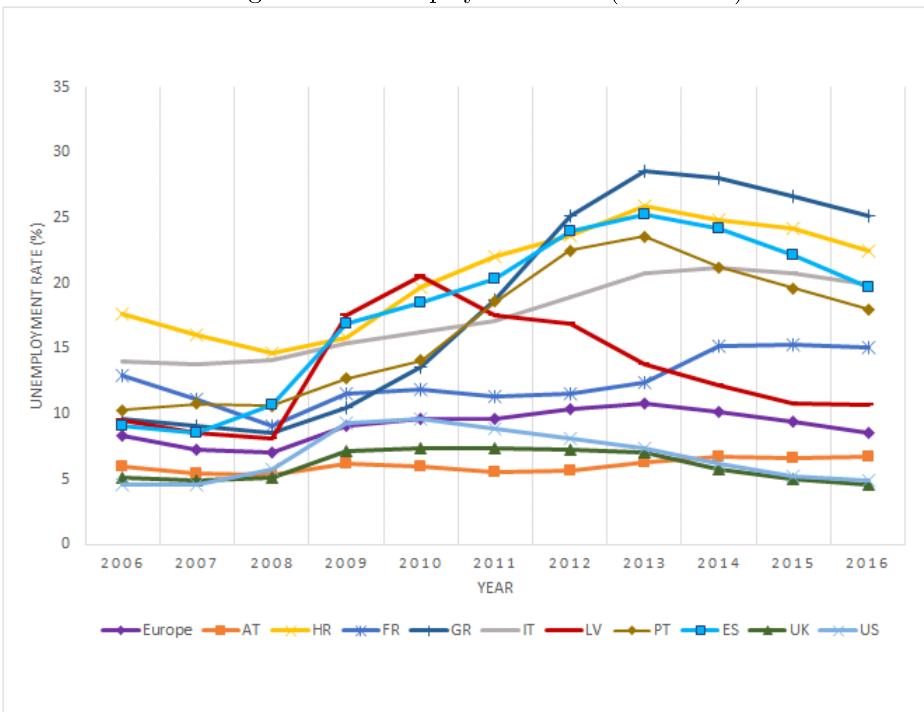


Figure 3.2: Inactivity Rate (2006-2016)

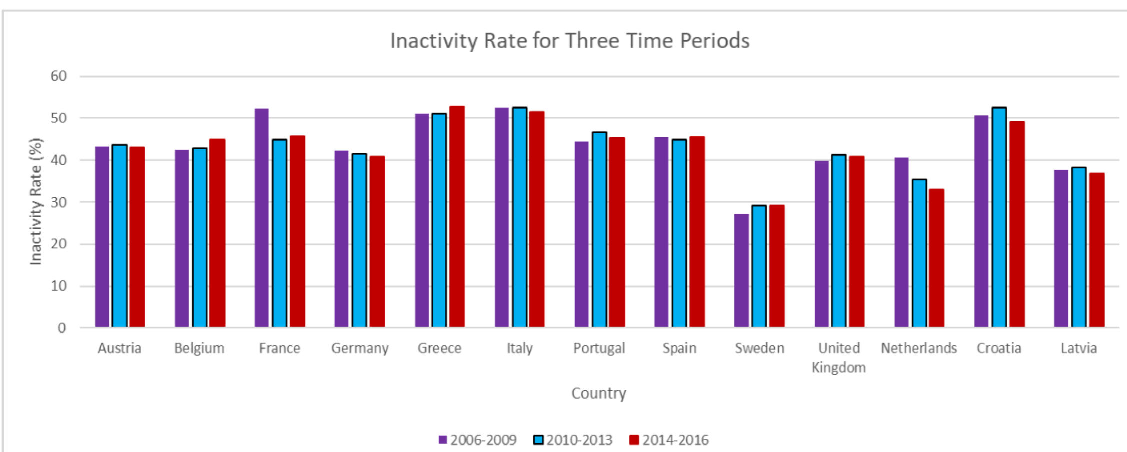


Figure 3.3: European Unemployment, Job Separation and Job Finding Rates.

