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# STUDIES ON WAGE DIFFERENTIALS AND LABOUR MARKET TRANSITIONS

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**ABSTRACT:** This thesis consists of four studies. The first study examines wage differentials between women and men in the Finnish manufacturing sector. A matched employer-employee data set is used to decompose the overall gender wage gap into the contributions of sex differences in human capital, labour market segregation, and residual within-job wage differentials. The topic of the second study is the relationship between the extended unemployment benefits and labour market transitions of older workers. The analysis exploits a quasi-experimental setting caused by a change in the law that raised the eligibility age of workers benefiting from extended benefits. Roughly half of the unemployed workers with extended benefits are estimated to be effectively withdrawn from labour market search. The risk of unemployment declined and the re-employment probability increased among the age groups directly affected by the reform. The third study provides an empirical analysis of a structural equilibrium search model. Estimation results from various model specifications are compared and discussed. The last study is a methodological study where the difficulties of interpreting the results of competing risks hazard models are discussed and a solution for a particular class of models is proposed. It is argued that a common practice of reporting the results of qualitative response models in terms of marginal effects is also useful in the context of competing risks duration models.

**Keywords: Gender wage differentials, unemployment duration, early retirement, competing risks models.**

**TIIVISTELMÄ:** Tutkielma koostuu neljästä tutkimuksesta. Ensimmäinen käsittelee naisten ja miesten välisiä palkkaeroja tehdasteollisuudessa. Yhdistetyn työnantaja-työntekijäaineiston avulla kokonaispalkkaero hajotetaan osiin, jotka kuvastavat sukupuolten välisiä eroja taustaominaisuuksissa, työmarkkinoiden segregoitumista ja työtehtävien sisäisiä palkkaeroja. Toinen tutkimus käsittelee laajennetun työttömyyspäivärahaoikeuden vaikutusta ikääntyneiden työmarkkinasiirtymiin. Empiirisessä analyysissä hyödynnetään lakimuutosta, jonka myötä laajennetun päivärahaoikeuden alaikäraja nousi. Tulosten mukaan joka toinen laajennetun päivärahaoikeuden piirissä oleva on käytännössä työmarkkinoiden ulkopuolella. Työttömyysriski laski ja työllistyminen kasvoi ikäryhmissä, jotka menettivät laajennetun päivärahaoikeutensa lakiuudistuksen myötä. Kolmannessa tutkimuksessa keskitytään työmarkkinoiden etsintäteoreettisiin rakennemalleihin. Useita eri mallispesifikaatioita estimoidaan ja niiden tuloksia vertaillaan. Viimeisessä tutkimuksessa pohditaan kilpailevien riskien duraatiomallien tulosten raportoinnin vaikeutta. Tutkimuksessa esitetään tietylle malliperheelle ratkaisu perustuen marginaalivaikutusten laskemiseen, mikä on yleinen käytäntö useiden diskreetin valinnan mallien yhteydessä. Tutkimuksessa väitetään, että sama käytäntö on hyödyllinen myös kilpailevien riskien duraatiomallien yhteydessä.

**Asiasanat: Sukupuolten väliset palkkaerot, työttömyyden kesto, varhaiseläke, kilpailevien riskien malli.**

## Acknowledgements

This thesis is a collection of studies that I have prepared while working at the Government Institute for Economic Research (VATT). It took a long time to reach this point. Once I had finished my Master's thesis in 1997, my former superior Dr Pasi Holm encouraged me to continue my studies towards the Doctor's degree. Now, ten years later, I have finally finished this project. Spending ten years on a single thesis is a poor performance in every way. For a long time I thought that the topics of my research papers are too dispersed, and that I should wait until my research converges enough to form a coherent collection of studies on a given subject. It never happened, however. I just became tired of waiting and finally wrote a thesis that is not tightly focused on a single topic, the result of a decision that I should have made much earlier.

I cannot blame my employer for the prolongation of this project because I have been lucky to be able to spend most of my time on research topics that I have chosen on the basis of what I have felt interesting and challenging. During this project VATT has provided a great working environment by providing appropriate computing facilities and access to high-quality data sets. I am indebted to my former superiors, Dr Pasi Holm, Dr Seija Ilmakunnas and Dr Heikki Räisänen, as well as to former Director General, Prof. Reino Hjerppe, for their understanding and patience.

Several persons have contributed to various parts of my thesis. Ossi Korkeamäki, the co-author of the first study, deserves special thanks for his contribution to that study and for his invaluable help with data sets used in other studies. Antti Luukkonen kindly provided his measures of job complexity levels for my use in the first study. The second study relies on results from two distinct joint projects, one carried out with Dr Ralf Wilke and another with Dr Virve Ollikainen. Prof. Michael Rosholm kindly gave me most of the Gauss programmes used to estimate equilibrium search models in the third study. Marja Riihelä and Risto Sullström were always ready to help me with Gauss programming. Remarks and suggestions from my pre-examiners, Prof. Pekka Ilmakunnas and Dr Roope Uusitalo, improved the final version of the thesis. Paul A. Dillingham kindly checked the language.

Helsinki, March 2007

Tomi Kyyrä

# Contents

# Chapter I

# Overview of the Thesis

This thesis consists of four studies. The first study examines wage differentials between women and men. The second one analyses the relationship between the extended unemployment benefits and labour market transitions of older workers. These studies are typical reduced-form microeconometric applications where no structural restrictions from economic theory are imposed. A rather different approach is taken in the third study, which provides an empirical analysis of a structural equilibrium search model. The last study is a methodological study where the difficulties of interpreting the results of competing risks hazard models are discussed and a solution for a particular class of models is proposed. Despite the apparent dissimilarities, the topics of the studies are related, though not very closely, and they have much in common in the statistical methods and data used. This chapter gives a brief overview of the studies and explains how they are related to each other. To motivate the different approach of the third study, we discuss some advantages and limitations of the structural equilibrium analysis compared with the reduced-form approaches followed in the first two studies. The topic of the last study is inspired by an econometric issue of competing risks duration analysis that arises in a specific context in the second study.

The first study in Chapter II contributes to a huge body of literature on gender wage differentials. It is well known that women are paid less on average than men in virtually all labour markets (e.g. Blau and Kahn, 1995, 2000). The Finnish labour market is no exception, and women are found to receive about a sixth and a quarter lower wages than men do among blue- and white-collar workers, respectively. The gender wage gaps of these sizes are well in line with evidence from other advanced countries. Wage differentials between women and men can arise in a variety of ways. The distribution of the sexes typically varies across occupations, industries, firms, and jobs, resulting in gender wage differentials in favour of men if the labour market segments occupied primarily by women are lower paid on average than those dominated by men. Employers may also pay lower wages to their female workers than male workers for the same job, which leads to within-job wage differentials between women and men. Such differentials, to the extent that they do not arise from differences in effort or human capital, can be interpreted as wage discrimination against women.

Identifying the different sources of wage differentials is crucial to understanding why the gender gap in pay persistently exists. Due to the increasing availability of comprehensive matched employer-employee data, this old issue has been reappraised in a number of recent studies. With such a data set one can study wage differentials within narrowly defined job categories between women and men who are working for the same employer (see e.g. Petersen and Morgan, 1995, Petersen et al., 1997, Meyersson Milgrom et al., 2001, Groshen, 1991, Datta Gupta and Rothstein, 2001, and Bayard et al., 2003). Exploiting this sort of matched data the overall gender wage gap can be decomposed into the contributions of sex differences in human capital, labour market segregation, and residual within-job wage differentials.

In Chapter II we study wage differentials between sexes in the Finnish manufacturing sector using a large matched employer-employee data set. Our approach departs from the existing sex segregation literature in that we explicitly model wage differentials between firms and jobs. We view the data as having a nested structure with three levels: firms, jobs within firms, and workers in jobs within firms. To account for this hierarchical data structure we estimate a correlated random effects model. In the second stage we decompose the raw gender wage gap among blue- and white-collar workers using the regression results and sample moments. We make use of information on the job complexity level, measuring the responsibility, skills, and effort required by a given job, to explain wage differentials between jobs. This unique feature of our data allows us to asses whether wage differentials between typical female and male jobs can be viewed as justified or not, a question that is beyond the scope of earlier literature.

We find that the major part of gender wage differentials among white-collar workers stems from the disproportionate concentration of women in lower-paying jobs within firms. Within firms high-paid managerial jobs are mainly occupied by men, and among non-managerial jobs men are concentrated in positions with higher skill requirements. Even after controlling for the complexity level and skill requirement of white-collar jobs, predominantly female jobs are associated with lower wages. In contrast to while-collar workers, a large part of the gender wage differentials of blue-collar workers is attributed to sex segregation among firms. The origin of lower pay in firms with a relatively high share of female blue-collar workers remains a puzzle, however. For both groups of workers we find women to be paid less than their equally qualified male co-workers within narrowly defined jobs within firms. Eliminating the sources of unexplained within-job wage differentials between sexes can at most account for a quarter of the overall gap of white-collar workers and one-fifth of the overall gap of blue-collar workers.

Whereas the sources of gender wage differentials have been disputed for decades, the topic of Chapter III has not attracted so much attention until recently. The tendency of older workers to withdraw from the labour market at ages well below the official retirement age is of growing concern in many OECD countries where the populations are ageing rapidly while people are living longer (see Gruber and Wise, 1998, and OECD, 2002). The financial pressure caused by these trends has led many governments to change their policies with respect to early retirement. Unemployment-related benefits effectively provide a particular pathway to early withdrawal from the labour market in many European countries (Duval, 2003). In Finland the entitlement period of unemployment insurance (UI) benefits of workers above a given age threshold is extended until age 60 when they can retire via a particular unemployment pension scheme. This scheme, known as the unemployment tunnel, effectively provides an indefinite period of UI benefits for the elderly unemployed. It facilitates the withdrawal of ageing workers from the labour market several years before the official retirement age of 65. In 1997 the eligibility age of workers benefiting from extended benefits was raised from 53 to 55. As a result, the entitlement period for the age group 53-54 was effectively reduced to the maximum of two years, while the other age groups remained unaffected by the reform. In Chapter III we take advantage of this quasi-experimental setting to study the effects of extended benefits on the incidence and duration of unemployment among elderly workers.

In the first stage we examine the effect of the 1997 reform on the inflow to unemployment. This effect turns out to be very strong. We find that disproportionate numbers of dismissals fall on employees who are old enough to be entitled to the extended UI period. Large employers, especially, are shown to exploit this feature of the UI system to get rid of their elderly employees, as a reasonable income level until retirement is fully secured for them. In the second stage we examine the effect of extended UI benefits on the labour market transitions of the elderly unemployed. We compare the unemployment experiences of the group affected by the reform under two schemes: the extended UI entitlement period (pre-reform scheme) and the conventional UI period of two years (post-reform scheme). A younger group is used to eliminate the business cycle effect in a difference-in-differences setting. Our analysis follows a growing literature that exploits policy reforms to identify the effects of different aspects of UI on unemployment duration (e.g. Hunt, 1995, Winter-Ebmer, 1998, Bratberg and Vaage, 2000, Card and Levine, 2000, Carling et al., 2001, Røed and Zhang, 2003, Lalive and Zweimüller, 2004, Uusitalo and Moisala, 2003, and Lalive et al., 2006). A novel feature of our analysis is that we explicitly allow for some older workers, registered as unemployed job seekers, to effectively withdraw from job search and simply wait for access to early retirement by applying a competing risks version of a split population duration (see Schmidt and Witte, 1989, Abbring, 2002, and Addison and Portugal, 2003, for discussion on this class of duration models). The idea is to model simultaneously both the likelihood that the worker is still active in the labour market and the timing of exit to various end-states conditional on being active. This approach allows us to distinguish the participation decision from labour market behaviour in the case of continued search.

We find that some half of those who are entitled to extended UI benefits are effectively withdrawn from the labour market. The likelihood of labour market withdrawal varies with occupation, the level of UI benefits, and the size of the past employer. There are no notable discrepancies in the employment hazards between active workers with extended UI benefits and those with the entitlement period of two years. However, active workers with extended UI benefits have much lower transition rates to labour market programmes and non-participation (prior to access to early retirement). As a consequence, compared with those who will lose their benefits after two years of unemployment, active workers entitled to extended UI benefits are more likely to enter employment but also more likely to still be unemployed 36 months after entry to unemployment.

In Chapters II and III we perform reduced-form analyses where no structural restrictions from theoretical models are imposed. The rationale of this approach is to make robust inference about the question of interest by making only minimal assumptions about the process that generated the observed data. A cost of this robustness is that many interesting policy questions are ruled out. To illustrate this point, consider the hypothetical implementation of a comparable worth policy that would improve the complexity ranking of some typical female jobs. From our data and regression estimates in Chapter II we could compute the effect of such a reform on the gender wage gap in a particular case where all workers remain in their current jobs. But the change in the relative wages is likely to induce more men to apply for these jobs, thereby leading to the change in the distribution of sexes across all jobs. This would have an effect on the size of the gender wage gap over time; the effect that cannot be predicted from our reduced-form results. We cannot predict this effect because the positions held by workers and the wage distribution are taken as given, and hence our analysis is silent about the process through which the workers were allocated to their current jobs. To sum up, although our empirical analysis implies some scope for a comparable worth policy, we cannot give very meaningful predictions for the effects of such a policy intervention.

In Chapter III we show that the 1997 reform of the UI system decreased the inflow and increased the outflow of unemployment among the age group directly affected by the reform. Compared with the analysis in Chapter II, we go further by estimating the behavioural effects associated with extended UI benefits. By exploiting the quasi-experimental setting caused by a change in the law, we identify these effects without making assumptions about the optimization behaviour of the unemployed and employers. Because such assumptions are always a crude simplification of real-world behaviour, this is a clear advantage from the viewpoint of the robustness of our results. A disadvantage is that we cannot say much about how the UI reform affected the overall unemployment rate or early retirement expenditures as a whole. It is possible that the decline in the incidence and duration of unemployment among the group aged 53-54 occurred at the expense of younger groups. Moreover, tightening the regulations of the unemployment tunnel scheme might have increased the use of other exit routes, and thereby increased early retirement expenditures. These sorts of general equilibrium effects, which are often of primary interest from the policy point of view, are beyond the scope of the partial approach adopted in Chapter III. In the absence of the policy reform, even the partial evaluation may be infeasible without some sort of behavioural assumptions.

In Chapter IV we take a different approach to the empirical analysis of labour market issues. We discuss a particular class of equilibrium search models and their estimation from micro-data. In these models wage dispersion arises as a result of search frictions in the form of time it takes for firms and workers to find matches that are acceptable to both parties. In other words, wage differentials across workers, the topic of the first study, are in large part determined by the layoff rate and the arrival rates of job offers, the topics of the second study. In the context of equilibrium models a policy reform or shock that directly affects some subgroup of firms or workers can change the behaviour of all agents on both sides of the market, leading to changes in the equilibrium wage distribution and unemployment rate. In this respect the equilibrium search models offer a useful framework for analysing many labour market issues.

When both sides of the labour market are modelled in a dynamic environment, a number of simplifying assumptions must be adopted to keep the model tractable. Despite the simplifying assumptions, the equilibrium solutions are typically rather complex, involving highly nonlinear functions of structural parameters. This makes the estimation of such models difficult. Typically, this sort of models is not estimated but calibrated. In calibration the author collects numbers from various sources for some parameters of the model and solves the model with respect to the remaining set of parameters. This procedure looks quite arbitrary at times, and therefore direct estimation of the structural parameters is arguably a more proper way to proceed. Another issue is to which extent stylized equilibrium search models are able to describe the real-world labour market. If the model has not been tested with the data, the reader must be gullible to take the model's predictions seriously. Estimating equilibrium search models from micro-data produces more credible parameter estimates, allows us to assess the model's fit, and yields valuable information for developing a more rigorous basis for equilibrium labour market analysis.

