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POST-UNEMPLOYMENT WAGES AND ECONOMIC INCENTIVES TO EXIT FROM UNEMPLOYMENT

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ABSTRACT: This study represents the results of a comparative econometric analysis of the determinants of earnings and unemployment durations. The analysis uses two sets of panel data, one drawn from the outflows of unemployment and another from the working age population. The earnings of people leaving unemployment are modelled in order to obtain estimates for starting wages in subsequent jobs. With these estimates, the expected income changes associated with labour market transitions are evaluated at the household level. Some 8% of the unemployed are estimated to be unable to increase disposable income of their households through employment, while as much as 43% have to be content with a 25% increase or less. The income variables, with controls for other factors, are then mapped into a flexible competing risks model of unemployment duration. The expected returns to employment are found to be an important determinant of the probability of becoming employed. It appears also that the relative importance of economic incentives has been strengthened in the recession years.

Keywords: Post-unemployment wages, sample selection, economic incentives, labour market transitions, duration models

TIIVISTELMÄ: Tutkimuksessa analysoidaan työtulojen ja työttömyyden keston määräytymistä ekonometrisin menetelmin. Analyysi perustuu kahteen yksilötason paneeliaineistoon, joista toinen on poimittu työttömyytensä päättäneistä henkilöistä ja toinen koko työikäisestä väestöstä. Työllistyneiden työtuloja mallintamalla saadaan estimaatit työttömyyden jälkeisille alkupalkoille. Näiden estimaattien avulla lasketaan työmarkkinasiirtymien aiheuttamat odotetut muutokset kotitalouksien tuloissa. Tulosten mukaan noin 8% työttömistä on tilanteessa, jossa työllistyminen ei lisää kotitalouden käytettävissä olevia tuloja, kun taas 43%:n arvioidaan joutuvan tyytymään enintään 25%:n tulojen lisäykseen. Tulomuuttujia käytetään myös selittäjinä kilpailevien riskien duraatiomallissa työttömyyden kestoa mallinnettaessa. Työllistymisen aiheuttama odotettu tulonlisäys osoittautuu tärkeäksi työllistymistodennäköisyyteen vaikuttavaksi tekijäksi. Lisäksi taloudellisten insentiivien merkityksen havaitaan korostuneen lamavuosina.

Asiasanat: Työttömyyden jälkeiset palkat, valikoituminen, taloudelliset insentiivit, työmarkkinasiirtymät, duraatiomallit

Foreword

Reasons for the slow progress of unemployment reduction in recent years have been discussed actively in Finland. Along with the rigidities of the labour market that result from the institutional structure, different incentive problems of the unemployed have been at the center of public discussion. It has been argued that the tax and social security system can occasionally reduce significantly the willingness of the unemployed to make themselves available for unfilled vacancies.

Most of the existing evidence on incentive traps is based on calculations with representative households, without connections to real-life data. Government Institute for Economic Research has, in recent years, put effort on empirical work in order to generate a fuller understanding of the extent of actual incentive problems and of their impact on labour market behaviour. This study belongs to a series of empirical research reports on incentive effects and individual labour market experiences.

The study represents the results of a comparative econometric analysis of the determinants of earnings and unemployment durations. The economic incentives are measured by computing expected changes in the disposable income of sample households that would result from employment of the unemployed member. The average impact of economic incentives on the probability of leaving unemployment is estimated with a flexible model of unemployment duration.

The expected returns of employment are found to be an important determinant of the probability of becoming employed, and their relative importance seems to be strengthened during the recession. It is, however, alarming that there seems to be unemployed people who are unable to increase disposable income of their households through employment with available wage offers. This kind of findings call a need to improve the incentive schemes of the unemployed.

Helsinki, May 1999

Reino Hjerppe

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Helsinki, May 1999

Tomi Kyyrä

Summary

Unemployment in Finland has persistently remained at high levels in spite of the rapid economic growth in recent years. It is discerned that the determinants of development in unemployment duration are the driving force behind the changes in aggregate unemployment. This has generated a growing interest in long-term unemployment. Several authors have argued that income transfers, combined with high labour taxes, can occasionally reduce significantly the willingness of the unemployed to make themselves available for unfilled vacancies. Insignificant returns to employment are likely to slow down the process of unemployment reduction.

As a result of a lack of data, progressive taxation, income transfers and other sources of household income are usually omitted in empirical work, although they have been at the center of the policy debate on incentives effects. Indeed, the certain shortcomings of the earlier studies call for a need to re-examine the importance of economic incentives, faced by the unemployed. The main attempt of this study is to generate a fuller understanding of the extent of real-life incentive problems and their impact on transitions out of unemployment.

The empirical analysis begins with an evaluation of the determinants of post-unemployment wages. This yields estimates for expected starting wages for the unemployed. These estimates, combined with a rich set of household income information in our data, enable us to account for incentive effects with a reasonable accuracy. To be more specific, the questions to be addressed in detail are:

- What are the determinants of the starting wages of people who leave unemployment?
- What is the distribution of the returns to employment among the unemployed?
- To which extent incentive factors contribute to the probability of leaving unemployment?

The analysis is based on two sets of micro-data, both gathered by Statistic Finland. The first one was constructed by pooling together samples, drawn from individuals flowing out of unemployment in 1988, 1990, 1992 and 1994. It is employed in studying the earnings of people leaving unemployment and the length of time they spend in unemployment. The second is a sample

from the working age population, and it serves as a comparable source in the analysis of wage determination. The longitudinal information for both data was collected for the period 1987–94 by combining several administrative registers.

An exceptional feature of the data sets is the fact that they include detailed income statistics, not only for actual sampled individuals, but for their spouses as well. Since the data sets also contain information on transfer payments to households, the outflow data provides an opportunity to consider changes in disposable income, resulting from labour market transitions, with an accuracy that is exceptional in empirical work. With this data source, it is possible to overcome several limitations imposed by the quality and scope of the underlying data from which the previous studies have suffered.

It should also be stressed that the time period under investigation is an exceptional one in the Finnish economic history, containing a business cycle from the boom of the late 1980's to the deep recession of the early 1990's. This brings an interesting time dimension to the analysis.

In the first stage, post-unemployment wages are studied by modelling the earnings of people who leave unemployment with the outflow data. For purposes of comparability, the determinants of general wages are estimated from the data on the working age population. According to the results, considerable returns to educational investments prior to the unemployment spell can be attached to each level of education for those exiting from unemployment to employment. The impact of schooling on starting wages, however, is found to be only half of that on general wages, corresponding to an increase of some 4.5% in the starting wage with respect to an additional year of schooling. In addition, the experience-wage profiles for the starting wages are estimated to be flatter than for the general wages, indicating the importance of firm-specific human capital for high-tenured workers. It is also notable that women enter employment at the earnings equal to those of men, although they are likely to suffer from wage discrimination later on in their career.

Cyclical fluctuations also have an impact on the wage structure. General wages are estimated to be slightly sensitive to regional demand conditions, whereas starting wages are affected by the relative supply of open vacancies across occupational groups. A standard search model result, that the longer spells of unemployment are associated with higher earnings from the subsequent job, is rejected, and the starting wage is found to depend negatively on the time an individual spend in unemployment. In particular, a hypothetical doubling of the length of the unemployment spell is associated with a fall of some 2% in subsequent earnings.

The second part of the study evaluates the income changes associated with labour market transitions. The actual change in the disposable income of the individual's household is computed for the subsample of those exiting to employment in the outflow data. In addition, the expected change in the household's disposable income is computed for each sampled individual using starting wage estimates. This measure of the expected returns to employment is then used to evaluate how the returns are distributed among the unemployed. According to the results, employment has increased the disposable income of households by slightly over 50% on average, while 4% of the applicants have accepted employment at the starting wage that caused a reduction in the household's disposable income. Moreover, some 8% of the sampled individuals are estimated to be unable to increase the disposable income of their households through employment, while as much as 43% have to be content with a 25% increase or less.

In the final part of the study, the conditional probability of leaving unemployment is modelled with a flexible competing risks model that allows unemployment spells to end at employment, at manpower programmes or at withdrawal from the labour force. Women are found to complete their unemployment spells more rapidly at employment and manpower programmes than men, though their behaviour is occasionally affected by family circumstances. The highest withdrawal rates from the labour force are estimated for the non-claimants of the unemployment compensation system, whereas a close labour force attachment is found for unemployment insurance benefit receivers. It further appears that non-claimants complete their spells at employment more rapidly than other benefit group receivers.

The income factors are found to play an important role. There is a strong positive relation between the probability of becoming employed and the expected returns to employment. The incentive effect turns out to be stronger at times of high unemployment, indicating that the relative importance of economic incentives has strengthened in the recession years. Higher expected returns to employment also make exit from the labour force less likely. After controlling for the expected returns, the high level of the household's unemployment income is found to increase the probability of becoming employed and reduces that of leaving the labour force.

To sum up, a high proportion of the unemployed is found to be faced with the relatively low returns to employment, and considerable incentive effects are found in the estimations. These findings suggest that there is undoubtedly a need to improve the incentive schemes of the unemployed. However, it should be stressed that several applicants are found to accept employment, despite insignificant, or even negative, short-term returns. This clearly mirrors the fact that the financial gain of employment is not the only thing that matters for the unemployed when searching for work.

Contents

1 Introduction

Unemployment in Finland has persistently remained at high levels in spite of the rapid economic growth in recent years. It is discerned that the determinants of development in unemployment duration are the driving force behind the changes in aggregate unemployment. This has generated growing interest in long-term unemployment. Depreciation of working skills during unemployment suggests that the long-term unemployed may drop out from the labour market permanently. This implies that with a high proportion of long-term unemployed, it can be very difficult to bring unemployment down again even in a favourable economic environment.

These perceptions have stimulated public discussion on the rigidities of the labour market. Institutional structure is often blamed for high levels of unemployment, as it delays, and partly prevents, the labour market from adjusting to changes in economic conditions. In addition, several authors have argued that income transfers, combined with high labour taxes, can occasionally reduce significantly the willingness of the unemployed to make themselves available for unfilled vacancies. Insignificant returns to employment are likely to slow down the process of unemployment reduction as well.

This kind of argumentation suggests that high unemployment in Finland is not merely a result of a business cycle, but is largely "structural" in the sense that it is sustained by outdated institutions and the tax and social security system that distorts incentives. Although the public discussion on the functioning of the labour market has been lively in Finland, micro-evidence on labour market adjustments around the turn of the decade is relatively sparse. This study aims to shed some light on the subject by analysing the determination of post-unemployment wages and unemployment durations. Special attention is paid to the role of economic incentives.

Economic incentives have occasionally been studied with "representative households" (e.g., Viitamäki, 1995, Salomäki, 1995). The idea is to calculate the change in the household's disposable income that results from employment of the unemployed member. This approach provides a wealth of detail, but it tells us very little about the *extent* of real-life incentive problems. Moreover, it is often plausible to expect that the fictional households chosen represent only a small proportion of the households suffering from unemployment.

Empirical studies, on the other hand, have commonly suffered from incomplete income information. As a result of a lack of data, it has been almost a rule rather than an exception in empirical work to omit progressive taxation, transfer payments and spouse's income, although they have been at the center of the policy debate on incentives. In addition, earnings categories obtained from the working population only (e.g., Arulampalam and Stewart, 1995) or earnings from the last job prior to unemployment (e.g., Kettunen, 1993a, Lilja, 1992) have often been used to measure the expected earnings in work.[1] These measures suffer from certain important drawbacks, however. The distribution of individual characteristics is generally different in the populations of the unemployed, employed, and in the labour force as a whole. This calls into a doubt whether approaches based on the earnings of the working population can produce adequate estimates of subsequent wages for the unemployed. The second drawback is the fact that there is empirical evidence that displaced workers return to work at lower earnings, and the earnings losses, associated with periods of unemployment, tend to be quite persistent (e.g., Jacobson *et al.*, 1993, Stevens, 1997).[2] In what follows, the evaluation of the returns to employment using prior earnings possibly produces upward-biased estimates for economic incentives.

An alternative approach, with more rich data, is adopted in studies by Holm and Kyyrä (1997), by Holm *et al.* (1998) and by Rantala (1998). In these studies, estimates of the earnings in subsequent jobs for unemployed applicants were obtained by using the parameter estimates of a post-unemployment wage model, borrowed from Kyyrä (1997). These estimates, taken together with a rich set of household income information, allowed them to compute expected changes in the disposable income of sample households that would result from employment of the unemployed member.[3] The expected change was then mapped as an explanatory variable into a probit model for the employment probability in Holm and Kyyrä (1997) and into a competing risks model of unemployment duration in Holm *et al.* (1998) and in Rantala (1998). A drawback of the probit setting is that it does not account for the dynamics of labour market behaviour, unlike the duration models adopted in two latter studies do.

In this study, the approach of Holm *et al.* (1998) and Rantala (1998) is followed, and their analysis is completed by applying semi-parametric duration models to a more recent source of data. The study begins, however, with an econometric analysis of the determinants of post-unemployment wages. Due

[1] The earnings prior to unemployment are occasionally incorporated into the replacement ratio, defined by the ratio of unemployment benefits to the prior earnings.

[2] In other words, the actual wage rate may remain below the expected level without the unemployment period, for several years after re-employment.

[3] Calculations for the disposable income of households took into account taxation, transfer payments, and other sources of household income.

to a more recent data and more precisely specified models, it is possible to address several new issues regarding the determination of post-unemployment wages that were beyond the scope of the earlier study of Kyyrä (1997). By modelling post-unemployment wages, we can also attach the estimate of the expected starting wage in the subsequent job directly to each sampled individual experiencing unemployment. This, in turn, enables us to account for incentive effects with a higher accuracy in the duration analysis than what was possible in Holm *et al.* (1998) and in Rantala (1998).[4]

The analysis is based on two sets of micro-data, both gathered by Statistic Finland. The first one was constructed by pooling together samples drawn from individuals flowing out of unemployment in 1988, 1990, 1992 and 1994. It is employed in studying the earnings of people leaving unemployment and the length of time they spend in unemployment. The second is a sample from the working age population, and it serves as a comparable source in the analysis of wage determination. The longitudinal information for both data was collected for the period 1987–94 by combining several administrative registers.

An exceptional feature of the data sets is the fact that they include detailed income statistics, not only for actual sampled individuals, but for their spouses as well. Since the data sets also contain information on transfer payments to households, the outflow data provides an opportunity to consider changes in disposable income, resulting from labour market transitions, with an accuracy that is exceptional in empirical work. With this data source, it is possible to overcome several limitations imposed by the quality and scope of the underlying data from which the previous studies have suffered.

It should also be stressed that the time period under investigation is an exceptional one in the Finnish economic history, containing a business cycle from the boom of the late 1980's to the deep recession of the early 1990's. This brings an interesting time dimension to the analysis.

In the first stage of our analysis, post-unemployment wages are studied by modelling the earnings of people who leave unemployment with the outflow data. For purposes of comparability, the determinants of earnings in a broader context are estimated from the data on the working age population.

[4] Although the underlying data is the same in Kyyrä (1997), in Holm *et al.* (1998) and in Rantala (1998), the estimation sample in Kyyrä (1997), from which the parameters of the post-unemployment wage model were borrowed, differs from those in two latter studies as a result of the different research agenda. In this study, the determinants of *both* starting wages *and* unemployment durations are analysed together, so that such differences will not arise, leading to more accurate starting wage estimates to be incorporated in the duration analysis.

The second stage involves evaluation of the returns to employment with the outflow data. The estimated earnings in the subsequent jobs are used to compute expected changes in the households' disposable income that would result from employment of the sampled individuals. The expected income changes serve as measures of economic incentives, and help us to evaluate the level and the extent of returns to employment among the unemployed. In the final stage, the impact of economic incentives on the probability of leaving unemployment is estimated by mapping the incentive variables into a competing risks model of unemployment duration.

The study is organised as follows. Chapter 2 takes a brief look at the theory of wage determination, with an emphasis on the human capital view. Chapter 3 introduces the data sets, and gives some descriptive figures. Chapter 4 discusses econometric problems associated with sample selection, and reports the results from estimation of the wage equations. Chapter 5 evaluates how the returns to employment are distributed among the unemployed, and Chapter 6 presents the estimation results from duration analysis. Chapter 7 concludes with a summary of the main findings, and suggests some topics for further work.

2 Theoretical Background of Wage Determination

The determination of wage structure is a complicated process that involves, among other things, wage bargaining, imperfect information and the matching of workers and jobs. Due to the complexity of wage determination, there is no generally accepted theoretical framework to approach it. Instead, there is a wide category of theoretical models which are used to describe the determination of wages. In this study, wage determination is considered from the individualistic point of view and hence workers' personal characteristics become emphasized. The theoretical framework is based on the human capital theory, the basic ideas of which are introduced in Section 2.1. Since the question of interest to us is principally the determinants of post-unemployment wages, the suitability of the human capital approach for that purpose is assessed as well. The alternative theoretical interpretations are briefly discussed in Section 2.2, and some further remarks are given in Section 2.3.

2.1 The Human Capital Theory

The revival of the concept in the late 50's was a response to the inadequacies of old growth theories. The human capital methodology developed rapidly in the 60's and early 70's, when Schultz (1961), Becker (1964, 1967), Ben-Porath (1967), and Mincer (1958, 1974) published their pioneering works. In the early context, the human capital theory was primarily used to study to what extent a rise in the average quality of the labour force over time could explain the observed residual in growth accounting that was left unexplained by old growth theories. Later it shifted attention to a major topic in labour economics, that of the determination of wage structure.

The term "human capital" refers to knowledge, ability, and other mental and physical characteristics affecting labour productivity. According to the human capital view, observed wage differentials are due to differences in human capital stocks across workers and over time. An important dimension to these differences is age differences in the stocks that are built up over a lifetime. Schooling and on-the-job training are viewed to be the most essential ways of accumulating human capital, while contributions from other activities, such as job mobility and health care, are supposed to play only a secondary role. In particular, both schooling and on-the-job training are interpreted as investment processes that create human capabilities, and therefore stimulate growth in labour productivity.

To illustrate the human capital approach more closely, I derive a simple wage function proposed by Mincer (1974), whose work was initiated by Ben-Porath's (1967) article on the production of human capital. Mincer's insights are chosen to be introduced here because his empirical specification of the wage function has become a benchmark in empirical work based on the human capital view. Since there is an extensive body of literature on Mincer's model, I will focus only on the "standard" version of the wage function in the following two sections.

2.1.1 A Theoretical Wage Function

First let us make a simplifying assumption that human capital is solely homogeneous in such a way that a given increase in the human capital stock will increase the individual's productivity by the same amount in all lines of work for all employers. Further, the labour market is supposed to operate under perfect competition and perfect information, so that the market wage is always equal to marginal labour productivity. As such, individuals with identical human capital stocks are equally paid in the labour market.

Mincer assumes that the individual has a given stock of human capital at the age of school entry. This initial stock of human capital, say y_0, is determined by exogenous factors, such as genotype and growth milieu, and it defines the individual's innate productivity. At the beginning, the individual devotes all her capacity to full-time schooling, i.e., to accumulating human capital. This is profitable because of the high rate of return and a long pay-off period. Each year of schooling increases the individual's human capital by a constant rate of return, r_s. When the individual completes schooling after s years and enters the labour force, her earnings capacity is[5]

$$y(s) = y_0 \exp\{r_s s\}. \tag{1}$$

If no further investments take place after the completion of schooling and human capital does not depreciate over time, the individual's life-cycle wage profile would be horizontal at the level of $y(s)$.

Instead, Mincer assumes that the individual continues to accumulate human capital after the labour force entry. These post-school investments in human capital consist of formal and informal on-the-job training. Rational allocation of resources for the post-school investments requires that such investments should decline over time. This is because later investments produce returns

[5] For simplicity, foregone earnings are assumed to be the only costs of schooling to the individual.

over a shorter payoff period, as the potential working life is getting shorter due to aging, and because the opportunity costs are greater at the later phase of the life cycle.

For simplicity, it is supposed that the fraction of the earnings capacity invested in on-the-job training declines linearly over time from the initial value of δ_0 at the beginning of the working life to a value of zero at the end.[6] Thus, denoting the length of individual's working life by K, the individual devotes the fraction of $\delta(k) = \delta_0 - (\delta_0/K)\,k$ of her earnings capacity to post-school investments, and hence leaves only the fraction of $1 - \delta(k)$ for work at working year k.[7] Then the potential earnings capacity after k years of work experience is

$$\begin{aligned} y(k,s) &= y(s)\exp\left\{r_k \int_0^k \left(\delta_0 - \frac{\delta_0}{K}u\right) du\right\} \\ &= y(s)\exp\left\{r_k\delta_0 k - \frac{r_k\delta_0}{2K}k^2\right\}, \end{aligned} \tag{2}$$

where r_k is the rate of return on post-school investments.

The individual is assumed to pay the costs of the post-school investments in the form of foregone earnings. Therefore, the market wage is obtained by subtracting the fraction of the earnings capacity used for post-school investments, $\delta(k)y(k,s)$, from the potential earnings capacity, $y(k,s)$. Using notations in (1) and (2), the individual's market wage function in the logarithmic form can be written as

$$\ln W = \ln\left([1-\delta(k)]\,y_0\right) + r_s s + r_k\delta_0 k - \frac{r_k\delta_0}{2K}k^2. \tag{3}$$

Suppose next that the individual loses her job after k years of work experience and is thrown into unemployment. What will be individual's starting wage in the subsequent job when she returns to work? Since the individual's market wage is merely determined by the initial human capital stock and investments in human capital, the unemployment spell in itself has no effect on the market wage unless the human capital stock has a property to depreciate during unemployment. If no further investments take place during the unemployment period, the prior and subsequent wage rates will be equal regardless

[6] Mincer (1974) considered also other possible forms for the time path of the post-school investments, but he did not find these to be preferable to the one described in the text.

[7] Note that the length of working life, K, is supposed to be independent from schooling years, s. As such, individuals with higher amounts of schooling are supposed to stay at work longer than their less-educated counterparts.

of potential differences in the work duties of two jobs. This is because the theory assumes that human capital is homogenous and the labour market is operating under perfect competition, without shortcomings in labour market information. Given these assumptions, the theoretical wage function in (3) would be an applicable tool to study post-unemployment wages as well.

However, it is well-documented that individuals with experiences of unemployment tend to suffer from earnings losses. To evaluate the extent of reduction in the wage rate, one might rewrite (2) for the potential earnings capacity after a spell of unemployment as

$$y(s,k,u) = y(s)\exp\left\{r_k\delta_0 k - \frac{r_k\delta_0}{2K}k^2\right\}u^{-\phi}, \tag{4}$$

where u is the duration of the unemployment spell, and ϕ is a measure of human capital depreciation during unemployment. Assuming that the path of post-school investments is not sensitive to experiences of unemployment, the starting wage function becomes

$$\ln W = \ln\left(\left[1-\delta(k)\right]y_0\right) + r_s s + r_k\delta_0 k - \frac{r_k\delta_0}{2K}k^2 - \phi\ln u. \tag{5}$$

When the unemployment duration, u, is mapped into the model in this way, one can see from (5) that ϕ is the wage elasticity of unemployment duration.[8] Of course, if the individual makes investments in human capital while unemployed, the wage function has to be modified so that these investments will also be accounted for.

2.1.2 The Econometric Specification

As an econometric specification to the theoretical wage function in (3), Mincer (1974) and numerous other authors after him have used

$$\ln W = \beta_0 + \beta_1 s + \beta_2 k + \beta_3 k^2 + \varepsilon, \tag{6}$$

where ε is the disturbance term with zero mean. The specification in (6) is occasionally interpreted as an approximation of the unknown functional form of the life-cycle earnings path, and its unknown parameters are most often estimated with ordinary least-squares (OLS). Comparison of (3) and (6) further implies that the schooling coefficient, β_1, provides a direct estimator

[8] Unemployment duration is added to the model on an *ad hoc* basis, but Blanchflower and Oswald (1995), among others, have argued that the logarithmic form is the adequate one to be added to log-linear wage equations.

for the rate of return to schooling, r_s, which is assumed to be constant in this specification.

Mincer's translation of the human capital theory into the operational empirical form includes, however, certain potential drawbacks. First, the initial stock of human capital, y_0, the rate of return to schooling, r_s, and the initial fraction of earnings capacity invested, δ_0, are treated as unobservable individual-specific constants, which may differ between individuals due to differences in ability, family background, etc. The effect of differences in these factors is captured by the disturbance term, ε. If these individual-specific factors are associated with schooling choices, their omission may generate correlation between the length of schooling and the disturbance term. Consequently, the OLS estimate of the rate of return to schooling may suffer from some bias.

Where unobserved individual-specific factors are concerned, the possibility of the economic return to schooling being affected by a positive correlation between schooling and ability is often recognized. In the background there is a presumption that ability has a positive impact on labour productivity and, hence, on the market wage. If individuals with higher ability choose higher levels of education on average, the years of schooling will be positively correlated with the disturbance term in the regression. One reason for this might be that high-ability individuals receive a higher benefit from a given amount of schooling, perhaps because they learn more rapidly or because they enjoy learning.[9] If so, the OLS estimate of the schooling effect will be upward-biased since the schooling variable captures a part of the omitted effect of ability. This potential bias in the estimates obtained with OLS is commonly referred as "ability bias."

A straightforward way to eliminate ability bias would be to add some measure of ability to the wage function. Unfortunately, the measures of ability are rarely available for the econometrician. Uusitalo's (1996) data makes the only exception from this rule among Finnish studies, since it includes the results of the Basic Ability Test (so called P-test) used by Finnish Defence Forces for a sample of male recruits. Uusitalo observed that mean scores in the P-test improve systematically with the educational level.[10] For instance, the mean

[9] The human capital model, however, does not naturally generate a positive correlation between ability differences and schooling. For example, if individuals with high ability are more productive at every level of schooling, they will have higher opportunity costs which in turn may lead them to leave school sooner. (Weiss, 1971.)

[10] Sampled individuals began their military service in 1970 when they also carried out the P-test. Educational attainments were obtained mainly after the military service period. The earnings to be regressed were collected from 1975, 1980, 1985 and 1990.

score in the mathematical part of the P-test for university graduates was almost twice as high as for those who have only completed comprehensive school. Inclusion of the P-test scores in the wage function reduced the OLS estimate of the rate of return to schooling by 17% (namely, from .087 to .072). Although the decrease is statistically significant, ability bias does not appear to be very large, [11] which is quite a common finding among empirical studies concerning earnings and ability differences.[12]

Yet, the estimates of schooling effects are likely to be less, or perhaps not at all, affected by omitted ability in modelling the starting wages of people who enter employment. This is because employers cannot directly observe ability differences between applicants when hiring new workers. So, the best they can do is to use observable characteristics, such as education and work experience, to draw inferences about unobservables.[13] The coefficient on schooling in the starting wage regression, however, fully captures the effects of that inference process. Even if some proxy measures of ability were available for the econometrician, the OLS estimate would not be affected by their inclusion in the wage function as long as employers do not have that kind of information available. Although employers could sort out job applicants only to the extent of observable characteristics, they are perhaps able to collect information about ability differences between their long-tenured workers through some monitoring period. If employers use this information to reward their more able workers, the problems caused by omitted ability will arise in modelling the earnings of long-tenured workers.

Overall, endogeneity of education may be a more serious problem than omitted ability. From the viewpoint of individual behaviour, the key assumption of human capital theory is the proposition that individuals choose to invest in human capital so as to maximize the present value of lifetime earnings. Although Mincer's derivation of the wage function is ostensibly based on this assumption, both the years of schooling and the time path of post-school investments are treated as exogenous variables in (6).

[11] It should be noted that the P-test is probably an unreliable indicator of ability for at least two reasons. First, there is no consensus on how ability should be defined or measured, so it is unclear to which extent the P-test measures "true" ability. Second, the P-test is used to select recruits for the different duties, so the interest of recruits whose attempt is to minimize their military-service time might be to carry out the P-test under their true skills.

[12] For a survey on the effects of ability, see Siebert (1990).

[13] In order to sort out applicants better-suited for an open vacancy, the employer can use the aptitude test which may contain a part for ability testing. The aptitude tests, however, are used mainly to look for managerial personnel who are rarely found from the unemployment register.

In the literature there are several attempts to circumvent the potential problem of the endogeneity of education. Lilja (1995) and Uusitalo (1996) have considered wage determination allowing for endogenous choice of education with Finnish data. In the first step, Lilja modelled the choice of the educational level, dependent upon family background, with the multinomial logit model using the Adult Education Study for 1990, collected by Statistic Finland. She used these estimates to correct selectivity bias, which potentially arise from the endogenous choice of education, in wage regressions. The wage functions were estimated separately for women and men at each educational level. She found statistically significant selectivity effects for women who have only completed comprehensive school and for men who have acquired an university degree, but any signs of selectivity bias for other groups didn't appear. Since Lilja considered principally the effects of family background on the wage rate and she estimated wage functions separately for each educational level, her results do not reveal the direction of these selectivity effects on the estimates of the return to schooling. Overall, Lilja's results are not very supportive of the endogeneity hypothesis.

Uusitalo controlled the problem of endogeneity by employing two different methods. In the first case, he created instruments for education using family background information and ability test results. The instrumental-variables (IV) estimate of the schooling impact was found to be twofold of that obtained with OLS. In the second case, Uusitalo estimated the ordered probit model for the choice of educational level, and used these estimates to construct the selectivity-correction terms that he then included in the wage function. This approach produced a 35% higher estimate of the return to schooling than the OLS method. To sum up, the selectivity caused by interdependence between schooling and the expected life-cycle earnings had a statistically significant impact on the results. In light of this, the schooling variable in the wage function should be treated as an endogenous regressor.[14]

At first sight, the problems discussed above bring into question the whole validity of Mincer's model as an empirical tool that makes it possible to apply OLS in studying wage determination. In practice, these problems are unlikely to invalidate the OLS estimates of schooling effects because biases arising from different sources tend to offset each other at least to some extent. The results from the studies in which several bias sources are controlled are badly mixed. For example, Ashenfelter and Krueger (1992), who considered ability bias and measurement errors in schooling variables, concluded,

[14] On the other hand, Uusitalo's study is in line with other corresponding studies in that the estimated schooling impact is quite sensitive to the method used in controlling endogeneity.

just like Uusitalo, that the OLS estimate is biased downwards. In contrast, the findings of Blackburn and Neumark (1993), in which ability bias, measurement errors and endogeneity bias were concerned, suggest that the OLS method ignoring unobserved ability produces an upward rather than downward biased estimate of economic return to schooling. Furthermore, a recent study of Ashenfelter and Zimmerman (1997), where biases arising from omitted variables and measurement errors in reported schooling are considered with sibling data, does not find notable overall bias in the OLS estimation at all.