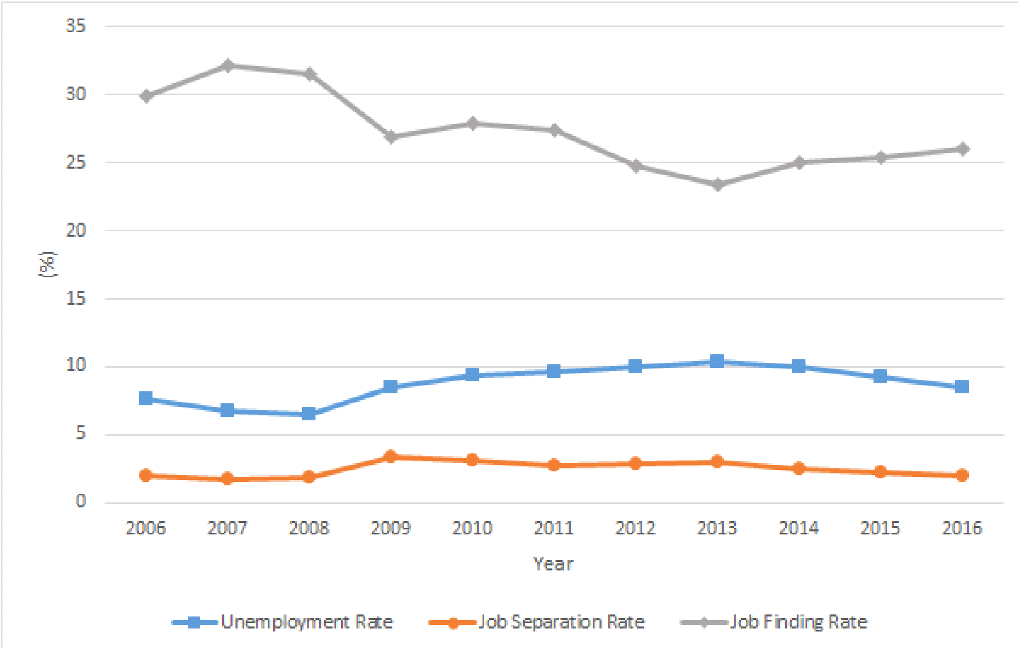


Figure 3.4: Changes in log inflow and outflow rates

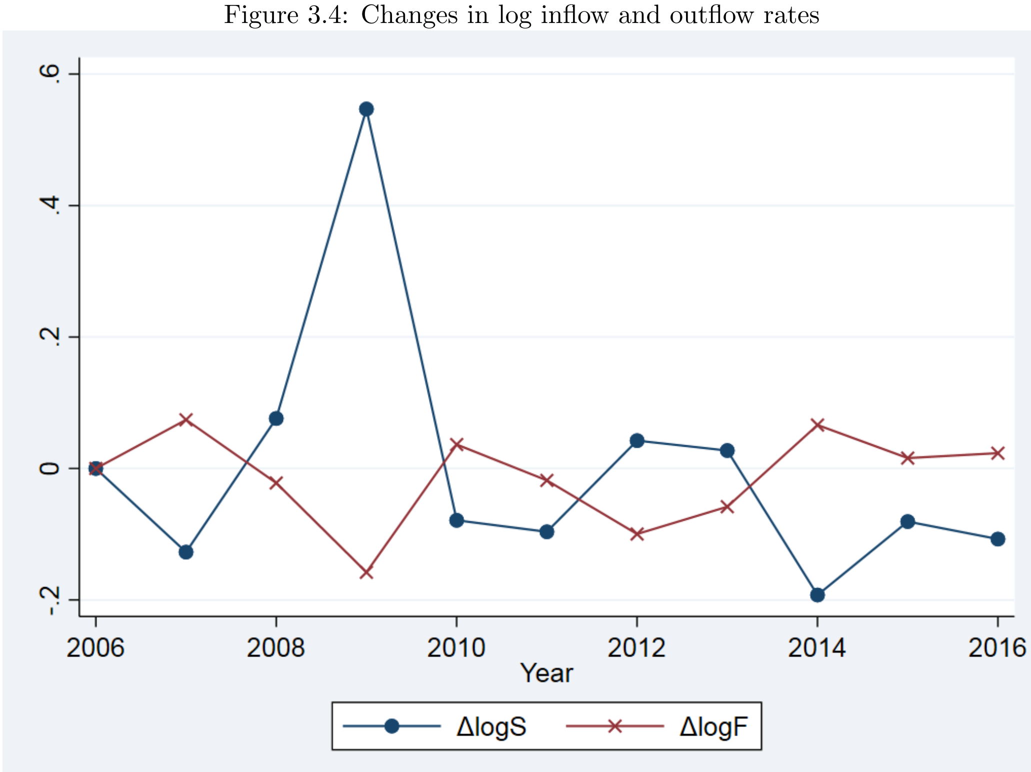
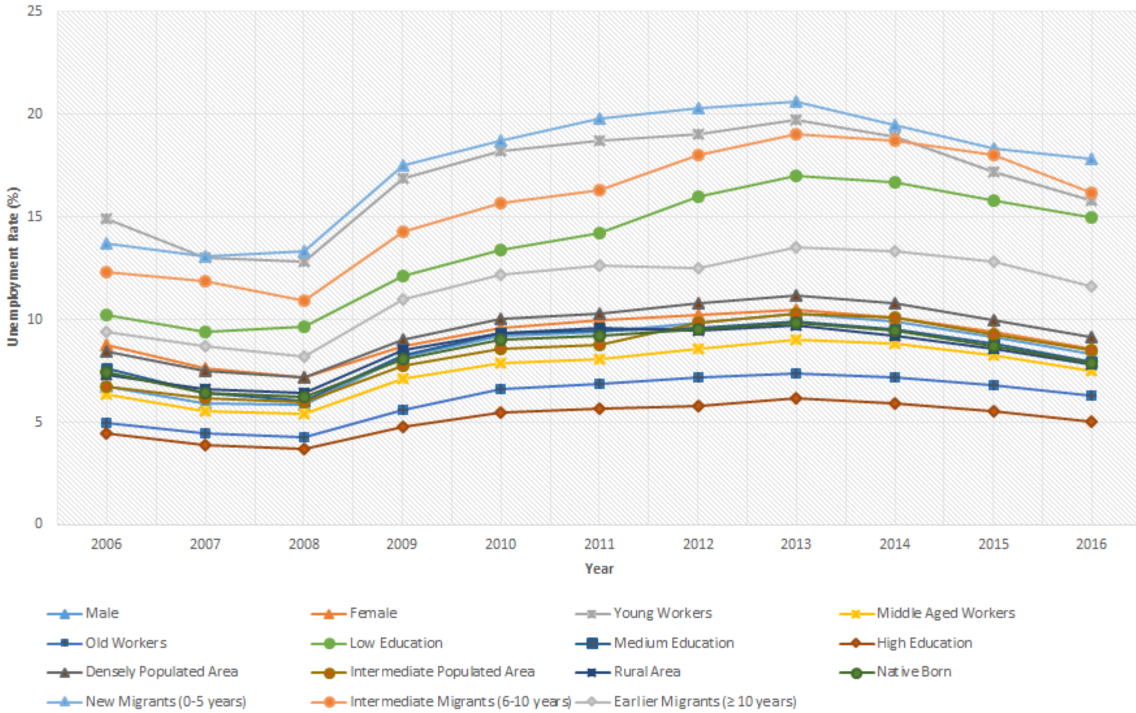


