THE EMPLOYMENT AND UNEMPLOYMENT EFFECTS OF FINNISH ACTIVE LABOUR MARKET PROGRAMMES

KARI HÄMÄLÄINEN

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Declaration

No part of this thesis has been presented to any university for any degree.

Summary

The persistence of high unemployment has placed increasing stress on the role of active labour market policies. They have been seen as the main policy tool in moving individuals from income support to employment. This thesis attempts to evaluate the effectiveness of active labour market policy in fulfilling the difficult task given to it. This is done by empirically exploring the impact of active labour market programmes on the overall level of open unemployment, participants' repeat unemployment incidence and their subsequent employment record. By this means, the thesis examines the achievement of both macroeconomic and individual goals given to active labour market policy. The main finding running through all chapters, and consequently through different estimation methods, samples and aggregation levels, is that active labour market policy improves the employment performance of the economy but it can help only so far as it goes. The beneficial effect remains far too limited to bring down the current high levels of unemployment or to wipe out the gap in labour market possibilities prevailing between advantaged and disadvantaged individuals. This is not to say that active labour market policy would not be useful in conjunction with other policies affecting unemployment, but without any support its effects will remain modest.

CHAPTER 1.

Introduction

During the 1990s governments' powerlessness in bringing down high unemployment has induced a substantial shift towards active labour market policies, OECD (1990, 1993). The view is supported by various studies which connect passive measures, most significantly the level and the duration of unemployment benefits, to persistent unemployment, see Jackman *et. al.* (1990), Layard *et. al.* (1991), Heylen (1993) and Scarpetta (1996), *inter alia*. Active labour market policy has been seen as a key to enhance the functioning of labour markets and to help the employability of hard-to-employ persons. To achieve these aims active labour market programmes should reduce the overall level of open unemployment together with improving the employment records of programme participants. These are the broad issues of interest in this thesis.

Active labour market policy originates from Sweden at the end of the 1940s. As a part of the Swedish model[1], it was given the role of ensuring full employment when restricting fiscal policy, together with solidaristic wage policy, was employed in combating inflation. To join the two seemingly controversial goals, active labour market policy was selectively employed in increasing the demand for labour and in reducing labour market mismatches. These macroeconomic goals have remained among the targets of active labour market policy throughout the decades. Nowadays they are combined with a variety of individual goals aimed at increasing human capital, improving work habits, preventing discouragement and stabilising work careers.

Because of the twofold aims, this study adopts both the macroeconomic and the microeconomic point of view. The effectiveness of active labour market programmes is

[1] The Swedish model was first explicitly laid down in 1951 by two central blue-collar trade union (LO) economists Rehn and Meidner (1951), Robinson (1995).

addressed through empirical evaluations for two reasons. First, the discussion in chapter 3 reveals that active labour market policy affects the employment performance of the economy in many different ways which tend to counteract each other. This leaves the overall effect ambiguous on theoretical reasonings. Second, a massive and yet unexplored data set is available for assessing the effectiveness of Finnish active labour market policy in helping the participants.

There remains the question of how to measure efficiency. As discussed at great length in chapter 2, the emphasis of Finnish active labour market policy centres on the employment and unemployment effects of active programmes. From the stated goals, this thesis examines the effectiveness of active programmes through assessing the achievement of three targets, viz. reduction in the overall level of open unemployment, increase in participants' job stability and improvement in participants' subsequent employment record. Further motivation for the adopted outcome variables is provided by the literature survey in chapter 3 which shows that the existing evidence on these issues is both limited and somewhat mixed.

The equilibrium unemployment effects of active labour market policy have been examined mainly through cross-country regressions which suggest that active programmes reduce unemployment. This beneficial view is forcefully challenged by time-series studies which assess the wage pressure effects of ALMPs. The contradiction motivates the macroeconometric part of the study in which the unemployment effects of programmes are scrutinised through time series analyses. The main questions put forward in chapter 4 are as follows. First, do active programmes increase wage pressures? Second, can they prevent discouragement among hard-to-employ persons, as hypothesised for instance in Layard et. al. (1991)? Third, what is the impact of ALMPs on open unemployment and does it depend on the overall unemployment situation?

The macroeconometric evaluation suggests that active labour market policy is more efficient in the high unemployment situation. To get a fuller picture of the relation between the effectiveness of active labour market programmes and the level of unemployment, the next two chapters of the thesis focus on the individual level. The fifth chapter examines the relation between participation and repeat unemployment incidence. The aim of this chapter is to shed some light on the differences in programme effects across different individuals according to their characteristics. By this means it is possible to identify individuals who are likely to capture higher than average gains from programme participation.

To complement the microeconometric findings of the fifth chapter, chapter 6 studies the different groups of active labour market programmes in the eras of low and high unemployment. This offers also a close link to chapter 4 and makes it possible to compare the findings to macroeconomic ones. The principal aim of chapter 6 is to assess the effects of different programmes on participants' subsequent employment record. This gives some guidance to the question of what is the effective structure of active labour market policy.

The microeconometric chapters raise many interesting issues about the benefits of active labour market programmes. The main questions put forward in chapters 5 and 6 are as follows:

- Do active programmes help to reduce participants' risk of renewing unemployment?
- Do they improve participants' subsequent employment record?
- At whom should active programmes be targeted?
- What is the ranking of labour market training and selective employment measures in terms of their efficiency?

- Which one is more effective, job placement in the public sector or job placement in the private sector?
- Are large scale job placement obligations useful?
- Are there any changes in the answers to the above questions between different eras of unemployment?

By seeking the answers to the above questions, together with ones put forward in chapter 4, this study aims at producing new insights into the functioning of active labour market policy and its possibilities in improving the employment performance of the economy. During the period of high and persistent European unemployment this task is surely worth under taking.

CHAPTER 2.

Introduction to Finnish Unemployment and Labour Market Policies

This chapter provides a short introduction to the main features of Finnish unemployment and unemployment policies. Since microeconometric evaluations in the thesis raise questions concerning different groups of individuals, the evolution of Finnish unemployment is introduced through differences in unemployment between sexes, age groups and regions.

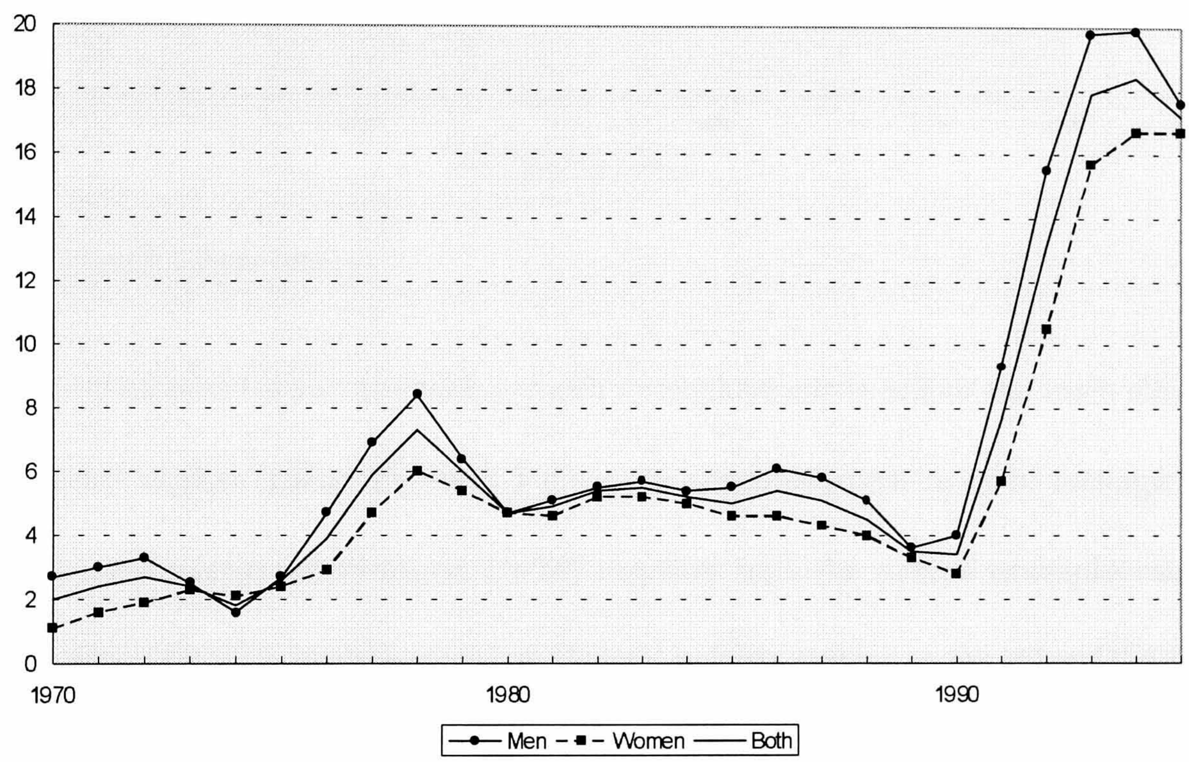
Even though the main focus of the study is on the 1980s and the 1990s, the history of Finnish active labour market policy is shortly introduced. When necessary, the discussion is related to the empirical work presented in later chapters.

2.1 Basic Features of Finnish Unemployment

Figure 2.1 shows the unemployment rates by gender. One special feature of the Finnish labour market is that, despite women's high labour force participation rate of some 70 per cent, their unemployment rate is lower than men's. Another noteworthy issue is women's high participation rate among all prime age groups, the distribution of age-specific participation rates having a similar inverted U-shaped curve to that of men (Lilja et. al., 1990). This suggests the significant role of the welfare state in removing the obstacles to the labour market participation of married women due to, for instance, childbearing.

The most dominant feature in figure 2.1 is, however, the occurrence of mass unemployment at the beginning of the 1990s; the overall unemployment rate more than quadrupled! A rapid worsening of labour market possibilities expanded the unemployment rates of both sexes. Analogously with previous recessions, an increase in unemployment was more pronounced among men. This reflects the persistence of sex segregation in employment. Male-dominated occupations are concentrated in cyclically sensitive industries, whereas women are typically employed in the public sector[1]. Since public sector employment is mainly full-time employment, part-time employment is fairly rare in Finland; only 11 per cent of the employed women worked in part-time basis in 1996 (Employment Outlook, 1997).

Figure 2.1 Unemployment Rates by Gender



Source: Finnish Labour Review.

Another picture of the occurrence of mass unemployment in the early 1990s is given in figure 2.2 which shows the average monthly flows in and out of unemployment. A net increase in the number of unemployed job seekers was over 10 000 persons per month during the years 1991 - 1993! To put this in context, the average number of unemployed persons was around 88 000 in 1989.

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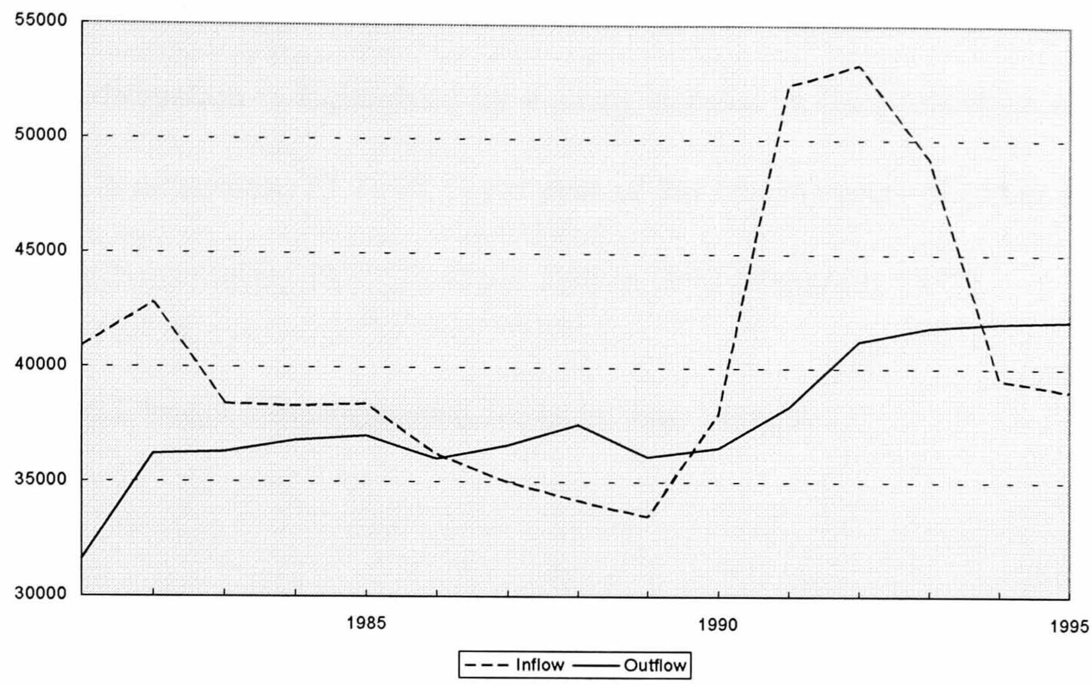
[1] According to Lilja et. al. (1990) some 85 per cent of women have always been employed in occupations where women comprise a majority. A good example of this is the proportion of women in health care and social work that was as high as 88.4 per cent in 1996, Santamaki-Vuori & Parviainen (1997).

Figure 2.2 Inflow and Outflow Figures; Monthly Averages in a Year.

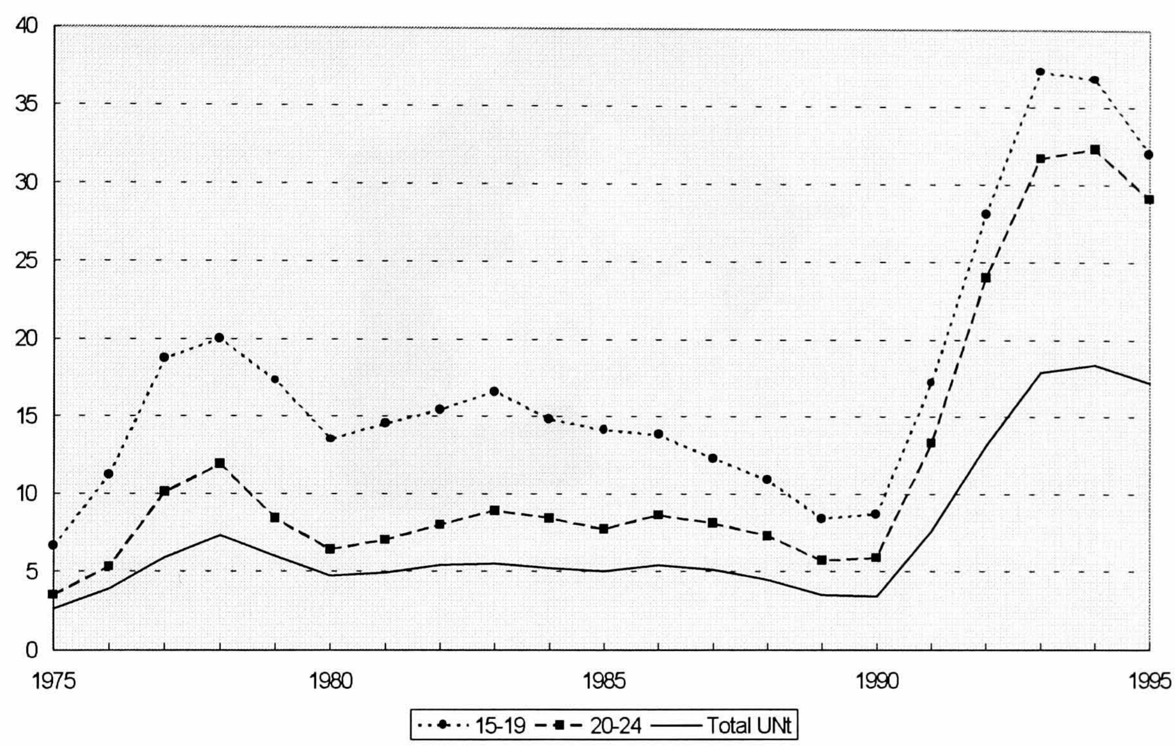


Source: Finnish Labour Review.

As discussed below, combating youth unemployment is one of the main aims of active labour market policy. Figure 2.3 gives the unemployment rates of teenagers (aged 15 - 19) and young adults (aged 20-24) together with the overall unemployment rate. The picture of youth unemployment in Finland is fairly similar to the other OECD countries. Even though the unemployment spells of young people are short, their unemployment rate is over two times higher than that of the adults. This gap tends to worsen in economic downturns and to improve when the economy is recovering. An increase in the relative rate of unemployment of young people in economic downturns can be partially explained by a decline in recruitment and by an increase in dismissals. The former makes it more difficult to find a job when entering the labour market, whereas the latter hits harder young persons who have had less time to accumulate firm-specific skills.

In addition to cyclical factors, also structural factors and the labour market participation of young people affect youth unemployment. Structural factors tend to reduce the demand for young workers through minimum wages, which are set through collective agreements, and employment security legislation. Labour market participation, on the other hand, affects the supply of labour. The greater flexibility of young persons' labour force participation is highlighted by a sharp increase in the proportion of young people enrolled in education; 27.3 (12.1) per cent of the 19 (24) years of old in 1989, the corresponding figure being 42.2 (20.4) per cent in 1993 (Parjanne, 1997).

Figure 2.3 Youth Unemployment Rates by Age Groups.



Source: Labour Force Survey.

Regional disparities in unemployment are persistent in Finland, the unemployment rate being the lowest in the Southern and Western parts of Finland and the highest in the Northern and Eastern parts of Finland. Figure 2.4 shows the location of selected labour districts. Low unemployment areas include two southern regions (the capital area Uusimaa and Turku) and one western region (Vaasa). High unemployment areas include the northern regions of Kainuu (situated in the Eastern half of Oulu) and Lappi as well as Pohjois-Karjala which is situated in the Eastern Finland.

Figure 2.4 The location of selected labour market districts

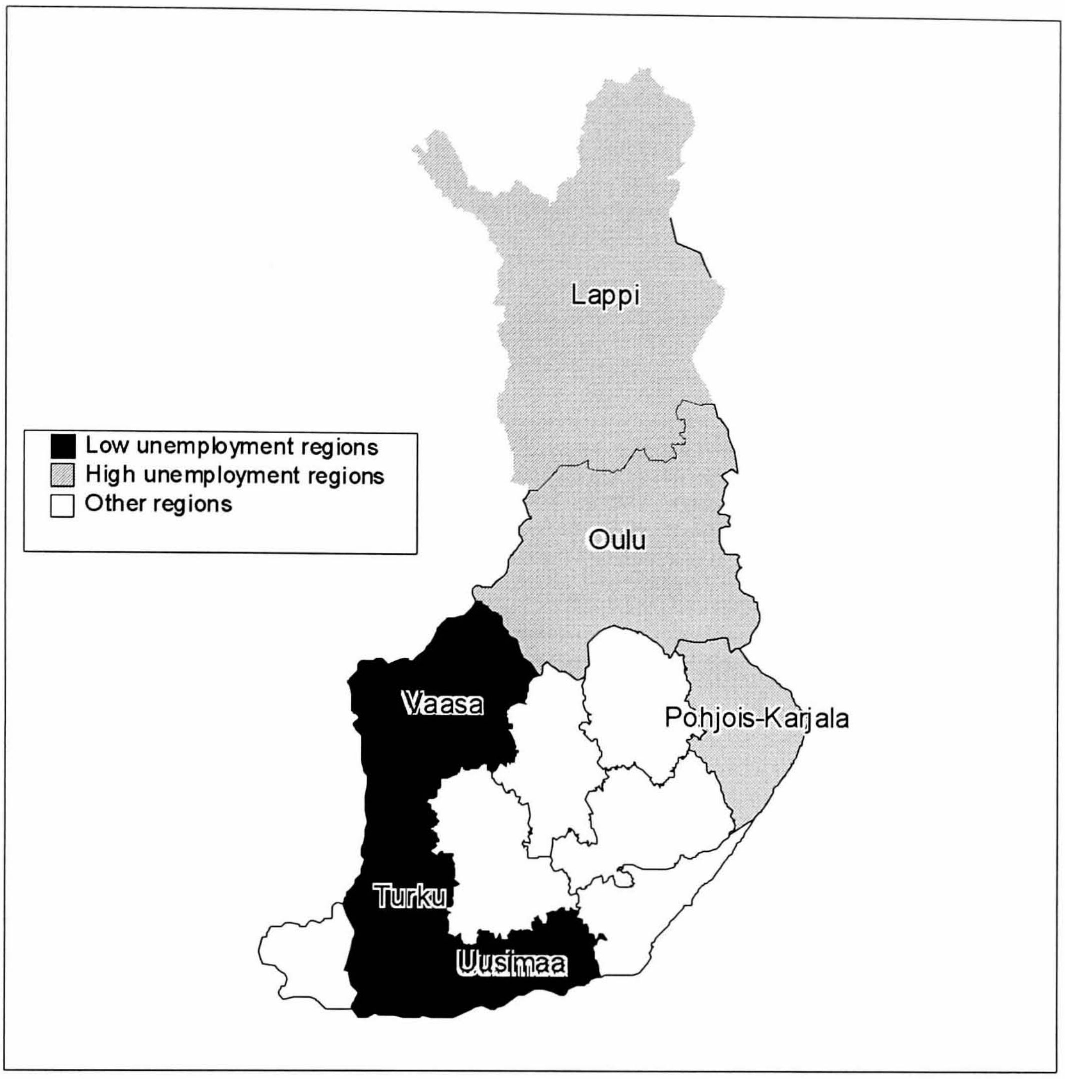
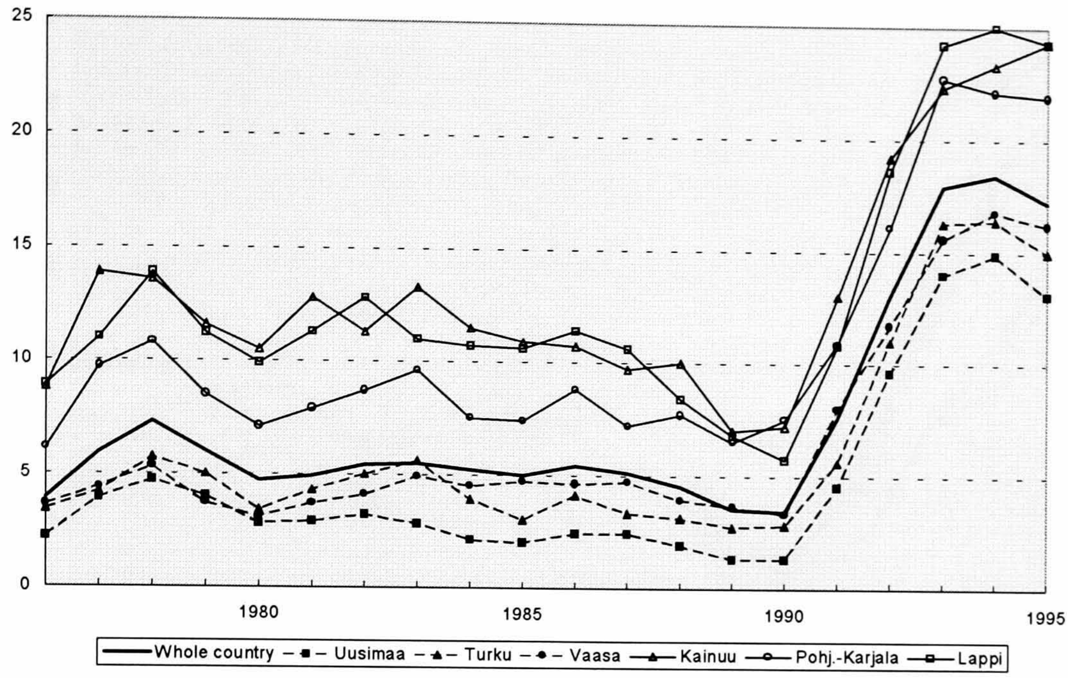


Figure 2.5 below reveals that the absolute difference between the highest and the lowest regional unemployment rate has remained in some 10 percentage points throughout the period of 1975 - 95. There are some indications that this gap declined at the end of the 1980s but it widened again during the recession years in the early 1990s. Accordingly, despite the target of reducing regional unemployment differences through active labour market programmes, there are no signs of convergence in regional unemployment rates. Whether this reflects the ineffectiveness of active labour market policy as a regional policy tool or not is one of the issues raised in chapters 5 and 6.

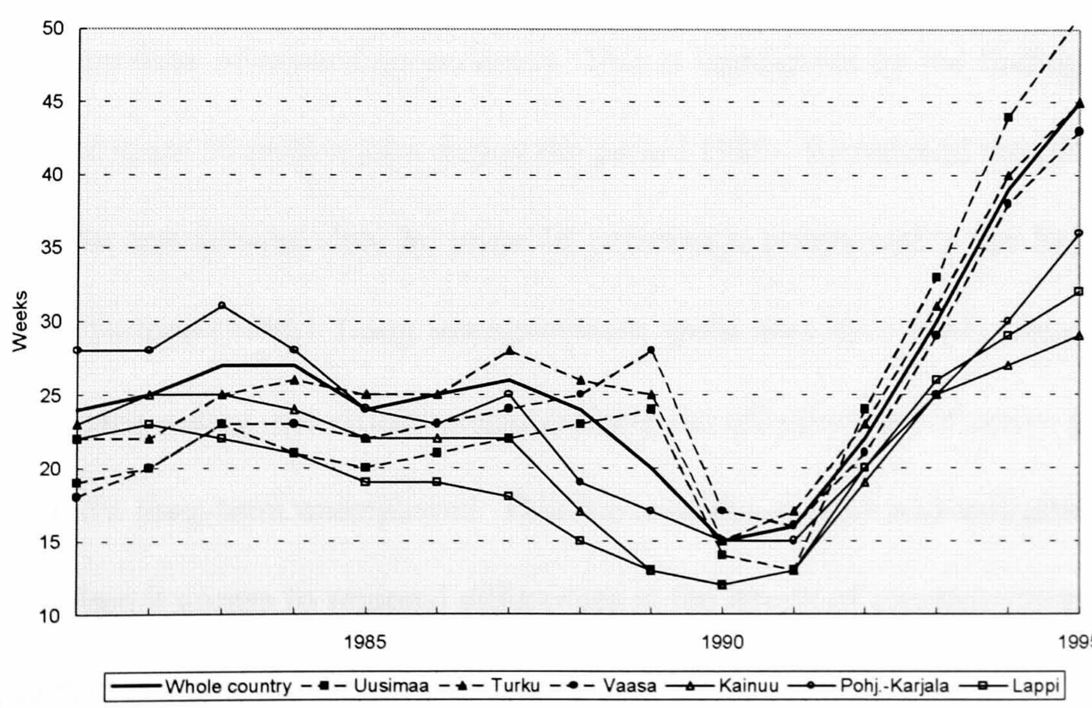
Figure 2.5 Unemployment Rates by Selected Labour Districts.



Source: Finnish Labour Review.

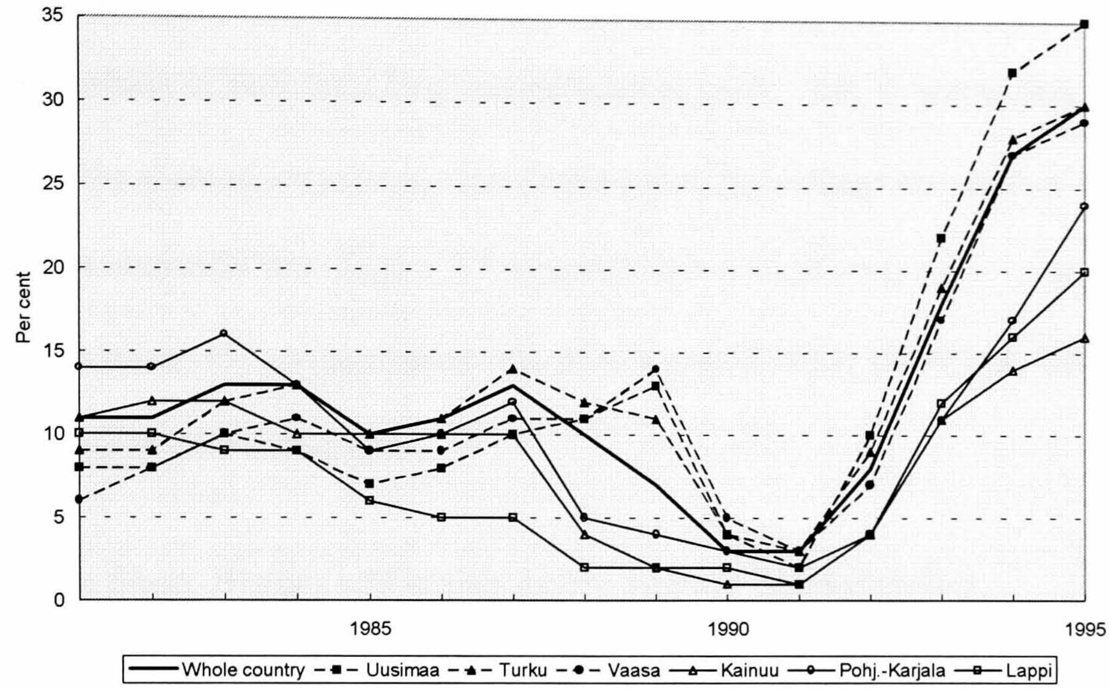
It is interesting to relate the picture of regional unemployment differences to regional differences in unemployment duration which are given in figures 2.6 and 2.7 below.

Figure 2.6 The Average Duration of Unemployment by Selected Labour Districts.



Source: Finnish Labour review.

Figure 2.7 Long-term Unemployment by Selected Labour Districts; Proportion of all Unemployed.



Source: Finnish Labour Review.

The figures above show the relation between lengthening unemployment spells and increasing unemployment. During the economic slump in the beginning of the 1990s the average duration of unemployment increased by 30 weeks and the share of the long-term unemployed by over 25 percentage points. The lengthening of unemployment spells implies that Finland is likely to experience high levels of unemployment also in near future, regardless of expanding economy. This is highlighted by the finding that a net increase of some 10 million jobs during the period 1985 - 91 reduced the proportion of the long-term unemployed only by some 15 percentage points within the EU, see Employment in Europe (1996). Long unemployment spells also have implications for active labour market policy, the crucial question being the effectiveness of active programmes in helping the long-term unemployed. This is one of the questions investigated in chapter 5.

When it comes to regional differences in the length of unemployment, it is surprising to find out that the duration of unemployment is adversely related to the overall level of unemployment shown in figure 2.5. This puzzle can be explained by the regional supply of active labour market programmes. Regions suffering from higher than average unemployment also receive a larger than average share of funds allocated to job placements, which in turn cuts long unemployment spells. But it seems that the reduction both in the share of long-term unemployed and in the average duration of unemployment is only a statistical one. Figure 2.5 suggests that a large proportion of programme participants return back to unemployment after a period of job placement. Chapters 5 and 6 take a closer look at this issue.

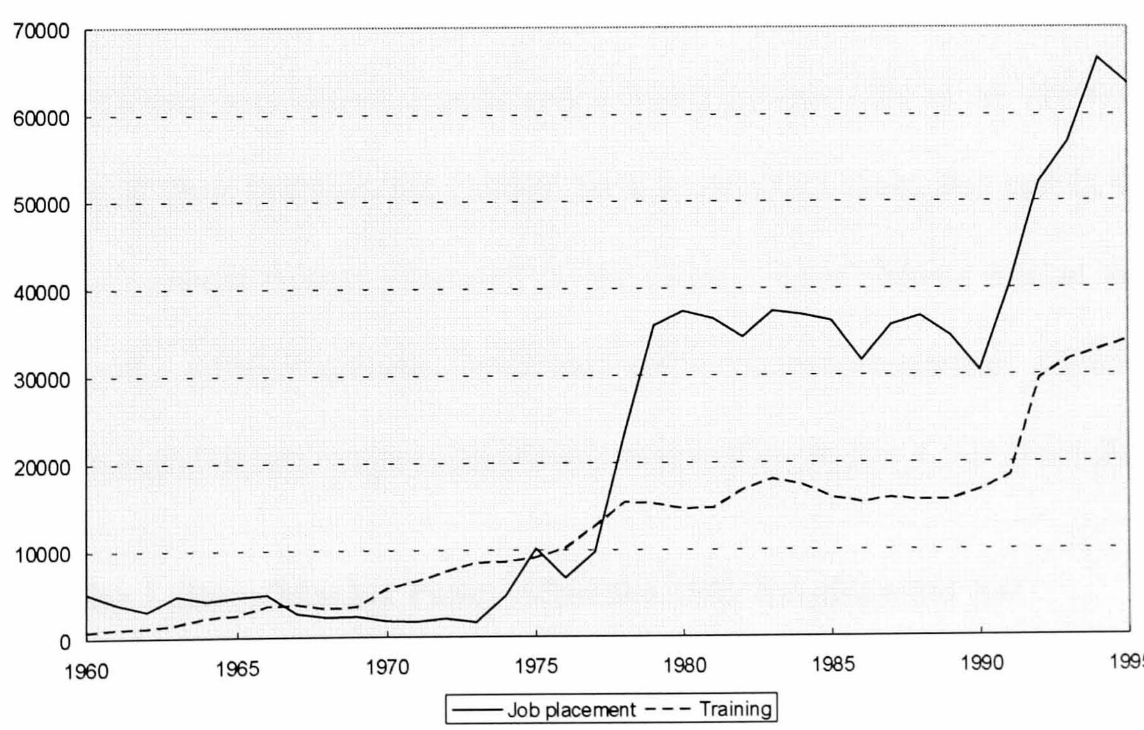
2.2. The Short History of Finnish Active Labour Market Policy

Before the 1963 Employment Act, Finland did not have a universal unemployment benefit system. Instead, municipalities were instructed to arrange jobs for the unemployed through public works. In the early 1960s over 50 per cent of the unemployed participated in public works. The total level of participants peaked at over 4 per cent of the labour force (about 90 000 persons) in 1960, after which it has steadily declined to under 2 per cent of the labour force. There are, however, considerable doubts over the importance of public works as an ALM policy. The labour administration's share of funds allocated to public works was around 25 per cent in 1960 and just 2 per cent in 1988. Accordingly, public works investments have not been carried out merely to create jobs for the unemployed implying that public works have been mainly used as another form of public employment, see Lilja et. al. (1990). Since this is even more pronounced in the 1980s, we have followed the labour administration and the OECD, according to which public works are not counted as selective employment measures.

Labour market training was established as a part of ALM policy by law in 1966, Mikkonen (1997). It was given the clearly structural goal of preventing labour shortages in rapidly growing manufacturing sector caused by the lack of vocational education among the middle aged. Figure 2.8 below implies that these structural targets have remained as principal goals of LMT until the early 1990s; its role in combating unemployment in economic slumps has been modest compared to selective employment measures. The unimportance of ALM policy as a demand side policy in the 1960s is clearly seen in the levels of programme participants during the recession years 1967 - 68.

The recession at the end of the 1960s lead to the revised Employment Act in 1971. The main outcome of this act was the introduction of the two scheme unemployment compensation system which consists of the means tested unemployment assistance scheme and the unemployment insurance scheme. In addition to strengthening the cash-support line, the Employment Act also strengthened the role of supply-side measures in labour market. This can be seen as an upward trend in the number of participants in labour market training.

Figure 2.8 The Number of Participants in Labour Market Training and Selective Employment Measures.



Sources: Finnish Labour Review and Juha Rantala.

Figure 2.8 shows that the level of selective employment measures remained modest until the first oil shock. The role of job placements as a demand side measure is clearly indicated by their growth in economic downturns in the 1970s; the number of participants more or less quadrupled during the two recessions in the years 1973 - 75 and 1977 - 80. While the growth of LMT programmes remained fairly modest, the focus of Finnish active labour market policy was shifted towards selective employment measures. One notable thing in Finnish employment measures is that they do not seem to move counter-cyclically. However, the clear-cut relation between expanding unemployment and increasing selective employment measures indicate the need to take account of the endogeneity of active programmes in chapter 4.

The administration and evaluation of labour market policy is the responsibility of the Labour administration which is directly responsible to the Ministry of Labour. The actual implementation of ALMPs is given to local public employment services agencies which are under the labour district administration. In line with Finnish corporatism employers' and employees' organisations can affect the design of labour market policy through various committees, boards and working groups, Lilja et. al. (1990). The most important of these bodies is the Council for Labour which takes also part in the Ministry of Labour's annual budget proposal. In this respect actual labour market policy is the outcome of a political process which may affect its macroeconomic efficiency, for instance through insiders' wage requirements analysed in chapter 4, see Saint-Paul (1996).

2.3. Active Labour Market Policy After the 1987 Employment Act

The microeconometric evaluations of the thesis employ the data from the years 1987 - 92. Hence, it is worth taking a closer a look at the changes introduced by the 1987 Employment Act which strengthened considerably the role of active labour market policy and especially its emphasis towards the youth and the long-term unemployed. The Employment Act introduced the obligation to arrange, as a last resort, either training or job placement for young persons and the long-term unemployed after 3 and 12 months in unemployment, respectively. Persons with a history of repeat unemployment spells became eligible after 12 unemployment months within the last 2 years. This raises the question of the effectiveness of large-scale employment measures, the issue which is put under scrutiny in chapter 6.

The obligation, which was almost totally fulfilled by selective employment measures, was implemented in stages during the years 1988 - 90. According to table 2.1, the main burden of implementation was carried out by municipalities, their share of all obligated, last resort job placements being around 70 per cent.

Table 2.1 Participant Outflow from Different Selective Employment Measures, Selected Years.

	1988		1990		1992	
	N	%	N	%	N	%
Persons employed as a last resort by the state	5836	8	13054	20	17982	17
Other state subsidies	4962	7	1971	3	2749	3
Persons employed as a last resort by municipalities	20537	28	29945	46	48132	44
Other municipal subsidies	20495	28	5580	9	4265	4
Employment by enterprises	10355	14	9049	14	24344	22
Enterprise allowance	3818	5	2716	4	3019	3
Other selective employment measures	7963	11	2907	4	8567	11
Total	73966	100	65222	100	109058	100

Notes: The figures correspond to the number of participants who have terminated a selective employment measure during the years 1988, 1990, and 1992. The first (second) column reports the number of (the percentage share of) participants in a job placement category.

Source: Aho, *et.al.* (1996).

Figures 2.6 and 2.7 above show the effectiveness of the 1987 Employment Act in cutting long unemployment spells. The obligation to arrange either training or job placement for the long-term unemployed was implemented in the high unemployment areas in 1988 and in the low unemployment areas in 1990[2]. During those years the proportion of the long-term unemployed dropped by some 5 percentage points in the high unemployment regions, the corresponding drop being around 10 percentage points in the low unemployment regions. But the overall effectiveness of large scale job placement programmes, such as one introduced in the 1987 Employment Act, requires that they do not merely reclassify the participants. They also need to improve the job prospects of the participants, the issue which is raised in chapters 4 and 6.

2.3.1. Unemployment Benefit System

At the end of the 1980s the main element of passive measures, i.e. the unemployment compensation system, consisted of the means tested unemployment assistance scheme and the earnings related unemployment insurance scheme governed by union funds.

During the period 1988 - 92 unemployment assistance was payable to all registered unemployed job-seekers aged 17 - 64 who were fit for work and looking for full-time employment, provided that they were not eligible for unemployment insurance. Persons under 55 years of age were subject to a means test. In contrast to unlimited unemployment assistance, unemployment insurance was payable for a maximum of 500 working days, provided that an unemployed person had been a union fund member for at least six months preceding the unemployment. The maximum payable days were further

[2] To recall, Kainuu, Pohjois-Karjala and Lappi are examples of high unemployment regions, whereas Uusimaa, Turku and Vaasa represent low unemployment regions.

increased by 400 days if an unemployed person was over 55 years of age at the end of the unemployment insurance period.

When it comes to compensation levels, the full unemployment assistance allowance was FIM 81 a day in 1988 (FIM 116 in 1992) with possible child increases. Income over a fixed maximum reduced the full amount of benefit by 75 per cent of the excess[3]. Nearly every type of income, personal as well as spouse's, is taken into account when determining the level of unemployment assistance allowance. In contrast, earnings related unemployment insurance does not have a means tested element in it. It also provides higher compensation levels, the allowance being the unemployment assistance allowance plus 45 per cent (42 after January 1992) of the difference between previous daily salary and the unemployment assistance allowance up to a break-point which is slightly higher than average earnings. After the break-point the addition is 20 per cent. Before July 1989 unemployment insurance allowance was reduced by 12.5 per cent after the first 200 days. Increases of unemployment insurance allowance for children are similar to unemployment assistance allowance and both unemployment compensation schemes are subject to taxation[4].

The replacement ratios of the unemployment assistance and unemployment insurance schemes were approximately 23 and 57 per cent for a single person in 1987[5]. The marked difference between the two schemes has remained throughout the 1990s; in 1994, the corresponding average monthly amounts of paid unemployment benefits were FIM 2554 and FIM 4487, respectively (Santamaki-Vuori & Parviainen, 1996). As

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[3] A fixed maximum for a single people was FIM 2690 a month in 1988 and FIM 3700 a month in 1992, the corresponding figures for people with dependants being FIM 4030 and FIM 5540. The income cut-off level was FIM 8710 for married couples without children and FIM 6870 for single persons in 1992.

[4] Statistical Yearbook of the Social Insurance Institution (1992)

[5] The ratios are based on average before tax hourly earnings of an employee which was FIM 44.87 in 1987 (Asplund, 1993).

mentioned above, unemployed union fund members became eligible (before 1996) for the higher compensated unemployment insurance scheme after six months in employment which equals the period of statutory obligation introduced in the 1987 Employment Act.

It would be surprising if the opportunity to become eligible for higher compensated unemployment insurance allowance through statutory obligation had no effect on the incentives of some unemployed persons to accept low paid jobs. Especially, since the previous salary employed in calculating unemployment insurance allowances remained unchanged if any temporary work done did not exceed six months. This hypothesis is among the things which are put under scrutiny in chapter 6. It is worth noticing that the coexistence of active and passive labour market measures is implicitly included in the estimated programme effects also in the other chapters of the thesis.

2.3.2. Labour market Training

Labour market training (LMT) is primarily adult, non-basic vocational training which often involves work practise. In principle it is offered only to persons over 20 years of age but in some cases younger persons are eligible for LMT. Trainees who are not members of union unemployment funds, or otherwise eligible for unemployment assistance, obtain a training allowance which takes the form of a basic allowance equalling unemployment assistance allowance. In 1991 the basic training allowance was payable at its full rate if a trainee's monthly income from primary employment was below FIM 700 and his additional monthly income from a statutory social security benefit or part-time employment did not exceed FIM 3139. The basic training allowance is reduced by 75 per cent of the income in excess of limits. The earnings related training allowance is payable to the unemployed who are eligible for unemployment insurance allowance.

Increases for children are payable in the same way as with the unemployment compensation schemes. In addition, a maintenance allowance is payable in respect of travel and food expenses incurred while participating in LMT. In 1992 the average unemployment assistance allowance and training allowance were FIM 119.8 and FIM 163.4 a day, respectively[6]. Since the training allowance is generally higher than unemployment compensation, it should provide incentives to participate in training programmes, at least when compared to open unemployment.

As mentioned above, labour market training was given structurally oriented targets in the 1960s. The aim of preventing labour shortages through LMT, which is one part of more general targets of equating labour demand and supply and facilitating economic growth/preventing unemployment, has remained throughout the decades. In addition, the law has two individual goals, viz. to stabilise unemployed persons' employment and/or to reduce the threat of unemployment. The latter also makes unemployed workers eligible for LMT. The share of trainees without unemployment experience has remained fairly low, being some 20 per cent in the 1980s, see Lilja et. al. (1990).

The economic slump in the early 1990s induced alterations in labour market training programmes. First, the acceptance ratio dropped by some 10 percentage points to 50 per cent. Second, the drop-out rate fell from 14 per cent in 1989 to below 9 per cent in 1995. Third, the share of laid-off trainees increased to over 40 per cent. This was a temporary phenomenon, their share returning back to under 10 per cent by the mid 1990s. Fourth, the monopoly of special vocational centres in offering training courses was broken down. The change has been rapid, the share of vocational centres from purchased training days was only 56 per cent in 1995, see Mikkonen (1997). One explanation for the decline in the share of vocational centres is an enormous increase in the number of

[6] Statistical Yearbook of the Social Insurance Institution (1992)

trainees during the early 1990s recession, a rival explanation being the effectiveness of training courses provided by outside vocational centres. The above changes raise questions concerning the effectiveness of training programmes in different eras of unemployment and especially the role played by a sharp increase in the proportion of laid-off trainees. These issues are analysed implicitly in chapter 4 and explicitly in chapter 6.

2.3.3. Selective Employment Measures

A standard employment subsidy paid to an employer varies among sectors, covering all wage costs in central government and equalling the unemployment allowance in local government and in the private sector. The employment subsidy can be increased by the maximum of 100 per cent under certain conditions. At the beginning of the 1990s the employment subsidy varied from FIM 2500 to FIM 4300 a month. Accordingly, the paid employment subsidies cover less than half of the average wage costs. During the placement period a participant receives the prevailing market wage set in collective agreements. In Finland collective agreements between employers' and employees' organisations are binding throughout the economy, so the wage rate is not dependent on the union status of a participant. Accordingly, job placements offer much higher compensation than training courses which may be reflected in some individuals choices' between different types of active programmes.

Unlike labour market training, selective employment measures are more directly targeted at young persons and the long-term unemployed. The relative importance of these two groups has, however, changed during the early 1990s. At the end of the 1980s the vast majority of placements were targeted at the young (61.8 per cent), the share of the long-term unemployed being under 10 per cent (based on figures given in Lilja et. al., 1990, table 63). The corresponding figures in 1993 were 23.6 and 43.6 per cent (based on figures given in Skog, 1994, appendix 4). There seems to be also great differences across placement sectors. Firms employ almost 70 per cent of the youth participants (24 per cent of the long-term unemployed), whereas municipalities concentrate on employing the long term unemployed participants (48.5 per cent and only 27.5 per cent of the youth). The targets, which are to be achieved by selective employment measures, are individually oriented and consist of cutting long unemployment spells, improving participants' labour market position and strengthening their possibilities for stable work careers. The changes in the composition and in the level of selective employment measures raise questions concerning the effectiveness of job placements across different individual characteristics, across employer sectors and at the different eras of unemployment. These issues are examined in chapters 5 and 6.

2.4. Finally

The aims given both to labour market training and to selective employment measures highlight the emphasis of Finnish active labour market policy towards employment related issues. There are no explicit targets of improving the earnings of the 'working poor' which are common, for instance, in the USA. For this reason, the emphasis of the thesis is naturally focused on evaluating Finnish ALMPs through their impact both on participants' employability and on the overall unemployment level.