In Section IV we consider the estimation of the various variants of the equilibrium search model of Burdett and Mortensen (1998). Since the key predictions of the Burdett-Mortensen model are consistent with many stylized features of the labour market, the various specifications of the model have been fitted to data sets from different countries (e.g. Kiefer and Neumann, 1993, Van den Berg and Ridder, 1998, and Bunzel et al., 2001). We give an introduction to equilibrium search theory along the lines of Burdett and Mortensen (1998) and Bontemps et al. (2002). Our focus lies on model specifications where all workers are identical but employers may differ in their production technology. The structural parameters of the model can be recovered from data on unemployment durations, job durations, and wages associated with jobs. We discuss difficulties in the estimation of different specifications, and compare results across model specifications and worker groups. Because the main purpose of Burdett and Mortensen (1998) was to give an explanation for wage differentials between observationally identical workers, we examine the performance of various specifications on the basis of their fit to the wage data. Not surprisingly, the simplest version of the Burdett-Mortensen model is found to give a poor fit. We need to introduce either measurement error in wages or employer heterogeneity in terms of labour productivity in order to obtain an acceptable fit to the wage data. These more complex specifications are found to yield almost identical estimates for the layoff rate and the arrival rates of job offers.

In Chapter V we leave the structural models again and discuss the difficulties of interpreting the results of competing risks duration models, an issue that arises in a particular context in the second study. In Chapter III we describe the importance of eligibility for extended UI benefits by comparing the cumulative probabilities of leaving unemployment via alternative routes between individuals covered by the two different UI schemes. In this way we summarise the effects of extended benefits on hazard functions for transitions to employment, labour market programmes, and non-participation in a coherent and policy-relevant way. We give also a simulated example where a longer UI entitlement period is associated with a higher employment hazard but a lower probability of leaving unemployment for employment. In other words, the increase in the entitlement period increases the transition rate to employment but decreases the overall probability of employment. This example illustrates the risk of confusion about the interpretation of covariate effects in the competing risks analysis. In general, the effect of a covariate on the hazard for a particular cause can be very different from its effect on the likelihood of exiting from that cause (Gray, 1988). This is because the latter effect is a function of the effects of the covariate on all cause-specific hazards, making the interpretation of covariate effects in the competing risks hazard model difficult. This issue has been overlooked in many econometric applications of competing risks data, an important exception being Thomas (1996).

In the context of some qualitative response models, like multinominal logit and ordered probit models, the analogous issue arises. As a consequence, the results of such models are usually reported in terms of the marginal effects, the effects of explanatory variables on the probability of interest. In Chapter IV we argue that a similar practice is equally useful in the context of competing risks models as well. More precisely, we consider the effects of covariates on the cumulative probability of exiting from a particular cause by a given time. These "marginal effects" are decomposed into direct effects via the hazard of interest and indirect effects via the competing hazards. We show that the marginal effects have simple closed-form solutions for a popular class of competing risks models with piecewise constant hazard functions. As a consequence, the marginal effects can be computed rather easily for this class from the standard hazard function estimates. Our main points are illustrated with an empirical application. We estimate a competing risks model of unemployment duration with distinct hazards for exits to employment, labour market programmes, and out of the labour force. We find clear differences, both in quantitative and qualitative terms, between the effects of covariates on cause-specific hazards and their marginal effects on the associated cumulative exit probabilities. In addition, by examining the distributions of marginal effects across individuals, we illustrate how marginal effects may work in opposite directions for different subgroups.

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# Chapter II

# Gender Wage Differentials: Evidence from Matched Employer-Employee Data

*In this study we evaluate the extent to which the gender wage gap in the Finnish manufacturing sector is attributable to within-job wage differentials, sex differences in individual qualifications, and disproportionate concentration of women in lower-paying firms and lower-paying jobs within firms. We use matched employer-employee data to compare wage differentials between similarly qualified female and male workers who are doing similar work for the same employer. Our modelling approach employs a correlated random effects specification to account for the hierarchical grouped structure of the underlying data.*[1]

## 1 Introduction

A huge body of literature has emerged to explain why the gender wage gap persistently exists in virtually all labour markets (see Altonji and Blank, 1999, and Blau and Kahn, 2000, for recent surveys). Traditional attempts to explain the wage gap focused on sex differences in individual qualifications and their rewards in the labour market. More recently, the importance of the segregation of women and men into different jobs has been recognised. This line of research emphasises that wages are closely tied to the properties of jobs, not only to the characteristics of individuals who hold them. If typical female jobs pay lower wages than jobs dominated by men, the mean earnings of women can fall short of men's earnings even in the absence of within-job wage differentials between sexes. Thus, a sizeable wage gap can exist even when female and male workers are equally rewarded by all employers.

[1]This study is joint work with Ossi Korkeamäki. Most of the results can be found in Korkeamäki and Kyyrä (2003, 2006).

Attempts to qualify the segregation effects on the wage gap were distorted by a lack of appropriate data for a long time. Consequently, most of the early analysis focused on segregation among occupations, firms, or industries only. This is clearly unsatisfactory, as women and men are further segregated into different jobs within firms. In recent years, important advances have been made by access to large matched employer-employee data sets that contain multiple observations on workers with the same employer. When information on occupations or job titles is available, such data enable wage comparisons between male and female workers who are doing similar work for the same employer. This kind of comparative analysis has been conducted by Petersen and Morgan (1995), Petersen et al. (1997), Meyersson Milgrom et al. (2001), Groshen (1991), Datta Gupta and Rothstein (2001), and Bayard et al. (2003). In the first three of these studies observed sex differentials in mean wages within jobs are simply aggregated to form various wage decompositions. This approach has the obvious drawback that variation in individual characteristics is left uncontrolled. In the other studies, wages are regressed against a set of control variables and fraction female in the worker's industry, firm, occupation, and/or job.[2] The key idea is that the regression coefficients of the various fraction female variables capture the relationship between the wage rate and "femaleness" of the underlying labour market structure.

It should be noted that a common practice in the fraction female regressions above has been to neglect the grouping in the underlying data. For example, observations on workers resulting from the same firm are interpreted as being independent. However, intuition suggests that we should expect workers in the same firm to be more homogeneous than those in a sample drawn randomly from the population of all firms. Workers in the same firm share many common factors, some of which may be observable (e.g. firm size, fraction female) but many are not (e.g. market power, managerial ability). In the regression analysis the effect of such unobservables serves as a latent firm effect that will be absorbed into the error term. Moreover, since different jobs require different skills and qualifications, we can further expect that within a given firm workers who are doing the same job are more homogenous than the firm's workforce as whole. This implies an additional source of dependence between workers within jobs.

In general, the matched employer-employee data exhibit a particular type of grouped structure, which contrasts the statistical properties of such data with the classical random sample case. A consequence of the grouping in the regression analysis is that the errors will be correlated within groups owing to the latent group effects. In the absence of correlation between the latent group effects and regressors included in the model, the OLS coefficients will be unbiased but inefficient. The standard errors, however, will be biased downwards, leading to the risk of spurious inference about the statistical significance of parameters of interest (Moulton, 1986). More generally, when the group effects are correlated with the regressors, the OLS coefficients will be biased and inconsistent. These econometric

[2] In a related paper we apply this method to the Finnish data; see Korkeamäki and Kyyrä (2002).

problems have been overlooked in the previous analysis of gender wage differentials using the matched employer-employee data.[3]

In this study, we explore wage differentials between sexes in the Finnish manufacturing sector using a large matched employer-employee data set. We view the data as having a nested structure with three levels: firms, jobs within firms, and workers in jobs within firms. A job is defined as an occupation within a firm. Along with individual characteristics, the wage rate is allowed to depend upon the employing firm and the job the worker is holding within the firm. The latent firm and job effects are modelled as a function of group characteristics, including the mean characteristics of individuals within the groups. We end up with a regression model with variables measured at the individual, job, and firm levels, and an error term that has a two-way nested structure with separate intercepts for firms and jobs within firms. The model is estimated with generalized least squares that exploits the nested structure of error variation for efficiency. Using the regression results we decompose the overall sex gap in pay into the contributions of sex segregation, sex differences in the individual qualifications, and the unexplained within-job gap.

Our approach departs from the existing segregation literature in that we explicitly model wage differentials between firms and jobs. In contrast with the standard fraction female regressions, we obtain consistent estimates of the parameters of interest in the presence of the correlated group effects that are likely to arise in the case of the matched employer-employee data. With respect to job segregation the previous studies have focused on quantifying what fraction of the overall wage gap can be attributed to disproportionate concentration of women in lower-paying jobs. In addition to identifying this quantity, we take a step further by addressing the issue *why* typical female jobs are lower paid. When evaluating the extent to which lower wages in predominantly female jobs can be explained by job attributes, we make use of an index of job complexity that measures the responsibility, skills, and effort required by a given job. Thus we are able to assess whether wage differentials between typical female and male jobs can be viewed as justified or not, a question that is beyond the scope of earlier analysis but crucial, for example, in the view of comparable worth policy.

The rest of the paper proceeds as follows. In the next section, we discuss the main results from some related studies for other countries. In Section 3 we give details on the econometric methods and wage gap decomposition. Section 4 describes the data and reports some descriptive statistics. The results are reported in Section 5, which is followed by a concluding section.

[3] Bayard et al. (2003) report the standard errors adjusted for intraestablishment error correlation but assume independence of the latent group effects and regressors.

## 2 Related literature

It is evident that the gender gap in pay exists in virtually all labour markets. The size of the gap is rather similar across different advanced countries, amounting to 15-35 percent lower mean wages for women than for men (see e.g. Blau and Kahn, 2000). Altonji and Blank (1999) give a comprehensive survey of research in economics investigating sex differences in the labour market. Here we discuss only some studies that are closely related to our approach. That is, we focus on studies that explore the importance of labour market segregation and wage differentials occurring within jobs (i.e. within occupations within firms/establishments) in explaining the gender wage gap. There are only a few such studies, as the evaluation of within-job wage differentials calls for high quality matched employer-employee data, which are not widely available. We emphasise that the results of these studies are not directly comparable and some differing conclusions are likely to result from dissimilarities in the data coverage, occupational classification, and/or statistical methods used. Throughout the following discussion the gender wage gap of a given percent is used to indicate that women's mean wage is less than men's mean wage by that percent.

The results for the U.S. labour market are mixed. Using the Industrial Wage Survey (IWS) data from the 1970s and 1980s,[4] Groshen (1991) and Petersen and Morgan (1995) find that sex segregation essentially explains all of the gender wage differentials in the U.S. labour market, within-job wage differentials between sexes being close to zero. These findings are in clear contrast to the results of Bayard et al. (2003) obtained from another source of data.[5] Bayard et al. (2003) find large gender wage differentials within jobs that explain as much as one-half of the overall wage gap. According to Groshen (1991) and Petersen and Morgan (1995), most of the overall gap is due to sex segregation among occupations. By contrast, Bayard et al. (2003) find a quantitatively unimportant effect for occupational segregation, whereas sex segregation among industries, firms, and jobs accounts for 40 percent of the overall gap. Because of these sharp discrepancies, Bayard et al. (2003) replicated their analysis using the IWS data with the identical occupational classifications and the same industries. Surprisingly, the results from the two data sets remained sharply different. Bayard et al. (2003) conclude that their different findings from Groshen's (1991) cannot be explained by differing levels of detail in occupational classifications nor by focus on different industries. Instead, they raise some doubts about the representativeness of the IWS data.

Petersen et al. (1997) and Meyersson Milgrom et al. (2001) report very similar patterns

[4] The IWS data cover only a narrow subset of occupations in 16 industries. Petersen and Morgan (1995) include all industries to their analysis, among which the gender wage gap varies between 38.5 and –5.3 percent with the average of 19 percent. Groshen (1991) focuses on five industries, where the gender wage gap lies between 21 and 37 percent.

[5] The data set used by Bayard et al. (2003) was constructed by matching individuals from the 1990 Decennial Census to establishments from the 1990 Standard Statistical Establishment List. While not entirely representative, the data include workers and establishments from all sectors of the U.S. economy. The size of the gender wage gap in the data is 31 percent.

of gender wage differentials for Norway and Sweden respectively.[6] In both countries white-collar women earn on average 27 percent less than their male counterparts do. The within-job wage gap among white-collar workers is 6 percent in Norway, compared with 5 percent in Sweden. Among the Norwegian blue-collar workers, the overall sex gap in pay is 12 percent and the within-job gap is 3.3 percent. The corresponding figures for Sweden are 13 percent and 1.4 percent respectively. In both Sweden and Norway occupational segregation alone explains over 70 percent of the overall wage gap of white-collar workers, whereas the contributions of sex segregation among industries, establishments, and jobs are quantitatively important only for blue-collar workers.

Using the Integrated Database for Labour Market Research, Datta Gupta and Rothstein (2001) study gender wage differentials in the Danish labour market. Their data include basically all salaried workers in the private sector. They find that occupational segregation accounts for roughly one-half of the overall gap of 29 percent, while over 40 percent of the gap remains attributable to unexplained within-job wage differentials between women and men. The latter finding is in contrast with the evidence for Sweden and Norway, being more in line with the U.S. results of Bayard et al. (2003).

## 3 Methodological framework

We assume that the wage rate is closely tied to the employing firm and the job held within that firm. That is, we expect systematic variation in wages across firms and jobs within firms that cannot be explained by the characteristics of workers in the underlying groups. Thus wage variation can occur at different levels: between firms, between jobs within firms, and between workers within jobs.[7] Within this framework the allocation of women and men to different positions in the labour market serves as a potential source of gender wage differentials. In the following sections we explain how to identify various sources of the wage differentials.

### 3.1 The wage model

Suppose our data consist of all employees of $F$ firms. Within firms employees who do similar work are grouped together, in which case they are said to hold the same job. Observations across firms are regarded as being independent, but within firms wages are correlated owing to common firm and job characteristics. We model the log wage of worker $i$ ($i = 1, 2, ..., n_{jk}$) who holds job $k$ ($k = 1, 2, ..., c_j$) in firm $j$ ($j = 1, 2, ..., F$) as

$$w_{jki} = \eta s_{jki} + \boldsymbol{\beta}' \mathbf{x}_{jki} + f_j + v_{jk} + \varepsilon_{jki}, \tag{II.1}$$

[6] The Norwegian data of Petersen et al. (1997) contain basically all workers in six business sectors in 1984 and 1990. The data used by Meyersson Milgrom et al. (2001) is more extensive, covering most privately employed workers in Sweden over the period 1970-1990. In the text we refer only to the results for the 1990s in the case of both studies.

[7] Obviously we could go further and introduce an additional level on top of this hierarchy by grouping firms by industry. For simplicity, we focus on the three levels and treat industry as a characteristic of firms rather than a hierarchy level of its own.

where $s$ is the female dummy, $\mathbf{x}$ is a vector of other individual characteristics, $v$ is the job effect that is "nested" within the firm effect $f$. For the idiosyncratic errors $\varepsilon$, we assume

$$E(\varepsilon_{jki} | \mathbf{X}_j, \mathbf{v}_j, f_j) = 0 \quad \text{and} \quad E(\varepsilon_{jki}\varepsilon_{jki'} | \mathbf{X}_j, \mathbf{v}_j, f_j) = 0 \text{ for } i \neq i', \tag{II.2}$$

where $\mathbf{X}_j$ includes $\mathbf{x}$ and $s$ for all employees of firm $j$, and $\mathbf{v}_j = \left(v_{j1}, v_{j2}, ..., v_{jc_j}\right)$.

Wage variation between firms and jobs beyond the observable individual characteristics is captured by $f$ and $v$ respectively. Without loss of generality, the job effects are defined in deviation from the firm effects, with the expected value within each firm equal to zero. Thus, $E(f + v | \text{firm } j) = f_j + E(v | \text{firm } j) = f_j$. We emphasize that $f$ and $v$ are likely to be correlated with $s$ and $\mathbf{x}$. In particular, women are expected to be concentrated in firms with low values of $f$, and further in jobs with low values of $v$. Since different firms and jobs require different qualifications, the group effects $f$ and $v$ are likely to be correlated also with the variables in $\mathbf{x}$. If $f_j > f_{j'}$, workers in firm $j$ earn more on average than workers in firm $j'$, after controlling for $s$ and $\mathbf{x}$. Similarly, provided that $v_{jk} > v_{jk'}$, workers in job $k$ are more highly paid on average than those in job $k'$ within the same firm $j$, after controlling for $s$ and $\mathbf{x}$.