Although the OLS estimation is subjected to several potential sources of bias, it is somewhat ambiguous to which direction, if any, overall bias pushes the estimate of the schooling impact. Indeed, the estimates of returns to schooling when several sources of bias are controlled for are often found to fall within the same range as unadjusted OLS estimates.[15] In this study, the standard approach based on Mincer's model, which omits ability differences and potential endogeneity of education, is adopted for a basis of the wage functions.[16] This is supported by hundreds of empirical studies based on Mincer's insights which have revealed considerable regularities in educational wage differentials and the life-cycle earnings path in spite of huge differences between societies studied and various time periods concerned. Based on these observations, Willis (1986, p. 526) pointed out in his survey: "As an empirical tool, the Mincer earnings function has been one of the great success stories of modern labour economics."

2.2 Critique of the Human Capital View

It has been argued that the human capital approach overstates the economic return to schooling because it assumes that increases in educational attainments systematically raise labour productivity. Two alternative explanations for the observed wage differentials across educational levels are briefly discussed in this section. The first one, the **signalling hypothesis**, which is also known as the screening or the filter hypothesis, forms a contrast to the human capital view since it completely rejects the productive value of education by arguing that the only role of education is to serve as a signal for

[15] It should be stressed that the alternative estimation methods to OLS are certainly not free from econometric problems. Indeed, the IV estimates and estimates from sibling and twin data sets are potentially affected by poor instruments, lack of representative samples, and increased problems of measurement errors.

[16] This is partly due to the lack of ability measures and family background information in the data available.

unobservable labour productivity. A less extreme aspect is offered by the **sorting hypothesis** which shares many views with both the human capital and signalling approach.

In Spence's (1974) well-known signalling model, workers are aware of their productivity which is exogenously given by nature, but employers are unable to observe that. Education does not increase productivity, but individuals who are innately more productive than others have a comparative advantage in obtaining education. Since education is observed in the form of diploma, it is a suitable characteristic to serve as a signal for unobservable labour productivity. Individuals take this into account when deciding how long to stay at school and employers use observed education to distinguish more able workers from less able ones when hiring workers.

Spence has explicitly shown how this kind of asymmetric information can produce an equilibrium in which education sorts out workers by their innate ability. As a result, better-educated workers can receive higher wages even if education has no effect on productivity. Spence has also proven that the signalling task of education is a sufficient condition to secure that individuals maximizing life-cycle earnings are willing to invest in education. The welfare effects of signalling activities are generally ambiguous. Signalling leads to a more efficient allocation of workers' labour by revealing information about unobserved productivity. On the other hand, innately more productive workers end up engaging in completely unproductive and costly schooling merely to distinguish themselves from their less able counterparts.

It is easily seen that the signalling hypothesis also treats education as a kind of investment. Educational investments, however, increase labour market information, not human capabilities, as the human capital theory tells us. The signalling hypothesis argues that innate productivity determines the educational level that will be chosen, whereas labour productivity is built up by educational investments over a lifetime in the human capital model.

As a less extreme view, the sorting hypothesis does not exclude the productive value of education since it assumes that education both increases productivity and serves as a signal of that. According to the sorting hypothesis, better-educated workers are not a random sample of workers, but they have lower propensities to be absent or sick, and to quit. Employers are unable to directly observe these unfavourable characteristics. Such characteristics, however, are associated with schooling for the same reasons as in the signalling model. So, employers can sort out workers by education in order to reduce their expected cost of sickness and job turnover. Individuals take this hiring criteria into account when making educational choices and signal their unobservable characteristics to employers. (Weiss, 1995.)

The sorting model can be viewed as an extension of the human capital model. It extends the human capital approach by allowing for some unobservable productivity differences to be correlated with the cost or benefits of education. Whereas the human capital theory primarily studies the role of learning in determining the return to education, the sorting model, while allowing for learning, analyses in which ways education serves as a signal of the productivity differences that employers cannot reward directly. (Weiss, 1995.)

Considering the earnings of people leaving unemployment from the viewpoint of the signalling hypothesis, one can draw the same (unrealistic) conclusion as in the context of the human capital model with no depreciation of human capital: periods of unemployment have no impact on the wage rate. This is because the unemployed can use education to signal their unobservable innate productivity to employers in the same manner as other workers. Consequently, the wage rate reflects worker's productivity regardless of his unemployment history. This conclusion could be drawn from the sorting model as well, if employers are allowed to take only education, not unemployment periods, into account when hiring workers.

It is also worth noting that the human capital, signalling and sorting model can all produce an identical correlation structure between education and wages. Unfortunately, there is no obvious way to differentiate empirically between these models. The difficulty in developing empirical methods to test direction of causation between education and labour productivity partly explains why empirical literature on the issue is relatively sparse. Although education undoubtedly affects labour productivity, the signalling role of education cannot be rejected without any danger. For instance, the findings of Bornmalm-Jardelöw (1988) in Sweden imply that there exists some degree of signalling, at least, at the highest levels of education. But since no empirical study has found the signalling effect to be a *major* factor in the demand for education, I will agree with Freeman's (1986, p. 362) statement: "Overall, while neither the studies focusing on screening/signalling nor those focusing on the direct productivity of education have yielded definitive results, the general tone of the findings is supportive of the human capital view."

2.3 Some Remarks

Workers with higher levels of education and more work experience tend to receive higher wages. Yet, it seems unlikely that accumulated human capital explains all the wage differences associated with schooling and work history.

Since other factors are likely to contribute to the wage profile as well, the significance of the human capital view depends on how much the observed wage profile can be attributed to human capital accumulation in a quantitative empirical sense. Although the signalling effect of schooling is undoubtedly a part of the world, a vast number of empirical studies indicate that accumulation of human capital is a major determinant of wage growth. In light of this, it seems plausible to adopt Mincer's model as a starting point for our empirical work. However, some of the conclusions derived earlier from Mincer's model may be misleading due to the strong assumptions on which the model is based. Therefore, let us briefly discuss the consequences of relaxing some of these assumptions in the context of post-unemployment wages.

As pointed out, one of the key assumptions underlying Mincer's model is that individuals acquire solely homogenous human capital. In order to relax this assumption, let us suppose that human capital can be divided into two categories: general and occupation-specific. General human capital is homogenous and includes skills valued by all employers. A particular occupation, however, requires particular skills, and these occupation-specific skills have to be acquired through on-the-job training (and learning-by-doing) in that particular occupation. Investments in schooling are supposed to increase general human capital, whereas post-school investments are factors in generating occupation-specific human capital. In addition, one should suppose that labour productivity is not directly observed by employers.

In the human capital model, where human capital is solely homogenous and the potential depreciation of human capital is disregarded, the unemployment spell has no impact on the market wage. Once occupation-specific human capital is introduced, one can draw a different conclusion. The assumption of heterogenous human capital suggests that the worker will lose, at least partly, that part of his productivity which was acquired through the post-school investments at the previous job, when he moves to a new job. The unemployment spell causes a reduction in the wage rate because it is not possible to completely utilize the productive value of work experience acquired prior to unemployment. The reduction is larger, the more different the work duties are at the prior and subsequent job. As such, the unemployed applicant should search primarily for jobs that demand the same kind of skills that the old job did. This is because his wage rate would collapse in another kind of job as a result of a huge reduction in labour productivity. In light of this, manpower programmes, such as training courses and job replacement periods provided by employment authorities, can be important ways to stimulate the re-employment process. With these programmes, the unemployed can extend their working skills, which in turn enables them to search for job opportunities from a wider sector of the labour market without a fear of huge earnings losses.

Although education is reliably documented by the diploma and hence capable to serve as a signal of the labour productivity that is built up at school, the unemployed applicant may have difficulties in signalling his occupation-specific working skills as they are rarely documented. If employers only use diplomas to draw inferences about labour productivity, wage offers to applicants with great amounts of occupation-specific skills may be systematically too low with respect to their true productivity.[17]

Moreover, the unemployed are not a random sample from the labour force, but workers with unfavourable characteristics are more likely to be out of work. It is quite possible that employers view experiences of unemployment as a signal of unfavourable characteristics that are not directly observable. If so, they may prefer job switchers and recently graduated applicants at the expense of the unemployed ones when hiring new workers.

All in all, the human capital model of wage determination is simplified in a host of ways. In the background, there is the fact that theoretical models in economics are always rough abstractions of reality. Theoretical models omit many obvious features of the world in order to provide insights about *particular* features of the world. The purpose of a theoretical model is not to be realistic but to offer an appropriate simplification of the world which itself is too complicated to understand. Consequently, a critical step in empirical work is the formulation of econometric models that are based on simplified theoretical models. This is because the parameters of the econometric models have to be estimated using real-world data which are affected by factors both considered and ignored by the theory. Only in cases where the effects of nuisance factors can be eliminated by experimental arrangements, can one disregard the factors that are not in the focus of the theory. Unfortunately, those kind of circumstances are rare in economics. Therefore, econometric wage functions in this study will contain a number of control variables to account for the disturbance effects of factors omitted by the theory.

[17] The difficulties associated with unobservables, however, are likely to diminish as the job spell increases in length as employers often have other ways to monitor and reward their long-tenured workers.

3 Descriptive Analysis

The aim of this chapter is to give a general view of the research agenda and the data sets to be used in the empirical analysis. Since individuals operating in the labour market have to make their choices within the macroeconomic framework, Section 3.1 gives a brief look at the Finnish economy at the time around the turn of the decade. Section 3.2 describes how the data sets were constructed and points out some advantages and limitations associated with the underlying administrative data. Section 3.3 gives some descriptive statistics for the most essential variables.

3.1 The Finnish Economy between 1987 and 1995

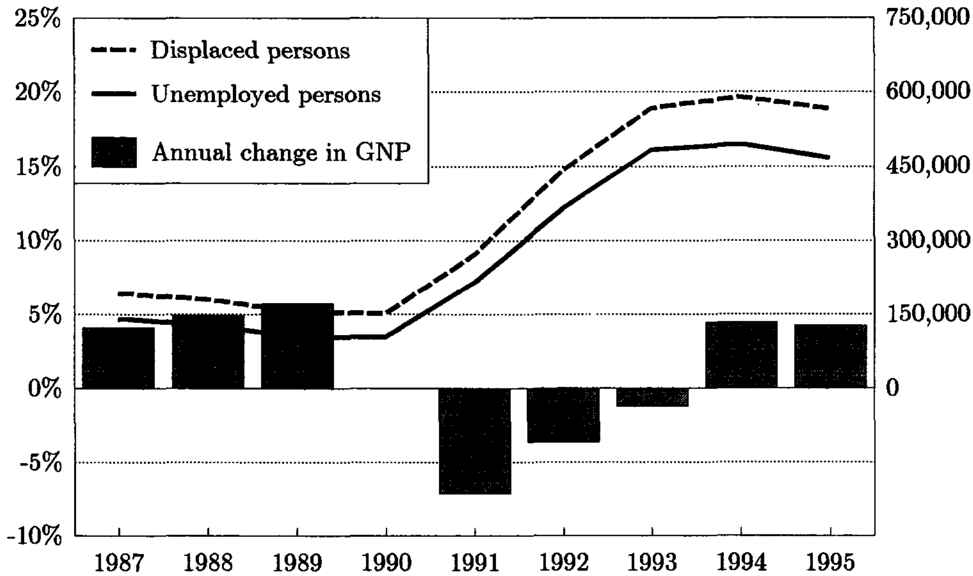
In order to consider labour market transitions and wage determination, it is convenient to take a brief look at changes in the macroeconomic environment to begin with. This is a relevant aspect especially for our case since the period under investigation is an exceptional one in Finnish economic history. The beginning of the 1980's in Finland was time of steady economic growth, but there was an overheating of the economy in the last years of the decade, and finally a collapse in the early 1990's.

There are several factors behind this development, although it is a somewhat open issue to which extent particular factors contributed to the outcome. It is believed that one of the major factors stimulating the boom was the liberalization of the monetary markets which took place in the mid-80's. This liberalization caused an expansion in bank credits and a huge rise in asset prices.[18] Annual growth of GNP was around 5% and the open unemployment rate within a range of 3 to 5%. Foreign indebtedness in the private sector increased rapidly due to the boom and essentially improved borrowing possibilities.

The collapse of the Soviet Union in 1991, with which the Finland's foreign trade was notable at that time, caused a negative demand shock. The deterioration of the economic environment in other western countries at the same time raised problems through Finland's dependence on foreign trade. Rapidly worsening economic conditions and foreign indebtedness in the private sector ran the hard-currency policy of the Bank of Finland into credibility problems. After a defending battle, the currency was devalued in 1991 and, finally, let float in 1992 as a result of continued speculative attacks. High interest rates

[18] For example, housing prices approximately doubled in the latter part of the 80's.

Figure 1: Unemployed and displaced persons and annual change in GNP in Finland, 1987–95. Note: Displaced workers are those either unemployed or in manpower programmes. Source: Statistical Yearbook of Finland 1996, Statistic Finland.



and falling asset prices caused a number of bankruptcies which in turn raised the credit losses of the banks. This caused a crisis in the Finnish banking sector and forced the government to fund the banks' credit losses with tens of billions marks in order to secure the reliability of the banking system.

The recession that hit the Finnish economy was exceptionally severe. The annual change in GNP was negative during the period 1991–93, and in the worst year of 1991 GNP decreased by over 7%. Large-scale job destruction took place in virtually every sector of the economy. The number of unemployed in 1994 was roughly fivefold of that at the end of the 1980's and the open unemployment rate reached almost 20%. This occurred even though masses of people were removed from the unemployment register and directed to manpower programmes. For example, almost 30,000 people were on training courses and over 65,000 people were employed by labour administrative measures in 1994.[19] Adding people on the manpower programmes to the figure of the unemployed indicates that some 590,000 people — almost the one-fourth of the entire labour force — were displaced from the open labour market in 1994. Although the economy turned onto the strong growth path

[19] The figures are monthly averages from the Statistical Yearbook of Finland 1996.

in 1994, aggregate unemployment has remained tenaciously at high levels.

3.2 Data Sets

The empirical analysis is based on two sets of micro-data, both housed at the Government Institute for Economic Research. The first one was constructed by pooling together samples drawn from the outflows of unemployment at four different points in time. It is employed in studying the earnings of people who leave unemployment and factors contributing to the exit probability of unemployment. The second is a sample from the working age population and it serves as a comparable source in the analysis of wage determination.

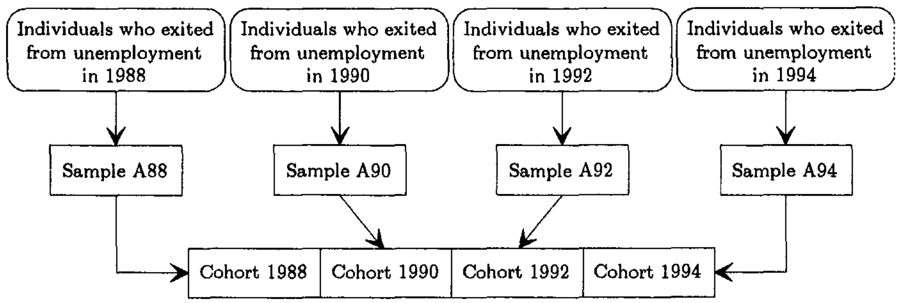
The construction of the outflow data involved two steps as illustrated in Figure 2. The first step was to draw four samples from individuals who left the unemployment register in 1988, 1990, 1992 and 1994.[20] These samples were then processed to yield a cross-sectional data in which each cross-section matches the outflow sample of that year. As a result, sampled individuals in the pooled data are in symmetric position with respect to the sampling criteria in the sense that each individual in the cross-section has a completed spell of unemployment in that year. The unemployment spell may end at a new job, at a manpower programme or at withdrawal from the labour force. In what follows, the data contain observations on people who entered employment, on those who left the labour force and on those whose unemployment discontinued only temporarily due to participation in a manpower programme.

It should be stressed that the macroeconomic circumstances at the times of the cohorts sampled were very different. In fact, the time period under investigation contains an entire business cycle from the boom of the late 1980's to the deep recession of the early 1990's. This brings an interesting time dimension to the analysis.

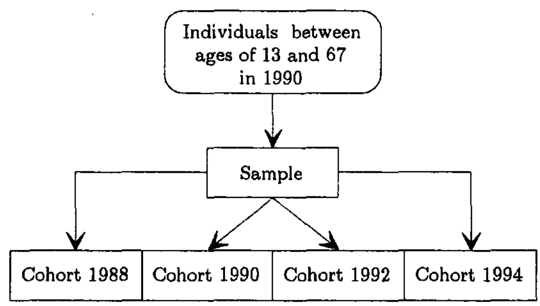
For purposes of comparability, another data set was drawn from the entire Finnish population between ages of 13 and 67 in 1990. In order to produce a cross-sectional setting similar to that of the pooled outflow data, the data was split randomly to match the sampling years of the first data (see Figure 2). The data was further restricted to cover only salary earners employed throughout the whole year. The aim of this source is to represent workers in the labour market in general and, hence, to help us distinguish factors con-

[20] Sampling intervals for systematic sampling were selected so that the size of each sample fell within a range of 5,000 to 6,000 observations. In practice, this implies that the sampling interval for Samples A88 and A90 was only half of that for two other samples.

Figure 2: Sampling of data sets



The Data from Outflows of Unemployment



The Data from the Working Age Population

tributing to wages in general from those associated with post-unemployment wages only.

For both data sets, the same set of variables for the period 1987–94 were gathered by combining administrative registers. The main source of information was the Longitudinal Worker Database of Statistics Finland.[21] The data sets were further complemented by access to the unemployment records of the Ministry of Labour from which detailed information for those registered as unemployed were collected. On the whole, there is a total of some 150 variables in the data sets, including variables for income levels, taxes paid, unemployment spells, and household composition.

The pooled outflow data initially contained over 20,000 observations, but it

[21] The Longitudinal Worker Database (Työssäkäyntirekisteri) combines information from 22 registers, including Population Census of the Finnish Bureau of Census, Tax Records of the Finnish IRS, Employment Registers of the Central Pension Security Institute (ETK), the Municipal (Kunnallinen Eläkevakuutus) and Government Pension Institute (Valtiokonttori), and the registers of the Social Insurance Institution (KELA).

shrank to cover a total of 14,438 observations due to missing and incomplete information on crucial variables. Workers temporary laid-off were also excluded because their subsequent wages are fixed by old jobs and their behaviour when unemployed is not of interest. The sample size of the data on the working age population was reduced from about 12,000 to 4,628 observations when it was restricted to cover only salary earners employed throughout the whole year, and observations with missing and incomplete information were excluded.

In the discussion that follows, I often speak of "starting wages," having post-unemployment wages of those exiting to employment in the outflow data in mind. The wage rate is the starting rate in the sense that attention is restricted throughout to wage rates received by workers just after entry to employment. Likewise, "general wages" is commonly used to refer to wages of sampled individuals in the data on the working age population.

Although the data sets are of the panel form, they are processed to the cross-sectional form, as described above. The cross-sectional approach is adopted because I am interested in starting wages in the first place, not in evaluating post-unemployment wages over time. It is also reasonable to suspect that the probability of becoming employed is attributed to what one expects to can earn by working. This calls for a need to control for selection bias in the regression analysis of starting wages, which would be very difficult within a panel framework.[22] Of course, the panel aspect of the data is heavily exploited in constructing necessary variables, as well as in detecting the labour market transitions of sampled individuals.

Some data limitations are worth noting. First of all, income statistics from tax authorities are rich but on an annual basis, resulting an inaccuracy in income variables that have to be converted to a monthly basis. In addition, the administrative registers contain only limited information about job durations and job attributes, suppressing from the analysis some particular features of wage formation. On the other hand, an advantage of the register-based data is its freedom from response bias and problems caused by untruthful answers that could be expected to arise in interview data, especially when economic incentives of the unemployed are studied. An exceptional feature of the data sets is the fact that they include detailed income statistics not only for actual sampled individuals, but for their spouses as well.[23] Since the data sets also

[22] In addition, the existence of multiple job losses would complicate the separation of wage rates associated with different jobs as the income statistics available are on an annual basis, making a panel study even more difficult.

[23] Yet, income and tax statistics for spouses are not available prior to 1990.

contain information, though limited, on transfer payments to households, the outflow data provides an opportunity to consider changes in disposable income associated with labour market transitions with an accuracy that is exceptional in empirical work.

Yet, a potential problem of the outflow data is that the long-term unemployed may be undersampled because the samples were drawn from individuals *leaving* unemployment. Indeed, the sampling frame excludes people who were continuously unemployed throughout the sampling years. On the other hand, job replacement programmes are outlined to cut long-duration spells of unemployment regularly, and the long-term unemployed exiting to employment were weighted in the sampling.[24] In these circumstances, sampling from the outflows of unemployment is likely to produce results similar to those the inflow sampling would produce.[25] Whether this is the case or not, it is important to bear in mind the sampling frame of the outflow data when interpreting the results.

Despite these few problems, I feel that these data sets are the richest available given their information content and our wide research agenda, that includes considerations of wage determination, labour market transitions and income changes associated with such transitions.

3.3 Some Descriptive Statistics

Since econometric models of the study will contain a vast number of variables, it is not reasonable to describe all of them at length. Therefore only some of the most essential variables are described below, whereas other variables are discussed in the context of the estimation results.

3.3.1 Education

Information on education was obtained from the Register of Completed Education and Degree.[26] In the register, educational qualifications above the

[24] Individuals whose unemployment spell was lasted for one year or more prior to exit to employment had four times higher weights in the sampling.

[25] Of course, sampling from the population flowing into and out of unemployment at a given point in time yield observations on unemployment spells that occur in different *calendar* time. As a result, samples drawn from the outflow and inflow at the same point in time represent different points in a business cycle.

[26] That is, Statistic Finland have collected educational information from the Register of Completed Education and Degree to be incorporated into the Longitudial Worker

basic level comprise all educational programmes lasting at least 400 hours and which are provided in the system of regular school and university education. The unit for classification is the educational programme group which consists of the level and field of education. The classification is based on the *highest* level of completed education. If a person has completed several educational degrees at the same level, the latest one is preferred for the classification. The level is a function of the duration of schooling. There is a total of eight level categories in the register, but the following six are used for our purposes:[27]

1) *Basic education* (9 years or less)
   - basic school, comprehensive school
   - forms the minimum level of education due to its compulsiveness
2) *High school education* (12 years)
   - no other completed degree than passed matriculation examination
3) *Lower vocational education* (10 to 11 years)
   - e.g., clerk, basic nurse
4) *Upper vocational education* (12 years)
   - e.g., commercial college graduate, nurse, artisan
5) *Undergraduate education* (13 to 15 years)
   - e.g., technician, HSO secretary, specialist nurse, engineer
6) *Graduate education* (16 years or more)
   - includes also postgraduate education
   - e.g., Master in Political Science, Doctor of Political Science

Education was measured by the years of schooling in the context of the human capital theory, but the register available provides information on the highest level of education completed by each individual. This information, however, can be converted into the years of schooling by using the mean years of schooling attached to the different levels of education. On the other hand, the use of the years of schooling in the theoretical considerations was based on the assumptions that the rate of return to schooling is constant

Database.

[27] The Register of Completed Education and Degree consists of the following educational levels: (i) lower level of basic education, (ii) upper level of basic education, (iii) lower level of upper secondary education, (iv) upper level of upper secondary education, (v) lowest level of higher education, (vi) undergraduate level of higher education, (vii) graduate level of higher education, and (viii) postgraduate or equivalent education (for details, see Handbook No. 1, Statistic Finland). For this study, I have combined levels (i) and (ii) to level 1. Level (iii) is equivalent to level 3, whereas level (iv) is split into levels 2 and 4. Furthermore, levels (v) and (vi) are combined to level 5, and levels (vii) and (viii) to level 6.

Table 1: Educational attainments of sample members

% of members in the data from outflows of unemployment	Cohort 1988	1990	1992	1994
Basic education	37.6	37.8	34.4	30.7
High school education	8.1	8.6	10.1	8.3
Vocational education				
Lower level	39.8	38.1	34.7	35.1
Upper level	10.5	10.9	13.4	15.9
Higher education				
Undergraduate level	2.5	3.2	5.4	7.5
Graduate level	1.5	1.4	2.0	2.5
% of members in the data on the working age population				
Basic education	36.4	34.5	28.9	27.9
High school education	4.7	4.9	4.7	4.1
Vocational education				
Lower level	30.7	30.6	31.1	30.1
Upper level	15.4	16.9	19.3	18.4
Higher education				
Undergraduate level	7.1	7.4	9.5	12.4
Graduate level	5.7	5.7	6.9	7.1

and human capital is totally homogenous. However, the schooling system in reality consists of a number of educational establishments in which the objects and quality of teaching varies. Therefore the qualitative classification for education may, in fact, capture the existing heterogenous in education better.

Table 1 shows how education is actually dispersed among sampled individuals. As expected, people with experiences of unemployment are poorly educated on average. It is interesting to note that the distribution of education in the data sets changes similarly over the period under investigation. The share of workers who have completed only the basic level shrinks with time, whereas the share of workers with higher education increases. In contrast, high school graduates and those with vocational education remain stable in their relative positions over the period.

In the outflow data, only 4% of sampled individuals in the 1988 cohort have a degree from the higher level of education, while the share is as high as 10%

for the 1994 cohort. This increase is notably larger than the corresponding increase in the share of people with higher education in the other data set, indicating that unemployment also became a problem for better-educated people during the recession. It should be stressed, however, that the unemployment rate among people with higher education has remained below 10% also in the recession years, while almost one-fourth of those having completed only the basic level were registered as unemployed in 1994 (Statistic Finland [66]). In light of this, one can say that less-educated persons have suffered most heavily from the deterioration of economic environment.[28]

3.3.2 Wage Differentials

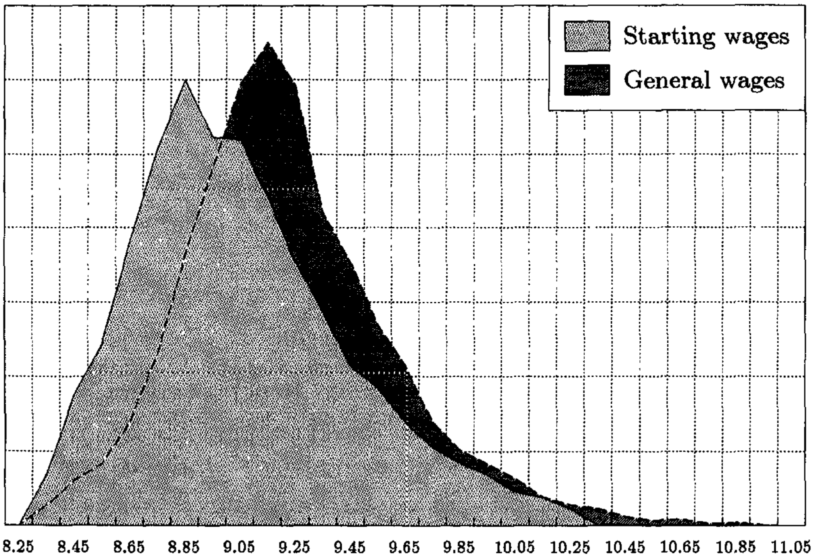
The income statistics come from tax records which contain income information on an annual basis. Monthly wages are computed by dividing annual salaries by the months worked. This, of course, produces some additional variation in the wage variables. Since information on hours worked is not available, wages and earnings are used interchangeably in the text. One should keep this fact in mind throughout the study.

Computing monthly wages from the annual income statistics induces some further problems. In the context of starting wages, there are difficulties in differentiating between distinct wage rates in the case where a worker who found a new job has been employed previously in the same year. When this separation problem appears, the first attempt to separate different wage rates involves the use of longitudinal information on earnings over the consecutive years. If this procedure fails and the separation problem results from a job replacement period in the same year, the mean salaries of local government workers are used as estimates for the wage rate associated with the job replacement period.[29] This is because the major part of job replacement programmes are placed under local governments. In some cases there is no way to circumvent this separation problem in a straightforward manner. These observations (there are only a few) are investigated case by case, and two wage quotas are differentiated as well as possible.

[28] In addition, the trend during the recession has been toward entering employment at older ages. The employed persons are older on average and the creation of jobs for the youth has been too slow to compensate for this trend. The number of jobs in the labour market has declined most among people aged under 25, raising difficulties in job search, especially, among the recently graduated youth who still found work rather easily at the end of the 1980's. (Statistic Finland [67].)

[29] Strictly speaking, a given proportion of the mean salaries associated with different levels of education by gender are used.

Figure 3: Wage distributions. Notes: Logarithmic scale. Monthly wages converted into 1994 money by Earnings Index, computed by Statistics Finland.



Due to some inaccuracies in the administrative registers and a lack of information on working time, there are some observations with an extremely low or high monthly wage in the data. Therefore, those whose wage rate is below 80% of the lowest salary grade of the central government, as well as those with an extremely high wage, are excluded from further considerations.[30]

The distributions of log earnings are plotted in Figure 3. The shape of the general wage distribution is close to log-normal, but starting wages are more concentrated at the lower rates, producing skewness in the distribution.[31] One reasonable explanation for the difference in the distributions is that job tenure is pushing earnings toward higher rates in the long run. The thickness of the right-hand tail of the starting wage distribution suggests the possibility that several applicants have found rather well-paid jobs. However, this is partly due to measurement errors in starting wages which result from the fact that annual earnings have to be converted into monthly wages, while job durations are known only with an accuracy of one month.[32]

[30] A total of 745 observations are dropped out by this criterion.

[31] Parjanne (1997) has reported similar differences in hourly wages between new jobs and other jobs.

[32] It should be stressed that the measurement errors do not disturb the consideration of general wages as the data drawn from the working age population is restricted to cover

Figure 4: Median wages by gender and education. Note: Monthly wages converted into 1994 money by Earnings Index, computed by Statistics Finland.