A rapid increase in unemployment during the early 1990s put the statutory obligations introduced in the 1987 Employment Act under pressure. The obligation was relaxed at the beginning of 1992 and finally totally lifted in 1993. However, since these changes do not concern the evaluation period of the thesis, they are not discussed above. The evaluation period is driven purely by the availability of data. The quarterly data employed in the macroeconometric part of the thesis is collected from the data sets of the

Bank of Finland and the Ministry of Labour. The Ministry of labour started to publish quarterly data in the year 1980 and the data set of the Bank of Finland was available only until the year 1992. The microeconometric parts of the thesis, on the other hand, are carried out by employing large, register based data set collected by the Statistics Finland. This data set covers the years 1987 - 1992. Finally, according to the government plan the number of participants in active programmes will remain at the current exceptionally high levels, at least, to the next millennium.

CHAPTER 3.

A review of the Literature

The purpose of this chapter is to briefly summarise the existing evidence on active programmes' employment effects. This question has been studied both from the macroeconometric and the microeconometric points of view. The increasing emphasis towards activating labour markets has been reflected especially in the number of macroeconometric studies which were virtually non-existent before the 1990s. In microeconometrics on-going programmes have been evaluated for decades. The bulk of this research has focused on earnings related issues of labour market training in the USA. Consequently, the question of individuals' subsequent employment prospects has remained relatively unexplored. This reflects the differences in the aims of active labour market policy that prevail between the USA and Europe. In the latter countries active programmes are mainly targeted against unemployment, whereas in the former country they are aimed at helping the working poor.

Both macro and micro approaches for assessing ALMPs have their own gains and drawbacks. Microeconometric evaluations have been criticised due to their partial equilibrium nature, see Blanchflower et. al. (1995) and Calmfors & Skedinger (1995). This inability of microeconometric evaluations to assess the changes in the equilibrium level of unemployment arises from three sources, viz. dead-weight effect, substitution effect and displacement effect. Each of these three effects reduces the potential downward impact of active programmes on total unemployment, either because some of the participants would have got hired anyway (dead-weight) or because they replace other workers in the same firm (substitution)/in other firms (displacement).

To be fair to microeconometric evaluations, it has to be said that many of the macroeconometric studies do not try to assess the equilibrium unemployment effects of ALMPs, either. Furthermore, the necessary condition for observing any macroeconomic gains is that active programmes benefit participants' subsequent employment prospects. Since macroeconometric studies cannot shed any light on this issue, these two research branches have to be considered as complements to each other. Especially, since nothing ensures that the policy implications of studies examining individual and macroeconomic effects will coincide with each other. This follows if participants, say, in training courses either give up or reduce their job seeking efforts during the course. Then even in the absence of displacement effects, potential increases in participants' employability do not necessary show up at the macro level as a reduction in total unemployment.

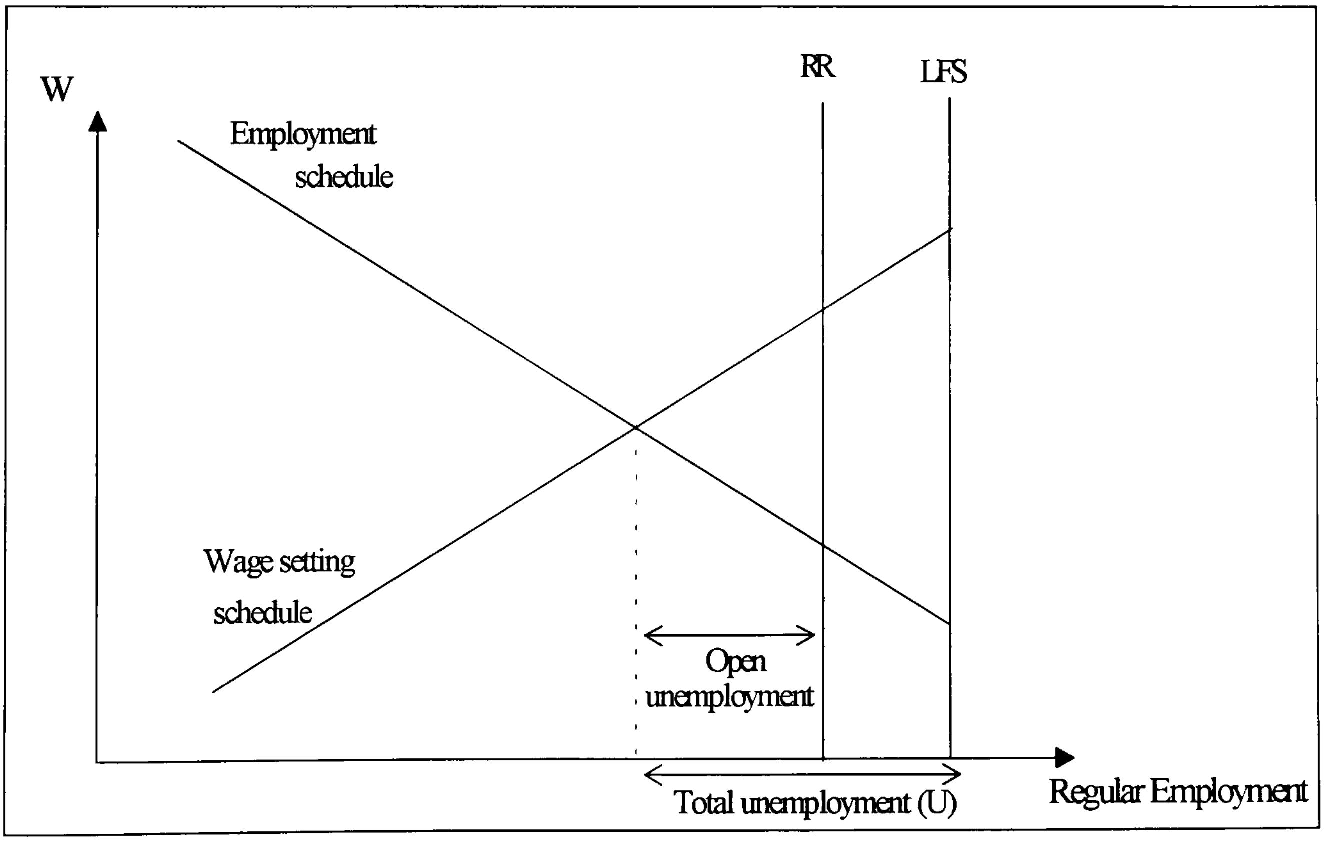
3.1. Macroeconomic Studies

3.1.1. Framework for Analysis

If labour markets are to be made more effective through active labour market programmes there has to be some inefficiencies which ALMPs can tackle. It is quite common to consider competitive markets as a benchmark for efficiently functioning markets. Blanchflower et. al. (1995) examine the arguments in favour of active labour market programmes against this benchmark. Market failures put forward in their study included inefficiencies in job search/recruiting, imperfect competition in product and labour markets, price distortions induced by labour market institutions, and imperfections in financial markets (insurance markets against the event of unemployment). A convenient way of introducing these market imperfections to a unified macroeconomic framework is through the following two figures employed in OECD (1993), Calmfors (1994) and Calmfors & Skedinger (1995), *inter alia*.

Figure 3.1 shows an upward sloping wage-setting schedule which, under imperfectly competitive labour markets, effectively replaces the labour supply curve in determining the labour market equilibrium. The setup is consistent with several models of involuntary unemployment, such as union wage bargaining models (for descriptions of different bargaining models, see for instance Pencavel, 1991, and Booth, 1994), Efficiency wage models (Shapiro & Stiglitz, 1984, and Akerlof & Yellen, 1986), and the Insider-Outsider theory (Blanchard & Summer, 1986, and Lindbeck & Snower, 1986). The downward sloping employment schedule hypothesises the negative relationship between real wages and regular employment. Under imperfectly competitive product markets and profit maximising firms it can be interpreted as the labour demand curve or equivalently as the price setting curve, see Layard & Nickell (1986).

Figure 3.1 The Labour Market Outcome in Imperfectly Competitive Labour Markets.



Notes: Modified from Calmfors (1994). RR = Labour force (LFS) less ALMP participants.

Figure 3.2 The Beveridge Curve.

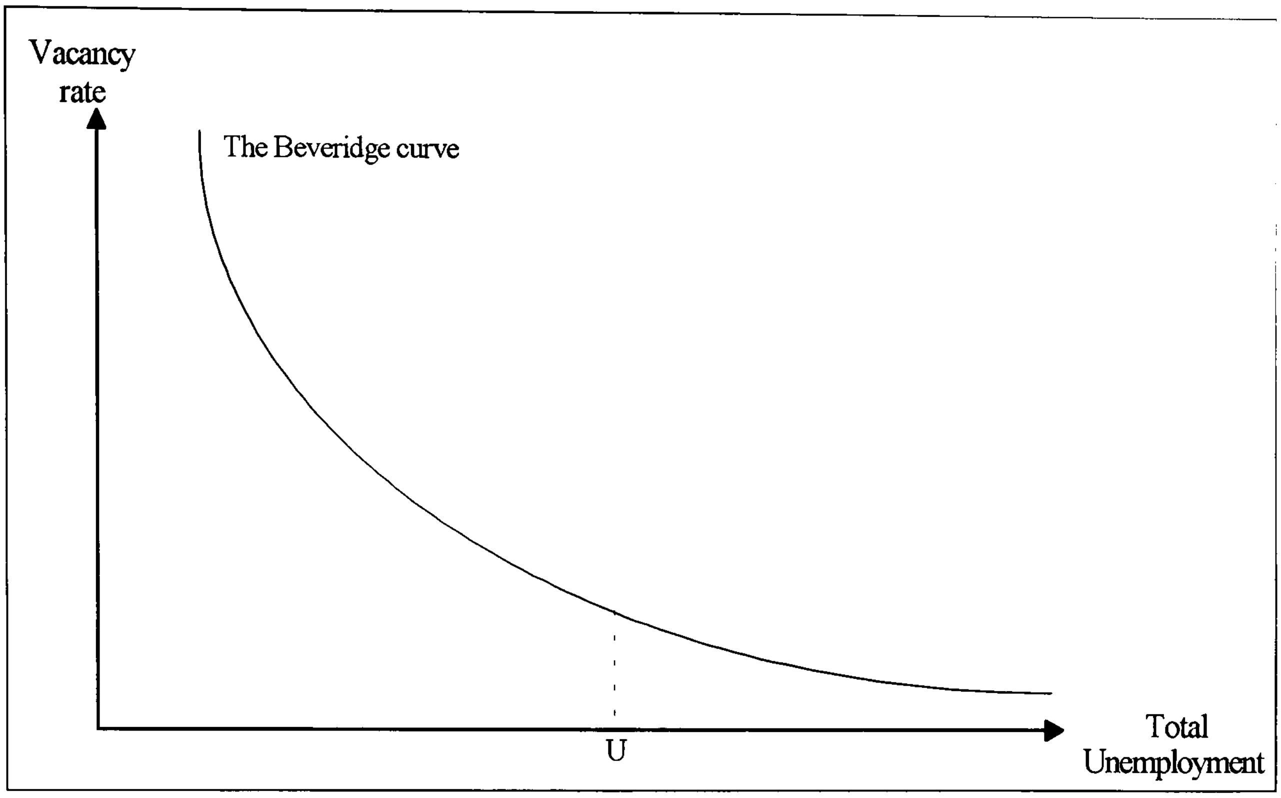


Figure 3.2 shows the Beveridge curve, see Blanchard & Diamond (1989), which traces the labour market equilibrium condition as a locus of points which equate the flow into and out of unemployment at the given unemployment rate. The downward sloping curve gives the negative relationship between vacancies and total unemployment, a higher rate of available jobs being associated with lower total unemployment. If figure 3.1 deals explicitly with the impact of non-competitive wage setting on labour market outcome, figure 3.2 measures the matching process in labour markets. Due to imperfect and costly information there exists simultaneously both unemployed job seekers and recruiting employers. The more effective is the matching process the closer is the Beveridge curve to the origin, associating a lower total unemployment rate to a given vacancy rate.

Empirical macroeconometric studies have employed either the Layard-Nickell (figure 3.1) or the Beveridge curve (figure 3.2) framework in assessing active labour market programmes. Even though the former concentrates on labour market institutions and the latter on matching effectiveness, they should yield similar conclusions given that the equilibrium levels of total unemployment implied by the two models must coincide (defined as U in figures 3.1 and 3.2). Below we have examined several channels through which active labour market policy may affect the equilibrium unemployment. Table 3.1 is based on the Layard-Nickell framework due to its analytical convenience for the current purpose.

Table 3.1 The Potential Impacts of ALMP on the Equilibrium Level of Unemployment.

Effect	*Total UNt*	*Open UNt*	*Shifting schedule in figure 3.1*
Improved matching	Reduce	Reduce	WS and E rightwards
Increased productivity of participants	Reduce (Increase)	Reduce (Increase)	E rightwards (WS leftwards)
Work test	Reduce	Reduce	LFS leftwards
Reduced discouragement	Increase (Reduce)	Increase (Reduce)	LFS rightwards (WS rightwards)
Deadweight/Substitution	Increase	Increase	E leftwards
Reduced welfare loss	Increase	Increase	WS leftwards

Notes: Modified by grouping together various effects presented in the following studies: OECD (1993), Calmfors (1994), Calmfors & Skedinger (1995). WS = Wage-setting schedule; E = Employment schedule; LFS = Labour force schedule.

Let us first concentrate on the impacts of ALMPs on labour demand (E = Employment schedule). An increase in the effectiveness of the matching process together with the better productivity of programme participants expands the demand for labour, and hence reduces unemployment, at the given wage level. To improve the efficiency of matching active programmes have either to reduce occupational (industrial, regional) mismatch or to boost job search activity. Or they may work as a signalling device (Spence, 1973) lessening employers' uncertainty about programme participants as recruits. However, the latter effect is likely to worsen non-participants' position reducing the overall matching process effect. This worsening of others' labour market possibilities is known as substitution/displacement which shifts the labour demand curve leftwards in figure 3.1 leading to higher unemployment, *ceteris paribus*.

Having said all that, it is likely that the impact of ALMPs on the labour demand schedule remains negligible. First of all, Blanchflower et. al. (1995) argue that the matching process is fairly effective in which case there is little room for improvement through active labour market policy. Secondly, an increase in productivity is also likely to introduce wage pressures captured by an upward shift of the wage-setting curve, see Bean et. al. (1986). This in turn tends to leave regular employment more or less untouched, see Calmfors (1994). Finally, a drop in open unemployment caused by more productive programme participants (the *ceteris paribus* result was that only regular employment remains untouched) is mostly offset by displaced regular workers.

Turning next to the impact of active programmes on wage-setting (WS = wage-setting schedule). *Ceteris paribus*, a lower wage level is connected to higher employment and hence lower unemployment. A fall in wages at the given employment level is captured by a rightward shift of the wage-setting schedule which may happen through the improved matching process and/or through the reduced discouragement effects of ALMPs. Both of these effects tend to tighten labour markets, the former by reducing the number of job seekers and the latter by increasing the competition which insiders face. This in turn leads to a fall in insiders' wage demands. As far as active programmes reduce welfare losses in the event of unemployment, they also have a counteracting impact on wages. This is suggested by wage bargaining theories which hypothesise a positive relationship between collectively set wages and alternative wages elsewhere in the economy. By offering the compensation level beyond unemployment benefits, ALMPs reduce the insiders' incentives to moderate wages.

Traditionally active programmes have been selective and targeted (mainly) at individuals with labour market difficulties. These persons have also the largest risk of becoming discouraged, which in turn tends to reduce the number of unemployed actively seeking work. Provided that ALMPs help to keep them in connection with labour markets by reducing discouragement, they increase the effective labour supply and hence shift the labour force curve (LFS) rightwards. Accordingly, reduced discouragement causes an increase in the equilibrium level of unemployment, the effect which is lowered by the reduction in wage pressures as discussed above. Active programmes may also lessen the supply of labour, and hence recorded unemployment, if they have a work test function. This, of course, requires that individuals who do not accept a programme offer become ineligible for unemployment benefits.

Before surveying the empirical macroevidence over the above effects, we conclude this section with a few things worth bearing in mind. On theoretical grounds the impact of active programmes on the equilibrium level of unemployment (employment) is ambiguous and hence basically an empirical question. It would be highly surprising if the same wage setting/employment effects raised in different countries since different labour market institutions result in different labour market outcomes. The differences become even more pronounced if unemployment elasticities of wages/labour supply or the wage elasticity of labour demand vary across countries. One part of the question mark about elasticities is highlighted in Blanchflower & Oswald (1994) who report remarkable similarities in the wages-unemployment relation across countries. Unfortunately, systematic studies of the same size over the elasticities of labour demand and labour supply have not been executed, making it hard to assess the importance of country specific slopes of these curves. Finally, both the size and the composition of active labour market programmes affect their impact. These, together with the overall unemployment situation, differ vastly both across countries and in time.

3.1.2. Cross-Country Studies

In cross-country studies the main issue of interest has centred on the general equilibrium effect of ALMPs which has been analysed through the relationship between cross-country differences in unemployment rates and in expenditures on ALMPs. In few cross-country studies the focus has been on cross-country differences in real wage flexibility or differences in changes in wages/employment. Excluding Jackman et. al. (1990), these studies have adopted the theoretical framework given in figure 3.1 that consists of imperfectly competitive product markets and wage-setting between workers and firms. Control factors differ from one study to another, the common elements mainly proxy the institutional features, especially the degree of corporatism and the generosity of unemployment benefits. In the Jackman et. al. (1990) study the main issue of interest is the location of the Beveridge curve, so the vacancy rate is included in the right hand side. The study by Scarpetta (1996) examines also some open economy factors, such as terms of trade and foreign competition, together with taxation effects through the wedge between product and consumer prices, and interest rates. The parameter estimates of the ALMP variable has to be interpreted as the net effect of various channels discussed in section 3.1.1. Table A3.1 in the appendix summarises the main findings of cross-country studies.

As a general overview, cross-country studies seem to suggest that higher expenditure on ALMPs in connected to lower unemployment, positive parameter values being reported only in the Forslund & Krueger (1994) study. Studies focusing on wage related issues seem to confirm the beneficial effects of ALMPs; active programmes have been found to increase real wage flexibility (Heylen, 1993) and reduce real wages (OECD, 1993). The views, however, differ on the question of which groups gain from active programmes. The results reported in Scarpetta (1996) indicate that active programmes might be effective in reducing short-term unemployment, whereas the results reported in Heylen (1991) and Jackman et. al. (1996) suggest that the target group should be the long-term unemployed.

These favourable results have not been unilaterally accepted, the main concern being the specification and the endogeneity of the ALMP variable, see Forslund & Krueger (1994), Calmfors (1994), and Kenyon (1994). Table A3.1 reveals that the impact of active programmes has usually been examined through some relative measure of programme expenditures that includes the number of unemployed persons in the denominator. This runs the risk of introducing negative correlation between the ALMP variable and the dependent unemployment variable since spending on ALMPs is in relation to unemployment. Excluding Sweden, the number of programme participants (accordingly total spending) has a tendency to rise less than proportionally with unemployment (Grubb, 1993), in which case an increase in unemployment leads to a reduction in the value of the ALMP variable. The same line of argument can also explain the negative relation between spending on ALMPs and employment reported in the OECD (1993) study given that the wage bill behaves procyclically.

Another worrying issue concerning the robustness of the results of cross-country studies follows from the limited number of observations. The sensitivity of estimates to 'outliers' is highlighted in two of the most recent studies; in Scarpetta's study the exclusion of Sweden from estimations increases the absolute value of the estimated coefficient of the ALMP variable up to -0.23, whereas in the study by Jackman et. al. the exclusion of Sweden eliminates the effect of ALM spending on long-term unemployment. One task for further research is to find out whether these differences arise from a different set of countries and/or different explanatory variables. It has to be noted that the random effects model adopted in the studies by Jackman et. al. and Scarpetta does not ease the problem of limited observations. When the time period is fixed, the parameter estimates, which in these studies are estimated by GLS, are consistent only with a large number of countries, Hsiao (1986). Furthermore, an increase in the number of observations may produce additional difficulties, such as serial correlation due to serially correlated omitted variables and the non-normality of the randomness of country specific effects. Hence there exists considerable doubt on whether two period random effect estimations give any additional information over and above traditional least squares estimations.

3.1.3. Time Series Studies on Wage Pressure

Unlike in general equilibrium cross-country studies, the focus of time-series studies has usually been on some particular aspect of active labour market policy. The main area where empirical research exists is the impact of ALMP on wage setting in unionised labour markets. In these studies the parameter estimates present the net effect of various counteracting channels through which ALMPs may shift the wage-setting schedule as discussed in section 3.1.1. A typical empirical wage equation consist of variables which come into analyses through a firm's revenue function and a union's objective function. To assess the wage pressures of ALMPs some combination of the number of unemployed persons (U) and programme participants (R) is also included in estimations. Equations (1) - (3) below report various specifications through which the relation between active programmes and wages has been examined. For explanatory purposes equations (1') - (3') give the rewritten forms of basic relations. The rewritten form of the first equation employs the condition u = 1 - n - r, in which n stands for regular employment.

$$(1)\quad w = \alpha_0 + \alpha_1 u + \alpha_2 r + \ldots \qquad (1')\quad w = \alpha_0 + \alpha_1(1 - n - r) + \alpha_2 r + \ldots$$

$$(2)\quad w = \beta_0 + \beta_1(r+u) + \beta_2\left(\frac{r}{r+u}\right) + \ldots \qquad (2')\quad w = \beta_0 + (\beta_1 - \beta_2)(r+u) + \beta_2 r + \ldots$$

$$(3)\quad w = \lambda_0 + \lambda_1(r+u) + \lambda_2\left(1 - \frac{r}{r+u}\right) + \ldots \qquad (3')\quad w = \lambda_0 + (\lambda_1 - \lambda_2)(r+u) + \lambda_2 u + \ldots$$

Usually the unemployment rate u and the programme participation rate r are measured as per cent of the labour force, but in some studies they are measured as relative to the level of employment. All studies have adopted the log-linearity assumption so the lower-case letters stand for logarithm transformations. The ratio of programme participants (r) to total unemployment (r+u) has been named as the accommodative stance in Calmfors & Forslund (1991). It proxies the probability of participating in a programme in the event of unemployment.

Negative parameter estimates in equation (1) suggest downward wage pressure from open unemployment (u) and active programmes (r). These effects are readily readable from the estimated parameters, $\alpha_1 < \alpha_2$ implying smaller wage resistance of active programmes than open unemployment. If the programme variable can be constrained to zero both from the statistical and the economic point of view, programme participants are perfect substitutes for regular employment in terms of wage setting. At the given level of open unemployment a reduction in regular employment that is totally offset by an increase in programme participants has no wage effect (Calmfors 1994). Finally, a positive parameter estimate for the programme variable indicates that ALMPs actually expand wage pressures. In terms of figure 3.1, the wage schedule shifts leftwards (the reduced welfare effect dominates) if $\alpha_1 < \alpha_2$.

In the last two equations the equivalent conditions for the wage pressure effect of active programmes can be obtained from equations (2') and (3'). Active programmes and open unemployment have the same impact on wages, i.e. only total unemployment matters, if β_2 (λ_2) does not differ from null. In the second equation active programmes have smaller impact on wages than open unemployment if $\beta_1 < 0$ and $\beta_2 > 0$, the equivalent condition being $\lambda_2 < 0$ in equation (3). If the total unemployment variable (r+u) disappears from equation (2'), i.e. $\beta_1 = \beta_2$, only active programmes have any impact on wages. In equation (3') the main determinant in suppressing wage pressures is open unemployment if the condition $\lambda_1 = \lambda_2$ holds.

Turning next to the estimates of the wage pressure presented in the literature. Given the greater emphasis towards ALMP in the Nordic countries, it is hardly surprising that empirical wage-setting studies have been executed with Nordic data. The first striking thing to be noticed from the summary table A3.2 in the appendix is that only 6 estimations out of 17 produce conventionally significant parameter estimates for the ALMP variable. This complicates the interpretation of the dependence between active programmes and wages if analyses are based on the accommodative stance variable, r/(r+u). On the one hand the reported parameter estimates imply smaller wage resistance of ALMPs than open unemployment. On the other hand the statistical insignificance of these estimates suggest that only total unemployment affects wages, in other words active programmes and open unemployment have the same downward effect on wages. This conflict does not arise when programme and open unemployment variables are separately included in estimated equations.

When it comes to differences across countries, the results largely agree that active labour market policy has increased wage pressures in Sweden and reduced them in Norway[1]. Given the Swedish emphasis towards ALMPs, the results suggest that the

[1] The study by Raaum and Wulfsberg (1998) examines the impact of ALMPs on wages by employing Norwegian industry level data which consists of 5428 firm over the years 1980 - 1991. The estimated total wage elasticity of active programmes is almost identical to the ones reported in time series studies being around -0.1

reduced-welfare loss effect is a dominate factor only when active labour market programmes are 'over ambitious' compared to prevailing unemployment. This is consistent with the Norwegian experience with low unemployment and moderate levels of active programmes. A rival explanation for the Swedish experience is the simultaneity bias due to the tendency of programme participation to increase more than proportionally with unemployment in Sweden. An increase in real wages, which leads to a fall in employment, expands the size of ALMPs by more than open unemployment, which might have biased the estimated parameters upwards, see Calmfors (1994).

The results estimated for the other countries, viz. Denmark and Finland, are less clear-cut. From the statistical point of view insignificant parameter estimates imply either zero effects or downward effects of ALMPs on wages, depending on the model. However, the signs of parameter estimates suggest a moderate upward pressure on negotiated wages. All in all it may be safe to conclude that previous studies support the view that Danish or Finnish active labour market policy has not had any wage pressure effects, the conclusion being slightly stronger for Denmark.

As was the case with the cross-country studies, the results produced by time series estimations have not been unilaterally accepted. All of the surveyed studies have employed yearly data in examining the wage-setting relation. Hence, these studies are not completely secured from the limited number of observations problem which has been one of the main arguments against cross-country studies. Another problem common for all macroeconometric studies is the simultaneity bias. In this respect time series studies have a comparative advantage over cross-country studies. They have a possibility, which is also usually employed, of constructing reliable instruments from past observations. A final difficulty associated with time series studies follows from cyclical effects which partially determine the scale of ALMPs, Jackman et. al. (1996). Provided that cyclical effects are not totally controlled in estimations, together with the usual assumption of fixed parameters, the end-point estimates may be give a biased picture if the impact of active programmes varies along the business cycle.

3.1.4. Other Studies

Calmfors & Skedinger (1995) examined the relationship between regional total unemployment rates and two categories of ALMPs, viz. training and job-creation. The data employed in the study consists of 24 Swedish regions over the years 1966 - 90. The first conclusion of the results is that job-creation programmes tend to crowd out regular employment, the effect being some 60 - 90 per cent. This implies a 1 - 4 percentage points fall in total unemployment if selective employment measures are expanded by 10 percentage points The second result is that training programmes have a more favourable effect on regional total unemployment. Finally, there is no substantial evidence that active programmes help young people.

Calmfors & Skedinger study employs dynamic panel data models and the fixed effect model with four year non-overlapping averages. They estimate these models both in levels and in first differences by employing both OLS and IV estimation methods. In the IV regressions all independent variables (active labour market policy variables and the lagged regional unemployment rate) are treated as endogenous. When the model is estimated in first differences, the lagged dependent variable is instrumented with its second lag as suggested by Anderson and Hsiao (1981).

From the methodological point of view, these results have to be considered with care for various reasons. First, all estimators employed in estimating the models are consistent only when the number of regions approaches infinity, see Sevestre & Trognon (1992). Second, other factors influencing employment are controlled either by regional dummy variables or by the national unemployment rate, so the results may suffer from omitted variable bias. Authors are well aware of this and they argue that the problem tends to disappear the longer the observation period since the actual rate of unemployment is then likely to be closer to the equilibrium rate. Third, the results tend to vary across different specifications which, according to authors, arise from simultaneity and identification problems common to all macroeconometric studies. Despite these shortcomings, the results are interesting given the attempt to separate the effects of different programmes.

The final category of which there exists macroeconometric research is the displacement effects of ALMPs. Time series evidence on displacement/substitution is based either on unemployment flow analyses (Rantala, 1995, Eriksson & Pehkonen, 1995) or on non-theoretical VAR models (Holmlund, 1995, Skedinger, 1995, Pehkonen, 1995b). In the Forslund & Krueger (1994) study a rival approach is adopted, namely a cross-section of 24 Swedish regions. The displacement/substitution results tend to differ across estimation methods; estimations based on matching functions imply negligible displacement effects in Finnish youth labour markets (Rantala), whereas VAR analyses indicate almost total crowding out effects of job-creation programmes in youth labour markets both in Sweden (Holmlund, Skedinger) and in Finland (Pehkonen). One explanation for this might be connected to omitted variables, since the studies based on matching functions tend to control more factors than the VAR studies. In the latter branch of studies the problem with omitted variables is potentially severe given that the displacement effect is studied by regressing residuals with each other. When it comes to displacement effects across unemployment durations, the results reported in Rantala (1995) and Eriksson & Pehkonen (1995) suggest that programmes directed to the long-term unemployed displace short-term employed persons but the estimated effects remain modest. Finally, in the Forslund & Krueger's study the results show the considerable displacement effect of some 70 per cent in the construction sector; no such evidence was found in the health sector.

3.2. Microeconometric Studies

The standard practise of evaluating social programmes at the administrative level is to produce information about the proportion of participants who are employed some time after participation. Being of interest in their own right these measures are not sufficient to measure the impact of various programmes for two reasons. First, summary measures do not provide any information about the importance of individual characteristics in determining the outcome. Second, what we really need to know is whether the outcome would have been observed even without an intervention.

The evaluation of government programmes has been a common practise in the United States for decades. The first major employment and labour market initiative in the US was the Manpower Development Training Act (MDTA) of 1962. The impact studies of MDTA were relatively unsophisticated by today's standards due to the lack of common data on both participants and non-participants, Riddell (1991)[2]. For this reason, the U.S. Department of Labor started to collect the Continuous Longitudinal Manpower Survey (CLMS) on participants after implementing the next initiative in the year 1973 called the Comprehensive Employment and Training Act (CETA). Data for CETA participants were supplemented with data for non-participants taken from the Current Population Survey (CPS). In 1982 CETA was replaced by the Job Training Partnership Act (JTPA)[3].

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[2] The study by Ashenfelter (1978) for MDTA trainees was one of the first studies which documented that participants in MDTA do not represent a random sample of eligible population.

[3] For more information about the design and target groups of CETA and JTPA, see Haveman and Hollister (1991).

Data for CETA participants and non-participants resulted in numerous evaluation studies[4]. In 1978 CETA was given the explicit target to increase the earned income of participants. For this reason, the main research question has been the impact of CETA on participants' subsequent earnings. According to a review by Haveman and Hollister (1991), CETA had small, positive effects on participants' earnings that materialised through higher hours of work rather than higher wage rates. The groups that benefited the most from these programmes consisted of disadvantaged individuals, women, and those with the least previous labour market experience. The most effective programme types were public sector employment and on-the-job training, whereas work experience and classroom training had little or no effect on participants' subsequent earnings.

The worrying finding of CETA evaluations was, however, that the estimated programme effects differed widely between different studies. The studies by Lalonde (1986) and Fraker and Maynard (1987) examined this issue by comparing the experimental and non-experimental estimates of the programme effects. The experimental data employed in these studies was collected from the National Supported Work Demonstration (NSWD) which was a temporary, natural experiment in the mid 1970s[5]. Both studies conclude that non-experimental evaluation methods fail to produce reliable estimates of the programme effect. Partially for this reason, the U.S. Ministry of Labor decided to employ random assignment in the evaluation of the JTPA, Riddell (1991). The experimental evaluations of JTPA have provided evidence that training increases adult participants' earnings by $585 - $625 per year. Unlike in CETA evaluation studies, the JTPA evaluations indicate that both men and women gain from participation. The impact of

4 Among others, Bassi (1983), Ashenfelter and Card (1985), Dickinson, *et. al.* (1987), Jantzen (1987), and Card and Sullivan (1988). A review by Barnow (1987) examines eleven major studies of this literature in detail.

5 For more information about the design and target groups of NSWD, see Haveman and Hollister (1991).

JTPA programmes on the earnings prospects of the youth is, however, less satisfactory. They may even harm the short-term earnings prospects of young men, Burtless (1993).

Nowadays, it seems to be widely acknowledged that social experiments produce more reliable estimates of the programme impact, provided that they are carefully introduced[6]. Having said that, the results by Heckman & Hotz (1989) imply that there is no reason why non-experimental econometric methods would not produce reliable estimates if the estimated models are carefully tested. Due to the emphasis of the study, this part of the survey focuses on non-experimental assessments of active labour market programmes. Following the same line of argument we concentrate purely on the empirical evidence of the relation between programme participation and subsequent employment, leaving aside studies in which the earnings impacts of ALMPs have been examined. The latter literature is extensively surveyed in Barnow (1987), OECD (1993) and Fay (1996).

3.2.1. Selection Bias

All microeconometric evaluations try to answer the question of whether participants have experienced improvements in their labour market position. To answer this question the focus is in estimating the conditional joint distribution of the outcome variable under evaluation (y) and the programme variable (p)

$$f(y, p \mid X, Z, \alpha, \gamma), \tag{4}$$

in which all subscripts have been omitted for exhibition purposes. X and Z stand for the determinants of the outcome variable and the participation decision, respectively. The

6 It has to be noted, however, that also social experiments are subject to limitations in evaluating government programmes, see Heckman (1992), Heckman & Smith (1993) and Burtless (1993), *inter alia*.

parameter vectors connected to explanatory variables are denoted by α and γ. The resulting likelihood function is a simplified version of a general model in which the duration of a programme, and possibly the duration of unemployment after a programme, are also jointly modelled, see Dolton (1994). As a further simplification the programme variable (p) is usually modelled within the context of net utility which leads to a dichotomous programme variable, see Heckman & Robb (1985).

The problem with microeconometric evaluations is the one of missing data since we do not observe the outcome under the counterfactual state, i.e. had a participant not participated in a programme. Let us define the counterfactual outcome by y_0 and the observed outcome by y_1. Provided that the joint distribution (4) can be determined, the impact of active programmes on the programme participants can be assessed through the distribution of impacts, see Heckman & Smith (1993),

$$f(y_1 - y_0 \mid d=1, X, Z, \alpha, \gamma). \tag{5}$$

In practise we do not observe the same individuals in different states, i.e. participating in a programme and non-participating. To deal with the problem an analyst needs a comparison group which is thought of as presenting the counterfactual outcome of programme participants. This raises an additional problem since the data is generated by individuals who make choices of belonging to one of the two groups. So called selection bias is present in estimations if the mean labour market outcome of programme participants differs from the mean outcome of control-group members even in the absence of an intervention. In a stylised framework the consequences of selection bias can be examined through the means of observed outcomes for programme participants (p = 1) and non-participants (p = 0)

$$(6) \qquad E(y_1 \mid p=1, X, Z, \alpha, \gamma) = \beta + E(y_0 \mid p=1, X, Z, \alpha, \gamma)$$

$$(7) \qquad E(y_1 \mid p=0, X, Z, \alpha, \gamma) = E(y_0 \mid p=0, X, Z, \alpha, \gamma).$$

The observed mean outcome of the participants consists of two terms; the programme effect (β) and the mean of the counterfactual outcome. Naturally the two means are the same for comparison-group members. If we attempt to evaluate a programme through the difference in mean outcomes, the result becomes

$$(8) \qquad \begin{aligned} &E(y_1 \mid d=1, X, Z, \alpha, \gamma) - E(y_1 \mid d=0, X, Z, \alpha, \gamma) = \\ &\beta + \{E(y_0 \mid d=1, X, Z, \alpha, \gamma) - E(y_0 \mid d=0, X, Z, \alpha, \gamma)\}. \end{aligned}$$

The conditional means in curly brackets form the selection bias term. If the mean outcome of participants in the non-participation state differ from that of non-participants, the conventional single equation estimation methods do not yield the consistent estimates of β, see Heckman & Smith (1993). The direction of bias is unknown *a priori*. If selection is based on comparative advantage due to ambition or motivation, ALMPs produce greater benefits under self-selection than under a random assignment, Roy (1951), see also chapter 9 in Maddala (1983). In the case of comparative disadvantage the reversed outcome emerges. Whatever the reason, selection bias makes it impossible to assess which part of the programme effect is due to active programmes and which part is due to uncontrolled factors[7].

The solution to the self-selection bias depends crucially on whether this bias arises, in Heckman & Hotz (1989) terminology, as selection on observables or as selection on unobservables. In the former case the bias is easily corrected by inserting the observed factors, which affect a person's participation decision and subsequent labour

[7] The direction of selection bias is less evident if some part of the population selects positively (comparative advantage) and others negatively (comparative disadvantage). In this case, the direction of selection bias in equation (8) depends on the relative effects of different selection criteria.

market possibilities, in the outcome equation. In the latter case one has to take account of the dependence between the error terms in the participation and outcome equations.

There are numerous ways of handling the selection bias parametrically, see Maddala (1983), Heckman & Robb (1985) and Limdep manual version 7, *inter alia*. The choice of method depends on the outcome variable (linear or non-linear), the selection process (bivariate or multinomial) and distributional assumptions. In principle all selection models can be estimated by specifying the joint distribution (4) between the outcome variable and the participation variable(s). In practise, however, the computational burden of calculating multiple integrals restricts the number of endogenous variables. In earnings oriented cross-section studies the outcome variable is linear in which case computations can be further simplified by 2-stage estimation methods, see Heckman (1979) for dichotomous participation choice and Lee (1983) for multinomial choice model. But in non-linear models, such as in limited dependent variable models, 2-stage estimation methods are not valid, see O'Higgins (1994). To take account of selection on unobservables one has to estimate the joint distribution given in equation (4). Needless to say, the exact formulation depends on the adopted distributional assumptions.

In specifying a parametric model one needs to make some distributional assumptions concerning error processes, the most common being the multivariate normal distribution. This assumption is hardly ever tested, even though the severe consequences of departures from normality are well reported in the case of 2-stage estimation methods, see Goldberger (1983), Duncan (1983), Maddala (1983) and Lee (1984). Recently the assumptions required in specifying all moments of a conditional distribution are challenged by semiparametric estimation methods which parametrically model only part of the model (for a survey of different estimators see Robinson, 1988). However, the applications of semiparametric estimation methods in selectivity models have remained limited, one exemption is Newey et. al. (1990). One reason for this is likely to be that the cost of weaker distributional assumptions is paid by fewer questions which can be asked of the data, see Heckman (1990).

3.2.2. Cross-Sectional Evaluations

In non-linear cross-sectional studies the focus is on latent variables y^* and p^*. Factors determining the outcome under evaluation, X and p, and the participation decision, Z, are connected to the latent variables via linear indicator functions. This set up leads to the following model

(9) $$y^* = \alpha X + \beta p + \varepsilon_y$$

(10) $$p^* = \gamma Z + \varepsilon_p.$$

The observed realisations of the latent outcome and participation variables are y and p. If only the sign of the latent variable is observed, the observed outcome variable is determined by the rule $y = 0$ if $y^* < 0$, otherwise $y = 1$. In Torp's (1994) study the outcome variable is employment months within a year in which case the relation becomes $y = 0$ if $y^* < 0$, $y = 12$ if $y^* > 12$, otherwise $y = y^*$. Excluding the Jensen & Jensen (1996) study, the joint distribution of error terms ε_y and ε_p is modelled as bivariate normal with the correlation coefficient ρ and variances σ_y^2 and σ_p^2. Table A3.3 in the appendix summarises the results of cross-sectional evaluations of active programmes as a manpower policy.

All studies report results in which the impact of programmes is examined by one or more dummy variables, but the specification of the participation decision differs amongst studies. In probit or logit estimations the participation status is treated as exogenous conditional on controlled factors. More precisely, the untested assumption in these studies is the zero restriction on the correlation coefficient, ρ. This may introduce a substantial bias in the estimated programme effect. For instance, Zweimuller and Winter-Ebmer (1996) report that the estimated programme effect changed from a small positive value to a significantly negative one when the joint distribution is estimated. Torp (1994) attempts to correct the selection bias via Heckman's (1979) method. Strictly speaking this is not valid in non-linear models as discussed in section 3.2.1. The proper likelihood function in her context would consist of six terms; four joint cumulative distributions of participation status and the limit values of employment months, together with two joint probabilities of observing an uncensored outcome variable multiplied by its conditional joint density.

Unfortunately, the unrestricted covariance matrix arises another difficulty, namely the question of identification. In the case of two dichotomous dependent variables, equations (9) and (10) form a model with mixture structure, as defined in Maddala (1983) p. 122. Unlike in the standard bivariate probit model the parameters of the outcome equation remain unidentified if both equations include the same regressors. Accordingly one has to have an instrument for the participation decision which does not enter the outcome equation (9). The four multiple equation studies have adopted the following identification restrictions: O'Higgins (1994) defines home background and labour market dummies differently in the two equations; Raaum et. al. (1995) include the participants to total applicants ratio in the participation equation but not in the employment equation; Torp (1994) excludes prior participation and participation rate in the home community variables from the employment months equation; and finally Zweimuller & Winter-Ebmer (1996) employ projected employment change in a district as an instrument.

Turning next to the estimated impact of active labour market programmes. The first two studies, which concentrate merely on programme participants, suggest that participants in labour market training have difficulties in getting a job directly after terminating a programme. This finding may reflect the lower job search incentives of the trainees during a programme in which case potential gains will materialise after some time of terminating a training programme. According to Ackum Agell's (1995) results the Swedish replacement programme is also superior to job placement programmes, the latter having no significant impact on the employment probability directly after participation. The Jensen & Jensen (1996) study implies that previous training experience does not have any effects over and above the most recent training period.

When it comes to the treatment group versus the control group comparisons, the studies seem to report more beneficial than damaging results. The only significantly negative impact is reported in the Main (1987a) study which evaluates Youth Training Scheme using Scottish data. However, the downward effect turns into a positive one within the next year, Main & Shelly (1990). An interesting contrast in evaluating the youth training scheme is found between Scotland and England/Wales, in the latter countries disadvantaged trainees gaining more from participation than advantaged, O'Higgins (1994). There are some implications that disadvantaged persons benefit more from participation also in Scotland but the gain difference reported in Main (1991) remains some 5 percentage points lower than that reported in O'Higgins. The study by Raaum et. al. (1995) aims to assess the relative efficiency of different training programmes by specifying three different training dummies. According to their results only training courses providing formal qualification have beneficial employment effects. The magnitude of the parameter estimate (training 6 in appendix A3.3) differs across estimation methods, the crucial thing being the significance of the estimated correlation coefficient. The standard bivariate probit model produces a well determined, positive correlation coefficient which seems to lower the significance of training variables. The positive dependence between the error terms implies that participants are more advantaged compared to controls. This is contrasted by the O'Higgins (1994) and Zweimuller & Winter-Ebmer (1996) studies which report significantly negative correlation coefficients. Accordingly their results suggest that participants are initially in a worse labour market position than controls[8].

The two studies in which the employment effect of labour market training is not assessed through the employment probability seem to give the greatest gains from participation. The significantly positive parameter estimate (0.677) reported in Torp (1994) indicates that the subsequent working career of the trainees is more stable than the non-trainees. Interestingly the next two estimations (duration variables not reported in table A3.3) connect this benefit to short and long training courses, employment months of trainees exceeding those of non-trainees by more than one month if a training course is either shorter than 5 weeks or longer than 37 weeks. The Zweimuller & Winter-Ebmer (1996) results confirm the greater job stability of training participants. Their standard man calculations imply that the trainees benefit almost by 40 per cent drop in their repeat unemployment probabilities[9]. If taken at face value it demonstrates the possibilities of labour market training as a manpower policy. One difficulty with Torp's (1994) results, of which the author is fully aware, is that the sampling procedure is based on two different random samples; one consisting of programme participants and the second of

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[8] It has to be noted that control groups differ amongst these studies. Raaum et. al. (1995) employ a control group which consists of rejected applicants, whereas O'Higgins (1994) and Zweimuller & Winter-Ebmer (1996) use unemployed persons without a programme period.

[9] The standard man calculation in Zweimuller & Winter-Ebmer (1996) is based on the marginal programme effect which is calculated for a reference person. In these calculations an analyst removes the programme effect from a participant. An alternative evaluation is employed in O'Higgins (1994) who calculates the programme effect as a difference between the outcomes of a reference participant and a reference non-participants. In terms of equations presented in section 2.2.1, Zweimuller & Winter-Ebmer employs equation (5) in which the counterfactual outcome is based on parameter estimates. O'Higgins, on the other hand, employs equation (8).

non-participants. This so called choice-based sampling results in overrepresentation of programme participants in estimations. When analysing choice-based samples in cross-sections through a parametric model, one really should use some modified estimator, such as the one developed by Manski & McFadden (1981).

Another shortcoming of some studies is the lack of misspecification tests. In particular, the adopted distributional assumption is rarely put under scrutiny. This is surprising given that relatively simple distributional tests, which are based on artificial regressions, have been proposed for the tobit and probit models in Lee & Maddala (1985) and Pagan & Vella (1989), and for the logit model in Poirier (1980) and Smith (1989). The score tests for the distributional assumption of bivariate normality have been derived in Lee (1984) and Smith (1985) but these tend to become fairly complicated due to the complexity of the likelihood function. A simpler version for testing normality in the bivariate probit model is recently given in Murphy (1994). In addition to distributional misspecifications, also other forms of misspecifications result in biased parameter estimates, and hence biased policy conclusions, in non-linear models. The importance of specification testing is highlighted in O'Higgins (1994). After correcting for heteroskedasticity (homoskedastic specifications are rejected against the heteroskedastic ones in all estimations) the beneficial programme effect on a disadvantaged person more than doubles, the selection correction making only little difference in heteroskedastic models. This together with theoretical results of misspecifications cast considerable doubts on the untested results. In this respect the current state of microeconometric evaluations can only be improved[10].

[10] Convenient specification tests, which are based on artificial regressions, are reported in Davidson & MacKinnon (1984, 1989), Newey (1985), Chesher & Irish (1987), Gourieroux et. al. (1987), Godfrey (1989), Pagan & Vella (1989), and Maddala (1995), *inter alia*.