Within jobs wage differentials are related to workers' sex ($s$), other individual characteristics ($\mathbf{x}$), and unobservables ($\varepsilon$). A parameter of particular interest is $\eta$ that gives the expected wage differential between equally qualified (in terms of $\mathbf{x}$) women and men who are doing the same work for the same employer. One may be tempted to view a negative value of $\eta$ as evidence of wage discrimination against women. Such an interpretation is justified only if all relevant explanatory variables were included in $\mathbf{x}$. This may not be the case in practice. In general, the influences of possible discrimination and unmeasured individual characteristics are indistinguishable in the value of $\eta$. Therefore, we interpret $\eta$ simply as a measure of the unexplained within-job wage differential between sexes.

At this point a few remarks on the restrictions imposed above are in order. First, the returns to individual qualifications, $\boldsymbol{\beta}$, are assumed to be equal for women and men. One should recognise that the interpretation of $\boldsymbol{\beta}$ is conditional on the position held in the labour market (i.e. conditional on $f$ and $v$), so $\boldsymbol{\beta}$ measures the returns *within a given job*. Since employers cannot apply very different reward schemes to their female and male employees who are doing the same work, our assumption is not as restrictive as it might first look. We will return to this issue and discuss also results from a regression model with gender-specific slopes. The assumption that the unexplained within-job wage gap is of the same size everywhere is rather restrictive. One might wish to allow the coefficient of the female dummy to vary across jobs, i.e. replace $\eta$ with $\eta_{jk}$. We adopt a very narrow definition for jobs in our empirical application. This results in a huge number of jobs, many of which include either female or male employees only, making the estimation of job-specific coefficients infeasible in practice.

## 3.2 Decomposing the gender gap in pay

The gender wage gap is defined as the difference in the expected wages between men and women, i.e. the wage difference between a randomly chosen man and woman. Using the model outlined above we decompose it as

$$\begin{aligned} E(w\,|s=0)-E(w\,|s=1) &= -\eta+\boldsymbol{\beta}'\left[E(\mathbf{x}\,|s=0)-E(\mathbf{x}\,|s=1)\right] \\ &\quad +\left[E(f\,|s=0)-E(f\,|s=1)\right] \\ &\quad +\left[E(v\,|s=0)-E(v\,|s=1)\right], \end{aligned} \tag{II.3}$$

where the contributions of sex segregation among firms and jobs are captured by the last two terms. A positive value of $E(f\,|s=0)-E(f\,|s=1)$ indicates that women are disproportionately concentrated in lower-paying firms. This term would be zero, if there were no variation in $f$ across firms or if women and men were identically distributed across firms. If women are relatively more frequently allocated to lower-paying jobs within firms, $E(v\,|s=0)-E(v\,|s=1)$ will take a positive value. It would be zero, if there was no systematic wage variation across jobs within firms beyond the differences in individual characteristics or if, within all firms, women and men were allocated identically across jobs. The amount of within-job wage differentials between sexes not accounted for by the explanatory variables $\mathbf{x}$ equals $-\eta$. The contribution of sex differences in individual characteristics is captured by the remaining term on the right-hand side.

To obtain an empirical counterpart of the decomposition, the conditional means of $w$ and $\mathbf{x}$ can be replaced with the sample means over women and men but the other components need to be estimated. Since the latent group effects are expected to be correlated with the explanatory variables, we will focus on estimation by fixed effects and correlated random effects.

## 3.3 The fixed effects approach

In our first approach we take $f$ and $v$ as fixed constants to be estimated along with $\eta$ and $\boldsymbol{\beta}$. So we consider the model conditional on the firm and job effects:

$$E(w_{jki}\,|\mathbf{X}_j,\mathbf{v}_j,f_j)=\eta s_{jki}+\boldsymbol{\beta}'\mathbf{x}_{jki}+f_j+v_{jk}. \tag{II.4}$$

In this case $\eta$ and $\boldsymbol{\beta}$ could be estimated by regressing $w$ on $s$, $\mathbf{x}$, and the full set of job dummies. As the number of job dummies may be too large to make estimation feasible, we obtain analytically equivalent estimators of $\eta$ and $\boldsymbol{\beta}$ by applying pooled OLS to the transformed model:

$$w_{jki}-\overline{w}_{jk\cdot}=\eta\left(s_{jki}-\overline{s}_{jk\cdot}\right)+\boldsymbol{\beta}'\left(\mathbf{x}_{jki}-\overline{\mathbf{x}}_{jk\cdot}\right)+\varepsilon_{jki}-\overline{\varepsilon}_{jk\cdot}, \tag{II.5}$$

where $\overline{w}_{jk\cdot}$, $\overline{s}_{jk\cdot}$, $\overline{\mathbf{x}}_{jk\cdot}$, and $\overline{\varepsilon}_{jk\cdot}$ denote averages over workers in the $k$th job of firm $j$. Under the assumptions (II.2), the resulting "fixed effects" (FE) estimators $\widehat{\eta}$ and $\widehat{\boldsymbol{\beta}}$ are consistent under arbitrary correlation between $(s, \mathbf{x})$ and $(f, v)$. Given the restriction $E(v \,|\text{firm } j) = 0$ for all $j$, the firm and job effects can be estimated as

$$\widehat{f}_j = \overline{w}_{j\cdot\cdot} - \widehat{\eta}\overline{s}_{j\cdot\cdot} - \widehat{\boldsymbol{\beta}}'\overline{\mathbf{x}}_{j\cdot\cdot}, \tag{II.6}$$

$$\widehat{v}_{jk} = \overline{w}_{jk\cdot} - \widehat{\eta}\overline{s}_{jk\cdot} - \widehat{\boldsymbol{\beta}}'\overline{\mathbf{x}}_{jk\cdot} - \widehat{f}_j, \tag{II.7}$$

where $\overline{w}_{j\cdot\cdot}$, $\overline{s}_{j\cdot\cdot}$, and $\overline{\mathbf{x}}_{j\cdot\cdot}$ denote averages over the employees of firm $j$. The point estimates of $f$ and $v$ are noisy because the number of observations per firm and, especially, per job can be small. However, the estimates of their expected values among women and men based upon sample averages are expected to be reasonably accurate. Thus, we proceed by inserting $\widehat{\eta}$ and $\widehat{\boldsymbol{\beta}}$ along with the sample means of $\widehat{f}$ and $\widehat{v}$ over women and men into (II.3). This gives the first version of our wage gap decomposition. It allows us to distinguish the contributions of sex segregation among firms and jobs to the overall wage gap from the contributions of the unexplained within-job gap and sex differences in individual characteristics.

### 3.4 The correlated random effects approach

In an alternative approach we take an explicit account of the relationship between the latent group effects and the explanatory variables. More precisely, we specify the expected values of $f$ and $v$ conditional on observables via auxiliary linear regressions. Let $\mathbf{X}_j^* = \left(\mathbf{X}_j, \mathbf{z}_j, \mathbf{g}_{j1}, ..., \mathbf{g}_{jc_j}\right)$ be the extended set of conditioning variables that includes firm attributes $\mathbf{z}_j$ (firm size, industry, etc.) and job attributes $\mathbf{g}_{jk}$'s (job size, job complexity index, etc.) in addition to $\mathbf{X}_j$. We specify the conditional mean of the firm effect as

$$E(f_j \left|\mathbf{X}_j^*\right.) = \alpha + \delta_0\overline{s}_{j\cdot\cdot} + \boldsymbol{\delta}_1'\overline{\mathbf{x}}_{j\cdot\cdot} + \boldsymbol{\delta}_2'\mathbf{z}_j \tag{II.8}$$

and that of the job effect as

$$E(v_{jk} \left|\mathbf{X}_j^*\right.) = \theta_0\left(\overline{s}_{jk\cdot} - \overline{s}_{j\cdot\cdot}\right) + \boldsymbol{\theta}_1'\left(\overline{\mathbf{x}}_{jk\cdot} - \overline{\mathbf{x}}_{j\cdot\cdot}\right) + \boldsymbol{\theta}_2'\left(\mathbf{g}_{jk} - \overline{\mathbf{g}}_{j\cdot}\right), \tag{II.9}$$

i.e. the first moments of the marginal distributions of $f$ and $v$ are assumed to be linear functions of the group means of $s$ and $\mathbf{x}$ and of other group level variables. All the explanatory variables on the right-hand side of (II.9) are measured in deviation from the firm mean in order to enforce the expected value of $v$ within firms to zero.[8]

Now we consider the model conditional on $\mathbf{X}_j^*$:

$$E(w_{jki} \left|\mathbf{X}_j^*\right.) = \eta s_{jki} + \boldsymbol{\beta}'\mathbf{x}_{jki} + E(f_j \left|\mathbf{X}_j^*\right.) + E(v_{jk} \left|\mathbf{X}_j^*\right.).$$

Defining $\xi_j \equiv f_j - E\left(f_j | \mathbf{X}_j^*\right)$ and $\omega_{jk} \equiv v_{jk} - E\left(v_{jk} | \mathbf{X}_j^*\right)$, we obtain the estimating wage equation:

$$\begin{aligned} w_{jki} \quad = \quad & \alpha + \eta s_{jki} + \delta_0\overline{s}_{j\cdot\cdot} + \theta_0\left(\overline{s}_{jk\cdot} - \overline{s}_{j\cdot\cdot}\right) + \boldsymbol{\beta}'\mathbf{x}_{jki} + \boldsymbol{\delta}_1'\overline{\mathbf{x}}_{j\cdot\cdot} + \boldsymbol{\theta}_1'\left(\overline{\mathbf{x}}_{jk\cdot} - \overline{\mathbf{x}}_{j\cdot\cdot}\right) \\ & + \boldsymbol{\delta}_2'\mathbf{z}_j + \boldsymbol{\theta}_2'\left(\mathbf{g}_{jk} - \overline{\mathbf{g}}_{j\cdot}\right) + u_{jki}, \end{aligned} \tag{II.10}$$

[8]This is only a matter of parametrization provided that $\overline{\mathbf{g}}_{j\cdot}$ is included in the set of firm covariates $\mathbf{z}_j$.

where $u_{jki} \equiv \xi_j + \omega_{jk} + \varepsilon_{jki}$. Conditional on $\mathbf{X}_j^*$, all components of $u_{jki}$ are assumed to be mutually independent, with zero means and constant variances $\sigma_\xi^2$, $\sigma_\omega^2$, and $\sigma_\varepsilon^2$ respectively. Within firm $j$, the variance-covariance structure of the errors is given by

$$E\left(u_{jki}u_{jk'i'}\left|\mathbf{X}_j^*\right.\right) = \begin{cases} \sigma_\xi^2 + \sigma_\omega^2 + \sigma_\varepsilon^2, & \text{if } k = k' \text{ and } i = i'; \\ \sigma_\xi^2 + \sigma_\omega^2, & \text{if } k = k' \text{ and } i \neq i'; \\ \sigma_\xi^2, & \text{if } k \neq k' \text{ and } i \neq i'. \end{cases} \tag{II.11}$$

This is known as the two-way nested error structure in econometrics (Fuller and Batesse, 1973). It models the residual correlation within firms that remains after conditioning on the observed firm, job, and individual characteristics. Such a correlation is likely to exist owing to unobservable job and firm factors. We estimate the model with generalized least squares (GLS) that exploits the particular form of the error structure for efficiency and produces appropriate standard errors.[9] The large unbalanced data raise some computational issues, as the inverse of the error variance-covariance matrix is required by the GLS procedure. These issues and the estimation of the variance components are discussed in the Appendix.

It should be stressed that including the group means of individual explanatory variables in (II.8) and (II.9) provides a way of allowing $s$ and $\mathbf{x}$ to be correlated with $f$ and $v$, an old idea by Mundlak (1978).[10] To emphasize this point, we refer to the specification outlined above as the "correlated random effects" (CRE) model.[11] Coefficients of the fraction female variables in (II.8) and (II.9) are of particular interest. A negative value of $\delta_0$ implies that firms with a high density of female workers pay lower wages after controlling for $\overline{\mathbf{x}}_{j\cdot\cdot}$ and $\mathbf{z}_j$. If within firms employees in predominantly female jobs are lower paid given $(\overline{\mathbf{x}}_{jk\cdot} - \overline{\mathbf{x}}_{j\cdot\cdot})$ and $\left(\mathbf{g}_{jk} - \overline{\mathbf{g}}_{j\cdot}\right)$, it will be indicated by a negative value of $\theta_0$. That is, $\delta_0$ and $\theta_0$ are kind of "residual gender effects", which imply that predominantly female firms and jobs pay different wages for reasons not accounted for by the observed worker and group characteristics.

Because $E(f\,|s=0) = E\left[E(f\,|\mathbf{X}^*)\,|s=0\right]$ by the law of iterative expectations, we

[9] Alternatives for GLS are the maximum likelihood (ML) and restricted maximum likelihood (RML) methods, both of which require an additional distributional assumption for the error terms (e.g. each component of $u_{jki}$ is an i.i.d. normal variable). The unknown variance components and regression coefficients are then estimated simultaneously by maximising the likelihood function. The RML method by Patterson and Thompson (1971) is a modification of the ML procedure in which the loss of degrees of freedom due to estimation of regression coefficients is taken into account when estimating the variance components. Monte Carlo evidence suggests that the GLS, ML and RML methods all perform equally well in estimating the regression coefficients but the variance components may be better estimated with ML and RML. See Maddala and Mount (1973) for evidence for the simple error component models, and Baltagi et al. (2001) for the two-way nested error structure.

[10] Chamberlain (1984) considers a general case where the latent group effects are modelled as linear predictors of $s$ and $\mathbf{x}$ of all employees within the group. Mundlak's (1978) specification is obtained by imposing a restriction that the coefficients of $s$ and $\mathbf{x}$ in the linear predictor are identical for all $i$ within the group. The unrestricted specification becomes cumbersome in our case where group sizes vary and some firms are very large.

[11] The model defined by (II.10) and (II.11) is known also under a variety of other names, including the nested error components model, variance components model, random intercepts model, mixed model, and hierarchical model.

obtain an estimate of $E(f\,|s=0)$ by averaging the right-hand side of (II.8) over all men. $E(f\,|s=1)$ is estimated analogously by averaging over women. The contribution of sex segregation among firms can then be expressed as

$$\begin{aligned} E(f\,|s=0)-E(f\,|s=1) &= \sum_{j=1}^{F}\left(o_j^m-o_j^f\right)\delta_0\bar{s}_{j\cdot\cdot} \\ &\quad+\sum_{j=1}^{F}\left(o_j^m-o_j^f\right)\left(\boldsymbol{\delta}_1'\bar{\mathbf{x}}_{j\cdot\cdot}+\boldsymbol{\delta}_2'\mathbf{z}_j\right), \end{aligned} \tag{II.12}$$

where $o_j^f$ $(o_j^m)$ is the fraction of all women (men) allocated to firm $j$. Similarly, the contribution of sex segregation among jobs within firms is given by

$$\begin{aligned} E(v\,|s=0)-E(v\,|s=1) &= \sum_{j=1}^{F}\sum_{k=1}^{c_j}\left(o_{jk}^m-o_{jk}^f\right)\theta_0\left(\bar{s}_{jk\cdot}-\bar{s}_{j\cdot\cdot}\right) \\ &\quad+\sum_{j=1}^{F}\sum_{k=1}^{c_j}\left(o_{jk}^m-o_{jk}^f\right)\left[\boldsymbol{\theta}_1'\left(\bar{\mathbf{x}}_{jk\cdot}-\bar{\mathbf{x}}_{j\cdot\cdot}\right)+\boldsymbol{\theta}_2'\left(\mathbf{g}_{jk}-\bar{\mathbf{g}}_{j\cdot}\right)\right], \end{aligned} \tag{II.13}$$

where $o_{jk}^f$ $(o_{jk}^m)$ is the fraction of all women (men) allocated to the $k$th job of firm $j$. Substituting (II.12) and (II.13) into (II.3) along with the GLS estimates of the regression coefficients gives us the second version of our wage gap decomposition.