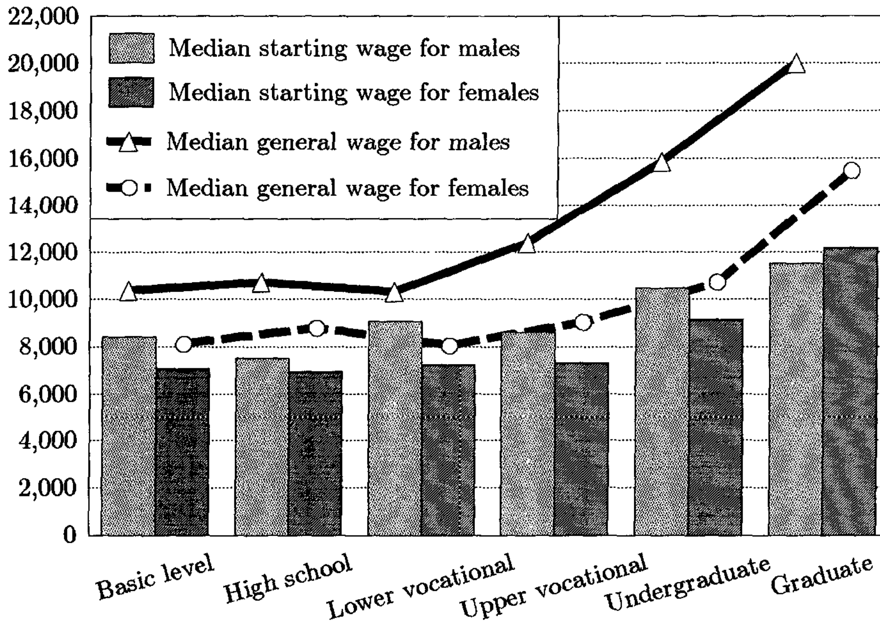


Figure 4 shows median wages by gender and educational level.[33] Only moderate differentials in starting wages between educational levels exist. It appears, though not surprisingly, that applicants with an undergraduate or graduate degree tend to get better paid jobs. High school graduates have to be content with the lowest starting wages, which makes sense as the nature of high school education is purely liberal-art and it does not graduate to any profession.[34] On the other hand, a large part of those who pass the matriculation exam in the spring continue schooling in some vocational or academic establishment in the autumn. These youth occasionally register as unemployed job seekers in order to find a summer job or, perhaps, just to receive unemployment benefits over the summer months. As such, their incentives to accept employment at a given starting wage may differ notably from those faced by other applicants. This calls for a need to treat high school graduates as a special group in the analysis.

only those employed throughout the whole year.

[33] There are only limited number of observations on individuals at the highest levels of education. The use of medians minimizes the impacts of outliers on the average wages.

[34] The nature of high school education is the major reason why high school graduates are separated from those with the upper level of vocational education.

The picture in general wages is quite similar, although the average level of general wages is above that of starting wages at every level of education. In addition, high school graduates do not suffer from earnings disadvantage over workers with basic or lower vocational education. Unlike in the case of starting wages, workers with a degree from the upper level of vocational education also earn more than those with lower levels of education. It appears that the difference between the average levels of general and starting wages is larger the higher the educational level is. This perhaps implies that a continuous work career produces a higher premium at higher levels of education, indicating better possibilities to get promoted.

There are no notable male-female differences in starting wages among high school graduates and persons with a degree from the graduate level of education. In contrast, women are clearly less well-paid at the basic and vocational levels of education. One explanation for this might be that less-educated women are often placed in low-paid service occupations, while men can receive rather high starting wages from the manufacturing sector even without proper education. In general wages a gender gap exists in favour of men at each level of education and the gap is deeper the higher the educational level is.

It should be stressed that the distribution of individual characteristics in the population flowing out of unemployment differs from that in the population of the employed. Important differences in these distributions are likely to lead to differences in the observed wage distributions as well. As such, the simple cross-tabulations of earnings against certain variables may be quite misleading in some cases.

In addition to individual heterogeneity, the *hedonic* wage analysis points out another potential source of heterogeneity that is likely to produce differences in the wage distributions. The focus in the hedonic wage literature is not on the individual's skills or attributes, but rather on the attributes of jobs. According to this view, wages are attached to jobs, not to the individuals who hold them.[35] This suggests the possibility that job attributes can be important explanatory variables along with human capital measures. If so,

[35] As a concrete example, consider earnings in construction and health care, of which construction is known to be more procyclic. Lay-offs are not high in construction because individuals in this industry were more unwilling to work, but rather the lay-off rates are high as a result of highly fluctuating demand conditions, specific to this industry. That is, the lay-off pattern is attached to the job, not to the individual who holds it. In contrast to the human capital view, the hedonic wage literature supposes that the higher wages in construction are likely to arise because the jobs there are risky, not because workers who hold them are more able. (Lazear, 1992.)

the differences in the wage distributions are likely to be related with the different attributes of jobs held by two different populations.

To highlight this point, note that hiring into some jobs is more likely than hiring into others. If firm-specific human capital is important, then individuals will be hired into low-level jobs and very few will be hired into the higher-level jobs. For example, very little hiring occurs at upper levels of management as most individuals entering such jobs are promoted within the firms. This kind of reasoning suggests that the attributes of the jobs which people enter from the unemployment register must significantly differ from the attributes of jobs in the labour market in general. Thus, one could expect that the observed differences in the wage distributions are associated with differences in job attributes as well.

In light of the above discussion, one should not make any concluding remarks about relations between wages, education and gender, because the observations here are likely to be affected by omitted background factors whose indirect effects are not observed from the graphs.

3.3.3 Flows Into and Out of Unemployment

The Ministry of Labour keeps records on the actions of the registered job applicants. Its records contain information about unemployment spells, periods in manpower programmes and individual characteristics, such as professional competence and ability to work. Using this information and other figures from the Longitudinal Worker Database of Statistic Finland, labour market experiences are detected for sampled individuals in the outflow data.

It is worth noting that I am using a somewhat weaker definition for the unemployment spell than that used by the Ministry of Labour. That is, consecutive spells of unemployment are combined into one spell if they are separated by less than three weeks.[36] This is due to the obvious reason that it would be inappropriate for our purposes to interpret a couple days break in unemployment as a labour market transition.

Recall that to be included in the outflow data, a person must have a terminated spell of unemployment in some of the outflow years. This leads one

[36] To be specific, two consecutive spells of unemployment are combined if the difference between one's ending date and another's beginning date is less than 20 days. The duration of the combinated spell is defined as the sum of durations of single spells and the break between these spells. For example, if an individual's unemployment is interrupted for a week because of a short working period, this break between two unemployment spells is omitted due to its shortness.

Table 2: Flows into and out of unemployment in the outflow data

	Cohort			
% of sample members enter unemployment from:	1988	1990	1992	1994
Employment	50.1	61.9	56.2	44.9
Training course	2.9	3.7	4.2	7.8
Job replacement programme	9.3	10.4	13.6	17.2
Outside the labour force	14.8	18.6	20.9	20.9
Unknown destination	22.9	5.4	5.2	9.3
% of sample members end unemployment at:				
Employment	70.4	64.2	33.9	32.3
Training course	6.2	7.7	9.9	10.4
Job replacement programme	3.1	6.0	30.1	31.5
Outside the labour force	20.4	22.1	26.2	25.8
Mean spell duration (in days)	145	100	199	303

to ask what was the cause of termination. Another question that naturally arises is the cause of becoming unemployed. To address these questions, Table 2 reports statistics on the flows into and out of unemployment, as proportions of sample members entering and leaving unemployment through different channels.[37]

The flow from outside the labour force into unemployment has strengthened a little bit over the period, while the share of those entering from the manpower programmes has doubled from 12% to 25%. A trend has been towards leaving unemployment into the manpower programmes at the expense of employment.[38] For example, applicants terminated their unemployment spells by exiting to job replacement programmes ten times more frequently in the 1992 and 1994 cohorts than in the 1988 cohort.[39] These figures are a reflec-

[37] Those whose post-unemployment labour market status was left unsolved are excluded from the data. A total of 1,024 observations were dropped out by this criterion.

[38] A large share of unknown cases in the 1988 cohort is explained by the fact that information about the prior labour market status is very limited if the unemployment spell began in 1986 or earlier. This is because the period for which complete information is available covers only the years 1987–94. However, a brief comparison of the entry shares between the cohorts suggests that most of the unknown-classified individuals were probably in work prior to unemployment in the 1988 cohort.

[39] Overall, 35,673 persons were employed by labour administrative measures on average in 1988, whereas the corresponding figures are 52,089 and 66,408 for 1992 and 1994,

tion of the active labour market policy that has involved an increasing path of sources to be allocated for manpower programmes during the recession. Further, it appears that the exit rate to employment has collapsed from some 70% to slightly over 30% in the period under investigation.[40] The growth in the mean duration of unemployment spells reflects that unemployment has turned into a somewhat semi-permanent state for a number of people during the recession.

respectively (monthly averages, Statistical Yearbook of Finland 1996, p. 345, Statistic Finland).

[40] In addition, the proportion of temporary and part-time jobs among new jobs has increased notably in the recession years (Parjanne, 1997).

4 Empirical Application for Wages

The parameters of log-linear wage equations are usually estimated with OLS for cross-sectional data. In the context of post-unemployment earnings, there is, however, potential for the presence of sample selection which in turn may bias the estimated effects of explanatory variables. Section 4.1 therefore begins by discussing econometric problems associated with sample selection, and introduces a selection model that helps us to overcome these obstacles in modelling starting wages. Section 4.2 gives a short description of the previous evidence on earnings differentials. Section 4.3 represents the results from estimation of wage equations.

4.1 Modelling Starting Wages

Common sense tells us that the effort an applicant puts into job search must bear some relation to what he can expect to earn by working. The harder the applicant looks for jobs, the more likely he is to get one and, hence, more likely his subsequent wage is to be observed. In addition, workers highly valued by employers may not only find higher wage offers, but they are also more likely to receive such offers. This kind of argumentation leads one to doubt whether the starting wage in the subsequent job and the probability of observing that wage are associated. If so, the OLS estimation of the earnings of people leaving unemployment will be inconsistent due to sample selection. The resulting bias in the estimates obtained with OLS is known as "selection bias." The best way to understand the implications of sample selection is to examine a simple model that is capable of producing bias in the OLS estimation in some detail. This is done in Section 4.1.1. The explicit model of starting wages on which the empirical work of the study will be based is formulated in Section 4.1.2.

4.1.1 Selection Bias in a Model of Sample Selection

As a concrete example, suppose that one likes to estimate how much an additional year of schooling increases the expected value of worker's earnings in the subsequent job. To address this question, one wishes to apply OLS for a random sample of entrants into unemployment. Each worker in the sample is followed over some period. Schooling information is available for all sample members, but one observes earnings in the subsequent job only for those who get hired by the end of the observation period.

It is convenient to think of a wage offer as the employer's estimate of labour productivity, so the wage offer corresponds to what is called the worker's market wage (with a random error) in the human capital theory. Suppose that applicants are willing to accept employment whenever a wage offer is received. The probability of being offered an open vacancy is a function of schooling and unobservable search intensity, called "motivation." Those who are more motivated do not only receive wage offers with a higher probability, but also find higher wage offers on average. So, the same unobservable factor contributes to both the probability of becoming employed *and* the subsequent wage. In what follows, selection into the observed sample is not random with respect to the variable of interest.

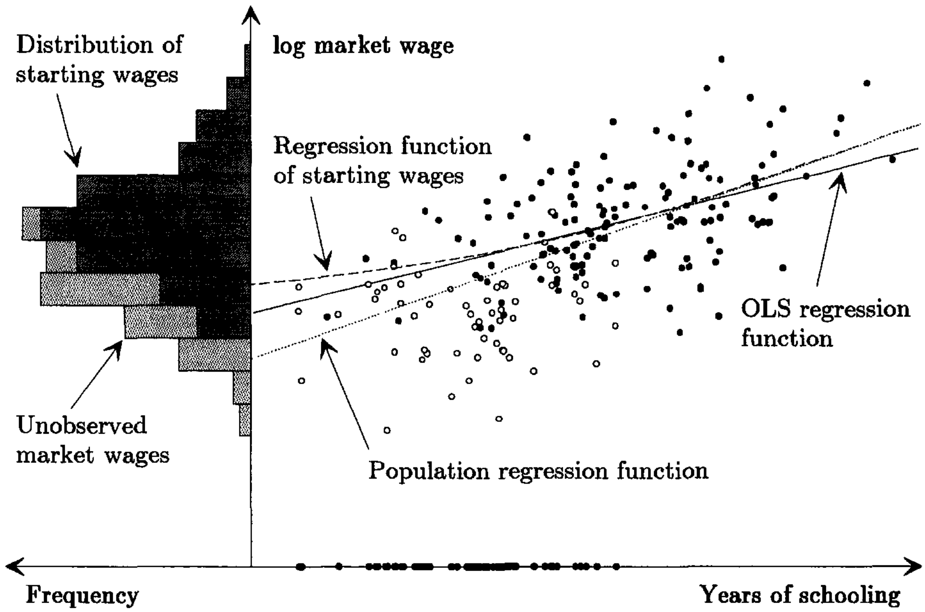
The story is illustrated in Figure 5 with a simulated data.[41] Each filled dot represents an observation on a starting wage and schooling of a worker who was hired during the observation period. Each empty dot shows the combination of a market wage and schooling of a worker who failed to get a job. Since the market wage is not realized in the form of a starting wage for applicants who remain unemployed, only the projections of empty dots to the horizontal axis are observed for them. In sum, the filled dots represent observed and empty dots unobserved characteristics of sample members. The market wage (or wage offer) is a *latent* variable. It is not directly observable but has an observable realization: the starting wage. In contrast to schooling that is observed for all sample members, the market wage is observed only for those who entered employment in the observation period. Observations on those who failed to get jobs are said to be *censored.*

A straightforward procedure would be to omit sample members who failed to get jobs and use OLS for the subsample of entrants into employment. Unfortunately, the interdependence between the probability of selection into the estimation sample and the dependent variable in the regression makes the OLS method inappropriate. The population regression function in Figure 5 depicts the relation between the market wage and schooling that one wishes to estimate.[42] The OLS regression function, obtained by regressing starting wages (i.e., observed market wages) on the intercept and schooling, is too flat

[41] The data in the figure were generated in two stages. First, a random sample of 200 observations on the log market wage and years of schooling was drawn from a bivariate normal distribution. Interpreting schooling as an exogenous variable yields a log-linear wage function for the market wage with a normal error term. At the second stage, a probit model, with the intercept and years of schooling as regressors was used, to determine who in the sample get jobs and who don't. In order to produce selection bias, the correlation between the error terms of the market wage and probit equation was assumed to be .60.

[42] The relation is the "population" regression function in the sense that it was used to generate the observations in the figure.

Figure 5: Selection bias in a simple model of sample selection



and produces a downward biased estimate of the return to schooling.[43] This is because the process of sample selection that is not random with respect to the underlying market wage destroys the linearity assumption. Indeed, the true regression function is non-linear as shown in the figure,[44] causing bias in the estimates obtained with OLS.

Another way of catching sight of the problem involves looking at the distributions that are projected on the vertical axis of the figure. The distribution of market wages is censored as only a part of it is observed in the form of starting wages. Since market wages at the upper tail of the distribution are observed more likely, starting wages do not serve as a representative sample

[43] The slope of the OLS regression function is .11, while the "unknown" value of interest is .15.

[44] To be specific, I supposed that for a worker with s years of schooling, the log market wage $w \sim N(\alpha + \beta s, \sigma_w^2)$ and the probability of finding a wage offer is $\Phi(\delta_0 + \delta_1 s)$. Then the regression function of starting wages is given by

$$E(w\,|w \text{ observed}) = \alpha + \beta s + \rho\sigma_w \frac{\phi(\delta_0 + \delta_1 s)}{\Phi(\delta_0 + \delta_1 s)},$$

where β (=.15) is the rate of return to schooling, ρ (=.60) is the correlation between the residuals in the wage and probit equation, $\phi(\delta_0 + \delta_1 s)$ and $\Phi(\delta_0 + \delta_1 s)$ is the density and distributional function of the standard normal variable evaluated at $\delta_0 + \delta_1 s$, respectevily.

from the underlying distribution of the variable of interest. Ignoring this will lead to biased inference.

The bias in the estimates obtained with OLS is assumed to arise because of the omission of motivation as an explanatory variable common to the wage equation and probability of finding a wage offer. Such a bias can arise from other sources as well. For example, consider an alternative model of the reservation wage in which each applicant is willing to accept a wage offer above the reservation wage, but wage offers below are rejected.[45] Consequently, the selection probability will be positively attributed to the random perturbation in wage offers even if applicants receive wage offers with a constant probability from the labour market. This is because only the wage offers *below* the reservation level are rejected. As such, the reservation wage can produce positive dependence between the observed earnings and probability of becoming employed in the same manner.

In the presence of sample selection, one must first determine a statistical model which can generate the observed data in order to obtain the consistent estimates of unknown parameters. The next section makes an attempt in that direction.

4.1.2 The Censored Regressor Model for Starting Wages

The sampling from the population flowing out of unemployment indicates that each sampled individual in the cross-section has a completed spell of unemployment in that year. A number of those who leave the unemployment register do not, however, enter employment. Some take part in training courses, some in job replacement programmes, and some leave the labour force. This outcome is described with a latent regression model, defined as

$$y^* = z'\delta + \eta, \tag{7}$$

where z is a vector of exogenous regressors, δ is a vector of unknown parameters, and η is the unobservable disturbance term with zero mean. The dependent variable, y^*, is defined so that it is greater than zero if and only if the unemployment spell ends at employment, and zero or negative otherwise. The variable y^* is unobservable but has an observable dichotomous

[45] When the reservation wage is common for all workers, one will observe the wage distribution that is truncated at the reservation level. In the case where the reservation wage varies from individual to individual, the picture might be similar to that in Figure 5.

realization

$$d = 1\{z'\delta + \eta > 0\}, \tag{8}$$

where $1\{A\}$ is the indicator function of the proposition A, taking a value of unity if A is true, and a value of zero otherwise. In words, the variable d tells us whether the individual terminates his unemployment spell by exit to employment or to some other destination.

Denoting the individual's log market wage by w^*, a log-linear wage function, consistent with the human capital theory, can be written as

$$w^* = x'\beta + \varepsilon, \tag{9}$$

where x is a vector of exogenous regressors, including those derived from the human capital theory, β is a vector of unknown parameters, and ε is the unobservable disturbance term with zero mean. Since the market wage, w^*, is a latent variable that is realized in the form of the starting wage only for those who get jobs, one observes

$$w = d\,[x'\beta + \varepsilon] \tag{10}$$

instead of w^*.

Writing the conditional mean of w given x and z with $d = 1$ yields the regression function for the available data:

$$E(w\,|x, z, d = 1) = x'\beta + E(\varepsilon\,|x, z, d = 1), \tag{11}$$

which depends, in general, on both x and z. However, if the conditional expectation of ε is zero, the regression function in (11) will be the same as the regression function based on unobservable market wages in (9). In that case, one could apply OLS to obtain consistent estimates of β from the subsample of those who enter employment. Then the only cost of observing wages only for this subsample would be a loss in efficiency as the sample size available for estimation decreases by the number of those who fail to get jobs.

The conditional expectation of ε would be zero if the disturbance terms were independently distributed. As pointed out earlier, there are good reasons to expect that it is not the case. In what follows, the regression of w on x for the subsample of entrants into employment (those with $d = 1$) produces the biased estimates of β. To state this formally, suppose that η and ε are generated by the bivariate normal process

$$\begin{bmatrix} \eta \\ \varepsilon \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{bmatrix}\right), \tag{12}$$

where σ_ε is the standard deviation of ε and ρ is the correlation between ε and η. Note that there is no way to identify the variance of η, since only the sign, not the magnitude, of y^* is observed. As such, one can impose a normalisation that the variance of η equals the unity without any loss in generality. With the distributional assumption in (12), the conditional expectation of ε is

$$E(\varepsilon\,|x,z,d=1) = \rho\sigma_\varepsilon\lambda\left(z'\delta\right),$$

where

$$\lambda\left(z'\delta\right) \equiv \frac{\phi\left(-z'\delta\right)}{1-\Phi\left(-z'\delta\right)} = \frac{\phi\left(z'\delta\right)}{\Phi\left(z'\delta\right)}$$

is the *inverse Mill's ratio*,[46] $\phi\left(z'\delta\right)$ and $\Phi\left(z'\delta\right)$ is the density and distributional function of the standard normal variable evaluated at $z'\delta$, respectively. Now the wage equation conditional on the exit to employment can be written as

$$w = x'\beta + \rho\sigma_\varepsilon\lambda\left(z'\delta\right) + \xi, \tag{13}$$

where the conditional moments of the disturbance term are

$$\begin{aligned} E(\xi\,|x,z,d=1) &= 0, && (14)\\ V(\xi\,|x,z,d=1) &= \sigma_\varepsilon^2\left[\left(1-\rho^2\right)+\rho^2\left(1-z'\delta\lambda\left(z'\delta\right)-\lambda\left(z'\delta\right)^2\right)\right], && (15)\end{aligned}$$

and

$$0 \le 1 - z'\delta\lambda\left(z'\delta\right) - \lambda\left(z'\delta\right)^2 \le 1. \tag{16}$$

One can now see that the OLS regression of w on x using the observed sample (i.e., observations with $d=1$) produces, in general, inconsistent estimates of β and a downward biased estimate of σ_ε^2. Heckman (1979) has pointed out that selection bias in the OLS estimation can be interpreted to arise from the ordinary problem of omitted variables. To see this point, note that one can obtain consistent estimates of β by regressing w on x and λ, but if λ is not included in the regression, inconsistency will arise due to the omission of λ. However, even if λ were observed, the least squares estimator would be inefficient due to heteroskedasticity apparent in (15).

There are two cases in which the OLS estimation will produce unbiased estimates of β. First, if $\rho = 0$, so that the coefficient of λ is zero, then (13) will reduce to the usual OLS regression. This corresponds to the case in which selection and outcome are independent. Second, if λ (or its estimate)

[46] $\lambda\left(z'\delta\right)$ is also known as Heckman's lamda and the hazard rate. It is a monotone decreasing function of the employment probability, $\Phi\left(z'\delta\right)$, and, in particular, $\lim_{\Phi(z'\delta)\to 0}\lambda\left(z'\delta\right) = \infty$, $\lim_{\Phi(z'\delta)\to 1}\lambda\left(z'\delta\right) = 0$, and $\partial\lambda\left(z'\delta\right)/\partial\Phi\left(z'\delta\right) < 0$ (Heckman, 1979, p. 156).

is uncorrelated with all variables in x, then the OLS estimates of β will be unbiased due to the well-known result concerning the effects of omitted variables in the OLS regression. As discussed earlier, the dependence of selection and outcome is what one can expect to result in modelling starting wages. In addition, correlation between λ and variables in x is likely to appear as the vectors z and x will share common elements in our settings.

In practice, λ are not known but in the case of the censored sample, when the vector z is observed for *all* sample members, one can apply a simple two-step method to estimate β and $\rho\sigma_\varepsilon$. *Heckman's two-step estimator* consists of the following steps:

1. Use the probit analysis to obtain a consistent estimator for the parameter vector δ of the selection equation (8);
2. Estimate β and $\rho\sigma_\varepsilon$ by regressing w on x and λ by least squares after the probit estimator $\hat{\delta}$ of δ is inserted into λ.

In other words, one models the probability of an observation being selected in the observed sample; that is, one models d as an indicator variable dependent upon variables z. The second step is to model the expected value of the market wage, w, as dependent upon variables x, but correcting for the fact that w is observed only when $d = 1$. It should be stressed that the consistency of this estimator, like that of the maximum likelihood estimator below, depends critically on the assumption of normality. This can be seen from (13) and the form of the inverse Mill's ratio, λ. When the elements of z are the same as, or a subset of, the elements of x, it is only the non-linearity of λ as a function of $z'\delta$ that makes the parameters of the second-step regression identifiable, while the exact form of the non-linearity comes from the normality assumption.

Instead of two-step estimation, maximum likelihood (ML) estimation is applied in this study as it is preferred on efficiency grounds.[47] To build up the likelihood function, recall that there are two types of observations: ones for which both d and w are observed to be zero, and ones for which $d = 1$ and w is equal to w^*. The likelihood contribution of the individual who fails to get a job is

$$\Pr(d = 0) = \Pr(\eta \leq -z'\delta) = \Phi(-z'\delta) = 1 - \Phi(z'\delta), \tag{17}$$

[47] An alternative approach that is not discussed here might be to construct a non-linear least squares estimator for (13).

whereas the contribution of the individual who gets one is

$$\begin{aligned}\Pr(d=1)\, f(w^* \mid d=1) &= \Pr(\eta > -z'\delta)\, f(w^* \mid \eta > -z'\delta) \\ &= \Phi(z'\delta)\, f(w^* \mid y^* > 0), \end{aligned} \tag{18}$$

where $f(w^* \mid \cdot)$ is the conditional density of the log market wage. In other words, (18) is the expression for the probability of being selected in the observed sample multiplied by the density of the market wage conditional on having been selected. To put this into a tractable form, some further manipulations are needed. Writing the conditional density of w^* as

$$f(w^* \mid y^* > 0) = \frac{\int_0^\infty f(w^*, y^*)\, dy^*}{\Phi(z'\delta)} = \frac{\int_0^\infty f(w^*)\, f(y^* \mid w^*)\, dy^*}{\Phi(z'\delta)} \tag{19}$$

and using a well-known property of the bivariate normal distribution that implies $y^* \mid w^* = \bar{w} \sim N\left(z'\delta + \rho\sigma_\varepsilon^{-1}(\bar{w} - x'\beta), 1 - \rho^2\right)$, one can rewrite (18) as

$$\frac{1}{\sigma_\varepsilon}\phi\left(\frac{w - x'\beta}{\sigma_\varepsilon}\right)\Phi\left(\frac{z'\delta + \rho\sigma_\varepsilon^{-1}(w - x'\beta)}{\sqrt{1-\rho^2}}\right) \tag{20}$$

Let the data be (w_i, d_i, x_i, z_i), for $i = 1, 2, \ldots, N$ observations. Putting (17) and (20) together, taking logarithms and summing over the observations, one obtains the log-likelihood function

$$\begin{aligned}\ell &= \sum_{i=1}^{N}\left[(1-d_i)\ln\left[1 - \Phi(z_i'\delta)\right] + d_i \ln\phi\left(\frac{w_i - x_i'\beta}{\sigma_\varepsilon}\right)\right. \\ &\quad \left. + d_i \ln\Phi\left(\frac{z_i'\delta + \rho\sigma_\varepsilon^{-1}(w_i - x_i'\beta)}{\sqrt{1-\rho^2}}\right) - d_i \ln\sigma_\varepsilon\right]. \end{aligned} \tag{21}$$

The ML estimates of the unknown parameters are obtained by maximizing (21) over δ, ρ and the transformed parameters $\alpha = \beta/\sigma_\varepsilon$ and $\gamma = 1/\sigma_\varepsilon$.[48] The resulting ML estimator of $\theta = (\beta, \sigma_\varepsilon^2)$ is consistent and asymptotically normal with the asymptotic variance-covariance matrix equal to $-\left(\partial^2\ell/\partial\theta\partial\theta'\right)^{-1}$.

Note that if $\rho = 0$, the log-likelihood function in (21) splits into two parts: the log-likelihood function for a probit model and the log-likelihood function for

[48] Recall that the outflow data was constructed by pooling together outflow samples that were sampled using different sampling intervals, and that a particular group of the long-term unemployed had higher weights in the sampling. The variation in the inclusion probability across observations will be taken into account in the estimation by weighting individual contributions to the log-likelihood accordingly. The weights, of course, are taken into account in computing the estimate of the variance-covariance matrix as well.

a linear regression model with normal disturbances. As these two likelihood factors share no common parameters, they can be estimated separately. This further illustrates that in the absence of the correlation between ε and η, the OLS estimation is the adequate one. Put differently, it is not the fact that observations on w are available only for those with $d = 1$ that causes difficulties, but rather that this selection is not random with respect to w. (Breen, 1996.)

A few words about parameter interpretation. The expected value of w is $E(w\,|x,z) = x'\beta$, and the derivative of this with respect to a given regressor in x, say x_k, is simply β_k. However, this is not the marginal effect on the observed starting wage, but rather the marginal effect on the expected value in the underlying population as a whole. Indeed, the *full* effect of a regressor that appears in both x and z, say x_k, in the subsample of those exiting to employment is

$$\frac{\partial E(w\,|x,z,d=1)}{\partial x_k} = \beta_k - \delta_k \rho \sigma_\varepsilon \left[z'\delta\lambda\left(z'\delta\right) + \lambda\left(z'\delta\right)^2 \right], \tag{22}$$

where β_k and δ_k are coefficients on the regressor x_k (Greene, 1993). The regressor has a *direct* effect of β_k, but also an *indirect* effect through its presence in λ. The indirect effect can be seen as a measure of bias in the OLS estimate of β_k. The expression in (22) further implies that the OLS estimates of coefficients on the regressors that do not affect the probability of employment are free from selection bias.

As a concrete example, suppose that the correlation, ρ, is positive and that schooling increases both the market wage and probability of exit to employment. The full effect of schooling now has two parts, one due to its positive impact on the probability of *entering* the observed sample and one due to its impact on earnings *within* that sample. Since the term in brackets in (22) is between zero and unity as a consequence of inequality in (16), the indirect effect serves to push down the full effect of schooling. As a result, the estimate of the return to schooling in the regression overstates the total effect of schooling on the earnings of those exiting to employment. Moreover, since the sizes of different components depend on the setting, it is quite possible that the magnitude, sign, and statistical significance of the total effect might all be different from those of β (Greene, 1993).