3.2.3. Duration Studies

The fundamental building block in duration models is the hazard function which gives the probability of ending a spell in the short interval of time conditional on having survived up to that time. If we denote the duration distribution function by F(t) and its density function by f(t), the hazard function becomes $\lambda(t) = f(t)/[1 - F(t)]$. The usual assumption adopted in duration studies is the proportionality of the hazard function by Cox (1972). This results in the conditional hazard $h(t|X) = \lambda(t)h_1(X)$ in which $\lambda(t)$ denotes the baseline hazard and $h_1(X)$ incorporates the explanatory variables into the model. The assumption of proportionality of hazards simplifies calculations considerably since it makes it possible to estimate the parametric part of the model without specifying the form of the common function $\lambda(t)$. As a further simplification the parametric part of the model is usually specified as exponential, i.e. $h_1(X) = \exp(\alpha'X)$.

Hazard function evaluations of active programmes try to model their impact on individuals' unemployment/employment spells. In terms of section 3.2.1 the main issue of interest is the joint distribution of the unemployment duration, τ, the programme duration, r, and the programme participation, p, see Dolton (1994),

$$f(\tau, r, p \mid X, Q, Z, \alpha, \zeta, \gamma). \tag{11}$$

The additional terms in equation (11) are the determinants of the programme duration (Q) and the parameter vector of these factors (ζ). Due to the complexity of the resulting likelihood function, most of the studies have concentrated merely on modelling the unemployment duration, τ, conditional on programme participation and other explanatory variables.

Duration models form an attractive alternative to cross-section models. Instead of modelling the employment probability at some point of time, duration models attempt to evaluate the conditional exit probabilities of different exit routes at any point of time. Not surprisingly, there are costs connected to more ambitious questions that duration studies ask of the data. Even in single-duration models the resulting competing risks model becomes fairly cumbersome to estimate. To simplify the task of optimisation an analyst is tempted to assume the independence of hazard functions. This makes it possible to treat exits to other states as censored observations in which case the estimation of the multiple destination model becomes a series of single destination models. But the implicit assumption incorporated in independent competing risks, and analogously in single destination models, is that individual's participation status is exogenous which may be implausible when evaluating active programmes.

There are three different ways employed in tackling the selection problem. Dolton et. al. (1994a) specify a two equation system which consists of the accelerated time model and the participation equation. The resulting system is essentially the linear outcome version of the equations shown in section 3.2.2, so the Heckman procedure is available for estimations. Gritz (1993) constructs a three-state duration model in which the time spent in programmes is among the states. To allow correlation across the states he introduces unobserved heterogeneity terms which follow the one-factor structure. This implies correlated risks but places limitations on possible correlation among survival times. The most attractive way of solving the endogeneity problem is to employ data from experimental designs as in Dolton et. al. (1996) and Ham & LaLonde (1996). Provided that these experiments are carefully introduced,[11] they assure that an individual's heterogeneity is independent of his programme status. Hence an analyst can leave

[11] For various potential problems in experimental design, see Heckman & Smith (1993).

aside the endogenous selection into treatments and controls and concentrate on solving other difficulties included in transition data. An experimental design does not, however, ensure that durations of treatments and controls are readily comparable, so nonexperimental methods have to be employed in analysing the programme effect, see Ham & LaLonde (1996).

The decision whether or not to allow for endogenous participation decision is just one of the difficulties in analysing transition data. One issue which has evoked considerable interest is unobserved heterogeneity. The need to control for unobservable individual differences provides another explanation for the popularity of Cox's (1972) proportional hazard model, since it includes the ability to correct for unmeasured heterogeneity. The resulting specification is a so called mixture model of the form $h(t|X,v) = v\lambda(t)h_1(X)$ where v is a random variable capturing uncontrolled heterogeneity. Failure to take account of unobserved heterogeneity may result in, not only spurious duration dependence, but also inconsistent slope estimates, Lancaster (1990). There are basically two ways of correcting this problem, either through a fully parametric model or through points of support. Heckman & Singer (1984) argued that the former approach leads to an overparametrised survival function and possibly to serious errors in inference. Whichever specification is chosen, the price to be paid comes in the form of the complexity of the likelihood function.

Another problem arises with censored samples. Right censoring is usually solved by including right censored observations in a separate component in the likelihood function. Even though this treats all right censored observations in a similar way, and may hence be unjustified, a bigger problem arises with left censored observations. That is with individuals who are observed in the middle of a spell at the beginning of the sample.

If one is willing to accept that there is no unobserved heterogeneity, and there are no functional relationships between the distributions of interrupted and completed duration times, the left censored observations could be excluded in estimations, Gritz (1993). These are, however, strong requirements since the requirement of no functional relationship between distributions is essentially the one of no duration dependence. In single-duration competing risks studies, which employ inflow data, the problem of left-censoring becomes the one of modelling the time spent in programmes, see Dolton et. al. (1994a). Sometimes the problem of programme spells has been left aside by analysing the inflow to open unemployment data. However, the non-random selection to unemployment spells may result in comparing a control group of higher than average unemployed persons to less than average programme participants, Ham & LaLonde (1996).

To identify the estimated models, one has to assume some functional form restrictions. The suitability of the adopted distributional assumptions is a common problem in microeconometric studies. In complicated likelihood functions these distributional assumptions become easily untestable.

As has become evident, there are various difficulties, and solutions to these difficulties, when evaluating ALMPs through duration models. Table A3.4 in the appendix summarises the main results an the adopted specifications in hazard function evaluations of active programmes. The discussion above may prove useful in comparing the results reported in different studies with each other.

We start the discussion about the results by comparing the three 'pure' evaluation studies which have not taken account of the endogeneity of the participation decision. The first thing to notice is that these studies report the most negative parameter estimates. For instance, the Ackum-Agell's (1996) study suggests that all forms of active programmes increase unemployment duration. Her results have to be taken as tentative due to four possible misspecifications arising from choice-based sample, unobserved heterogeneity, left-censoring and the endogeneity of the participation decision. In particular the choice-based sampling procedure may affect the results since the similar kind of inflow study by Jensen & Jensen (1996) report more favourable results. According to their results labour market training up to a year before entering unemployment increases the pace at which participants get hired in a new job. Older training courses, on the other hand, seem to have a beneficial effect on returning to an old job. These gains are more pronounced for women. Since Jensen & Jensen's study assumes the independence of different spells, the total employment effect is easily calculated by summing up separate employment effects. Due to some negative training parameters the employment effects remain quite small. The third study in this category, namely Dolton et. al. (1994a), highlights the dependency of the results from the control group. If programme participants are compared to unemployed persons, significantly beneficial effects on transition to either a job or a good job is found for both men and women. When the control group is specified as all school leavers, the only gain from YTS is obtained by women in terms of a transition to a good job. Dolton et. al. (1994a) also put their results under scrutiny by assessing the impacts of training spells, unobserved heterogeneity, and the selection problem on their results. Due to the adopted estimation method (competing risks) they have to introduce these potential misspecifications one at the time by (in some cases) second best solutions. According to their results, only the choice whether or not to subtract training spells from the time taken to get a job matters.

Turning next to two studies which assess ALMPs in an indirect way, namely Carling et. al. (1996) and Mealli et. al. (1996). In the former study the programme variable is measured as the availability of programmes in a region. The authors' aim is to test the impact of active programmes on the reservation wage through their effect on the escape rate from unemployment to employment. Their results do not support the view that ALMPs increase unemployment duration by increasing reservation wages. Not surprisingly, the local supply of active programmes has a strong effect on the rate at which individuals enter programmes. The positive parameter estimate in the third hazard function, i.e. the transition from unemployment to out of the labour force, suggests that ALMPs have a work test effect discussed in section 3.1.1. Mealli et. al. (1996) acknowledge that the programme spell is necessarily truncated at the upper limit which in the case of the YTS is two years. They develop a limited competing risk model which they apply on YTS trainees data. According to their results YTS places in clerical and another non-manual occupations significantly reduce the transition time from unemployment to employment.

The final category of duration studies takes account of the endogeneity of the participation decision, Gritz (1993) being the only purely non-experimental study. He allows unobservable differences among individuals which are correlated with the duration times. The other two studies, viz. Dolton & O'Neill (1996) and Ham & LaLonde (1996), employ data on experimental designs. The results seem to differ somewhat between experimental and non-experimental training studies. Gritz (1993) finds that training courses offered by the public sector increase unemployment duration and decrease employment duration. This is challenged by Ham & Lalonde (1996) whose results suggest that they increase employment duration, having no effect on unemployment duration. In another study based on completely different experimental data, Dolton & O'Neill (1996) report beneficial effects of restart interviews on unemployment duration. Furthermore, the restart interview seems to work also as a work search test since it increases the transition rate from unemployment to out of the labour force.

There are several reasons which may cause the diverged results reported in Gritz (1993) and Ham & LaLonde (1996). To highlight the differences in modelling strategies, we take a closer look at some potential factors. First, the studies evaluate separate programmes. Gritz's study employs data on the Youth Cohort of the National Longitudinal Study (YNLS) whereas Ham & Lalonde's study examines the National Supported Work (NSW) demonstration which provided work experience to a random sample of eligible disadvantaged women. According to the results summarised in appendices A3.3 and A3.4, females tend to benefit more from programmes, in which case Ham & LaLonde's results may give the upper bound of possible programme effects. The second explanation may be connected to the specification of left-censored observations. In Gritz's study these observations are treated as if there is no distributional relationship between left censored spells and completed duration times. This may introduce a downward bias on parameter estimates. When Ham & LaLonde allowed the correlation between the interrupted and fresh unemployment spells, the effect of training on unemployment duration turned from positive to insignificant. Similarly, the positive effect on employment duration became more pronounced. Third, Gritz does not condition the heterogeneity distribution on being eligible for training (Ham & LaLonde, 1996). Accordingly, in his study the evaluation question concerns the effect of training on a randomly selected person, whereas Ham & LaLonde evaluate the effect on programme participants. Fourth, the data employed by Gritz does not contain all information about the programme spells, so he is forced to model training status through a dummy variable. Dolton (1994) points out that this may introduce a downward bias on programme effects. Finally, as Gritz remarks, his method of correcting the endogeneity bias may not adequately capture the impacts of government sponsored training. Especially since the private sector training seems to be highly effective in shortening unemployment spells. A rival explanation might be the small number of individuals in the sample (77) who actually have received public sector training makes it hard to assess government training courses. Most probably the explanation is the mixture of all these factors. Whatever the reasons, these studies are welcome contributions to hazard based evaluations of active labour market programmes.

To conclude this section we briefly mention three other types of panel data studies which have evaluated the employment effects of ALMPs and which are not summarised in appendices. Jantzen (1987) examines the impact of the Comprehensive Employment and Training Act (CETA) on quarterly hours worked through the tobit model. According to his findings, participation increases males' working hours by 74 - 135 hours in a quarter, the equivalent results being 132 - 315 hours for females. Ridder (1986) employs non-stationary Markov chains in analysing different forms of active programmes. He assumes that selection into programmes depends on the labour market state, unemployed persons being more likely to participate in a programme. His results imply that employment programmes are more effective than recruitment programmes, which in turn are more effective than training programmes. Females, minority workers and young workers benefit the most. Finally, Card & Sullivan (1988) evaluate the CETA programme by modelling the selection into programmes through previous labour market history. This solves the endogeneity problem provided that sample selection is purely based on past work histories and these histories are adequately captured by the employed profiles. Their results imply that the CETA programme has a small to moderately large positive impact on the post-training employment probabilities in every year after training, the effects ranging from 2 to 5 percentage points.

3.3. The Lessons of Previous Studies

What have we learned about the effectiveness of active labour market policy in improving employment prospects? The evidence is rather mixed, especially when it comes to macroeconomic effects, but it seems reasonable to hypothesise the following. First, active programmes seem to reduce unemployment. This piece of evidence is mainly based on cross-country analyses so time series studies about the impact of ALMPs on equilibrium unemployment are urgently needed. Second, Swedish evidence suggests that active programmes increase wage pressures only if they are overambitious compared to prevailing unemployment. Whether or not this results in higher unemployment remains to be seen. According to cross-country studies this is not the case. Third, the displacement effects may be large. Before drawing any definite conclusions, more studies about displacements at the occupational/industry level are needed. Especially since studies based on different framework (matching function vs. VAR) tend to give diverse results. Fourth, microeconomic evaluations suggest that training courses increase subsequent employment prospects at the individual level. It is noteworthy that this piece of evidence does not seem to depend on the exact evaluation method. But it is still based on very limited number of evaluations which have evaluated active programmes of even fewer countries. And it has to be noted that the robustness of the results remains somewhat unsure due to the lack of misspecification tests.

Since the literature does not completely agree on the main issues, such as whether ALMPs reduce unemployment or not, it is not surprising that there exists different views also on the target groups of active programmes. Microeconometric cross-section evaluations indicate that disadvantaged participants experience an increase in their employment probability of some 10 percentage points and possibly a huge reduction in their repeat unemployment probability. Most of the panel studies suggest similar quantitative outcomes, the most benefited group being women. In some cross-country studies ALMPs have been found of being the most effective when targeted to the long-term unemployed. But this result has not been unilaterally accepted by all macroeconometric evaluations. When it comes to relative effectiveness of separate programmes, the results are almost non-existent. To sum up, there are indications that active labour market policy may be effective as a manpower policy. But since there is no unilaterally accepted truth about ALMPs, and convergence to one is slow (or non-existent), more evaluation is urgently needed, not only about the statistical significance of the estimated parameters but also about the economic importance of active labour market policy in combating unemployment.

Appendix 3.1. Summary Tables of Previous Studies

Table A3.1 Empirical Findings of Cross-country Studies.

Study	Dependent variable	The measure of ALMP	Impact of ALMP	Sample	Estimation method	Special notes
Jackman et. al. (1990); table 4	UN^t rate	ALMP1	-0.01 (2.2) - -0.03 (2.7)	14 countries in the years 1971 - 88	2SLS on pooled data	Focused on the UV curve
Heylen (1991); table 3	Share of long-term unemployment	ALMP spending per unemployed person	-0.87 (0.7) - -3.43 (2.6)	9 - 16 countries	OLS	Number of observations varies with explanatory variables
Layard et. al. (1991)	Average UN^t rate in 1983 - 88	ALMP1	-0.13 (2.3)	20 countries	OLS	
Forslund & Krueger (1994); table 6	UN^t rate in 1993 [average in 1983 - 88]	ALMP spending relative to GDP	1.73 (1.42) [-0.42 (1.18)]	20 countries	OLS	Estimated the same equation as in Layard et. al. (1991)
Forslund & Krueger (1994); table 6	UN^t rate in 1993 [average in 1983 - 88]	ALMP spending relative to all labour market measures	10.19 (9.49) [-8.78 (3.19)]	20 countries	OLS	Estimated the same equation as in Layard et. al. (1991)
Jackman et. al. (1996); table 3	Average log (UN^t rate) in 1983 - 94	ALMP spending as % of GDP divided by unemployment	-0.008 (0.7)	20 countries in 1983 - 88 and 1989 - 94	Random effects GLS	Estimated the same equation as in Layard et. al. (1991); the ALMP variable instrumented

Jackman et. al. (1996); table 3	Average log (long-term UN^t rate) in 1983 - 94	ALMP spending as % of GDP divided by unemployment	-0.03 (2.0)	20 countries in 1983 - 88 and 1989 - 94	Random effects GLS	Estimated the same equation as in Layard et. al. (1991); the ALMP variable instrumented
Scarpetta (1996); table 1	UN^t rate	ALMP1	-0.04 (1.17) - -0.06 (1.83)	17 countries in the years 1983 - 93	Random effects GLS	Estimates also for youth unemployment and non-employment
Scarpetta (1996); table 6	Long-term UN^t rate	ALMP1	-0.01 (0.45) - -0.03 (1.15)	17 countries in the years 1983 - 93	Random effects GLS	Estimates also for youth unemployment and non-employment
Heylen (1993); table 6	Wage responsiveness to UN^t	Expenditure on ALMPs relative to passive measures	9.19 (3.96)	17 countries	Weighted LS	Weighted by the inverse of the variance of wage responsiveness estimates in 8 studies
OECD (1993); table 2.2. eq. 1	Change in log (employment) in 1985 - 90	Change in log(spending on ALMPs relative to the wage bill) in 1985 - 90	-0.11 (2.3)	19 countries	OLS	Explanatory variables consist of GDP, real wages and the interaction term between GDP and ALMP
OECD (1993); table 2.3	Change in real wages in 1985 - 90	Change in log(spending on ALMPs relative to the wage bill) in 1985 - 90	Significantly negative for 10 countries, significantly positive for 2 countries	19 countries	OLS	Explanatory variables consist of unemployment rate, productivity growth and terms of trade

Notes: ALMP1 = Total spending on active programmes per unemployed person relative to GDP per person; The number of observations equals the number of countries except in those cases where specific years have been reported; If tables report several equations, the lowest and the highest parameter estimate have been reported; Forslund & Krueger (1994) estimated the same equations with two different time periods of which the former one is given in square brackets.

Table A3.2 Long-run Estimates of Wage Pressure.

Study	ALMP	Un[t]	Period	The ALMP effect on wages	Special comments
Denmark					
C & N (1990)[a]	0.009	-0.125*	1960 - 89	Perfect substitute for regular employment ($\alpha_2 = 0$)	
C & N (1990)[b]	0.34	-0.126*	1960 - 89	Either increase wages ($\beta_1 < 0$ & $\beta_2 > 0$) or reduce ($\beta_2 = 0$)	
Nymoen et. al. (1996)[c]	-0.29	-0.123*	1969 - 93	Either increase ($\lambda_1 - \lambda_2 > 0$) or reduce ($\lambda_2 = 0$)	Specified as first differences. Long-run parameters consist of variables shown in equation (3).
Finland					
C & N (1990)[a]	0.018	-0.017	1960 - 89	Perfect substitute for regular employment ($\alpha_2 = 0$)	
C & N (1990)[b]	0.08*	n/a	1960 - 89	Small increase since eq. (2') becomes w= -0.08(r+u) - 0.08r	Unemployment did not enter the cointegration vector
Nymoen et. al. (1996)[c]	-0.33	-0.048*	1962 - 94	Either increase ($\lambda_1 - \lambda_2 > 0$) or reduce ($\lambda_2 = 0$)	See Denmark.
E-S-V (1990)[a,b]	n/a	-0.031	1960 - 85	Perfect substitute for regular employment ($\alpha_2 = 0$)	No estimates for the ALMP variable presented since they were insignificant.
Norway					
C & N (1990)[a]	-0.085*	n/a	1960 - 89	Reduce wage effects ($\alpha_2 < 0$)	Unemployment did not enter the cointegration vector

C & N (1990)[b]	n/a	-0.155*	1960 - 89	Reduce ($\beta_2 = 0$)	The programme variable did not enter the cointegration vector
Nymoen et. al. (1996)[c]	-	-0.089*	1964 - 94	Reduce ($\lambda_2 = 0$)	See Denmark.
Sweden					
C & N (1990)[a]	n/a	-0.228*	1960 - 89	Perfect substitute for regular employment ($\alpha_2 = 0$)	The programme variable did not enter the cointegration vector
C & N (1990)[b]	0.41*	-0.236*	1960 - 89	Increase ($\beta_1 < 0$ & $\beta_2 > 0$)	
C & F (1991)[a]	0.05* - 0.34*	-0.11* - -0.17*	1960 - 86	Increase ($\alpha_2 > 0$)	Estimated several different specifications. Lowest and highest values shown.
C & F (1991)[b]	0.15* - 0.25*	-0.85 - -2.00	1960 - 86	Increase ($\beta_2 > 0$)	See above.
N & S (1987)[a]	-0.35	-5.26*	1965 - 83	No effect ($\alpha_2 = 0$)	Unemployment term measured in levels.
Nymoen et. al. (1996)[c]	-0.25*	-0.17*	1965 - 93	Increase ($\lambda_1 - \lambda_2 > 0$)	See Denmark.
Forslund (1995)[b]	0.13	-0.05	1960 - 93	increase ($\beta_1 < 0$ & $\beta_2 > 0$)	Estimated as a part of the Layard- Nickell model. Employed 2SLS. No standard errors presented for long-run solutions

Notes: (a) Specification as in equation (1) ; (b) Specification as in equation (2); (c) Specification as in equation (3); * = significant at the 5 per cent significance level; Estimation method is OLS if not otherwise stated; C & N = Calmfors and Nymoen; C & F = Calmfors and Forslund; N & S = Newell and Symons; E-S-V = Eriksson, Suvanto and Vartia.

Table A3.3 Summary of Employment Related Cross-sectional Studies

Study and (country)	Programme dummy	Estimate	Δ probability (%)		Method	Dependent variable = 1	N	Comments
			Adv	Disadv				
Employment probability								
Ackum Agell (1995); table 3; (Sweden)	Training Replacement Job placement	-0.436^{*} $+0.209^{*}$ -0.091	n/a	n/a	Probit Probit Probit	Employment directly after a programme	2486	Estimated for programme participants only.
Jensen & Jensen (1996); table 4a; (Denmark)	Training 1; men Training 2; men Training 1; women Training 2; women	-0.140 +0.140 -0.280^{*} +0.330	n/a n/a	n/a n/a	Logit Logit Logit Logit	Employment directly after a training course following the unemployment spell	1281 748	Register based random data. Estimated for programme participants only. Training 1 (2) for participation upto a year (1 - 2 years) before entering unemployment
Main (1987); table 2; (Scotland)	On YTS in Oct 1984	-1.443^{***}	n/a	n/a	Probit	Employment in April 1985 of those who left-school in 1983/84	2617	Data based on survey sent to randomly selected school leavers.

Main (1987); table 8.11; (Scotland)	On YOP in October 1982	Females: +0.551***	18	18	Probit	Employment in April 1983 of those who left school 1981/82 and were not employed in October 1982	871	See Main (1987). Probability values calculated for a reference man.
		Males: +0.170*	4	4	Probit		922	
Main (1991); table 2 (both sexes); (Scotland)	Ever on YTS	+0.460***	14	19	Probit	Employment in October 1987 of those who left school in 1983/84	1383	See Main (1987). Results also available for separate sexes.
	Completed YTS	+0.068			Probit			
Main & Shelly (1990); table 3; (Scotland)	Ever on YTS	+0.400***	17	11	Probit	Employment in April 1986 of those who left school in 1983/84	1198	See Main (1987).
	Completed YTS	+0.079			Probit			
O'Higgins (1994); tables (2) and (6); (England and Wales)	Ever on YTS	+0.270***	3	4	Probit	Employment in spring 1986 of those who left school in 1983/84	2855	See Main (1987). Joint distribution estimations corrected for heteroskedasticity
	Ever on YTS	+0.550***	0	11	Hetsked. probit			
	Ever on YTS	n/a	1	12	Bivariate probit			
	Ever on YTS	n/a	1	9	Swit. biv.probit			
Raaum et. al. (1995); Tables 5.1.1 and 5.1.2; (Norway)	Training 4	+0.055	n/a	n/a	Probit	Employment in November 1992 for participants in August and September 1991	915	Control group consists of rejected applicants. Training 4 denotes public service, technical / administrative work, training 5 manufacturing and transport work. Training 6
	Training 5	+0.064			Probit			
	Training 6	+0.241**			Probit			
	Training 4	-0.004			Bivariate probit			
	Training 5	+0.071			Bivariate probit			
	Training 6	+0.176			Bivariate probit			

	Training 4 Training 5 Training 6	-0.012 +0.110 +0.213*			Bivariate probit with interaction terms			provides formal qualification.
Employment months								
Torp (1994); table 2; (Norway)	Training Training Training	+0.667** +4.437*** +3.667***	n/a	n/a	2-limit tobit 2-limit tobit Heckman corrected 2-limit tobit	Employment months between June 1989 - May 1990	6406	Choice based sample. In the last two estimations duration of training and duration squared are included as regressors
Job Stability								
Zweimuller & Winter-Ebmer (1996); tables 2 and 3; (Austria)	Training Training	+0.073 -1.261**	n/a -39.7	n/a -39.7	Probit Bivariate probit	Repeat unemployment within one year of terminating a programme	1945	Register based random data of unemployment leavers Probability values calculated for a reference man.

Notes: * = significant at the 10 per cent significance level; ** = significant at the 5 per cent significance level; *** = significant at the 1 per cent significance level; Training stands for a training programme; If no significance levels are given the standard errors have been employed in calculating the t-statistic; Job placement denotes a selective employment measure; Replacement is the scheme introduced in 1991 in Sweden in which a programme participants replaces a regular worker who is on leave for education; YTS = youth training scheme; YOP = Youth Opportunity Scheme; Hetsked. Probit denotes the heteroskedasticity corrected probit estimation; Swit.biv. probit stands for the switching bivariate probit model

Table A3.4 Summary of Programme Effects in Duration Studies.

Study (Country)	Estimated effect	Unobserved heterogeneity	Specification of the programme variable	Specification of the model	N	Comments
Hazard estimations						
Gritz (1993); table 3 (USA)	Government training (N=77): λ_{en} = +0.374 (0.163)** λ_{ne} = -0.397 (0.174)** λ_{ep} = +1.064 (0.523)** λ_{np} = -0.345 (1.078) Private training (N=535): λ_{en} = -0.099 (0.099) λ_{ne} = -0.095 (0.091) λ_{ep} = +0.390 (0.282)* λ_{np} = +0.251 (0.440)	Controlled through five points of support.	(i) Dummy variables that obtain values of one if participated in private or government sponsored training. (ii) Endogeneity allowed by specifying training as another state and by allowing for the existence of unobserved heterogeneity which follows the one-factor structure.	(i) Baseline hazard Log-logistic. (ii) Three-state duration model based on continuous time Cox's proportional hazard.	1703	(i) A subsample of YNLS over the years 1978 - 82. (ii) Duration variables defined as time spent in employment / unemployment during the sample period. (iii) Left censoring by assuming independence between fresh and interrupted unemployment spells. (iv) Interaction terms for women not shown in column 2.

Dolton et. al. (1994a); (England)	Control group: unemployed *Women* λ_{ue} = +0.386 (0.126)*** $\lambda_{ue(good)}$ = +0.851 (0.245)*** *Men* λ_{ue} = +0.206 (0.127)* $\lambda_{ue(good)}$ = +0.419 (0.208)** Control group: all *women* λ_{ue} = -0.324 (0.045)*** $\lambda_{ue(good)}$ = +0.442 (0.071)*** *men* λ_{ue} = -0.333 (0.052)*** $\lambda_{ue(good)}$ = +0.048 (0.068)	Not controlled. Experiments with gamma distribution produced similar results.	(i) Dummy variable which obtains a value one if participated in YTS. (ii) Endogeneity not allowed.	(i) Baseline hazard not estimated. (ii) One destination model based on Cox's proportional hazard.	*Women* 1076 *Men* 927	(i) Sample consists of persons who left full time education within March 1987 - March 1989. (ii) The duration variable is the time taken to enter the first job (λ_{ue}) or the first good job ($\lambda_{ue(good)}$). (iii) Attempts are made to correct the endogeneity bias, see text.
Ackum-Agell (1996); table 5, column 3 (Sweden)	Labour market training: λ_{ue} = -0.935 (0.147)*** Replacement scheme: λ_{ue} = -1.097 (0.205)*** Relief job: λ_{ue} = -1.449 (0.189)***	Not controlled.	(i) Separate dummy variable for labour market training, replacement scheme and relief jobs. (ii) Endogeneity not allowed.	(i) Baseline hazard not estimated. (ii) One destination model based on Cox's proportional hazard.	3980	(i) Choice based sample from the inflow to open unemployment and ALMPs in three points of time in 1993 - 94. (ii) Duration variable is the time taken to enter a regular job.

Carling et. al. (1996); Table 3 (Sweden)	$\lambda_{ue} = +0.082\ (0.078)$ $\lambda_{up} = +1.984\ (0.115)^{***}$ $\lambda_{un} = +0.276\ (0.133)^{**}$	Not controlled.	(i) Regional proportion of programme participants to unemployed. (ii) Endogeneity not allowed.	(i) Baseline hazard not estimated. (ii) Independent competing risks based on Cox's proportional hazard.	12098	(i) A sample from the inflow to open unemployment in three points of time in 1991. (ii) Duration variable is the time taken to end the first unemployment spell.
Ham & LaLonde (1996) table 4, columns 3 and 5 (USA)	$\lambda_{ui} = +0.024\ (0.217)$ $\lambda_{ei} = -0.403\ (0.156)^{***}$	Controlled through two points of support.	(i) Dummy variable for belonging to the treatment group which has obtained training. (ii) Endogeneity controlled through experimental design.	(i) Statistical model which allows for the last two cases in the comments column.	541	(i) The sample consists of the NSW experiment in 1976 - 77. The sample was followed for 26 months after the baseline. (ii) Duration variables defined as time spent in employment / unemployment during the sample period. (iii) Endogenous left censoring controlled. (iv) Spells are allowed to depend on each other.

Dolton & O'Neill (1996); table 1 (Britain)	Control group: λ_{ue} = -0.284 (0.124)** λ_{up} = -0.338 (0.216)* λ_{un} = +0.389 (0.282)* Restart interview: λ_{un} = +0.724 (0.357)**	Not controlled.	(i) Dummy variable for belonging to the treatment group which participated in the first Restart interview *and* Time varying covariate which obtains a value one after the Restart interview. (ii) Endogeneity controlled through experimental design.	(i) Baseline hazard not estimated. (ii) Independent competing risks based on Cox's proportional hazard.	4728	(i) The sample based on the experimental Restart data in 1989. (ii) Duration variable is the time taken to end the unemployment spell. (iii) The treatment group got the Restart interview after being unemployed for 6 months. The control group got their Restart interview after 12 months of unemployment.
Mealli et. al. (1996); table A2a (Britain)	λ^1_{pe} = +0.319 (0.119)*** λ^2_{pe} = -0.195 (0.087)** λ^3_{pe} = +0.271 (0.110) *** λ^1_{pu} = -0.003 (0.243) λ^2_{pu} = -0.404 (0.169)*** λ^3_{pu} = +0.281 (0.207)* λ^1_{po} = -0.241 (0.294) λ^2_{po} = -0.302 (0.194)* λ^3_{po} = +0.327 (0.235)*	Controlled through points of support.	(i) Separate dummies for YTS place in clerical occupation (λ^1), in technical/craft occupation (λ^2) and in another non-manual occupation (λ^3).	(i) Baseline hazard Weibull. (ii) Limited competing risks based on Cox's proportional hazard.	3113	(i) The sample of school leavers in 1988 who joined the YTS before February 1991. (ii) Duration variable is the time spent in YTS. (iii) Only data on training participants employed in estimations.

Jensen & Jensen (1996); tables 2a and 3a (Denmark)	*Women* $\lambda^1_{ue(old)}$ = -0.11 (0.06)** $\lambda^1_{ue(new)}$ = +0.12 (0.05)*** λ^1_{up} = +2.09 (0.10) *** $\lambda^2_{ue(new)}$ = +0.28 (0.06)*** $\lambda^2_{ue(old)}$ = +0.02 (0.06) λ^2_{up} = -0.10 (0.14) *Men* $\lambda^1_{ue(old)}$ = -0.32 (0.05)*** $\lambda^1_{ue(new)}$ = +0.09 (0.04)** λ^1_{up} = +1.64 (0.07) *** $\lambda^2_{ue(new)}$ = +0.07 (0.05)* $\lambda^2_{ue(old)}$ = +0.03 (0.04) λ^2_{up} = +0.04 (0.09)	Not controlled.	(i) Dummy variables for a training period up to a year before entering unemployment (λ^1) and for a training period from one to two years before entering unemployment (λ^2). (ii) Endogeneity not allowed.	(i) Baseline hazard specified as the step function. (ii) Independent competing risks based on Cox's proportional hazard	*Women* 34949 *Men* 34427 spells	(i) Sample of unemployment spells from the period 1981 - 87. (ii) Duration variable is the time taken to enter an old job, a new job or training.

Notes: * (**,***) = significant at the 10 (5, 1) per cent significance level. λ = the probability of leaving a state in which the subscript gives the origin and the destination state. The states are defined as follows: e = employment; n = non-employment; p = programme participation; o = out of the labour force; i = terminating a spell for another state. YTS = Youth Training Scheme. NSW = National Supported Work Demonstration.

CHAPTER 4.

Active Labour Market Programmes and Unemployment: a Macroeconometric Study

Unemployment is one of the most serious problems facing modern society. Long lasting high unemployment tends to bring about extensive costs, not only unemployment benefits paid and income taxes lost, but also even more serious social costs, such as increasing crime rates, wider social inequalities, and decreasing family stability. Active labour market programmes (ALMPs) have been introduced to reduce these problems by improving the employment performance of the economy. As pointed out in chapter 2, this is also the principal aim of Finnish ALMPs.

The discussion in chapter 3 highlighted that there are major controversies over the macroeconomic efficiency of active labour market policy in reducing unemployment. The results of cross-country studies have been generally favourable for active programmes; spending on active programmes is found to reduce unemployment and wages, and increase real wage flexibility. The orthodox view of the usefulness of ALMPs offered by cross-country estimations has been challenged by studies that have employed time series data and focused on the impact of active programmes on wage-setting in the unionised labour market. According to these studies, active programmes increase union's fallback level leading to increased wage demands, which in turn implies lower employment and perhaps even deteriorating unemployment. Hence, despite the central position of active programmes in handling the unemployment problem (OECD 1990, 1993), the outcomes of these programmes are, by and large, unclear and controversial.

This chapter contributes to existing literature by combining two popular views of how ALMPs operate, through labour supply and through wage-setting, into a small supply side model that is estimated by employing Finnish time series data from the period

1980Q1 - 1992Q4. The choice of the evaluation period is is purely based on the availability of data, see chapter 2. The objectives of the study are: (i) to generalise the model analysed in Calmfors & Forslund (1991) by incorporating labour demand and labour supply behaviour into analysis; (ii) to estimate theorised effects and to employ estimated parameter values in examining the impact of active labour market policy on aggregate unemployment. It turned out in chapter 3 that on theoretical grounds the effect of ALMPs on both wage-setting and labour supply is ambiguous, *a priori*. Empirical results imply that in the long-run equilibrium more accommodative active labour market policies expand the size of the labour force, and increase both wages and open unemployment when unemployment is low, whilst having a downward effect on wages and open unemployment in the high unemployment situation.

The remainder of the chapter is organised as follows. The theoretical model is set up in section 4.1. Section 4.2 discusses the empirical model and reports the estimations results. The aggregate impact of active labour market programmes on unemployment is examined in section 4.3. Finally, section 4.4 concludes the study.

4.1. Theoretical Model

4.1.1. Labour Demand

A representative firm produces value-added output using labour input (E), capital (K), and raw materials (M) via the general production function

(1) $$Y = f(E,K,M).$$

It is assumed that the firm operates in imperfectly competitive product markets, where the downward sloping demand for its products is given by

(2) $$P = Y^{-\frac{1}{\eta}},$$

η being the elasticity of demand for the firms outputs.

The first order condition, which equates marginal revenue with marginal costs, gives the following relations

$$(3) \qquad (1-\frac{1}{\eta})Y^{-\frac{1}{\eta}} = W(1+s)g'(Y,K,M)$$

$$(3') \qquad f'(E,K,M) = (1-\frac{1}{\eta})^{-1}\frac{W(1+s)}{P} \ ,$$

where g is the inverse of the production relation, and labour costs consist of gross wages (W) and payroll taxes (s). The first equation gives prices as a mark-up over wages, the mark-up factor being $(1 - 1/\eta)^{-1}$. As noted in Layard & Nickell (1986), there is no reason to expect this mark-up factor as being constant, so it is modelled as a function of aggregate demand; and consequently, denoted by $\psi(AD)$. The exact dependence of the mark-up factor on aggregate demand, AD, is uncertain, but it is likely to behave countercyclically, see Layard et. al. (1991).

According to the latter equation, the marginal product of labour is equal to total real labour costs times the mark-up factor. Given that prices have been set in advance, equation (3') determines the demand for labour as

$$(4) \qquad E = f^{E}(\underset{(-)}{W/P}, \underset{(-)}{s}, \underset{(-)}{\psi(AD)}, \underset{(+)}{K}, \underset{(+)}{USRC}, \underset{(-)}{P_{mpr}/P}) \ .$$

The general labour demand equation hypothesises the negative dependence of labour demand on its own price, which consists of real wages (W/P) and payroll taxes (s). An increase in the user cost of capital (USRC) is expected to have a positive impact on labour demand through the partial substitutability of labour and capital. Higher aggregate demand, AD, leads to rising production levels, which in turn affects positively the demand for labour through the countercyclical mark-up factor, $\Psi(AD)$. Finally, an increase in the real price of raw materials (P_{mpr}/P) reduces labour demand. It is assumed that active labour market programmes do not have any significant effect on labour demand directly, but they do have an indirect impact through their wage effect, which is discussed below[1].

4.1.2. Wage Formation

Since the unionisation rate in Finland (over 80%) is among the highest in the OECD and wage negotiations are fairly centralised, the natural way for modelling wage formation is to adopt the union model. The union is assumed to have the utilitarian utility function of the form

(5) $$U(\omega) = \lambda_i \, u(W(1-t_1)) + (1-\lambda_i) \, u(A),$$

where λ_i is the probability of a union worker maintaining his union job, t_1 is the income tax rate, and A is the alternative wage obtainable to those union workers who are not able to keep their union jobs. The alternative wage is defined as the weighted average between the wage rate elsewhere, W^A, and the income while out of work, B,

(6) $$A = [1-\theta(u,r)]W^A + \theta(u,r)B \ ,$$

where the weight, θ(u,r), is defined as the probability of NOT getting a hire. This probability depends positively on the unemployment rate, u, and negatively on the probability of participating in a labour market programme, r. According to equation (6), active programmes raise the alternative wage provided that $W^A > B$.

By building a standard Nash-bargaining problem assuming that under no agreement, the union's payoff equals the utility gained from the alternative wage, and the firm has to stop production, the first order condition for the bargaining problem can be shown to be

(7) $$\frac{\omega \cdot u'(W(1-t))}{u(W(1-t)) - u(A)} = \varepsilon_{sw} + \frac{1-\beta}{\beta}\varepsilon_{\Pi w} \quad .$$

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[1] Job placement programmes could affect firms' labour demand through wage subsidies. Recent studies, which are summarised in chapter 3, suggest that these programmes can have substantial displacement effects, which in turn implies that firms' labour demand is not significantly affected by ALMPs.

This familiar result says that in the negotiated wage equilibrium the percentage marginal benefit of the wage increase to union equals its marginal costs. Marginal costs consist of percentage reduction in the survival probability of a union worker due to wage increase, ε_{sw}, and percentage reduction in profits due to wage increase, $\varepsilon_{\Pi w}$. The weight at which the profit reduction affects the negotiated outcome depends on union's bargaining strength, β.

Based on equation (7), wage setting is affected by all variables entering the utility function of the union, and all variables entering the profit function of the firm via the production function and demand specifications. This hypothesises the general wage relation of the form

$$(8) \qquad \frac{W}{P} = f^{W}(\underset{(+)}{(1-t_1)},\ \underset{(-)}{(1+s)},\ \underset{(-)}{(1+t_2)},\ \underset{(+)}{\frac{B}{P}},\ \underset{(-)}{u},\ \underset{?}{r},\ \underset{(+)}{\beta},\ \underset{(+)}{K},\ \underset{(+)}{AD}).$$

The signs of these effects are widely known. The income tax rate (t_1), the payroll tax rate (s), and the indirect tax rate (t_2) form the wedge between product and consumer wages, $\frac{W(1+s)/P_p}{W(1-t_1)/P_{cpi}} = \frac{(1+s)(1+t_2)}{(1-t_1)}$, which determines the signs of these terms. An increase in unemployment benefits, $\frac{B}{P}$, rises union's fallback level introducing an upward pressures on wages. Unemployment, u, places downward pressures on union's wage demands because of its adverse effect on an unemployed union worker to get a job elsewhere. A rise in union power, β, gives more strength to unions in wage negotiations which creates upward pressures on wages. An increase in capital stock, K, tends to raise union's wage demands because of the increased profitability of union workers. Finally, aggregate demand is allowed to have a positive effect on wages, but this variable is dropped out in empirical estimations. This is consistent with Layard & Nickell (1986) who argued that the firm does not allow short-run fluctuations to affect longer term wage negotiations.

To recall, more accommodative active labour market policy can affect wages through several channels which tend to counteract each other (see chapter 3). First, ALMPs reduce the welfare loss of being out of work by offering compensation levels over unemployment benefits. This in turn tends to increase union's wage demands, see Calmfors & Forslund (1991). Second, provided that ALMPs increase the size of the labour force, the increased competition over existent jobs has a downward effect on wages. Third, substitution and dead-weight losses of active programmes have also a downward effect on wages, due to reduction in regular employment. Since the estimate for the impact of ALMP on wages captures all these effects, the sign remains ambiguous, *a priori*.

4.1.3. Labour Supply

It is often argued that active programmes prevent hard-to-employ persons becoming discouraged and thus help to keep those persons in connection with the labour market.[2] By increasing the effective labour supply ALMPs are expected to create a downward pressure on bargained wages through competition over existent jobs; competition forces insiders to keep their wage demands at the lower level. The impact of active programmes on an individual's labour force participation decision, and hence on the size of the labour force, can be modelled by the standard labour supply model. An individual chooses to consume goods, x, and leisure, l, to maximise utility U(l,x) subject to the budget constraint x = E(W)/P + Z/P, where E(W)/P is the expected wage and Z/P is income received while out of work. Real expected wages are assumed to be determined by $\varphi(u, r)\frac{(1-t_1)W}{P}$, which says that the expected real wage for an unemployed person is

[2] See Layard (1986, 1990), Layard et. al. (1991), OECD(1993), among others.

some fraction of prevailing real market wage. The fraction term, φ, reflects the probability of becoming hired, depending negatively on unemployment and positively on ALMPs. In a period of high unemployment the competition over jobs is stronger lowering the probability of employment, whilst human capital accumulation and the work experience offered by active programmes are likely to increase the employment probability.

The first-order condition for this utility maximisation problem leads to the demand functions$l = l(\frac{E(W)}{P}, \frac{Z}{P})$ and $x = x(\frac{E(W)}{P}, \frac{Z}{P})$, which gives a general function for labour force participation as

$$L = f^L(\underset{(-)}{(1-t_1)}, \underset{(+)}{\frac{W}{P}}, \underset{(-)}{u}, \underset{(?)}{r}, \underset{(-)}{\frac{Z}{P}}) \quad . \tag{9}$$

An increase in income received while out of work, $\frac{Z}{P}$, has a downward effect on participation by reducing the welfare loss of being out of work. A higher income taxation, $(1\text{-}t_1)$, reduces participation by making the corner solution more probable. The impact of unemployment and active programmes on labour supply work through the probability of an unemployed person of getting a hire. Since both the employed and the unemployed are registered as belonging to the labour force, the participation decision depends crucially on unearned income, which does not include unemployment benefits, B/P. Accordingly, an individual participates the labour force if his reservation wage is less than the weighted sum of market wages, W/P, and unemployment benefits, B/P, weighted by the employment probability, φ(u,r), i.e., less than $(1-t_1)[\varphi(u,r)\frac{W}{P} + (1-\varphi(u,r))\frac{B}{P}]$ = $(1-t_1)[\frac{B}{P} + \varphi(u,r)(\frac{W}{P} - \frac{B}{P})]$. Given that higher unemployment reduces the employment probability, φ(u,r), it reduces labour force participation (discouragement effect). Similarly, provided that ALMPs rise the employment probability, they make the labour force participation more likely by increasing the required reservation wage for being indifferent between participation and non-participation. In addition to the preventing effect on discouragement, ALMPs may also be used as a work test, which tends to reduce participation (see chapter 3). Since these two effects work in different directions, the net effect remains uncertain.

4.2. Empirical Examinations

As discussed in chapter 3, theoretical reasoning does not offer any clear prediction for the net effect of active programmes, so it remains an empirical question. The building blocks of our empirical model are theoretical relationships hypothesised in equations (4), (8), and (9). Instead of modelling the dynamics of the system through strict theoretical formulations, we use an autoregressive distributed lag model of the form

$$y_t = \sum_{i=1}^{l} \gamma_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{m} \theta_{ji} x_{j,\, t-i} + v_t \quad , \tag{10}$$

where l and m denote the lag lengths of dependent variable and k exogenous variables, respectively. This can be written equivalently as

$$\Delta_4 y_t = \sum_{i=1}^{l} \gamma_i \Delta_4 y_{t-i} + \sum_{j=1}^{k} \sum_{i=1}^{m} \theta_{ji} \Delta_4 x_{j,\, t-i} + \sum_{i=4}^{r+4} \alpha_i (y_{t-i} - \sum_{j=1}^{k} \beta_{ji} x_{j,t-i}) + v_t \ , \tag{11}$$

where $\alpha_4 = \gamma_4 - 1$, $\beta_4 = \dfrac{\theta_0 + \theta_1}{1 - \gamma_4}$, $\alpha_i = \gamma_{i-4}$, $\beta_i = \dfrac{\theta_{i-4}}{\gamma_{i-4}}, i = 5, \ldots, r+4$, and r = max(l,m). In estimations the error-correction terms, $(y_{t-1} - \Sigma_{j=1}^{k} \beta_{ji} x_{j,t-i})$, are collected into a single error-correction term at lag r, $\left[y_t - (\sum_{i=1}^{m} \theta_{ji}) / (1 - \sum_{i=1}^{l} \gamma_i) x_t \right]_{t-r}$. This simplification has two advantages: it produces results that are easier to interpret especially with respect to the long-run equilibrium relationship, and avoids the multicollinearity problem likely to be present when estimating trending variables in levels with generous lag lengths. What is more, this framework is correctly specified even when variables are non-stationary[3]

[3] Preliminary data analysis by unit-root tests, spectral densities, and ARIMA models indicates the presence of non-stationarities in variables. For the results of unit-root tests, see appendix 4.1.

provided that they are cointegrated as proved by the Granger representation theorem, see Engle & Granger (1987).

Some moderations are needed between theoretical and empirical models. First, the labour supply effect of ALMPs is examined by employing the size of the labour force as a dependent variable. This variable is modified by subtracting the number of programme participants from the labour force variable in order to avoid spurious correlation. Second, several combinations of demand side factors, such as real money supply, total consumption and competitiveness, were tried in modelling aggregate demand without finding any meaningful effect. Our solution to this problem was to adopt the so called two sector Scandinavian model, Lindbeck (1979), which introduces the output of the closed sector as a demand shift variable into the analysis. Third, the real income while out of work, Z/P, is modelled as consisting of unemployment benefits, B/P, and non-labour assets. However, non-labour assets had to be dropped from estimations because of its strong correlation with the wage variable. Fourth, the impact of the capital stock is allowed to enter the wage equation through the productivity term measured as capital stock per hours worked. This is consistent with Bean et. al. (1986) who argued that capital stock must increase faster than the labour input in order to affect real wages. Fifth, union power is approximated by union density measured as the ratio of union members to the labour force; even though, there are likely to be endogeneity problems with this variable, see Booth & Chatterji (1993), Naylor & Raaum (1993). Estimations are carried out by employing seasonally unadjusted quarterly data over the period 1980Q1 - 1992Q4 collected from the data set of the Bank of Finland and from various publications of the Ministry of Labour. The choice of the estimation period is driven purely by the availability of the data.