In the case of the CRE model the segregation contributions can be expressed as sums of various terms. These terms pass on useful information, which is not available from the FE model. For example, if typical female jobs are found to be characterised by low values of $v$, one may speculate that lower wages in such jobs result from lower skill requirements. If this is the case, a large fraction of the contribution of sex segregation among jobs in (II.13) will be attributed to differences in the mean education (incorporated in $\bar{\mathbf{x}}_{jk\cdot}-\bar{\mathbf{x}}_{j\cdot\cdot}$) and job complexity (incorporated in $\mathbf{g}_{jk}-\bar{\mathbf{g}}_{j\cdot}$), while the component associated with the fraction female ($\bar{s}_{jk\cdot}-\bar{s}_{j\cdot\cdot}$) will be close to zero. By contrast, if wage differentials between typical female and male jobs arise to a large extent from some unobserved sources, this will be indicated by a strong effect of the fraction female term in (II.13).

### 3.5 Discussion

In the case of the FE model we cannot say anything about why predominantly female firms and jobs are lower paid on average. This of course is a cost of the robustness of the fixed effect method: we do not assume anything about the relationship between the group effects and regressors. Compared with the FE model, the CRE specification is more restrictive, as the conditional expectations of $f$ and $v$ are assumed to be linear. However, when the group means of $s$ and $\mathbf{x}$ are included in (II.8) and (II.9), the GLS estimators of $\eta$ and $\boldsymbol{\beta}$ are identical to their FE estimators, and hence not affected by these additional restrictions. In this respect we do not loose anything by imposing more structure on the model. The additional structure of the CRE model is exploited in explaining wage variation between firms and jobs. While both the FE and CRE model are able to produce identical results for the effects of individual level regressors, only the latter is informative about sources of wage differentials between firms and jobs. For this reason the CRE model is our preferred choice. A potential drawback of the method is that the sum of various contributions does not necessarily equal to the raw wage gap in finite samples. This is a consequence of the more complex error structure.

Our approach departs from the decomposition exercises in Groshen (1991), Datta Gupta and Rothstein (2001), and Bayard et al. (2003) in some essential ways. Of course, the main difference is that our CRE approach is informative about the determinants of lower wages in predominantly female firms and jobs. Secondly, the interpretation of the regressor coefficients $\eta$ and $\boldsymbol{\beta}$ comes from the wage model defined in (II.1) and (II.2), i.e. they measure wage differentials within jobs (that is, the firm and job effects held constant). This interpretation is trivial when the model is estimated by fixed effects, but the coefficients have the same meaning also in the CRE specification as we allow $f$ and $v$ to be correlated with $s$ and $\mathbf{x}$. The coefficients in the standard fraction female regressions do not generally have the same within-job interpretation. Thirdly, we define the segregation contributions as differences in the mean values of the firm and job effects between men and women.[12]

Despite the differences in the modelling framework, the estimating wage equation in (II.10) and the associated decomposition are not much different from those in the previous studies. If occupational segregation is omitted, the standard fraction female decompositions can be viewed as special cases of our CRE decomposition. If we set $\boldsymbol{\delta}_1$, $\boldsymbol{\delta}_2$, $\boldsymbol{\theta}_1$, and $\boldsymbol{\theta}_2$ to zero, we obtain a specification similar to those in Datta Gupta and Rothstein (2001) and Bayard et al. (2003). If we impose further $\boldsymbol{\beta} = \mathbf{0}$, the model is reduced to Groshen's (1991) specification. Within our framework, the restriction $\boldsymbol{\delta}_1 = \boldsymbol{\theta}_1 = \mathbf{0}$ is equivalent to assuming that the firm and job effects are uncorrelated with $\mathbf{x}$. This of course is a rather restrictive assumption, and it may lead to inconsistent estimates of $\eta$ and $\boldsymbol{\beta}$. The importance of this sort of restrictions is an empirical issue, and it depends on the data in hand. For example, both Datta Gupta and Rothstein (2001) and Bayard et al. (2003) find only a minor change in the female dummy coefficient when the fraction female variables were replaced with the full set of job dummies. In general, it does make a difference whether one conditions on the job held or only on the femaleness of the worker's position. In our application we find quantitatively significant discrepancies in the estimated coefficients, standard errors, and decomposition results between the CRE model and standard fraction female specification.

[12] Additional, less important, differences are: (1) we measure the fraction female in job as a deviation from the firm mean, (2) we do not include the fraction female in occupation nor in industry in our model, and (3) we apply GLS, not OLS.

# 4 Data and descriptive statistics

## 4.1 Evaluation of job tasks in the collective agreements

In Finland working conditions are determined in large part by collective bargaining between employers' organisation and labour unions. The collective agreements are made along broad occupational lines and signed at industry level. Within an industry, all employees, irrespective of their union status, are covered by the collective agreement of their occupational group if the unionization rate exceeds a certain threshold level (which is true in almost all cases). A specific collective agreement determines, among other working conditions, a minimum rate of pay for a particular type of job. For this purpose, most job tasks are evaluated according to the responsibility, skills, and effort they require, and thereby mapped onto a scale of complexity levels. Each level of job complexity is then associated with a given basic wage that serves as the wage floor for that type of job. Actual wages received by workers generally exceed the basic wages because of firm premiums and rewards for individual qualifications and performance.

We emphasise that employers do not hold the evaluation of job tasks in the palm of their hands, but it is highly regulated and supervised by the representatives of unions. The key principle is that the basic wage is determined by job attributes only, independently of the individual characteristics of the current job holder (e.g. sex and education). The evaluation process of jobs has two important implications for our analysis. First, it explicitly states that the wages are closely tied to jobs, not only to the workers who hold them. Second, knowledge of job complexity ranking provides valuable information about job attributes that we can exploit in explaining wage variation between jobs.

## 4.2 TT data

Our data come from the records of the Confederation of Finnish Industry and Employers (TT). TT is the central organisation of manufacturing employers and its member firms account for more than three-quarters of the value added of the Finnish manufacturing sector.[13] Each year TT conducts three surveys covering basically all employees of its member firms. All surveys are directed to the employer, one asking information about white-collar workers and the other two about blue-collar workers. These surveys contain detailed information on wages, working hours, job complexity levels, and occupations (or job titles), as well as some demographic background information. Each individual in the records is associated to his or her employer with a unique firm identifier.

We stress that the TT data are of high quality and have several advantages over most of the other data sets employed in previous research. First, our data can be regarded as highly reliable since all information comes directly from the employer records. There is practically no response bias and all information is reported with high accuracy compared with the

[13]TT does not exist any more. In 2005 the Confederation of Finnish Industries (EK) was established as a result of the unification of TT and the Employers' Confederation of Service Industries (PT).

standard employee surveys. Second, the data cover all employees of each firm surveyed. Thus we get rid of the measurement error issues in measuring the mean characteristics of workers within firms and jobs.[14] Third, our data contain precise information on the standard human capital characteristics, such as education (level and field), firm tenure, and age, making the analysis less prone to omitted variable bias. Fourth, knowledge of the job complexity ranking provides a rare opportunity to take into account heterogeneity across jobs.

In the subsequent analysis we focus on the cross-section of full-time workers aged between 18 and 65 who were employed in 2000 by TT firms with at least five workers. White- and blue-collar workers will be analysed separately as they are subject to different compensation schemes and covered by different collective agreements.

#### White-collar workers

The collective agreements for white-collar workers specify three broad groups: managerial, technical, and clerical workers. Each group is covered by a separate industry-specific agreement, though the clerical and technical employees are combined and covered by the same agreement in some industries. White-collar workers are also classified into 78 occupational groups that are common to all white-collar groups and all industries.

We define a job as an occupation *within* an employing firm (this results in 26,236 jobs).[15] However, where workers covered by different agreements are allocated to the same job, we split the job into parts, each one including only technical, clerical, or managerial employees. The number of jobs increases to 30,281. Finally, jobs that include workers with differing levels of job complexity are further divided into jobs including only workers with the same level of job complexity. This raises the number of jobs to 40,664. At the end, all workers within a given job have the same occupation and job complexity classification, and are covered by the same collective agreement.

As a part of the collective agreements, jobs of technical and clerical workers are evaluated and classified into complexity levels. There are two complications regarding the use of this information in the regression analysis. First, job complexity information is missing for all the managerial jobs, which are not subject to any evaluation process. This is because the managerial employees are regarded as high-paid employees whose wages are of less interest to the unions. Secondly, the scale of the complexity classification is not constant, but 9 different scales are applied in different industries. Where no distinction

[14] If only a sample of the firm's workforce is available, the fraction of female employees, for example, will be measured with error. This in turn tends to bias their regression coefficients towards zero. It is also quite common that information on the worker composition of the underlying labour market structure is obtained from another survey through some incomplete matching process.

[15] Additionally, we use information on each worker's job location (municipality) to sub-divide jobs within firms. Workers with the same occupation but who are working in different plants of the same firm are allocated to separate jobs, if the plants are located in different municipalities. We do not consider it prudent to divide firms into plants with this indirect information on job locations. Thus, the employer unit in our analysis is firm, not plant.

between the technical and clerical employees is made, the number of complexity levels lies somewhere between 3 and 15 (being 8, 9, or 10 in most cases). In other industries the number of complexity levels is 6 for technical employees and 12 for clerical employees. However, the different scales for job complexity cover roughly the same range of logarithmic basic wages and the relationship between the job complexity levels and basic wages is approximately log-linear within each scale. Therefore, we re-scale the original complexity variables on the interval 0 to 9 by applying a suitable stretch or compression factor to each industry-specific scale (i.e. the lowest level of job complexity is set to 0 and the highest level to 9).[16]

Table II.1 reports some sample statistics. The wage variable is constructed by dividing the monthly salary in December 2000 (bonuses etc. excluded) by regular working hours. In the Finnish manufacturing sector, 37 percent of white-collar workers are female and they earn on average 23 percent less than their male counterparts do. There are no large sex differences in the average age, work experience, or firm tenure. While men are only slightly more educated as measured by the education level, sex differences in terms of the field of education are quite substantial. Of men, 65 percent have received a technical education, compared with 17 percent of women. Moreover, 41 percent of women have obtained a degree in social sciences, business, or law. The mean value of the job complexity level is clearly higher for men, indicating that more demanding clerical and technical jobs are mainly occupied by men.

To give a hint of the role of sex segregation, Table II.2 shows the gender wage ratio and sex composition by 2-digit occupation group and white-collar group (i.e. managerial vs. technical and clerical workers). Variation in the female share indicates a large degree of sex segregation among occupations, perhaps reflecting differences in education. Women appear to be concentrated in the administrative occupations. By contrast, less than 10 percent of white-collar workers in production occupations are female. The gender wage ratio within the occupation groups ranges from .670 to 1.062, being on average clearly higher than the raw wage ratio on the bottom line. This suggests that occupational segregation plays a role in explaining the gender wage gap. There is no clear relationship between the female share and the size of the within-occupation gender wage gap: the correlation coefficient between these variables is .26 and statistically insignificant at the 5 percent level.[17]

We emphasize that the allocation of workers to different jobs is based on a more detailed 3-digit occupation code, which corresponds to the finest classification level. That is, each occupation group in Table II.2 includes 1–6 more detailed occupations, resulting in a total of 78 occupations. For example, Office services in Administration include Recep-

[16] This conversion idea came from Antti Luukkonen, who found by comparing various wage regressions that the single variable works relatively well compared with the huge number of industry-specific complexity dummies. See Luukkonen (2003*a*) for details.

[17] When the observations are weighted by the size of the occupation group, the correlation coefficient is even lower (.06).

Table II.1: Sample statistics for white-collar workers

| | Women | | Men | | All | |
|---|---|---|---|---|---|---|
| Hourly wage, euro | 12.107 | (3.926) | 15.763 | (5.59) | 14.409 | (5.336) |
| Log hourly wage | 2.452 | (.276) | 2.702 | (.326) | 2.610 | (.331) |
| Age | 41.146 | (9.794) | 41.128 | (9.920) | 41.135 | (9.874) |
| Schooling years | 12.065 | (2.164) | 12.810 | (2.200) | 12.534 | (2.216) |
| Firm tenure, years | 12.395 | (10.648) | 11.860 | (10.552) | 12.058 | (10.591) |
| Work experience, years | 22.081 | (10.632) | 21.318 | (10.381) | 21.601 | (10.481) |
| Job complexity (0-9 scale) | 3.707 | (1.69) | 4.909 | (2.201) | 4.379 | 2.078 |
| Job complexity missing, share | .437 | | .569 | | .520 | |
| Job size | 242 | (665) | 310 | (754) | 285 | (723) |
| Employer size | 3,445 | (4,772) | 3,526 | (4,759) | 3,496 | (4,764) |
| **Education level, %** | | | | | | |
| Basic or unknown | 19.256 | | 11.966 | | 14.665 | |
| Secondary | 29.916 | | 22.621 | | 25.322 | |
| First stage of tertiary | 31.544 | | 27.030 | | 28.701 | |
| Bachelor's degree | 8.247 | | 22.559 | | 17.259 | |
| Master's degree | 10.528 | | 14.808 | | 13.223 | |
| PhD | .509 | | 1.017 | | .829 | |
| **Field of education, %** | | | | | | |
| General | 8.070 | | 6.382 | | 7.007 | |
| Education | .372 | | .069 | | .181 | |
| Humanities and art | 2.825 | | 0.413 | | 1.306 | |
| Social sciences, business and law | 40.975 | | 9.500 | | 21.156 | |
| Science | 2.687 | | 2.491 | | 2.563 | |
| Technical | 17.091 | | 64.722 | | 47.083 | |
| Agriculture | 1.115 | | 3.062 | | 2.341 | |
| Health and welfare | 2.591 | | 0.364 | | 1.188 | |
| Services | 5.006 | | 1.029 | | 2.502 | |
| Unknown | 19.270 | | 11.969 | | 14.673 | |
| Fraction female in firm | .436 | (.165) | .332 | (.137) | .370 | (.156) |
| Fraction female in job | .778 | (.293) | .131 | (.185) | .370 | (.388) |
| Sample size | 55,158 | | 93,786 | | 148,944 | |

Notes: Unless otherwise indicated, the figures in the table are means. Standard deviations are in parentheses. Hourly wage is computed dividing the monthly wage by regular working hours. Schooling years is defined as the mean years of schooling attached to a given level of education. Work experience is approximated by subtracting the years of schooling and seven years for time prior to the age of school entry from the worker's age. The mean level of job complexity is computed using non-missing values only. Employer and job sizes are the average firm and job size over workers. The mean firm size in the data is 102 and the mean job size is 3.7. The total number of firms is 1,464 and that of jobs is 40,664.

tionists, Switchboard Operators, Copyists and Mail Dispatchers, and Office Messengers; and Purchasing in Logistics includes Purchasing Managers, Purchasers, and Purchasing Assistants. Recall that employees of a given firm with the same detailed occupation are assumed to be doing the same job only if they are covered by the same collective agreement, their jobs are located in the same municipality, and in the case of technical and clerical employees their job tasks have been ranked to be of equal worth.