The model described belongs to the family of Tobit models. This family refers to regression models in which the range of the dependent variable is constrained in some way. In economics, such a model was first used in a study by Tobin (1958), but models including *limited* dependent variables have a longer history among biometricians. In our special case, the model is known as the **Type II Tobit model** (due to Amemiya's survey, 1984), as well as the **censored regression model.**

4.2 Previous Evidence on Earnings Differentials

Since there is a huge body of literature explaining earnings differentials, this section does not aim to survey the entire field, but instead takes a brief look at previous Finnish studies. A comprehensive comparison of the findings would be a difficult task because of great differences in the data sets used and in the variables included in the analysis. Therefore, only some general findings with emphasis on the effects of education and on the unemployment elasticities of wages are presented here. Concerning the determinants of post-unemployment wages, some international evidence is discussed briefly at the end of the section as the subject is a somewhat unexplored research field when using Finnish data.[49]

The early study by Lilja and Vartia (1980) considers the effects of education on the annual disposable income of the household. Their data contained a sample of households from the Finnish Household Survey for 1971. Wage equations included a number of control variables for the characteristics of the household head and of the household as a whole. The OLS estimate of the rate of return to schooling was 9%, when the years of schooling of the household head was used as the schooling variable in the regression. Ingberg (1987) has obtained estimates of the same magnitude with a data set constructed by combining the Labour Force Survey for 1980 and the Housing and Population Census of the same year. The estimates of the return to schooling fell into a range of 9 to 12%, when a simple human capital model was estimated for several subsamples of the data. The dependent variable in the regressions was annual taxable income and education was measured by the years of schooling.

Brunila (1990), Vainiomäki and Laaksonen (1992), Eriksson (1992), and Asplund (1993) have all used the highest level of completed education as a measure of schooling when evaluating the returns to education. Asplund's analysis was based on a sample from the Labour Force Survey, whereas the data sets for the other studies were drawn from the Finnish Population Censuses. Brunila estimated full-sample and gender-specific earnings equations for cross-sections 1975 and 1985 using annual pre-tax earnings as the depen-

[49] The study by Kyyrä (1997) is the only one which tackled the issue with Finnish data. Since it is the predecessor of this work, the results are parallel to those presented at the end of this chapter and hence they are not discussed here.

dent variable. The cross-sectional analysis of Vainiomäki and Laaksonen was based on a sample of private-sector employees in 1975, 1980 and 1985. Eriksson estimated his earnings equations for a panel with the data from 1971, 1975, 1980 and 1985. The dependent variable was the monthly wage in both of these studies. Asplund in turn estimated full-sample and gender-specific earnings functions by using the pre-tax hourly earnings as the dependent variable.

The general findings from these studies suggest that workers with vocational education tend to earn 10 to 25% more than those who have only completed the basic level, while those graduated from the higher levels of education are paid 50 to 90% more. The studies with multiple time periods point further to a decline in the return to schooling in the 1980's when compared to the 1970's. Overall, the findings of these studies are parallel to each other, indicating that the estimate of the schooling effect in Finland (at a particular point in time) is quite robust with respect to the choice of data, sample and wage measure.

The only deviation from this consensus is a study by Uusitalo (1997) in which the choice of education is allowed to be endogenous. Uusitalo's data was drawn from male recruits who began their military service in 1970. Information for 1975, 1980, 1985 and 1990 was collected by combining the records of the Finnish Defence Forces and those of the Finnish Population Censuses. The final data was constructed by pooling four cross-sections together. His OLS estimate of the rate of return to schooling fell within the same range as reported in Lilja and Vartia (1980) and in Ingberg (1987). However, treating the years of schooling as an endogenous variable in the regressions yielded estimates that fell within a range of 10 to 15%.[50]

Vartia and Kurjenoja (1992) have investigated male-female wage discrimination among factory and clerical workers within large firms in the forest and metal industries in 1990. The data of the study was based on the registers of the Confederation of Finnish Employers (STK),[51] and it covered exceptionally detailed information on job attributes, allowing the authors to control for a number of differences in work characteristics and duties. Their cross-sectional findings suggest that the gender gap in favour of men is less than 5% among factory workers. Yet, wage discrimination turned out to be a more serious problem among clerical workers, since the estimated wage difference

[50] Uusitalo controlled endogeneity of education in two different ways: by using IV estimation and by adding selection-correction terms, constructed by modelling the choice of educational level with the ordered probit model in the first step, to the wage equations.

[51] As a result of re-nomination, the STK is currently known as the Confederation of Finnish Industry and Employers (TT).

was 9% in female-dominated and 14% in male-dominated clerical work.

A recent study by Koev (1996) investigates the same phenomenon with a cross-sectional sample of clerical workers who worked on a full-time basis in the Finnish manufacturing sector in 1993.[52] The data was drawn from the records maintained by the Confederation of Finnish Industry and Employers (TT). The regression results are consistent with those reported in Vartia and Kurjenoja (1992), suggesting that female clerical workers receive 9% lower wages in female-dominated and 11% lower wages in male-dominated work duties than men doing the same work. In addition, wage discrimination was found to vary strongly from sector to sector.

One important question of interest is whether the wage structure allows for adjustments with respect to cyclical fluctuations. In a textbook framework, where unemployment is the gap between a supply curve of labour and demand curve for labour, wages and unemployment are positively associated. The opposite results in empirical literature, however, give support for non-competitive explanations of the labour market. There are competitive reasons why the wage structure may be sensitive to *local* labour market conditions, which may pertain to the region or industry.

The models by Harris and Todaro (1970) and by Hall (1972), for example, predict a positive correlation between wages and regional unemployment. In these models migration across regions leads to a spatial equilibrium in which all regions provide the same expected utility. Then, according to the idea of "compensating differentials," higher wages must appear in areas of high unemployment to compensate for the undesirable features of unemployment. These models were especially constructed for less-developed countries where migration from rural to urban areas takes place despite the high levels of urban unemployment. Indeed, the models' predictions are usually rejected in empirical analysis with data on western countries.

In contrast, Blanchflower and Oswald (1994, 1995) have found a negative relation between wages and regional unemployment levels. They tackled the issue empirically by simply adding the log of the unemployment rate in the worker's region as an additional regressor to log-linear wage equations. Their findings, based on samples from twelve countries, imply that the elasticity of wage with respect to the regional unemployment rate is roughly $-.10$. In

[52] Koev had access also to a panel with the data from 1991 and 1993, collected from the same source. However, the estimates from his fixed-effect model were affected by serious econometric problems, arising from too little variation in the regressors between time periods and difficulties to specify a model that captures the gender-effect correctly. Consequently, the analysis based on the panel turned out to be unfruitful.

other words, a hypothetical doubling of the regional unemployment rate is associated with a drop in earnings of one-tenth. They suggested that this connection should be portrayed by the "wage curve" as a downward-sloping locus on a graph with the level of unemployment on the horizontal axis and the level of wages on the vertical axis. Blanchflower and Oswald further argued that this relation is approximately the same across countries and constant over time. They did not give a single theoretical justification for the wage curve, but pointed out that it may arise from several non-competitive labour market models — namely, from a wage bargaining model, an efficiency wage model, or a model of labour contract theory.[53]

Recent studies by Pekkarinen (1997) and Parjanne (1997) provide evidence for the existence of the wage curve with Finnish data. Pekkarinen applied OLS estimation to a cross-sectional data for the period 1992–95, drawn from the records maintained by the Confederation of Finnish Industry and Employers (TT). The estimated elasticity of wages with respect to the regional unemployment rate did not appear to be very robust with respect to the model specification, depending on whether it was obtained from cross-sections or from the pooled data and whether the regional indicators were included in the regression. Yet, the estimated elasticity of –.09 that Pekkarinen believed to be the most reasonable one is consistent with the findings of Blanchflower and Oswald.[54]

The findings of Parjanne (1997) also give support for the wage flexibility of the labour market. She examined how wages vary in response to differences in regional and industrial unemployment using a cross-sectional data from the Finnish Labour Surveys for 1987, 1989, 1991 and 1993. The elasticity of the hourly wage with respect to the regional unemployment rate was within a range of –.05 to –.15 and that with respect to the industrial unemployment rate was within a range of –.08 to –.13.

Continually high levels of unemployment have lead several authors to analyse

[53] A relevant story for Finland might be a bargaining model where an employer organization negotiates with a trade union that worries about both its employed members and its unemployed members. High unemployment means that more union members are out of work and those who hold jobs face an increased threat of job loss. An increase in unemployment may shift the union's preferences from the concern for wages toward a greater concern for the number of jobs. This kind of argumentation, combined with the observation that wage negotiations in Finland often take place at the industry level, leads one to ask whether the wage structure allows for some adjustments, especially, with respect to differences in the industrial unemployment rates.

[54] This estimate was obtained from the pooled data using the hourly wage as the dependent variable and excluding the regional dummies with insignificant coefficients from the regression.

the earnings losses associated with experiences of unemployment. Jacobson *et al.* (1993), for example, have investigated earnings losses caused by displacement using a panel of high-tenured Pennsylvania workers. They found that workers with six or more years of prior job tenure experienced large long-term earnings losses during mass lay-offs, with little evidence of substantial recovery after the third year of re-employment. In particular, the typical pattern of the high-tenured worker was a sharp drop in earnings in the quarter of job loss, followed by a rapid recovery during the next couple of years towards an eventual level of 25% less than that earned from the prior job. The earnings losses were found to be only slightly attributed to age and gender, but vary with regional labour market conditions, industry and firm size. They found larger losses among workers displaced from very large firms, as well as among those displaced in regions that have depressed rates of employment growth.

The findings of Stevens (1997), from a U.S. panel data, also imply that the impact of displacement is quite persistent as the wage rate tends to remain about 9% below the level expected without displacement for six years after a spell of unemployment. She further found that the driving force behind the slow recovery of the wage rate is subsequent experiences of unemployment. Topel (1990) has argued that the loss of specific human capital acquired prior to the unemployment spell largely determines the extent of reduction in earnings at the time of re-employment.

4.3 Estimation Results

This section represents the results from estimation of two earnings models, one for starting wages and the other for general wages. In contrast to the discussion about selection bias in modelling starting wages, the division of labour force participants to those in work and those out of work are omitted in the model of general wages, so that attention is paid to the employed persons only. Although there are reasons to expect that some sort of sample selection appears in this case as well,[55] the implications of such selection are

[55] If one thinks hard enough, some sort of selection process underlying any piece of economic data can probably be found. Whether a particular process of sample selection is likely to have significant effects will be a matter of judgment. When the determinants of general wages are studied, the role of sample selection is likely to be less important. In addition, selection bias is a function of the proportion of censored observations which is not very high in this case.

likely to be insignificant, and it is reasonable to ignore that.[56]

The general wage model outlined in column (1) of Table 3 is estimated with OLS from the data on the working age population. The estimates of the starting wage model in column (2) are obtained by applying the ML method discussed earlier in this chapter to the pooled outflow data.[57] The estimates of the underlying selection equation are given in the appendix. The explanatory power of the general wage model is quite satisfactory as half of the wage dispersion is explained by the included regressors, but the starting wage model accounts for only one-fifth of the variation in subsequent earnings (not observable from the table). Measurement errors in the dependent variable are responsible for much of the lower explanatory power in the starting wage model. Such errors result from the use of annual salaries and months worked in the computations of monthly wages, and they can be quite substantial in cases where the subsequent job has persisted only for a short time. General wages are not subjected to such measurement errors as the estimation sample was restricted to cover only those people who worked throughout the whole year.

The measurement errors do not bias the regression analysis as long as the errors are not correlated with the regressors. As it is likely that they are not correlated, the measurement errors can be seen to be harmless for the analysis in the sense that the estimated coefficients are not affected — though the errors decrease the explanatory power of the starting wage model by increasing the amount of "independent variation" in the dependent variable. One should also recall that the hedonic wage theory implies that job attributes can be important explanatory variables along with human capital measures. If the relative importance of human capital measures increases with job tenure, the earnings of entrants into employment will be affected by job attributes to a greater extent.[58] As such, the lower explanatory power in

[56] Asplund (1993, Chapter 3) has applied a selection model with a probit selection index in the corresponding study without finding any signs of sample selection.

[57] The dependent variable in the regressions is the log monthly wage (converted into 1994 money by Earnings Index), the use of which was justified in Chapter 2 in the context of the human capital theory. Although the framework of the human capital view is open to questions, there are still several supporting arguments for the use of logarithms in the regression analysis. The main point is that by using logarithms, one can avoid the problems arising from differences in the absolute levels of the variables and focus on the relative differences. In addition, the advantage of relative differences over absolute differences is that they are independent of the units of measurement, so that they are directly comparable for variables having different units of measurement. The reader should refer to Törnqvist *et al.* (1985) for an extensive discussion about the practicality of logarithms in the considerations of relative changes.

[58] To see this point, note that employers must have difficulties when sorting out appli-

Table 3: Estimation results for wage equations

Regressor	General wages Coefficient (1)	Starting wages Coefficient (2)	Starting wages Indirect effect (3)
Intercept	8.0178 (.0001)	8.2241 (.0001)	
Years of schooling	.0758 (.0001)	.0438 (.0001)	-.0016 (.7067)
Experience	.0327 (.0001)	.0237 (.0001)	
Experience^2/100	-.0519 (.0001)	-.0486 (.0001)	
Female × experience	-.0095 (.0019)	-.0093 (.0008)	
Female × experience^2/100	.0177 (.0114)	.0172 (.0187)	
Female	-.1330 (.0001)	-.0348 (.0863)	.0071 (.7355)
Foreigner	-.0844 (.1907)	-.0985 (.1138)	.0472 (.5619)
Family status: (*vs.* single)			
Female with partner	-.0198 (.0863)	-.0372 (.0153)	.0006 (.9798)
Male with partner	.0445 (.0094)	.0569 (.0001)	-.0064 (.7962)
Female × children	-.0732 (.0001)	-.0220 (.2567)	.0272 (.3205)
Male × children	.0045 (.7765)	-.0271 (.1477)	.0091 (.7724)
Living with parents	-.0735 (.0001)	-.0259 (.0570)	.0036 (.8763)
Health disability		-.0423 (.1333)	.0290 (.4472)
Home owner	.0459 (.0001)	.0215 (.0540)	-.0108 (.5484)
Capital city area	.1257 (.0001)	.0825 (.0001)	-.0092 (.7191)
Get hired on one's own		.0386 (.0004)	
Entry channel: (*vs.* work)			
Training course		-.1328 (.0001)	.0271 (.4002)
Job replacement prog.		-.1077 (.0001)	.0396 (.1007)
Outside labour force		-.0782 (.0001)	.0303 (.1436)
Unknown		-.0171 (.2329)	.0167 (.4715)
Employer: (*vs.* private)			
Central government	.0009 (.9349)	.0205 (.2585)	
Local authority	-.0255 (.0507)	.1808 (.0001)	
Unknown	-.3382 (.1778)	.0417 (.0384)	
Re-entry in the industry		.0500 (.0001)	
ln(industrial unemployment rate)	-.0147 (.6294)		
ln(regional unemployment rate)	-.0248 (.0570)	.0014 (.9324)	.0059 (.8456)
ln(vacancy-unemployment ratio)		.0204 (.0005)	-.0077 (.3985)
ln(participation ratio)		.0689 (.0007)	.0047 (.8943)
ln(spell duration)		-.0184 (.0130)	.0225 (.0003)
Interruptions: (*vs.* none)			
Unemployment spell	-.1326 (.0001)		
Other period out of work	-.0617 (.0001)		
ρ		.2836 (.0060)	
σ_ε		.3609 (.0001)	
Adjusted R^2	.5021		
Log-likelihood (abs.)		11,506	
Observations (# uncensored)	4,628	14,438 (7,302)	

Notes: Dependent variable is the log monthly wage. Industry and cohort indicators included in both models. P-values in parentheses. Results in column (1) corrected for heteroskedasticity. Indirect effects are computed at the means of explanatory variables.

the starting wage model can be attributed to the lack of sufficient controls for job attributes as well.

It appears from the table that the correlation between disturbances in the starting wage model is highly significant, pointing to the presence of sample selection.[59] Since the correlation is positive — though its absolute value is relatively small — sample selection makes good economic sense: those who find wage offers relatively high with respect to their characteristics are more likely to get hired. The indirect effects of the regressors common for both the starting wage and selection equation are presented in column (3). The indirect effects are, in general, of low magnitude when compared to the direct effects in column (2). Except for the indirect effect of the spell duration, the indirect effects do not differ significantly from zero. This suggests that OLS estimation applied to the outflow data would produce the same kind of estimates, though still biased, for the parameters of the starting wage model. Yet, the OLS predictions of starting wages would be biased in a qualitative empirical sense due to the omission of sample selection.

The following discussion concerning the suggestions of individual coefficients is divided into subsections according to the issues addressed. For purposes of comparability, estimation results from the general and starting wage model are discussed concurrently. Since the models include a wide range of regressors, some of the estimated coefficients are bypassed with a few words, while the most essential ones are discussed at length.

4.3.1 Education and Work Experience

The coefficient on schooling in column (1) implies that the average rate of return to schooling is roughly 8%.[60] This is slightly less than the studies based on the late-80's data have found, suggesting the possibility that the decreasing trend in the return to schooling still persists. This trend is argued

cants with respect to personal characteristics when hiring new workers. This is because many personal characteristics are not directly observable and because the applicant's interest is to bring out his favourable characteristics and cover up the unfavourable ones in the job interview. It quite possible that employers can, however, collect some information about unobservables for their long-tenured workers through some monitoring process. If so, the relative importance of human capital factors will increase with job tenure.

[59] The joint normality of the disturbance terms in the starting wage model was tested with a "RESET" type test suggested by Pagan and Vella (1989). The F-statistic for the null hypothesis of the joint normality didn't reflect any signs of serious mis-specification.

[60] The percentage figures in the text are obtained by taking antilogs from the regressor coefficients. That is, when the coefficient of the kth regressor is denoted by β_k, the percentage impact of the unit change in that regressor on earnings is $100 \times (e^{\beta_k} - 1)$.

to arise from the growth of the supply of better-educated workers which in turn is likely to decrease wage differentials across educational levels. The impact of schooling on post-unemployment earnings is found to be much weaker. The coefficient in column (2) points to a 4.5% increase in the starting wage with respect to an additional year of schooling.

One possibility is that the difference in the estimates results from the omission of ability differences. It is quite possible that employers can collect some information about ability differences for their long-tenured workers, but not for job applicants when hiring new workers.[61] If so, the best employers can do when hiring workers is to use observable characteristics (such as education) to draw inferences about unobservables. Since the regression includes controls for these characteristics, the coefficient on schooling in column (2) should be unaffected by unobserved ability differences. However, if employers can reward their more able long-tenured workers, the estimate obtained from the general wage model may be biased upwards. If this kind of reasoning is followed, one may expect that the difference in the estimates of two models is associated with the lack of ability measures to some extent.

Recall that Uusitalo (1996) found the OLS estimate of the rate of return to schooling to reduce by 17% when the measures of ability were added to the wage equation. The difference in our estimates is clearly higher as the estimate in column (2) is over 40% less than the estimate obtained from the general wage model. Unfortunately, difficulties in measuring ability, among other things, make it impossible to give an exhaustive answer to which extent the observed difference in our estimates is associated with ability differences.

There are also other possible explanations for the difference in the schooling coefficients. Firstly, the stock of human capital is likely to depreciate during unemployment. If the return to schooling depreciates more rapidly, the higher the educational level is, a lower rate of the return is likely to appear in the starting wage model. On the other hand, the existing difference in the estimated returns can also be related to the dependence between education and work career prospects. If the possibilities to proceed in a career are associated with educational attainments, the quadratic work experience terms in the general wage equation may be unable to account for the impact of work experience appropriately. In that case, the rate of return to schooling in the general wage model may capture a part of the wage dispersion that results from differences in prospects to proceed in a career between workers

[61] Employers can use aptitude tests to sort out more able applicants from less able ones when hiring new workers. However, such tests are used, principally, in selecting managerial workers who are rarely found from the pool of unemployed.

with different levels of education.[62]

Using the years of schooling as a regressor restricts the impact of education to taking the linear form. In order to allow a more flexible form for the schooling effect, the models in Table 3 are re-estimated with educational level indicators in place of the schooling years. These indicator coefficients serve as estimates for the relative earnings advantages of persons who have acquired different levels of education over workers who have completed only the basic level.[63] The antilogs of these indicator coefficients are shown in Figure 6. Since the regression results for other explanatory variables are not sensitive to the form of the schooling effect, they are not represented here.

As was pointed out earlier, graduation from the high school takes the same number of schooling years as it takes to acquire a degree from the upper level of vocational education, but high school education differs in that it is purely liberal-art and does not graduate to any occupation. With this in mind, one can see that both the starting and general wage increases systemically with the level of education, while high school graduates are slightly lower paid than those with upper vocational education.

The results from the general wage model imply that high school graduates tend to earn one-fifth more than those who have completed only the basic level of education. In addition, the return to high school education in general wages is about fourfold of that to lower vocational education.[64] As such, high school education seems to be quite valuable compared to vocational education despite the fact that it does not qualify for any occupation. This may suggest that there is some signalling device attached to high school education. Graduation from higher levels of education is found to have a striking impact on earnings. While other things held constant, acquiring a degree from the graduate level of education would almost double the general wage rate. Overall, the estimated returns to different levels of education in general wages are quite similar to the findings of the previous Finnish studies that have used data sets from the end of the 1980's.[65]

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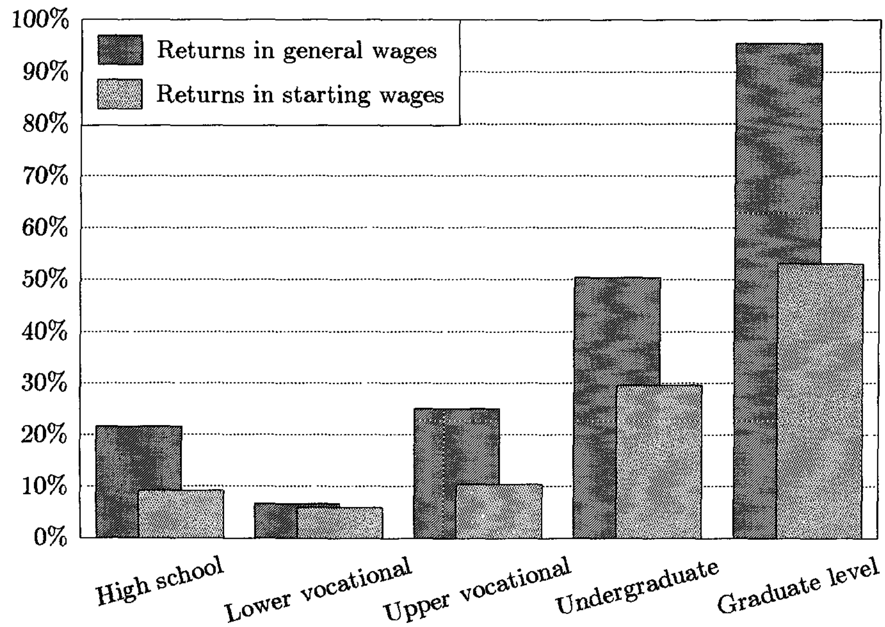
[62] One should recall that the data sets contain information on the highest *level* of completed education which is converted into the years of schooling by using the mean years of schooling attached to different levels of education. This procedure may also affect the estimates of the return to schooling.

[63] The years of schooling in the selection equation is replaced by the educational level indicators in the starting wage model. The coefficients on the educational level indicators, while the basic level serves as the reference level, are all highly statistically significant in both wage equations.

[64] The relative earnings advantage of high school education over vocational education among clerical workers is reported in Kettunen (1993b).

[65] In other studies, high school and upper vocational educations are occasionally placed

Figure 6: Estimated returns to educational levels over the basic level, %



It is worth emphasising that also job applicants receive notable economic returns from prior educational investments when entering employment. The regression results point to a clear premium in the subsequent earnings for workers with vocational education over the reference group. High school graduates are found to receive almost one-tenth higher starting wages than those who have completed only the basic level. Once again, it appears that workers with higher levels of education are especially valued by employers. Earnings from the subsequent jobs for workers with a degree from the graduate level are some 50% above the level received by those who have completed only the basic level.

Recall that notable differences were not found in median earnings between workers with basic education and those who have acquired a degree from the vocational levels of education in Chapter 3. In addition, high school graduates were found to be the worst paid group among entrants into employment. In contrast to such findings, the regression results point to considerable impacts on earnings associated with the lower levels of education as well. When a number of background characteristics are controlled for, also high school education is found to be valuable in pecuniary terms.

under the same title as they require the same number of schooling years.

As suggested by the human capital theory, the quadratic terms of work experience point to concave experience-wage profiles in both models. Further, the coefficients on the female-experience interactions indicate flatter profiles for women.[66] Figure 7 plots these profiles as cumulative percentage impacts on earnings. Due to the gender difference in the profiles, the total impact of experience on earnings is notably lower for women on average. This may suggest that women make smaller amounts of post-school investments in human capital, as pointed out by Asplund (1993). It is also quite possible that women get less promotions in their work career due to discrimination or other reasons. On the other hand, the experience variables refer to the *potential* years of work experience, obtained by subtracting the years of schooling and seven years for a time prior to the age of school entry from the current age.[67] This suggests the possibility that the flatter experience-wage profiles for women can be attributed to their greater tendency to interruptions in the work career due to family reasons.

It should be noted that the accumulation of skills with experience is captured differently in the starting and general wage models. For a worker who just got a job after a period of unemployment, work experience refers to the stock of general human capital built up over time prior to unemployment. However, for a worker employed by a single firm for a longer time, work experience also contains job tenure in that firm, so both general and firm-specific human capital are captured by the experience variables. Since job tenure is found to play a notable role in wage formation (e.g., in Asplund, 1993), it is not very surprising that experience-wage profiles are flatter when starting wages are considered.[68]

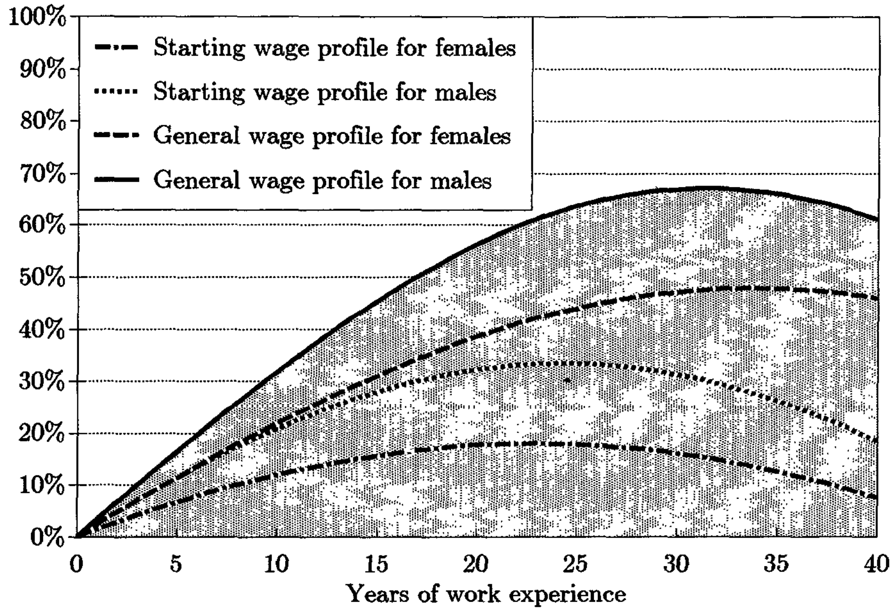
The maximum of the cumulative impact on general earnings is reached after some 30 years of work experience, corresponding to the early fifties for a worker with the average amount of schooling. Due to this late turning point, earnings do not have time to fall notably before retirement. In contrast, the starting wage profiles reach their turning points earlier and begin to drop rapidly when work experience exceeds 25 years. This observation is consis-

[66] The human capital theory assumes that simple cross-sectional coefficients on work experience are able to capture the life-cycle dynamics of earnings. This is a very strong assumption which should be kept in mind.

[67] Aspund's (1993) data contained information on the actual (self-reported) years of work experience, so that she was able to test how sensitive the estimation results are to the measure of work experience. She found that the potential years of work experience serve as a good approximation of the actual ones for men, but not for women.

[68] The findings by Addison and Portugal (1989) from U.S. data on displaced workers imply that the returns to tenure from a prior job do not vanish during unemployment, but previous tenure has a positive impact on the subsequent wage rate as well.

Figure 7: Wage-experience profiles by gender, %



tent with public discussion about age discrimination in hirings, suggesting the possibility that elderly applicants do not only face greater difficulties in finding jobs, but they tend to find less well-paid jobs as well. The earlier peaks in the starting wage profiles can also be attributed to the lack of firm-specific capital. The main stress of investments in general human capital is in the early phase, but investments in firm-specific capital take place over the working life. If the unemployed lose a major part of firm-specific capital acquired in prior jobs, accumulated firm-specific capital among high-tenured workers will serve to push the peaks toward later points in the general wage profiles.

4.3.2 Socio-Economic Factors

The female indicator has a coefficient with the expected sign in both models. The earnings difference of 3.5% in starting wages is only one-fourth of that in general wages and statistically significant only at the 10% level. This suggests the possibility that the gender gap in wages is associated with job tenure. The gender gap of 12% in general wages is of the same magnitude as obtained by Asplund (1993), but it is relatively high when compared to the estimates in Vartia and Kurjenoja (1992) and in Koev (1996), both of which consider male-female wage discrimination. The findings of two latter studies imply that much of the gender gap in wages is driven by differences in work duties and standards, i.e., by factors that are not controlled for in our regressions. Thus, a significant part of the estimated gender effects in Table 3 is probably due to failure in controlling for some gender-specific factors. So, it is perhaps best to interpret these results by saying that women do not suffer from wage discrimination when seeking a job, although they will potentially suffer later on in their career.