4.2.1. Estimated Wage Equations

Optimally a non-stationary system, formed from equations such as (11), is estimated by some data-based estimation procedure, such as Johansen (1988). However, in the current setting the number of variables made an unrestricted VAR model unmanageable, i.e., we faced a trade off between omission of theoretically relevant variables and *a priori* restrictions based on theory. For that reason, we were forced to estimate the cointegrating vectors by static OLS estimations which can be shown to be asymptotically consistent for the parameters in the current context. It has to noted, however, that this superconsistency property may require large amount of observations to introduce negligible bias, see Banerjee et. al. (1993). Since, the estimation procedure adopted in this study is inevitably the second best, we try to ease the problems connected to finite samples (Banerjee et. al., 1986) and endogeneity[4] (Banerjee et. al., 1993) by experimenting with dynamic models and by instrumenting some potentially endogenous variables when estimating cointegrating vectors[5]. Dynamic models may also alleviate the problem of non-standard distributions of the coefficient estimates when modelling non-stationary variables with static regressions (Banerjee et. al. 1993, p. 167 - 168).

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[4] Due to super-consistency, endogeneity does not asymptotically affect the parameter estimates in static cointegrating regressions. However, it may be a problem in finite samples (Banerjee et. al. 1993). The results of the unreported estimations, in which instrumented variables were replaced by their uninstrumented counterparts, are well in line with the results reported in tables 4.1 and 4.2.

[5] Some confidence on the results reported in tables 4.1 and 4.2 is gained by experiments with system estimation methods. The estimated parameter values for key variables obtained by employing 3SLS estimation method are $Ln(W/HP_p) = -0.06ln(U/L) - 0.12ln(R/L) + Z_1$; $ln(L) = -0.02ln(U/L) + 0.10ln(R/L) + 0.20ln(W/HP_p) + Z_2$; $ln(E/K) = -1.27ln(W/HP_p) + Z_3$. Notes: All parameter estimates are significant, excluding the unemployment variable (U/L) in the labour supply equation; Equations pass all misspecification tests as a system, but there are some indications of autocorrelation in single equation test statistics; Unreported parameters (Zs) are also well in line with the results reported in tables 2 and 3. We also experimented with various dummies to represent the 1987 Employment Act. None of these entered the cointegrating regressions reported in tables 4.1 and 4.2.

Table 4.1 Estimated Wage Equations.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W/H}{P_p})^a$	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W/H}{P_p})$	$Ln(\frac{W}{P_p})$
Const	-0.36 (0.32)	0.15 (0.15)	0.14 (0.15)	-0.62 (0.70)	-0.11 (0.37)	0.06 (0.35)	3.66 (0.30)	1.31 (0.47)
$Ln(\frac{B}{P_p})$	0.27 (0.15)	-	-	0.29 (0.37)	0.01 (0.16)	-0.08 (0.14)	0.66 (0.13)	0.47 (0.22)
$Ln(\frac{R}{L})^*$	-0.22 (0.05)	-0.16 (0.04)	-0.15 (0.04)	-0.17 (0.11)	-	-	-0.40 (0.05)	-0.29 (0.08)
$Ln(\frac{U}{L})^*$	-0.04 (0.02)	-0.05 (0.02)	-0.05 (0.02)	-0.09 (0.08)	-	-0.11 (0.01)	-0.08 (0.02)	-0.13 (0.03)
$Ln(\frac{LTU}{U})^*$	0.03 (0.01)	0.02 (0.01)	-	0.03 (0.04)	0.01 (0.01)	0.01 (0.01)	0.07 (0.01)	0.06 (0.02)
Ln(1+s)	-1.16 (0.77)	-0.94 (0.78)	-2.01 (0.47)	-1.62 (3.10)	-1.29 (0.93)	-0.79 (0.90)	-0.74 (0.36)	-1.90 (1.14)
$Ln(1+t_2)$	-0.91 (0.55)	-0.63 (0.54)	-0.56 (0.55)	-0.50 (1.87)	-0.58 (0.65)	-0.65 (0.65)	-0.96 (0.63)	-1.13 (0.82)
$Ln(1-t_1)$	-0.45 (0.27)	-0.63 (0.54)	-0.51 (0.22)	-1.07 (0.94)	-0.35 (0.33)	-0.21 (0.32)	-1.14 (0.32)	-0.43 (0.41)
$Ln(\frac{K}{H})$	1.08 (0.08)	1.20 (0.05)	1.24 (0.05)	1.09 (0.17)	1.21 (0.10)	1.20 (0.09)	0.88 (0.10)	0.94 (0.13)
$Ln(\frac{R+U}{L})$	-	-	-	-	-0.16 (0.03)		-	-
Ln(1-acc)	-	-	-	-	-0.00 (0.07)	-	-	-
Diagnostics								
R^2	0.98	0.98	0.98	0.99	0.98	0.98	0.98	0.95
DW	1.54	1.52	1.56	2.01	1.27	1.32	2.26	1.28
AR_4	1.02 [0.40]	0.81 [0.52]	0.98 [0.42]	1.06 [0.40]	1.62 [0.19]	1.26 [0.30]	0.39 [0.81]	2.44 [0.06]

Table 4.1 Estimated Wage Equations.

$ARCH_4$	1.36 [0.26]	1.84 [0.14]	2.06 [0.10]	0.32 [0.85]	0.50 [0.73]	0.17 [0.94]	0.79 [0.54]	0.95 [0.44]
J-B	0.35 [0.83]	1.83 [0.40]	0.36 [0.83]	0.25 [0.87]	1.05 [0.58]	0.41 [0.81]	0.49 [0.78]	0.31 [0.85]
HET	0.41 [0.96]	0.40 [0.96]	0.42 [0.95]	n/a	0.40 [0.97]	0.76 [0.71]	0.75 [0.72]	0.33 [0.98]
RESET	9.88 [0.00]	3.24 [0.08]	4.85 [0.03]	0.02 [0.88]	15.86 [0.00]	15.18 [0.00]	5.88 [0.02]	8.00 [0.00]
DF 1	-5.29^{++}	-5.23^{++}	-5.49^{++}	-7.08^{++}	-4.70^{++}	-4.67^{++}	-5.28^{++}	-4.79^{++}
DF 2	-5.24^{++}	-5.19^{++}	-5.48^{++}	-7.01^{++}	-4.64^{++}	-4.62^{++}	-5.21^{++}	-4.74^{++}
DF 3	-5.19^{++}	-5.15^{++}	-5.48^{++}	-6.91^{++}	-4.61^{++}	-4.59^{++}	-5.15^{++}	-4.72^{++}
ADF 1	-3.88^{++}	-3.82^{++}	-3.29^{++}	-3.44^{++}	-3.42^{++}	-3.09^{++}	-2.93^{++}	-3.66^{++}
ADF 2	-3.90^{+}	-3.85^{++}	-3.39^{+}	-3.38^{+}	-3.44^{++}	-3.08^{++}	-2.90	-3.71^{++}
ADF 3	-3.81^{+}	-3.75^{+}	-3.29	-3.21	-3.33	-2.94	-2.89	-3.63^{++}

Notes: (a) Estimates are obtained as a long-run solution of the ADL(2,2) model. Standard errors are reported in parenthesis. Starred variables are instrumented. The instrument set consists of the lagged values of variables introduced in the theoretical models in sections 4.1.1 - 4.1.3. Estimation method is OLS in which the fitted values of the instrumented variables are included as regressors. All the reported models include seasonal dummies which control for seasonal variation in quarterly data employed in estimations. Acc refers to the accommodative stance. The tests are as follows: DW is the Durbin-Watson statistic for the first order autocorrelation, AR_i is the LM test for the i^{th} order autocorrelation; $ARCH_i$ is the test statistic for the i^{th} order autoregressive conditional heteroscedasticity; J-B is the Jarque - Bera test statistic for normality; HET is the White's heteroscedasticity test; RESET is the test statistic for the functional form. P-values are reported next to test statistics. DF 1 (DF 2, DF 3) is the Dickey-Fuller test for the stationarity of residuals which does not include a constant (includes a constant, includes a constant and a trend). ADFs are the corresponding augmented Dickey-Fuller tests for the stationarity of residuals which are derived from the DF tests by adding five lagged differences into estimations. In stationarity tests one (five) per cent significance is marked by ++ (+). The estimations were carried out by using PC-GIVE 8.0 (Doornik & Hendry, 1994). For variable definitions, please see the data appendix.

The estimated long-run wage relations are reported in table 4.1. In terms of diagnostic tests all error terms are well behaved, and stationary, but some equations suffer from functional form problems as indicated by low p-values in the Reset test. However, since the estimated parameter values are well in line with *a priori* expectations, estimated long-run wage relations are rather satisfactory.

It is surprising to find that, regardless of the exact specification, active programmes seem to have a large, well determined, downward effect on wages. It is even more surprising that the downward pressure created by active programmes, R/L, exceeds that of open unemployment, U/L, being in strong contrast to Swedish time series studies which tend to give wage increasing effects for active programmes, see Calmfors (1993). Since the result is unexpected, we put it under scrutiny by several means. First, we examined whether the estimated impact of active programmes depends on other variables which might drive the results through their close connection to the decision to participate a programme. This was modelled by excluding the unemployment benefits variable, B/P_p, and the long-term unemployment variable, LTU/U, from the estimations in columns (b) and (c). There are some indications that these variables magnify the estimated effect of ALMPs on wages, but the qualitative outcome remains. Second, it may be that the sample period employed in this study is too short for estimating long-run relations via static regressions, in which case the parameter estimates could be severely biased. Since the dynamic modelling strategy for estimating long-run relations is found to be less sensitive to small sample bias, we estimated an ADL(2,2) model in column (d). The long-run solution of this model also suggests that more accommodating labour market policy has a wage reducing effect, but with a less pronounced parameter estimate. Third, instead of controlling for open unemployment and measuring active programmes as the ratio of participants to labour force, we estimated the wage equation by including the total unemployment variable and the accommodative stance variable as regressors. The results reported in column (e) confirm that ALMPs have a downward effect on wages[6], since it seems to be total unemployment rather than open unemployment which determines wages. Fourth, we experimented by estimating the wage equation without the ALMP variable. Even though, this specification indicates higher responsiveness of wages with respect to open unemployment, the effect remains smaller than any of the estimated impacts for the ALMP variable. Fifth, since the majority of participants in job placement programmes work in the public sector, we examined whether it makes a difference to estimate the wage equation for the private sector only. According to the results reported in column (g), the downward effect of ALMPs on wages is even greater in the private sector. Finally, because the dependent variable is measured as hourly wages, it is possible that the wage setting specification is picking up the situation where changes in working hours are driving the results. Especially, since the estimation period covers two OECD recessions, when working hours per employee tend to become longer affecting labour demand, and hence also programme participation. This possibility is examined in column (h), and once again the negative parameter estimate for the active programmes variable remains.

According to other parameter estimates, unemployment benefits, B/P, have a wage increasing effect. Unemployment rate, U/L, reduces union's wage demands, the long-run coefficient varying from -0.04 to -0.13. The estimates which indicate some resistance of unemployment in union wage demands are higher than in previous Finnish studies which report the parameter estimates around -0.04, see Pehkonen (1991), being

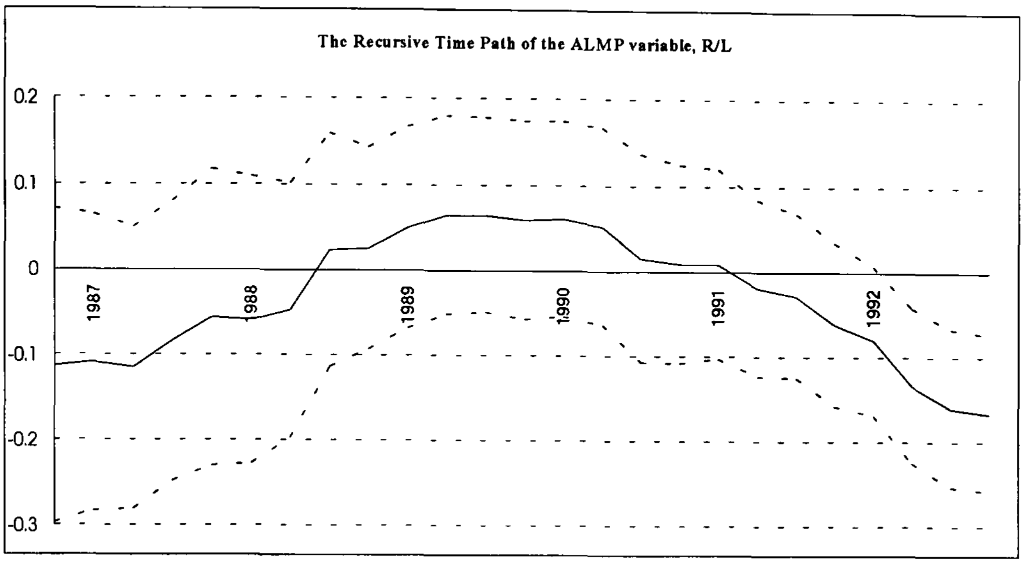
[6] The discussion in chapter 3 revealed that if we denote the ALMP variable by r, and open unemployment variable by u, the wage equation in column (e) becomes $Ln(W)=\alpha Ln(r+u)+\beta Ln(1-r/(r+u))$. This can be written equivalently as $Ln(W)=(\alpha-\beta)Ln(r+u)+\beta Ln(u)$. The insignificance of the β coefficient implies that only total unemployment affects wages, which in turn indicates that open unemployment and ALMPs have the same effect on wages.

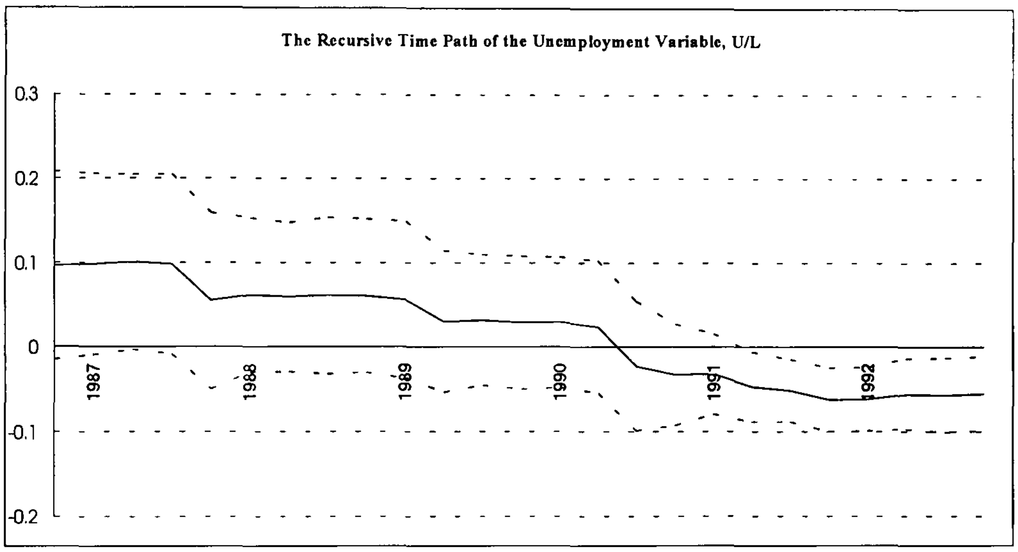
closer to the results reported for instance in Nickell (1987) and Calmfors & Forslund (1991). The third 'unemployment variable' used in estimations is the proportion of long term unemployed persons in open unemployment, LTU/U. There are some indications that an increase in long-term unemployment rises wages, but this effect is quite modest and not extremely well determined across different specifications. Finally, the results concerning taxation variables are well in line with previous studies. Higher income taxes, t_1, add to wage pressures, the effect being around half of the initial impact, on average. More than half of a rise in employers' taxes, s, is shifted backwards to lower wages. Indirect taxes, t_2, contribute by lowering wages, whilst also raising labour costs as indicated by parameter estimates below the unity, in absolute values.

The discussion above suggests that active labour market policy reduces wage pressures, which in turn has a beneficial effect on employment. One has to notice, however, that the parameter values are end-point estimates for the period during which unemployment more than quadrupled. Further doubts on the recursive stability of estimated parameters is cast by changes in economic policy, such as deregulation of credit markets and a general shift towards more disinflatory policies, both of which occurred in the 1980s. For the above reasons, we estimated our most preferred wage equation, reported in column (b), recursively. The recursive parameter values of the key variables for this study, viz. the open unemployment variable and the ALMP variable, are presented in figure 4.1, together with their standard errors multiplied by two[7].

[7] Even though the parameter estimates are asymptotically unbiased, the reported standard errors have to be considered as tentative due to the presence of unit roots which typically induces non-standard distributions of the coefficient estimates.

Figure 4.1 Recursive Estimates of Key Variables in the Wage Equation.





The finding that active programmes do not have any significant effect on wages during the era of low unemployment confirms the results reported in previous studies in which the relation between active programmes and wage setting in Finland has been analysed, see table A3.2 in chapter 3. The unimportant open unemployment effect on wages during the 1980s is not a total outlier either, see Pehkonen (1991). It is interesting to note that the time path for the ALMP variable seems to depend negatively on the general unemployment situation having the wage reducing effect when unemployment is high, whilst increasing wages when unemployment is low. This gives some support for the views expressed in Calmfors (1993), according to whom active programmes may be more favourable at higher levels of unemployment.

4.2.2. Estimated Labour Supply and Labour Demand Equations

Table 4.2 reports the estimated labour supply equations in columns (i) - (l), and the estimated labour demand equations in columns (m) - (p). The static long-run labour force relations reported in columns (i) and (j) differ by the inclusion of total population at working age variable, N, which is included to control for demographic factors of labour supply. The inclusion of this variable causes some changes both in static regressions and in dynamic regressions which are reported in columns (k) and (l). However, dynamic regressions seem to be more robust to the inclusion, since the additional variable turns out to be insignificant with an unrealistic parameter estimate of -4.09.

When it comes to other parameters, the most robust result is the negative effect of unemployment benefits on the size of the labour force. The interpretation of this finding is by no means clear, given that labour force participation is a requirement for claiming unemployment benefits. One explanation for the strong presence of the unemployment benefit variable in the labour force equation may be connected to the practically unlimited duration of unemployment assistance benefits in Finland, which might have lengthened unemployment spells when higher compensation levels have been introduced. This in turn might have affected the labour force via the discouragement of the long-term unemployed. Another fairly well established effect is that higher real wages expand the size of the labour force, hypothesising the upward sloping labour supply schedule. Finally, there are some indications that an increase in income taxation, t_1, reduces the size of the labour force, but this effect is found only in static cointegrating regressions.

Table 4.2 Estimated Labour Demand and Labour Supply Equations.

	(i)	(j)	(k)	(l)	(m)	(n)	(o)	(p)
	Ln(L)	Ln(L)	Ln(L)[a]	Ln(L)[a]	Ln(E/K)	Ln(E/K)	Ln(E/K)[a]	Ln(E/K)[a]
Const.	4.90 (0.06)	-2.59 (1.72)	4.96 (0.17)	22.81 (41.71)	-2.48 (0.64)	-1.55 (0.37)	-1.90 (0.55)	-1.88 (0.35)
$Ln(\frac{B}{P_p})$	-0.26 (0.02)	-0.12 (0.03)	-0.29 (0.06)	-0.91 (1.23)	-	-	-	-
$Ln(\frac{U}{L})^*$	-0.009 (0.004)	0.006 (0.01)	-0.06 (0.03)	-0.02 (0.05)	-	-	-	-
$Ln(\frac{R}{L})^*$	0.01 (0.01)	-0.009 (0.01)	0.16 (0.07)	0.29 (0.50)	-	-	-	-
$Ln(\frac{W/H}{P_p})$	0.24 (0.01)	0.02 (0.04)	0.12 (0.05)	0.83 (1.33)	-	-	-	-
t_1	-0.67 (0.12)	-0.25 (0.11)	-	-0.78 (1.40)	-	-	-	-
Ln(N)	-	1.69 (0.35)	-	-4.09 (9.57)	-	-	-	-
$Ln(\frac{W/H(1+s)}{P_p})$	-	-	-	-	-1.18 (0.07)	-1.11 (0.08)	-1.05 (0.11)	-1.05 (0.07)
Ln(USRC)	-	-	-	-	0.008 (0.02)	0.03 (0.02)	0.04 (0.02)	0.04 (0.01)
$Ln(\frac{Pmpr}{Pp})$	-	-	-	-	-0.18 (0.08)	-0.29 (0.05)	-0.20 (0.07)	-0.20 (0.05)
$LN(Q_{pub})^*$	-	-	-	-	0.11 (0.06)	-	0.00 (0.06)	-
Diagnostics								
R^2	0.82	0.91	0.93	0.96	0.96	0.95	0.99	0.99
DW	1.35	1.54	2.20	2.10	1.25	1.25	1.62	1.64
AR_4	1.38 [0.25]	0.67 [0.61]	2.55 [0.06]	2.31 [0.04]	2.09 [0.10]	2.44 [0.06]	0.70 [0.59]	0.50 [0.73]
$ARCH_4$	0.71 [0.58]	0.40 [0.80]	1.24 [0.31]	0.08 [0.98]	0.52 [0.72]	0.63 [0.64]	0.12 [0.97]	0.16 [0.95]

Table 4.2 Estimated Labour Demand and Labour Supply Equations.

J-B	0.80 [0.66]	0.81 [0.66]	3.33 [0.18]	0.48 [0.78]	6.19 [0.04]	7.60 [0.02]	0.48 [0.78]	0.69 [0.20]
HET	0.88 [0.57]	0.72 [0.75]	0.56 [0.88]	n/a	1.74 [0.11]	2.15 [0.05]	n/a	0.22 [0.91]
RESET	0.85 [0.36]	n/a	0.14 [0.70]	n/a	46.32 [0.00]	40.56 [0.00]	33.75 [0.00]	17.54 [0.00]
DF 1	-5.54^{++}	-5.25^{++}	-7.44^{++}	-7.54^{++}	-4.30^{++}	-4.36^{++}	-6.90^{++}	-6.85^{++}
DF 2	-5.67^{++}	-5.27^{++}	-7.36^{++}	-7.63^{++}	-4.25^{++}	-4.31^{++}	-6.81^{++}	-6.77^{++}
DF 3	-6.36^{++}	-5.61^{++}	-7.28^{++}	-7.55^{++}	-4.22^{++}	-4.32^{++}	-6.73^{++}	-6.69^{++}
ADF 1	-4.07^{++}	-4.27^{++}	-4.41^{++}	-4.13^{++}	-2.29^{+}	-1.99^{+}	-2.66^{++}	-2.16^{+}
ADF 2	-4.32^{++}	-4.35^{++}	-4.20^{++}	-3.95^{++}	-2.20	-1.93	-2.63	-2.13
ADF 3	-4.87^{++}	-4.62^{+}	-4.09^{++}	-3.84^{+}	-1.99	-1.62	-2.59	-2.08

Notes: see table 4.1. For variable definitions, please see the data appendix. The instrument set of Q_{pub} consists of lagged values of the general government output, import prices, user cost of capital, general government employment, general government productivity, and general government hourly wages.

Turning next to the group of variables reflecting unemployment. The unemployment rate itself does not seem to have any great influence on labour force. Only the specification reported in column (k) gives a well determined downward effect of unemployment on the size of the labour force. When it comes to the relatively unstudied aspect of active programmes, namely their role in determining the size of the labour force, the results are somewhat mixed. According to static specifications, ALMPs have not affected the labour force. However, estimated dynamic models suggest that ALMPs have a quite substantial, statistically significant, labour force expanding effect. As discussed above, the dynamic regressions seems to be more robust to changes in specification. In what follows, both of these specifications are used in examining the effect of ALMPs on unemployment in section 4.3.

The estimated labour demand equations are presented in columns (m) - (p) in table 4.2. The standard assumption of constant returns to scale technology, which hypothesises the unit elasticity of capital stock in the labour demand equation, is adopted also in this study. Estimated equations pass all diagnostic tests, excluding the test for functional form (Reset). This is explained by the rapid deterioration of employment which happened during the last two years of the estimation period, equations passing all misspecification tests when the last few observations are excluded from estimations. Parameter estimates are remarkably similar between static and dynamic models, excluding the variable which captures the effect of the closed sector output on labour demand. Despite this, the performance of the closed sector output variable dominates other demand shift variables.

In each of the estimated labour demand equations, the real labour cost variable has a suspiciously large, one-to-one, impact on labour demand. The reason for this is the parameter instability caused by the extreme observations in the 1990s, as shown below.

An increase in user cost of capital, USRC, seems to have a small beneficial effect on employment. Finally raw materials, approximated by the real import prices variable, P_{mpr}/Pp, have a downward effect on labour demand; the long-run coefficient being around -0.20.

In order to examine the stability of parameters, we estimated the long-run labour supply and labour demand equations recursively. The time paths of the key variables for this study are graphed in figures 4.2 and 4.3 for the models reported in columns (k) and (m).

Figure 4.2 Recursive Estimates of Key Variables in the Labour Force Equation.

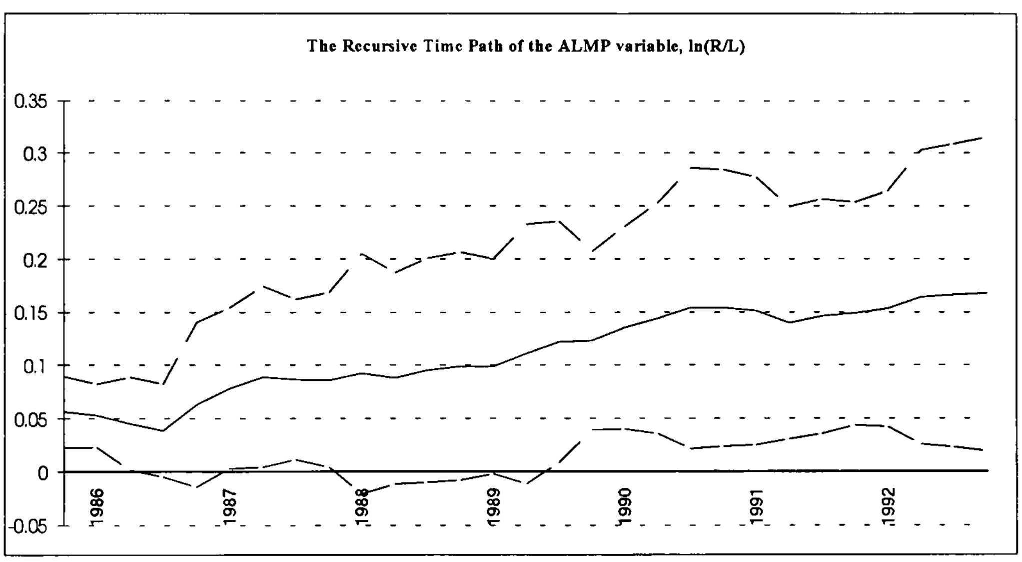


Figure 4.2 Recursive Estimates of Key Variables in the Labour Force Equation.

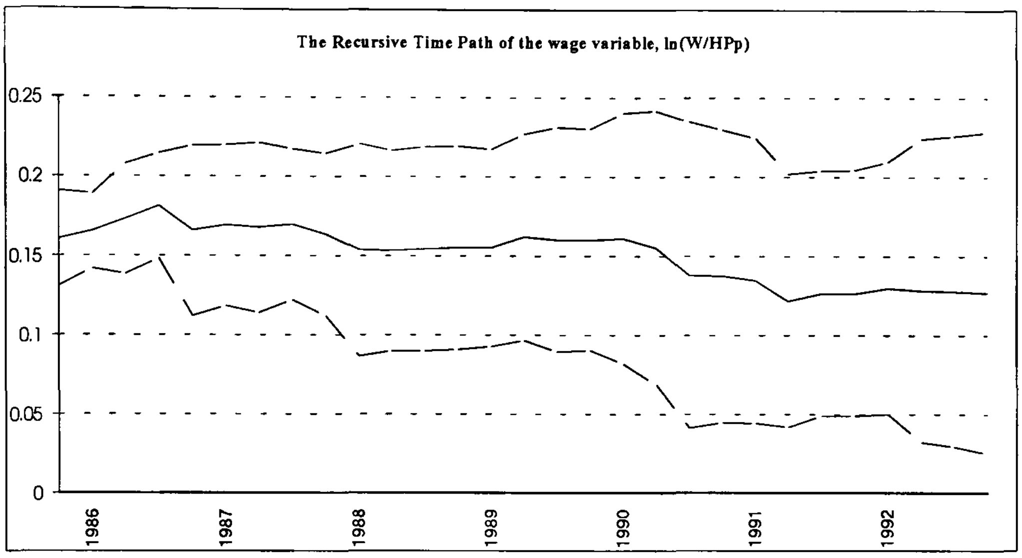


Figure 4.2 Recursive Estimates of Key Variables in the Labour Force Equation.

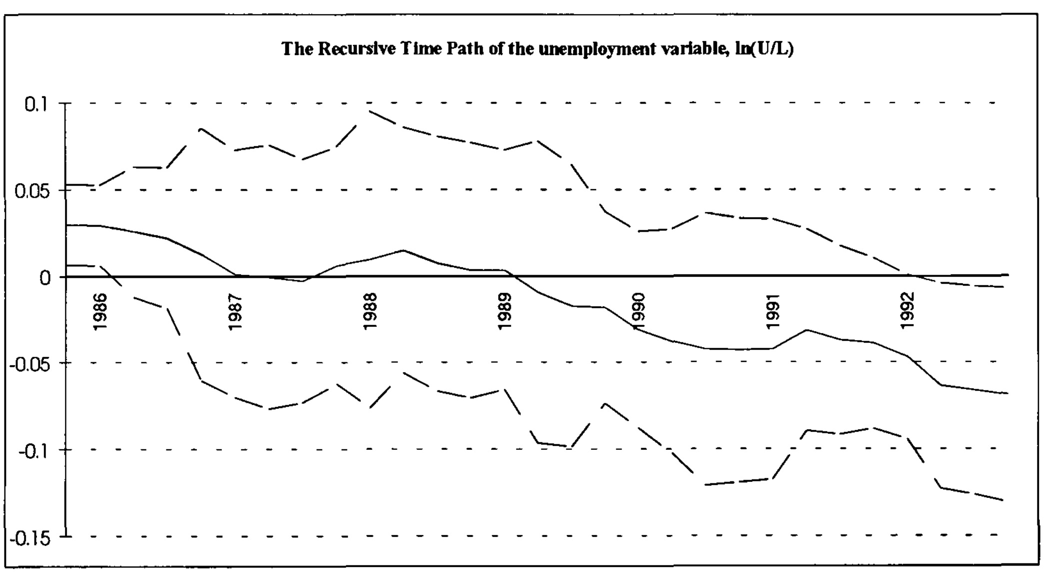
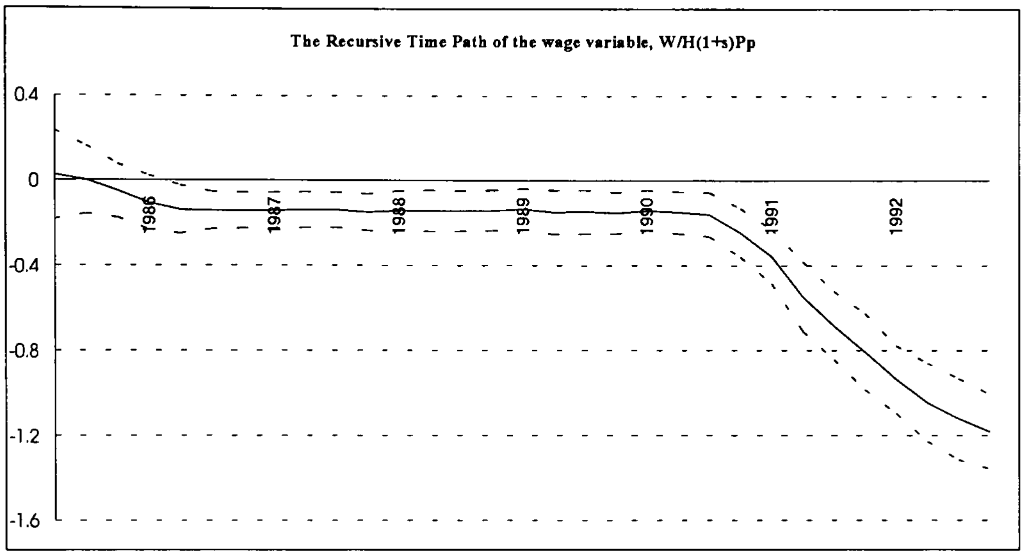


Figure 4.3 Recursive Estimates of the Wage Variable in the Labour Demand Equation.



The recursive estimates for the labour supply equation are quite stable, the estimates staying within the two times standard error lines. Unemployment, U/L, seems to have a significant downward effect on the size of the labour force only after the year 1992 when unemployment rate rose well above 10 per cent. This indicates that the discouragement effect has been negligible during the late 1980s. Having said that, the recursive time path for the ALMP variable, R/L, suggests that active labour market policies adopted in Finland have managed to increase the labour force, that is to prevent discouragement. It is interesting to note, that the beneficial effect of ALMPs has increased in the late 1980s when the unemployment rate was unusually low. Finally, the positive wage effect on the size of the labour force is well established, the long-run coefficient centring around 0.15. As a final remark on the recursive estimates for the long-run labour force equation, we say that the dynamic estimates are superior to the static ones in terms of parameter stability, unlike in estimated long-run wage relations.

If the recursive estimates for the labour force equation are stable, this is not the case for the estimated labour demand equations. In all specifications reported in columns (m) - (p), the key variable for our purposes, the elasticity of labour demand with respect to wages, is extremely stable during the 1980s, the long-run elasticity being -0.13 -

-0.14. After the unemployment situation started to deteriorate at the 1990s, the real wage elasticity of labour demand increased substantially, the latest observations indicating a one-to-one relation across different specifications.

4.3. The Effect of Active Programmes on Open Unemployment

To conclude the discussion so far. First, recursive estimates cast some doubts on fixed parameter assumptions. Second, there are some implications that active programmes have a downward effect on wages during the era of high unemployment. During the era of low unemployment this effect was negligible. Third, the results suggest that active labour market policies expand the size of the labour force. Fourth, the real wage elasticity of labour demand has increased considerably during the period of high unemployment. Hence, active programmes might have some beneficial effect on open unemployment in the 1990s through their wage resistance impact which in turn seems to have a substantial effect on labour demand. However, on the other side of the coin is the expanding impact of ALMPs on the size of the labour force, which tends to increase open unemployment. In order to examine the relative magnitudes of these effects, we rewrite the estimated long-run relations as

$$(12) \qquad Ln(\frac{W/H}{P_p}) = \alpha_1 Ln(\frac{R}{L}) + \alpha_2 Ln(\frac{U}{L}) + Z_1$$

$$(13) \qquad Ln(L) = \beta_1 Ln(\frac{R}{L}) + \beta_2 Ln(\frac{U}{L}) + \beta_3 Ln(\frac{W/H}{P_p}) + Z_2$$

$$(14) \qquad Ln(E) = \gamma_1 Ln(\frac{W/H}{P_p}) + Z_3 \ .$$

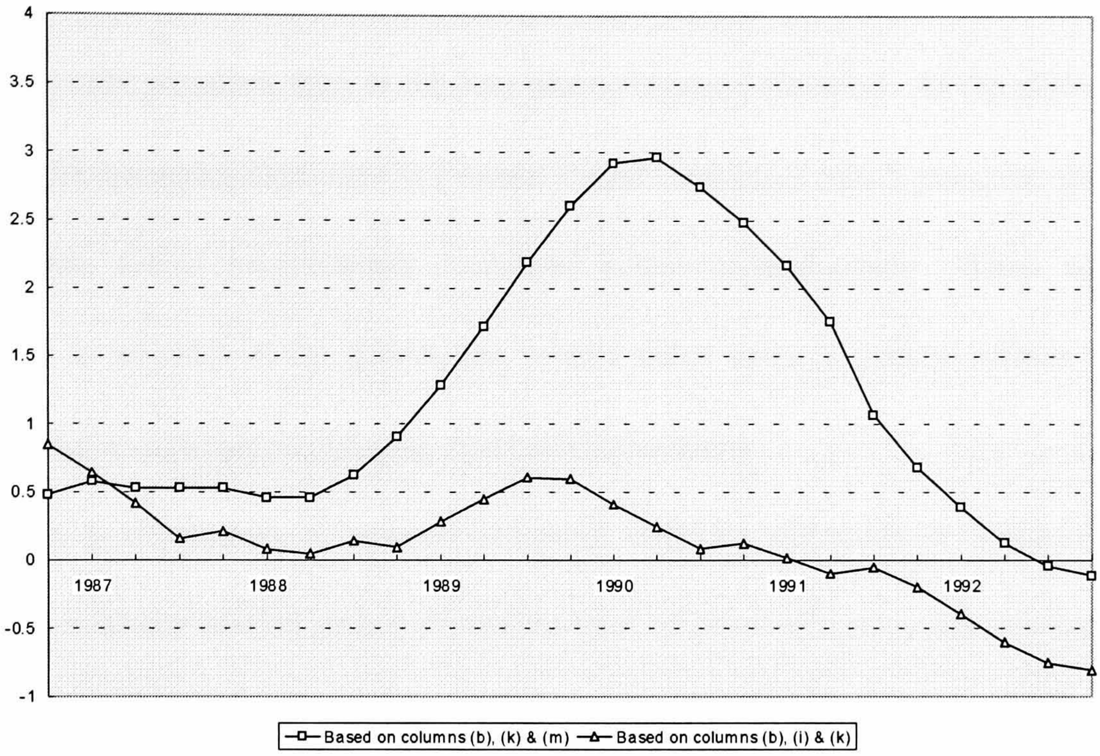
The variables expressed in equations (12) - (14) are as follows: $\frac{W/H}{P_p}$ is the real hourly product wage; $\frac{U}{L}$ and $\frac{R}{L}$ denote the open unemployment rate and the programme participation rate, respectively; L is the labour force of which programme participants have been subtracted out; E is total employment thought of reflecting labour demand; and finally Zs' include all other parameters used in estimations. After using the identity Ln(E) = Ln(1-U/L) + Ln(L), the elasticity of open unemployment with respect to active programmes can be obtained in two steps. First, employment and wage variables are substituted out from equation (13). Second, the total differential is taken with respect to the open unemployment rate (U/L = u) and the programme participation rate (R/L = r). After these steps the elasticity measure becomes

$$\text{(15)} \qquad \varepsilon_{UR} = \frac{du/u}{dr/r} = \frac{\beta_1 + (\beta_3 - \gamma_1)\alpha_1}{u/(1-u) - \beta_2 - (\beta_3 - \gamma_1)\alpha_2}.$$

According to equation (15), the effect of active programmes on open unemployment depends on the responsiveness of both wages and labour force to changes in open unemployment and programme participants, together with the level of unemployment and the real wage elasticities of labour supply and labour demand. The evaluation of the elasticity measure is presented in figure 4.4 below.

There are two evaluations of active programmes in figure 4.4: a 'pessimistic' one and an 'optimistic' one. In the latter specification (columns b, i & m) the labour force expanding effect of ALMPs is estimated as being modest, whereas in the former specification (columns b, k & m) it turned out to be substantial. The particular choice of other equations used in evaluation is immaterial due to the robustness of key variables across different specifications in wage and labour demand equations. The time paths, generated by different parameter estimates for the ALMP variable in static and in dynamic labour supply models, illustrate well the conflict between different targets that active labour market policies can have. If the main interest is in preventing discouragement, the effect of ALMPs on unemployment deteriorates, and vice versa.

Figure 4.4 The Elasticity of Open Unemployment with Respect to Active Labour Market Programmes.



Notes: The reported elasticity measures are based on calculations in which all insignificant parameter estimates are set to zeros; The series are smoothed.

Turning next to the main issue of interest, the results strongly suggest that Finnish active labour market policy has not helped to reduce open unemployment during the late 1980s. The estimated elasticity of open unemployment with respect to active programmes varies from 0.05 to 0.5 according to the 'pessimistic view', the corresponding figures being 0.5 and 3 for the 'optimistic view'. Having said that, estimates tend to become more and more favourable towards the end of the sample. At the last period both specifications suggest a downward effect of ALMPs on open unemployment, elasticity measures varying from -0.1 to -0.8. There are, however, some indications that the pace, at which ALMPs became more beneficial, started to slow down at the end of the estimation period. One explanation for this may be connected to decreasing marginal returns for which active programmes are likely to be exposed, Calmfors (1994).

All in all, figure 4.4 gives some support for the views expressed in Calmfors (1993, 1994), i.e. that active programmes are likely to be more effective in the high unemployment situation than in the low unemployment situation. At the end of the 1980s, when the unemployment rate in Finland varied between 3 and 5 per cent, the results suggest that active programmes worsened open unemployment. When unemployment started to increase in the 1990s, the results show some beneficial effects for active labour market policies in reducing open unemployment.

It is informative to employ end point elasticity estimates in evaluating the impact of active labour market policy on the number of persons openly unemployed. The exact number of participants in the fourth quarter of 1992 is 88610 persons, the level of open unemployment being 417 600. The results reported above imply that a 10 per cent increase in the number of programme participants would reduce open unemployment by 8 (1) per cent according to the 'optimistic' case, ('pessimistic' case). This in turn suggests that more accommodative policy reduces open unemployment by 4 000 - 33 400 persons depending on the exact model employed in calculations. One has to consider these figures as tentative, but as such they indicate that an increase in programme participants has to be sizeable in order to have any significant effect on unemployment. It would be interesting to know how this finding compares with active labour market policies adopted in other countries, but this is left for further research.

4.4. Concluding Remarks

In this chapter we have examined the effect of active labour market programmes on wage-setting and labour supply. By this means, we have incorporated two popular views of active programmes into a small supply side model that we have employed in calculating indirectly the impact of active programmes on unemployment. The main findings reported in this chapter can be summarised as follows: (i) some of the estimated equilibrium relationships indicate that active programmes increase labour supply giving some empirical support for the views of ALMPs preventing discouragement among unemployed persons expressed in Layard (1986, 1990) and Jackman et. al. (1990), among others. However, the finding has to be treated with caution due to large elasticity measures reported in figure 4.4; (ii) the impact of active programmes on wage-setting behaviour seems to depend on the level of unemployment, being positive when unemployment is low and negative when unemployment is high; (iii) based on parameter estimates, active labour market programmes have only modest effect on total unemployment. Hence, it is easy to agree with Calmfors (1994), according to whom most countries in Western Europe could do better with more active programmes, but not a lot better. They are not a 'miracle cure'.

Appendix 4.1. The Results of the Augmented Dickey-Fuller Tests.

Variable	1980 - 1992			1980 - 1989		
	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3
$Ln(W/HP_p)$	-0.89	-3.73*	-0.55	0.16	-2.52	0.06
	-1.16	*-5.85**	*-0.52*	*-0.98*	*-5.67**	*-0.47*
$Ln(B/P_p)$	0.95	-1.37	1.13	1.62	0.00	1.61
	0.62	*-1.41*	*0.85*	*0.46*	*-0.75*	*1.68*
Ln(U/L)	-1.80	-2.31	-1.97	-2.00	-1.10	-1.42
	0.93	*0.29*	*2.17*	*-2.36*	*-2.86*	*0.26*
Ln(R/L)	-1.87	-2.16	-1.35	-3.36*	-3.22	-2.84
	-0.53	*0.29*	*1.31*	*-3.84**	*-3.88**	*-2.11*
Ln(LTU/U)	-3.05	-4.03*	-2.89	-2.30	-1.66	-2.19
	-0.17	*-2.03*	*-1.07*	*-1.54*	*-1.53*	*-1.47*
Ln(1+s)	0.41	-2.31	0.42	0.49	-1.77	-0.48
	0.33	*-2.70*	*0.36*	*-0.55*	*-2.32*	*-0.53*
$Ln(1+t_2)$	-0.90	-0.20	-0.87	0.64	-0.79	0.51
	-4.53*	*-4.43**	*-3.95**	*-3.13**	*-4.49**	*-2.86*
$Ln(1-t_1)$	-2.57	-3.10	-2.20	-1.90	-2.79	-1.34
	-1.78	*-2.15*	*-1.74*	*-1.93*	*-2.34*	*-1.62*
Ln(K/H)	0.31	-1.96	0.78	0.75	-3.16	0.73
	1.07	*-1.03*	*2.27*	*-0.05*	*-6.69**	*0.37*
Ln((R+U)/L)	-1.21	-1.98	-1.34	-2.69	-1.92	-1.91
	1.74	*0.98*	*2.11*	*-2.23*	*-2.41*	*-1.23*
Ln(1-acc)	-0.72	-0.90	-0.98	-1.56	-1.43	-1.42
	-1.03	*-1.50*	*1.01*	*-3.32**	*-3.66**	*-0.82*
Ln(L)	-1.76	-0.85	-1.47	-2.15	-1.82	-2.01
	-1.37	*-1.33*	*-1.55*	*-2.78*	*-2.73*	*-2.54*
Ln(E/K)	1.91	-0.02	1.85	1.83	-1.08	1.67
	5.85	*1.59*	*5.86*	*1.14*	*-2.18*	*1.08*
Ln(USRC)	-1.01	-1.79	-1.54	-1.54	-1.62	-1.45
	-1.01	*-1.95*	*-1.59*	*-1.71*	*-1.76*	*-1.66*
$Ln(P_{mpr}/P_p)$	-1.95	-1.34	-1.61	1.42	-1.22	1.30
	-1.66	*-1.78*	*-1.32*	*-0.11*	*-2.95*	*1.00*
$Ln(Q_{pub})$	-1.88	-1.69	-1.81	0.76	-1.63	0.35
	-2.17	*-0.61*	*-3.82**	*-0.39*	*-3.16**	*-0.29*

Ln(N)	-0.17 *-0.35*	-2.65 *-1.00*	-0.43 *-0.85*	-2.85 *-5.13**	-1.42 *-1.82*	-2.61 *-5.13**

Notes: Test 1 (Test 2, Test 3) refers to the Augmented Dickey-Fuller test in which a constant (constant and trend, constant and seasonal dummies) are included among the regressors. All test are implemented by adding five lagged differences among the regressors. The test statistics in italics refer to the corresponding Dickey-Fuller tests in which the lag length is zero. The critical values are based on the response surfaces in MacKinnon (1991). Five per cent significance is marked by *.