It is worth emphasizing that we have made an attempt to define jobs as narrowly as possible in order to be able to compare workers who are doing the "same" work for the same employer. The managerial employees are a problematic group in this respect, as they had to be grouped into jobs without information on the complexity levels of their job tasks. Therefore, we expect more heterogeneity in job tasks within managerial jobs than

Table II.2: Fraction female and gender wage ratio by white-collar occupation

| | **Managerial** | | | **Technical & clerical** | | | **All white-collar** | | |
|---|---|---|---|---|---|---|---|---|---|
| Occupational group | N | Fem | Gap | N | Fem | Gap | N | Fem | Gap |
| **R&D** | **28,128** | **.163** | **.909** | **19,102** | **.422** | **.791** | **47,230** | **.268** | **.759** |
| R&D management | 1,320 | .135 | .847 | 4,956 | .528 | .859 | 6,276 | .445 | .614 |
| Product design | 21,444 | .133 | .914 | 8,824 | .279 | .826 | 30,268 | .176 | .843 |
| Quality management | 1,397 | .327 | .894 | 3,316 | .555 | .854 | 4,713 | .487 | .800 |
| Research | 3,967 | .277 | .885 | 2,006 | .572 | .846 | 5,973 | .376 | .781 |
| **Production** | **8,469** | **.079** | **.842** | **24,627** | **.102** | **.865** | **33,096** | **.096** | **.841** |
| Production and maintenance management | 5,498 | .053 | .864 | 17,810 | .074 | .857 | 23,308 | .069 | .836 |
| Production support | 2,971 | .127 | .858 | 6,817 | .177 | .866 | 9,788 | .162 | .842 |
| **Logistics** | **2,082** | **.230** | **.812** | **4,870** | **.460** | **.908** | **6,952** | **.391** | **.794** |
| Materials and logistics | 472 | .138 | .825 | 2,515 | .274 | .883 | 2,987 | .252 | .825 |
| Purchasing | 1,467 | .241 | .811 | 1,647 | .583 | .842 | 3,114 | .422 | .725 |
| Shipping | 143 | .413 | .844 | 708 | .833 | .930 | 851 | .763 | .805 |
| **Sales and marketing** | **8,807** | **.231** | **.831** | **14,231** | **.663** | **.765** | **23,038** | **.498** | **.662** |
| Sales | 7,211 | .207 | .823 | 12,720 | .681 | .767 | 19,931 | .510 | .643 |
| Sales promotion | 709 | .453 | .845 | 721 | .544 | 1.009 | 1,430 | .499 | .876 |
| Production and marketing co-operation | 887 | .246 | .828 | 790 | .467 | .764 | 1,677 | .350 | .766 |
| **PR** | **1,828** | **.398** | **.884** | **2,992** | **.575** | **.846** | **4,820** | **.508** | **.803** |
| PR | 650 | .697 | .836 | 629 | .812 | .891 | 1,279 | .754 | .806 |
| Information technology | 1,178 | .233 | .861 | 2,363 | .512 | .817 | 3,541 | .419 | .750 |
| Juridical & tax assistance | 366 | .377 | .868 | 402 | .560 | .670 | 768 | .473 | .723 |
| **Administration** | **4,169** | **.658** | **.763** | **14,480** | **.915** | **.871** | **18,649** | **.857** | **.682** |
| Administration mngmt. | 1,470 | .468 | .836 | 400 | .678 | .864 | 1,870 | .513 | .800 |
| Pay office | 100 | .790 | .746 | 1,734 | .948 | .961 | 1,834 | .939 | .837 |
| Bookkeeping | 328 | .811 | .869 | 2,832 | .951 | .942 | 3,160 | .937 | .832 |
| Accounting | 975 | .461 | .915 | 1,595 | .669 | .830 | 2,570 | .590 | .804 |
| Secretarial work | 1,264 | .977 | .932 | 5,049 | .992 | .956 | 6,313 | .989 | .893 |
| Office services | 18 | .778 | 1.062 | 1,746 | .861 | .953 | 1,764 | .861 | .953 |
| Clerical work, small firms | 14 | .857 | .758 | 1,124 | .943 | .887 | 1,138 | .942 | .878 |
| **Human resources** | **1,650** | **.524** | **.798** | **2,953** | **.858** | **.813** | **4,603** | **.739** | **.674** |
| HR management | 388 | .479 | .874 | 95 | .663 | .968 | 483 | .516 | .865 |
| Competence development | 417 | .511 | .887 | 179 | .508 | .845 | 596 | .510 | .877 |
| Recruiting and employing | 279 | .616 | .820 | 131 | .740 | .835 | 410 | .656 | .799 |
| Payroll administration | 101 | .832 | .866 | 1,670 | .985 | .963 | 1,771 | .976 | .800 |
| Safety and health care | 336 | .351 | .710 | 465 | .619 | .889 | 801 | .507 | .705 |
| Personnel services | 129 | .713 | .847 | 413 | .850 | .859 | 542 | .817 | .802 |
| **Other groups together** | | | | **9,788** | **.299** | **.957** | **9,788** | **.299** | **.957** |
| **All** | **55,499** | **.221** | **.877** | **93,445** | **.459** | **.839** | **148,944** | **.370** | **.768** |

Notes: N is the number of observations. Fem is the fraction of female employees in the group. Gap is the sex wage ratio as obtained by dividing the women's mean wage by men's mean wage. Two-digit occupational groups are further divided into managerial and non-managerial occupations (technical and clerical groups are combined).

within technical and clerical jobs. One should keep this in mind throughout the paper. We also report a separate analysis for a sub-sample of technical and clerical workers in Section 5.

**Blue-collar workers**

Blue-collar workers are classified into 516 occupations. Most of the blue-collar occupations are specific to a particular industry, which explains the large number of occupational groups compared with the number of white-collar occupations. The complexity classification of blue-collar jobs includes 39 industry-specific scales, where the number of complexity levels varies between 3 and 15. In the case of white-collar jobs, each industry-specific scale was found to cover roughly the same range of logarithmic basic wages irrespective of the total number of complexity levels. This is not the case for blue-collar jobs, and hence we apply a slightly different method to translate the industry-specific complexity levels into a single variable. We went through all the industry-level collective agreements and looked up the percentage increase in the minimum hourly wage associated with each complexity level compared with the lowest level. This percentage number serves as our unified measure of job complexity for the blue-collar jobs. To keep results comparable with the white-collar case, the complexity measure is further scaled to take values on the interval 0 to 9.

Once again, we define a job as an occupation within a firm (this results in 12,633 jobs). The resulting jobs are further divided by the level of job complexity, which raises the final number of jobs to 24,020. The wage variable is the hourly wage of the regular working time in the last quarter of 2000. We exclude pay for overtime, Sundays, holidays, and late shifts, which are typically paid at a higher hourly rate. Including such pay components would overstate the wage differential between sexes, as men typically work more overtime hours (see e.g. Table 2 in Korkeamäki and Kyyrä, 2002).

From Table II.3 we see that only 24 percent of blue-collar workers are female. This low figure reflects the fact that the manufacturing sector has been traditionally dominated by men, rather than a low labour force participation rate by the Finnish women. Compared with the white-collar workers, the gender wage gap among blue-collar workers is much lower, being .18 in log wages. This amounts to a 16 percent lower mean wage for women.

Some 60 percent of blue-collar workers have received a secondary education, but a third have not completed any formal degree since the (compulsory) comprehensive school. Men are highly concentrated in technical education, which is in accordance with the findings for the white-collar workers. Women's degrees are obtained mainly in the technical or service fields. Sex differences in other individual background characteristics are quite moderate. Blue-collar women are slightly older, have more work experience but less job tenure than men. The mean value of the job complexity variable for women is substantially lower than that for men, indicating that less complex blue-collar jobs are mainly occupied by women.

Table II.3: Sample statistics for blue-collar workers

| | Women | | Men | | All | |
|---|---|---|---|---|---|---|
| Hourly wage, euro | 9.845 | (1.818) | 11.782 | (2.198) | 11.323 | (2.269) |
| Log hourly wage | 2.271 | (.175) | 2.451 | (.177) | 2.408 | (.192) |
| Age | 42.624 | (10.691) | 40.536 | (10.557) | 41.031 | (10.626) |
| Schooling years | 10.196 | (1.199) | 10.479 | (1.047) | 10.412 | (1.091) |
| Firm tenure, years | 12.598 | (10.142) | 14.188 | (11.025) | 13.811 | (10.844) |
| Work experience, years | 25.429 | (11.191) | 23.057 | (10.891) | 23.619 | (11.009) |
| Job complexity (0−9 scale) | 2.506 | (1.352) | 4.449 | (1.782) | 3.987 | (1.881) |
| Job complexity missing, share | .037 | | .063 | | .057 | |
| Job size | 79 | (162) | 52 | (92) | 58 | (113) |
| Employer size | 1,535 | (2,658) | 1,538 | (2,453) | 1,537 | (2,503) |
| **Education level, %** | | | | | | |
| Basic or unknown | 45.837 | | 29.899 | | 33.673 | |
| Secondary | 48.886 | | 66.484 | | 62.316 | |
| First stage of tertiary | 4.783 | | 3.246 | | 3.610 | |
| Bachelor's degree | .407 | | .324 | | .343 | |
| Master's degree | .084 | | .048 | | .056 | |
| PhD | .002 | | . | | .001 | |
| **Field of education, %** | | | | | | |
| Education | .065 | | .014 | | .026 | |
| Humanities and art | 1.477 | | .388 | | .646 | |
| Social sciences, business and law | 7.109 | | 2.043 | | 3.243 | |
| Science | .107 | | .052 | | .065 | |
| Technical | 21.926 | | 60.560 | | 51.410 | |
| Agriculture | 1.413 | | 2.473 | | 2.222 | |
| Health and welfare | 2.771 | | .256 | | .852 | |
| Services | 15.952 | | 2.038 | | 2.50 | |
| Unknown | 49.179 | | 32.176 | | 36.203 | |
| Fraction female in firm | .459 | (.249) | .168 | (.172) | .237 | (.230) |
| Fraction female in job | .734 | (.273) | .083 | (.175) | .237 | (.343) |
| Sample size | 40,271 | | 129,762 | | 170,033 | |

Notes: Unless otherwise indicated, the figures in the table are means. Standard deviations are in parentheses. Hourly wage is the wage paid for regular working hours, omitting overtime pay, Sunday supplements, etc. Schooling years is defined as the mean years of schooling attached to a given level of education. Work experience is approximated by subtracting the years of schooling and seven years for time prior to the age of school entry from the worker's age. The mean level of job complexity is computed using non-missing values only. Employer and job sizes are the average firm and job size over workers. The mean firm size in the data is 124 and the mean job size is 7.1. The total number of firms is 1,373 and that of jobs is 24,020.

# 5 Results

## 5.1 White-collar workers

The results from various wage regressions for white-collar workers are given in Table II.4. The explanatory variables are grouped into three categories. The individual regressors cover the female dummy ($s_{jki}$) and other person-specific explanatory variables ($\mathbf{x}_{jki}$-variables), including the years of schooling, work experience, and the time spent with the current employer. The job regressors ($\overline{s}_{jk\cdot}$ and $\mathbf{g}_{jk}$-variables) include the job means of the individual regressors and controls for the size, location, type, and complexity level of the job. Information on job complexity is missing for all managerial jobs and for some non-managerial jobs in which cases the dummy for missing job complexity takes a value of one. The job regressors are measured in deviation from the firm mean. The firm regressors ($\bar{s}_{j\cdot\cdot}$ and $\mathbf{z}_j$-variables) are level variables, including the firm means of the individual and job regressors plus industry dummies, the worker mix variable (= the ratio of white-collar employees to all employees), and firm size.

Coefficients of all individual regressors are statistically highly significant in all specifications. Let us consider the fixed effects (FE) model first. Recall that this specification does not impose any restrictions on the correlation between the individual regressors and unobservable group effects. The coefficient of the female dummy takes a value of $-.0627$, indicating that women and men are not equally rewarded by employers.[18] A woman can expect to receive a 6 percent lower wage than her equally qualified male co-worker doing the same job within the same firm.

One additional year of schooling is estimated to increase the expected wage in a given job by 2.6 percent. This is clearly below the conventional estimates for the returns to schooling. The much lower estimate obtained here by conditioning on the job held suggests that the wage effect of education works largely through the differential allocation to jobs. That is, better educated workers are qualified for more demanding jobs that pay higher wages than the jobs held by their less educated counterparts (see discussion below). As expected, wages increase with tenure and the effect of work experience takes the familiar quadratic form. It should be stressed that the potential years of experience has a tendency to overestimate women's experience because of their higher propensity to be out of work owing to family responsibilities. Asplund's (2001) findings, however, suggest that this may be a less serious problem in our case.[19]

The RE model is the most parsimonious version of our random effects models, including only the fractions of female employees in the set of job and firm regressors. This specification resembles the specifications estimated by Groshen (1991), Bayard et al. (2003), and Datta Gupta and Rothstein (2001).[20] As expected, the coefficients of both fraction female variables are negative and statistically highly significant, indicating lower wages for predominantly female firms and jobs mainly occupied by women within firms. A firm whose total white-collar workforce is female is estimated to pay 13 percent lower wages on average than a firm that employs only male white-collar workers. Within a firm, a hypothetical switch to a job with a 10 percent points higher female share would cause an

[18] The coefficient of the female dummy takes a value $-.0632$ if we do not control for $\mathbf{x}$.

[19] Asplund (2001) has studied this issue within the Finnish context. Using survey data she found that among women the mean potential work experience exceeds the mean of actual (self-reported) one by three years while among men the difference is close to zero. Replacing potential work experience with the actual one in the standard gender-specific wage models had only a small and statistically insignificant impact on the experience (and schooling) coefficients for both women and men. Moreover, note that the coefficients of work experience in Asplund's setting comprise wage growth resulting from accumulation of general human capital as well as movements in the job ladder towards better paid jobs over time. In our setting, by contrast, we are conditioning on the job held, and this conditioning picks up – without error – wage growth that is due to climbing up the job ladder. Thus we expect the potential bias resulting from measurement error in experience to be more limited in our case.

[20] The main differences are: (1) we measure the fraction female in job as a deviation from the firm mean, and (2) we do not include the fraction female in occupation nor in industry in our model.

Table II.4: Wage regression results for white-collar workers

| | Model specification | | | | |
|---|---|---|---|---|---|
| | FE | OLS | RE | CRE1 | CRE2 |
| Intercept | | 1.3483 (.0054) [.0834] | 1.8744 (.0083) | 1.6734 (.0555) | 1.6540 (.0561) |
| **Individual regressors** | | | | | |
| Female | −.0627 (.0012) | −.0732 (.0022) [.0054] | −.0653 (.0015) | −.0627 (.0012) | −.0627 (.0012) |
| Schooling years | .0258 (.0003) | .0886 (.0003) [.0051] | .0425 (.0003) | .0258 (.0003) | .0258 (.0003) |
| Experience | .0151 (.0002) | .0182 (.0003) [.0013] | .0175 (.0002) | .0151 (.0002) | .0151 (.0002) |
| Experience$^2$/100 | −.0228 (.0004) | −.0224 (.0006) [.0040] | −.0254 (.0004) | −.0228 (.0004) | −.0228 (.0004) |
| $\sqrt{\text{Firm tenure}}$ | .0138 (.0004) | −.0065 (.0005) [.0038] | .0085 (.0005) | .0138 (.0004) | .0138 (.0004) |
| **Job regressors** | | | | | |
| Fraction female | | −.1794 (.0028) [.0124] | −.2155 (.0026) | −.1266 (.0022) | −.0779 (.0023) |
| Mean schooling | | | | .0324 (.0006) | .0218 (.0006) |
| Mean experience | | | | .0075 (.0005) | .0046 (.0005) |
| Mean (experience)$^2$ /100 | | | | −.0084 (.0010) | −.0044 (.0010) |
| Technical | | | | .0317 (.0030) | .0363 (.0029) |
| Managerial | | | | .3070 (.0022) | .3112 (.0030) |
| Mean $\sqrt{\text{firm tenure}}$ | | | | −.0102 (.0010) | −.0110 (.0009) |
| Complexity level | | | | | .0457 (.0006) |
| Complexity missing | | | | | .0348 (.0027) |
| Large city | | | | .0535 (.0029) | .0460 (.0028) |
| Log (job size) | | | | −.0151 (.0009) | −.0137 (.0008) |
| **Firm regressors** | | | | | |
| Fraction female | | −.1796 (.0046) [.0572] | −.1407 (.0157) | −.0758 (.0129) | −.0637 (.0130) |
| Mean schooling | | | | .0280 (.0037) | .0258 (.0038) |
| Mean experience | | | | −.0006 (.0030) | −.0067 (.0030) |
| Mean (experience)$^2$ /100 | | | | .0179 (.0064) | .0198 (.0064) |
| Fraction technical jobs | | | | .0496 (.0127) | .0554 (.0128) |
| Fraction managerial jobs | | | | .2021 (.0120) | .1667 (.0138) |
| Mean $\sqrt{\text{firm tenure}}$ | | | | −.0329 (.0030) | −.0321 (.0030) |
| Mean job complexity | | | | | .0099 (.0015) |
| Fraction complexity missing | | | | | .0681 (.0108) |
| Fraction jobs in large cities | | | | .0441 (.0044) | .0438 (.0044) |
| Worker mix | | | | .0734 (.0106) | .0688 (.0107) |
| Mean log (job size) | | | | −.0187 (.0046) | −.0198 (.0048) |
| Log (firm size) | | | | .0197 (.0028) | .0191 (.0029) |
| **Variance components** | | | | | |
| $\sigma_\varepsilon^2$ (individual error) | | | .0270 | .0173 | .0173 |
| $\sigma_\omega^2$ (job random effect) | | | .0192 | .0117 | .0101 |
| $\sigma_\xi^2$ (firm random effect) | | | .0115 | .0029 | .0031 |

Notes: FE is the fixed effects model with the heteroskedasticity-consistent standard errors in parentheses. For the OLS model the heteroskedasticity-consistent standard errors are in parentheses and standard errors robust to arbitrary heteroskedasticity and intrafirm correlation are in square brackets. RE, CRE1, and CRE2 are the (correlated) random effects models with the GLS standard errors in parentheses. All job regressors are measured in deviation from the firm mean. The clerical jobs include also non-managerial jobs in industries where no distinction between the clerical and technical jobs has been made. CRE1 and CRE2 models include 38 industry dummies. Number of observations is 148,944 in all regressions.

expected wage loss of about two percent.