Figure 3.5: European Unemployment Rate by Socio Demographic Groups, Degree of Urbanisation and Migration Status.



3.7.3 Countries in the Sample.

Western Europe

- Austria (AT)
- Belgium (BE)
- France (FR)
- Germany (DE)
- Luxembourg (LU)

Southern Europe

- Spain (ES)
- Italy (IT)
- Portugal (PT)
- Greece (GR)
- Croatia (HR)
- Slovenia (SI)

Northern Europe

- United Kingdom (UK)
- Sweden (SE)
- Denmark (DK)
- Estonia (EE)
- Finland (FI)
- Latvia (LV)
- Lithuania (LT)
- Norway (NO)

Eastern Europe

- Czech Republic (CZ)
- Hungary (HU)
- Poland (PO)
- Romania (RO)
- Slovakia (SK)

Chapter 4

Concluding Remarks

The main objective of this thesis was to make contribution to the literature on the consequences of labour market shocks on unemployment and wages. To achieve this objective, we undertook the following: (i) the examination of the impact of sector-specific shocks on sectoral allocation of workers; (ii) a critical assessment of the impact of immigration on wage in the host country through meta-analysis; and (iii) the evaluation of the role played by labour market transitions between employment and unemployment in shaping overall unemployment in Europe.

In chapter 1, we solved a two sector search and matching model to derive three productivity levels amongst workers based on which workers are located in the two sectors. The model is calibrated to US construction and non-construction sector. The results showed that employment in construction sector decreases and unemployment for low and medium productivity workers increases. Medium productivity workers move to non-construction sector to find employment while low skilled workers remain unemployed in construction sector as they do not possess the necessary skill set to work in non-construction sector. The increase in the unemployment levels of low and medium productivity workers increases the overall unemployment in economy but some of it is offset by the fact that some medium productivity workers find jobs in non-construction sector. Given the findings in this chapter with regards to the impact of sector-specific shocks on unemployment/employment dynamics, an interesting direction forward for future research on the link between structural changes in the economy and labour market dynamics may be detailed by empirical estimations.

In chapter 2, a meta-analysis is conducted to investigate the effect of immigration on wages in the host country. The aim of this chapter was to identify the sources of heterogeneity in research papers that assessed the impact of immigration on wages and to provide the consensus estimate on what the impact is. The estimation results showed that impact of immigration on wages is generally small and negative significant. A detailed look at the estimations showed that wage impact of immigration varies across countries and are also related to the type of modelling approach and estimation specification. One of the most important results in the estimations is that the labour market conditions of the country during the times when authors conduct their analysis also play a significant role in shaping the the impact of immigration and wages. This chapter also tests for publication bias and p-hacking which are considered to be two risks associated with conducting a meta-analysis. The results of the tests show that publication bias and p-hacking are not a problem in our meta-analysis. There are a number of interesting directions in which the framework presented in this chapter could be furthered by assessing the impact of immigration on dynamic aspects of labour markets.

Chapter 3 provided an in depth assessment of the European unemployment rate by assessing the contribution of worker flows between employment and unemployment. It also evaluated the importance of socio-demographics, degree of urbanisation and immigration status of workers in shaping the labour market transitions. The results show that unemployment inflow account for around 73.5% of the unemployment variance. The estimations identifying correlation between different socio-demographic groups and worker flows show that less educated workers, young workers, workers in cities, recent and intermediate immigrants and workers from Southern European countries have high probability of employment losses and low probability of job findings. There is scope for exploring underlying processes behind these results for future research.

Chapter 5

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