Data Appendix

Data source: The data set of the Bank of Finland if not otherwise mentioned.

W: Wages and salaries, FIM millions.

H: Perfomed working hours, millions of hours.

P_p: Valued added deflator at factor costs.

B: The level of unemployment benefits, an index was made available to me by Hannu Tanninen.

R: The number of persons in ALMPs, R = persons employed with selective measures + Persons on employment training, Finnish Labour Review, Ministry of Labour.

U: Unemployment, 1000 persons.

L: Labour force, L = Labour force - the number of participants in job placement programmes, 1000 persons.

acc: Accommodative stance, R/(R+U).

LTU: Long-term unemployment, duration of unemployment exceeded 1 year, Finnish Labour Review, Ministry of Labour.

SOCC: Employers' social security contributions, FIM millions.

s: Employers' tax rate, s = SOCC/W.

t_1: Average income tax rate.

GDPF: GDP at factor costs, millions of 1985 FIM.

TIN: Indirect taxes minus subsidies, millions of 1985 FIM.

t_2: Indirect tax rate, t_2 = GDPF/TIN.

K: Net stock of fixed capital, millions of 1985 FIM.

N: Population of working age (15-74 years), 1000 persons.

E: Employment, 1000 persons.

USRC: User cost of fixed capital.

P_{mpr}: Import prices of raw materials.

Q_{pub}: Production at factor cost, general government, millions of 1985 FIM.

CHAPTER 5

The Impact of Active Labour market Programmes on Repeat Unemployment Incidence

One of the most worrying aspects of unemployment is that the unemployed who manage to get hired have a high risk of returning to unemployment. This is highlighted in Layard, Nickell & Jackman (1991) who report that 41 per cent of British men in the 1987 cohort who found a job within the first 9 months also experienced a repeat unemployment spell within that time. The study by Zweimuller & Winter-Ebmer (1996) reports similar results for Austria; 46 per cent of unemployment leavers returned back to unemployment within 12 months in 1986. The instability of early work careers is further confirmed by the finding that employees who have been in a job less than a year are some six times more likely to become unemployed than average workers, Stern (1983).

Since the proportion of unemployment leavers renewing their unemployment within a relatively short period of time is substantial, the phenomenon is not likely to arise from the pure optimising behaviour of individuals. The study by Stern (1986) lends support to the view that individuals suffering from unstable work careers are likely to have some unfavourable characteristics which worsen their labour market possibilities. If this is the case, then public sector intervention through active labour market policy may be effective in reducing the participants' risk of returning to unemployment, provided that active labour market programmes increase human capital and/or improve the work habits of hard-to-employ persons.

As discussed in chapter 3, there is a large literature evaluating the effects of active labour market programmes on earnings, and less extensive examining the employment status impact of active programmes. However, their impact on repeat unemployment incidence has remained relatively unexplored[1]. In a few studies the hazard function approach has been adopted in modelling the effect of training programmes on the duration of employment (Ridder 1986, Card & Sullivan 1988, Gritz 1993, Ham & LaLonde 1996). These studies report some beneficial effects of active programmes, but this view is by no means universal. A rival approach is adopted in Zweimuller & Winter-Ebmer (1996) who employed cross-sectional methods in examining the stability of a work career. According to their findings training programmes have a substantial beneficial effect on the stability of the participants' work career within the first 12 months.

This chapter adopts the probabilistic framework in evaluating the impact of ALMPs on job stability. The starting point for the analysis is the bivariate probit model employed in Zweimuller & Winter-Ebmer (1996). The standard bivariate probit model is then generalised by loosening the assumptions of homoskedasticity and constant programme effect across individuals. In addition, the reliability of the results is put under scrutiny by constructing various misspecification tests including the test for the distributional assumption of bivariate normality. Our main reason for preferring cross-sectional analysis to more sophisticated hazard function estimations is the ability to deal with self-selectivity within the well established framework. In hazard function estimations the endogenous selection of programme participants requires strong assumptions to produce analytically convenient models unless analysis is based on experimental data, see chapter 3[2]. Another advantage of the adopted framework arises from the possibility of constructing a test for the distributional assumptions. We believe that these two gains more than outweigh the loss of being able to assess active programmes only at some single point of time.

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[1] There is, however, a large literature examining repeat unemployment incidence through state dependence, see Heckman & Borjas (1980), Narendranathan & Elias (1993), and Belzil (1995), among others.

[2] Recent examples of hazard function analyses in which experimental data is employed in controlling for endogenous selection are Ham & LaLonde (1996) and Dolton & O'Neill (1996).

The remainder of this chapter is organised as follows. In section 5.1, two ways of modelling the programme effect are discussed. Section 5.2 introduces the data. Section 5.3 reports the estimates of programme participation and repeat unemployment incidence. Section 5.4 takes a closer look at the possible gains of active labour market programmes. Finally, section 5.5 concludes the study.

5.1. Empirical Model

The problem with non-experimental evaluation studies is one of missing information; we do not observe the participants' counterfactual outcomes. To overcome this problem one needs a control group which is thought of as representing the labour market outcome of participants had they not participated in a programme. What makes the estimation of the programme effect more involved is that the decision to participate in a programme is endogenous to a given individual, see Bassi (1983), Bjorklund & Moffitt (1987), Dolton et. al. (1994b), Gritz (1993), *inter alia*. Unless this individual behaviour is incorporated in evaluation models, the estimated effects of active labour market programmes are potentially biased. The direction of bias depends on unobservable characteristics influencing both the participation decision and the outcome under evaluation. If participants are more motivated and/or more capable than controls, the estimated programme effect is biased upwards. In the contrary case the programme effect is biased downwards. Below we present two ways of taking individual self-selectivity into account. The difference between the models arises from the assumptions required in modelling the programme effect.

5.1.1. The Bivariate Probit Model

There are underlying response variables p^* and u^*, which measure the propensity to participate in a programme (p^*), and the propensity to renew unemployment (u^*). Our information consists only of whether or not some particular event occurred, so we observe mere signs of these latent variables via indicator functions $u_i = 1_{u_i^*>0}$ and $p_i = 1_{p_i^*>0}$. In a usual manner, variables explaining the participation decision and the repeat unemployment incidence are introduced into the model via linear index functions $X\beta$ and $Z\gamma$. If we further assume that the programme effect, α, is invariant across individuals the bivariate latent variable model can be written as

$$
\begin{aligned}
u_i^* &= X_i\beta + \alpha p_i + \varepsilon_i \\
p_i^* &= Z_i\gamma + \eta_i \ .
\end{aligned} \tag{1}
$$

The endogeneity of individuals' participation decisions results in the correlation between the programme dummy, p_i, and the error term, ε_i, in the repeat unemployment equation. In terms of Heckman & Hotz (1989) this dependence can arise either from selection on observables or from selection on unobservables. In the former case the selection bias can be removed from parameter estimates by controlling for the determinants of the participation decision. In the latter case, however, inference based on mere repeat unemployment equation is biased due to the correlated error terms, ε_i and η_i. In the current setting the problem of selection on unobservables cannot be solved by the standard Heckman method (Heckman, 1979) due to non-linearities, see O'Higgins (1994). An attractive alternative is to model the joint distribution of error terms. The bivariate probit model analysed in Zweimuller and Winter-Ebmer (1996) is then specified by assuming standard bivariate normality of disturbance terms[3].

[3] The bivariate probit model has been employed in other contexts for instance in Van de Ven et. al. (1981), Ham (1982), Tunali (1986), Dolton and Makepeace (1993), and Zweimuller et. al. (1996).

The standard bivariate probit model may suffer from limited information on dependent variables. Since we can only observe the signs of latent variables, the error variances, σ_ε and σ_η, remain unidentified, Maddala (1983). This in turn means that one is able to estimate mere ratios β/σ_ε, $\alpha/\sigma_\varepsilon$ and γ/σ_η. The standardisation of error variances to one is perfectly legitimate provided that error variances remain constant across individuals, that is under the assumption of homoskedasticity. As pointed out in Davidson & MacKinnon (1984) uncorrected departures from homoskedasticity bias both the estimated standard errors and the estimated parameters. To incorporate heteroskedasticity in the model error terms are specified as $\varepsilon_i \sim$ NID[O,Exp(2$W_{iu}\delta$)] and $\eta_i \sim$ NID[O, Exp(2$W_{ip}\theta$)], where the W matrices include the variables affecting error variances, δ and θ being the additional parameter vectors. Normalised error terms follow the standard bivariate normal distribution, in which case the log-likelihood function for the heteroskedastic bivariate probit model becomes

$$(2) \qquad \ln L = \sum_i \ln \Phi_2\left[\frac{(2u_i - 1)(X_i\beta + \alpha p_i)}{Exp(W_{iu}\delta)},\ \frac{(2p_i - 1)Z_i\gamma}{Exp(W_{ip}\theta)},\ (2p_i - 1)(2u_i - 1)\rho\right],$$

where Φ_2 stands for the standard bivariate normal cumulative distribution function. In this setting the heteroskedastic model can be tested against its homoskedastic alternative by any classical testing procedure. Another issue of interest, namely selection on unobservables can be tested through the correlation coefficient, ρ. Low values of test statistics imply that the assignment on active programmes is random, at least as regards the unobservables, and the model can be consistently estimated by single equation probit models. These tests are, however, conditional on the distributional assumption of bivariate normality. Clearly the violation of this assumption results in inconsistent parameter estimates. Since the distributional assumption is hardly ever tested in applied work, the appendix reports the score contributions needed in testing normality both in the heteroskedastic bivariate probit model and in the heteroskedastic switching bivariate probit reported below.

5.1.2. The Endogenously Switching Bivariate Probit Model

An unattractive feature of the bivariate probit model is that it restricts the estimated programme effect to be equal for all participants. O'Higgins (1994) loosens these restrictions by formulating the switching bivariate probit model of the form

$$
(3) \qquad \begin{aligned} u_i^* &= X_i\beta_1 + \varepsilon_{1i} \quad && \text{iff } p_i^* > 0 \\ u_i^* &= X_i\beta_2 + \varepsilon_{2i} \quad && \text{iff } p_i^* \leq 0 \\ p_i^* &= Z_i\gamma + \eta_i \end{aligned}
$$

The switching model consists of the same participation equation, p_i^*, as the bivariate probit model but it allows separate parameter vectors for the participants, $p_i^* > 0$, and the non-participants, $p_i^* < 0$. The selection into different groups is endogenously determined through the latent participation equation. Unlike in the bivariate probit model, the programme effect is allowed to vary across individual characteristics, that is across the observed variables included in the model. Since the first two equations define marginal distributions, O'Higgins (1994) imposes the restriction $\varepsilon_{1i} = \varepsilon_{2i}$, which essentially assumes the equality of variances in two subgroups. By assuming bivariate normality O'Higgins estimated the following heteroskedasticity corrected log-likelihood function

$$
(4) \qquad \begin{aligned} \ln L = \sum_{i=1}^{N} \Bigg(& p_i \cdot \ln \Phi_2 \left[\frac{(2u_i - 1)X_i\beta_1}{Exp(W_{iu}\delta)}, \frac{Z_i\gamma}{Exp(W_{ip}\theta)}, (2u_i - 1)(2p_i - 1)\rho \right] + \\ & (1 - p_i) \cdot \ln \Phi_2 \left[\frac{(2u_i - 1)X_i\beta_2}{Exp(W_{iu}\delta)}, \frac{-Z_i\gamma}{Exp(W_{ip}\theta)}, (2u_i - 1)(2p_i - 1)\rho \right] \Bigg). \end{aligned}
$$

The drawback of this model is a substantial increase in the number of parameters that makes the user specified likelihood function rather time consuming to maximise. An alternative way of estimating the switching model arises from the restriction $\varepsilon = \varepsilon_{1i} = \varepsilon_{2i}$ which ensures that the distribution is well defined on the whole population. To show this, we change the notation by writing the non-participants' parameter vector as $\beta_2 = \beta$. If we further allow the programme effect to vary across individual characteristics through the parameter vector t, we can rewrite the participants' parameter vector as $\beta_1 = \beta + \tau$. Under these notations the first two equations of the switching model (3) can be combined to

(5) $$u_i^* = p_i \cdot [X_i(\beta + \tau)] + (1 - p_i) \cdot X_i\beta + \varepsilon_i = X_i\beta + p_i X_i \tau + \varepsilon_i .$$

This says that it is possible to estimate the switching model used by O'Higgins (1994) by introducing interaction terms $p_i X_i$ into the bivariate probit[4].

5.2. Data Description

It was pointed out in chapter 2 that Finnish active labour market policy has two explicit aims connected to repeat unemployment incidence, viz. permanent work and reducing the risk of unemployment. To put the achievement of these targets under scrutiny this chapter employs data based on a random sample of 180 000 individuals (around 5 per cent of the working age population) drawn from the 1990 population census. Statistics Finland has expanded the data set by merging individual information from various official registers, such as tax registers and registers of employment service offices. This offers rich information on different income sources, labour market status, occupations, changes between labour market states etc. What is especially interesting for this study,

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[4] I owe this point to Wiji Arulampalam.

the data set contains all information collected by employment service offices about the unemployed and the programme participants[5].

Since the focus of this study is on the effect of active programmes on the probability of repeating unemployment, the sample used in the analyses consists of a representative sample of persons who obtained a job in open labour markets after the first unemployment or programme participation spell during the year 1989[6]. In order to concentrate on actually unemployed persons, the following selection criteria are used: age between 16 and 50, not a student, pensioner, or in the army. Since the attachment of entrepreneurs to labour markets is likely to differ from that of wage-earners, we decided to exclude persons whose income derives mainly from entrepreneurial activities. Finally, temporarily laid-off persons are excluded from the sample since their transition probabilities between labour market states are likely to be affected by the lay-off.

As a further modification of the sample, we employed the available data to track down those persons who ended their employment spell by a transition out of the labour force. This transition is treated as a repeat unemployment incidence, i.e., the repeat unemployment dummy takes the value 1 if a person has experienced a transition to non-employment within 12 months after starting the first job in 1989. Otherwise it takes the value 0. A person is defined as a programme participant if (a) he has experienced a transition from a programme to open employment or (b) he has participated in a programme during the year 1988. The actual sample used in estimations consists of 1553 programme participants and 2963 non-participants. Within 12 months after starting the first

[5] Since the main interest of this chapter is on assessing the differences in programme effects across individuals, all programmes had to be combined together. Accordingly, the estimated programme effects have to interpreted as average impacts of various programmes. The effects of different programmes are examined in chapter 6.

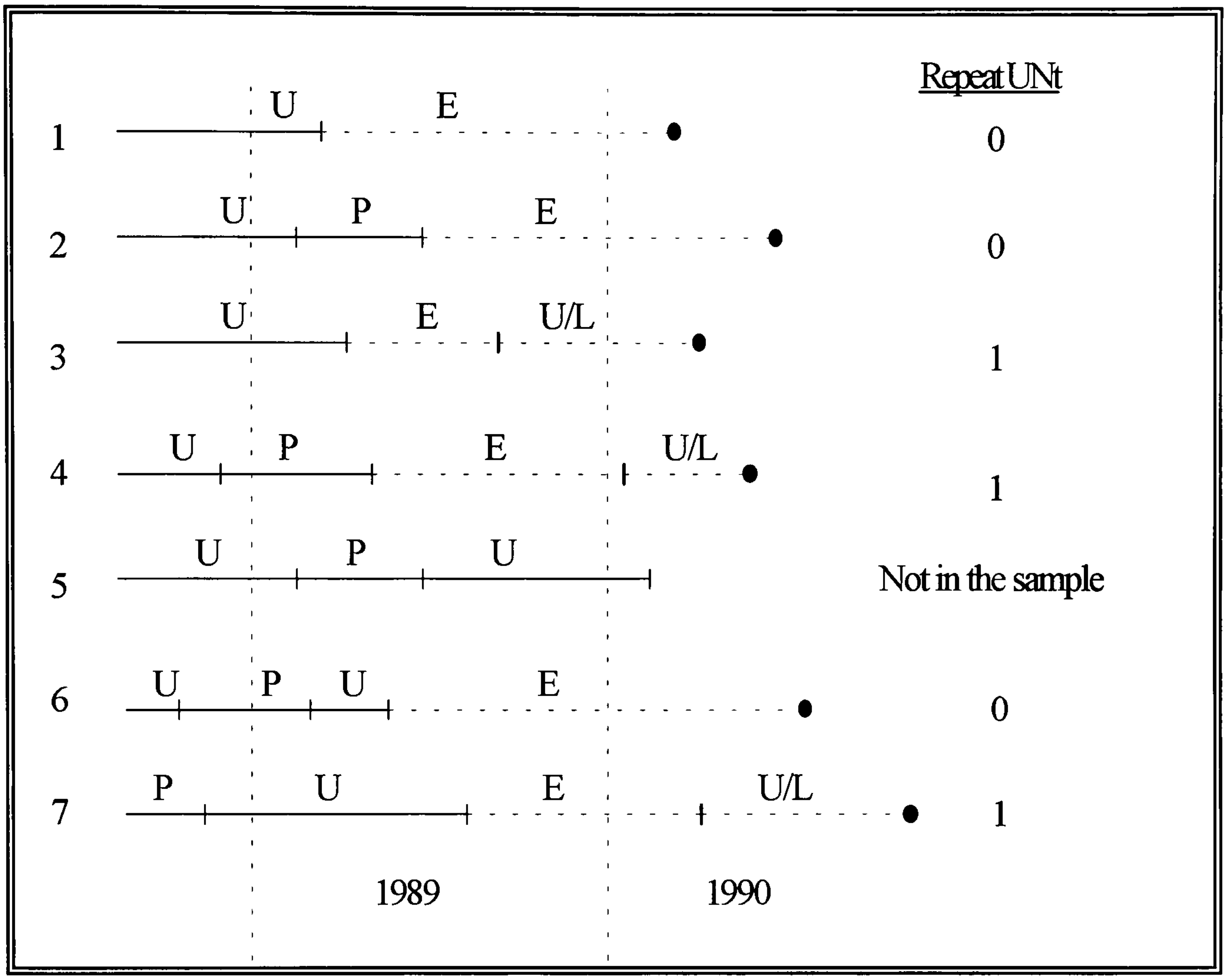
[6] Since we have information only on the latest participation spell, we have to assume that those 98 cases with more than one programme period do not have any employment spells between the first and the last programme period. Similarly we have to assume that the sample selection is exogenous, i.e. unobservables between the employment probability (prerequisite for entering the sample is to become employed) and repeat unemployment equations are uncorrelated.

employment spell 58.6 per cent of the participants, and 58.9 per cent of the controls, experienced a transition to non-employment.

It is informative to examine different transition patterns between labour market states, and how these patterns are related to the sampling procedure. All individuals in the sample have become employed in non-subsidised labour markets during the year 1989. Participants in training programmes or selective employment measures who return back to unemployment immediately after a programme participation, and who do not become openly employed during the year 1989, are not included in the sample. That is to say, both unemployment and programme spells are treated as time spend outside open labour markets.

Some hypothetical transition patterns are presented in figure 5.1. Subsequent work histories under examination, i.e. 12 months after becoming employed in open labour markets in 1989, are presented by dashed lines. Individuals 1 and 2 have got a job in open labour markets (E) during the year 1989 either after a period of unemployment (U) or after a period of programme participation (P), and stayed in their job longer than 12 months. Accordingly, the repeat unemployment dummy takes the value 0 in these cases. Individuals 3 and 4 have also got hired in open labour markets in 1989, but they have experienced a transition either to unemployment or out of the labour force (L) within 12 months of starting a job. They are recorded as repeat unemployment cases, i.e., the repeat unemployment dummy takes the value 1. Those who have not experienced a transition to open employment during the year 1989 do not enter the sample (individual 5). Finally, individuals 6 and 7 have continued their unemployment spell which was temporary interrupted by a programme participation. They have, however, managed to get a job in open labour markets in 1989, in which case they enter the sample.

Figure 5.1 The transition chart.



Notes: Repeat UNt refers to the value of the dependent repeat unemployment dummy.

5.3. Empirical Results

There are three groups of variables explaining the participation decision and the repeat unemployment incidence. The first group of variables consists of individual characteristics which control for observable differences in individuals' social status, human capital accumulation, family background and work ability. These are allowed to affect an individual's labour market possibilities as well as his decision whether or not to participate in a programme.

The second group of variables relates to local labour markets, individuals' labour market experience and occupation. The unemployment rate in a travel-to-work area is one of the reasons for targeting active programmes to a region. This clearly affects the probability of participating in an active programme, whilst also having a potential effect on repeat unemployment incidence. Dummy variables for the type and the location of a living community reflect the size of the labour market which can be expected to affect the labour market outcome. Union membership and previous unemployment experience are also among potential factors influencing individuals' labour market possibilities and programme participation decisions. Since we are examining a future event, i.e., repeat unemployment incidence within the next 12 months, we have to be careful when measuring the past labour market experience. Clearly, the decision to terminate the latest unemployment spell is influenced by received work offers. The acceptance probability can be expected to be higher, and the subsequent probability of returning to unemployment lower, if an offer is considered as 'a good one'. This indicates the endogeneity of the latest unemployment spell, and for this reason it is subtracted from the unemployment experience variable[7]. The final group of labour market variables consists of occupational dummies. It is evident that individuals working in seasonal occupations, such as agriculture and construction, have higher risk of experiencing a repeat unemployment spell that calls for the inclusion of occupational controls in the repeat unemployment equation. These are also entered in the participation equation since the lack of occupation is likely to characterise hard-to-employ individuals to whom ALMPs are primarily targeted.

Finally, the model includes several income variables. The replacement ratio is specified as two separate terms; unemployment benefits and wage income. The financial independence of an individual may also affect his/her labour market behaviour. This is

[7] It is possible that the subtraction of the latest unemployment spell is not sufficient for removing the endogeneity bias due to some uncontrolled factors affecting both past unemployment experiences and the repeat unemployment probability. The correction of this potential bias would, however, lead to trivariate normal integrals and it is not undertaken here. Accordingly, we have to assume that after subtracting the latest unemployment spell this bias becomes negligible.

captured by two separate variables; (i) the sum of individual's income from other sources than unemployment benefits or wage income, and (ii) the sum of spouse's income.

Turning next to identification issues. As discussed in Davidson and MacKinnon (1984), the parameters of heteroskedasticity correction terms are identified provided that there is no constant term in W matrices. The real difficulty arises, however, when estimating the parameters of the participation and repeat unemployment equations. As pointed out in Maddala (1983) p. 122 - 23, the framework set up in section 5.1 belongs to the class of mixed structured models. To identify the parameters of the repeat unemployment equation there has to be at least one exclusion restriction in it. In this study the main instrument for the programme participation is produced by the local supply of ALMPs which is measured as the proportion of participants to working age population in a labour market district. The supply of active programmes affects the probability of participating in a programme but there is no clear reason why it should have any effect, over and above the programme effect itself, on the repeat unemployment incidence[8]. Furthermore, the chosen instrument is consistent with the aims of improving the functioning of labour markets in less advantaged regions through active labour market policy. Another identifying restriction is obtained by measuring the union status variable in different years in the two equations. However, due to the strong correlation of individuals' union membership over time the identification based merely on the union variable is likely to be weak.

[8] Employing the local supply of ALMPs as an instrument is not without caveats. It may depend on local repeat unemployment incidence via political pressure. The possible endogeneity problem is, however, likely to be smaller when examining individuals' probabilities of renewing unemployment than in aggregated data sets.

5.3.1. The Determinants of Programme Participation

Before analysing the estimated participation equations it is worth recalling the aims and the target groups of active labour market programmes discussed in chapter 2. Finnish labour market training has twofold aims. The first aim is to improve the employment performance of the economy by increasing labour market flexibility and eliminating labour shortages. The second aim is more individually oriented focusing on preventing unemployment, and reducing the risk of unemployment. Selective employment measures, on the other hand, are more directly targeted to disadvantaged individuals. These are aimed at: (i) helping hard-to-employ persons in the labour market; (ii) preventing long-term unemployment; and (iii) reducing regional unemployment differences. Since a single participation equation combines the factors affecting the behaviour of both potential participants and the administrators, the aims above are expected to show up in the results.

Table 5.1 reports a selected sample of participation equations from the estimated bivariate models. Differences across models arise from two sources; the specifications of error terms (homoskedastic vs. heteroskedastic) and the programme effect (constant vs. varying). The parameter estimates show that the exact specification of the programme effect does not have any significant effect on the inference concerning the determinants of participation. On the contrary, the parameter estimates of the heteroskedastic bivariate probit model given in column 2 seem to be poorly defined compared to other models. This is not surprising given that the participation equation suffers from non-normality, cumulants κ_{03} and κ_{04} being highly significant (see also the test statistics reported for the general heteroskedastic model in table 5.2, column 3)[9]. Closer

[9] For the score contributions employed in normality tests and for the definition of cumulants, please see appendix 5.1.

examination uncovered that the problem was connected to the monthly earnings variable employed in the heteroskedastic function. Column 3 reports the results of the specification in which the monthly earning variable has been removed from correction terms. This also eliminates the problem of non-normality and produces the results which are more in line with other specifications.

Table 5.1 The determinants of programme participation.

	Estimated model				
	Homo-skedastic Bivariate probit	Hetero-skedastic Bivariate probit	Hetero-skedastic Bivariate probit	Switching Bivariate probit (homosked)	Switching Bivariate probit (heterosked)
Intercept	-0.285 (0.347)	0.046 (0.036)	-0.108 (0.161)	-0.284 (0.349)	-0.122 (0.173)
Individual characteristics					
Gender	0.012 (0.054)	-0.003 (0.002)	-0.002 (0.024)	0.011 (0.054)	-0.004 (0.026)
Age	0.018 (0.020)	0.000 (0.000)	0.006 (0.008)	0.018 (0.020)	0.006 (0.009)
$Age^2 \times 10^{-3}$	-3.631 (3.082)	-0.059 (0.113)	-0.662 (1.290)	-3.690 (3.100)	-0.851 (1.409)
Number of children under 7 years of old	0.013 (0.066)	0.000 (0.002)	0.004 (0.032)	0.015 (0.067)	0.005 (0.034)
Age of the youngest child 0 - 1 years	0.065 (0.123)	0.002 (0.004)	0.010 (0.060)	0.063 (0.124)	0.006 (0.064)
Age of the youngest child 2 - 4 years	-0.044 (0.113)	-0.000 (0.004)	-0.018 (0.053)	-0.047 (0.114)	-0.020 (0.056)
Age of the youngest child 5 - 7 years	0.011 (0.105)	-0.000 (0.003)	-0.014 (0.049)	0.013 (0.106)	-0.015 (0.052)
Education	0.109 $(0.030)^{***}$	0.003 (0.002)	0.043 $(0.015)^{***}$	0.108 $(0.030)^{***}$	0.047 $(0.016)^{***}$
Home ownership	-0.020 (0.043)	-0.000 (0.001)	-0.015 (0.019)	-0.022 (0.043)	-0.017 (0.021)
Disability	0.274 $(0.074)^{***}$	0.009 $(0.005)^{*}$	0.123 $(0.040)^{***}$	0.275 $(0.074)^{***}$	0.132 $(0.043)^{***}$

Table 5.1 The determinants of programme participation.

Broader job seeking	-0.117	-0.081	-0.774	-0.113	-0.734
	(0.089)	(0.111)	(0.777)	(0.089)	(0.714)
Spouse's education	-0.036	-0.000	-0.018	-0.037	-0.019
	(0.029)	(0.000)	(0.012)	(0.029)	(0.014)
Marital status	-0.094	-0.001	-0.048	-0.096	-0.054
	(0.059)	(0.002)	(0.030)	(0.059)	(0.032)*
Head of a family	-0.071	-0.003	-0.038	-0.069	-0.040
	(0.058)	(0.002)	(0.024)	(0.059)	(0.026)
Labour market					
travel-to-work	0.043	0.001	0.022	0.042	0.023
Unemployment rate	(0.011)***	(0.000)*	(0.006)***	(0.011)***	(0.007)***
Urban area	-0.055	-0.002	-0.028	-0.057	-0.030
	(0.045)	(0.002)	(0.020)	(0.045)	(0.022)
Unemployment duration	0.096	0.003	0.041	0.095	0.044
before the latest spell x 10^{-2}	(0.010)***	(0.001)*	(0.009)***	(0.010)***	(0.010)***
Southern Finland	-0.232	-0.006	-0.084	-0.228	-0.087
	(0.079)***	(0.004)	(0.039)**	(0.080)***	(0.042)**
Central Finland	-0.093	-0.002	-0.026	-0.088	-0.024
	(0.071)	(0.002)	(0.033)	(0.072)	(0.035)
<u>Occupation:</u>					
Technical	-0.874	-0.031	-0.436	-0.872	-0.465
	(0.120)***	(0.016)*	(0.092)***	(0.121)***	(0.100)***
Health care	-0.664	-0.024	-0.300	-0.670	-0.329
	(0.102)***	(0.012)*	(0.067)***	(0.102)***	(0.074)***
Administrative	-0.263	-0.011	-0.151	-0.266	-0.162
	(0.088)***	(0.006)*	(0.045)***	(0.088)***	(0.049)***
Mercantile	-0.631	-0.027	-0.324	-0.630	-0.347
	(0.106)***	(0.014)*	(0.068)***	(0.106)***	(0.074)***
Farming/Forestry	-0.836	-0.034	-0.430	-0.835	-0.456
	(0.104)***	(0.017)*	(0.086)***	(0.105)***	(0.092)***
Transport	-0.954	-0.039	-0.502	-0.952	-0.534
	(0.126)***	(0.020)*	(0.102)***	(0.126)***	(0.110)***
Manufacture	-0.570	-0.025	-0.304	-0.571	-0.326
	(0.068)***	(0.012)*	(0.059)***	(0.068)***	(0.064)***
Construction	-0.863	-0.035	-0.430	-0.874	-0.463
	(0.090)***	(0.018)*	(0.082)***	(0.091)***	(0.089)***

Table 5.1 The determinants of programme participation.

Service	-0.516 (0.078)***	-0.022 (0.011)*	-0.278 (0.056)***	-0.522 (0.079)***	-0.301 (0.061)***
Income variables					
Ln(monthly unemployment benefits)	-0.027 (0.005)***	-0.001 (0.000)*	-0.017 (0.004)***	-0.027 (0.006)***	-0.017 (0.005)***
Ln(monthly earnings)	-0.031 (0.011)***	-0.007 (0.005)	-0.016 (0.006)**	-0.031 (0.011)***	-0.017 (0.007)**
Ln(other income)	-0.015 (0.006)**	-0.000 (0.000)	-0.004 (0.002)*	-0.015 (0.006)**	-0.005 (0.002)*
Ln(spouse's income)	0.004 (0.005)	0.000 (0.000)	0.001 (0.002)	0.004 (0.005)	0.001 (0.002)
Identification					
Union member in 1988	0.103 (0.044)**	0.009 (0.000)*	0.125 (0.032)***	0.114 (0.045)**	0.144 (0.036)***
Local supply of ALMP	0.072 (0.015)***	0.002 (0.001)*	0.026 (0.008)***	0.074 (0.015)***	0.030 (0.009)***
Heteroskedasticity correction terms	No	Yes	Yes	No	Yes
Age		-0.019 (0.004)***	-0.025 (0.004)***		-0.022 (0.005)***
Broader job seeking		1.661 (1.068)	1.320 (0.771)*		1.247 (0.723)*
Ln(monthly unemployment benefits)		0.028 (0.011)**	0.021 (0.011)**		0.014 (0.011)
Union member in 1988		-0.285 (0.096)***	-0.387 (0.095)***		-0.404 (0.097)***
Marital status			0.163 (0.091)**		0.157 (0.093)*
Unemployment duration before the latest spell x 10^{-2}			0.043 (0.022)**		0.048 (0.023)**
Ln(monthly earnings)		-0.310 (0.058)***			
Spouse's education		-0.089 (0.045)*			
ρ	0.322 (0.219)	0.396 (0.095)***	0.394 (0.102)***	0.112 (0.298)	0.169 (0.184)

Table 5.1 The determinants of programme participation.

Log-likelihood	5206.505	5153.582	5162.062	5175.141	5139.707
Diagnostics					
WALD test for identifying restriction	-0.001 [p=0.925]	0.006 [p=0.633]	0.006 [p=0.661]	-0.016 [p=0.287]	-0.012 [p=0.437]
LR test for heteroskedasticity	**133.14 [p=0.000]**	27.29 [p=0.746]	**44.25 [p=0.091]**	**70.86 [p=0.000]**	n/a
LM test for normality (joint test)	**15.60 [p=0.075]**	**23.49 [p=0.005]**	7.13 [p=0.623]	10.25 [p=0.330]	7.34 [p=0.601]
LM tests for the significance of cumulants:					
κ_{30}	**3.57 [p=0.058]**	0.00 [p=0.957]	0.00 [p=0.942]	1.49 [p=0.222]	0.53 [p=0.466]
κ_{21}	0.44 [p=0.507]	0.33 [p=0.565]	0.11 [p=0.740]	0.19 [p=0.718]	0.36 [p=0.548]
κ_{12}	0.17 [p=0.680]	0.12 [p=0.729]	0.14 [p=0.708]	2.42 [p=0.119]	0.68 [p=0.409]
κ_{03}	0.99 [p=0.319]	**9.43 [p=0.002]**	0.55 [p=0.458]	2.14 [p=0.143]	0.44 [p=0.507]
κ_{40}	1.96 [p=0.161]	0.01 [p=0.920]	0.07 [p=0.791]	**4.50 [p=0.033]**	2.36 [p=0.124]
κ_{31}	1.20 [p=0.273]	0.24 [p=0.624]	0.25 [p=0.617]	0.95 [p=0.329]	0.85 [p=0.356]
κ_{22}	0.00 [p=0.993]	1.31 [p=0.252]	0.46 [p=0.497]	**4.19 [p=0.040]**	2.09 [p=0.148]
κ_{13}	0.00 [p=0.982]	0.01 [p=0.920]	0.05 [p=0.823]	0.05 [p=0.823]	0.63 [p=0.427]
κ_{04}	0.00 [p=0.995]	**10.49 [p=0.001]**	1.27 [p=0.259]	0.09 [p=0.764]	2.17 [p=0.140]
N	4516	4516	4516	4516	4516

Notes: * (**,***) = significant at the 10 (5, 1) per cent significance level; All variables refer to the year 1989 if not otherwise stated; For the definitions of variables, please see appendix 5.2; For the discussion of diagnostic tests, please see the text and appendix 5.1; Parenthesis following test statistics report the p-values; Test statistics which are significant at the 10 per cent significance level are written in bold. All estimations are carried by using LIMDEP 7.0 (Greene, 1995).

As regards other diagnostic tests, there are some indications that terms in heteroskedastic functions ease the distributional misspecification of the repeat unemployment equation. This is implied by cumulants κ_{30} and κ_{40} which are estimated of being significant in homoskedastic models reported in columns 1 and 5. The need to correct for heteroskedasticity is further confirmed by the massive test statistics produced by homoskedastic models[10]. Finally, we put the identifying restriction under scrutiny. This indirect test is implemented in two steps: first, we removed all insignificant variables from the repeat unemployment equations; and second, we re-estimated the models with the local supply of ALMPs variable included in both equations. The reported test statistic is based on the estimated t-value of the local supply of ALMPs variable in the repeat unemployment equation. In all cases the t-value of the identifying variable is far from conventional significance levels strengthening the confidence on the adopted instrument.

Turning next to the determinants of programme participation on which all models in table 5.1 seem to paint a similar picture. The aims of ALMPs show up nicely in the results, the participation probability being increased if an individual is disabled, without occupation (omitted category) or he has experienced long spells in unemployment. These individuals may also be more prone to apply for programmes either because they benefit the most or because their opportunity costs are low, or both. The target of reducing regional unemployment differences via active programmes is also reflected in the results; individuals living in high unemployment areas outside the southern Finland are more likely to end up in a programme. Having said that, there are also some implications of creaming as indicated by the well determined positive impact of education on the

[10] Reported tests for heteroskedasticity are implemented against the general heteroskedastic model which included all variables, excluding occupational dummies, as correction terms. Due to the large number of controlled factors the heteroskedasticity correction in the switching bivariate probit model is based on the model reported in column 3.

participation probability. This result is in line with Greenhalgh & Stewart (1987), according to whom higher educated persons obtain more retraining than those with lower educational levels.

Turning next to the group of variables representing social status, namely other income sources, earnings and occupation. These variables enter the participation equation with negative parameter estimates implying lower participation probability for an individual with higher social ranking. This finding can be explained in one of two ways; either individuals with higher social status have better connections to labour markets which increases their transition probabilities out of unemployment before any participation decisions or they can afford to wait longer before participating in a programme.

Finally we focus on the identifying variables, namely the union status and the local supply of active programmes variables. It is interesting to note that union members are more likely to participate in programmes. The positive union effect is a usual finding in studies of private sector training, see Booth (1991), Lynch (1992), Tan et. al. (1992), inter alia. One explanation for the finding that union membership increases also the probability of participating in public sector programmes is that their greater attachment to labour markets is characterised by greater willingness to acquire working skills through active labour market programmes. When it comes to the other identifying variable, its presence in the participation equation is confirmed by all specifications. Moreover the positive-parameter estimate is well in line with *a priori* expectations, with the greater supply of programmes increasing the participation probability.

5.3.2. Repeat Unemployment Incidence

Tables 5.2 and 5.3 below give the estimated repeat unemployment equations; the former for the constant programme effect and the latter for the varying one.

Encouragingly all models paint a fairly similar picture of the factors affecting repeat unemployment incidence. Unlike in the participation equations the exact specification of hetero- skedasticity correction terms does not have any great impact on the parameter estimates. This is not surprising given that non-normality was found only in the participation equation. Otherwise diagnostic tests follow the same lines as above. There are signs of non-normality in homoskedastic specifications which can be eased by heteroskedasticity correction terms. All homoskedastic models are rejected against their heteroskedastic alternatives; also in single equation probit estimations which are reported in appendix 5.2. And finally, identifying restrictions are clearly accepted in all cases.

As can be expected, characteristics reflecting disadvantaged individuals, viz. low education, long unemployment spells and disability, seem to increase the risk of renewing unemployment. An opposite effect is found for the group of variables representing individuals' social status, namely variables capturing differences in home ownership, spouse's income, education, and family status. Provided that social ranking also reflects individuals' motivation/capabilities, the greater stability of their work careers is to be expected, *a priori*. The results also suggest the similar outcome for another motivation variable measured as a job seeker's willingness to accept a job outside his home community (broader job seeking).

Table 5.2 The repeat unemployment incidence; Invariant programme effect.

	Estimated model				
	Hetero-skedastic Probit	Homo-skedastic Bivariate Probit	Hetero-skedastic Bivariate Probit	Hetero-skedastic Bivariate Probit	Hetero-skedastic Bivariate Probit
Intercept	0.352 (0.312)	0.565 (0.369)	0.619 (0.424)	0.847 $(0.399)^{**}$	0.717 $(0.392)^{*}$
Individual characteristics					
Gender	0.009 (0.049)	0.030 (0.053)	0.014 (0.066)	0.009 (0.063)	0.017 (0.062)
Age	0.008 (0.017)	0.012 (0.019)	0.017 (0.023)	0.021 (0.022)	0.021 (0.022)
$Age^2 \times 10^{-3}$	-1.299 (2.633)	-1.454 (2.966)	-2.763 (3.505)	-3.103 (3.392)	-3.196 (3.378)
Number of children under 7 years of old	0.048 (0.060)	0.052 (0.065)	0.047 (0.072)	0.035 (0.075)	0.035 (0.075)
Age of the youngest child 0 - 1 years	0.012 (0.114)	0.024 (0.120)	0.025 (0.138)	0.058 (0.142)	0.051 (0.141)
Age of the youngest child 2 - 4 years	-0.076 (0.102)	-0.080 (0.110)	-0.079 (0.127)	-0.057 (0.128)	-0.067 (0.127)
Age of the youngest child 5- 7 years	-0.039 (0.094)	-0.044 (0.104)	-0.057 (0.111)	-0.032 (0.121)	-0.040 (0.120)
Education	-0.120 $(0.034)^{***}$	-0.088 $(0.031)^{***}$	-0.126 $(0.055)^{**}$	-0.116 $(0.038)^{***}$	-0.111 $(0.038)^{***}$
Home ownership	-0.073 $(0.041)^{*}$	-0.077 $(0.042)^{*}$	-0.091 (0.058)	-0.098 $(0.049)^{**}$	-0.096 $(0.049)^{*}$
Disability	0.101 (0.076)	0.190 $(0.082)^{**}$	0.265 $(0.145)^{*}$	0.207 $(0.093)^{**}$	0.210 $(0.093)^{**}$
Broader job seeking	-0.140 $(0.085)^{*}$	-0.179 $(0.089)^{**}$	-0.178 (0.121)	-0.199 $(0.107)^{*}$	-0.209 $(0.107)^{*}$
Spouse's education	-0.007 (0.026)	-0.006 (0.027)	-0.013 (0.032)	-0.019 (0.034)	-0.020 (0.034)
Marital status	-0.068 (0.054)	-0.105 $(0.059)^{*}$	-0.079 (0.073)	-0.095 (0.067)	-0.095 (0.067)
Head of a family	-0.102 $(0.054)^{*}$	-0.130 $(0.055)^{**}$	-0.147 $(0.082)^{*}$	-0.156 $(0.067)^{**}$	-0.146 $(0.067)^{**}$

Table 5.2 The repeat unemployment incidence; Invariant programme effect.

Labour market					
travel-to-work	0.014	0.039	0.032	0.038	0.039
Unemployment rate	(0.010)	(0.012)***	(0.015)**	(0.013)***	(0.013)***
Union member	-0.139	-0.181	-0.192	-0.201	-0.197
	(0.049)***	(0.048)***	(0.082)**	(0.056)***	(0.056)***
Urban area	-0.010	-0.011	-0.031	-0.023	-0.020
	(0.042)	(0.045)	(0.056)	(0.053)	(0.053)
Unemployment duration	0.138	0.130	0.177	0.157	0.160
before the latest spell x10^{-2}	(0.030)***	(0.013)***	(0.057)***	(0.020)***	(0.020)***
Southern Finland	0.041	-0.056	-0.011	-0.052	-0.052
	(0.058)	(0.086)	(0.077)	(0.077)	(0.077)
Central Finland	0.012	-0.051	-0.019	-0.048	-0.045
	(0.056)	(0.072)	(0.075)	(0.074)	(0.074)
<u>Occupation:</u>					
Technical	0.005	-0.195	-0.174	-0.258	-0.265
	(0.114)	(0.155)	(0.157)	(0.155)*	(0.157)*
Health care	0.033	-0.115	-0.093	-0.127	-0.122
	(0.101)	(0.137)	(0.137)	(0.135)	(0.135)
Administrative	-0.046	-0.130	-0.154	-0.147	-0.149
	(0.081)	(0.092)	(0.115)	(0.104)	(0.104)
Mercantile	-0.146	-0.350	-0.331	-0.352	-0.346
	(0.093)	(0.123)***	(0.150)**	(0.120)***	(0.120)***
Farming/Forestry	0.419	0.302	0.350	0.347	0.343
	(0.125)***	(0.163)*	(0.176)**	(0.148)**	(0.151)**
Transport	0.099	-0.081	-0.082	-0.133	-0.131
	(0.111)	(0.166)	(0.151)	(0.153)	(0.155)
Manufacture	0.049	-0.123	-0.074	-0.115	-0.117
	(0.066)	(0.102)	(0.092)	(0.091)	(0.092)
Construction	0.578	0.429	0.518	0.476	0.477
	(0.133)***	(0.156)***	(0.211)**	(0.140)***	(0.142)***
Service	0.178	0.029	0.112	0.056	0.055
	(0.080)**	(0.107)	(0.109)	(0.100)	(0.101)
Income variables					
Ln(monthly unemployment	0.085	0.082	0.104	0.101	0.099
benefits)	(0.015)***	(0.008)***	(0.032)***	(0.012)***	(0.013)***
Ln(monthly earnings)	-0.079	-0.094	-0.098	-0.122	-0.109
	(0.018)***	(0.015)***	(0.025)***	(0.019)***	(0.019)***

Table 5.2 The repeat unemployment incidence; Invariant programme effect.

Ln(other income)	0.006 (0.005)	0.008 (0.006)	0.008 (0.007)	0.006 (0.007)	0.006 (0.007)
Ln(spouse's income)	-0.015 (0.005)***	-0.015 (0.005)	-0.018 (0.008)**	-0.017 (0.006)***	-0.017 (0.006)***
Participation					
Participation dummy	-0.069 (0.044)	-0.594 (0.361)*	-0.645 (0.226)***	-0.827 (0.187)***	-0.826 (0.198)***
Heteroskedasticity correction terms	Yes	No	Yes (21 terms; not shown)	Yes	Yes
travel-to-work Unemployment rate	-0.043 (0.013)***			-0.023 (0.012)**	-0.024 (0.012)**
Education	0.117 (0.042)***			0.120 (0.039)***	0.119 (0.039)***
Ln(monthly unemployment benefits)	0.049 (0.015)**			0.053 (0.012)***	0.053 (0.012)***
Ln(other income)	-0.022 (0.009)*			-0.017 (0.008)**	-0.016 (0.008)**
Age	-0.008 (0.004)**				
Union member	0.169 (0.077)**				
Unemployment duration	0.041 (0.019)**				
ρ	n/a	0.322 (0.219)	0.296 (0.092)***	0.396 (0.095)***	0.394 (0.102)***
Log-likelihood	2597.836	5206.505	5139.933	5153.582	5162.062
Diagnostics					
WALD test for identifying restriction	n/a	-0.001 [p=0.925]	0.002 [p=0.866]	0.006 [p=0.633]	0.006 [p=0.661]
LR test for heteroskedasticity	7.22 [p=0.925]	**133.14** **[p=0.000]**	n/a	27.29 [p=0.746]	**44.25** **[p=0.091]**
LM test for normality (joint test)	2.77 [p=0.250]	**15.60** **[p=0.075]**	**73.99** **[p=0.000]**	**23.49** **[p=0.005]**	7.13 [p=0.623]

Table 5.2 The repeat unemployment incidence; Invariant programme effect.