It is illustrative to consider the OLS estimates of the same model. The OLS standard errors adjusted for heteroskedasticity but derived under the assumption of random sampling are given in the parentheses. In addition, the standard errors that are robust to heteroskedasticity and arbitrary intrafirm correlation are shown in the square brackets (see Wooldridge, 2002, pp. 328-331). The difference between the standard errors is substantial for all coefficients. The OLS standard errors that do not take into account the grouped structure of the underlying data are dramatically understated.

Compared with the fixed effects model, the coefficients of the RE and OLS models are quite different for some individual regressors. Within the random effects framework, this calls into question whether the random effects associated with firms and jobs are uncorrelated with the individual explanatory variables. In the presence of such a correlation the regression coefficients in the RE model are biased and inconsistent. In the CRE1 model a number of job and firm controls, including the group means of the individual variables, are added to the model. Testing statistical significance of the coefficients of the group means can be interpreted as a Hausman-type test for the random effects specification. Since the coefficients of the group means of $\mathbf{x}$ in the CRE1 model are highly significant, we conclude that the RE model is not valid (i.e. the firm and job error components are correlated with $\mathbf{x}$). By implication, the OLS model must be miss-specified as well. In the CRE1 and CRE2 specifications this problem is solved by adding the group means of $\mathbf{x}$ to the model, as proposed by Mundlak (1978). As a consequence, the coefficients of all individual regressors are identical to those of the FE model.

In the CRE1 model the coefficients of the fraction female variables are reduced by one-half in absolute value when compared with the RE model. This implies that the fraction female variables in the RE model serve in large part as a proxy for other factors responsible for wage differentials between firms and jobs within firms. Coefficients of job and firm regressors generally have signs that seem intuitively reasonable. Larger firms pay higher wages. Firms and jobs within firms that require higher education are associated with higher wages. This is consistent with the claim above that better educated workers are allocated to firms and further to jobs that pay higher wages. Workers whose jobs are located in large cities receive better wages, perhaps to compensate for higher living costs. Within firms wage differentials between technical and clerical jobs are relatively small, being around 3 percent in favour of technical jobs. A white-collar worker holding a managerial job receives 36 percent higher wage than an equally qualified worker doing clerical work within the same firm.

In the CRE2 specification the job complexity level is added to the model. This is our preferred model specification. Information on job complexity is missing for all managerial jobs and for some non-managerial jobs. In these cases the dummy for missing job complexity takes a value of one. One additional level of (re-scaled) job complexity is found to be associated with a wage increase of almost five percent. Compared with the CRE1 model, the coefficients of managerial and technical job dummies remain almost unchanged. Provided that more complex jobs require higher education, it is not surprising to find a considerable fall in the effect of the mean schooling years in job. The coefficient of the fraction female in job is reduced by over one-third in absolute value. Even after controlling for job complexity, average education, and many other factors, it is quite remarkable that wages remain negatively associated with the fraction female variables. This indicates that firms and jobs within firms mainly occupied by women pay lower wages for reasons that cannot be explained by observables. This may be due to sex differences in preferences but it may also reflect discrimination through differential access to higher-paying jobs at the point of hire or subsequent promotions. On the other hand, these findings may be driven to some extent by missing job complexity information for the managerial jobs. We elaborate on this issue below.

Before turning to the wage gap decompositions, let us take a look at the estimates of variance components that are shown on the bottom lines of the table. Of course, the magnitude of error variation falls as more controls are added to the model (i.e. when we move from the RE model towards the CRE2 model). Estimates of variance components imply that most of the unexplained wage variation is related to individuals within jobs. In the CRE2 specification, for example, the individual error variance $\sigma_\varepsilon^2$ accounts for about 60 percent of the total error variance, $\sigma_\varepsilon^2 + \sigma_\omega^2 + \sigma_\xi^2$. Note also that the variance of firm random effects is clearly below that of job random effects. This implies that adding firm level regressors to the model cannot notably improve the model's fit.

The residual intrajob correlation, $(\sigma_\omega^2+\sigma_\xi^2)/(\sigma_\varepsilon^2+\sigma_\omega^2+\sigma_\xi^2)$, describes correlation between the wage outcomes of two randomly chosen workers in a randomly chosen job within a randomly chosen firm, after controlling for $s$ and $\mathbf{x}$. In the CRE2 model this correlation is as high as .43, which highlights the importance of accounting for the grouping in the econometric modelling.

Table II.5 shows the gender wage gap decompositions for white-collar workers based upon the different model specifications. The first two columns report the sample means of the regressors among men and women, and the third column shows the difference. The absolute contribution of each variable to the wage gap is obtained by multiplying the sex difference in the sample means by the associated regressor coefficient. These contributions are reported in the last five columns of the table, where each column corresponds to the model specification in Table II.4. The aggregate contribution of each group of regressors is shown below the horizontal lines.

From the fixed effect specification we conclude that roughly one-third of the overall gender wage gap of .2505 can be attributed to unexplained within-job wage differentials between sexes (.0627) and within-job sex differences in education, work experience, and firm tenure (.0154). Sex segregation among firms explains 16 percent (.0391), while over one-half of the overall gap is owing to sex segregation among jobs within firms (.1334).

The OLS and RE models, which were found to be inconsistent, give a different picture

Table II.5: Gender wage gap decompositions for white-collar workers

| | Sample means | | | Contribution to the wage gap | | | | |
|---|---|---|---|---|---|---|---|---|
| | Men | Women | Diff. | FE | OLS | RE | CRE1 | CRE2 |
| **Individual regressors** | | | | | | | | |
| Female | .0000 | 1.0000 | −1.0000 | .0627 | .0732 | .0653 | .0627 | .0627 |
| Schooling years | 12.8100 | 12.0654 | .7446 | .0192 | .0660 | .0316 | .0192 | .0192 |
| Experience | 21.3181 | 22.0808 | −.7627 | −.0115 | −.0139 | −.0133 | −.0115 | −.0115 |
| $\text{Experience}^2/100$ | 5.6217 | 6.0056 | −.3839 | .0088 | .0086 | .0097 | .0088 | .0088 |
| $\sqrt{\text{Firm tenure}}$ | 3.0579 | 3.1327 | −.0748 | −.0010 | .0005 | −.0006 | −.0010 | −.0010 |
| | | | | .0781 | .1344 | .0933 | .0781 | .0781 |
| **Job regressors** | | | | | | | | |
| Fraction female | −.2011 | .3420 | −.5431 | | .0974 | .1170 | .0688 | .0423 |
| Mean schooling | .1784 | −.3033 | .4817 | | | | .0156 | .0105 |
| Mean experience | −.0465 | .0791 | −.1257 | | | | −.0009 | −.0006 |
| Mean $(\text{experience})^2/100$ | −.0242 | .0412 | −.0654 | | | | .0005 | .0003 |
| Technical job | .0334 | −.0568 | .0901 | | | | .0029 | .0033 |
| Managerial job | .0620 | −.1054 | .1674 | | | | .0514 | .0521 |
| Mean $\sqrt{\text{firm tenure}}$ | −.0066 | .0112 | −.0178 | | | | .0002 | .0002 |
| Complexity level | .2075 | −.3527 | .5602 | | | | | .0256 |
| Complexity missing | .0340 | −.0579 | .0919 | | | | | .0032 |
| Large city | .0008 | −.0014 | .0022 | | | | .0001 | .0001 |
| Log (job size) | .1778 | −.3023 | .4801 | | | | −.0073 | −.0066 |
| | | | | .1334 | .0974 | .1170 | .1312 | .1304 |
| **Firm regressors** | | | | | | | | |
| Fraction female | .3318 | .4359 | −.1042 | | .0187 | .0147 | .0079 | .0066 |
| Mean schooling | 12.6462 | 12.3440 | .3022 | | | | .0085 | .0078 |
| Mean experience | 21.3802 | 21.9753 | −.5950 | | | | .0033 | .0040 |
| Mean $(\text{experience})^2/100$ | 5.6635 | 5.9345 | −.2711 | | | | −.0049 | −.0054 |
| Fraction technical jobs | .1353 | .1122 | .0231 | | | | .0011 | .0013 |
| Fraction managerial jobs | .3992 | .3274 | .0719 | | | | .0145 | .0120 |
| $\sqrt{\text{Mean firm tenure}}$ | 3.0445 | 3.1554 | −.1108 | | | | .0036 | .0036 |
| Mean job complexity | 4.2717 | 4.0381 | .2336 | | | | | .0023 |
| Fraction complexity missing | .5345 | .4952 | .0393 | | | | | .0027 |
| Fraction jobs in large cities | .5859 | .5698 | .0161 | | | | .0007 | .0007 |
| Worker mix | .6724 | .6855 | −.0131 | | | | −.0010 | −.0009 |
| Mean log (job size) | 2.8923 | 2.8272 | .0651 | | | | −.0012 | −.0013 |
| Log (firm size) | 6.8822 | 6.8259 | .0563 | | | | .0011 | .0011 |
| Industry dummies | | | | | | | .0043 | .0051 |
| | | | | .0391 | .0187 | .0147 | .0380 | .0395 |
| **Overall sum** | | | | .2505 | .2505 | .2243 | .2473 | .2480 |

Notes: The raw wage gap, as measured by the sex difference in mean log wages, is .2505. The first two columns report the samples means of all regressors among men and women; the third column gives the difference. The last five columns show the absolute contribution of each regressor obtained from various model specifications. The contributions are obtained by multiplying the coefficients in Table II.4 by the sex differences in sample means in Table II.5. The cumulative effect of each group of regressors is shown below the horizontal lines.

about the relative importance of the various determinants of gender wage differentials. The CRE1 and CRE2 models, however, produce decompositions consistent with the fixed effect specification. Contrary to the fixed effects approach, the correlated random effects models allow us to address the question as to why predominantly female firms and jobs are lower paid.

Consider the decompositions associated with the CRE1 and CRE2 models. There are no dominating factors that could be argued to be responsible for most of the aggregate effect of sex segregation among firms (which in turn is quite moderate). The fraction female in firm especially has only a minor impact on the gender wage gap, accounting for less than .0080 in both specifications. Likewise, the industry dummies and hence sex segregation among industries do not play any role in explaining the gender wage gap. Sex segregation among jobs within firms is a more interesting case. It appears that over .0500 of the overall wage gap is explained by the disproportionate concentration of men in high-paid managerial jobs. This accounts for about 40 percent of the aggregate effect of sex segregation among jobs. Among technical and clerical jobs women are more likely to hold less complex jobs, which explains .0256 of the overall gap in the CRE2 decomposition.

Once we control for job complexity, the contribution of the fraction female in job falls from .0688 to .0423, where the latter figure still accounts for 17 percent of the overall wage gap. In other words, predominantly female jobs pay lower wages for reasons that cannot be explained by differences in schooling requirements or job complexity levels between jobs. However, it will turn out that this result is partly driven by the missing complexity information of managerial jobs (we will discuss this below).

### 5.2 Blue-collar workers

Table II.6 displays the results of wage regressions for blue-collar workers. The coefficient of the female dummy in the fixed effects specification indicates that a blue-collar woman receives a 3.5 percent lower wage for the same job than her equally qualified male co-worker does. This amounts to one-fifth of the overall gender gap of blue-collar workers, i.e. the similar amount that we found for white-collar workers.

Compared with the (correlated) random effects results for white-collar workers in Table II.4, the qualitative results in Table II.6 are rather similar, though the coefficients of the job size and large city dummy have reversed signs. Some interesting discrepancies in the magnitude of different factors exist, however. Education, for example, contributes very little to wage differentials within jobs. Conditional on the job held, one additional year of schooling results in an increase of only .2 percent in the expected wage rate.

As expected, the coefficients of the fraction female variables are always negative and statistically highly significant. When the measure of job complexity is added to the analysis, the absolute value of the coefficient of fraction female in job is reduced by one-half, as in the case of white-collar workers. Interestingly, the effect of the fraction female in firm exceeds that of the fraction female in job and remains very strong in all random ef-

Table II.6: Wage regression results for blue-collar workers

| | Model specification | | | | |
|---|---|---|---|---|---|
| | FE | OLS | RE | CRE1 | CRE2 |
| Intercept | | 2.2557 (.0046) [.0182] | 2.2712 (.0050) | 1.7501 (.0930) | 1.8373 (.0921) |
| **Individual regressors** | | | | | |
| Female | −.0357 (.0009) | −.0389 (.0016) [.0035] | −.0372 (.0009) | −.0357 (.0009) | −.0357 (.0009) |
| Schooling years | .0023 (.0003) | .0090 (.0004) [.0011] | .0034 (.0003) | .0023 (.0003) | .0023 (.0003) |
| Experience | .0038 (.0001) | .0054 (.0002) [.0008] | .0047 (.0001) | .0038 (.0001) | .0038 (.0001) |
| Experience$^2$/100 | −.0075 (.0002) | −.0120 (.0003) [.0012] | −.0092 (.0002) | −.0075 (.0002) | −.0075 (.0002) |
| $\sqrt{\text{Firm tenure}}$ | .0123 (.0003) | .0283 (.0003) [.0032] | .0141 (.0003) | .0123 (.0003) | .0123 (.0003) |
| **Job regressors** | | | | | |
| Fraction female | | −.1101 (.0022) [.0063] | −.1002 (.0023) | −.1011 (.0022) | −.0521 (.0023) |
| Mean schooling | | | | .0119 (.0010) | .0033 (.0009) |
| Mean experience | | | | .0087 (.0004) | .0051 (.0003) |
| Mean $\overline{(\text{experience})^2}$ /100 | | | | −.0159 (.0008) | −.0091 (.0007) |
| Mean $\overline{\sqrt{\text{firm tenure}}}$ | | | | .0103 (.0009) | .0003 (.0008) |
| Complexity level | | | | | .0286 (.0005) |
| Complexity missing | | | | | −.0500 (.0060) |
| Large city | | | | −.0173 (.0024) | −.0202 (.0022) |
| Log (job size) | | | | .0161 (.0006) | .0135 (.0005) |
| **Firm regressors** | | | | | |
| Fraction female | | −.3102 (.0023) [.0240] | −.2943 (.0116) | −.2632 (.0127) | −.2421 (.0136) |
| Mean schooling | | | | .0250 (.0083) | .0120 (.0083) |
| Mean experience | | | | .0186 (.0034) | .0159 (.0033) |
| Mean $\overline{(\text{experience})^2}$ /100 | | | | −.0277 (.0072) | −.0236 (.0071) |
| Mean $\overline{\sqrt{\text{firm tenure}}}$ | | | | −.0187 (.0036) | −.0219 (.0036) |
| Mean job complexity | | | | | .0234 (.0026) |
| Fraction complexity missing | | | | | .0697 (.0147) |
| Fraction jobs in large cities | | | | −.0272 (.0056) | −.0258 (.0055) |
| Worker mix | | | | .0226 (.0142) | .0223 (.0141) |
| Mean log (job size) | | | | .0126 (.0036) | .0174 (.0039) |
| Log (firm size) | | | | .0238 (.0028) | .0199 (.0031) |
| **Variance components** | | | | | |
| $\sigma_\varepsilon^2$ (individual error) | | | .0088 | .0085 | .0085 |
| $\sigma_\omega^2$ (job random effect) | | | .0054 | .0049 | .0041 |
| $\sigma_\xi^2$ (firm random effect) | | | .0113 | .0060 | .0059 |

Notes: FE is the fixed effects model with the heteroskedasticity-consistent standard errors in parentheses. For the OLS model the heteroskedasticity-consistent standard errors are in parentheses and standard errors robust to arbitrary heteroskedasticity and intrafirm correlation are in square brackets. RE, CRE1, and CRE2 are the (correlated) random effects models with the GLS standard errors in parentheses. All job regressors are measured in deviation from the firm mean. The reference category in the job regressors is job located outside large cities. CRE1 and CRE2 models include 49 industry dummies. Number of observations is 170,033 in all regressions.