The foreigner indicator does not provide clear evidence on differences in wages with respect to ethnic background in either model.[69] With reference to the family background, it appears that married and cohabiting men earn more than single men in general, whereas married and cohabiting women receive about 4% lower starting wages than women with no partner. Intuition might suggest that applicants with young dependents have an incentive to demand higher starting wages because transfer payments and day-care fees depress their pecuniary returns to employment. Instead, a child under seven in the family does not affect starting wages significantly for either gender.[70] The interaction term in column (1), however, reveals that women with young children earn 7% less than single women in general. This is probably due to women's greater potential for absences and interruptions in their career as much of the burden of child-rearing falls on the shoulders of women. Young applicants who still live at home with parents earn 8% less than single people in general, while the earnings difference in starting wages is much smaller.[71]

The coefficient on the capital city area indicator points to 13% higher earnings for workers living in the capital city area.[72] It is interesting to note that also entrants into employment gain from the higher earnings levels in the capital city area by some 8%. Surprisingly, the disability indicator, which refers to reduced mental or physical ability to work, has an insignificant coefficient in column (2).[73] Workers living in an owner-occupied flat are found to earn

[69] It should be emphasised that the foreigner indicator is not based on nationality but refers to people whose native language is neither Finnish nor Swedish. In addition, if those who speak Swedish as their native language were to be separated from the Finnish speakers by an indicator variable, it will not get a statistically significant coefficient.

[70] The interactions of gender and children in the table refer to a child under seven in the family.

[71] The indicator for single parents is excluded from the regressions as its coefficient wouldn't differ significantly from zero in either model.

[72] The capital city area covers municipalities in Uusimaa.

[73] Information about disability was gathered from the administrative records of the Ministry of Labour, indicating that a disability code requires that a worker has been registered as unemployed. Therefore, the indicator for health disability is excluded from

some 5% more than their non-owning counterparts in the labour market. Since ownership cannot have a direct impact on the wage rate, it must serve as some kind of signal for prior success in the labour market. There is also weak evidence that job applicants who own their flat tend to find slightly higher wage offers than others, perhaps because they are able to search for jobs longer due to higher wealth.

4.3.3 Unemployment Related Factors

The regional unemployment rate in the individual's travel-to-work area is added to both models to account for demand conditions which pertain to the region. The industrial unemployment rate aims to capture differences in employment conditions across industries in the general wage model,[74] but it is replaced by the vacancy-unemployment ratio in the starting wage model.[75] This is because the vacancy-unemployment ratio measures the demand for a work force with particular occupational qualifications, and hence offers a more precise measure of the demand conditions faced by the unemployed. Due to the high variation in aggregate unemployment in the period under investigation, there are differences in the levels of unemployment measures between sample members originating from different cohorts. To account for this level effect, indicators for the 1988, 1990 and 1992 cohorts are added to both models. Although the cohort indicators are included in the regressions, their coefficients are excluded from the table as they do not differ significantly from zero in either model.

The general wages are found to be slightly sensitive to regional differences in unemployment levels, thought the coefficient on the regional unemployment rate in column (1) is statistically significant only at the 10% level.[76] In particular, a one-tenth increase in the regional unemployment rate is associated with a reduction of some .25% in the average earnings in that area.

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the general wage model.

[74] The industry classification for the industry unemployment rate is identical to that for the industry indicators in the regression.

[75] To be specific, the vacancy-unemployment ratio was computed from the aggregate figures gathered by the Ministry of Labour. The unemployed were classified into ten occupational groups (one for unskilled workers) according to the occupation they have reported to the employment authorities. The vacancy-unemployment ratio for a sampled individual was then calculated by dividing the total number of open vacancies for the individual's occupational group in the employment agencies by the total number of the unemployed in that group.

[76] The coefficient is robust with respect to the exclusion of the industrial unemployment rate as well as to the exclusion of the cohort indicators from the model.

This gives weak support for the wage curve discussion in Blanchflower and Oswald (1995), in Pekkarinen (1997) and in Parjanne (1997), although the estimated impact of the regional unemployment level is only one-fourth of that suggested by the authors.

Intuition suggests that much of wage adjustments, with respect to business cycle, should fall on new entrants into employment. In light of this, it is surprising to note that an insignificant coefficient on the regional unemployment rate appears in column (2). On the other hand, one should recall that the monthly wages were computed by dividing the annual earnings by months worked, so that the variation in the monthly wages comprises also the variation in working hours. It is quite possible that in regions that have higher unemployment rates, firms are more cautious about hiring new workers, and when they finally hire, the new workers are made to work for extra time which in turn raises their earnings. This may explain the insignificance of the coefficient of the regional unemployment rate in the starting wage model. In contrast, the vacancy-unemployment ratio is estimated to have a strong positive effect. This implies that the higher the relative supply of open vacancies in an occupational group is, the higher the level of starting wages of workers qualified for that group is.

The fact that wage negotiations in Finland often take place at the industry level leads one to expect that earnings vary in response to differences in industrial unemployment. Yet, the coefficient on the industrial unemployment rate in column (1) does not differ significantly from zero.[77] Replacing the vacancy-unemployment ratio in column (2) with the industrial unemployment rate would not produce a significant coefficient for the starting wage model either. These findings are perhaps a reflection of the deep recession that has produced concession bargaining at the economy level, reducing the stress of industry aspects in the wage negotiations.

The labour market history prior to the unemployment spell is controlled by including indicators for different entry channels to unemployment in the starting wage model.[78] The coefficients on these indicators point to the substantial variation in the subsequent earnings with respect to the entry channel. People outside the labour force prior to their unemployment spell

[77] However, dropping the cohort dummies from the regression would produce a highly significant coefficient of –.033 for the industrial unemployment rate.

[78] In addition, differences in starting wages between applicants under different unemployment benefit schemes were detected by adding indicators for unemployment insurance benefit receivers and for basic unemployment assistance benefit receivers to the starting wage model. However, no statistically significant benefit scheme effects were found, and hence the indicators are excluded from the final model.

suffer from the earnings disadvantage of roughly 8% over those previously employed. People who entered from job replacement programmes and training courses are found to be content with over 10% lower starting wages than those previously in work. These findings, however, should not be taken to mean that programme participation has a negative impact on the subsequent earnings, but they are probably driven by the underlying selection process. This is because most of the manpower programmes are targeted to those unemployed people with the worst employment prospects. As such, the negative coefficients on the participation indicators indicate existing difficulties in job search rather than the harmfulness of the programmes.

The occurrence of mass unemployment was followed by continuously increasing amounts of resources for the active labour market policy. Since an unemployed worker can influence the length of time she is eligible for unemployment benefits by participating in manpower programmes, the availability of such programmes may contribute to the search intensity or wage claims of the unemployed. To account for this possibility, the participation ratio, defined as the ratio of programme participants to the unemployed in the individual's labour administration district, is added to the starting wage model. The coefficient on the participation ratio in column (2) indicates that the higher the proportion of displaced workers in manpower programmes, the higher the level of starting wages is. One may interpret this result to give support for the hypothesis that the unemployed demand higher starting wages when facing an option to participate in the programmes.

A contradictory argument might be that manpower programmes succeed so well in upgrading the skills of the unemployed that the higher levels of starting wages appear in areas where such programmes are widely available, due to increased labour productivity. In light of the previous finding that those who entered unemployment from the programmes have to be content with the worst paid jobs, this explanation is unlikely to hold. All in all, any reasonable evaluation of the impact of the manpower programmes should account for the underlying selection procedure of programme participation. As this is left undone here, one should be careful when thinking about the importance of the programmes.

Mincer (1986) has argued that less-motivated job seekers may not only experience longer periods out of work but also find lower wage offers. To account for this possibility, an indicator for those who found a new job without the help of employment authorities is added to the starting wage model to serve as a kind of signal for the applicant's motivation. Indeed, the coefficient on the indicator implies that applicants who are able to enter employment by themselves find jobs that pay 4% higher starting wages than those jobs obtained through employment agencies.

Theory suggests several reasons why a period of unemployment may be followed by earnings losses. The efficiency wage argument suggests that firms are willing to pay wage premiums to induce workers to put more effort into their work. The need for such premiums, however, is likely to weaken in a recession because the cost of job loss increases due to a growing threat of unemployment. As such, workers separated from jobs that paid wage premiums will suffer from earnings losses if their subsequent jobs pay standard wages (Jacobson *et al.*, 1993). In addition, workers with skills especially suited to their previous jobs, resulting from the accumulation of firm-specific human capital, are likely to be less productive, at least initially, in their subsequent jobs.

To address the issue of earnings losses associated with unemployment periods, one should study how earnings vary over employment spells that are separated by experiences of unemployment. Instead, because of our cross-sectional approach, an indicator for workers with a period of unemployment in the previous year is added to the general wage model. The coefficient on the indicator in column (1) indicates that workers being unemployed in the previous year earn roughly 12% less than those employed throughout the whole previous year.[79] In addition, those out of work, but not in unemployment, for one month or more in the previous year, are paid 6% less than the reference group. These findings reflect the importance of seniority as a determinant of the wage rate.

One important question is the extent to which the earnings in the subsequent job depend on the time an individual spent in unemployment. In the absence of human capital depreciation, a standard search model with a constant reservation wage implies that longer spells of unemployment are associated with higher earnings in the subsequent job (see e.g., Lippman and McCall, 1976). In contrast, a negative coefficient on the spell duration appears in the starting wage model, suggesting that a 10% increase in the length of unemployment

[79] Curti (1997) has obtained a corresponding indicator estimate of 16% with Swiss data by using a similar cross-sectional setting. However, for workers who became unemployed due to job loss, an appropriate way to think of the earnings losses would be to look at differences between the worker's earnings in a number of post-unemployment periods and earnings in a period immediately prior to separation. The findings of Jacobson *et al.* (1993) from U.S. data on long-tenured workers, employing such an approach, point to much larger and long-lasting losses for displaced workers with six or more years prior job tenure.

is associated with a fall of some .2% in the earnings in the subsequent job.[80] This opposite result suggests the possibility that the unemployed suffer from some depreciation of human capital, potentially coupled with a "stigma" effect associated with longer periods of unemployment (Heckman and Borjas, 1980). A negative correlation between starting wages and unemployment duration can also result from reductions in the reservation wage as a period of unemployment insurance benefits approaches exhaustion.[81]

Note also that the indirect effect of the spell duration in column (3) is slightly stronger with the opposite sign than the direct effect in column (2). Indeed, the OLS estimate of wage elasticity with respect to the spell duration would not differ significantly from zero due to the omission of a strong negative relation between the spell duration and the probability that the spell will end at employment.

4.3.4 Employer and Industry Factors

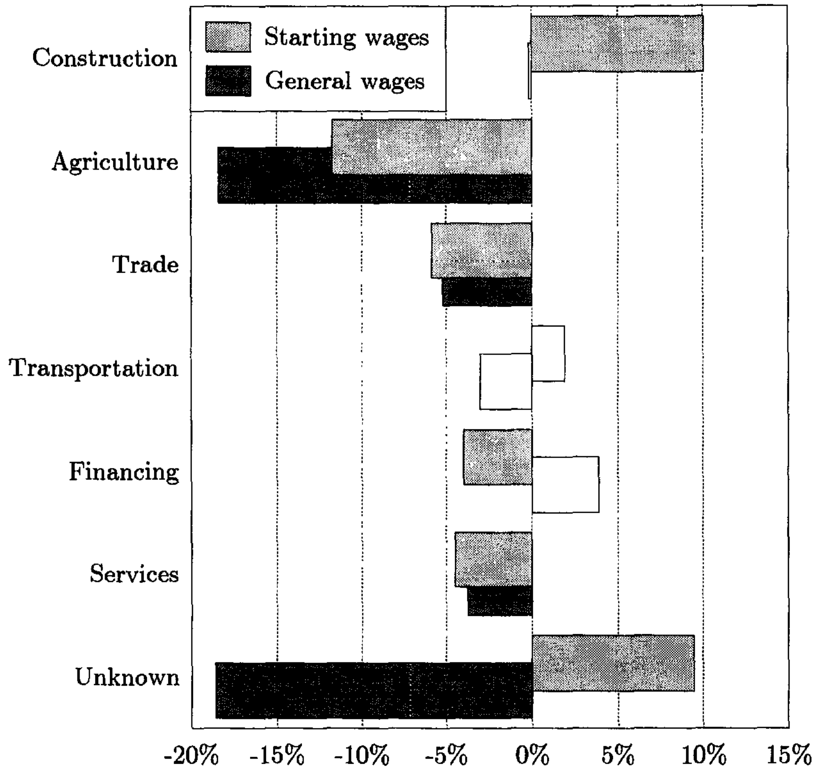
The indicator for workers employed by central government has a statistically insignificant coefficient in both models, indicating that there are no notable differences in wages paid by private-sector employers and wages paid by central government.[82] Surprisingly, local governments are found to pay roughly one-fifth higher starting wages than private-sector employers, although there is weak evidence that workers employed by local authorities tend to earn slightly less in general. These contradictory findings may be associated with job replacement programmes that are usually placed under local governments. Indeed, local authorities may favour job applicants formerly employed in similar duties within a job replacement programme when filling open vacancies. As such, the relative earnings advantage of workers hired by local authorities may result from exiting job tenure that is not taken into account in the regression.

[80] The estimates obtained by Addison and Portugal (1989) for the elasticity of post-unemployment earnings with respect to unemployment duration fell into a higher range of .6 to .8 with U.S. data. However, their data was on displaced workers, i.e., on those who became unemployed as a result of job loss.

[81] In a more adequate theoretical framework, the length of the unemployment spell and subsequent earnings are determined at the same time, so there is potential for the endogeneity of the spell duration in the starting wage model. One should keep this in mind.

[82] The public and private sector consist of different industries which might lead one to ask whether the effects of different employers are affected by the presence of industry indicators in the regressions. However, dropping the industry indicators from the regressions do not make the central government indicator statistically significant in either model.

Figure 8: Inter-industry wage differentials with respect to manufacturing, %.
Note: Empty bars refer to insignificant differences at the 5% level.



Wage differentials between industries are depicted in Figure 8, where the antilogs of the coefficients of the industry indicators excluded from Table 3 are plotted. Manufacturing acts as the reference industry, so that industry differentials are measured as differences with respect to manufacturing. It appears that although general wages in the manufacturing and construction sectors are at the same level, workers entering the construction sector receive one-tenth higher starting wages. One explanation for this is the nature of the construction industry, which is exceptionally sensitive to economic fluctuations. For example, the unemployment rate in the construction sector was 7% in 1988, but as high as 37% in 1994.[83] The level of activity in construction is further seasonally affected as most building projects take place in the summer for seasonal convenience. Workers on building sites are often paid on a piecework basis and working overtime is very common, both shift-

[83] 455 workers in the outflow data entered the construction sector in the 1988 cohort, while the corresponding figure for the 1992 cohort is only 135.

ing summer earnings of building workers upward. Since many hirings take place at that time, starting wages in the construction sector are likely to be affected by the "summer boom."

It further appears that agricultural workers earn clearly less than manufacturing workers in both cases. Yet, it is probably best to keep differences in wage levels apart from differences in earnings levels in this special case. This is because agricultural production usually takes place at the farm level and the resulting income is commonly property, not salary income. Furthermore, entrants into the financing sector are found to be paid less than those who find jobs from manufacturing, while earnings in the trade and service sectors are overall below the earnings of manufacturing workers.

Information on the individual's industry comes from the firm records. Consequently, workers with unknown industries are mainly those employed by a private person, such as taxi drivers, house helps, etc. One might expect that jobs offered by private persons are more uncertain and of a shorter duration than jobs in firms. The unemployed may be more cautious in accepting such jobs and hence ask for wage premiums. This might explain why entrants into jobs where the industry is not specified from the firm records receive relatively high starting wages. However, such jobs seem to pay quite low wages in general as the earnings of workers in an unknown industry are some 18% below the average level of earnings in manufacturing.

If the skills required in two jobs in the same industry are more similar, workers who enter the same industry as their old jobs were in should experience earnings advantage over other hired workers. To explore this possibility, an indicator for workers returning their old industry is added to the starting wage model. The coefficient on the indicator points to 5% higher earnings in the subsequent job for those able to return to their old industry at the time of re-employment.[84]

[84] Addison and Portugal (1989) have found with U.S. data that changes in industry following job loss are associated with a disadvantage in subsequent earnings of 18% compared to a return to the same industry. The findings by Jacobson *et al.* (1993), however, suggest that workers incur large losses with respect to earnings prior to unemployment even when they find work in the same industries as their old jobs. In addition, a panel study by Eriksson and Jäntti (1995), focusing on changes in male earnings associated with industry transitions, imply quite persistent negative earnings losses for industry switchers, even without experiences of unemployment.

5 Economic Incentives to Exit from Unemployment

This chapter aims to evaluate how the returns to employment are distributed among individuals suffering from unemployment. Considerations of the chapter are based on the samples drawn from individuals flowing out of unemployment in 1990, 1992 and 1994.[85] The returns are appraised by computing income changes associated with transitions from unemployment into employment. Attention is paid throughout to changes in the disposable income of households as I believe that it is important to consider economic incentives at the household level. This is because income transfers generally depend on the financial standing of the household, not the individual's, and because the income transfers are essential for most of the households involved with unemployment.

Section 5.1 gives first a short description of calculations for disposable income, and defines the measures of the returns to employment. In Section 5.2 these measures are used to evaluate how the returns are distributed among the unemployed.

5.1 Measuring Economic Incentives

To appraise returns to employment, one needs information on income in different labour market states. For this reason, the disposable income of the sample member's household is computed in three cases: (i) while the sample member is unemployed, (ii) while *really* employed and (iii) while *fictionally* employed. The household's income during unemployment is computed for all sample households using the income statistics available in the data. Using observed starting wages from the subsequent jobs, the disposable income while really employed is obtained for those who actually got hired. While fictionally employed, the sample member is supposed to be employed by a firm that pays the starting wage equal to the estimated one.[86] Since the estimate

[85] The outflow sample of 1988 is not analysed because income statistics for spouses are available only from 1990 onwards.

[86] The expected value of the starting wage can be computed either conditional on the exit channel or without such a condition. In particular, using the notations in Chapter 4, the unconditional expected value is $E(w\,|x,z) = x'\beta$, and the expected value conditional on the exit channel is $E(w\,|x,z,d=1) = x'\beta + \rho\sigma_\varepsilon\phi/\Phi$ for those exiting to employment and $E(w\,|x,z,d=0) = x'\beta - \rho\sigma_\varepsilon\phi/(1-\Phi)$ for those leaving the labour force and for entrants into manpower programmes, where ϕ and Φ are evaluated at $z'\delta$. Two kinds of starting wage estimates, conditional and unconditional, can be obtained by replacing β, δ, ρ and

of the starting wage is available for each sample member, disposable income during fictional employment can be computed for all sample households.[87]

Young applicants who live at home with their parents are excluded from the analysis because it is unclear how one should define the household-level income variables for them. The precise description of income calculations is given in the appendix, with tables for gross and net income. As a broad outline, the calculations for disposable income take into account: (i) gross earnings from different sources, (ii) income, municipal and church taxes, social security and pension contributions, (iii) the spouse's net income, if any, and (iv) income transfers, including child benefits, single parent's maintenance allowance, day-care fees, and social security allowance.

Although the data contains a wide range of income variables, information on income transfers is somewhat limited. This forces us to estimate some items of disposable income. The evaluation of day-care fees, for instance, presumes that the unemployed and those outside the labour force take care of their children at home, whereas households in which both parents are in work are assumed to use communal day-care services for their children aged under 7. Moreover, households whose disposable income fall short of the lower limit of the estimated legal level are assumed to receive such amounts of means-tested social security allowance that bring them back to the lower limit.

Since disposable income varies strongly with respect to the composition of the household, it is instructive to begin by taking a brief look at disposable income across different kinds of households. For this reason, sample households are classified into the following four categories: singles, single parents, couples and couples with children. *Singles* are people with no partner, but who may have children over the age of 17 living in the same household. *Single parents* rely on a child aged under 18 for support. *Couples with children* are two-parents households with a child aged under 7, while childless pairs and those with older children together form the group of *couples.* Couples include both married and those that cohabit, and their children can either be

σ_ε in the above expressions with their ML estimates. In the text, both conditional and unconditional starting wage estimates are used to compute household's disposable income during fictional employment. Which one is used is reported case by case.

[87] In order to obtain estimates for workers who failed to get jobs in reality, some assumptions about their subsequent jobs are made: (i) they find a new job on their own, so that the indicator for a worker who got hired without help from the employment authorities takes a value of unity, (ii) their subsequent jobs are in the private sector, and (iii) they are assumed to find employment from manufacturing if their old industry was not known, otherwise they return to the same industry their old jobs were in.

Table 4: Mean disposable household income by cohort, FIM/month

	Sample member's labour market state					
	Unemployed		Fictionally employed		Really employed	
Singles	(1)		(2)		(3)	
1990	3,170	(728)	5,320	(728)	5,910	(461)
1992	3,450	(655)	5,300	(655)	6,250	(221)
1994	3,730	(936)	5,540	(936)	6,850	(323)
Single parents						
1990	5,470	(130)	6,530	(130)	7,180	(89)
1992	5,730	(120)	6,500	(120)	7,610	(34)
1994	6,480	(154)	7,560	(154)	9,230	(37)
Couples						
1990	7,860	(1,038)	10,670	(1,038)	11,460	(697)
1992	8,370	(1,083)	10,710	(1,083)	12,390	(421)
1994	9,300	(1,501)	11,380	(1,501)	12,750	(541)
Couples with children						
1990	9,260	(553)	11,280	(553)	11,850	(335)
1992	10,290	(450)	11,590	(450)	12,730	(176)
1994	10,930	(697)	11,990	(697)	13,180	(222)
All households						
1990	6,660	(2,444)	9,000	(2,499)	9,680	(1,582)
1992	7,210	(2,308)	9,130	(2,308)	10,680	(852)
1994	7,930	(3,288)	9,670	(3,288)	11,020	(1,123)

Notes: Income while a sample member is fictionally employed is computed using unconditional starting wage estimates. Children in the family refer to dependents aged under 7. The number of observations in parentheses.

common or originate from a previous relationship of one spouse or the other. The threshold age for the youngest child, that is used to split couples into two groups, is equal to the age of school entry in Finland. As such, couples with children are those who are assumed to use day-care services when both parents are at work. Single parents are not split due to the limited number of observations of them (a total of 404).

Table 4 shows mean disposable income by cohort for different kinds of households. Differences in income levels between household groups are consistent with what one could expect. As a result of two income receivers, mean income are highest for couples. Disposable income for single parents exceed those for singles especially during unemployment, due to income transfers. The increasing trend in disposable income over the period appears largely because the figures in the table are in nominal terms. An additional explanation is, however, that well-off people with higher incomes have been involved with unemployment to a greater extent in the recession years, raising income levels for the latter part of the observation period.

For each household group, mean disposable income while unemployed is less than income while really or fictionally employed. The difference for both groups of couples and for single parents, however, is considerably small. Moreover, the estimated income in column (2) are systemically slightly lower than the observed ones in column (3). Since the mean income while fictionally employed is computed using all sample households, this suggests that workers who failed to get jobs are predicted to earn less in the subsequent jobs than those who actually entered employment (or, in the case of couples, their spouses are lower paid on average).[88]

As comparisons of income *levels* can be misleading in some cases, it is more convenient to look at *relative* changes in disposable income. Let us, therefore, consider the ratio of disposable income in the subsequent job to disposable income while unemployed. Using the observed starting wage, the **observed income ratio** (OIR) is defined as

$$\mathrm{OIR} = \frac{\text{Household's disposable income during real employment}}{\text{Household's disposable income during unemployment}}.$$

This measure can be computed for the subsample of those who actually got hired directly from the income statistics available in the data. The OIR tells us how much in relative terms an unemployed worker was actually able to increase the disposable income of his household through employment. The second measure, the **estimated income ratio** (EIR) is computed by using the estimated (conditional or unconditional) starting wage instead of the observed one:

$$\mathrm{EIR} = \frac{\text{Household's disposable income during fictional employment}}{\text{Household's disposable income during unemployment}}.$$

The EIR is available for all sample members and it gives us an estimate of the relative change in the household's disposable income that would result

[88] One should recall that the correlation between the disturbances in the starting wage model was estimated to be positive. In what follows, the unconditional starting wage estimates for entrants into employment are on average less than the observed wages from the subsequent jobs (see equation (13) in Section 4.1.2). However, this alone does not explain the difference in the mean disposable income between columns (2) and (3).

from the sample member's entry into a job that pays the starting wage equal to the expected one.[89]

It should be stressed that the income ratio accounts for change in disposable income that occurs at the time of entry into employment. So, attention is restricted throughout to *short-term* incentives of the unemployed. Economic theory assumes that individuals make their choices so as maximise the present value of earnings over some period. If this interpretation is followed strictly, one should build up a behavioural model which can be used to provide a reasonable account of how the unemployed take actions with respect to their beliefs about the future. Building that kind of model is an important topic but beyond the scope of this study, and hence it is left for future work.

The question then becomes whether the estimated income ratio is capable of detecting the impact of economic incentives on the probability of leaving unemployment sufficiently well? A brief look at the data shows that the labour market history of sample members is very unstable as they have usually had several labour market transitions in the past and most of the subsequent jobs last only for a short time. In such uncertainty, it must be very difficult to make far-reaching strategies for job search and the short-term aspects may, in fact, play a major role. In light of this, the income ratio is likely to serve as a reasonable approximation for economic incentives.

5.2 Returns to Employment

Theory suggests that applicants ask for a premium for the loss of leisure when negotiating for a job. Ruuskanen (1996) has estimated that such a premium might be some 25% of the household's unemployment income in Finland. In light of this, it is interesting to note that 31% of those exiting to employment in the data are placed at the left-hand side of the vertical line at 1.25, in Figure 9.[90] In other words, roughly one-third of those who actually got hired had to be content with a 25% increase in disposable income or less. In addition, 4% of the entrants accepted employment at the starting wage that caused a reduction in the disposable income of their households.[91]

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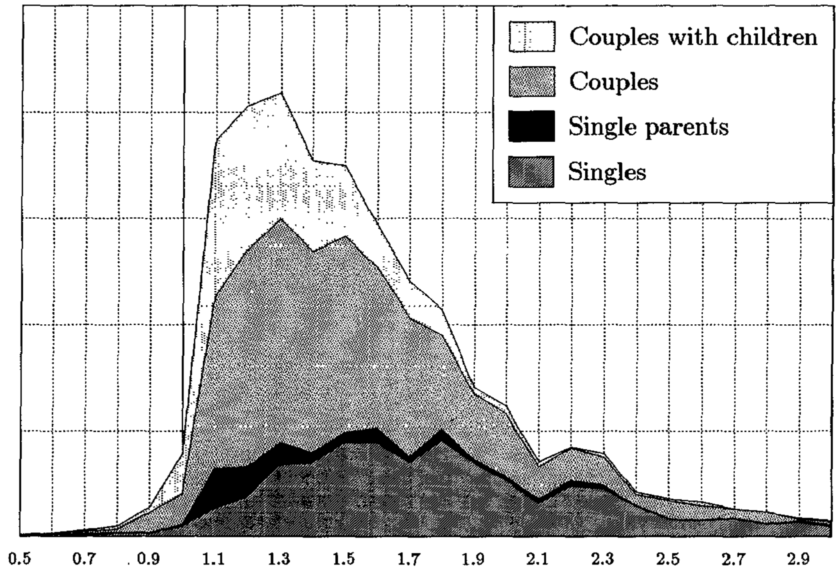
[89] Since there exist notable differences in income levels between household groups, comparisons of absolute changes in households' disposable income resulting from exits to employment are not very meaningful. Therefore, it is more convenient to consider relative changes in a spirit of index number calculations.

[90] The line is not depicted in the graph.

[91] Recall that the calculations for disposable income presume that all household which are entitled for social security allowance receive it the full amount. This can lead to underestimation of the true income ratio in some cases. Yet, the proportion of those who

Figure 9: Distribution of observed income ratios for entrants into employment. Note: Income ratios are pooled over the cohorts.

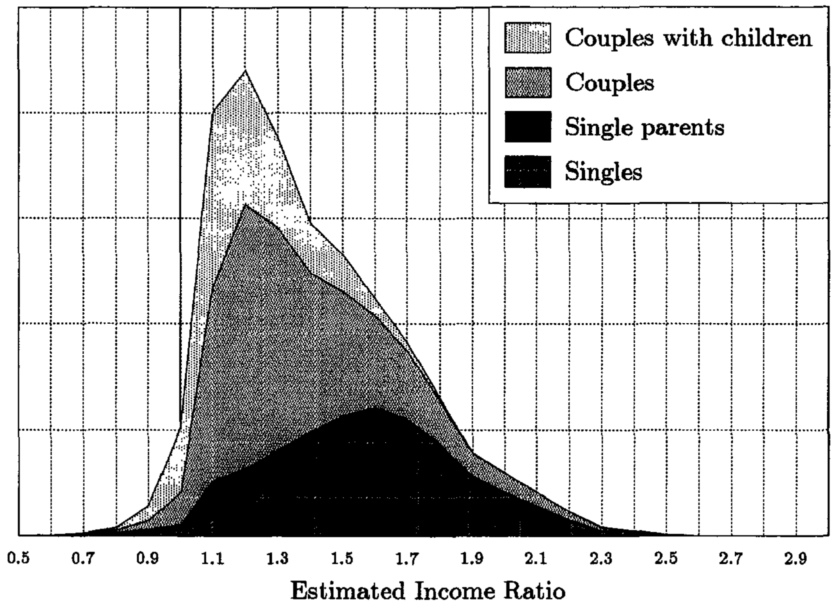


There are several potential explanations why it may be meaningful in some cases to accept employment at the starting rate with insignificant, or even negative, short-term returns. Promising career prospects or an expected reduction in the household's unemployment income can raise incentives to work for a lower starting wage.[92] Some people may even be willing to accept jobs that are associated with long-term income losses if they enjoy working or if they simply feel shame to be unemployed. On the other hand, people have different tastes over nonmarket time and consumption for reasons that cannot be controlled for using observable information. All findings of our analysis should be interpreted in light of this.

are assumed to receive social security allowance in the data fits pretty well to the true figures. On the other hand, the income calculations omit housing allowance which in turn may lead to overestimation of the true value in some cases. Overall, I believe that the figures in the text serve as reasonable estimates of the true number of the unemployed suffering from poor incentives to work.

[92] The expected reduction in unemployment income can result, for example, from the threat of spouse's unemployment or from an anticipated reduction in unemployment benefits. Moreover, an unemployed worker may lose part of her unemployment benefits if she refuses to take an offered job. This rule can in turn induce the worker to accept low-wage jobs as well.