LM test for normality (Pred^2)	0.89 [p=0.345]				
LM test for normality (Pred^3)	**2.76 [p=0.096]**				
LM tests for the significance of cumulants:					
κ_{30}		**3.57 [p=0.058]**	0.08 [p=0.777]	0.00 [p=0.957]	0.00 [p=0.942]
κ_{21}		0.44 [p=0.507]	0.03 [p=0.862]	0.33 [p=0.565]	0.11 [p=0.740]
κ_{12}		0.17 [p=0.680]	0.25 [p=0.617]	0.12 [p=0.729]	0.14 [p=0.708]
κ_{03}		0.99 [p=0.319]	**39.92 [p=0.000]**	**9.43 [p=0.002]**	0.55 [p=0.458]
κ_{40}		1.96 [p=0.161]	0.09 [p=0.764]	0.01 [p=0.920]	0.07 [p=0.791]
κ_{31}		1.20 [p=0.273]	0.65 [p=0.420]	0.24 [p=0.624]	0.25 [p=0.617]
κ_{22}		0.00 [p=0.993]	0.99 [p=0.319]	1.31 [p=0.252]	0.46 [p=0.497]
κ_{13}		0.00 [p=0.982]	0.35 [p=0.554]	0.01 [p=0.920]	0.05 [p=0.823]
κ_{04}		0.00 [p=0.995]	**16.12 [p=0.000]**	**10.49 [p=0.001]**	1.27 [p=0.259]
N	4516	4516	4516	4516	4516

Notes: See table 5.1; Normality test for the heteroskedastic probit model is a RESET-like test for normality presented in Pagan & Vella (1989), p. S43.

One variable of considerable interest when studying the unemployment incidence is the replacement ratio. In this study it is specified as two separate variables; monthly unemployment benefits received during unemployment, and wage income in a subsequent job. According to search theory, a higher compensation level out of work reduces incentives to work which in turn increases the probability of renewing unemployment. The results lend some support for this hypothesis, the benefits variable having a well determined downward effect on job stability. Before pushing this interpretation too far, it is worth noting that the single unemployment benefit variable reflects the whole unemployment benefit system, for a thorough discussion see Atkinson & Micklewright (1991)[11]. Moreover, the effect of unemployment benefits on the repeat unemployment probability is affected by its downward effect on the participation probability, which in turn may reflect the duration of unemployment and not unemployment benefits, *per se*. After all, the short-term unemployed, who are less likely to participate in a programme, are still under the higher compensation UI scheme.

An increase in the denominator of the replacement ratio, i.e. in monthly earnings, seems to reduce the repeat unemployment probability. The finding is in line with the Krueger & Summers (1987) study, according to which industrial wage differentials are associated with lower quits. This in turn implies that differentials reflect rents to better quality jobs. Accordingly, as far as wages can be used as an indicator of job quality, individuals in high quality jobs are less likely to experience a repeat unemployment spell than individuals in low quality jobs. This can be interpreted in one of two ways. Either individuals are less willing to quit a better paid job due to greater opportunity costs or firms put more effort into a hiring decision when filling a higher paid vacancy that improves the matching process. In contrast to other income variables, an increase in non-labour income does not seem to have any significant effect on the repeat unemployment probability

It is interesting to note that the union status variable, which is measured in the year 1989 (1988) in the repeat unemployment (participation) equation, seems to have a

[11] As discussed in chapter 2, unemployment compensation can be obtained either under the means tested unemployment assistance (UA) scheme or under the earnings related unemployment insurance (UI) scheme, normally limited to 500 days.

substantial downward effect on the repeat unemployment probability. This result has similarities with the studies which report a downward effect of the presence of unions on the turnover rate, see Freeman & Medoff (1984) and Miller & Mulvey (1993), *inter alia*. One explanation for this is that, instead of quitting an unsatisfactory job, unionised workers can voice their complaints to management. A rival explanation could be that, together with the earnings variable, the union status variable is an indicator of job quality. The rationale behind this follows from a large body of empirical work indicating the existence of union wage gap (for a survey, see Pencavel 1991). A likely response of management to higher union wages is to upgrade the quality of their workforce by recruiting more productive workers.

In addition to the reported estimates, insignificant variables are of interest in their own right. The results suggest that neither age nor gender has any significant impact on programme participation/repeat unemployment incidence. The likely reason for the lack of age profile is the age criteria used in choosing the sample. When it comes to gender differences, it is possible that a single dummy variable is not sufficient to capture the complicated nature of women's labour market behaviour. If this is the case, it could be fruitful to concentrate separately on men and women by estimating different parameter vectors for both sexes, which could uncover some interesting differences between men and women. A rival explanation for the lack of gender differences could hinge behind the welfare state which increases women's labour market possibilities, for instance by providing child care and legal protection during the motherhood leave.

Turning next to the main issue of interest, namely the impact of active labour market programmes. The results of bivariate probit models shown in table 5.2 suggest a quite substantial, statistically significant, decline in participants' probability of experiencing a repeat unemployment spell. In addition, the significant parameter estimate of the correlation coefficient, ρ, implies that the selection into the controls and the treatments is endogenously determined. Positive correlation between the error terms uncovers the role of unobservable characteristics; they make participation more likely whilst also increasing the individuals' risk of renewing unemployment. Due to these unobservables programme participants' initial labour market possibilities, in terms of the repeat unemployment incidence, are inferior to that of controls.

What happens if we loosen the implicit assumption of an invariant programme effect of bivariate probit models? The estimates reported in table 5.3 show that this does not affect the inference concerning non-programme related factors. There are, however, two rather important changes in the parameter estimates of ALMP variables. First, correlation between error terms turns out to be insignificantly different from zero, i.e. the selection bias can be eased, at least in this study, by introducing interaction terms in the probit model. This implies that omitted interaction terms cause there to appear to be endogenous selection. A likely explanation for the finding is that, due to a large number of control variables, additional terms reduce considerably the unexplained part of repeat unemployment incidence. This in turn is reflected in the estimated correlation coefficient between the error terms in the repeat unemployment and participation equations. Second, the significance levels of programme participation dummies fall. Unlike the impact on correlation coefficients, the introduction of interaction terms affects mainly the standard errors of programme dummies, not their absolute values. Hence, provided that differences in programme effects across individual characteristics more or less cancel each other out, it is possible to estimate the mean programme effect by employing bivariate probit models.

Table 5.3 Repeat unemployment incidence; Varying programme effect.

	Estimated model			
	Homoskedastic Switching Bivariate Probit Model		Heteroskedastic Switching Bivariate Probit Model	
		Interaction Terms		Interaction Terms
Intercept	0.349 (0.476)		0.582 (0.469)	
Individual characteristics				
Gender	-0.015 (0.068)	0.106 (0.114)	-0.030 (0.074)	0.104 (0.126)
Age	0.022 (0.024)	-0.002 (0.044)	0.020 (0.025)	0.013 (0.048)
$Age^2 \times 10^{-3}$	-2.182 (3.601)	-0.938 (6.739)	-2.398 (3.753)	-3.043 (7.403)
Number of children under 7 years of old	0.058 (0.080)	-0.061 (0.147)	0.065 (0.084)	-0.108 (0.158)
Age of the youngest child 0 - 1 years	0.021 (0.152)	0.093 (0.260)	0.010 (0.167)	0.159 (0.284)
Age of the youngest child 2 - 4 years	-0.058 (0.134)	0.030 (0.250)	-0.064 (0.142)	0.065 (0.269)
Age of the youngest child 5 - 7 years	-0.037 (0.130)	0.025 (0.225)	-0.010 (0.141)	0.000 (0.242)
Education	-0.077 (0.034)***	-0.068 (0.066)	-0.090 (0.045)**	-0.087 (0.082)
Home ownership	-0.011 (0.053)	-0.153 (0.093)*	-0.029 (0.056)	-0.160 (0.102)
Disability	0.081 (0.111)	0.185 (0.165)	0.046 (0.118)	0.222 (0.182)
Broader job seeking	-0.188 (0.109)*	-0.002 (0.205)	-0.173 (0.118)	-0.055 (0.234)
Spouse's education	-0.008 (0.032)	0.003 (0.062)	-0.015 (0.038)	-0.008 (0.071)
Marital status	-0.073 (0.073)	-0.076 (0.127)	-0.053 (0.077)	-0.098 (0.138)
Head of a family	-0.125 (0.068)*	-0.010 (0.126)	-0.125 (0.075)*	-0.043 (0.138)

Table 5.3 Repeat unemployment incidence; Varying programme effect.

Labour market				
travel-to-work	0.039	-0.020	0.029	-0.003
Unemployment rate	(0.016)**	(0.022)	(0.015)*	(0.025)
Union member	-0.107	-0.194	-0.105	-0.218
	(0.059)*	(0.102)*	(0.063)*	(0.114)*
Urban area	0.000	-0.035	-0.020	0.015
	(0.057)	(0.100)	(0.062)	(0.109)
Unemployment duration	0.150	-0.074	0.171	-0.079
before the latest spell x10^{-2}	(0.019)***	(0.025)***	(0.026)***	(0.030)**
Southern Finland	0.093	-0.189	0.100	-0.203
	(0.110)	(0.130)	(0.099)	(0.142)
Central Finland	0.039	-0.078	0.048	-0.097
	(0.096)	(0.130)	(0.093)	(0.140)
<u>Occupation:</u>				
Technical	-0.298	0.456	-0.311	0.406
	(0.188)	(0.278)	(0.183)*	(0.319)
Health care	-0.152	0.191	-0.121	0.170
	(0.168)	(0.249)	(0.156)	(0.269)
Administrative	-0.251	0.252	-0.236	0.243
	(0.125)**	(0.185)	(0.130)*	(0.201)
Mercantile	-0.461	0.418	-0.430	0.435
	(0.154)***	(0.223)*	(0.145)***	(0.238)*
Farming/Forestry	0.218	0.450	0.291	0.329
	(0.190)	(0.270)*	(0.179)	(0.278)
Transport	-0.146	0.441	-0.145	0.435
	(0.196)	(0.308)	(0.182)	(0.317)
Manufacture	-0.250	0.393	-0.210	0.379
	(0.130)*	(0.156)**	(0.116)*	(0.166)**
Construction	0.426	0.032	0.483	0.012
	(0.179)**	(0.218)	(0.165)***	(0.228)
Service	-0.017	0.180	0.039	0.142
	(0.134)	(0.176)	(0.124)	(0.184)
Income variables				
Ln(monthly unemployment	0.065	0.062	0.079	0.051
benefits)	(0.008)***	(0.013)***	(0.012)***	(0.021)**
Ln(monthly earnings)	-0.110	0.041	-0.119	0.046
	(0.020)***	(0.032)	(0.024)***	(0.035)

Table 5.3 Repeat unemployment incidence; Varying programme effect.

Ln(other income)	0.007 (0.007)	0.006 (0.014)	0.001 (0.008)	0.013 (0.015)
Ln(spouse's income)	-0.018 (0.006)***	0.004 (0.011)	-0.020 (0.007)***	0.006 (0.012)
Participation				
Participation dummy	-0.420 (0.900)		-0.830 (0.870)	
Heteroskedasticity correction terms	No		Yes	
travel-to-work			-0.027 (0.013)**	
Unemployment rate				
Education			0.118 (0.041)***	
Ln(monthly unemployment benefits)			0.043 (0.013)***	
Ln(other income)			-0.023 (0.010)**	
ρ	0.112 (0.298)		0.169 (0.184)	
Log-likelihood	5175.141		5139.707	
Diagnostics				
WALD test for identifying restriction	-0.016 [p=0.287]		-0.012 [p=0.437]	
LR test for heteroskedasticity	70.86 [p=0.000]		n/a	
LM test for normality (joint test)	10.25 [p=0.330]		7.34 [p=0.601]	
LM tests for the significance of cumulants:				
κ_{30}	1.49 [p=0.222]		0.53 [p=0.466]	
κ_{21}	0.13 [p=0.718]		0.36 [p=0.548]	
κ_{12}	2.42 [p=0.119]		0.68 [p=0.409]	
κ_{03}	2.14 [p=0.143]		0.44 [p=0.507]	
κ_{40}	**4.50 [p=0.033]**		2.36 [p=0.124]	
κ_{31}	0.95 [p=0.329]		0.85 [p=0.356]	
κ_{22}	**4.19 [p=0.040]**		2.09 [p=0.148]	
κ_{13}	0.05 [p=0.823]		0.63 [p=0.427]	

Table 5.3 Repeat unemployment incidence; Varying programme effect.

κ_{04}	0.09 [p=0.764]	2.17 [p=0.140]
N	4516	4516

Notes: See table 5.1; The second column gives the parameter estimates of interaction terms which are obtained by multiplying the variable in question with the programme dummy.

5.4. Assessing the Effects of Active Labour Market Programmes

It is difficult to get a comprehensive picture of the determinants of repeat unemployment incidence from the parameter estimates alone. The signs of slope estimates indicate the direction of the impact but the magnitude remains unclear due to indirect effects via the participation equation and the terms in heteroskedastic functions. For that reason it is informative to take a closer look at our main issue of interest; the impact of active labour market programmes on repeat unemployment incidence. Table 5.4 shows the predicted repeat unemployment probabilities and the estimated marginal programme effects for three types of individuals; disadvantaged, standard and advantaged. Column 1 gives the results of the heteroskedasticity corrected probit model which has to be thought of as a baseline specification due to selection bias. The next five columns report the results of more convincing models; two bivariate probit specifications and three switching specifications.

Table 5.4. Estimated Repeat Unemployment Probabilities and Marginal Programme Effects.

	Model					
	Hetero-sked. Probit	Homo-sked. Bivariate Probit	Hetero-sked. Bivariate Probit	Switching Hetero-sked. Probit	Switching Homo-sked. Bivariate Probit	Switching Hetero-sked. Bivariate Probit
Selection correction	No	Yes	Yes	No	Yes	Yes
Estimated Repeat Unemployment Probabilities						
Disadvantaged participant	84.13	66.04	68.00	81.02	63.97	65.32
Standard participant	64.76	36.73	38.54	70.56	40.34	38.66
Advantaged participant	34.55	3.46	10.60	34.96	4.12	8.49
Estimated Marginal Programme Effect						
Disadvantaged participant	-2.37	-11.61	-11.14	-6.94	-9.97	-8.03
Standard participant	-2.86	-10.90	-11.65	0.83	-3.76	-4.57
Advantaged participant	-1.48	-3.47	-3.84	0.79	-0.39	-1.83

Notes: (i) A standard participant is unmarried and evaluated at the means of continuous variables by setting all dummy variables to zeros. (ii) A disadvantaged participants is disabled with less than upper secondary education. His unemployment experience exceeds the average value by one standard deviation (s.d). He lives in the high unemployment area (mean + 1 s.d.) where the local supply of ALMPs exceeds the average by 1 s.d. His unemployment benefits and monthly earnings are 1 s.d. below the average and he does not have any non-labour income. (iii) An advantaged participant is married with a standard spouse. He lives in the southern Finland in a low unemployment area (mean - 1 s.d.) where the local supply of ALMPs is 1 s.d. below the average. He has a university degree and works in a merchandise occupation, owns a home, belongs to a union and was willing to accept a job offer outside his home community. His unemployment experience is 1 s.d. below the average. And finally, his unemployment benefits, earnings and non-labour income are 1 s.d. above the average values.

The actual values of the estimated repeat unemployment probabilities cannot be given too much weight given that they have been calculated for very specific individuals. It is more interesting to examine the variation between individuals which is estimated as being some 46 - 68 percentage points. To get some idea of the economic significance of active labour market policy, post-programme differences in the risk of renewing unemployment should be compared to the marginal programme effect of disadvantaged participants that centres around 10 percentage points. These two figures suggest that disadvantaged participants benefit considerably from participation but the gain is far from eliminating the differences in labour market outcomes due to their initially inferior labour market possibilities.

All models agree that an advantaged participant benefits the least from active programmes. Depending on a model this result arises from different sources. In the heteroskedastic probit model (column 1) it follows from the non-linearity of the model, the constant programme dummy having smaller effect on the probability value in the lower end of the cumulative distribution function than in the middle parts of it. The non-linearity plays a role also in constant effect bivariate probit models (columns 2 and 3), but the larger role is played by the participation equation. An advantaged person has characteristics which reduce the probability of participating in an active programme and this in turn is reflected in the marginal programme effect via the estimated positive correlation coefficient[12]. Finally in switching models the gain difference arises from individual characteristics. The flexibility of switching models in assessing ALMPs is particularly pronounced when comparing the marginal programme effects between disadvantaged and standard participants.

The results reported in table 5.4 give some insight to the question of who benefits the most from ALMPs, but the analysis can be more detailed than that. To find out 'pure' differences across individual characteristics, we calculated marginal programme effects by adding specific characteristics, one at a time, to a standard participant defined in table 5.4. After calculating marginal programme effects for newly defined persons, we

[12] If the characteristics of an advantaged individual are removed from the participation equation the estimated marginal programme effect increases nearer to 9 percentage points.

subtracted the ones reported for a standard participant in table 5.4 from them. These deviations are given in table 5.5.

Even though the heteroskedastic bivariate probit model reported in column 1 does not allow the programme effect to differ across individual characteristics, there are some fairly large departures from the estimated mean programme effect. The discussion above reveals that this arises from two sources, viz. non-linearity and the determinants of participation. The participation equation has some effects also on switching models, particularly on the magnitudes of programme effects across occupations. This is caused by the strong presence of occupation variables in the participation equation which seems to level out the differences in bivariate switching models. Having said that, it is encouraging to note that the switching model is otherwise fairly robust to changes in specification.

Table 5.5. The marginal programme effect according to individual characteristics; deviations from the mean programme effect.

	Estimated deviation from the mean programme effect			
	Heterosked Bivariate Probit	Switching Heterosked Probit	Switching Homosked Bivariate Probit	Switching Heterosked Bivariate Probit
Individual characteristics				
Age + 5 years	***-0.46***	***-0.40***	***-0.57***	***-0.31***
Education +1 category	***-0.61***	***-2.02***	***-2.04***	***-1.57***
Home ownership	***-0.50***	***-5.83***	***-2.71***	***-2.80***
Disability	***-0.56***	6.53	3.57	3.53
Broader job seeking	3.86	***-1.41***	***-0.09***	0.67
Head of a family	***-0.39***	***-1.57***	***-0.28***	***-0.78***

Labour market				
Local unemployment rate + 1 s.d.	***-0.69***	***-1.42***	***-1.09***	***-0.48***
Union member	***-5.83***	***-7.19***	***-5.19***	***-7.16***
South	1.12	***-6.66***	***-2.44***	***-2.35***
Unemployment duration + 3 months	0.45	***-2.89***	***-1.25***	***-1.00***
Unemployment duration + 6 months	1.06	***-5.15***	***-2.40***	***-1.86***
Occupation:				
Technical	6.14	15.16	5.97	5.48
Health care	4.59	4.40	3.79	3.50
Administrative	1.78	7.69	4.73	4.04
Mercantile	4.00	14.67	6.54	6.11
Farming/Forestry	8.31	9.68	5.22	5.80
Transport	7.49	14.85	5.43	5.42
Manufacture	4.68	12.68	6.15	5.49
Construction	8.77	1.44	2.98	3.32
Service	5.13	4.00	3.59	3.28
Income variables				
UNt benefits + 1 s.d.	4.03	5.86	4.16	3.50
Other income + 1 s.d.	0.03	0.61	0.60	0.69

Notes: Figures in bold indicate larger than average programme gains.

If we loosen the restriction that the programme effect is equal for all participants, the results differ in two important respects. First, the estimates show that the programme effect is about 4 - 6 percentage points lower for the disabled participants with other characteristics equal. Second, long unemployment experience increases the marginal programme effect in switching models. The latter is in line with the results reported in table 5.4, justifying the targeting of active programmes on hard-to-employ individuals. This is further confirmed by the finding that individuals without occupation (the omitted category) have more than average gains from participation with all other characteristics equal.

It is also evident that the mere comparison between disadvantaged and advantaged participants hides some interesting factors affecting the magnitude of the programme effect. Many characteristics, which cannot be thought of as describing disadvantaged persons, bring about larger than mean benefits from active programmes. Regardless of the exact estimation method, factors connected to higher social status, such as education, home ownership and family status, increase the programme gain by some 1 - 5 percentage points each. In addition, individual motivation/closer attachment to labour markets, measured by broader job seeking and union membership variables, increases the beneficial effect of active programmes. Finally, the results cast some doubts over the aim of reducing regional unemployment differences through active labour market policy. Participants living in the southern part of Finland benefit some 2 - 6 percentage points more than participants in other parts of Finland with other characteristics equal.

5.5. Conclusions

In this chapter the effect of active labour market programmes on repeat unemployment incidence has been examined, the main technical issues of interest being (i) the specification of error processes, (ii) the specification of the programme effect and (iii) misspecification testing of microeconometric models. The estimations suggest that heteroskedasticity correction, despite the massive rejections of homoskedastic specifications, does not have any significant effect on the inference concerning ALMPs. This is an interesting result in its own right since it lends some support to the results of conventional evaluation studies based on the assumption of homoskedastic disturbances. Unlike heteroskedasticity, the specification of the programme effect has some implications both for the modelling strategy and for the policy recommendations. Conventional invariant programme effect specifications call for the estimation of a bivariate system, whereas the results indicate that the varying programme effect model can be estimated within a single equation framework. The greatest differences due to the specification of the programme effect arise when assessing the impacts of individual characteristics on programme gains. More precisely, policy recommendations concerning the use of active labour market policy in helping the disabled and the long-term unemployed in labour markets were found to differ drastically.

Unlike the bulk of previous studies the estimated models were put under scrutiny by various misspecification tests. The implemented tests show that homoskedastic specifications suffer from non-normalities which can be eased by proper specification of terms in the heteroskedastic function. Distribution tests proved to be valuable in constructing alternatives for homoskedastic models. Furthermore, misspecification tests lend some support on the estimated programme effects. Preferred specifications pass the implemented tests, most notably the ones for distributional assumptions and for identifying restrictions.

To summarise the effects of active programmes, it seems reasonable to hypothesise the following. First, the targeting of active programmes on hard-to-employ persons is justifiable. The results imply that disadvantaged participants benefit from an active programme by a 7 - 11 percentage points reduction in the risk of renewing unemployment. Closer examination revealed notable differences across different groups of disadvantaged individuals. More precisely, the results of the switching models imply that active programmes do not improve the labour market possibilities of disabled participants. This lends some support to the views expressed in Blanchflower et. al. (1995), according to whom the public sector should help disabled persons by other means than active labour market policy. Second, there is no clear evidence that advantaged individuals benefit from programmes. Switching models estimate the marginal programme effect being close to zero, the constant programme effect models implying moderate gains. Interestingly the closer examination of individual characteristics shows that some factors connected to higher social status, such as education, home ownership and family status, increase the mean programme effect by some 1 - 5 percentage points each. Third, the results cast considerable doubt on the aim of reducing regional unemployment differences through active labour market policy. Fourth, individuals' attachment to labour markets brings about greater programme benefits with union members' programme gain exceeding that of non-members by some 6 percentage points with other characteristics being equal.

Finally, active labour market policy can help disadvantaged participants only so far. Even though they benefit considerably from participating in an active labour market programme, their post-programme risk of repeat unemployment remains some 50 - 60 percentage points higher than that of advantaged participants. Accordingly, the programme gain is far from removing the differences in labour market outcomes arising from initially inferior labour market possibilities of disadvantaged participants. This is well in line with the macroeconomic conclusion of the previous chapter which argued that active labour market policy helps to reduce open unemployment, at least in the high unemployment situation, but it is not a miracle cure.

Appendix 5.1. Diagnostic Tests for Bivariate and Endogenously Switching Bivariate Probit Models.

In order to simplify expressions, we employ the following notation:

$$\text{(A1)}\quad q_{iu} = 2u_i\text{-}1;\qquad q_{ip} = 2p_i\text{-}1;\qquad \rho^* = q_{iu}q_{ip}\rho;\quad h_{iuj} = \frac{X_i\beta_j}{\exp(W_{iu}\delta)};$$

$$h_{ip} = \frac{Z_i\gamma}{\exp(W_{ip}\theta)};\quad b_{iuj} = \frac{q_{ip}h_{ip} - \rho^* q_{iu}h_{iuj}}{(1-\rho^{*2})^{1/2}};\quad b_{ipj} = \frac{q_{iu}h_{iuj} - \rho^* q_{ip}h_{ip}}{(1-\rho^{*2})^{1/2}}\quad .$$

Subscripts u and p refer to repeat unemployment and participation equations, respectively. The subscript j = 1,2 denotes separate parameter vectors of participants (β_1) and non-participants (β_2) in the repeat unemployment equation of the switching model. In bivariate probit models the parameter vectors are equal for both groups, i.e., $\beta_1 = \beta_2 = \beta$.

By adopting the notations above, log-likelihood functions for the bivariate probit model (A2) and for the switching bivariate probit (A2') can be written as

$$\text{(A2)}\quad \ln L = \sum_{i=1}^{N} \ln \Phi_2(q_{iu}h_{iu}, q_{ip}h_{ip}, \rho_i^*)$$

$$\text{(A2')}\quad \ln L = \sum_{i=1}^{N} \{p_i \ln \Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*) + (1-p_i)\ln \Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)\}\ .$$

Note the notational convention. Since participants and non-participants have the same parameter vector in the bivariate probit model, the subscript j=1,2 does not enter equation (A2). The subscript 2 refers to the standard bivariate cumulative distribution when used in Φ_2, otherwise it refers to non-participants in the switching model.

LM-test for heteroskedasticity can be based on the log-likelihood functions above. However, if we want to construct a test for the distributional assumption of bivariate normality, we have to allow local departures from normality. Lee (1984) constructed an alternative by expanding the joint density by a series of derivates of the standard bivariate normal density. An attractive alternative to Lee's bivariate marginals is given in Murphy (1994) who based a series expansion on univariate marginals, i.e. a series of derivates of the standard normal density, which simplifies calculations considerably. In constructing a series expansion one needs orthogonal polynomials corresponding to the marginals. The general procedure for doing this has been set up by Cameron & Trivedi (1990). For normal densities, however, the generating function is known to consist of Hermite polynomials, which are tabulated in Kendall & Stuart (1969, p. 155), *inter alia*. Formulas for constructing an alternative to bivariate normality are given in Ord (1972) and Murphy (1994), so they are not repeated here. If an expansion is up to the fourth order, it is straightforward to show that the normality test can be based on the log-likelihood function in which the following expansion term is added to joint densities, Φ_2

$$
\begin{aligned}
\text{(A3)}\quad & [q_{iu}\frac{\kappa_{30}}{3!}H_2(-h_{iuj})\phi(h_{iuj})\Phi(q_{ip}h_{ip}) + q_{iu}q_{ip}\frac{\kappa_{21}}{2!1!}H_1(-h_{iuj})\phi(h_{iuj})\phi(h_{ip})+ \\
& q_{iu}q_{ip}\frac{\kappa_{12}}{1!2!}\phi(h_{iuj})H_1(-h_{ip})\phi(h_{ip}) + q_{ip}\frac{\kappa_{03}}{3!}\Phi(q_{iu}h_{iuj})H_2(-h_{ip})\phi(h_{ip})+ \\
& q_{iu}\frac{\kappa_{40}}{4!}H_3(-h_{iuj})\phi(h_{iuj})\Phi(q_{ip}h_{ip}) + q_{iu}q_{ip}\frac{\kappa_{31}}{3!1!}H_2(-h_{iuj})\phi(h_{iuj})\phi(h_{ip})+ \\
& q_{iu}q_{ip}\frac{\kappa_{22}}{2!2!}H_1(-h_{iuj})\phi(h_{iuj})H_1(-h_{ip})\phi(h_{ip}) + q_{iu}q_{ip}\frac{\kappa_{13}}{1!3!}\phi(h_{iuj})H_2(-h_{ip})\phi(h_{ip})+ \\
& q_{ip}\frac{\kappa_{04}}{4!}\Phi(q_{iu}h_{iuj})H_3(-h_{ip})\phi(h_{ip})],\ j = 1, 2\ .
\end{aligned}
$$

In equation (A3), H_l's are Hermite polynomials of the l^{th} order; Φ and ϕ denote the standard normal cumulative distribution and the standard normal probability distribution, respectively; and κs refer to cumulants. Expansion term for testing the distributional assumption of the bivariate probit model is obtained by setting $h_{iu1} = h_{iu2} = h_{iu}$. As a final remark, the resulting log-likelihood functions account for all necessary sign changes needed in calculating different probabilities.

The LM test statistics reported in this paper all take the form

$$\text{(A4)}\qquad \psi = 1'C(C'C)^{-1}C'1$$

where 1 is an n-dimensional vector of ones and C is a n X k - matrix, each column of which contains individual score contributions corresponding to k parameters of the general model. In other words, the elements of C - matrix consist of the first order partial derivates of the log-likelihood function for the alternative that are evaluated under the null hypothesis. It has to be noted that the test statistic can also be calculated through the explained sum of squares from an uncentered artificial regression of the column vector 1 on each column of C.

Normality test

Under the null hypothesis of bivariate normality all expansion terms in equation (A3) are zero, which can be tested through $\kappa_{30} = \kappa_{21} = \ldots = \kappa_{04} = 0$. In the switching model the score contributions needed in constructing the i^{th} row of the C - matrix are follows

$$\text{(A5)}\quad \frac{\partial \ln L}{\partial \beta_1} = \left\{\frac{p_i q_{iu}\phi(q_{iu}h_{iu1})\Phi(b_{iu1})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)}\right\}\exp(-W_{i1}\delta)X_i$$

$$\frac{\partial \ln L}{\partial \beta_2} = \left\{\frac{(1-p_i)q_{iu}\phi(q_{iu}h_{iu2})\Phi(b_{iu2})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}\right\}\exp(-W_{i1}\delta)X_i$$

$$\frac{\partial \ln L}{\partial \gamma} = \left\{\frac{p_i q_{ip}\phi(q_{ip}h_{ip})\Phi(b_{ip1})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} + \frac{(1-p_i)q_{ip}\phi(q_{ip}h_{ip})\Phi(b_{ip2})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}\right\}\exp(-W_{i2}\theta)Z_i$$

$$\frac{\partial \ln L}{\partial \rho_1} = \frac{p_i q_{iu}q_{ip}\phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} + \frac{(1-p_i)q_{iu}q_{ip}\phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}$$

$$\frac{\partial \ln L}{\partial \delta} = \Big(\frac{p_i q_{iu}\phi(h_{iu1})\Phi(b_{iu1})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)}(X_i\beta_1) +$$
$$\frac{(1-p_i)q_{iu}\phi(h_{iu2})\Phi(b_{iu2})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}(X_i\beta_2)\Big)\exp(-W_{iu}\delta)(-W_{iu})$$

$$\frac{\partial \ln L}{\partial \theta} = \Big(\frac{p_i q_{ip}\phi(h_{ip})\Phi(b_{ip1})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} +$$
$$\frac{(1-p_i)q_{ip}\phi(h_{ip})\Phi(b_{ip2})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}(Z_i\gamma)\Big)\exp(-W_{ip}\theta)(-W_{ip})$$

$$\frac{\partial \ln L}{\partial \kappa_{30}} = \frac{1}{6}\Big(\frac{p_i q_{iu}((-h_{iu1})^2 - 1)\phi(h_{iu1})\Phi(q_{ip}h_{ip})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} +$$
$$\frac{(1-p_i)q_{iu}((-h_{iu2})^2 - 1)\phi(h_{iu2})\Phi(q_{ip}h_{ip})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}\Big)$$

$$\frac{\partial \ln L}{\partial \kappa_{21}} = \frac{1}{2}\Big(\frac{p_i q_{iu}q_{ip}(-h_{iu1})\phi(h_{iu1})\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} +$$
$$\frac{(1-p_i)q_{iu}q_{ip}(-h_{iu2})\phi(h_{iu2})\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)}\Big)$$

$$\frac{\partial \ln L}{\partial \kappa_{12}} = \frac{1}{2}\left\{ \frac{p_i q_{iu} q_{ip} \phi(h_{iu1})(-h_{ip})\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} + \frac{(1-p_i) q_{iu} q_{ip} \phi(h_{iu2})(-h_{ip})\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)} \right\}$$

$$\ldots$$

$$\frac{\partial \ln L}{\partial \kappa_{04}} = \frac{1}{24}\left(\frac{p_i q_{ip} \Phi(q_{iu}h_{iu1})((-h_{ip})^3 - 3(-h_{ip}))\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu1}, q_{ip}h_{ip}, \rho_i^*)} + . \right.$$
$$\left. \frac{(1-p_i) q_{ip} \Phi(q_{iu}h_{iu2})((-h_{ip})^3 - 3(-h_{ip}))\phi(h_{ip})}{\Phi_2(q_{iu}h_{iu2}, q_{ip}h_{ip}, \rho_i^*)} \right)$$

Under the null the test statistic is asymptotically χ^2-distributed with 9 degrees of freedom. Instead of the joint test one can also test each cumulant (κ) in turn, each test being χ^2-distributed with 1 degree of freedom. The score contributions for testing normality in bivariate probit models are obtained by setting $\beta_1 = \beta_2 = \beta$, which indicates that $h_{iu1} = h_{iu2} = h_{iu}$.

Heteroskedasticity test

When testing for heteroskedasticity under the assumption of bivariate normality, the C - matrix does not include the score contributions of expansion terms, $\frac{\partial \ln L}{\partial \kappa_{30}}, \frac{\partial \ln L}{\partial \kappa_{21}}, \ldots, \frac{\partial \ln L}{\partial \kappa_{04}}$. Another modification needed in equations (A5) is that the parameter vectors of heteroskedasticity correction terms, δ and θ, are zeros when evaluating the score contributions under the null hypothesis of homoskedasticity. The corresponding test statistic is then asymptotically χ^2 - distributed with degrees of freedom equalling the number of excluded heteroskedasticity correction terms.

Independence test

As above, under bivariate normality the C - matrix does not include partial derivates of expansion terms, $\frac{\partial \ln L}{\partial \kappa_{30}}, \frac{\partial \ln L}{\partial \kappa_{21}}, \ldots, \frac{\partial \ln L}{\partial \kappa_{04}}$. Under the null hypothesis of independence the correlation term is zero, i.e. $\rho = 0$. It can be easily shown that the score contributions evaluated under the null become the generalised residuals of the probit model. The resulting test statistic is asymptotically χ^2 - distributed with one degree of freedom.

Appendix 5.2. The Determinants of the Repeat Unemployment Incidence; Probit Specifications.

	Estimated model				
	Homoskedastic Probit	Heteroskedastic Probit	Heteroskedastic Probit	Heteroskedastic Switching Probit	
					Interaction Terms
Intercept	0.325 (0.344)	0.298 (0.352)	0.352 (0.312)	0.292 (0.366)	
Individual charcteristics					
Gender	0.029 (0.053)	0.014 (0.057)	0.009 (0.049)	-0.026 (0.059)	0.075 (0.106)
Age	0.009 (0.020)	0.010 (0.020)	0.008 (0.017)	0.014 (0.020)	0.010 (0.040)
$Age^2 \times 10^{-3}$	-0.738 (2.995)	-1.694 (3.014)	-1.299 (2.633)	-1.721 (3.007)	-2.237 (6.093)
Number of children under 7 years of old	0.054 (0.065)	0.054 (0.064)	0.048 (0.060)	0.051 (0.070)	-0.083 (0.132)
Age of the youngest child 0 - 1 years	0.011 (0.120)	-0.002 (0.118)	0.012 (0.114)	0.017 (0.138)	0.134 (0.241)
Age of the youngest child 2 - 4 years	-0.073 (0.110)	-0.085 (0.112)	-0.076 (0.102)	-0.056 (0.116)	0.039 (0.226)
Age of the youngest child 5 - 7 years	-0.048 (0.103)	-0.053 (0.104)	-0.039 (0.094)	-0.019 (0.114)	0.011 (0.196)
Education	-0.110 (0.026)***	-0.140 (0.056)**	-0.120 (0.034)***	-0.089 (0.034)***	-0.051 (0.063)
Home ownership	-0.074 (0.042)*	-0.069 (0.050)	-0.073 (0.041)*	-0.011 (0.046)	-0.140 (0.087)
Disability	0.147 (0.080)*	0.123 (0.106)	0.101 (0.076)	0.019 (0.094)	0.177 (0.152)
Broader job seeking	-0.163 (0.090)*	-0.144 (0.111)	-0.140 (0.085)*	-0.152 (0.097)	-0.034 (0.188)
Spouse's education	-0.000 (0.026)	-0.003 (0.027)	-0.007 (0.026)	-0.007 (0.030)	-0.012 (0.057)
Maritial status	-0.090 (0.057)	-0.060 (0.063)	-0.068 (0.054)	-0.043 (0.062)	-0.081 (0.114)

Appendix 5.2. The Determinants of the Repeat Unemployment Incidence; Probit Specifications.

Head of a family	-0.124	-0.115	-0.102	-0.096	-0.038
	(0.056)**	(0.072)	(0.054)*	(0.060)	(0.112)
Labour market					
travel-to-work	0.028	0.013	0.014	0.021	-0.014
Unemployment rate	(0.010)***	(0.011)	(0.010)	(0.012)*	(0.019)
Union member	-0.195	-0.168	-0.139	-0.059	-0.190
	(0.046)***	(0.073)**	(0.049)***	(0.052)	(0.095)**
Urban area	-0.005	-0.019	-0.010	-0.010	-0.005
	(0.045)	(0.049)	(0.042)	(0.050)	(0.091)
Unemployment duration before	0.116	0.153	0.138	0.179	-0.087
the latest spell x10^{-2}	(0.012)***	(0.053)***	(0.030)***	(0.039)***	(0.032)***
Southern Finland	0.035	0.052	0.041	0.115	-0.169
	(0.061)	(0.067)	(0.058)	(0.073)	(0.121)
Central Finland	0.006	0.020	0.012	0.055	-0.074
	(0.061)	(0.064)	(0.056)	(0.072)	(0.117)
<u>Occupation:</u>					
Technical	-0.041	0.022	0.005	-0.168	0.387
	(0.113)	(0.126)	(0.114)	(0.135)	(0.265)
Health care	0.009	0.054	0.033	-0.063	0.109
	(0.104)	(0.110)	(0.101)	(0.120)	(0.223)
Administrative	-0.080	-0.066	-0.046	-0.169	0.183
	(0.087)	(0.095)	(0.081)	(0.106)	(0.168)
Mercantile	-0.238	-0.162	-0.146	-0.299	0.343
	(0.101)**	(0.116)	(0.093)	(0.117)**	(0.204)*
Farming/Forestry	0.466	0.449	0.419	0.246	0.364
	(0.112)***	(0.172)***	(0.125)***	(0.133)*	(0.232)
Transport	0.082	0.107	0.099	-0.055	0.418
	(0.119)	(0.127)	(0.111)	(0.126)	(0.266)
Manufacture	-0.015	0.061	0.049	-0.128	0.325
	(0.070)	(0.074)	(0.066)	(0.085)	(0.145)**
Construction	0.598	0.649	0.578	0.440	0.067
	(0.095)***	(0.223)***	(0.133)***	(0.135)***	(0.191)
Service	0.130	0.211	0.178	0.081	0.112
	(0.080)	(0.103)**	(0.080)**	(0.094)	(0.153)

Appendix 5.2. The Determinants of the Repeat Unemployment Incidence; Probit Specifications.

Income variables					
Ln(monthly unemployment benefits)	0.089 (0.005)***	0.096 (0.031)***	0.085 (0.015)***	0.061 (0.012)***	0.057 (0.014)***
Ln(monthly earnings)	-0.092 (0.015)***	-0.075 (0.021)***	-0.079 (0.018)***	-0.087 (0.022)***	0.026 (0.029)
Ln(other income)	0.011 (0.006)*	0.007 (0.006)	0.006 (0.005)	0.004 (0.006)	0.004 (0.011)
Ln(spouse's income)	-0.016 (0.005)***	-0.017 (0.007)**	-0.015 (0.005)***	-0.017 (0.006)***	0.004 (0.010)
Participation					
Participation dummy	-0.063 (0.045)	-0.076 (0.053)	-0.069 (0.044)	-0.324 (0.681)	
Heteroskedasticity correction terms	No	Yes (21 terms; not shown)	Yes	Yes	
travel-to-work Unemployment rate			-0.043 (0.013)***	-0.031 (0.013)**	
Education			0.117 (0.042)***	0.100 (0.042)**	
Ln(monthly unemployment benefits)			0.049 (0.015)**	0.036 (0.014)**	
Ln(other income)			-0.022 (0.009)*	-0.021 (0.010)**	
Age			-0.008 (0.004)**	-0.009 (0.004)**	
Union member			0.169 (0.077)**	0.160 (0.077)**	
Unemployment duration			0.041 (0.019)**	0.058 (0.020)***	
ρ	n/a	n/a	n/a	n/a	
Log-likelihood	2614.806	2594.224	2597.836	2566.569	
Diagnostics					
LR test for heteroskedasticity	**41.16 [p=0.005]**	n/a	7.22 [p=0.925]	n/a	
LM test for normality (joint test)	**7.13 [p=0.028]**	4.10 [p=0.128]	2.77 [p=0.250]	1.12 [p=0.571]	

Appendix 5.2. The Determinants of the Repeat Unemployment Incidence; Probit Specifications.

LM tests for normality (Pred^2)	1.06 [p=0.303]	1.79 [p=0.180]	0.89 [p=0.345]	0.97 [p=0.324]
LM tests for normality (Pred^3)	**6.10 [p=0.013]**	**3.83 [p=0.050]**	**2.76 [p=0.096]**	0.65 [p=0.420]
N	4516	4516	4516	4516

Notes: See tables 5.1 and 5.2.

Data Appendix. Means and Definitions of the Variables.

Variables	Mean
Individual characteristics	
Gender (= 1 if female)	0.47
Age#	31.66
Number of children under 7 years of old#	0.29
Age of the youngest child 0 - 1 years	0.08
Age of the youngest child 2 - 4 years	0.08
Age of the youngest child 5 - 7 years	0.04
Education# (ranges between 0 = less than upper secondary education and 5 = more than master's degree)	0.86
Home ownership	0.56
Disability	0.07
Broader job seeking (= 1 if willing to accept a job offer outside a home community)	0.05
Spouse's education# (as education)	0.52
Marital status (=1 if married)	0.35
Head of a family	0.22
Labour market	
Travel-to-work Unemployment rate#	5.95
Union member 1988	0.54
Union member 1989	0.64
Urban area (= 1 if lives in an urban area)	0.53
Unemployment duration before the latest spell# (days)	138.88
Southern Finland	0.53
Central Finland	0.25
<u>Occupation</u>	
Technical	0.05
Health care	0.05
Administrative	0.10
Mercantile	0.05
Farming/Forestry	0.05

Transport	0.03
Manufacture	0.23
Construction	0.09
Service	0.13
Income variables	
Ln(Monthly unemployment benefits)#	5.26
Ln(Monthly earnings)#	8.26
Ln(Other income)#	2.22
Ln(Spouse's income)#	6.18

Notes: # denotes that a variable is not a dichotomous one. The variable names are largely self-explanatory but for some variables definitions are given.

CHAPTER 6.

The Impact of Active Programmes on Employment in the Eras of High and Low Unemployment

The point made strongly in earlier chapters is that active labour market policy is useful in combating unemployment but its effect is rather limited. To get a fuller picture of the functioning of Finnish active labour market policy at the individual level, this chapter aims to shed some light on the relative efficiency of different programmes. By this means it complements the previous chapter which focused on variations in programme effects across different individuals according to their characteristics.

Chapter 4 raised the question of the effectiveness of active labour market policy in different unemployment situations. Whether or not the macroeconomic conclusions hold also at the individual level is an interesting issue in its own right. For that reason, this chapter examines active programmes through their impact on participants' months of employment in the eras of low and high unemployment with the open unemployment rates of 4.5 and 15.5 per cent, respectively. The choice of the dependent variable is motivated by the possibility of incorporating both the employment probability and the job stability aspects of active programmes into a single outcome variable. By this means the chapter also broadens the view taken in chapter 5 in which the focus was purely on job stability.

A number of interesting questions are raised by examining various types of programmes in different unemployment situations. Surely high unemployment worsens employment prospects, but does it have the same effect on programme participants and non-participants? Do participants in selective employment measures have a better chance of becoming hired given that they can demonstrate their ability to a potential employer? Is labour market training useless in the high unemployment situation when vacancies are low? These are questions about which we know desperately little and which cannot be fully answered by official statistics. After all, the fact that the proportion of programme participants who are employed after some time since terminating a programme is inversely related to unemployment, does not tell us much about the effectiveness of programmes.

6.1. Modelling Self-Selection and Employment Months

The focus of this chapter is on modelling annual working months. The dependent variable is measured as the number of months in open employment during one calendar year, i.e. subsidised working months have not been included in the dependent variable. This results in the censored dependent variable, observed months in employment being constrained between 0 and 12 months. Since the rapid increase in unemployment in the early 90s the proportion of relatively short, fixed term contracts of new recruits[1] has increased, we allow for multiple employment periods in the dependent variable. In this setting, conditional on normality and exogenous selection on programmes, ALMPs can be assessed by the two-limit tobit model which is reported, for instance, in Maddala (1983) and used in Stewart & Swaffield (1997). Chapter 3 revealed, however, that several studies have reported non-random selection of programme participants and non-participants. The endogeneity of individuals' programme participation decisions can be modelled through the following two equation system

(1) $y_i^* = \beta X_i + \alpha p_i + \varepsilon_i$; $y = 0$ if $y^* < L$; $y = y^*$ if $L \leq y^* \leq U$; $y = U$ if $y^* > U$

(2) $p_i^* = \gamma Z_i + \eta_i$; $p = 0$ if $p^* \leq 0$; $p = 1$ if $p^* > 0$.

---

[1] The proportion of fixed term contracts of all new contracts has increased from 40 to 60 per cent between the years 1989 and 1993 (Parjanne, 1997).

The observed employment months, y, and the observed participation status, p, are realisations of the underlying latent variables y^* and p^*. In the usual manner, the variables determining employment (X_i and p_i) and programme participation (Z_i) are connected to the latent variables via linear indicator functions. The information about the limited dependent variables differs between equations. The observed employment months variable gives some quantitative information between the limits L and U, whereas the participation variable, p, reveals merely the sign of the underlying latent variable. In this setting the second equation can be interpreted as the propensity to participate in an active programme. If the latent employment variable y^* is analogously interpreted as 'desired' months in employment, the model has similarities to second generation labour supply models, see Killingsworth (1983). The analogy cannot be pushed too far given that working months are constrained at the upper limit by the research design, not by the economic environment which affects individuals' labour supply decisions. Accordingly, the exact specification of the employment equation is motivated by the search theoretic framework below.