Table II.7: Gender wage gap decompositions for blue-collar workers

| | Sample means | | | Contribution to the wage gap | | | | |
|---|---|---|---|---|---|---|---|---|
| | Men | Women | Diff. | FE | OLS | RE | CRE1 | CRE2 |
| **Individual regressors** | | | | | | | | |
| Female | .0000 | 1.0000 | −1.0000 | .0357 | .0389 | .0372 | .0357 | .0357 |
| Schooling years | 10.4790 | 10.1956 | .2835 | .0006 | .0026 | .0010 | .0006 | .0006 |
| Experience | 23.0571 | 25.4285 | −2.3715 | −.0089 | −.0128 | −.0111 | −.0089 | −.0089 |
| $\text{Experience}^2/100$ | 6.5024 | 7.7185 | −1.2161 | .0091 | .0146 | .0112 | .0091 | .0091 |
| $\sqrt{\text{Firm tenure}}$ | 3.4148 | 3.2060 | .2088 | .0026 | .0059 | .0029 | .0026 | .0026 |
| | | | | .0390 | .0492 | .0412 | .0390 | .0390 |
| **Job regressors** | | | | | | | | |
| Fraction female | −.0853 | .2747 | −.3600 | | .0396 | .0361 | .0364 | .0188 |
| Mean schooling | .0309 | −.0994 | .1303 | | | | .0016 | .0004 |
| Mean experience | −.2135 | .6879 | −.9014 | | | | −.0078 | −.0046 |
| Mean $(\text{experience})^2/100$ | −.1196 | .3854 | −.5049 | | | | .0080 | .0046 |
| Mean $\sqrt{\text{firm tenure}}$ | .0287 | −.0926 | .1214 | | | | .0013 | .0000 |
| Complexity level | .1886 | −.6080 | .7966 | | | | | .0228 |
| Complexity missing | .0021 | −.0067 | .0088 | | | | | −.0004 |
| Large city | −.0018 | .0058 | −.0076 | | | | .0001 | .0002 |
| Log (job size) | −.0451 | .1454 | −.1905 | | | | −.0031 | −.0026 |
| | | | | .0444 | .0396 | .0361 | .0364 | .0392 |
| **Firm regressors** | | | | | | | | |
| Fraction female | .1678 | .4594 | −.2916 | | .0905 | .0858 | .0768 | .0706 |
| Mean schooling | 10.4289 | 10.3570 | .0719 | | | | .0018 | .0009 |
| Mean experience | 23.7848 | 23.0838 | .7010 | | | | .0130 | .0112 |
| Mean $(\text{experience})^2/100$ | 6.8443 | 6.6170 | .2273 | | | | −.0063 | −.0054 |
| Mean $\sqrt{\text{firm tenure}}$ | 3.4219 | 3.1832 | .2387 | | | | −.0045 | −.0052 |
| Mean job complexity | 3.9454 | 2.9767 | .9687 | | | | | .0227 |
| Fraction complexity missing | .0614 | .0439 | .0174 | | | | | .0012 |
| Fraction jobs in large cities | .6890 | .7197 | −.0306 | | | | .0008 | .0008 |
| Worker mix | .2844 | .2774 | .0069 | | | | .0002 | .0002 |
| Mean log (job size) | 2.9812 | 3.1357 | −.1545 | | | | −.0019 | −.0027 |
| Log (firm size) | 6.3066 | 6.2456 | .0610 | | | | .0015 | .0012 |
| Industry dummies | | | | | | | .0177 | .0066 |
| | | | | .0958 | .0905 | .0858 | .0991 | .1020 |
| **Overall sum** | | | | .1793 | .1793 | .1631 | .1745 | .1802 |

Notes: The raw wage gap, as measured by the sex difference in mean log wages, is .1793. The first two columns report the samples means of all regressors among men and women; the third column gives the difference. The last five columns show the absolute contribution of each regressor obtained from various model specifications. The contributions are obtained by multiplying the coefficients in Table II.6 by the sex differences in sample means in Table II.7. The cumulative effect of each group of regressors is shown below the horizontal lines.

fects specifications. A firm with only female blue-collar employees is found to pay over 20 percent lower wages than a firm employing only male blue-collar workers, suggesting that sex segregation among firms is an important piece of the explanation of the gender wage differentials between female and male blue-collar workers. In the CRE2 specification, each level of job complexity is estimated to increase the wage rate by two percent, i.e. much less than what was the case with white-collar workers.

By looking at the estimates of the variance components on the bottom lines of the table, we see that the largest fraction of unexplained wage variation occurs between workers within jobs, which is in accordance with the findings for the white-collar workers. Interestingly, the variance of the firm random effects exceeds that of the job random effects in all specifications. This further supports the view that wage differentials between firms play a more important role for blue-collar workers than for white-collar workers.

Table II.7 shows the decomposition results for blue-collar workers. It appears that sex segregation among firms accounts for over one-half of the wage gap. This is in contrast with the finding that segregation of white-collar workers among firms does not play an important role in explaining the gender wage differentials. The explanation is two-fold and related to the fraction female variable. First, among blue-collar workers, there exists a much stronger negative association between the wage rate and fraction female in firm, which does not get weaker even after controlling for a number of firm level factors. Second, the strong effect of the gender composition of the firm is reinforced in the wage gap decomposition by a large degree of sex segregation among firms (see the sex difference in the sample means of the fraction female). In other words, firms with a high fraction of female blue-collar employees pay lower wages for unobservable reasons, and this widens the sex gap in pay considerably because of the large degree of sex segregation among firms.

The segregation of blue-collar women into lower paying jobs within firms accounts for one-fifth of the wage gap, which is clearly less than what was the case with white-collar workers. Most of the aggregate effect of job segregation in the CRE2 specification (.0392) results from the allocation of women to less complex jobs (.0228) but almost one-half is attributed to the fraction female in job (.0188). The aggregate contribution of individual characteristics is .0390, which is attributed almost entirely to unexplained gender wage differentials within jobs.

### 5.3 Robustness of the results

In this section we test how sensitive our regression and decomposition results are with respect to the model specification and data restrictions adopted.

#### Missing job complexity information

In the case of white-collar workers, information on job complexity is missing for many observations, including all workers in managerial jobs and some workers in technical and clerical jobs. This has two implications. First, the degree of detail in the classification of managerial jobs is low compared with the classification of technical and clerical jobs. This is likely to have an effect on the relative importance of job segregation and that of within-job wage differentials. Secondly, job complexity is only partly controlled for in the CRE2 specifications in Tables II.4 and II.5. Therefore, we have performed the same analysis for a white-collar sample that excludes observations with missing values for the level of job complexity. This sub-sample represents only technical and clerical workers, among whom the raw wage gap is much lower (.1570). The regression results are shown in Table II.10 in the Appendix. Compared with the previous results, the magnitude of coefficients is different but signs remain unchanged. In the fixed effects model the coefficient of the female dummy equals −.0283. In the CRE1 specification both fraction female variables have coefficients around −.150. Adding the level of job complexity to the analysis reduces the unexplained segregation effects considerably. The coefficient of the fraction female in job drops to a value of −.0335, and that of the fraction female in firm is reduced by one-third. This means that a major part of wage variation between jobs within firms can be explained by differences in the complexity levels of jobs.

In the Appendix Table II.11 displays the wage gap decompositions for the sub-sample of technical and clerical workers. The overall relative contribution of wage differentials arising from wage differentials within jobs is lower for the sub-sample than for the entire white-collar data in Table II.5. In particular, the unexplained within-job wage gap of .0283 accounts now for 18 percent of the overall gap among technical and clerical workers (compared with 25 percent for the entire data). The importance of sex segregation among firms appears to be slightly weaker now, whereas the contribution of segregation among jobs dominates, accounting for two-thirds of the overall gap. The major part of the effect of sex segregation among jobs within firms (.0738) is attributable to sex differences in complexity levels in the jobs held by women and men. This in fact explains approximately one-half of the overall gender wage gap among technical and clerical employees.

In the sample of blue-collar workers, we have valid information on the job complexity level for 96 percent of observations. Dropping those with missing information out of the sample does not change the results in Tables II.6 and II.7.

#### Varying size thresholds for jobs

Obviously, our definition for the job is quite strict. This leads to a large number of jobs with only one or two workers in the white-collar data. One might wonder whether this feature of the data would be partly driving the results. To explore this possibility, we replicated our analysis by excluding all white-collar workers in jobs with less than three workers (17 percent of all observations). As a result the raw wage gap changes by less than one percentage point. While the regression results of the CRE2 model remain qualitatively unchanged, the variance of the job random effects shrinks (by 20 percent) and the coefficients of the job regressors change to some extent. Importantly, changes in the wage gap decomposition turned out to be very small.

In the blue-collar data, the weight of small jobs is much lower – less than 4 percent of blue-collar workers are in jobs with less than three employees – and their exclusion from the analysis does not change the results.

### Jobs with both sexes present

Another potential problem with our data setup is that apart from being small, quite many jobs consist of only men or women. It is obvious that observations in such jobs contribute to the role of sex segregation, but not to the role of gender wage differentials within jobs. So we replicated our analysis using samples restricted to integrated jobs with at least three workers. This restriction results in considerably smaller sub-samples. In the case of white-collar workers, the number of jobs drops from 40,663 to 3,890, that of workers drops from 148,944 to 76,375, and the raw wage gap shrinks from .2505 to .2070. Considering the CRE2 specification, the coefficients of job regressors are affected but those of individual and firm regressors remain almost unchanged. The most notable differences are more negative coefficients for the fraction female variables. In the wage gap decompositions these changes are reflected in the relative importance of the various sources of gender wage differentials. In the CRE2 decomposition the absolute contribution of job segregation drops from .13 to .05, that of firm segregation rises from .04 to .09, whereas the contribution of unexplained within-job wage differentials and sex differences in individual characteristics remains around .08. The decrease in the importance of job segregation stems from a smaller degree of sex segregation among jobs and from smaller complexity differences between female and male jobs in this sub-sample.

By imposing the same restriction to the blue-collar data, the number of jobs drops from 24,020 to 3,446, that of workers drops from 170,033 to 78,937, and the raw wage gap reduces from .179 to .126. The regression and decomposition results change in the same way as was the case with the white-collar workers. Namely, the regressor coefficients do not change much, but the relative importance of job segregation in the wage gap decompositions falls, owing to a smaller degree of job segregation and reduced sex differences in the job complexity levels.

### Gender-specific slopes

In the Oaxaca-type decompositions the regression coefficients are usually allowed to be gender-specific. Table II.8 shows results for white-collar workers from an extended version of the CRE2 model where all individual level regressors are interacted with the female dummy. For ease of interpretation the education, experience, and tenure variables are measured in deviation from their values for the average worker. The intercept of the model and the female dummy coefficient are shown in the first row of columns 4 and 5 respectively. The other coefficients in column 4 measure returns to education, experience, and tenure for men. Women's returns are obtained as the sum of the coefficients in columns 4 and 5. The female dummy coefficient gives the size of the unexplained within-job sex

Table II.8: Regression coefficients and gender wage gap decompositions from the CRE2 model with female interactions in individual level variables for white-collar workers

| | Sample means | | | CRE2 coefficients | | Contribution to the wage gap | |
|---|---|---|---|---|---|---|---|
| | | | | Male | Female | | |
| | Men | Women | Diff. | coefficient | interaction | Means | Coeff. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Intercept | 1.0000 | 1.0000 | .0000 | 2.1946 (.0515) | −.0795 (.0018) | .0000 | .0795 |
| Schooling years | .2757 | −.4688 | .7446 | .0289 (.0003) | −.0105 (.0004) | .0215 | −.0049 |
| Experience | −.2824 | .4802 | −.7627 | .0180 (.0002) | −.0081 (.0003) | −.0137 | .0039 |
| Experience$^2$/100 | .9559 | 1.3398 | −.3839 | −.0276 (.0005) | .0127 (.0007) | .0106 | −.0171 |
| $\sqrt{\text{Firm tenure}}$ | −1.4146 | −1.3398 | −.0748 | .0127 (.0005) | .0026 (.0007) | −.0010 | .0035 |
| | | | | | | .0174 | .0649 |

Notes: From education, experience, and tenure variables we have subtracted their values for the average worker. Coefficients of the regressors and their interactions with the female dummy are given in columns 4 and 5 respectively. The interaction for the intercept corresponds to the female dummy. The GLS standard errors are in parentheses. The contributions of sex differences in background characteristics in column 6 are obtained by multiplying the coefficients in column 4 with the sex differences in the variable means in column 3. The contributions of sex differences in coefficients in column 7 are obtained by multiplying the interaction coefficients with the sample means for women in column 2 and changing the sign. Cumulative contributions are shown below the horizontal lines.

gap in pay for workers with the average years of education, experience, and tenure. We do not show results for job and firm level regressors, as they remain basically unchanged.

When $\boldsymbol{\beta}$ is allowed to differ between sexes, we find a lower return to education but a higher return to firm tenure for white-collar women. In the presence of substantial sex differences in the field of received education, women's lower return to education may indicate that the employers value most technical education, which is received by the majority of men. The absolute value of the female dummy coefficient is slightly higher than in the corresponding specification where $\boldsymbol{\beta}$ was restricted to be equal for both sexes. Among workers with the average years of education, experience, and tenure, white-collar women are found to receive some 7.6% lower wages than their male co-workers who are doing the same job. The expected wage rate increases over the first 35 years of experience but at a lower rate for women. As a consequence, the unexplained wage gap within jobs is small for workers with little experience but grows with experience.[21] There is no evidence of the within-job sex gap in favour of men among workers with no experience and tenure; in fact, women may be even slightly better paid in such cases.

The potential years of work experience has a tendency to overestimate actual experience, and the problem is more acute for women because of their higher propensity to be out of work owing to family responsibilities. The imposed functional form for the effect of work experience is also rather rigid. These remarks suggest that our findings may be sensitive with respect to the way how work experience is measured and incorporated in the model. If we adjust our measure of experience for likely career interruptions and replace

[21] Strictly speaking, the within-job wage gap between women and men begins to shrink after 35 years of experience. This phenomenon is, however, driven by the imposed quadratic form for the effect of experience, and does not occur when the experience dummies are used (see the following discussion and footnote 22).