Figure 10: Distribution of estimated income ratios for all sample members.
Notes: EIRs are computed using unconditional starting wage estimates. Income ratios are pooled over the cohorts.



The distribution of the observed income ratios probably gives too rosy a view about the range of returns to employment. This is because some of the wage offers are turned down by applicants in the labour market and because by weakening attitudes toward job search, poor economic incentives are likely to make wage offers less likely for those who are faced with them. Indeed, the distribution of the estimated income ratios suggests that the returns to employment in the whole data are weaker on average. Some 8% of the sampled individuals are estimated to be unable to increase disposable income of their households by exit to employment, while as much as 43% have to be content with a 25% increase or less.

Households faced with (expected) income losses are almost entirely couples in both distributions. A closer look at the data indicates that the spouse's high income is responsible for much of the negative income ratios. The graphs further imply that the returns to employment among single parents fall typically into a range of zero to 25%, whereas the income ratios vary widely among singles. The right-hand tail of both distributions consists mainly of singles, while many singles face very low incentives at the same time. This clearly mirrors the great heterogeneity of the single group.

Column (1) of Table 14 represents mean observed income ratios by cohort for different kinds of households (see also Figure 11).[93] It appears that employment has raised the disposable income in each household group on average. The average impact of employment, however, is quite different between household groups. The returns to employment are highest for singles, whereas income transfers cut the returns to a great extent for households with young children. Singles acquire an income advantage of roughly 90% over unemployment, but the average increase in disposable income is less than one-third for couples with young children.[94] The average returns to employment are roughly 40% for single parents, being slightly below that for the couples with no young children.

It is interesting to note that there is a declining trend in the returns to employment over the first half of the 1990's. Exits to employment have increased disposable income on average by 59% in the 1990 cohort, while the corresponding increase is 51% for the 1994 cohort.[95] In contrast to a decrease of about 10 percentage points in the couple groups, the average returns for singles and single parents have been quite stable over the period.

Up until now, our discussion has concerned how the returns to employment are distributed among different kinds of households. Such comparisons, however, do not tell us much about how the economic incentives are related to the labour marker behaviour of the unemployed. One way of assessing this issue is to compare estimated income ratios between applicants leaving unemployment through different channels. The intuition underlying such comparisons relies on the assumption that the expected returns to employment contribute to the probability of becoming employed to a great extent, making both participation in manpower programmes and withdrawal from the labour force less likely.[96]

In addition, one may view entrants into manpower programmes as a group who potentially face economic disincentives for at least two reasons. First, the choice of participation may be attributed to an attempt to fulfill the administrative requirements that make the reception of unemployment benefit

[93] Median income ratios are given in the income appendix.

[94] Of course, the relative importance of the sample member's income at the household level is less in two-adult households, pushing down the income ratios for couples.

[95] By the nature of the sampling design, sampled individuals in different cohorts entered unemployment at very different points in the business cycle. As such, important differences in the composition of the unemployed between the cohorts may be a major cause of the decrease in the average returns over the period under investigation.

[96] The same kind of reasoning suggests that unemployment duration is associated with economic incentives.

Table 5: Mean income ratios by cohort for different groups of households

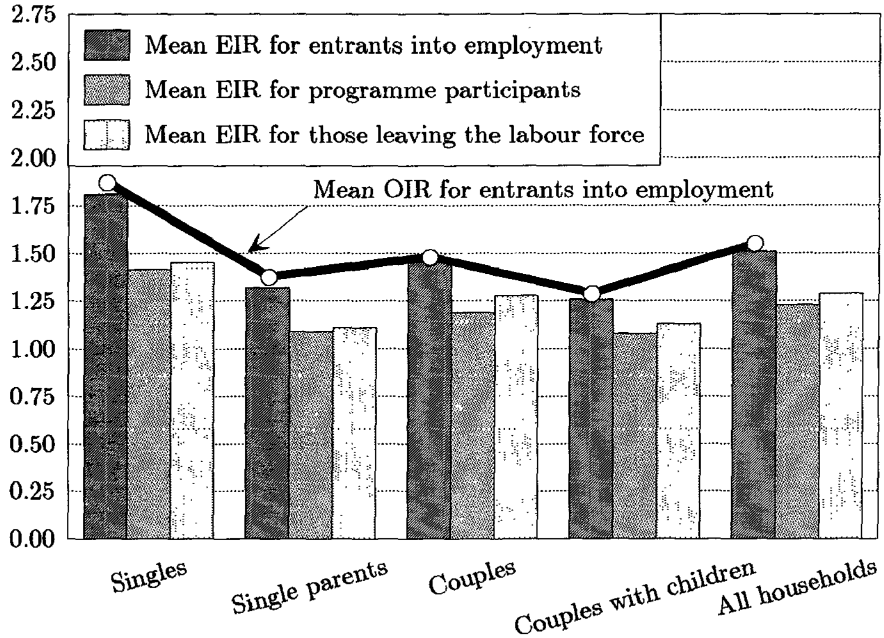
	OIR	*EIRs by exit channel*				*% of hired*
		Work	MP prog	Out LF	*All*	
Singles	(1)	(2)	(3)	(4)	(5)	(6)
1990	1.89	1.75	1.64	1.61	1.70	63
1992	1.84	1.69	1.49	1.51	1.56	34
1994	1.88	1.65	1.44	1.47	1.52	35
Single parents						
1990	1.37	1.26	1.08	1.12	1.21	68
1992	1.37	1.25	1.10	1.10	1.14	28
1994	1.42	1.28	1.13	1.20	1.18	24
Couples						
1990	1.53	1.47	1.27	1.37	1.42	67
1992	1.48	1.39	1.24	1.32	1.32	39
1994	1.41	1.33	1.20	1.27	1.26	36
Couples with children						
1990	1.33	1.28	1.16	1.22	1.25	61
1992	1.28	1.20	1.11	1.13	1.15	39
1994	1.24	1.17	1.09	1.11	1.12	32
All households						
1990	1.59	1.50	1.34	1.39	1.45	65
1992	1.53	1.42	1.28	1.32	1.34	37
1994	1.51	1.39	1.24	1.30	1.30	34

Note: EIRs are computed using unconditional starting wage estimates. Children in the family refer to dependents aged under 7.

possible in the future. Second, programme participation is usually associated with a prolonged period of unemployment, while it reflects the willingness to remain in the labour force at the same time. Since programme participants are involuntarily separated from the open labour market and they usually return to the unemployment register as the programme period comes to end, programme participation could be viewed as a kind of analogous state to unemployment.

The choice of leaving the labour force is more problematic, because reasons for leaving can vary widely from individual to individual. For example, while some aged applicants can just wait for access to the retirement, some young applicants may return to school to acquire a higher degree if no jobs are available. Even when a worker faces a meaningful option outside the labour

Figure 11: Mean income ratios by exit channel. Notes: EIRs are computed using starting wage estimates conditional the exit channel. Income ratios are pooled over the cohorts.



force, the high expected returns to employment are likely to induce more effort being put into job search while unemployed, increasing the probability of becoming employed with respect to that of leaving the labour force. As such, the probability of withdrawal from the labour force is likely to be negatively associated with the economic incentives to a some extent. If so, workers leaving the labour force can also be viewed as a reference group for those exiting to employment.

There is no notable differences in the expected returns to employment between applicants exiting to manpower programmes and those leaving the labour force, though the estimates are slightly higher on average for the latter, especially among couples (see also Figure 11). As the mean income ratio is above unity in each cell of columns (3) and (4), individuals who actually failed to find jobs are estimated to be able to increase the disposable income of their households through employment on average. It is noteworthy that the estimated returns are clearly highest for those exiting to employment in each household group and in each cohort, indicating that applicants with higher expected returns terminate their unemployment spells at employment more likely. This suggests the possibility that the expected returns play a significant role in the labour market behaviour of the unemployed.

It is interesting to note that the proportion of those exiting to employment in column (6) does not vary essentially across household groups, although the average level of the returns to employment is quite different between the groups. Single parents are the only exception as they end their unemployment spells at employment less frequently than other groups in the 1992 and 1994 cohorts.

There are some important caveats to be borne in mind at this point. Firstly, the factors of labour demand and those of economic incentives are easily mixed in the descriptive analysis of income ratios. This is because the worker's characteristics valued by employers are not only associated with the expected starting wage — on which the EIR is partly based — but also with the probability of finding a job. So, even in the case where economic incentives do not play any role, the estimated level of returns to employment for entrants into employment is likely to be higher on average than for those exiting through other channels.

A further caveat concerns the fact that sorting people according to exit channel only omits an important source of misery attached to the experiences of unemployment, that of unemployment duration. Common sense tells us that the individual's welfare is likely to be more closely related to the time he spend in unemployment than to the fact that he is experiencing unemployment. Indeed, in order to generate a fuller understanding of the role of economic incentives, one should account for the dynamic nature of the job search process as well. The next chapter introduces econometric tools that enable us to account for the dynamics of labour market behaviour and to control for the effects of several background factors simultaneously.

6 Transitions Out of Unemployment

It is the *length* of the unemployment spell that plays a crucial role in the search theory. In view of this, the analysis that relies on comparing income ratios between people leaving unemployment through different channels must be incomplete due to the omission of differences in unemployment durations. In this chapter the preceding analysis is elaborated by investigating the determinants of the probability that the individual leaves unemployment at a particular point in his spell, as well as the variation in this probability over the spell.

The search theory tells us that the probability of becoming employed is a function of variables contributing to the individual's chances of being offered an open vacancy and of variables affecting the acceptance probability. Since the individual is assumed to maximise his net income in this framework, both of these variable sets contain income while unemployed and expected income in work. An important empirical question is the extent to which the expected returns to employment contribute to the individual's probability of becoming employed. Reasoning parallel to that used before suggests that it is more reasonable to consider the expected returns at the household level than at the individual level. Therefore, in order to account for the impact of incentive factors on the exit probability, the household-level income variables are mapped into a competing risks model of unemployment duration in this chapter.

I begin in Section 6.1 with a description of the econometric model to be used in the analysis. Section 6.2 discusses the previous evidence on the effects of income variables on unemployment duration. Section 6.3 contains the estimation results of duration models.

6.1 Semi-Parametric Estimation of Duration Data

Duration models have been extensively used in biometrics, but over the last decade they have found increasing use, especially, in applied labour economics. The studies of unemployment durations usually begin by specifying the individual's probability of leaving unemployment at a particular point in the spell. These studies commonly use very restrictive models that force this probability to take a particular parametric form. Such restrictions, however, potentially bias the estimated effects of explanatory variables. In contrast to a strictly parametric specification, this study adopts a more flexible approach, with only minimal assumptions about the underlying duration distribution.

Section 6.1.1 first introduces some basic concepts of duration analysis within a single risk framework and describes a semi-parametric approach to estimate the parameters of the model. Section 6.1.2 extends the model by allowing for alternative exit channels out of unemployment. Although the models will be specified purely on statistical grounds, these models can be regarded as reduced forms resulting from behavioural models of job search. As such, the search theory can be used to facilitate the specification and the interpretation of the models in an economically meaningful manner. Yet, the restrictions implied by structural models of job search are not imposed here.[97]

6.1.1 A Single Risk Model

The variable of interest is the length of time an individual spends in unemployment. This is represented by the random variable T. Suppose that it has a continuous probability distribution, specified by the distributional function $F(t)$, where t is a realization of T. The central concept in the analysis of duration data is the conditional probability of leaving unemployment, specified by the *hazard function,*

$$\begin{aligned}\lambda(t) &= \lim_{dt\to 0}\frac{\Pr\left(t\leq T<t+dt|\,T\geq t\right)}{dt}\\ &= \lim_{dt\to 0}\frac{F(t+dt)-F(t)}{dt}\frac{1}{1-F(t)}\\ &= \frac{f(t)}{1-F(t)}.\end{aligned}\tag{23}$$

In words, $\lambda(t)dt$ gives the conditional probability that the unemployment spell will end in the next short period, dt, given that it has lasted until t.

It is commonly said that *negative duration dependence* exists at the point t^* if $d\lambda(t)/dt<0$ at $t=t^*$. The negative duration dependence means that the probability that a spell will end in the next period, given that it is still in progress, decreases as the spell increases in length. This may occur if employers discriminate against the long-term unemployed or if the individual's search intensity decreases with elapsed duration. The opposite case is that of increasing hazard; that is, *positive duration dependence* exists at the point t^* if $d\lambda(t)/dt>0$ at $t=t^*$. This can result, for example, if the unemployed become increasingly desperate for a job and accept the first job offered as time passes.

[97] For a survey of job search models, see Mortensen (1987).

Explanatory variables can contribute to unemployment duration in many ways. The addition of explanatory variables to duration models is rather straightforward. The statistical model adopted for this study is of the *proportional hazard* form, in which the hazard function is supposed to depend on a vector of explanatory variables x, known as "covariates," with unknown coefficients β and the *base-line hazard,* $\lambda_0(t)$, as

$$\lambda(t) = \lambda_0(t) \exp\{-x'\beta\}. \tag{24}$$

The base-line hazard can be interpreted as the hazard function for an individual for whom $\exp\{-x'\beta\} = 1$. The specification in (24) is a convenient one because non-negativity of $\exp\{-x'\beta\}$ does not impose any restrictions on β and the interpretation of the effects of the covariates is straightforward. In particular, the specification implies that

$$\frac{\partial \ln \lambda(t)}{\partial x} = -\beta, \tag{25}$$

so the covariates have constant proportional effect, which is independent of duration t, on the hazard rate. This is analogous to the usual partial-derivative interpretation of coefficients in the linear regression model, in which the explanatory variables affect the distribution of the dependent variable by moving its mean around.[98] From (25), one can further see that the coefficient of the continuous variable that enters in the logarithmic form can be interpreted as the elasticity of the hazard rate with respect to that covariate.

The proportional hazard model, with the hazard function of the form (24), can be expressed in the form of a linear regression model as

$$\delta_t = x'\beta + \epsilon, \tag{26}$$

where $\delta_t = \ln \int_0^t \lambda_0(u)du$ is the log of the *integrated base-line hazard* and the disturbance term, ϵ, is of an extreme value form. It should be stressed that the distribution of ϵ follows directly from the proportional hazard specification, so that no additional assumption is made beyond (24). (Han and Hausman, 1986, 1990.)

[98] It should be stressed that this is a special feature of the proportional hazard specification. The coefficient in the duration model, in general, does not have a clear interpretation as a partial-derivate analogous to the linear regression model. Although the sign of the coefficient always reveals the direction of the impact of the covariate on the hazard rate, the numerical value of this effect, in general, depends on duration and other included covariates. (Kiefer, 1988.)

Thus, the proportional hazard model has a convenient interpretation as a linear regression model with a fully specified disturbance term. When the data is not badly censored and knowledge of the integrated base-line hazards is available,[99] it is possible to apply least-squares regression methods to estimate β. In that case, one should take into account the non-normality of the disturbance term and its non-zero mean. However, there are estimation methods that are preferred on efficiency grounds. (Kiefer, 1988.)

In this study, instead of using the continuous time specification, the estimation of the unknown parameters of the model is based on the likelihood for the discrete or grouped data as suggested by Han and Hausman (1986, 1990). For this reason, suppose that t is measured in months by grouping durations into intervals equal to the months *completed* in unemployment. That is, an observed duration of t whole months indicates a duration on the continuous time scale between t and $t+1$ months. Then the probability of a spell being completed in interval $[t, t+1)$ is

$$\Pr\left(t \leq T < t+1\right) = \int_{\delta_t - x'\beta}^{\delta_{t+1} - x'\beta} g(\epsilon) d\epsilon,$$

where $g(\cdot)$ is the density function of the extreme value distribution.

Let the data be (t_i, x_i) for $i = 1, 2, ..., N$ observations. Using observations t_i one can define indicator variables y_{it} that take on a value of unity if unemployment terminates after t_i completed months for person i, and zero otherwise. Then the log-likelihood function of the model is

$$\ell = \sum_{i=1}^{N} \sum_{t=0}^{\overline{T}} y_{it} \ln \int_{\delta_t - x_i'\beta}^{\delta_{t+1} - x_i'\beta} g(\epsilon) d\epsilon, \tag{27}$$

where $\overline{T}$ is the longest spell group in the data.[100] The maximum likelihood (ML) estimates of the unknown parameters are obtained by maximizing (27) over β and $\delta = (\delta_0, \delta_1, ..., \delta_{\overline{T}})$. Under suitable regularity conditions, the ML estimator of $\theta = (\beta, \delta)$ can be shown to be consistent and asymptotically normal with the asymptotic variance-covariance matrix equal to $-\left(\partial^2 \ell / \partial\theta\partial\theta'\right)^{-1}$.[101] (Han and Hausman, 1986, 1990.)

Since economic theory is not informative about the shape of the hazard function, the specification of the above model is reasonably flexible. The model is

[99] Censoring can be controlled by Tobit-like methods when the normal assumption is replaced by the extreme value distribution (Kiefer, 1988).

[100] Those familar with the literature on discrete choice models will recognize that the log-likelihood function is of an ordered logit form.

[101] Asymptotics here refer to the case where $\overline{T}$ is fixed and N goes to infinity.

"semi-parametric" in the sense that the base-line hazard is non-parametric, which requires no prior assumptions of parametric form, while the effect of the covariates takes a particular functional form. The log integrated base-line hazards, δ_t, are specified as a series of dummy variables that are estimated simultaneously along with the parameters β.[102] The model is especially suited to discrete data as it is unhindered by a large number of ties, i.e., simultaneous exits in the data. In addition, the true parameters of the covariates are invariant to the length of time intervals chosen, so that one can choose the grid of intervals finer as the sample size increases. (Han and Hausman, 1986, 1990.)

The derivation of the likelihood function above involves a direct specification of the individual's probability of leaving unemployment in a particular period. An alternative strategy would be to describe the outcome as a sequence of hazard rates; that is, one could consider the probability of leaving in the first period, then the probability of leaving in the second period, conditional that the individual didn't leave in the first period, and so on. The approach adopted here seems more complicated as it involves simultaneous consideration of the possibilities of leaving in several periods. Indeed, it is often easier and more natural to model duration data in terms of hazard functions than in terms of densities. Of course, conditional and unconditional probabilities are related, so that both approaches are mathematically equivalent, representing only two different ways of describing the same set of probabilities.[103] The approach based on the density functions is adopted here due to the intention of putting the log-likelihood function into an ordered logit form. This is because the duration models in this study are, in fact, estimated with a ML procedure for the ordered logit model.

6.1.2 Multiple Exit Channels — A Competing Risks Model

The preceding section presented the method for analysing completed spells of unemployment without specifying the cause of termination; that is, there were no questions regarding *alternative* channels out of unemployment. This section extends the proportional hazard model to the case where unemployment is terminated by exit to one of several possible destinations. Models which accommodate multiple causes of termination are commonly referred

[102] Han and Hausman (1990) pointed out that Cox's partial-likelihood procedure treats the base-line hazards as nuisance parameters and conditions them out of the likelihood function.

[103] For more detailed discussion about the differences between the two concepts, see Kiefer (1988).

to as **competing risks models.**

Suppose that when a transition out of unemployment occurs, it can be a result of one of three causes, which are mutually exclusive and denoted by $k = \{1, 2, 3\}$. Namely, the unemployment spell can end at employment, at a manpower programme or at withdrawal from the labour force. Let us define a set of indicator variables, $\{D_k\}$, taking a value of unity if the unemployment spell is terminated by exit to destination k, and a value of zero otherwise.

The competing risks model can be placed into a latent variable framework by postulating the existence of three independent latent variables, T_1^*, T_2^* and T_3^*, one for each destination. In particular, T_k^* would be the length of the unemployment spell if destination k were the only destination present. As before, T_k^* are supposed to have continuous probability distributions, specified by the distributional functions $F_k(t_k)$. The actual destination entered is determined by whichever of $\{T_k^*\}$ is the least and this minimum is the duration that is observed, so that instead of observing the latent variables T_k^*, one observes

$$T = \min\{T_1^*, T_2^*, T_3^*\}. \tag{28}$$

Now the rate of exit to destination k at time t, given x and the presence of the other destination states, is defined with a *destination-specific transition* (or cause-specific hazard) *rate,*

$$\lambda_k(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T_k^* < t + dt \,|T_k^* \geq t)}{dt} = \lambda_0^k(t) \exp\left\{-x_k' \beta^k\right\} \tag{29}$$

for $k = 1, 2, 3$. In addition to the base-line hazard, covariates can also vary with respect to the destination. The (overall) hazard rate out of unemployment is the sum of the destination-specific transition rates over the destination states,

$$\lambda(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T < t + dt |\, T \geq t)}{dt} = \sum_{k=1}^{3} \lambda_k(t). \tag{30}$$

Using the notations from the single risk specification, the competing risks model can be expressed in the form of a set of linear equations as

$$\begin{aligned}
\delta_t^1 &= x_1' \beta^1 + \epsilon_1, \\
\delta_t^2 &= x_2' \beta^2 + \epsilon_2, \\
\delta_t^3 &= x_3' \beta^3 + \epsilon_3,
\end{aligned} \tag{31}$$

where the stochastic disturbances, ϵ_1, ϵ_2, and ϵ_3, are independently distributed. (Han and Hausman, 1986, 1990.)

To illustrate the individual's contribution to the likelihood function, suppose that the unemployment spell is terminated after t whole months by exit to destination 1. Given the grouping of the underlying data and independence of ϵ_1, ϵ_2, and ϵ_3, the probability of this outcome is

$$\int_{\delta_t^1 - x_1'\beta^1}^{\delta_{t+1}^1 - x_1'\beta^1} g(\epsilon_1)\, d\epsilon_1 \int_{\delta_t^2 - x_2'\beta^2}^{\infty} g(\epsilon_2)\, d\epsilon_2 \int_{\delta_t^3 - x_3'\beta^3}^{\infty} g(\epsilon_3)\, d\epsilon_3. \tag{32}$$

The contributions of observations on individuals exiting to other destinations can be expressed analogously.

Let the data be $(t_i, x_{i1}, x_{i2}, x_{i3}, d_{i1}, d_{i2}, d_{i3})$ for $i = 1, 2, ..., N$ observations. Once again, define indicator variables y_{it} that take on a value of unity if the unemployment spell terminates after t completed months for person i, and zero otherwise. Then the log-likelihood function of the model is

$$\begin{aligned}
\ell \; = \; & \sum_{i=1}^{N}\sum_{t=0}^{\overline{T}} y_{it} \Bigg[d_{i1} \left(\ln \int_{\delta_t^1 - x_{i1}'\beta^1}^{\delta_{t+1}^1 - x_{i1}'\beta^1} g(\epsilon_1)\, d\epsilon_1 + \sum_{k \neq 1} \ln \int_{\delta_t^k - x_{ik}'\beta^k}^{\infty} g(\epsilon_k)\, d\epsilon_k \right) \\
& + d_{i2} \left(\ln \int_{\delta_t^2 - x_{i2}'\beta^2}^{\delta_{t+1}^2 - x_{i2}'\beta^2} g(\epsilon_2)\, d\epsilon_2 + \sum_{k \neq 2} \ln \int_{\delta_t^k - x_{ik}'\beta^k}^{\infty} g(\epsilon_k)\, d\epsilon_k \right) \\
& + d_{i3} \left(\ln \int_{\delta_t^3 - x_{i3}'\beta^3}^{\delta_{t+1}^3 - x_{i3}'\beta^3} g(\epsilon_3)\, d\epsilon_3 + \sum_{k \neq 3} \ln \int_{\delta_t^k - x_{ik}'\beta^k}^{\infty} g(\epsilon_k)\, d\epsilon_k \right) \Bigg],
\end{aligned} \tag{33}$$

where

$$-\infty < \delta_0^k < \delta_1^k < ... < \delta_{\overline{T}}^k < \infty,$$

for $k = 1, 2, 3$.

Note that the factors in the log-likelihood function (33) can be rearranged into a separate component for each destination. This can be stated formally by partitioning the log-likelihood function as

$$\ell = \ell^1 + \ell^2 + \ell^3,$$

where

$$\ell^k = \sum_{i=1}^{N}\sum_{t=0}^{\overline{T}} y_{it} \left[d_{ik} \ln \int_{\delta_t^k - x_{ik}'\beta^k}^{\delta_{t+1}^k - x_{ik}'\beta^k} g(\epsilon_k)\, d\epsilon_k + \sum_{h \neq k} d_{ih} \ln \int_{\delta_t^k - x_{ik}'\beta^k}^{\infty} g(\epsilon_k)\, d\epsilon_k \right]$$

is a function of the parameters of the transition rate to destination k only. Thus, the parameters of a given destination-specific transition rate, $\lambda_k(t)$, can be estimated by maximizing ℓ^k over β^k and $\delta^k = (\delta_0^k, \delta_1^k, ..., \delta_{\overline{T}}^k)$.

In what follows, one can apply the method described in the previous section by treating observations on unemployment spells finishing by exit to other destinations as "censored" at the point of completion. That is, in estimation of the parameters of the transition rate to destination k, observation i on the spell that ends at some another destination after t whole months contributes

$$\ln \int_{\delta_t^k - x'_{ik}\beta^k}^{\infty} g\left(\epsilon_k\right) d\epsilon_k \tag{34}$$

to the log-likelihood function. In other words, the only information used is that the relevant duration is at least t.

6.1.3 Some Remarks

The model specification above assumes that all heterogeneity among individuals is captured by the observed characteristics, incorporated in the individual-specific covariates. As there are also unobservable sources of population heterogeneity, differences in the duration distributions remain, even after the effects of observed variables are accounted for. One well-known consequence of uncontrolled heterogeneity is a downward biased estimate of duration dependence.

The effect of heterogeneity on apparent duration dependence can be illustrated by using a simple example. Consider an unobservable characteristic, "motivation," that is positively associated with the effort an individual puts into job search. In a sample of the unemployed, those who are better motivated will complete their unemployment spells faster, so that the fraction of better-motivated individuals in the sample falls as time passes. As a result of a lower hazard function for less-motivated individuals, the decline in the fraction of the better-motivated pushes down the estimate of the transition rate to employment, producing negative duration dependence of a spurious form.

The problems associated with heterogeneity are related to the sampling design as well. This is because the entry and exit probabilities of unemployment are affected by both observable and unobservable individual characteristics. As a consequence, the joint distributions of observables and unobservables are generally different in the populations flowing into or out of unemployment, in the populations of the unemployed or employed and in the labour force as a whole. For example, in non-stationary and disequilibrium models, the joint distribution of observable and unobservable characteristics differs in flow and stock samples and varies continuously over time, even if the distribution of individual characteristics in the whole labour force is static.[104] This suggests that estimates of labour market behaviour should be interpreted carefully as the results may be sensitive to the population sampled and to the time period studied. (Chester and Lancaster, 1983.)

There are several ways of extending duration models to account for unobserved heterogeneity. One approach is to introduce a stochastic disturbance term, with some density function, into the destination-specific transition rates. The practical problem concerns the distribution of these terms and a possible correlation between them. The simplest approach assumes a particular functional form for the unobservable heterogeneity and independence of these disturbance terms. Instead of the parametric modelling of heterogeneity, one can also apply more complicated procedures that use non-parametric approximation of the unknown disturbance distributions and allow for non-zero correlation between the destination-specific transition rates.

However, there is evidence that in certain cases the omitted heterogeneity may not be particularly serious. Indeed, with a sufficiently flexible base-line hazard, the omitted heterogeneity is unlikely to have serious consequences for the ML estimates. For example, Han and Hausman (1986, 1990) have extended the model adopted in this study by adding (gamma) heterogeneity that permits unrestricted correlation among destination-specific transition rates. The addition of heterogeneity had only a minor effect on the results in their empirical example of unemployment duration. This result is in line with other findings on semi-parametric methods, indicating that unobserved heterogeneity is less important when flexible base-line hazard specifications are used (see e.g., Meyer, 1990, and Narendranathan and Stewart, 1993). Indeed, the unobserved heterogeneity seems to be more of a problem of parametric models that assume a particular parametric form for the base-line hazard. Taken together with the fact that the data available contains a rich set of control variables, it is likely that the impact of unobservable characteristics in the present context will be moderate.

6.2 The Studies of Income Impacts on Labour Market Transitions

Once again, it is convenient to take a brief look at the previous findings before turning to the estimation results. There are a number of studies concerning income effects on the labour market behaviour of the unemployed. This

[104] As participation in the labour force is sensitive to cyclical fluctuations, even this point is unlikely to hold within the period under investigation.

section presents only some selected references on the empirical findings from Finnish data. A more extensive survey on the Finnish evidence is found in Rantala (1998). For international surveys on the subject, one may refer to Atkinson and Micklewright (1991) or to Pedersen and Westergård-Nielsen (1993).

Eriksson (1985) and Pääkkönen (1992) have applied strictly parametric methods to model unemployment duration. Eriksson assumed that the underlying duration distribution is log-normal in his sample of individuals who left the unemployment records of the employment agency of Turku in November 1983. Pääkkönen in turn applied the Weibull model to a sample from the Finnish Labour Force Survey for 1987.[105] Eriksson concluded his analysis by arguing that there is no significant relation between unemployment duration and unemployment benefits. The findings of Pääkkönen, however, suggest that basic unemployment assistance (UA-benefit) receivers experience longer periods of unemployment than applicants under other benefit schemes.

Pyy (1994) has studied the determinants of the probability of finding a job among young people. She applied Cox's proportional hazard model to a sample of unemployed applicants aged under 30. Eligibility for unemployment insurance (UI) benefit was found to increase the probability of becoming employed among young men, whereas it did not appear to be a significant factor among young women.