Active programmes have a potential impact on the probability of working exactly the limit number of months in a year, together with the effect on the expected number of employment months between the censoring points L and U. If we further allow the endogeneity of the individual participation decision, the likelihood function becomes

$$
\begin{aligned}
(3) \qquad L = {} & \prod_{N_1} \Pr(y^* \le L,\ p^* \le 0) \prod_{N_2} \Pr(y^* \le L,\ p^* > 0) \\
& \prod_{N_3} \Pr(L < y^* < U,\ p^* \le 0) f(y \mid L < y^* < U,\ p^* \le 0) \\
& \prod_{N_4} \Pr(L < y^* < U,\ p^* > 0) f(y \mid L < y^* < U,\ p^* > 0) \\
& \prod_{N_5} \Pr(y^* > U,\ p^* \le 0) \prod_{N_6} \Pr(y^* > U,\ p^* > 0)\ .
\end{aligned}
$$

Equation (3) divides the two dimensional plane into six parts; two censored regions and one uncensored region both for the participants ($p^* > 0$) and for the non-participants ($p^* < 0$). The number of observations in each of the regions is denoted as N_j, j running from one to six. It is easily seen that the likelihood function reduces to Amemiya's (1984) type 2 tobit model when the upper limit goes to infinity and only observations from, say, programme participants are in hand. If, on the other hand, the selection is purely based on observables, as defined in Heckman & Hotz (1989), the likelihood function reduces to the 2-limit tobit model.

O'Higgins (1994) has pointed out that in the bivariate probit model the self-selection bias arising from the non-random selection of programme participants cannot be consistently corrected by the standard Heckman procedure (Heckman, 1979) due to non-linearities. In the current setting, this rules out the two-stage estimation method in which the correction terms are based on the probit estimates of participation equation. The reason for this is that the four censored regions (N_1, N_2, N_5, N_6) in the likelihood function (3) correspond to the bivariate probit model under the assumption of normality.

Let us now concentrate on the two regions in which the employment months variable is uncensored, i.e. the regions N_3 and N_4. We can rewrite the third component of the likelihood function as

$$(4) \qquad \prod_{N_3} \Pr(L < y^* < U,\, p \leq 0) \times \left\{ \frac{1}{\Pr(L < y^* < U,\, p \leq 0)} \times \int_{L-\beta X_i}^{U-\beta X_i} \int_{-\infty}^{-\gamma Z_i} f(\varepsilon, \eta)\, d\eta\, d\varepsilon \right\}.$$

It is assumed that the joint density $f(\varepsilon, \eta)$ is bivariate normal with the correlation coefficient ρ and standard deviations σ_y and σ_p. Since we only observe the sign of the latent participation variable, we normalise $\sigma_p = 1$. After this modification the joint density becomes

$$(5) \qquad f(\varepsilon, \eta) = \frac{1}{2\pi\sigma_y\sqrt{1-\rho^2}} \exp\left\{-\frac{(\varepsilon/\sigma_y)^2 + \eta^2 - 2\rho(\varepsilon/\sigma_y)\eta}{2(1-\rho^2)}\right\} = \frac{1}{\sigma_y} \times \phi_2(\xi, \eta, \rho) ,$$

where ϕ_2 denotes for the standard bivariate normal density function for $\xi = \varepsilon/\sigma_y$ and η.

To write down the likelihood function, we employ the joint density (5) and the correspondence of limit observation probabilities with the bivariate probit model. All necessary sign changes due to different participation status can be taken into account by defining $q = 2p - 1$. If we further define the standardised censoring points as $a_1 = (U - \beta X_i - \alpha p)/\sigma_y$ and $b_1 = (L - \beta X_i - \alpha p)/\sigma_y$, the likelihood function (3) can be rewritten as

$$(6) \qquad L = \prod_{N_1+N_2} \Phi_2(b_1, q\times\gamma Z_i, -q\times\rho) \prod_{N_3} \frac{1}{\sigma_y} \int_{b_1}^{a_1} \int_{-\infty}^{-\gamma Z_i} \phi_2(\xi, \eta, \rho)\, d\eta d\xi$$
$$\prod_{N_4} \frac{1}{\sigma_y} \int_{b_1}^{a_1} \int_{\gamma Z_i}^{\infty} \phi_2(\xi, \eta, \rho)\, d\eta d\xi \prod_{N_5+N_6} \Phi_2(-a_1, q\times\gamma Z_i, q\times\rho) .$$

The non-standard distribution of employment months shown in figures 6.1a and 6.1b below suggests an alternative to the likelihood function above. Since the limit observations contain the bulk of information, the empirical part of the paper reports also the results of the model which merely employs information about whether observations are at the standardised censoring points or between these limits. This is a straightforward extension of the two-limit probit model reported in Rossett and Nelson (1975), see also Maddala (1983) p. 162, to a bivariate case. Under the assumption of normality, the likelihood function of the limit observation model becomes

$$(7) \qquad L = \prod_{N_1+N_2} \Phi_2(b_1, q\times\gamma Z_i, -q\times\rho) \prod_{N_3+N_4} \{\Phi_2(a_1, q\times\gamma Z_i, -q\times\rho) -$$
$$\Phi_2(b_1, q\times\gamma Z_i, -q\times\rho)\} \prod_{N_5+N_6} \Phi_2(-a_1, q\times\gamma Z_i, q\times\rho) .$$

It has to be noted that the procedure is not fully efficient, since it merely employs information about the number of observations at the standardised censoring points and between these limits. However, it offers an interesting alternative to the likelihood function (6), since the massive number of limit observations may result only in modest efficiency loss[2].

6.2. Data Description

The analyses in the study are based on two separate random samples originating from the longitudinal data set which has been constructed from the 1990 population census by the Statistics Finland. As discussed in the previous chapter, the population census is based on various registers including tax registers, pension and benefit registers, student registers, and registers collected by employment service offices. The main benefit of register data is that analyses are not subject to recall bias which may be a problem in survey based data sets. Having said that, register based data sets tend to be standardised, lacking characteristics which are likely to affect individual decisions. Fortunately the trade-off between reliability and information tends to become less pronounced greater the number of data sources.

In evaluation studies the problem of modelling arises from the fact that we do not have observations of the same individuals in different states, i.e. participating in a programme and non-participating. For that reason one needs a comparison group which is thought of presenting the labour market outcome under evaluation had participants not participated in programmes. In this chapter the programme participation dummy obtains the value one if an individual has entered and terminated an active programme between January 1 and December 31 in 1988 (1991 when the era of high unemployment is under consideration). A natural control group for assessing the effectiveness of ALMPs consists of eligible non-participants. The eligibility criteria is deemed to be fulfilled if a

2 In what follows, we use the name full information model when referring to the likelihood function (6) and the limited information model when referring to the likelihood function (7).

person has been registered as an unemployed job seeker at the employment agency in 1988 (1991 when the era of high unemployment is under consideration). The dependent variable measures the annual working months of these persons in open employment in 1989 (1992 when the era of high unemployment is under consideration). The choice of the dependent variable is motivated by the possibility of incorporating both the employment probability and the job stability aspects of active programmes into a single outcome variable, i.e. getting a hire is not the prerequisite for entering the sample as it was in chapter 5. Finally, to concentrate on persons truly unemployed, we excluded pensioners, students and men in military service. For the same reason, only persons who have finished the comprehensive school, i.e. over 16 years of old, are included in the sample.

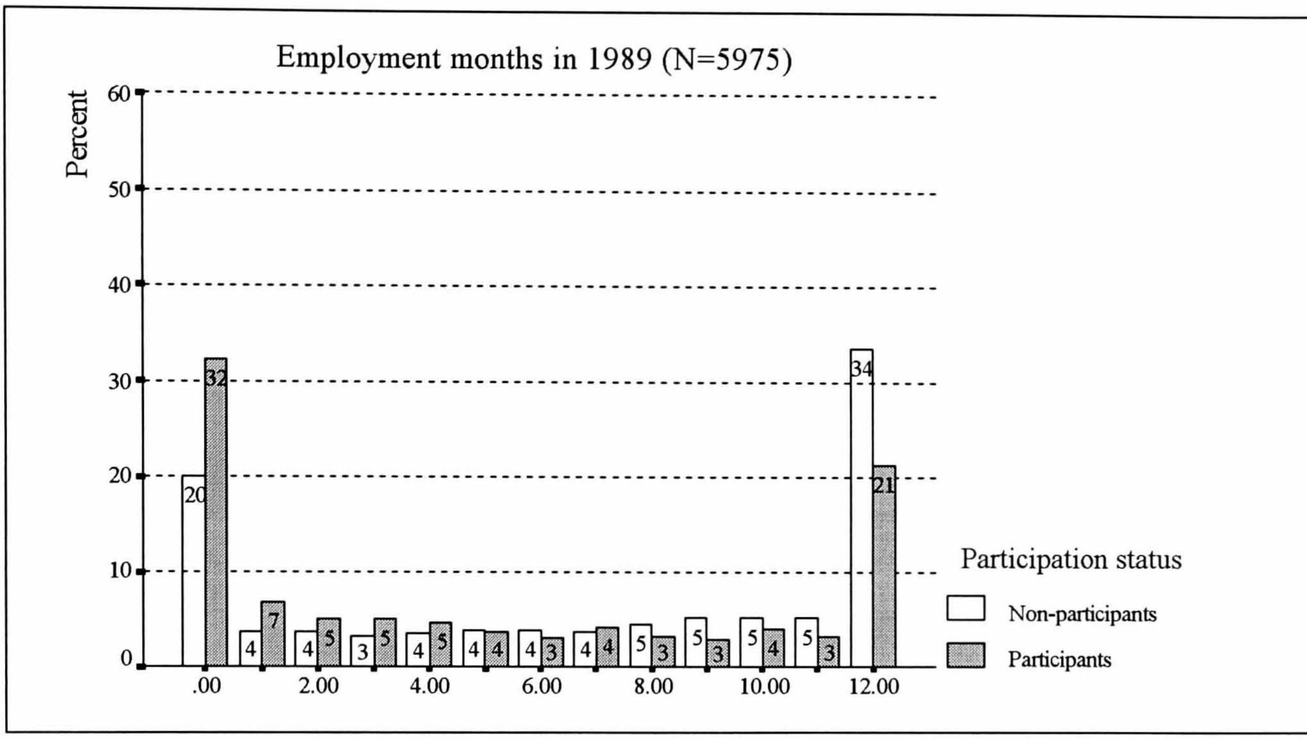
One objective of the study is to examine possible differences in the effectiveness of active labour market programmes in different unemployment situations. Finland offers an ideal 'natural experiment' for trying to answer this question since open unemployment rose from 4.5 to 15.5 per cent during the sample years 1988 - 92, see chapter 2. This is shown in the inflow figures of the two separate samples, the sample size doubling in three years from 5975 to 10915 observations[3]. To shed some light on the largely neglected issue of repeat programme participation, figure 6.1b reports regular working months for subsamples excluding recurrent programme participants. There are 855 (1903) persons who participated in a programme in 1989 (1992), of which 46 (29) per cent participated in a programme also in the previous year. Clearly a programme participation in 1989/1992 reduces regular employment months used in assessing the effectiveness of ALMPs. In the current context it is not possible to allow two endogenous participation decisions without considerably increasing the complexity of the model.

[3] In drawing the samples the original data of some 180 000 individuals has been randomly divided to two, roughly equally sized parts. Accordingly, the same individuals do not contribute to unemployment in different eras.

Given this restriction, we can either exclude recurrent participants or introduce an exogenous dummy variable into estimations. In both cases we are able to control observable factors affecting the 'subsequent' programme participation decision.

The first thing to notice from figures 6.1a and 6.1b is that expanding unemployment has a strong impact on the number of censored observations. In both groups the percentage share of persons having no regular employment months has increased by some 20 percentage points. Interestingly, deteriorating employment prospects have mainly affected the non-participants observed as upper limit cases. The control group has experienced a 20 percentage points drop in individuals working full twelve months whereas the corresponding proportion of programme participants has remained more or less equal between the two eras. It is somewhat surprising that programme participants seem to polarise into limit observations, the phenomenon requiring closer examination. This is done in table 6.1 which shows the number of participants in censoring points across different programme categories.

Figure 6.1a The Percentage Shares of Individuals According to Their Employment Months; Full Sample.



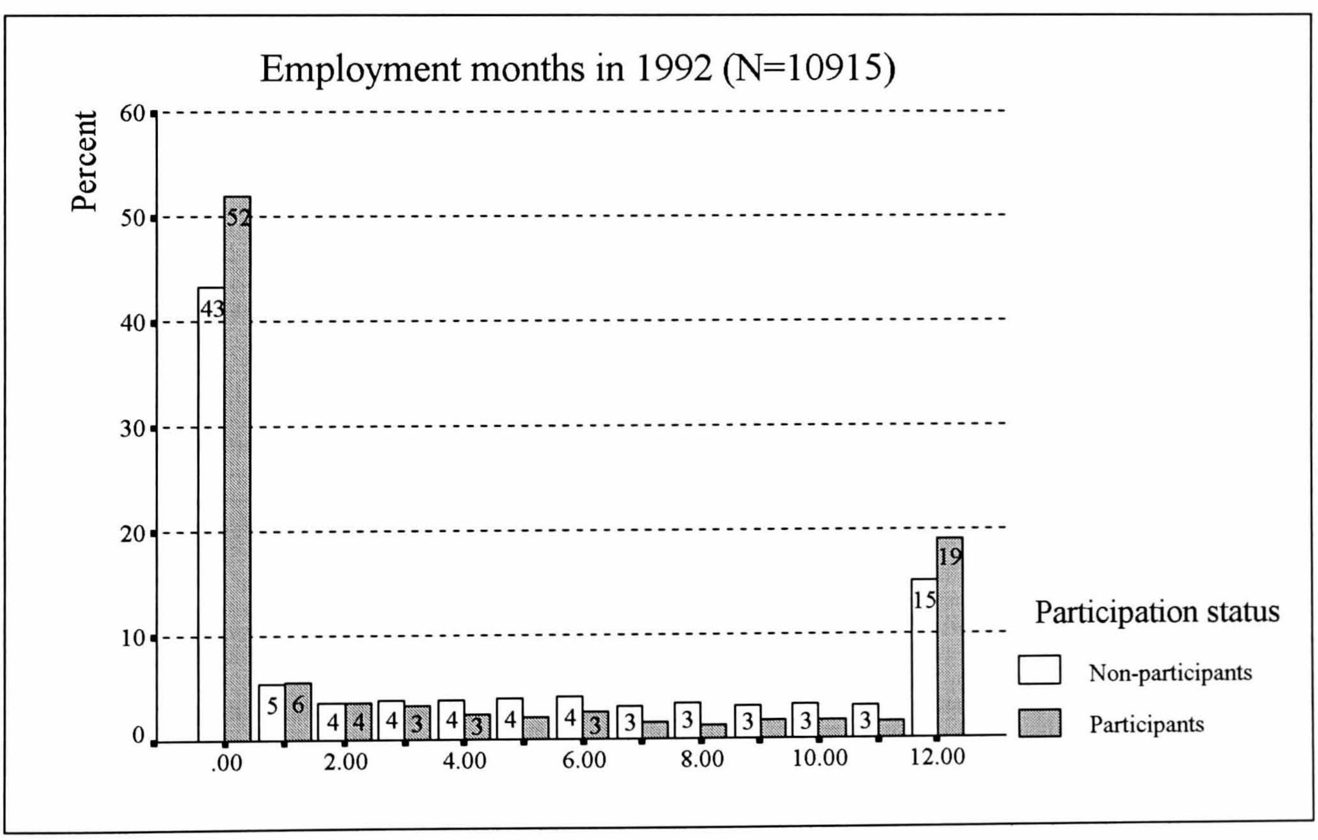
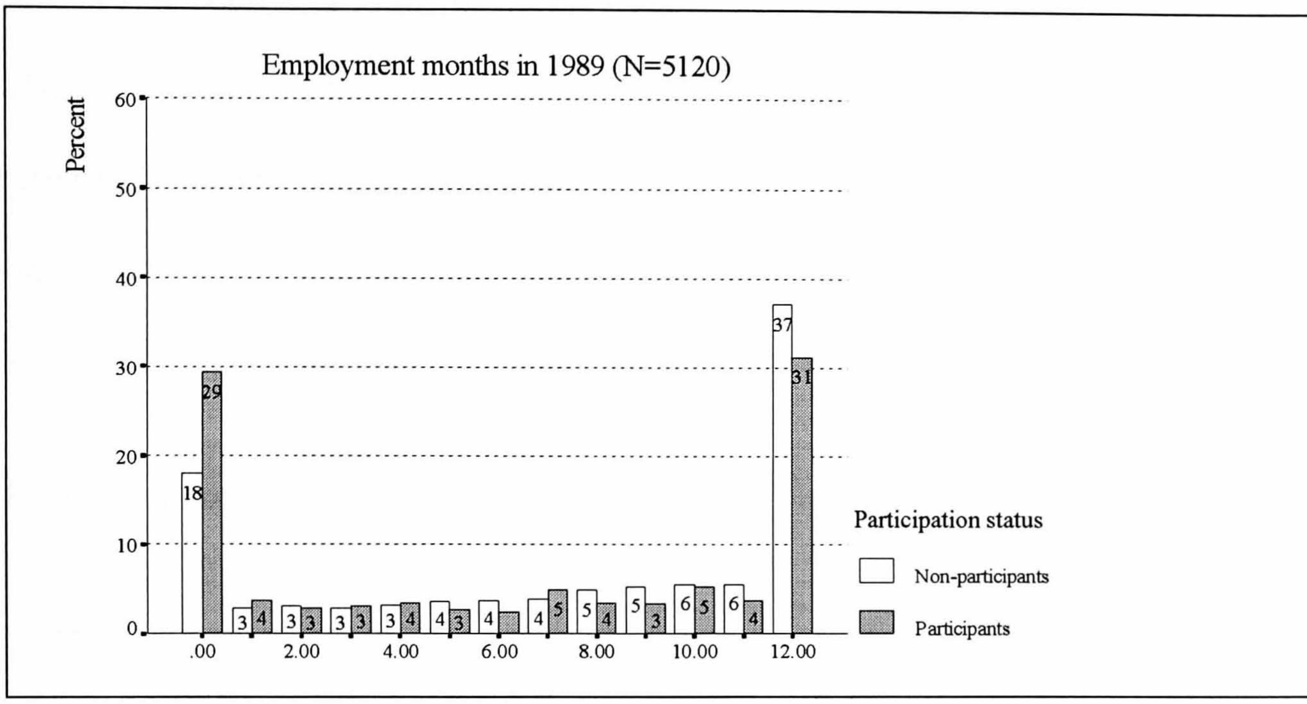
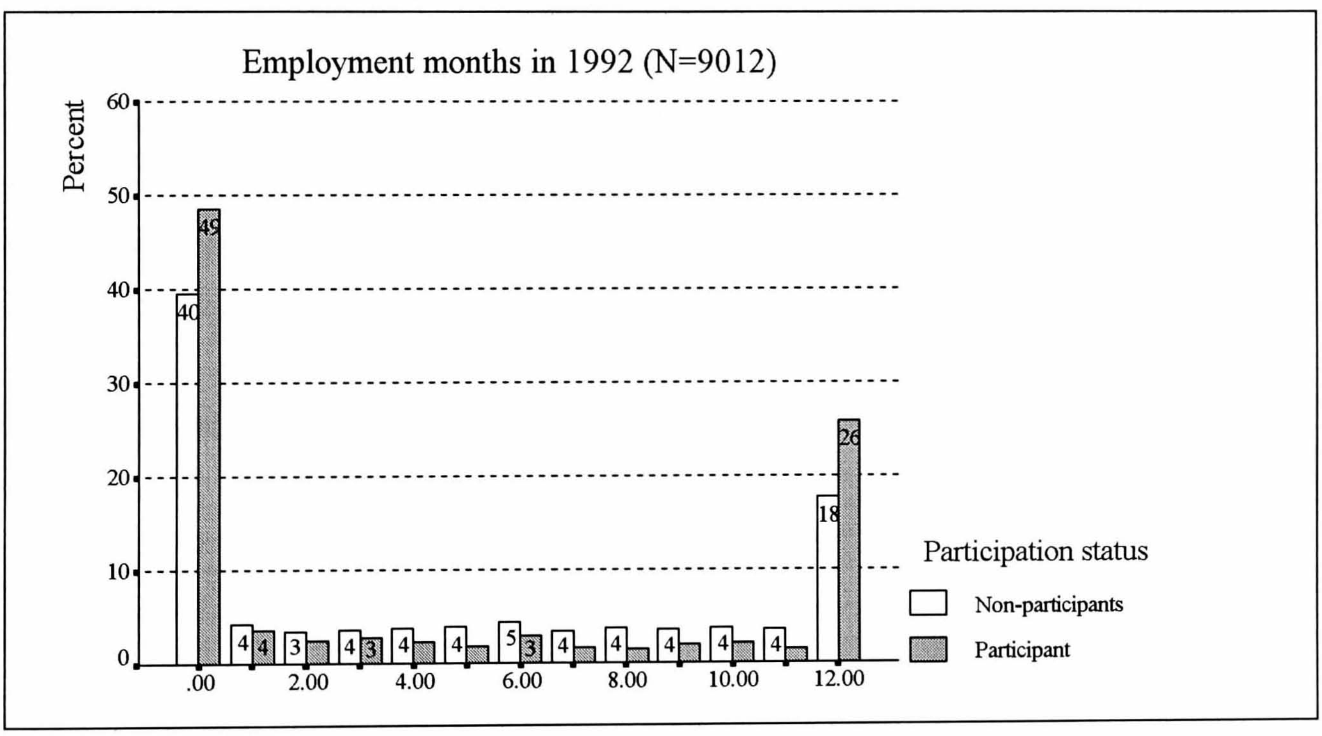


Figure 6.1b The Percentage Shares of Individuals According to Their Employment Months; Subsample.





The first column of table 6.1 reports the number of participants in the years 1988 and 1991. These figures are well in line with the figure 2.7 in chapter 2 which showed the number of participants in labour market training and in selective employment measures. Finnish ALM policy has a strong emphasis towards selective employment measures, even though the share of participants in training programmes increased at the beginning of the 1990s. A substantial increase in the actual number of trainees shown in table 6.1 is consistent with the official figures (Finnish Labour Review) according to which the number of trainees completing a training course increased from 1900 to 3600 between December 1988 and December 1991. The introduction of the 1987 Employment Act is also reflected in table 6.1, the proportion of job placements offered as a last resort increasing sharply between the years 1988 and 1991.

Table 6.1 Proportions of Participants in Censoring Points.

1988	Number of participants	Full sample		Subsample	
	(full sample)	Lower	Upper	Lower	Upper
Job placement	924	347 / 37.6%	143 / 15.5%	207 / 36.1%	141 / 24.6%
Job placement in the private sector	152	40 / 26.3%	47 /30.9%	27 / 24.8%	47 / 43.1%
Half-time job placement	124	44 / 35.5%	16 / 12.9%	23 / 27.7%	16 / 19.3%
Job placement as a last resort	392	188 / 48.0%	29 / 7.4%	109 / 52.2%	27 / 12.9%
Labour market training	301	44 / 14.6%	115 / 38.2%	32 / 13.1%	114 / 46.7%
ALMPs in total	1205	388 / 32.2%	256 / 21.2%	238 / 29.3%	253 / 31.2%
1991	**Number of participants**	**Full sample**		**Subsample**	
	(full sample)	Lower	Upper	Lower	Upper
Job placement	1216	824 / 67.8%	66 / 5.4%	560 / 68.6%	66 / 8.1%
Job placement in the private sector	217	96 / 44.2%	19 / 8.8%	58 / 40.9%	19 / 13.4%
Half-time job placement	36	19 / 52.8%	2 / 5.6%	15 / 48.4%	2 / 6.5%
Job placement as a last resort	832	646 / 77.6%	17 / 2.0%	443 / 80.4%	17 / 3.1%
Labour market training	738	194 / 26.3%	304 / 41.2%	121 / 20.9%	294 / 50.8%

Training offered to laid-off persons	361	20 / 5.5%	236 / 65.4%	11 / 3.5%	227 / 71.8%
ALMPs in total	1920	1000 / 52.1%	368 / 19.2%	669 / 48.6%	358 / 26.0%

Notes: The first column reports the number of participants across programme categories. The next two columns show the number of participants/the percentage share of participants in specific programme categories observed as limit cases when the whole sample is employed. The last two columns give the corresponding figures when recurrent programme participants are excluded from the sample.

Table 6.1 suggests that increasing unemployment affects participants in different programmes in different ways. The proportion of labour market training participants, who have been employed for 12 months, has remained well above 30 per cent regardless of the sample. Even though the share of training participants having no employment months has increased substantially, a rise has remained some 20 percentage points smaller than the one experienced by participants in selective employment measures. Following the discussion in chapter 2, one obvious explanation for the finding is the difference in target groups of labour market training and selective employment measures.

It is possible to identify one group of trainees which is relatively advantaged compared to other programme participants, namely persons in laid-off training. These persons form almost a half of all labour market trainees in 1991 and only some 30 per cent of them have reported unemployment periods in 1990 - 91. Despite the superior employment record of laid-off trainees, we have included them in the analysis for two reasons. First, the advantage does not seem to be universal, some laid-off trainees having no employment months. Second, chapter 2 revealed that this increase in the number of training places offered to laid-off persons was a temporary phenomenon. Nevertheless, there is a clear case for controlling participation in laid-off training when analysing the data from the early 1990s.

As a part of the data analysis, we fitted simple bivariate probit models for limit observation probabilities. The estimated models consist of two equations; one for the participation decision and the other one either for the probability of having no employment months (Lower) or for the probability of working a full twelve months (Upper). Table 6.2 reports the estimated coefficients of participation variables together with the correlation coefficient[4]. For the sake of completeness the results are given both for the whole sample and for the subsample excluding recurrent participants.

The results are largely consistent with the figures given in table 6.1. Participation in an active programme has a beneficial effect on the probability of working the whole year regardless of a sample. When it comes to the lower limit, different eras of unemployment produce different results. The participation dummy has a well determined negative parameter only in the era of high unemployment. The estimated differences across programme categories are also in line with the figures reported in table 6.1. Most of the beneficial effects of ALMPs are produced by training programmes. Placements in the private sector seem to yield greater benefits than job placements in the public sector, even though its effect on the probability of working full twelve months has dropped between the eras of unemployment. This may reflect the impact of relatively short fixed term contracts which have become more common in the early 1990s. The results also indicate that the obligation to employ the long-term unemployed was unsuccessful, this group of programme participants showing the worst record in terms of limit observations across different programme groups.

[4] Other variables included in estimations are the same as used in estimating likelihood functions (6) and (7), see table 6.3 for the employment equation and appendix 6.3 for the participation equation.

Table 6.2 The results of the Bivariate Probit Models for Limit Probabilities.

1989	Whole sample		Recurrent participants excluded	
	Lower	Upper	Lower	Upper
Placement in the private sector	0.097	0.395	0.035	0.421
	(0.13)	(0.14)***	(0.15)	(0.14)***
Half-time placement	0.018	-0.391	-0.167	-0.372
	(0.14)	(0.18)**	(0.18)	(0.18)**
Placement as a last resort	0.527	-0.305	0.613	-0.384
	(0.09)***	(0.13)**	(0.13)***	(0.14)***
Programme participation in 1989	0.261	-2.045	n/a	n/a
	(0.05)***	(0.18)***		
Participation dummy	-0.016	0.538	0.555	0.562
	(0.32)	(0.32)*	(0.32)*	(0.36)
ρ	-0.079	-0.143	-0.338	-0.158
	(0.17)	(0.17)	(0.16)***	(0.19)
1992	**Whole sample**		**Recurrent participants excluded**	
	Lower	Upper	Lower	Upper
Placement in the private sector	-0.057	-0.361	0.020	-0.328
	(0.10)	(0.14)**	(0.13)	(0.14)**
Half-time placement	0.151	-0.511	0.037	-0.474
	(0.24)	(0.26)*	(0.25)	(0.26)*
Placement as a last resort	0.709	-0.824	0.882	-0.779
	(0.07)***	(0.13)***	(0.09)***	(0.13)***
Programme participation in 1992	0.440	-1.604	n/a	n/a
	(0.03)***	(0.11)***		
Participation dummy	-1.011	1.881	-1.170	1.939
	(0.17)***	(0.12)***	(0.18)***	(0.12)***
ρ	0.370	-0.610	0.448	-0.640
	(0.09)***	(0.06)***	(0.09)***	(0.06)***

Notes: * = significant at the 10 per cent significance level; ** = significant at the 5 per cent significance level; *** = significant at the 1 per cent significance level. The first two columns refer to whole sample estimates when recurrent programme participation is controlled by an exogenous dummy variable. The last two columns give the results when recurrent participants have been omitted from estimations. ρ is the estimated correlation coefficient.

Finally it is interesting to note that unobservable factors are more pronounced in the era of high unemployment. The signs of the estimated correlation coefficients reveal that programme participants have some unobservable factors which make the participation more likely and increase (reduce) the probability of working zero months (twelve months). Statistically significant correlation coefficients in the early 1990s may indicate that the control group has become relatively more advantaged compared to programme participants. A sharp increase in inflow rates has also affected advantaged workers who usually are immune to unemployment, whereas programme participants might have been selected according to old, e.g.. the length of unemployment, rules.

6.3. Empirical Results

The actual participation in an active programme is a complicated process which consists of several stages as discussed in Raaum et. al. (1995). Accordingly a single participation equation should include the factors affecting both individual decisions and programme administrators' decisions. Broadly speaking, active programmes are offered to hard-to-employ persons. This calls for inclusion of variables, such as education, disability, occupational status, and previous labour market experience, all of which can be thought of as characterising disadvantaged individuals. In addition to supply side effects, these factors are also likely to affect the demand of active programmes by lowering the opportunity cost of participation. Another objective of Finnish active programmes is to reduce regional unemployment differences. To embody this aim into the programme participation equation, characteristics of a living community, such as travel-to-work unemployment rate and the dummy variable for urban communities, are included in estimations. Since the local supply of ALMPs affects the participation probability, we have followed Torp (1994) and included the local programme participation rate variable in the participation equation. Other potential determinants of participation decision included among regressors consist of various individual characteristics together with different income sources and spouse's characteristics.

The outcome variable, that is working months, is composed of two elements, viz. the employment probability and the work stability. One way of thinking about the probability of employment is within the search theoretical framework surveyed by Pissarides (1985) and Devine & Kiefer (1991), *inter alia*. Unemployed persons are searching for a job which offers compensation equalling, at least, their reservation wage and employers are sampling applicants to fulfil vacancies up to the point where the marginal costs of recruitment equal marginal benefits. This determines the demand side and the supply side of labour markets through factors affecting the reservation wage and the firms recruiting decision. The impact of labour market training on job stability has been studied empirically in Zweimuller & Winter-Ebmer (1996). Their study, which uses many of the variables motivated by the discussion below, is quite successful in predicting recurrent unemployment probabilities. This indicates that in addition to the probability of becoming hired, evaluations in this study are also likely to capture the job stability aspects incorporated in the outcome variable.

In the stylised sequential search model an optimising job hunter maximises the net benefit from search which is the difference between the expected wage conditional on successful search (plus the conditional expected return from further search if unsuccessful) and the cost of searching. In this setting the greater the reservation wage the lower is the probability of success. The main determinant of the reservation wage is non-labour income, the effect of which is captured by unemployment benefits, other non-wage income, and spouse's income. The impact of these variables on regular working months is by no means clear, *a priori*. Even though they may reduce the employment probability, they may also provide means for searching for a better match and hence contribute positively to job stability. Other factors affecting the heterogeneity of reservation wages are captured by human capital variables, spouse's education, and individual characteristics. Variables representing individuals' accumulated human capital, such as education and previous work history, tend to increase both the reservation wage and the number and/or the quality of job offers. Individual characteristics on the other hand control for observable differences in marital status, age, children etc. These factors are also likely to be relevant for employers' recruitment decisions.

When it comes to the demand side, the number of, and the competition over, vacancies clearly has an impact on the employment probability and hence on months spent in employment. In the search theoretic framework this is modelled through the probability of getting a job offer which is likely to be positively correlated with the reservation wage. The tightness of local labour markets is measured through the unemployment rate and the geographical position of a living community. Another variable capturing differences in labour demand is occupational status. Together with the union status it also works as a supply side proxy as far as they characterise the closer attachment to labour markets.

In the search theory framework ALMPs can be introduced into analyses through Spence's (1973) signalling theory which considers firms hiring decisions as investments under uncertainty. An employer is uncertain about an applicant's true productivity and for this reason employs a signalling device(s) in the recruitment decision. Provided that active programmes improve participants' productivity and work habits, and employers are aware of that, participation may increase the employment probability and hence the number of working months. Another route to beneficial effects could be through a reduction in turnover provided that ALMPs contribute to a better match. There are also studies, according to which active programmes make wage expectations of young participants more realistic which in turn tends to increase the employment probability through lower reservation wages, see Main (1987a) and O'Higgins (1995). Accordingly ALMPs operate both in the supply and in the demand side of labour markets. Since different programmes are likely to give different signals and have different effects on reservation wages, empirical equations include various ALMP variables, such as laid-off training, job placement in the private sector, half-time placement and placement as a last resort. The last variable consists of programme participants to whom the labour authorities have been obliged to offer a job placement, as stated in the 1987 Employment Act.

Next a word on identification. In estimating the selection corrected models of equations (6) and (7) one needs at least one instrument in the selection equation which does not affect employment. In this study the identification restriction is provided by omitting the local ALMP supply variable from the employment equation. It is evident that the ratio of programme participants to unemployed persons in a labour district affects individuals' participation probability whereas there are no clear reasons why it should have any effect on participants subsequent employment record. To examine the validity of the instrumental variable we included it among the regressors in single equation models given in the first four columns. In all cases the parameter estimate of the local ALMP supply variable turned out to be insignificant giving some support to the selection corrected estimations. Especially since the parameter estimate of the local ALMP supply variable is correctly signed and highly significant in participation equations reported in appendix 3. Other 'identification restrictions' consist of unemployment rate, other income, and spouse's income variables which are measured in different years depending on whether they are included in the participation or in the employment equation. However, since these variables are highly correlated over time the identification based merely on these variables would be unsatisfactory.

Having presented the variables and the theoretical underpinnings underlying equations (1) and (2), we turn next to the empirical results which are reported in tables 6.3 and 6.4. These correspond to the full sample estimates which are well in line with the unreported results based on subsamples in which recurrent programme participants have been omitted. The first column in both tables reports the baseline least squares estimates which are inconsistent even if the selection is based purely on observables. The next two columns give the results of 2-limit tobit models which differ by the inclusion of heteroskedasticity correction terms in column three. The heteroskedasticity correction terms consist of seven continuous variables employed in the analyses. The likelihood ratio test produces test statistics of 72.8 and 51.3 for the years 1989 and 1992, respectively, clearly rejecting the homoskedastic model (the critical value at the 5 per cent significance level is 14.07). The fourth column shows the results of the type 2 tobit model, see Amemiya (1984). These estimates cannot be given too much weight given that the estimations use information only about programme participants and the upper limit is set to infinity. However, it is interesting to compare the estimated correlation coefficients between this model and the two selection corrected models reported in columns 5 and 6.

Table 6.3. The results of employment months estimation; The dependent variable is the number of employment months in 1989.

	Estimation method						
	OLS	2-limit tobit	2-limit tobit	Type 2 tobit	Equation 6	Equation 7	Means
Constant	7.385 (0.65)***	8.803 (1.35)***	8.569 (1.33)***	11.251 (2.76)***	6.792 (1.64)***	7.563 (0.80)***	
Woman	-0.637 (0.14)***	-1.424 (0.28)***	-1.325 (0.27)***	-1.461 (0.42)***	-1.776 (0.30)***	-1.403 (0.14)***	0.443
Age	-0.090 (0.03)**	-0.181 (0.07)**	-0.179 (0.07)**	-0.320 (0.12)**	-0.117 (0.08)	-0.112 (0.04)***	34.850
Age squared/1000	0.189 (0.49)	0.351 (1.01)	0.445 (1.00)	3.531 (1.70)**	-0.293 (1.14)	-0.166 (0.54)	1.335
Married	0.045 (0.15)	0.080 (0.32)	0.121 (0.32)	0.335 (0.52)	0.184 (0.35)	0.074 (0.17)	0.406
Education in 1988	0.173 (0.07)**	0.365 (0.14)**	0.623 (0.16)***	0.799 (0.24)***	0.284 (0.15)*	0.236 (0.07)***	0.806
Number of children	-0.623 (0.14)***	-1.171 (0.27)***	-1.020 (0.31)***	-0.131 (0.39)	-0.925 (0.28)***	-0.774 (0.13)***	0.251
Youngest child 0-3 years	0.089 (0.27)	-0.048 (0.52)	-0.382 (0.57)	0.027 (0.95)	-0.246 (0.56)	-0.395 (0.26)	0.079
Youngest child 4-6 years	0.511 (0.23)**	0.945 (0.47)**	0.819 (0.49)*	-0.341 (0.72)	0.708 (0.50)	0.596 (0.24)**	0.071
Youngest child 7-16 years	0.274 (0.16)*	0.625 (0.33)*	0.624 (0.31)**	0.339 (0.48)	0.647 (0.35)*	0.501 (0.17)***	0.159
House owner	0.428 (0.11)***	0.815 (0.23)***	0.761 (0.23)***	0.023 (0.35)	0.768 (0.26)***	0.639 (0.12)***	0.594
Spouse's education	-0.000 (0.07)	0.038 (0.14)	0.159 (0.15)	0.160 (0.23)	0.088 (0.15)	0.060 (0.07)	0.529
Disability	-1.302 (0.23)***	-2.951 (0.48)***	-2.843 (0.44)***	-1.669 (0.70)**	-3.394 (0.54)***	-2.397 (0.26)***	0.061
Union member in 1988	1.649 (0.11)***	3.280 (0.24)***	3.182 (0.23)***	0.949 (0.37)**	4.310 (0.25)***	3.762 (0.12)***	0.542
Unemployment rate	-0.066 (0.02)**	-0.161 (0.05)***	-0.154 (0.05)***	-0.126 (0.10)	-0.303 (0.06)***	-0.209 (0.03)***	5.799
Ln(monthly unemployment benefits in 88)	-0.097 (0.01)***	-0.226 (0.02)***	-0.246 (0.02)***	-0.154 (0.03)***	-0.253 (0.02)***	-0.212 (0.01)***	4.584

Table 6.3. The results of employment months estimation; The dependent variable is the number of employment months in 1989.

Ln(Other income)	-0.034 (0.00)***	-0.065 (0.01)***	-0.049 (0.01)***	-0.061 (0.02)**	-0.055 (0.01)***	-0.048 (0.00)***	1.259
Ln(Spouse's income)	0.034 (0.00)***	0.069 (0.01)***	0.063 (0.02)***	0.065 (0.03)**	0.054 (0.02)**	0.042 (0.01)***	4.421
Urban living community	-0.070 (0.11)	-0.139 (0.24)	-0.146 (0.24)	0.034 (0.40)	-0.115 (0.27)	-0.220 (0.13)	0.526
Middle Finland	0.229 (0.13)*	0.472 (0.28)	0.434 (0.28)	0.488 (0.49)	0.257 (0.32)	0.305 (0.15)*	0.299
Northern Finland	0.239 (0.17)	0.447 (0.36)	0.466 (0.36)	0.855 (0.68)	-0.096 (0.46)	0.255 (0.22)	0.192
Technical occupation in 1988	1.032 (0.30)***	2.371 (0.61)***	2.356 (0.65)***	1.681 (1.10)	2.955 (0.69)***	2.071 (0.33)***	0.055
Health care occupation in 1988	1.016 (0.29)***	2.454 (0.58)***	2.703 (0.57)***	2.017 (1.02)**	3.056 (0.63)***	2.073 (0.30)***	0.055
Administrative occupation in 1988	0.991 (0.26)***	2.112 (0.52)***	1.995 (0.51)***	1.089 (0.70)	1.966 (0.53)***	1.465 (0.25)***	0.075
Mercantile occupation in 1988	1.269 (0.28)***	2.759 (0.56)***	2.840 (0.52)***	2.668 (0.92)***	2.990 (0.60)***	2.122 (0.28)***	0.056
Farming/forestry occupation in 1988	1.239 (0.26)***	2.537 (0.55)***	2.581 (0.53)***	1.786 (0.77)**	2.424 (0.63)***	1.711 (0.30)***	0.057
Transport occupation in 1988	1.879 (0.31)***	3.537 (0.64)***	3.383 (0.64)***	4.080 (2.09)*	3.692 (0.79)***	2.617 (0.38)***	0.038
manufacture occupation in 1988	1.114 (0.17)***	2.205 (0.37)***	2.205 (0.35)***	1.475 (0.62)**	2.282 (0.43)***	1.568 (0.21)***	0.379
Service occupation in 1988	1.259 (0.22)***	2.512 (0.45)***	2.509 (0.44)***	1.473 (0.78)*	2.633 (0.52)***	1.840 (0.25)***	0.111
Employment months in 1987	0.150 (0.01)***	0.276 (0.02)***	0.274 (0.02)***	0.231 (0.06)***	0.308 (0.03)***	0.244 (0.01)***	5.932
Unemployment months in 1987	-0.128 (0.01)***	-0.277 (0.04)***	-0.264 (0.03)***	-0.193 (0.07)***	-0.322 (0.04)***	-0.226 (0.02)***	3.128
Placement in the private sector	0.605 (0.40)	1.131 (0.78)	1.148 (0.68)*	0.573 (0.53)	0.939 (0.81)	1.001 (0.40)**	0.025
Half-time placement	-0.451 (0.36)	-1.167 (0.83)	-0.843 (0.83)	-0.648 (0.59)	-1.226 (0.96)	-0.770 (0.48)	0.020
Placement as a last resort	-1.384 (0.26)***	-2.913 (0.58)***	-2.425 (0.53)***	-2.194 (0.46)***	-3.185 (0.65)***	-2.367 (0.32)***	0.065

Table 6.3. The results of employment months estimation; The dependent variable is the number of employment months in 1989.

Days in 1988	0.003 (0.00)***	0.008 (0.00)***	0.008 (0.00)***	0.002 (0.00)	0.010 (0.00)***	0.008 (0.00)***	238.400
Recurrent participation in 1989	-3.289 (0.13)***	-5.420 (0.33)***	-5.170 (0.35)***	-2.507 (0.38)***	-4.587 (0.41)***	-4.166 (0.21)***	0.143
Programme participation	0.623 (0.20)***	1.611 (0.41)***	1.329 (0.40)***	n/a	5.382 (1.82)***	1.655 (0.96)*	0.201
σ	4.080	7.661 (0.11)***	6.963 (0.45)***	5.213 (0.20)***	7.948 (0.16)***	4.727 (0.03)***	
ρ	n/a	n/a	n/a	-0.078 (0.27)	-0.240 (0.12)**	-0.011 (0.11)	
Log L	R^2_{adj} = 0.30	12183.030	12146.610	5343.055	7939.664	12877.480	
Heteroskedasticity corrected	Standard errors	No	Yes	No	No	No	

Notes: * (**,***) = significant at the 10 per cent (5 per cent, 1 per cent) significance level. σ = the estimated standard error. ρ = the estimated correlation coefficient. Excluding programme dummies (measures in the year 1988) all variables are measured in the year 1989 if not otherwise stated. The recurrent participation variable refers to a period of programme participation in 1989. All estimations are carried out by using LIMDEP 7.0 (Greene, 1995).

Table 6.4. The results of employment months estimation; The dependent variable is the number of employment months in 1992.

	Estimation method						
	OLS	2-limit tobit	2-limit tobit	Type 2 tobit	Equation 6	Equation 7	Means
Constant	4.344 (0.51)***	2.878 (1.28)**	2.295 (1.28)*	6.802 (3.34)**	3.812 (1.37)***	3.543 (0.67)***	
Woman	0.172 (0.09)*	0.422 (0.22)*	0.446 (0.21)**	0.121 (0.37)	0.318 (0.23)	0.094 (0.11)	0.380
Age	-0.100 (0.02)***	-0.287 (0.06)***	-0.293 (0.06)***	-0.224 (0.11)**	-0.374 (0.07)***	-0.227 (0.03)***	36.090
Age squared/1000	0.448 (0.34)	1.522 (0.86)*	1.639 (0.84)*	1.673 (1.48)	2.702 (0.93)***	1.288 (0.46)***	1.424
Married	0.359 (0.11)***	0.805 (0.27)***	0.840 (0.26)***	0.947 (0.40)**	0.697 (0.28)**	0.510 (0.13)***	0.407
Education in 1992	0.375 (0.04)***	0.893 (0.11)***	0.888 (0.12)***	0.635 (0.19)***	0.813 (0.11)***	0.662 (0.05)***	0.886
Number of children	0.099 (0.09)	0.235 (0.22)	0.219 (0.23)	0.332 (0.32)	0.173 (0.23)	0.152 (0.11)	0.225
Youngest child 0-3 years	-1.197 (0.15)***	-3.068 (0.36)***	-3.000 (0.36)***	-1.933 (0.57)***	-2.933 (0.39)***	-2.238 (0.18)***	0.135
Youngest child 4-6 years	-0.816 (0.21)***	-1.918 (0.51)***	-1.851 (0.49)***	-1.327 (0.70)*	-1.637 (0.52)***	-1.221 (0.25)***	0.064
Youngest child 7-16 years	0.124 (0.11)	0.223 (0.28)	0.248 (0.29)	-0.385 (0.47)	0.298 (0.31)	0.237 (0.15)	0.152
House owner	0.502 (0.08)***	1.299 (0.21)***	1.316 (0.20)***	0.965 (0.32)***	1.099 (0.22)***	0.786 (0.10)***	0.613
Spouse's education	0.029 (0.05)	0.016 (0.11)	0.023 (0.11)	-0.077 (0.18)	0.038 (0.11)	0.048 (0.11)	0.521
Disability	-0.919 (0.15)***	-3.232 (0.48)***	-3.229 (0.44)***	-1.695 (0.51)***	-3.421 (0.48)***	-2.298 (0.24)***	0.052
Union member in 1991	1.191 (0.09)***	2.988 (0.21)***	2.974 (0.21)***	0.801 (0.44)*	5.295 (0.22)***	4.313 (0.11)***	0.553
Unemployment rate	-0.005 (0.01)	0.000 (0.03)	0.043 (0.03)	0.016 (0.06)	-0.105 (0.03)***	-0.035 (0.01)**	19.360
Ln(monthly unemployment benefits in 91)	-0.178 (0.00)***	-0.390 (0.01)***	-0.391 (0.01)***	-0.349 (0.03)***	-0.376 (0.02)***	-0.327 (0.01)***	4.916

Table 6.4. The results of employment months estimation; The dependent variable is the number of employment months in 1992.

Ln(Other income)	-0.003 (0.00)	0.014 (0.01)	0.008 (0.01)	0.044 (0.02)*	0.043 (0.01)***	0.026 (0.00)***	0.555
Ln(Spouse's income)	0.046 (0.00)***	0.113 (0.01)***	0.114 (0.01)***	0.075 (0.02)***	0.090 (0.01)***	0.070 (0.00)***	4.489
Urban living community	-0.176 (0.08)**	-0.505 (0.20)**	-0.490 (0.20)**	-0.154 (0.34)	-0.370 (0.22)*	-0.375 (0.10)***	0.561
Middle Finland	0.185 (0.09)*	0.424 (0.23)*	0.398 (0.23)*	0.084 (0.39)	0.049 (0.25)	0.215 (0.12)*	0.281
Northern Finland	0.167 (0.12)	0.557 (0.31)*	0.489 (0.31)	-0.152 (0.48)	0.173 (0.34)	0.249 (0.16)	0.157
Technical occupation in 1991	-0.163 (0.21)	-0.248 (0.51)	-0.311 (0.52)	0.088 (1.18)	0.899 (0.60)	-0.453 (0.31)	0.069
Health care occupation in 1991	1.099 (0.23)***	2.414 (0.54)***	2.298 (0.52)***	1.740 (1.08)	3.081 (0.61)***	1.427 (0.31)***	0.043
Administrative occupation in 1991	0.084 (0.19)	0.076 (0.46)	0.040 (0.45)	-0.986 (0.90)	0.907 (0.51)*	-0.154 (0.27)	0.080
Mercantile occupation in 1991	0.678 (0.19)***	1.503 (0.47)***	1.449 (0.46)***	1.951 (1.06)*	2.576 (0.55)***	1.009 (0.29)***	0.069
Farming/forestry occupation in 1991	0.831 (0.19)***	2.079 (0.51)***	2.019 (0.53)***	1.135 (0.88)	3.075 (0.61)***	1.441 (0.32)***	0.048
Transport occupation in 1991	1.067 (0.22)***	2.457 (0.54)***	2.391 (0.55)***	1.732 (1.19)	3.711 (0.66)***	1.752 (0.34)***	0.043
manufacture occupation in 1991	0.226 (0.12)*	0.487 (0.35)	0.474 (0.34)	0.528 (0.90)	1.437 (0.46)***	0.028 (0.25)	0.462
Service occupation in 1991	0.257 (0.22)	0.604 (0.56)	0.654 (0.54)	0.035 (0.92)	1.553 (0.63)**	0.209 (0.32)	0.040
Employment months in 1990	0.170 (0.01)***	0.407 (0.02)***	0.401 (0.02)***	0.377 (0.04)***	0.381 (0.02)***	0.295 (0.01)***	7.344
Unemployment months in 1990	-0.065 (0.01)***	-0.179 (0.05)***	-0.166 (0.04)***	-0.214 (0.12)*	-0.390 (0.06)***	-0.127 (0.03)***	1.451
Placement in the private sector	0.147 (0.29)	1.262 (0.80)	1.140 (0.79)	1.034 (0.50)**	0.992 (0.85)	1.195 (0.45)***	0.019
Half-time placement	-0.709 (0.62)	-1.541 (1.70)	-1.181 (1.68)	-0.024 (0.96)	-2.216 (1.92)	-1.559 (1.02)	0.003
Placement as a last resort	-1.250 (0.20)***	-4.465 (0.62)***	-4.006 (0.59)***	-2.543 (0.41)***	-4.883 (0.62)***	-3.118 (0.33)***	0.076

Table 6.4. The results of employment months estimation; The dependent variable is the number of employment months in 1992.

Laid-off training	2.585 (0.28)***	6.476 (0.74)***	6.486 (0.73)***	1.900 (0.55)***	4.535 (0.79)***	4.171 (0.40)***	
Days in 1991	0.005 (0.00)***	0.012 (0.00)***	0.011 (0.00)***	0.002 (0.00)	0.013 (0.00)***	0.011 (0.00)***	200.300
Recurrent participation in 1992	-2.579 (0.07)***	-5.712 (0.27)***	-5.537 (0.28)***	-1.900 (0.32)***	-5.181 (0.28)***	-4.319 (0.15)***	0.174
Programme participation	1.023 (0.19)***	2.271 (0.46)***	2.122 (0.45)***	n/a	8.693 (1.26)***	2.431 (0.77)***	0.175
σ	4.017	8.502 (0.10)***	11.085 (0.86)***	5.150 (0.26)***	8.672 (0.13)***	5.089 (0.03)***	0.388
ρ	n/a	n/a	n/a	-0.260 (0.19)	-0.368 (0.06)***	-0.024 (0.07)	
Log L	$R^2_{adj} = 0.27$	19926.530	19900.880	7171.880	13198.990	21134.040	
Heteroskedasticity correction	Standard errors	No	Yes	No	No	No	

Notes: * (**,***) = significant at the 10 per cent (5 per cent, 1 per cent) significance level. σ = the estimated standard error. ρ = the estimated correlation coefficient. Excluding programme dummies (measured in the year 1991) all variables are measured in the year 1992 if not otherwise stated. The recurrent participation variable refers to a period of programme participation in 1992.

All models paint a similar picture of the determinants of employment months that is fairly consistent between the two eras of unemployment. As can be expected, characteristics reflecting hard-to-employ persons, i.e. low education, no occupation (left-out category), disability and poor employment record in 1987/90, reduce employment months[5]. The employment prospects become even fainter if an individual does not belong to a union, lives in a high unemployment area or had little time for searching a job. The last variable, days in 1988 (1991), controls for differences in the time for search for a job after becoming unemployment or terminating a programme[6].

The well determined downward effect of unemployment benefits on subsequent employment record implies that an increase in received monthly unemployment benefits reduce annual working months. As discussed in chapter 2, in Finland an unemployed person is eligible for higher compensated unemployment insurance allowance for the first 500 days (provided that he is a member of an insurance fund and the employment condition is satisfied). Hence, the negative parameter estimates give some support to the reservation wage hypothesis which connects higher reservation wages to lower employment probabilities[7]. A rival explanation is that higher unemployment benefits make it possible for an unemployed person to search longer for a suitable vacancy. These beneficial longer term effects on job stability may not be visible within a span of one year.

The changes in parameter estimates are of interest in their own right. Unlike other factors reflecting individuals' social status, marital status and non-wage income have positive well determined coefficients only in the high unemployment situation. This

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5 We have omitted employment/unemployment months during the years 1988/91 since their exogeneity is somewhat questionable. The decision to terminate the latest unemployment spell is likely to depend on job offers received. This clearly affects subsequent employment record.

6 Unfortunately, we do not have information on days actually searched for a job. This variable is employed merely to control for differences in potential time for job search before the response period, i.e. before the year 1989 (1992) when the era of low (high) unemployment is under consideration..

7 The result is robust across different samples, i.e. recurrent programme participation does not explain fewer employment months.

implies indirectly that the deteriorating impact of unemployment on employment prospects was more pronounced among individuals in the lower categories of social status. The rapid deterioration of employment prospects is also highlighted by the variables which control the age of the youngest child. The results show that having a child under the age of seven reduces employment months in the era of high unemployment, the impact being negligible at the end of the 1980s. That is to say, parents with under school age children have chosen to stay at home after becoming unemployed; possibly due to the difficulties in returning back to working life after the maternity leave[8]. Finally, expanding unemployment improved women's employment record relative to that of men's. The finding is well in line with the improvement in women's relative unemployment rate shown in figure 2.1 in chapter 2.

Next we turn to the main interest of the study namely the impact of active programmes on subsequent employment record. Regardless of the exact estimation method, the results show a well determined positive impact of ALM participation on subsequent working months. The effect is, however, almost totally offset if an individual has participated in a placement programme offered as a last resort, the obligation which was introduced in the 1987 Employment Act. The most likely explanation for the finding is the coexistence of active and passive measures. It was hypothesised in chapter 2 that some individuals' search incentives might have been worsened by the automatic eligibility for another obligated job placement after 12 months in unemployment (3 months for the youth). A rival explanation is that last resort placements are targeted to persons with great difficulties in labour markets. However, since last resort placements do not seem to increase participants human capital, or to work as a positive signalling device, the

[8] In Finland all mothers are eligible for the maternity leave of eleven months during which they receive earnings-related maternity allowances. After 11 months it is possible to get child home care allowance which is aimed at facilitating the day care arrangements, as an alternative to municipal day care, of children under three years of old.

results casts considerable doubts on the usefulness of large scale obligations, at least when the outcome is measured in terms of subsequent employment record. When it comes to other selective employment measures, the results suggest that job placements provided by the private sector yield greater benefits than public sector placements.

Another issue of interest in evaluation studies is the selection bias. This can be examined through selection corrected estimations given in columns 5 and 6. The different specifications agree on the sign of the correlation coefficient, ρ, but its magnitude varies across models, the results of the full information model showing substantially smaller, insignificant parameter estimates. The negative signs of correlation coefficients indicate that programme participants, as a whole, are initially in a worse labour market position than non-participants. They have some unobservable characteristics which both increase their participation probability and deteriorate their subsequent employment record. The evidence of significant selection bias is, however, produced only by the limited information model. This implies two things. First, the inefficient use of information in estimation, i.e. using merely the information about the number of individuals between the limits and not their exact months in employment, makes it appear that there is endogenous selection. Second, the variables included in participation equations, which are reported in appendix 6.3, manage to control for endogenous selection in the full information model.

6.4. Closer Examination of the Programme Effect

The aim of this section is to give some insight into the economic significance of active labour market policy in improving participants' subsequent employment record. Table 6.5 gives the expected employment months for three different types of individuals, and marginal programme effects for the standard person, implied by single equation methods. Because the focus is both on programme participants and on non-participants, the figures shown in the upper panel of table 6.5 are based on the unconditional expectation formula for the 2-limit tobit model reported in Maddala (1983) p. 161. The lower panel reports the programme effects which are calculated as the difference between a standard programme participant's expected employment months and his expected working months had he not participated in a programme. These are also based on unconditional expectations that is perfectly legitimate given the assumption of selection process being purely determined by observable factors.

Table 6.5 Expected Employment Months and the Estimated Marginal Programme Effects in Single Equation Models

	1989			1992		
	OLS	2-limit tobit	2-limit tobit	OLS	2-limit tobit	2-limit tobit
Expected employment months						
Advantaged person	11.10	10.79	10.35	9.59 *9.67*	9.88 *10.01*	9.32 *9.42*
Disadvantaged person	1.69	1.67	1.36	0.06 *-0.07*	0.58 *0.58*	0.46 *0.48*
Standard person	5.39	5.28	5.36	3.27 *3.39*	2.96 *3.19*	2.93 *3.19*
Marginal programme effect						
Placement in the private sector	1.23	1.55	1.44	1.17 *1.34*	1.62 *1.36*	1.48 *1.69*
Half-time placement	0.17	0.25	0.28	0.32 *0.68*	0.31 *0.66*	0.40 *0.76*
Placement as a last resort	-0.76	-0.71	-0.63	-0.22 *-0.09*	-0.86 *-0.78*	-0.71 *-0.67*
Laid-off training	n/a	n/a	n/a	3.61 *n a*	4.29 *n a*	4.22 *n a*
Rest of ALMPs	0.62	0.91	0.79	1.03 *2.00*	1.01 *2.21*	0.93 *2.07*
Heteroskedasticity corrected	No	No	Yes	No	No	Yes

Notes: Figures reported in italic are based on estimations in which laid-off training is not included among programme dummies (these estimations are reported in the first four columns of appendix 6.2).

(i) A standard person is evaluated at the means of continuous variables by setting dummy variables equal to null. (ii) A disadvantaged person has a disability, lives in a community where the unemployment rate exceeds the mean by one standard deviation, has been unemployed the whole year of 1987/1990 and he has completed only the compulsory education. (iii) An advantaged person owns a house in a low unemployment community (mean - standard deviation), he is married with a standard spouse, has a university degree, belongs to a union, and has worked the whole year of 1987/1990 in a health care occupation.

Almost universally ordinary least squares estimates imply smaller programme effects than 2-limit tobit estimates which take account the censored nature of the dependent variable. Even though the homoskedastic tobit model was clearly rejected against the heteroskedastic one, there seems to be little to choose between the models when it comes to the magnitudes of programme effects[9]. It is surprising to find out that the estimated programme effects are practically invariant between the estimation period. Encouragingly, the sharp increase in the share of laid-off trainees affects only the average gain of ALMPs, if left uncontrolled (figures in italic). The robustness of results implies that the lacking information about the training undertaken in 1988 has no significant impact on the estimated job placement effects. Especially, since the share of laid-off trainees was below 10 per cent of all trainees at the end of the 1980s compared to almost half in 1991.

When it comes to the effectiveness of different programmes, laid-off training stands out quite impressively with the beneficial effect of some 4 months. It is worth remembering that laid-off trainees formed the most advantageous group of all in terms of employment months. However, if taken at face value the results indicate that participation has significantly reduced their threat of unemployment. Job placement in the private sector increases participants' working months by some 1.5 months, other things equal. The benefit exceeds the gains of other controlled groups of selective employment

[9] In heteroskedasticity corrected tobit models the unconditional expectation formula in Maddala (1983) can be modified by incorporating multiplicatively modelled heteroskedasticity into the equation as $\sigma_i = \sigma^*\mathrm{Exp}(\lambda W)$, where λ is the parameter vector to be estimated and W is the data matrix of heteroskedasticity correction variables.

measures by 1 - 2 months and the effect of unspecified ALMPs by half a month. Finally, the obligation introduced in the 1987 Employment Act has actually worsened the employment prospects of participants for the reasons discussed above.

To put the estimated programme effects in context it is useful to take a closer look at other personal characteristics associated with individuals' employment. The difference between the expected employment months of advantaged and disadvantaged persons is estimated as being close to ten months. This indicates that active programmes can help only so far as they go, the combined effect of other factors playing a larger role on individuals' employment possibilities. An interesting result is that the deterioration of employment prospects between 1989 and 1992 has affected all types of people, the impact being the largest for a standard person.

Next we turn to the results of selection corrected models given in equations (6) and (7) which take account of the correlation between primary and selection equations. The figures documented in table 6.6 are produced in a slightly different way to those given in the previous table. Instead of calculating the figures for some specific individuals, we calculated the expected employment months for every individual and the marginal programme effect for the participants. The means of these distributions are then reported in the table.

Table 6.6 The Estimated Marginal Programme Effects in Selectivity Corrected Estimations.

		1989			
		Equation 6		Equation 7	
	Y	E(Y|P)	ALMP effect	E(Y|P)	ALMP effect
The group:					
Non-participants	7.01	7.26	n/a	7.14	n/a
Participants	5.03	5.31	1.92	5.18	0.61
Placement in the private sector	6.28	6.32	2.91	6.31	1.72
Half-time placement	4.21	4.49	1.57	4.35	0.40
Placement as a last resort	2.92	3.33	0.84	2.95	-0.38
Rest of ALMPs	6.29	6.53	2.44	6.55	1.02
		1992			
		Equation 6		Equation 7	
	Y	E(Y|P)	ALMP effect	E(Y|P)	ALMP effect
The group:					
Non-participants	4.14	4.20	n/a	3.88	n/a
Participants	3.68	3.92	2.32	3.82	1.02
Placement in the private sector	3.02	3.75	2.68	3.46	1.52
Half-time placement	2.83	2.79	1.63	2.50	0.26
Placement as a last resort	0.95	1.21	0.54	0.98	-0.29
Laid-off training	9.78	9.97	5.72	10.31	3.63
Rest of ALMPs	4.17	4.21	2.72	4.06	1.16

Notes: The first column shows the observed mean of employment months. The E(Y|P) column gives the mean of the estimated employment months. The ALMP effect -column reports the estimated marginal programme effects as discussed in the text and in appendix 6.1.

Because of endogenous participation status, the focus is naturally on conditional expectations $E(y \mid p=0)$ and $E(y \mid p=1)$ which tell us the expected employment months given the selection process. In the current context these formulas, which are reported in appendix 6.1, become rather involved since the bivariate normal distribution under examination is censored in three directions. The estimated mean employment months are given for non-participants and various participant categories in E(Y | P) columns. Estimated models seem to predict the average employment months pretty well regardless of the exact group under consideration. The figures show that programme participants have worse subsequent employment record than participants but the gap has narrowed between the years 1989 and 1992, mainly due to an increase in the number of laid-off trainees. The average (and predicted) employment months of non-participants have dropped by almost three months, the reduction being one and a half months less for the programme participants. Table 6.6 documents also a reduction in working months across job placement programmes. The fall has been by far the greatest in private sector placements but these programmes still have the best expected (and realised) employment record of all selective employment measures. As confirmed by the earlier results, laid-off trainees' employment record is superior regardless of the exact group under comparison.

Even though the comparison of predicted employment months is interesting in its own right, it is more fruitful to try to assess the impact of ALMPs on participants. The third and the fifth column (ALMP effect) show the estimated mean programme effects which are given by marginal effect calculations $E(y=\beta X+\alpha p \mid p=1) - E(y=\beta X \mid p=1)$. The first thing to notice is that the results produced by the likelihood function (7) imply greater gains than the estimates of the likelihood function (6), the difference being over one month across programme groups. This is explained by strong negative correlation between primary and selection equations in the former likelihood function. To recall, the limited information model employs mere information about the numbers of observations in the limits and between them. Even though, limit observations contain the bulk of information, and the parameter estimates are well in line with other estimation methods, the results shown in table 6.6 cast some doubts on the limited information model in assessing ALMPs. Due to insignificant correlation coefficient the results based on the full information model are almost equal to ones given in table 6.5 for single equation estimations.

All in all, the estimated programme effects given in table 6.6 indicate an improvement in participants' employment record due to participation, the average gain being about a month. In other words, if programme participants had not participated in a programme their yearly employment record would have been a month shorter. Surprisingly, the marginal programme effect remains fairly stable regardless of the overall unemployment. There are some implications that the average gain of programme participants has increased but this increase is only a matter of a few weeks and mainly due to labour market training. When it comes to differences between programme groups, the already familiar pattern emerges. Job placements in the private sector are superior to public sector placements. In the high unemployment situation training programmes are more beneficial than selective employment measures mainly due to training offered to laid-off persons. Finally, the obligation introduced by the 1987 Employment Act has worsened participants subsequent employment record, on average.

6.5. Conclusions

The findings of this chapter can now be summarised with respect to the usefulness of various programme groups in the eras of high and low unemployment. First, the large scale job placement obligation introduced in the 1987 Employment Act was unsuccessful. It might be fair to conclude that the obligated placements worsened participants' subsequent employment record. Second, all other types of active programmes seem to improve participants' employment. Regardless of the estimated model or its exact specification, labour market training and job placements in the private sector yield the greatest gains in terms of participants' subsequent employment record, the improvement being over a month in a year. One group of programme participants stands out, namely laid-off trainees, whose benefit from participation is estimated as being over three months. Third, the estimates suggest that the programme effect has remained remarkably constant despite a rapid increase in unemployment which happened at the beginning of the 1990s. As a consequence of this, also the ranking of different programme groups has remained the same. It has to be noticed, however, that active labour market programmes can help only so far as they go. The joint effect of other factors associated with individuals' employment record, which was estimated as being close to 10 months, more than cancels out the programme gains.

From the methodological point of view, the study focuses on modelling endogenous programme participation when the outcome variable is censored both in the lower and in the upper limit. Two different models are proposed; one which employs all information and the other one which employs mere information about the numbers of observation in both limits and in between them. The latter model is motivated by the finding that the majority of individuals are observed as limit cases, i.e. either having no employment months or working the full 12 months in a year. These models are then compared to various single equation models.

All models agree with the determinants of programme participation and employment months. But the two selection corrected models disagree on the role played by unobservables. The correlation coefficient is estimated as being insignificantly different from zero in full information estimations and significantly negative in limited information estimations. The differences in the magnitude of the correlation coefficient is reflected in the programme effects, the limited information model estimating the beneficial effect as being over a month greater than other models. The similarity of the results produced by single equation methods and the selection corrected full information method is encouraging given that various tobit models are special cases of the proposed model. This implies that the proposed method is likely to prove useful in correcting the selection bias if it cannot be totally controlled through observables.

How do the results of this chapter compare to the macroeconomic ones presented in chapter 4, according to which active labour market programmes are more effective in a period of high unemployment? The results imply only a slight increase in the average marginal programme gain between the years 1989 and 1992 which does not indicate any significant improvements in the efficiency of active programmes, with other things equal. There has been, however, two changes which may have affected the macroeconomic efficiency of active labour market programmes. First, there was a notable reduction in the number of working months across different groups of participants and non-participants. Accordingly, an improvement in participants' employment months increased from some 15 per cent to over 30 per cent in the early 1990s, when compared to a hypothetical situation of non-participation. Second, the number of programme participants who experienced an average marginal programme gain of some one month doubled in the early 1990s, which in turn increased the beneficial programme effect on the whole population. Hence, regardless of the fact that the effects of active labour market policy do not need to coincide at the macroeconomic and microeconomic levels, due to substitution and displacement, the findings of these two chapters seem to be consistent with each other.

Appendix 6.1. Conditional Expectations of Employment Months

The conditional expectation of working months consists of two terms; (i) the conditional probability of being observed in the upper censoring point times the expected employment months in the upper limit (expected working months in the lower limit equals zero) and (ii) the conditional probability of being observed between the limits times the conditional expectation of uncensored employment months. In the general form conditional expectations can be written as (to simplify expressions all subscripts have been omitted)

(A1)
$$E(y \mid p^* \le 0) = \Pr(y^* \ge U \mid p^* \le 0) \times 12 +$$
$$\Pr(L < y^* < U \mid p^* \le 0) \times E(Y \mid L < y < U, p^* \le 0)$$

(A1')
$$E(y \mid p^* > 0) = \Pr(y^* \ge U \mid p^* > 0) \times 12 +$$
$$\Pr(L < y^* < U \mid p^* > 0) \times E(Y \mid L < y < U, p^* > 0)$$

The conditional probabilities result in joint probabilities divided by the probability of the participation status. Under normality joint probabilities are given by standard bivariate normal distribution functions after the censoring points are suitably normalised. With the aid of general formulas given in Muthen (1990), the conditional expectation terms for bivariate normal distribution truncated in three directions can be written as

(A2)
$$E(Y \mid L < y < U, p^* \le 0) = \beta X + \alpha p + \sigma_y E(\upsilon \mid b_1 < \upsilon < a_1,\ \eta \le -\gamma Z) =$$
$$\beta X + \alpha p + \frac{\sigma_y}{\pi}[-\phi(a_1)\Phi[(-\gamma Z - \rho a_1)c] + \phi(b_1)\Phi[(-\gamma Z - \rho b_1)c] -$$
$$\rho\phi(\gamma Z)\{\Phi[(a_1 - \rho(-\gamma Z))c] - \Phi[(b_1 - \rho(-\gamma Z))c]\}]$$

(A2')
$$E(Y \mid L < y < U, p^* > 0) = \beta X + \alpha p + \sigma_y E(\upsilon \mid b_1 < \upsilon < a_1,\ \eta > -\gamma Z)$$
$$\beta X + \alpha p + \frac{\sigma_y}{\pi}[-\phi(a_1)\Phi[-(-\gamma Z - \rho a_1)c] + \phi(b_1)\Phi[-(-\gamma Z - \rho b_1)c] +$$
$$\rho\phi(\gamma Z)\{\Phi[(a_1 - \rho(-\gamma Z))c] - \Phi[(b_1 - \rho(-\gamma Z))c]\}],$$

where $\upsilon = \varepsilon/\sigma_y$, σ_y being the standard deviation of the employment equation; $a_1 = \frac{L-(\beta X+\alpha p)}{\sigma_y}$ and $b_1 = \frac{U-(\beta X+\alpha p)}{\sigma_y}$ are the standardised upper and the lower censoring points, respectively; π stands for the joint probability of observing non-censored employment months, $\Pr(L < y < U, p=x)$, $x = 0,1$; ϕ refers to the standard normal density function and Φ refers to the cumulative normal; and finally $c = \frac{1}{1-\rho^2}$ where ρ is the estimated correlation coefficient between the error terms in primary and in selection equations.

By employing equations (A2) in equations (A1) the expected employment months for non-participants (p = 0) and programme participants (p = 1) become

$$\text{(A3)}\quad E(y \mid p=0) = \frac{1}{\Phi(-\gamma Z)} \times \{\Phi_2(-b_1, -\gamma Z, -\rho) \times 12 + [\Phi_2(b_1, -\gamma Z, \rho) - \Phi_2(a_1, -\gamma Z, \rho)] \times \beta X + \sigma_y \times (-\phi(a_1)\Phi[(-\gamma Z - \rho a_1)c] + \phi(b_1)\Phi[(-\gamma Z - \rho b_1)c] - \rho\phi(\gamma Z)\{\Phi[(a_1 - \rho(-\gamma Z))c] - \Phi[(b_1 - \rho(-\gamma Z))c]\})$$

$$\text{(A3')}\quad E(y \mid p=1) = \frac{1}{\Phi(\gamma Z)} \times \{\Phi_2(-b_1, \gamma Z, \rho) \times 12 + [\Phi_2(b_1, \gamma Z, -\rho) - \Phi_2(a_1, \gamma Z, -\rho)] \times (\beta X + \alpha p) + \sigma_y \times (-\phi(a_1)\Phi[-(-\gamma Z - \rho a_1)c] + \phi(b_1)\Phi[-(-\gamma Z - \rho b_1)c]) + \rho\phi(\gamma Z)\{\Phi[(a_1 - \rho(-\gamma Z))c] - \Phi[(b_1 - \rho(-\gamma Z))c]\}).$$

The reported marginal programme effects in table 6 are obtained from equation (A3') by giving programme dummies zero values and subtracting the expected, hypothetical working months from the ones given by equation (A3').

Appendix 6.2. The Results of Employment Months Estimation; the Year 1992.

	Estimation method				
	OLS	2-limit tobit	2-limit tobit	Type 2 tobit	Equation 7
Constant	4.168 (0.51)***	2.500 (1.28)*	1.854 (1.29)	7.205 (3.39)**	3.263 (1.37)**
Woman	0.125 (0.09)	0.314 (0.22)	0.334 (0.21)	-0.006 (0.38)	0.300 (0.23)
Age	-0.088 (0.02)***	-0.259 (0.06)***	-0.263 (0.06)***	-0.210 (0.11)*	-0.369 (0.07)***
Age squared/1000	0.321 (0.34)	1.241 (0.87)	1.348 (0.84)	1.590 (1.50)	2.640 (0.92)***
Married	0.348 (0.11)***	0.778 (0.27)***	0.807 (0.26)***	0.974 (0.41)**	0.713 (0.28)**
Education	0.390 (0.04)***	0.926 (0.11)***	0.920 (0.12)***	0.678 (0.19)***	0.790 (0.12)***
Number of children	0.112 (0.09)	0.262 (0.22)	0.257 (0.23)	0.373 (0.32)	0.121 (0.25)
Youngest child 0-3 years	-1.201 (0.15)***	-3.089 (0.37)***	-3.019 (0.36)***	-1.998 (0.57)***	-2.879 (0.38)***
Youngest child 4-6 years	-0.827 (0.21)***	-1.938 (0.51)***	-1.873 (0.49)***	-1.385 (0.71)*	-1.573 (0.53)***
Youngest child 7-16 years	0.124 (0.12)	0.217 (0.29)	0.245 (0.29)	-0.412 (0.47)	0.343 (0.30)
House owner	0.518 (0.08)***	1.335 (0.21)***	1.359 (0.20)***	0.984 (0.32)***	1.108 (0.22)***
Spouse's education	0.023 (0.05)	0.004 (0.11)	0.011 (0.11)	-0.101 (0.18)	0.048 (0.11)
Disability	-0.997 (0.15)***	-3.450 (0.48)***	-3.435 (0.44)***	-1.783 (0.52)***	-3.285 (0.47)***
Union member	1.285 (0.08)***	3.222 (0.21)***	3.195 (0.21)***	1.110 (0.45)**	5.302 (0.22)***
Unemployment rate	-0.003 (0.01)	0.005 (0.03)	0.048 (0.03)	0.010 (0.06)	-0.065 (0.03)*
Ln(monthly unemployment benefits in 91)	-0.189 (0.00)***	-0.414 (0.01)***	-0.416 (0.01)***	-0.373 (0.03)***	-0.386 (0.02)***

Appendix 6.2. The Results of Employment Months Estimation; the Year 1992.

Ln(Other income)	-0.004	0.012	0.006	0.041	0.038
	(0.00)	(0.01)	(0.01)	(0.02)*	(0.01)**
Ln(Spouse's income)	0.046	0.113	0.115	0.073	0.095
	(0.00)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***
Urban living community	-0.184	-0.525	-0.510	-0.194	-0.395
	(0.08)**	(0.20)**	(0.20)**	(0.35)	(0.22)*
Middle Finland	0.179	0.410	0.386	-0.006	0.072
	(0.09)*	(0.23)*	(0.23)	(0.39)	(0.25)
Northern Finland	0.114	0.440	0.384	-0.309	0.194
	(0.13)	(0.31)	(0.31)	(0.49)	(0.33)
Technical occupation	-0.481	-1.003	-1.046	-0.326	0.734
	(0.21)**	(0.50)**	(0.52)**	(1.21)	(0.62)
Health care occupation	0.830	1.768	1.668	1.383	2.883
	(0.23)***	(0.54)***	(0.51)***	(1.09)	(0.61)***
Administrative occupation	-0.208	-0.630	-0.657	-1.500	0.764
	(0.19)	(0.45)	(0.45)	(0.92)	(0.53)
Mercantile occupation	0.373	0.773	0.738	1.397	2.413
	(0.19)*	(0.46)*	(0.45)	(1.08)	(0.55)***
Farming/forestry occu.	0.628	1.639	1.602	0.997	2.927
	(0.19)***	(0.51)***	(0.53)***	(0.89)	(0.60)***
Transport occupation	0.744	1.693	1.651	1.146	3.499
	(0.22)***	(0.54)***	(0.54)***	(1.19)	(0.66)***
manufacture occupation	-0.060	-0.211	-0.198	0.175	1.287
	(0.12)	(0.34)	(0.34)	(0.92)	(0.46)***
Service occupation	0.006	-0.009	0.071	-0.315	1.409
	(0.21)	(0.56)	(0.53)	(0.93)	(0.62)**
Employment months in 1990	0.178	0.427	0.422	0.413	0.380
	(0.01)***	(0.02)***	(0.02)***	(0.04)***	(0.02)***
Unemployment months in 1990	-0.074	-0.202	-0.186	-0.226	-0.332
	(0.01)***	(0.05)***	(0.04)***	(0.12)***	(0.06)***
Placement in the private sector	-0.652	-0.683	-0.755	0.777	0.993
	(0.28)**	(0.77)	(0.76)	(0.50)	(0.82)
Half-time placement	-1.316	-3.146	-2.673	-0.234	-1.892
	(0.63)**	(1.70)*	(1.63)	(0.97)	(1.85)
Placement as a last resort	-2.087	-6.575	-6.061	-2.869	-4.550
	(0.18)***	(0.58)***	(0.55)***	(0.41)***	(0.61)***

Appendix 6.2. The Results of Employment Months Estimation; the Year 1992.

Laid-off training	n/a	n/a	n/a	n/a	4.403 (0.80)***
Unemployment days in 1991	0.005 (0.00)***	0.013 (0.00)***	0.012 (0.00)***	0.003 (0.00)**	0.013 (0.00)***
Recurrent participation	-2.609 (0.07)***	-5.787 (0.27)***	-5.609 (0.28)***	-1.994 (0.32)***	-5.093 (0.28)***
Programme participation	1.977 (0.15)***	4.608 (0.38)***	4.398 (0.38)***	n/a	7.622 (1.19)***
σ	4.031	8.539 (0.10)***	11.374 (0.88)***	5.214 (0.27)***	10.268 (0.82)***
ρ	n/a	n/a	n/a	-0.279 (0.19)	-0.316 (0.06)***
Log L	$R^2_{adj} = 0.27$	19969.760	19938.970	7179.539	13144.420
Heterosked. correction	Standard errors	No	Yes	No	Yes

Notes: see table 6.4.

Appendix 6.3. The Results of Participation Equations.

	The year 1988			The year 1991		
	Probit	Equation 6	Equation 7	Probit	Equation 6	Equation 7
Constant	-0.618 (0.24)**	-0.574 (0.25)**	-0.616 (0.25)**	-2.322 (0.20)***	-2.375 (0.20)***	-2.340 (0.20)***
Woman	0.131 (0.05)**	0.127 (0.05)**	0.131 (0.05)**	-0.196 (0.03)***	-0.206 (0.03)***	-0.197 (0.03)***
Age	-0.030 (0.01)**	-0.033 (0.01)**	-0.030 (0.01)**	0.062 (0.01)***	0.063 (0.01)***	0.063 (0.01)***
Age squared/1000	0.226 (0.19)	0.268 (0.19)	0.229 (0.19)	-0.797 (0.14)***	-0.795 (0.14)***	-0.809 (0.14)***
Married	-0.099 (0.06)	-0.100 (0.06)	-0.099 (0.06)	-0.071 (0.04)	-0.056 (0.04)	-0.067 (0.04)
Education	0.036 (0.02)	0.042 (0.03)	0.037 (0.03)	-0.018 (0.02)	-0.011 (0.02)	-0.015 (0.02)
Number of children	0.011 (0.04)	0.011 (0.04)	0.011 (0.04)	0.013 (0.03)	0.017 (0.03)	0.014 (0.03)
Youngest child 0-3 years	-0.334 (0.10)***	-0.333 (0.09)***	-0.334 (0.09)***	0.029 (0.06)	0.022 (0.06)	0.032 (0.06)
Youngest child 4-6 years	0.030 (0.08)	0.023 (0.08)	0.030 (0.08)	0.091 (0.08)	0.079 (0.08)	0.090 (0.08)
Youngest child 7-16 years	-0.004 (0.06)	-0.008 (0.06)	-0.005 (0.06)	-0.003 (0.05)	-0.004 (0.05)	-0.002 (0.05)
House owner	-0.038 (0.04)	-0.044 (0.04)	-0.039 (0.04)	-0.057 (0.03)	-0.047 (0.03)	-0.056 (0.03)
Spouse's education	-0.010 (0.02)	-0.010 (0.02)	-0.010 (0.02)	0.016 (0.02)	0.010 (0.02)	0.195 (0.06)***
Disability	0.444 (0.07)***	0.441 (0.07)***	0.444 (0.07)***	0.196 (0.06)***	0.200 (0.06)***	0.413 (0.03)***
Union member	0.120 (0.04)***	0.137 (0.04)***	0.121 (0.04)***	0.413 (0.03)***	0.404 (0.03)***	0.042 (0.00)***
Unemployment rate	0.036 (0.00)***	0.036 (0.00)***	0.036 (0.00)***	0.042 (0.00)***	0.043 (0.00)***	-0.023 (0.00)***
Ln(monthly unemployment benefits)	-0.012 (0.00)***	-0.012 (0.00)***	-0.012 (0.00)***	-0.023 (0.00)***	-0.023 (0.00)***	-0.001 (0.00)

Appendix 6.3. The Results of Participation Equations.

Ln(Other income)	-0.002 (0.00)	-0.002 (0.00)	-0.002 (0.00)	-0.002 (0.00)	-0.001 (0.00)	-0.003 (0.00)
Ln(Spouse's income)	-0.005 (0.00)	-0.005 (0.00)	-0.005 (0.00)	-0.003 (0.00)	-0.003 (0.00)	-0.003 (0.00)
Urban living community	-0.147 (0.04)***	-0.149 (0.04)***	-0.147 (0.04)***	-0.147 (0.03)***	-0.147 (0.03)***	-0.146 (0.03)***
Middle Finland	0.075 (0.05)	0.077 (0.05)	0.075 (0.05)	0.097 (0.04)**	0.105 (0.04)**	0.096 (0.04)
Northern Finland	0.123 (0.07)	0.128 (0.07)*	0.122 (0.07)	-0.017 (0.05)	-0.004 (0.05)	-0.018 (0.05)
Technical occupation	-0.475 (0.11)***	-0.479 (0.12)***	-0.475 (0.12)***	-1.166 (0.08)***	-1.197 (0.08)***	-1.163 (0.08)***
Health care occupation	-0.458 (0.10)***	-0.455 (0.10)***	-0.458 (0.10)***	-1.094 (0.09)***	-1.107 (0.09)***	-1.092 (0.09)***
Administrative occupation	-0.094 (0.08)	-0.106 (0.09)	-0.095 (0.09)	-0.895 (0.07)***	-0.939 (0.07)***	-0.895 (0.07)***
Mercantile occupation	-0.305 (0.10)***	-0.309 (0.09)***	-0.305 (0.10)***	-1.073 (0.08)***	-1.082 (0.08)***	-1.071 (0.08)***
Farming/forestry occupation.	-0.245 (0.09)***	-0.243 (0.09)***	-0.245 (0.09)***	-0.854 (0.07)***	-0.871 (0.07)***	-0.856 (0.08)***
Transport occupation	-0.703 (0.13)***	-0.688 (0.13)***	-0.703 (0.13)***	-1.203 (0.09)***	-1.199 (0.09)***	-1.203 (0.09)***
manufacture occupation	-0.410 (0.06)***	-0.414 (0.06)***	-0.410 (0.06)***	-1.096 (0.04)***	-1.095 (0.04)***	-1.097 (0.04)***
Service occupation	-0.430 (0.08)***	-0.438 (0.08)***	-0.430 (0.08)***	-0.919 (0.08)***	-0.927 (0.09)***	-0.921 (0.09)***
Employment months in t-1	-0.037 (0.00)***	-0.037 (0.00)***	-0.037 (0.00)***	-0.015 (0.00)***	-0.011 (0.00)***	-0.014 (0.00)***
Unempl. months in t-1	0.052 (0.00)***	0.052 (0.00)***	0.052 (0.00)***	0.153 (0.00)***	0.155 (0.00)***	0.153 (0.00)***
Local supply of ALMPs	0.019 (0.00)***	0.018 (0.00)***	0.019 (0.00)***	0.018 (0.00)***	0.017 (0.00)***	0.018 (0.00)***

Notes: The first (last) three columns refer to the year 1988 (1991). All variables refer to these years if not otherwise stated.

Data Appendix. Means and Definitions of the Variables.

	The sample	
	t = 1989	t = 1992
Woman	0.44	0.38
Age#	34.85	36.09
Married	0.40	0.40
Education (t-1) (ranges between 0 = less than upper secondary education and 5 = more than master's degree)	0.80	0.88
Number of children under 7 years of age#	0.25	0.22
Age of the youngest child 0-3 years	0.07	0.13
Age of the youngest child 4-6 years	0.07	0.06
Age of the youngest child 7-16 years	0.15	0.15
House owner	0.59	0.61
Spouse's education (as education)#	0.52	0.52
Disability (t-1)	0.06	0.05
Union member (t-1)	0.54	0.55
Unemployment rate#	5.79	19.36
Unemployment rate (t-1)#	6.89	13.42
Ln(monthly unemployment benefits in t-1)#	4.58	4.91
Ln(Other income)#	1.25	0.55
Ln(Spouse's income)#	4.42	4.48
Urban living community	0.52	0.56
Middle Finland	0.29	0.28
Northern Finland	0.19	0.15
Technical occupation (t-1)	0.05	0.06
Health care occupation (t-1)	0.05	0.04
Administrative occupation (t-1)	0.07	0.08
Mercantile occupation (t-1)	0.05	0.06
Farming/forestry occupation (t-1)	0.05	0.04
Transport occupation (t-1)	0.03	0.04
manufacture occupation (t-1)	0.37	0.46
Service occupation (t-1)	0.11	0.04
Employment months (t-2)#	5.93	7.34

Unemployment months (t-2)#	3.12	1.45
Recurrent participation	0.14	0.17
days in (t-1)# (potential time for job search before the response period)	238	200
Placement in the private sector (t-1)	0.02	0.01
Half-time placement (t-1)	0.02	0.00
Placement as a last resort (t-1)	0.06	0.07
Programme participation (t-1)	0.20	0.17

Notes: The two samples refer to the low unemployment situation when t = 1989 and to the high unemployment situation when t = 1992. # denotes that a variable is not a dichotomous one.

CHAPTER 7.

Summary and Concluding Comments

Assessing the effects of any public sector intervention is by no means a straightforward task. At the macroeconomic level an intervention and an outcome variable are likely to be related to each other often in a complex way. At the individual level an analyst needs to construct counterfactual states to approximate participants' labour market positions in a hypothetical situation of non-participation. This thesis has employed both macro and micro data in examining the effectiveness of active labour market policy in reducing the overall level of open unemployment, reducing participants' repeat unemployment incidence and improving participants' subsequent employment record. The main finding is that active labour market programmes improve the employment performance of the economy but they are not a miracle cure.

Chapter 4 focused on the functioning of active labour market programmes at the macroeconomic level. To be able to address the equilibrium unemployment effects through wage-setting, labour demand and labour supply curves, the Layard-Nickell model with imperfectly competitive firms and unionised wage setting was augmented by endogenous labour supply. The attempt to evaluate the influence of active labour market programmes both on discouragement and on open unemployment through time series analysis distinguishes chapter 4 from earlier studies. The main result suggested the dependence between the efficiency of active labour market programmes and the overall level of unemployment. They become more effective in the high unemployment situation, confirming the hypothesis put forward in Calmfors (1994).

To get a fuller picture of the functioning of active labour market policy, chapter 5 went beyond the aggregated data and analysed the relation between participation in a programme and participants' job stability. The main issue of interest was in assessing the differences in programme gains across individuals according to their characteristics. In contrast to the common practise of leaving the estimated microeconometric models untested, the estimated models were put under scrutiny by various misspecification tests. Most notably, the distributional assumption of bivariate normality was tested both in the bivariate probit model and in the switching bivariate probit model. The results confirmed, with some exceptions, the emphasis towards targeting active programmes at disadvantaged persons expressed for instance in Jackman et. al. (1996).

The complementary view to the effectiveness of active labour market programmes at the individual level was provided in chapter 6 which examined the effects of different groups of programmes on participants' subsequent employment record. This required the formulation of a generalised tobit model which tackled the problem of self-selection by estimating the bivariate normal distribution truncated in three directions. The main finding was, quite surprisingly, that the marginal programme effect remained fairly stable between the eras of low and high unemployment. Accordingly, the differences in relative effectiveness of various active labour market programmes has remained unaltered despite a sharp increase in unemployment.

The empirical analysis of the thesis therefore reported a significant influence of active labour market policy on various outcome variables regardless of estimation method, exact sample or the level of aggregation. To complement the broad findings stated above, the answers to the questions put forward in chapter 1 can be summarised as follows:

- Active labour market programmes have not affected wage-setting during the 1980s. The results suggest that they have some downward effect on wages in the high unemployment situation.

- There seems to be some discouragement preventing effects of ALMPs which show up at the macroeconomic level.
- When it comes to overall unemployment, the results imply that Finnish active labour market programmes increased open unemployment in the 1980s but the effect was reversed during the early 1990s.
- The microeconometric evaluations strongly suggest that active programmes improve participants' subsequent employment record, the estimated effect being, on average, some 10 percentage points on job stability and about 1 month on employment months during the following year. But these beneficial effects are far from removing the initial differences in employment prospects between advantaged and disadvantaged individuals.
- The results lend some support to targeting active programmes to hard-to-employ persons with the notable exception of the disabled. This is not universal, however, the gains of higher educated persons also exceeding the average ones.
- The results place the aim of reducing regional unemployment differences through active programmes under serious doubt.
- There are clear indications that training programmes and job placements in the private sector are the most efficient type of active programme.
- The results cast considerable doubt on large scale job placement obligations. The effects of the statutory obligation introduced in the 1987 Employment Act were estimated as being either negligible or even negative.
- The estimated marginal programme effects are almost invariant between the eras of high and low unemployment. When combined with a reduction in actual working months and a sharp increase in the number of

participants between the years 1989 and 1992, this finding implies that active programmes have bigger gains at the macroeconomic level in the high unemployment situation.

- The ranking of different programmes does not depend on the overall level of unemployment.
- Characteristics which can be thought of as describing a hard-to-employ person have well determined positive impacts on individuals' participation decisions. There are some indications that the selection is also based on unobservables, the correlation coefficients suggesting that programme participants' initial labour market possibilities are inferior compared to non-participants' ones.

Like all empirical studies, the estimated models are not without caveats. In the macroeconomic part of the study all estimations are based on single equation methods. Even though standard system estimations by 3SLS verified the parameter estimates, we do not know what would happen in full system cointegration estimations. Unfortunately, the number of variables made it impossible to identify any meaningful cointegrating vectors from the unrestricted cointegration space. So in this sense the results rely on asymptotic results about the endogeneity bias vanishing in cointegration regressions when the number of observations becomes large enough. Another possible shortcoming of the macroeconomic study is the recursive instability of the wage variable in the labour demand equation in the 1990s. As such this is not too surprising given that in the early 1990s the number of employed persons collapsed whereas real wages remained more or less the same. One possible explanation for this is that the employment stock is not a suitable measure of labour demand. However, since the specification is a standard one in labour demand literature it is felt that there is no need to challenge it in current context.

The drawback of microeconomic evaluations is that ALMPs are assessed within an arbitrarily selected period of time. It is argued that the gains of the adopted modelling strategies, i.e. the ability to deal with the self-selectivity within the well established framework and the ability to test the distributional assumptions, more than offset this caveat. Unfortunately, the latter argument is not valid in chapter 6 due to the complexity of the likelihood function. All in all, it would have been an interesting challenge to estimate employment related programme effects in the non-stationary environment of the early 1990s. Most likely it would have required some new techniques to simultaneously tackle rapidly changing employment possibilities and endogenous selections of individuals within non-linear models. Having said that, we strongly believe that the evaluations of this study, despite their cross-sectional nature, offer valuable information both about the functioning of Finnish active labour market programmes and about the methods of estimating programme effects.

Finally, in conclusion, it is worth presenting the main finding running though all chapters of the thesis. Active labour market programmes improve the employment performance of the economy, but the gains remain much too limited either to solve the current unemployment problem or to clear away the gap in labour market possibilities between advantaged and disadvantaged individuals. This is not to say that active labour market policy would not be useful in conjunction with other policies, but without any support its effects will remain modest.

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