Lilja (1992, 1993) has analysed the impact of the unemployment compensation system on unemployment duration using the data from the Finnish Labour Force Survey for the period 1984–87. She estimated a semi-parametric competing risks model for the whole sample, as well as for three different benefit groups separately — namely, for UI-benefit receivers, for UA-benefit receivers and for uncompensated applicants (non-claimants). In addition to the exit to employment, Lilja allowed for two kinds of exits from the labour force, one due to voluntary choice (starting of studies or homemaking) and one due to necessity (military service, disability or related causes). According to the results, the probability of finding a job is three times higher for a non-claimant and roughly twice for a UI-benefit receiver than for a UA-benefit receiver with otherwise similar characteristics. For the analysis of income effects, Lilja pooled these three benefit groups together. She found a clear positive dependence between the earnings prior to the unemployment spell

[105] The shortcoming of these models is that they force the hazard function to take a particular functional form. The hazard function for the log-normal distribution is increasing up to a particular point in the spell and thereafter decreasing, and that for the Weibull distribution is monotonically decreasing or increasing over the whole spell depending on the shape parameter.

and the probability of becoming employed. Yet, the replacement ratio did not appear to be a significant determinant of the employment probability.[106]

Kettunen (1989, 1990, 1993a) has applied different duration models to the data sampled by picking up every hundredth individual flowing into unemployment in 1985. Sampled individuals were followed at the end of 1986 or at the end of the unemployment spell if it was terminated earlier. Information about prior earnings and income while unemployed were gathered from tax records, from the Social Insurance Institution and from the records of Postipankki. The results obtained with the Weilbull model indicate that the replacement ratio has a negative effect on the probability of becoming employed among UA-benefit receivers, but an insignificant effect among UI-benefit receivers. The findings from Cox's proportional hazard model, in which the income effects were allowed to vary over the spell, suggests that the replacement ratio has a negative effect on the re-employment probability during the first three months, but turns to positive thereafter.

In addition to unemployment income and "backward-looking" measures of economic incentives, there are few attempts to account for (expected) income changes resulting from the entry into employment. Holm *et al.* (1996) have computed changes in households' disposable income that result from the unemployed member's transition into employment using the same outflow samples of 1988, 1990 and 1992 as used in this study. Of course, the results from this exercise are similar to those associated with the observed income ratios in the preceding chapter. This descriptive analysis is brought forward in the study by Holm and Kyyrä (1997), in which the estimated income ratios based on the starting wages estimates were introduced. The estimated income ratio was mapped as an explanatory variable into the probit model for the probability that the terminated spell of unemployment was ended at employment.[107] The findings suggest that the expected returns to employment have a highly significant impact on the employment probability, and that the high level of the spouse's income tends to increase the employment probability as well. The major drawback of this modelling strategy is that it omits the differences in unemployment durations between individuals.

Rantala (1998) has applied a semi-parametric competing risks model to the same outflow samples of 1998, 1990 and 1992 as used in this study.[108] By

[106] The replacement ratio is the ratio of unemployment benefits to the earnings in the last job prior to unemployment.

[107] That is, the probit setting is similar to the selection equation underlying the starting wage regression.

[108] The results concerning the income effects from this analysis are discussed in more detail in Holm *et al.* (1998).

borrowing the parameter estimates of the starting wage equation from Kyyrä (1997), Rantala was able to calculate a proxy variable for the expected returns to employment at the household level, which was then included in the set of covariates. According to the results, the probability of becoming employed is higher for applicants with high expected returns. In addition, the level of the household's disposable income while unemployed was found to be negatively associated with unemployment duration. Since the focus of the study was not on income effects, but rather on the effects of individual characteristics and importance of manpower programmes, the setting used was not the most preferable to the evaluation of the role of economic incentives. The aim of this chapter is, in fact, to complete Rantala's analysis by evaluating the effects of incentive variables in more detail.

6.3 Estimations Results

This section represents the estimation results of the flexible competing risks models with unrestricted base-line hazards.[109] Instead of using the pooled data, the original samples from outflows of unemployment are analysed separately. This is because the macroeconomic circumstances at the times of the cohorts sampled were very different. For example, the unemployment rate in 1994 was more than fivefold of that in 1990. There was also a much higher proportion of long-term unemployed and the availability of manpower programmes was essentially different. This dramatic rise in unemployment and fall in the rate of exit call into doubt whether the determinants of unemployment duration are the same for each cohort. Important differences in the composition of the unemployed between the cohorts may lead to differences in the average effects of certain factors if these effects vary with the characteristics of the individual. Reasonable accounting for these difficulties through covariates seems very hard to implement in practice. Thus, the use of original samples brings required additional flexibility to the analysis.

The determinants of the transition rates to each destination are discussed

[109] Since the log-likelihood function for the competing risks model splits into a separate component for each destination, the estimation of the model is done in three steps by estimating the parameters of each destination-specific transition rate separately. Each step uses all observations (in the cohort), but in estimation of the parameters of the transition rate to a particular destination, observations on spells that end at other destinations are treated as censored at the point of completion, as descriped in Section 6.1.2. In addition, the higher weights in the sampling for those long-term unemployed exiting to employment are taken into account in the estimations by weighting individual contributions to the log-likelihood function accordingly.

in separate subsections below. Particular attention is paid to the impact of income variables, although the models include a wide range of controls for the effects of other factors as well. Readers especially interested in other contributing factors should refer to the study by Rantala (1998), in which similar methods are used with the same source of data.

6.3.1 Transition Rates to Employment

The estimated effects of explanatory variables on the transition rates to employment are given in Table 6,[110] where the signs of all coefficients are reversed.[111] Since the range of unemployment durations varies over the period under investigation, the point to which the base-line hazard can be estimated differs between the cohorts. The right endpoint of the base-line hazard is therefore selected for each cohort separately. The estimated coefficients, however, are not sensitive to the choice of the endpoint, as could be expected due to non-parametric specification of the base-line hazard.

It appears that the impact of education on the transition rate to employment is quite moderate. The coefficients on high school and vocational education do not differ significantly from zero in any cohort. A degree from the undergraduate or graduate level of education increases the probability of finding a job in the 1992 and 1994 cohorts and, surprisingly, decreases that in the 1990 cohort. The lack of professional qualifications has a strong effect as job seekers registered as unskilled in the employment agencies are found to have much weaker possibilities to find jobs in each cohort.

The sensitivity of the employment probability with respect to age varies across cohorts. Differences in the probability between age groups are most clear in the 1990 cohort in which a clear negative dependence appears. It is interesting to note that applicants aged over 52 have unusually low chances to find work in each cohort. One explanation might be that employers are more cautious about hiring older workers due to their greater propensity to

[110] When interpreting the results, one should recall that the proportional hazard specification implies that the coefficient on the log of a continuous variable can be interpreted as the elasticity of the transition rate with respect to that variable. In the case of an indicator variable, one may in turn compute the relative probability of becoming employed compared to the reference group by taking the exponential of its coefficient. For example, the monthly probability of finding a job in the 1990 cohort is 1.43 ($\approx e^{.3553}$) times higher for a woman than for a man with otherwise similar characteristics.

[111] Since the transition rate specification incorporates the effect of the covariates as $\exp\{-x'\beta\}$, a positive coefficient *lowers* the transition rate. The signs of the coefficients in the table are reversed for interpretational purposes.

be sick and the risk of early retirement. On the other hand, the exhaustion of UI-benefits at 500 days is not enforced for the long-term unemployed aged over 52, but instead they are allowed to receive UI-benefits up to the age of retirement without any sanctions. This suggests the possibility that the lack of the threat to drop out of the UI system may depress the search intensity of the older applicants.

Applicants in the capital city area find jobs with a higher probability in the boom cohort of 1990, while living in the countryside contributes positively to the employment probability in the 1994 cohort. The indicator variable for health disability has a significant coefficient with the expected sign in each column, indicating that it is much harder to find employment when experiencing health problems.

Women complete their spells at employment more rapidly, though the gender effect in the last cohort is only half of that in two of the earlier cohorts. As expected, the effects of family background are differentiated by gender. Married and cohabiting women are less likely to find jobs than single women, whereas a partner does not contribute significantly to the men's probability of exit to employment in any cohort. Children aged under 7 are found to reduce women's transitions to employment, suggesting that the responsibility of child-rearing contributes not only to the labour force participation of women, but also to behaviour in the labour market when involved. The effect of young children is generally positive for men, though it is not statistically significant in any cohort.

Coefficients on the indicators for different entry channels imply that prior labour market history does matter. Individuals flowing into unemployment from job replacement programmes and from outside the labour force have exceptionally low chances to find jobs compared to those who became unemployed because of job loss. The probability of becoming employed for applicants who were on a training course prior to the unemployment spell does not differ from that of the reference group. However, a note of caution is required here because the selection of individuals into manpower programmes is not controlled by any means and because the programme participation serves occasionally as a signal of existing obstacles in job search. So, the indicators for the entry channels act more like controls for individual heterogeneity than variables accounting for the impact of programme participation.

Demand constraints in the labour market are controlled by two variables, both familiar from the starting wage model. The unemployment rate in the individual's travel-to-work area is used to measure regional demand conditions, whereas the vacancy-unemployment ratio is included to account for the

Table 6: Semi-parametric estimates for the covariates of the transition rate to employment

Covariate	1990 (1)	1992 (2)	1994 (3)
Education: (*vs.* basic)			
High school	.1781 (.1150)	–.1004 (.4455)	–.0619 (.6166)
Vocational level	.0758 (.1426)	.0982 (.1274)	.0342 (.5510)
Higher level	–.2385 (.0326)	.3331 (.0018)	.2464 (.0023)
Unskilled	–.3365 (.0004)	–.7707 (.0001)	–.7025 (.0001)
Age: (*vs.* 36–45)			
Under 20	.5576 (.0001)	–.5005 (.0621)	.4928 (.0435)
20–25	.3808 (.0001)	.2413 (.0084)	.3873 (.0001)
26–35	.1492 (.0165)	.0885 (.2213)	.1177 (.0618)
46–52	–.1883 (.0208)	–.0583 (.5455)	–.1429 (.0692)
Over 52	–.6663 (.0001)	–.2022 (.0706)	–.4173 (.0001)
Female	.3553 (.0001)	.3617 (.0002)	.2007 (.0157)
Family status: (*vs.* single)			
Female with partner	–.2308 (.0210)	–.3950 (.0014)	–.3206 (.0018)
Male with partner	.0603 (.5502)	–.2351 (.0592)	–.1188 (.2391)
Female × number of children	–.1721 (.0012)	–.1368 (.0399)	–.1688 (.0041)
Male × number of children	.0413 (.4976)	.1011 (.1087)	.0040 (.9388)
Health disability	–.4649 (.0001)	–.4607 (.0019)	–.4478 (.0006)
Capital city area	.5263 (.0001)	–.0577 (.5877)	.1231 (.1248)
Countryside	.0588 (.2707)	.0539 (.4032)	.1556 (.0055)
Entry channel (*vs.* from work)			
Training course	.1681 (.1132)	–.1637 (.2383)	–.1132 (.1604)
Job replacement programme	–.4071 (.0001)	–.6166 (.0001)	–.5545 (.0001)
Outside labour force	–.2446 (.0008)	–.4755 (.0001)	–.4162 (.0001)
Unknown	.0215 (.7906)	–.1193 (.2541)	.0313 (.6506)
ln(regional unemployment rate)	.4857 (.0001)	1.8563 (.0001)	–.0104 (.9355)
ln(vacancy-unemployment ratio)	–.0208 (.5606)	–.1080 (.0001)	–.0926 (.0005)
ln(participation ratio)	–.1455 (.1060)	–.5986 (.0001)	.2709 (.0256)
ln(income ratio)	.9460 (.0001)	1.5170 (.0001)	1.9114 (.0001)
ln(unemployment income)	.3009 (.0075)	.7011 (.0001)	.4898 (.0001)
ln(debt)		.0119 (.0255)	.0222 (.0001)
UI receiver (*vs.* UA receiver)	–.0516 (.3816)	–.2055 (.0036)	.1172 (.0729)
Non-claimant (*vs.* UA receiver)	.5182 (.0001)	.4497 (.0001)	.4969 (.0001)
Log-likelihood (abs.)	3,588	2,772	3,929
Total observations	2,449	2,308	3,288
Completed spells	1,582	852	1,123

Notes: Duration data measured in completed months that are defined as four weeks (i.e., 28 days) periods. Intercepts vary monthly. Number of children refers to dependents aged under 7. Asymptotic P-values in parentheses. The effects of the covariates are not allowed to vary over the unemployment spell. The signs of all coefficients are reversed.

availability of open vacancies suited to the individual's occupational qualifications.[112] The coefficient on the regional unemployment rate obtains somewhat unexpectedly a positive sign in the 1990 and 1992 cohorts. Similar results, however, have been obtained by Meyer (1990) with U.S. data and Lilja (1993) and Rantala (1998) with Finnish data.[113] Meyer argued that the positive relationship between regional unemployment and the employment probability could be a result of the counter-cyclical nature of lay-offs. Indeed, because the fraction of laid-off people in the unemployment register rises in a recession and because lay-off spells are usually shorter than other unemployment spells, the overall exit rate to employment may actually fall when the unemployment figures decrease. This explanation, however, is unlikely to hold here as laid-off people were sorted out from our data.

Lilja has suggested that another potential cause for the positive coefficient on the regional unemployment level might be a regionally practised labour market policy, which provides a larger than average proportion of displaced workers employed by labour administrative measures in regions which have higher unemployment rates. Neither is this explanation very convincing here because the exits to job replacement programmes are separated from the exits to "real" jobs in our analysis, and because the model contains a control variable for the regional availability of manpower programmes; the participation ratio. It is also surprising to note that the vacancy-unemployment ratio is negatively associated with the probability of becoming employed in the 1992 and 1994 cohorts.

A strong caveat is required at this point. Both the regional unemployment rate and vacancy-unemployment ratio are early averages for the year the individual *entered* unemployment. This calls into doubt whether the demand constraints are taken into account appropriately. Consider, for example, a person in the 1992 cohort who entered in the unemployment register in 1990 and exited in 1992. As a result of the business cycle, a relatively low (regional or occupational) unemployment rate will be attached to this person as compared to an otherwise similar person but who experienced a short period of unemployment in 1992. In what follows, the unemployment duration will be *negatively* associated with the level of unemployment. This kind of reasoning suggests that the detection of demand side effects requires time-dependent covariates that vary with calendar time over the spell. So, it is probably best to interpret our findings on the impacts of demand constraints by saying that the model does not provide a clear account of how the probability of becom-

[112] Both are yearly averages for the year of unemployment entry.

[113] All these studies use the time-variant vacancy-unemployment ratio in the individual's area of residence.

ing employed responds to changes in regional and occupational employment conditions.[114] For the same reasons, the model is not able to give a clear account for the importance of the availability of manpower programmes either. Indeed, the participation ratio has a strong negative effect on the transition rate in the 1992 cohort, but the effect turns to positive in the 1994 cohort.[115]

The quite different eligibility criteria for the unemployment compensation schemes lead one to ask whether other aspects of the compensation system than just the benefit level (incorporated in the household's unemployment income) can affect labour market transitions. To account for this possibility, the indicator variables for UI-benefit receivers and for uncompensated non-claimants are included into the model, while UA-benefit receivers serve as a reference group.[116] It appears that non-claimants complete their unemployment spells at employment more rapidly than other benefit groups in each cohort. This may reflect lower reservation wages for non-claimant as they do not suffer from benefit losses. The probability of becoming employed is approximately the same for UI- and UA-benefit receivers in the 1990 and 1994 cohorts, but UA-benefit receivers enter employment more rapidly in the 1992 cohort.

In the analysis of unemployment durations, one commonly-used measure of expected income in work is the individual's (net) earnings in the last job prior to the unemployment spell — possibly incorporated into the replacement ratio. However, there is evidence that workers who lost their jobs usually return to work at lower earnings, and such earnings losses are found to be quite persistent.[117] These findings and the importance of income transfers call into doubt whether such a measure is able to appropriately account for the expected income in the subsequent job. Therefore, instead of using "backward-looking" measures, the estimated income ratio, as introduced in

[114] If the regional unemployment rate and vacancy-unemployment ratio are measured in the year of exit, the coefficients will be reversed in the 1992 cohort, while the coefficients in the 1990 and 1994 cohorts will not differ significantly from zero.

[115] Recall that the participation ratio is the ratio of programme participants to the unemployed in the individual's labour administration district.

[116] Earnings-related UI-benefit is received by trade union fund members who have been in work and contributed insurance payments to the fund for at least 6 months prior to unemployment. UA-benefit receivers are either union members not eligible for UI-benefit or non-members. Eligibility for UA-benefit is further determined by the household's income and the number of dependent children. Uncompensated non-claimants are those eligible neither for UI- nor UA-benefits. Since the data does not contain direct information on individual's eligibility for different types of benefits, the individual's compensation scheme was deduced using the observed level of unemployment benefits.

[117] In addition, many people enter the unemployment register for other reasons than job loss, so there is no prior wage rate for them.

Chapter 5,[118] is included into the model to serve as a measure of the expected returns to employment. Recall that high returns, measured with the income ratio, can result either from low unemployment income or from high expected earnings in the subsequent job. To control for the income levels as well, the model is further complemented by adding the household's disposable income while the sample member is unemployed to the set of covariates.

It appears that all income variables enter highly significantly in each column. After controlling for the expected returns to employment, the impact of the household unemployment income is found to be positive. The elasticity of the exit probability with respect to unemployment income is under half in the 1990 and 1994 cohorts, being about .3 and .5 respectively. A somewhat stronger effect is found for the 1992 cohort as the coefficient on unemployment income in column (2) is roughly .7. It is also interesting to note that the household's total debt has a significant coefficient in both cohorts for which the debt statistics are available. In particular, a hypothetical doubling of debt would increase the monthly probability of finding employment by around 1% in the 1992 cohort and by 2% in the later one.

The estimated coefficient on the income ratio in each column points to the existence of a strong positive relation between the probability of becoming employed and the expected returns to employment. The estimated elasticity with respect to the income ratio gets stronger over the period under investigation. A 10% increase in the expected returns increases the monthly probability of exit to employment by around 9% in the 1990 cohort and by as much as some 19% in the 1994 cohort.[119] The strengthening of the effect over the business cycle is consistent with the findings in Rantala (1998), thought the estimated elasticities here are of a higher magnitude.

On should recall that income levels and ratios vary with the household composition. This leads one to ask whether the estimates of income elasticities

[118] To be specific, the income ratio was re-computed for each sampled individual by using the unconditional starting wage estimate, after the spell duration in the starting wage equation was set at the cohort average.

[119] An alternative way to assess the effects of income variables is to compute the elasticities of the exit probability with respect to income levels directly. Since the income ratio is the ratio of the household's expected income in work to its unemployment income, this can be done in a straightforward manner using the estimates in Table 6. The elasticity with respect to the expected income in work equals the coefficient of the income ratio, whereas the elasticity with respect to unemployment income is the difference between the coefficient of unemployment income and that of the income ratio. Since the coefficient of the income ratio is higher in each column, the elasticity of the exit probability with respect to unemployment income is always negative when expressed in this manner, being $-.65$, $-.82$, and -1.42 in the 1990, 1992 and 1994 cohorts, respectively.

Table 7: The estimates of income elasticities with varying controls

Controls excluded for:	1990 (1)	1992 (2)	1994 (3)
Family background			
ln(income ratio)	.8206 (.0001)	1.2338 (.0001)	1.8358 (.0001)
ln(unemployment income)	.1560 (.0164)	.3673 (.0001)	.2380 (.0032)
ln(debt)		.0131 (.0134)	.0210 (.0001)
Compensation system			
ln(income ratio)	1.4193 (.0001)	2.1250 (.0001)	1.9364 (.0001)
ln(unemployment income)	.3307 (.0031)	.7595 (.0001)	.5154 (.0001)
ln(debt)		.0122 (.0220)	.0227 (.0001)
Both			
ln(income ratio)	1.2625 (.0001)	1.8501 (.0001)	1.8429 (.0001)
ln(unemployment income)	0.2267 (.0004)	.4652 (.0001)	.2851 (.0003)
ln(debt)		.0137 (.0092)	.0230 (.0001)

Note: Other controls as in Table 6.

depend on how the family background is incorporated into the model. In addition, because unemployment benefits are a major item of unemployment income, the estimated elasticities may be sensitive with respect to controls for the unemployment compensation scheme as well. To test the robustness of the estimated income effects, three variants of the preceding models are estimated, each one relaxing a set of controls for factors associated with the income variables. The results of this exercise are presented in Table 7.

The top panel reports coefficients on the income variables when controls for family background are excluded. The effects of income ratios are found to weaken slightly compared to the original estimates in Table 6, while the unemployment income elasticities are only half of the earlier estimates. It appears from the central panel that dropping controls for the unemployment compensation scheme has a more striking influence on the impacts of income ratios. The estimated elasticity with respect to the income ratio jumps at the higher level in each cohort, and the estimate is found to be of the same magnitude for the 1992 and 1994 cohorts. The coefficients on unemployment income are only slightly affected, being just above the original estimates. In light of these findings, the exclusion of controls for both the family background and unemployment compensation system has the expected impact on the estimates in the bottom panel. That is, the income ratio elasticities are of a higher magnitude and those for unemployment income are of a lower magnitude when compared to the original estimates in Table 6.

One can interpret these findings by saying that the expected returns to employment is an important determinant of the probability of becoming employed, and that this result is robust with respect to the model specification. The effect of the expected returns is also found to be higher in the recession cohorts than in the 1990 cohort, indicating that the relative importance of economic incentives has strengthened in the recession.[120] In addition, the positive impact of unemployment income appears to be strongest for the 1992 cohort, regardless of the specification. It is also interesting to note that the elasticity of the transition rate with respect to the household debt is totally robust, being about .01 and .02 for the 1992 and 1994 cohorts respectively.

An interesting question is why the effect of the expected returns to employment gets stronger over the period. Arulampalam and Stewart (1995), for example, have argued that income elasticities should be reduced in a recession as demand constraints (the lack of job offers) become relatively more important. On the other hand, the pressure imposed by the surrounding society on the unemployed individual is likely to weaken at times of high unemployment,[121] while the relative importance of search intensity as a determinant of the employment probability increases. This kind of reasoning suggests the possibility that economic incentives may, in fact, contribute to the behaviour of the unemployed to a greater extent in a recession.

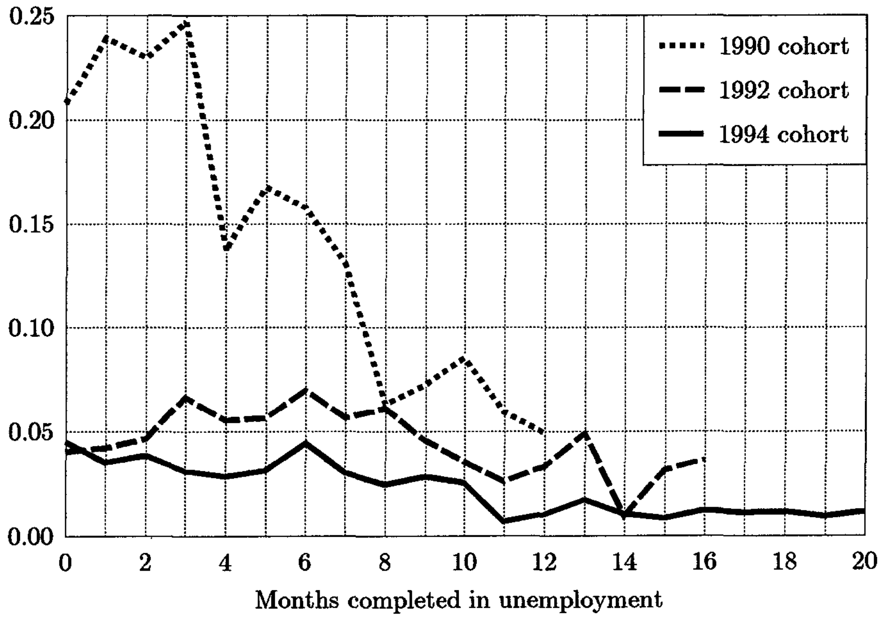
In the end, the estimates of the conditional probabilities of becoming employed are plotted in Figure 12. The transition rates to employment are scaled to the characteristics of a "standard" applicant, defined by setting all covariates at their sample means. Since the model is of the proportional hazard type, the evaluation at sample means acts merely to fix the scale on the vertical axis, without altering the shape of the transition rates.

The main feature of these plots is the huge difference in the levels of exit probability between the 1990 cohort and two later cohorts, especially during the first months of job search. The exit probability to employment in the 1990 cohort is estimated to be decreasing up to 8 months. This is in contrast to the 1992 and 1994 cohorts in which the exit probability is relatively flat up to the same point and then slightly decreasing over the following few months. It is also interesting to note that there is a peak in the employment probability at 10 months in the 1990 cohort and that the same appears in

[120] However, one should keep in mind that the model does not provide a clear account for the effect of demand side factors. The results must be interpreted in light of this.

[121] It is less burdensome to be unemployed when half of the neighborhood is also involved.

Figure 12: Monthly transition rates to employment for a "standard" applicant. Notes: Months refer to four weeks (i.e. 28 days) periods in unemployment.



the 1992 cohort, though three months later.[122]

6.3.2 Transition Rates to Manpower Programmes

The results from estimations of the transition rates to manpower programmes are presented in Table 8. Except for a few variables which would have very small asymptotic t-values in each cohort when added, the set of covariates is the same as in the case of the transition rates to employment. As before, the right endpoint of the base-line hazard is selected to fit the data for each cohort separately, and the signs of all coefficients are reversed.

Before turning to the results, it is useful to recall some features of Finnish labour market policy. The active labour market policy in recent years has involved a heavy stress on manpower programmes, of which the major ones are job replacement programmes and training courses. These programmes are commonly allocated to particular groups with exceptionally poor em-

[122] It should be kept in mind that the number of observations decreases as the spell increases in length, so that the inference concerning long-duration spells is on weaker grounds.

ployment prospects. The 1987 Employment Act introduced an obligation for employment authorities to offer temporary jobs for the long-term unemployed. The option to participate in job replacement programmes became available for all applicants whose unemployment spell has lasted for at least 12 months, and sooner for applicants aged under 20 (after 3 months) and those aged between 20 and 25 (after 6 months). At the beginning of 1992 this obligation was slightly alleviated and at the beginning of 1993 it was totally removed. As such, access to job replacement programmes has became more discretionary over the period under investigation.

Access to a job replacement programme commonly requires the applicant to have spent a particular time in unemployment, while participation in training courses depends more on the applicant's own activity. Thus, the programme participation is, in part, beyond the control of the unemployed and depends to a large extent on the rules of the employment administration. The estimated effects of the covariates must therefore be interpreted carefully, especially if one would like to view the model as a reduced form resulting from the search theory.

At the turn of the decade, most of the unemployed found a job within couple of months and only a small fraction of the spells ended at manpower programmes. In light of this, it is not especially surprising that most of the coefficients in the 1990 cohort do not differ significantly from zero.[123] Only two later cohorts contain such numbers of observations on exits to the manpower programmes that enable us to estimate the individual effects accurately.

According to the results, unskilled applicants enter the programmes more slower than other applicants in the 1992 and 1994 cohorts. This is perhaps surprising as one target of the active labour market policy is to upgrade the skills of the unemployed. Further, it appears that education has a positive effect on the transition rate to manpower programmes in the latest cohort. One possibility might be that educated applicants are more motivated to upgrade their skills by participating in training courses, while their less-educated counterparts do not enter manpower programmes until a job replacement programme becomes available.[124]

The participation probability is extremely low for applicants aged over 52 in each cohort. This makes sense as they have an unlimited duration of UI-

[123] Yet, the chi-squared statistic for the hypothesis that all coefficients are jointly zero strongly rejects the hypothesis.

[124] 23% of applicants with basic education out of those whose spell ends at manpower programmes exits to training courses, while the same share is 28% for their better-educated counterparts in the data.

Table 8: Semi-parametric estimates for the covariates of the transition rate to manpower programmes

Covariate	1990 (1)	1992 (2)	1994 (3)
Education: (*vs.* basic)			
High school	–.0319 (.8957)	–.3849 (.0107)	.1913 (.0860)
Vocational level	.2090 (.0260)	.0535 (.4072)	.1037 (.0489)
Higher level	.0966 (.6091)	.1884 (.1703)	.3012 (.0009)
Unskilled	.3873 (.0149)	–.3074 (.0097)	–.2236 (.0294)
Age: (*vs.* 36–45)			
Under 20	.1598 (.5421)	.6269 (.0033)	.8673 (.0001)
20–25	.0753 (.5588)	.1451 (.1290)	.5119 (.0001)
26–35	.1651 (.1045)	–.1039 (.1841)	.1400 (.0265)
46–52	–.1967 (.1528)	–.0419 (.6712)	–.0934 (.2198)
Over 52	–.7123 (.0001)	–.8385 (.0001)	–.7319 (.0001)
Female	.1021 (.4610)	.4265 (.0001)	.2259 (.0044)
Family status: (*vs.* single)			
Female with partner	–.1468 (.4191)	–.1702 (.1926)	–.2733 (.0039)
Male with partner	–.2111 (.2610)	.1360 (.3125)	–.0760 (.4313)
Female × number of children	–.3211 (.0005)	–.2136 (.0082)	–.2710 (.0001)
Male × number of children	–.1157 (.3527)	–.0316 (.6599)	–.0901 (.0779)
Entry channel (*vs.* from work)			
Training course	.0072 (.9682)	.0429 (.7381)	.5621 (.0001)
Job replacement programme	–.2119 (.0921)	.1090 (.1997)	.0894 (.1665)
Outside labour force	–.0676 (.5789)	–.0337 (.7185)	.2388 (.0007)
Unknown	–.0379 (.7908)	.6695 (.0001)	.7476 (.0001)
ln(regional unemployment rate)	.3848 (.0004)	1.9306 (.0001)	1.0781 (.0001)
ln(vacancy-unemployment ratio)	.0820 (.1868)	–.1801 (.0001)	–.0466 (.0708)
ln(participation ratio)	.1360 (.3488)	–.3851 (.0001)	–.0885 (.3288)
ln(income ratio)	–.5586 (.1048)	–.2382 (.3776)	–.9517 (.0001)
ln(unemployment income)	.0674 (.7314)	.0549 (.7273)	.1261 (.2435)
ln(debt)		.0003 (.9566)	.0115 (.0132)
Log-likelihood (abs.)	1,216	2,538	5,053
Total observations	2,449	2,308	3,288
Completed spells	341	954	1,400

Notes: As in Table 6.

benefits, if the eligibility criteria is met, and the upgrading of working skills is perhaps a little too late for them. The youth aged under 20 in the 1992 cohort and all those under 35 in the 1994 cohort are found to have relatively high transition rates to manpower programmes when compared to the reference group. Women end their unemployment spells more rapidly at manpower programmes, although their participation willingness is depressed by young children in the family. Furthermore, applicants entering unemployment from training courses and from outside the labour force are more likely to terminate their spells by exiting to manpower programmes in the 1994 cohort, whereas the entry channel does not make any difference in the earlier cohorts.

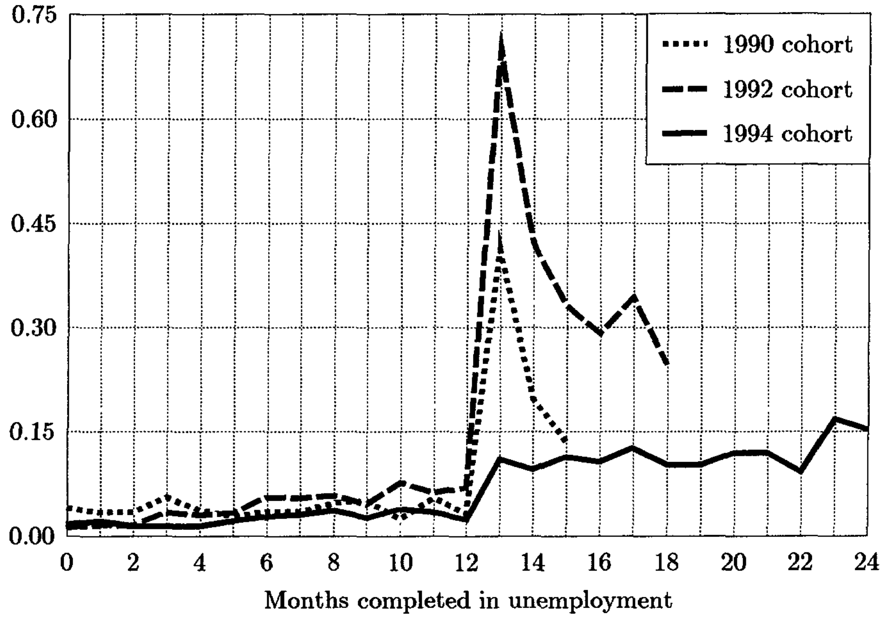
The higher the level of unemployment in the individual's travel-to-work area, the more likely the unemployment spell ends at manpower programmes. This is consistent with the object of the active labour marker policy to iron out regional differences in open unemployment. The coefficient on the vacancy-unemployment ratio indicates that the lack of jobs in the individual's occupational category increases the participation probability in the 1992 cohort. Surprisingly, the measure of the availability of manpower programmes, the participation ratio, has a negative coefficient in the 1992 cohort and insignificant coefficients in other cohorts.[125] Once again, these findings should be interpreted in light of the fact that the variables are measured at the year of unemployment entry.[126]

Intuition suggests that both training courses and job replacement programmes are likely to be less attractive alternatives than employment. In addition, participation in the manpower programme must notably reduce the individual's ability to put effort into job search. It is therefore plausible to expect that those with reasonable probability of finding an open vacancy with an acceptable wage are initially looking for jobs and the programme participation becomes interesting only if no acceptable jobs are found. Thus, one might expect that the willingness of the unemployed to take part in such programmes is negatively associated with expected returns to employment. Although the coefficient on the income ratio has the expected sign in each column, it is statistically significant only in the last column. Moreover, there is no evidence of the significant relation between the participation propensity

[125] Dropping the regional unemployment rate from the model makes the coefficient on the participation ratio positive, though not statistically significant.

[126] When these variables are measured at the exit year, the participation ratio gets a positive coefficient in the 1992 and 1994 cohorts and an insignificant one in the 1990 cohort, whereas coefficients on the regional unemployment rate and vacancy-unemployment ratio do not enter significantly in any cohort.

Figure 13: Monthly transition rates to manpower programmes for a "standard" applicant. Notes: Months refer to four weeks (i.e. 28 days) periods in unemployment.



and the level of the household's income while unemployed in any cohort.[127]

The estimates of the transition rates to manpower programmes, evaluated at the sample means of the covariates, are shown in Figure 13. For each cohort, the transition rate exhibits a relatively flat time pattern up to 12 months and is then followed by a rise at 13 months. The rise is of the form a huge spike for the 1990 and 1992 cohorts, whereas the transition rate in the 1994 cohort jumps at 12 months at a new stable level that is about fourfold compared to the previous one.[128] The spikes in the 1990 and 1992 cohorts appear because most of sample members in these cohorts left unemployment in 12 months and those who didn't were somewhat routinely picked up into

[127] Whether or not the transition rates for applicants under different unemployment benefit schemes differ significantly from one another was also tested by adding indicator variables for different benefit groups, but no statistically significant benefit scheme effects were found in the estimations.

[128] In the 1990 cohort, 59 spells out of those 144 that last 13 months or more actually end at 13 months, and 33 of them end by exit to manpower programmes. Likewise, in the 1992 cohort, 286 spells out of those 573 still in progress end at 13 months, and 249 of them end at manpower programmes.

the programmes when the requirement for one year in unemployment was met. Due to a much higher proportion of long-term unemployed and the government's attempts to suppress increasing budget deficits, the possibilities of employment authorities to apply such comprehensive administrative measures to terminate long-duration spells were considerably reduced at the time relevant for the 1994 cohort.

6.3.3 Transition Rates Out of the Labour Force

The estimated parameters of the transition rates to outside the labour force are given in Table 9. The educational indicators do not have significant coefficients in the 1990 and 1992 cohorts,[129] but for the latest cohort it appears that high school graduates and those with an undergraduate or graduate degree are more likely to leave the labour force than applicants who have completed only the basic level. In addition, the withdrawal rate for applicants registered as unskilled is estimated to be quite high in the 1990 cohort.

Surprisingly, the probability of leaving the labour force does not differ significantly between age groups in the 1990 cohort. For the later cohorts, the age effects are found to exist at the tails of age distribution. Applicants aged under 25 are more likely to leave the labour force than those aged between 26 and 49. This makes sense as young applicants often face a reasonable option to continue their studies if no jobs are available. There is also a strong trend to withdrawal from the labour force among the older age groups in the 1992 and 1994 cohorts, which may be due to the increased attractiveness of premature retirement arrangements.[130]

The probability of leaving the labour force does not notably depend on gender as the only significant coefficient on the female indicator appears in the 1990 cohort. However, women's probability of leaving the labour force is found to be associated with family background. Married and cohabiting women are more likely to leave the labour force than single women in the 1990 and 1992 cohorts, and women's leaving propensity is further affected by young children in the family. These findings are perhaps a reflection of higher payoffs from homemaking and child-rearing for women.

[129] The insignificance of the effect of high school education in columns (1) and (2) is somewhat surprising as one might expect that applicants with a high school diploma are more likely to start studying, as the high school is generally a prerequisite for studying at several educational establishments.

[130] The premature retirement may become more attractive in a recession as the chances of being offered an open vacancy weaken.

Table 9: Semi-parametric estimates for the covariates of the transition rate to outside the labour force

Covariate	1990 (1)	1992 (2)	1994 (3)
Education: (*vs.* basic)			
High school	.1349 (.4388)	.1452 (.2949)	.3857 (.0005)
Vocational level	.0792 (.3250)	.0917 (.2519)	.0883 (.1673)
Higher level	.1149 (.4978)	.2980 (.0449)	.3126 (.0036)
Unskilled	.4474 (.0004)	−.1025 (.4326)	.0466 (.6663)
Age: (*vs.* 26–49)			
Under 20	.3246 (.1300)	.0865 (.6758)	.4624 (.0076)
20–25	.0197 (.8432)	.3128 (.0007)	.4086 (.0001)
50–55	−.1098 (.3618)	.2785 (.0267)	.0211 (.8514)
56–60	−.0854 (.5092)	.5357 (.0029)	.4527 (.0001)
Over 60	−.0579 (.8330)	.9101 (.0001)	.9262 (.0002)
Female	−.3182 (.0136)	.0895 (.4611)	−.0299 (.7486)
Family status: (*vs.* single)			
Female with partner	.4441 (.0059)	.4373 (.0030)	.0888 (.4367)
Male with partner	.1790 (.2219)	.3967 (.0111)	.0265 (.8228)
Female × number of children	.3144 (.0001)	.5566 (.0001)	.4348 (.0001)
Male × number of children	−.0294 (.7910)	.1308 (.1769)	−.0163 (.8331)
Capital city area	.5787 (.0001)	.1569 (.2562)	.0738 (.4325)
Entry channel (*vs.* from work)			
Training course	.0494 (.7718)	.1072 (.4774)	.1222 (.2302)
Job replacement programme	−.0137 (.8909)	−.2844 (.0153)	−.1530 (.0558)
Outside labour force	.1512 (.1076)	−.0877 (.3548)	.2249 (.0027)
Unknown	−.1949 (.1248)	.0480 (.7140)	.4320 (.0001)
ln(regional unemployment rate)	.2980 (.0069)	2.0449 (.0001)	.4453 (.0025)
ln(vacancy-unemployment ratio)	.1353 (.0155)	−.1555 (.0001)	−.0682 (.0224)
ln(participation ratio)	.0565 (.6695)	−.6753 (.0001)	.1502 (.2732)
ln(income ratio)	−.9534 (.0010)	−.6113 (.0346)	−.3542 (.1449)
ln(unemployment income)	−.6398 (.0001)	−.6410 (.0003)	−.2786 (.0341)
ln(debt)		−.0102 (.1498)	−.0044 (.4243)
UI receiver (*vs.* UA receiver)	−.2317 (.0128)	−.3856 (.0001)	−.2259 (.0019)
Non-claimant (*vs.* UA receiver)	.8250 (.0001)	.6838 (.0001)	.9103 (.0001)
Log-likelihood (abs.)	1,677	1,855	3,158
Total observations	2,449	2,308	3,288
Completed spells	526	502	765

Notes: As in Table 6.

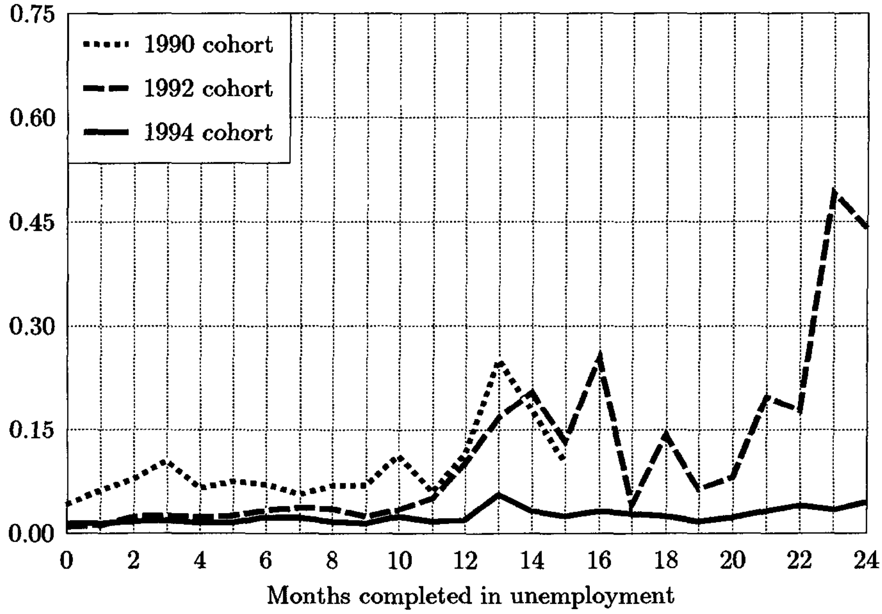
The unemployed in the capital city area leave the labour force more frequently than those with residence elsewhere in the 1990 cohort. Differences in withdrawal rates between applicants entering unemployment through different channels are quite moderate. Applicants who entered unemployment from outside the labour force tend to complete their spells by exiting to the same destination in the 1994 cohort. There is also weak evidence that those who were previously in job replacement programmes are less likely to leave the labour force than those previously in work. Applicants taking part in job replacement programmes are mainly those with a long unemployment history and the programme participation may reflect the willingness to remain in the labour force. So, if programme participants have meaningful alternatives outside the labour force, they would have exploited these possibilities already.

It is interesting to note that the decision to leave the labour force seems to be quite sensitive with respect to the business cycle. The higher the unemployment rate in the individual's travel-to-work area, the more likely he is to terminate his spell by leaving the labour force. The coefficients on the vacancy-unemployment ratio in columns (2) and (3) suggest that a reduction in the availability of vacancies in the individual's occupational group makes departure more likely. Yet, it should be stressed that all these effects are wiped out once the variables are measured at the exit year.

The estimated elasticity with respect to unemployment income is of the same magnitude in the 1990 and 1992 cohorts, being about –.6, while a weaker effect of –.3 is found for the 1994 cohort. The expected returns to employment are found to significantly reduce the exit probability in the 1990 and 1992 cohorts, while the coefficient on the income ratio does not differ significantly from zero in the latest cohort. Note that the income ratio serves here as a kind of measure of opportunity cost for the applicant who is deliberating exit from the labour force. The weakening of the effect over the period is perhaps a reflection of the lack of job offers in the later cohorts. As the chances of being offered an open vacancy weaken, the relative importance of the expected earnings at the subsequent job is likely to decrease as well.

The indicator for UI-benefit receivers has a significant negative coefficient in each column, reflecting a strong labour force attachment for trade union fund members when compared to UA-benefit receivers. This was expected as UI-benefits are available to unemployed trade union fund members who have been members of the fund for at least six months prior to unemployment. So, UI-benefit receivers have a strong attachment to the labour force by definition. Moreover, the withdrawal rates are estimated to be highest for

Figure 14: Monthly transition rates to outside the labour force for a "standard" applicant. Notes: Months refer to four weeks (i.e. 28 days) periods in unemployment.



non-claimants which is perhaps not very surprising as the exit does not cause benefit losses for them.

The estimates of the withdrawal rates from the labour force are plotted in Figure 14. Except a small peak at 13 months, the leaving probability in the 1994 cohort is estimated to be quite flat over the whole spell. This is in contrast to the 1990 and 1992 cohorts in which the leaving probability is stable up to 11 months and thereafter clearly increasing over the following few months. Yet, the transition rate in the 1992 cohort seems to drop back to the original level at 17 months which is followed by a strong upward slope after 20 months.

It is also interesting to note that the transition rate in the 1994 cohort, as scaled to the characteristic of a "standard" man, lies completely below those of the earlier cohorts. One potential explanation for this observation might be the sensitivity of the labour force participation with respect to the business cycle. The lack of job offers in the recession reduces the participation of those with reasonable alternatives outside the labour force. If these people generally shift more into and out of the labour force, the lower transition rate for the 1994 cohort can be a result of their reduced participation at the time of the highest level of unemployment.

7 Conclusions

In this study, determinants of earnings and unemployment durations are analysed using two sets of micro-data. The data drawn from the outflows of unemployment is used in modelling the earnings of people leaving unemployment, and the length of time they spend in unemployment. The other data set was drawn from the working age population to serve as a comparable source in the analysis of earnings differentials.

The first part of the study focuses on explaining the earnings differentials among entrants into employment and among those employed in general. Considerable returns to educational investments prior to the unemployment spell are attached to each level of education for entrants into employment. The impact of schooling on starting wages, however, is found to be only half of that on general wages, corresponding to an increase of some 4.5% in the starting wage with respect to an additional year of schooling. In addition, the experience-wage profiles for the starting wages are estimated to be flatter than for the general wages, indicating the importance of firm-specific human capital for high-tenured workers. It is also notable that women are found to enter employment at the earnings equal to those of men, although they are likely to suffer from wage discrimination later on in their career.

Cyclical fluctuations also have an impact on the wage structure. General wages are estimated to be slightly sensitive to regional demand conditions, whereas starting wages are affected by the relative supply of open vacancies across occupational groups. A standard search model result, that the longer spells of unemployment are associated with higher earnings in the subsequent job, is rejected, and the starting wage is found to depend negatively on the time an individual spend in unemployment. In particular, a hypothetical doubling of the length of the unemployment period is associated with a fall of some 2% in subsequent earnings.

The second part of the study evaluates the income changes, resulting from labour market transitions, with the outflow data. The actual change in disposable income of the individual's household is computed for the subsample of those exiting to employment. In addition, the expected change in the household's disposable income is computed for each sampled individual using starting wage estimates. This measure of the expected returns to employment is then used to evaluate how the returns are distributed among the unemployed. According to the results, employment has increased disposable income of households by slightly over 50% on average, while 4% of the applicants in the data have accepted employment at the starting wage that caused a reduction in the household's disposable income. Moreover, some 8% of the sampled individuals are estimated to be unable to increase the disposable income of their households through employment, while as much as 43% have to be content with a 25% increase or less.

In the final part of the study, the conditional probability of leaving unemployment is modelled with a flexible competing risks model that allows unemployment spells to end at employment, at manpower programmes or at withdrawal from the labour force. Women are found to end their unemployment spells more rapidly at employment and manpower programmes than men, though their behaviour is occasionally affected by family circumstances. The highest withdrawal rates from the labour force are estimated for the non-claimants of the unemployment compensation system, whereas a close labour force attachment is found for unemployment insurance benefit receivers. It further appears that non-claimants complete their spells at employment more rapidly than other benefit group receivers.

The income factors are found to play an important role. There is a strong positive relation between the probability of becoming employed and the expected returns to employment. The incentive effect turns out to be stronger for the recession cohorts than for the 1990 cohort, indicating that the relative importance of economic incentives has strengthened in the recession. Higher expected returns also make exit from the labour force less likely. After controlling for the expected returns to employment, the high level of the household's unemployment income increases the probability of becoming employed and reduces that of leaving the labour force.

To sum up, a high proportion of the unemployed is found to be faced with the relatively low returns to employment, and considerable incentive effects are found in the estimations. These findings suggest that there is undoubtedly a need to improve the incentive schemes of the unemployed. However, it should be stressed that several applicants are found to accept employment, despite insignificant, or even negative, short-term returns. This clearly mirrors the fact that the financial gain of employment is not the only thing that matters for the unemployed when searching for work.

Several interesting questions concerning the topic of this study remain open for future research. For example, the duration of subsequent jobs and the time path of subsequent earnings produce interesting questions on economic incentives. Addressing these questions may help us to explain why some of the unemployed are willing to accept employment at a starting wage that causes income losses for the household.

In the duration analysis, a logical step would be to relax the assumption that the income effects are constant over the spell. If the unemployed become increasingly desperate, and accept the first job offered, the effect of incentive variables will decline with elapsed duration. This should be accounted for if one aims to derive specific policy recommendations to improve the incentive schemes of the unemployed. The presence of labour administrative measures with an attempt to terminate long-duration spells calls for a need to elaborate the duration analysis by allowing for multiple spells of unemployment and dependence between these spells. This extension would be especially important for research on the long-term unemployed and the threat of their permanent displacement from the open labour market.

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A Selection Equation of the Starting Wage Model

The estimation results of the selection equation of the starting wage model are given in Table 10. Marginal effects in column (2) are partial derivatives of the probability that the unemployment spell end at employment with respect to explanatory variables. Namely, using the notations in Chapter 4, the marginal effect with respect to a given regressor, say z_k, is

$$\frac{\partial \Pr(d=1\,|x,z)}{\partial z_k} = \frac{\partial E(y^*\,|x,z)}{\partial z_k} = \delta_k \phi\left(z'\delta\right),$$

where δ_k is the coefficient on the regressor z_k and $\phi\left(z'\delta\right)$ is the density function of the standard normal variable evaluated at $z'\delta$.

Table 10: ML estimates of the paramaters of the selection equation

Regressor	*Coefficient* (1)	*Marginal effect* (2)
Intercept	.7134 (.0024)	.2780 (.0047)
Years of schooling	.0238 (.0002)	.0093 (.0006)
Unskilled	–.2502 (.0001)	–.0975 (.0001)
Age	.0968 (.0001)	.0377 (.0001)
$\text{Age}^2/10$	–.0142 (.0001)	–.0055 (.0001)
Female	–.1069 (.0012)	–.0417 (.0023)
Foreigner	–.7153 (.0001)	–.2788 (.0001)
Family status: (*vs.* single)		
Female with partner	–.0091 (.8111)	–.0035 (.8199)
Male with partner	.0976 (.0115)	.0380 (.0193)
Female × children	–.4122 (.0001)	–.1606 (.0001)
Male × children	–.1379 (.0046)	–.0537 (.0088)
Living with parents	–.0544 (.1295)	–.0212 (.1588)
Health disability	–.4388 (.0001)	–.1710 (.0001)
Home owner	.1638 (.0001)	.0638 (.0001)
Capital city area	.1396 (.0004)	.0544 (.0011)
Entry channel: (*vs.* from work)		
Training course	–.4096 (.0001)	–.1596 (.0001)
Job replacement programme	–.5999 (.0001)	–.2338 (.0001)
Outside labour force	–.4573 (.0001)	–.1782 (.0001)
Unknown	–.2532 (.0001)	–.0987 (.0001)
ln(unemployment benefits)	–.0061 (.1927)	–.0024 (.2398)
ln(regional unemployment rate)	–.0898 (.0498)	–.0350 (.0761)
ln(vacancy-unemployment ratio)	.1163 (.0001)	.0453 (.0001)
ln(participation ratio)	–.0707 (.1863)	–.0276 (.2274)
ln(spell duration)	–.3402 (.0001)	–.1326 (.0001)
Year 1988 (*vs.* 1994)	.5315 (.0001)	.2071 (.0001)
Year 1990 (*vs.* 1994)	.1949 (.0443)	.0759 (.0639)
Year 1992 (*vs.* 1994)	–.0277 (.3367)	-.0108 (.3613)
Log-likelihood (abs,)	11,506	
Observations	14,438	

Notes: Asymptotic P-values in parentheses. Marginal effects are computed at the means of explanatory variables.

A Details for Income Calculations

Household's income is computed while the sample member is unemployed, while really employed and while fictionally employed. Income during unemployment and fictional employment are computed for all sample households, whereas income while the sample member is really employed can be computed only for the subsample of households in which the sample member actually entered employment. Table 11 shows the steps of income calculations.

Gross Monthly Income The first step is to compute gross monthly income. The sample member's gross monthly income is computed at each labour market state. While unemployed, the sample member's income consists mainly of unemployment benefits, with possible increments, and of other taxable income. While really (fictionally) employed, the gross income consists of observed (estimated) earnings from the subsequent job and of other taxable income. The other taxable income covers mainly property income, irregular earnings and homecraft allowance, which are all divided evenly for each month of the year. To compute the spouse's gross monthly income for couples, the spouse's annual income which is subject to state taxation is simply divided by twelve. The gross monthly income of the household is obtained by adding the sample member's and spouse's gross income together.

Net Monthly Income Calculations for the sample member's net monthly income take into account estimated taxes, as well as social security and pension contributions. Because tax deductions and the income tax rate depend on annual earnings, the gross annual earnings for the sample member are evaluated by assuming that a given labour market state persists for the whole year. Annual taxable income, which is separate for state and municipal taxation, is estimated by subtracting estimated deductions from the annual gross earnings.[131] After this, gross annual taxes, which consist of income, municipal and church taxes, are estimated at each labour market state.[132] Monthly taxes are obtained by dividing the annual taxes evenly for each month of the

[131] The data contains information on taxable income and taxes actually paid by individuals for the period 1990–92. By cross-tabulating these figures, the proportion of tax deductions out of the income subject to taxation across different income levels is estimated separately for taxable income in state and municipal taxation. These proportions are thereafter applied to estimate the tax deductions in state and municipal taxation.

[132] The income tax rate is simply chosen from the relevant tax table, whereas local and church tax rates are computed from income statistics in the data as they do not vary with respect to income levels.

Table 11: Calculations for household incomes

Sample member's gross monthly income at labour market state j
+ (spouse's gross annual income) / 12
= Household's gross monthly income at labour market state j
Sample member's net monthly income at labour market state j
+ (spouse's gross annual income − annual taxes) / 12
= Household's net monthly income at labour market state j
Household's net monthly income at labour market state j
+ income transfers received by household at labour market state j
− day-care fees paid by household at labour market state j
= Household's disposable income at labour market state j

Note: Labour market state j refers to the time when the sample member is either unemployed, really employed or fictionally employed.

year. The sample member's net monthly income at a given labour market state is obtained by subtracting estimated monthly taxes, social security and pension contributions from gross monthly earnings. For couples, the spouse's net monthly income is directly computed using income statistics in the data by subtracting taxes paid by the spouse from the spouse's taxable annual income and dividing the difference by twelve. Calculating the net income of the sample member and that of the spouse, if any, together gives net monthly income for the household.

Disposable Monthly Income The household's disposable income is obtained by adding child benefits, single parent's maintenance allowance, day-care fees and social security allowance to the calculations.[133] The addition of child benefits is straightforward as they are directly determined by the ages and number of children in the family. For single parents, the government's maintenance allowance is added to the net income because information on single parent's allowance paid by another parent of the dependents are not

[133] Only one important item of disposable income is not accounted for. Namely, housing allowance is excluded because I didn't find a reasonable way to incorporate that in the calculations.

Table 12: Mean gross household income by cohort, FIM/month

	Sample member's labour market state					
	Unemployed		Fictionally employed		Really employed	
Singles	(1)		(2)		(3)	
1990	2,000	(728)	7,050	(728)	8,120	(461)
1992	3,060	(655)	7,130	(655)	8,830	(221)
1994	3,560	(936)	7,300	(936)	9,620	(323)
Single parents						
1990	2,790	(130)	6,930	(130)	8,200	(89)
1992	3,880	(120)	6,950	(120)	9,210	(34)
1994	4,560	(154)	7,150	(154)	9,600	(37)
Couples						
1990	9,790	(1,038)	14,270	(1,038)	15,630	(697)
1992	10,660	(1,083)	14,530	(1,083)	17,530	(421)
1994	11,560	(1,501)	14,930	(1,501)	17,410	(541)
Couples with children						
1990	10,260	(553)	14,630	(553)	15,720	(335)
1992	11,830	(450)	15,230	(450)	17,730	(176)
1994	12,090	(697)	14,980	(697)	17,150	(222)
All households						
1990	7,210	(2,449)	11,810	(2,449)	13,040	(1,582)
1992	8,380	(2,308)	12,170	(2,308)	14,980	(852)
1994	9,070	(3,288)	12,400	(3,288)	14,860	(1,123)

Notes: Income while a sample member is fictionally employed uses unconditional starting wages estimates. Children in the family refer to dependents aged under 7. The number of observations in parentheses.

available in the data.[134]

The data does not contain information on the amounts of social security allowance received by sample households. Since there are households which have no income at all during unemployment, it seems reasonable to expect that at least these households had to receive the social security allowance. As such, households whose disposable income falls short of the lower limit of the estimated legal level are assumed to receive such an amount of social security allowance that brings them back to the lower limit. Because entitlement to social security allowance is determined case by case, the mean lower limits

[134] The government's maintance allowance is received by a single parent who does not receive the maintenance allowance from other sources.

Table 13: Mean net household income by cohort, FIM/month

	Sample member's labour market state					
	Unemployed		Fictionally employed		Really employed	
Singles	(1)		(2)		(3)	
1990	1,670	(728)	5,320	(728)	5,910	(461)
1992	2,500	(655)	5,300	(655)	6,250	(221)
1994	2,940	(936)	5,540	(936)	6,850	(323)
Single parents						
1990	2,280	(130)	5,250	(130)	5,960	(89)
1992	3,100	(120)	5,190	(120)	6,530	(34)
1994	3,650	(154)	5,390	(154)	6,740	(37)
Couples						
1990	7,330	(1,038)	10,530	(1,038)	11,310	(697)
1992	7,890	(1,083)	10,510	(1,083)	12,180	(421)
1994	8,750	(1,501)	11,060	(1,501)	12,420	(541)
Couples with children						
1990	7,980	(553)	11,080	(553)	11,650	(335)
1992	9,090	(450)	11,340	(450)	12,650	(176)
1994	9,210	(697)	11,140	(697)	12,280	(222)
All households						
1990	5,530	(2,449)	8,830	(2,449)	9,510	(1,582)
1992	6,350	(2,308)	8,920	(2,308)	10,510	(852)
1994	6,950	(3,288)	9,240	(3,288)	10,600	(1,123)

Notes: As in the preceding table.

estimated by Viitamäki (1995, p. 28) are used in the calculations.

The unemployed and those outside the labour force are assumed to take care of their children at home, whereas households in which both parents are in work are assumed to use communal day-care services for their children aged under 7. Communal day-care fees are based on the norms defined by the Ministry of Social Affairs and Health, but the income limits associated with fee grades vary between municipalities. Therefore, the weighted averages of the income limits used by municipalities, given in Viitamäki (1995, p. 26), are used to determinate the household's fee grade at a given labour market state. The final step is to subtract day-care fees, if any, from the household's net income. The resulting disposable income are found in Table 4 of Section 5.1, whereas Tables 12 and 13 represent mean gross and net income by cohort for different groups of households.

Table 14: Median income ratios by cohort for different groups of households

	OIR	*EIRs by exit channel*				*% of hired*
		Work	MP prog	Out LF	*All*	
Singles	(1)	(2)	(3)	(4)	(5)	(6)
1990	1.72	1.76	1.63	1.58	1.69	63
1992	1.74	1.69	1.47	1.51	1.56	34
1994	1.75	1.67	1.45	1.47	1.52	35
Single parents						
1990	1.20	1.22	1.06	1.13	1.19	68
1992	1.32	1.22	1.08	1.06	1.12	28
1994	1.26	1.26	1.13	1.21	1.18	24
Couples						
1990	1.46	1.41	1.21	1.32	1.36	67
1992	1.42	1.33	1.20	1.28	1.26	39
1994	1.31	1.28	1.17	1.23	1.22	36
Couples with children						
1990	1.27	1.26	1.13	1.20	1.21	61
1992	1.22	1.17	1.08	1.09	1.11	39
1994	1.18	1.14	1.08	1.10	1.10	32
All households						
1990	1.46	1.47	1.25	1.36	1.41	65
1992	1.42	1.37	1.23	1.28	1.28	37
1994	1.36	1.33	1.19	1.26	1.24	34

Note: EIRs are computed using unconditional starting wage estimates. Children in the family refer to dependents aged under 7.

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