Table II.9: Regression coefficients and gender wage gap decompositions from the CRE2 model with female interactions in individual level variables for blue-collar workers

| | Sample means | | | CRE2 coefficients | | Contribution to the wage gap | |
|---|---|---|---|---|---|---|---|
| | | | | Male | Female | | |
| | Men | Women | Diff. | coefficient | interaction | Means | Coeff. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Intercept | 1.0000 | 1.0000 | .0000 | 1.9574 (.0921) | −.0426 (.0011) | .0000 | .0426 |
| Schooling years | .0671 | −.2163 | .2835 | .0025 (.0003) | −.0013 (.0005) | .0007 | −.0003 |
| Experience | −.5617 | 1.8098 | −2.3715 | .0045 (.0001) | −.0027 (.0002) | −.0107 | .0049 |
| $\text{Experience}^2/100$ | .9240 | 2.1401 | −1.2161 | −.0089 (.0003) | .0052 (.0005) | .0108 | −.0112 |
| $\sqrt{\text{Firm tenure}}$ | −.3015 | −0.5103 | .2088 | .0120 (.0003) | .0005 (.0005) | .0025 | .0003 |
| | | | | | | .0034 | .0362 |

Notes: From education, experience, and tenure variables we have subtracted their values for the average worker. Coefficients of the regressors and their interactions with the female dummy are given in columns 4 and 5 respectively. The interaction for the intercept corresponds to the female dummy. The GLS standard errors are in parentheses. The contributions of sex differences in background characteristics in column 6 are obtained by multiplying the coefficients in column 4 with the sex differences in the variable means in column 3. The contributions of sex differences in coefficients in column 7 are obtained by multiplying the interaction coefficients with the sample means for women in column 2 and changing the sign. Cumulative contributions are shown below the horizontal lines.

the quadratic experience terms with the set of experience dummies,[22] our main findings remain unchanged, though the female interaction with tenure becomes insignificant.

The last two columns of Table II.8 show the contributions of sex differences in the background characteristics (column 6) and regressor coefficients (column 7), i.e. the explained and unexplained part of the wage differential between the average woman and average man who are doing the same work for the same employer respectively. Some 80% of the overall within-job wage differential remains unexplained, being attributed to different coefficients for women and men. Only a small fraction of the gender wage differential is attributable to sex differences in the background characteristics, namely to women's lower education level. Not surprisingly, these are the same conclusions we jumped to in the case of the model without gender-specific slopes.

Table II.9 reports the results of the same exercise for blue-collar workers. The findings are in line with the white-collar results. Namely, returns to education and work experience are different for women, and the absolute value of the female dummy coefficient is higher than with the previous estimate. However, the difference in returns to tenure between sexes is not statistically significant among blue-collar workers. Over 90% of the within-job wage gap is attributed to different coefficients for blue-collar women and men. Stated differently, sex differences in the observed background characteristics do not explain the within-job gap. This is the same conclusion we obtained from the model where the coefficients were restricted to be equal for both sexes.

It is important to recognize that the results of decomposition exercises with gender-

[22] From men's experience we subtracted one year for military service. We subtracted 1, 2, or 3 years from women's experience if the original experience variable was 2-4, 5-7, or more than 7 years respectively. These modifications are based on Asplund's (2001) comparisons of the potential and actual (self-reported) years of work experience.

specific slopes are somewhat arbitrary. First, the male coefficients are taken as a reference structure that is used to evaluate the contributions of sex differences in the background characteristics in Tables II.8 and II.9. Alternatively, one could choose the female coefficients or some weighted average of male and female coefficients. If we use the female coefficients as the reference structure, our main insights do not change much. Second, the estimated contributions of sex differences in the slopes are affected by the location transformations of the explanatory variables (Oaxaca and Ransom, 1999), making the decomposition results in column 7 arbitrary. We found that the unexplained within-job wage differential among both groups of workers is attributed mainly to the female dummy coefficient, while women's different returns to education and experience have only moderate contributions. These findings are driven by our choice to measure the education, experience, and tenure variables in deviation from their values for the average worker. If these variables were transformed to range from zero upwards, we would find a negligible (or slightly negative) female dummy effect and strong positive contributions for women's lower returns to education and experience. In such a case the female dummy coefficient would pick up the size of the within-job sex gap in pay among the lowest educated workers with no experience and tenure. In other words, the results in the last column depend on the interpretation we put on the female dummy coefficient. Importantly, the overall effect of sex differences in the regression coefficients is not affected by the location transformations, nor the estimated contributions of sex differences in the background characteristics in column 6.

Despite these difficulties in interpretation, it is safe to make the following conclusions that apply to both groups of workers. First, only a small fraction of the within-job wage gap between sexes can be explained by sex differences in background characteristics, while most of the gap remains unexplained, being attributable to differences in the coefficients. Second, the unexplained within-job wage differential increases with education and experience (over the major part of the career), being very small or negligible among low educated workers with little experience and tenure.

## 5.4 Comparisons with results from other studies

We conclude this section by contrasting our main findings with the findings from other countries and a related Finnish study. One should not forget that the results of different studies are not directly comparable owing to dissimilarities in the data coverage, occupational classification, and statistical methods used.

### White-collar workers in Nordic countries

Our results for white-collar workers are most directly comparable with evidence for Norway (Petersen et al., 1997), Sweden (Meyersson Milgrom et al., 2001), and Denmark (Datta Gupta and Rothstein, 2001). We found that in Finland white-collar women earn some 23 percent less on average than men do, compared with 29 percent in Denmark and 27 percent in Norway and Sweden. Sex segregation among firms accounts for about 16 percent of the Finnish raw gap, while the industry effects have no significant role at all. These results are consistent with the findings for other Nordic countries that sex segregation among industries or employers does not play an important role in the case of white-collar workers.

Roughly one-half of the raw gap of the Finnish white-collar workers is attributable to the disproportionate concentration of women in lower-paying jobs within firms. Within firms high-paid managerial jobs are mainly occupied by men, and among other types of jobs men are concentrated in positions with higher skill requirements. In Denmark occupational and job segregation explains less than one-half of the raw gap but in Norway and Sweden as much as 80 percent. Finally, we found that within jobs white-collar women are paid some 6 percent lower wages on average than their male co-workers with equal education, work experience, and tenure. This figure is roughly identical to the size of the (unconditional) within-job wage gap found for Sweden and Norway but much lower than what has been found for Denmark (about 14 percent after controlling for a number of individual characteristics).

### Blue-collar workers in Nordic countries

In the Finnish manufacturing sector blue-collar women's mean wage is 16 percent lower than men's mean wage. Petersen et al. (1997) and Meyersson Milgrom et al. (2001) report somewhat lower wage gaps for blue-collar workers in Norway and Sweden respectively. We found that most of the sex gap results from sex segregation among firms. This is in accordance with a strong effect of establishment segregation among the Swedish blue-collar workers. By contrast, Petersen et al. (1997) find employer segregation less important in the case of Norway. Furthermore, we found that blue-collar women are paid 3.5 percent less than their equally qualified male counterparts who are doing the same job for the same employer. This figure is very close to the (unconditional) within-job gap in Norway, being above the Swedish level.

### U.S. evidence

Comparisons with U.S. evidence are less straightforward because the U.S. findings are mixed and because the U.S. studies do not make a clear difference between white-collar and blue-collar workers. Compared with the U.S. results of Bayard et al. (2003), our results point to a smaller (unexplained) within-job gender gap and a stronger role for sex segregation in Finland. These conclusions are reversed, if the findings of Groshen (1991) or Petersen and Morgan (1995) are taken as a reference.

**Finnish service industries**

In a complementary study Luukkonen (2003*b*) explores gender wage differentials in the Finnish service sector using the methods developed in this paper. His data, obtained from the records of the Employers' Federation of Service Industries (PT),[23] cover some 190,000 workers in 3,900 private services firms. In the service sector analysis white- and blue-collar workers were not analysed separately, owing to a different occupational structure. Keeping this in mind, the raw wage gap of 20 percent in the service sector corresponds quite closely to our findings for the manufacturing industries. According to Luukkonen (2003*b*), one-half of the overall gap in the service industries results from sex segregation among jobs, one-third from sex segregation among firms, and one-sixth is owing to unexplained within-job wage differentials and sex differences in individual characteristics. Within-job wage differentials between sexes remain mostly unexplained, women being paid 3.7 percent less for the same job than their equally qualified male co-workers.

# 6 Conclusion

In this paper, we have introduced a new way of decomposing the gender wage gap based upon the nested correlated random effects model. Our modelling approach took an explicit account of the hierarchical grouped structure of the matched employer-employee data. The decomposition allowed us to assess the extent to which the overall sex gap is attributable to within-job wage differentials and sex segregation among firms and jobs within firms. Importantly, by explicitly modelling the firm and job effects, the approach proved to be informative about the sources of lower pay in predominantly female firms and jobs. Compared with the standard fraction female decomposition, the correlated random effects specification led to quantitatively different results. These differences suggest that the latent firm and job effects may bias the coefficients in the simple fraction female regressions and lead to misleading conclusions.

A major part of the gender wage differentials among white-collar manufacturing workers was attributed to the disproportionate concentration of women in lower-paying jobs. Within firms high-paid managerial jobs are mainly occupied by men, and among other types of jobs men are concentrated in positions with higher skill requirements. This may reflect discrimination through differential access to higher-paying jobs, or it may result from sex differences in preferences. Becker (1985) for example illustrates how women's greater responsibility for child care and homework may induce them to crowd into less-demanding jobs, as well as to spend less effort for the same job than men do. Although reasons for women's concentration in lower-paying jobs remain a puzzle, our findings highlight the importance of equal opportunities in education, hiring, and promotion.

When explaining wage differentials between white-collar jobs, we found that lower

[23] PT does not exits any more but its member associations belong to EK along with the member associations of the former TT.

wages in predominantly female jobs are in large part attributable to lower skill requirements and job complexity (especially when managerial jobs were excluded). However, our results suggest that, in the same firm, predominantly female jobs pay lower wages than predominantly male jobs that are associated with the same level of average education, average tenure, and job complexity. That is, jobs of equal worth are differently rewarded depending on whether they are occupied by men or women. Of course, one can always speculate how accurate our job complexity variable is, but if we assume that this measure is reasonably good, our results would imply that policies like comparable worth might be worth considering. This does assume that men and women exert equal effort in these jobs (e.g. Becker, 1985). Even if effectively implemented, the scope of such measures is likely to be relatively limited, however, because the part of lower wages in predominantly female jobs that was left unexplained accounts for less than one-fifth of the overall gender gap.

Designing an effective policy for reducing the gender wage differentials of blue-collar workers would be a trickier task. Among this group of workers, much of gender wage differentials results from sex segregation among firms. The origin of such a strong effect of firm segregation, however, remains a puzzle. That is, firms with a high fraction of blue-collar female employees pay lower wages for some unobserved reasons.

Finally, it is notable that we found women to be lower paid within narrowly defined jobs within firms. Compared with equally qualified men who are doing similar work for the same employer, white-collar women are paid 6 percent less (2.8 percent less in the case of non-managerial white-collar workers) and blue-collar women 3.5 percent less on average. Eliminating the sources of unexplained within-job wage differentials can at most account for a quarter of the overall gap of white-collar workers and one-fifth of the overall gap of blue-collar workers.

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## II.A Generalized least squares estimation

### II.A.1 Regression coefficients

We rewrite the regression model defined in (II.10) and (II.11) for the block of observations resulting from the $j$th firm as

$$\mathbf{w}_j = \widetilde{\mathbf{X}}_j \boldsymbol{\varphi} + \mathbf{u}_j, \qquad j = 1, 2, ..., F,$$

where $\boldsymbol{\varphi}$ is a vector of all regression coefficients and $\widetilde{\mathbf{X}}_j$ is a matrix of all explanatory variables in (II.10), including a column of ones for the constant. The observations are stacked group-wise in such manner that the slowest running index is the firm index $j$, the second slowest running index is the job index $k$, and the fastest running index is the person index $i$. Given this ordering of observations, the wage vector can be decomposed as $\mathbf{w}_j' = (\mathbf{w}_{j1}', \mathbf{w}_{j2}', ..., \mathbf{w}_{jc_j}')'$, where $\mathbf{w}_{jk}' = (w_{jk1}, w_{jk2}, ..., w_{jkn_{jk}})$ and $n_{jk}$ denotes the number of workers in job $k$ within firm $j$. The $\widetilde{\mathbf{X}}_j$ and $\mathbf{u}_j$ are constructed similarly.

Given the independence of observations across firms, the GLS estimator is

$$\widetilde{\boldsymbol{\varphi}}_{\text{GLS}} = \left( \sum_{j=1}^{F} \widetilde{\mathbf{X}}_j' \boldsymbol{\Sigma}_j^{-1} \widetilde{\mathbf{X}}_j \right)^{-1} \sum_{j=1}^{F} \widetilde{\mathbf{X}}_j' \boldsymbol{\Sigma}_j^{-1} \mathbf{w}_j, \tag{A1}$$

and its variance-covariance matrix is

$$V\left(\widetilde{\boldsymbol{\varphi}}_{\text{GLS}}\right) = \left( \sum_{j=1}^{F} \widetilde{\mathbf{X}}_j' \boldsymbol{\Sigma}_j^{-1} \widetilde{\mathbf{X}}_j \right)^{-1}. \tag{A2}$$

The error variance-covariance matrix for the $j$th block of observations can be expressed as

$$\boldsymbol{\Sigma}_j = \sigma_\varepsilon^2 \left( \mathbf{I}_{n_j} + \mathbf{D}_j \mathbf{D}_j' \right),$$

where $\mathbf{I}_{n_j}$ is an identity matrix of dimension $n_j$, and $\mathbf{D}_j = [\mathbf{d}_{j1} \ \mathbf{D}_{j2}]$ is a matrix of dimension $n_j \times (c_j + 1)$, where $n_j \equiv \sum_{k=1}^{c_j} n_{jk}$ is the size of firm $j$. All elements of the first column of $\mathbf{D}_j$ $(= \mathbf{d}_{j1})$ are equal to $\sigma_\xi / \sigma_\varepsilon$, and other $c_j$ columns are represented by the block diagonal matrix $\mathbf{D}_{j2}$, where the $k$th block is a column vector of dimension $n_{jk}$, with all elements equal to $\sigma_\omega / \sigma_\varepsilon$, $k = 1, 2, ..., c_j$.

The direct computation of $\widetilde{\boldsymbol{\varphi}}_{\text{GLS}}$ from (A1) would require inverting matrices $\boldsymbol{\Sigma}_j$'s, whose dimensions correspond to firm sizes $n_j$, $j = 1, 2, ..., F$. If, as in our application, there are several large firms in the data, the numerical inversions of $\boldsymbol{\Sigma}_j$'s would become computationally burdensome. With balanced data, inversions of the error variance-covariance matrices can usually be avoided by use of certain variable transformations. Fuller and Batesse (1973) consider a special case where $n_{jk}$ is constant for all $k$ within each $j$. They show how the GLS estimator can be obtained by applying OLS to the transformed model. This transformation method, however, does not easily generalise to the case where $n_{jk}$

varies within firms, so we remain stuck with the problem of inverting a series of potentially very large matrices.

Fortunately, the computational burden can be considerably reduced by the use of a bit of matrix algebra. More specifically, using Lemma 2 of Davis (2002), we can express $\mathbf{\Sigma}_j^{-1}$ as

$$\mathbf{\Sigma}_j^{-1} = \frac{e_j \mathbf{Q}_j - \mathbf{Q}_j \mathbf{d}_{j1} \mathbf{d}_{j1}' \mathbf{Q}_j}{e_j \sigma_\varepsilon^2}, \tag{A3}$$

where

$$\begin{aligned}
\mathbf{Q}_j &= \mathbf{I}_{n_j} - \mathbf{D}_{j2} \left( \mathbf{I}_{c_j} + \mathbf{D}_{j2}' \mathbf{D}_{j2} \right)^{-1} \mathbf{D}_{j2}', \\
e_j &= 1 + \mathbf{d}_{j1}' \mathbf{Q}_j \mathbf{d}_{j1}.
\end{aligned}$$

$\mathbf{I}_{c_j} + \mathbf{D}_{j2}' \mathbf{D}_{j2}$ is a diagonal matrix with the $k$th element equal to $1 + n_{jk}(\sigma_\omega^2/\sigma_\varepsilon^2)$, $k = 1, 2, ..., c_j$, and so its inverse is obtained analytically by inverting each of the diagonal elements.[24] With this in mind, it is evident that the expression in (A3) provides a very convenient way of computing $\mathbf{\Sigma}_j^{-1}$ as it avoids numerical inversions entirely. Consequently, using (A3) for $\mathbf{\Sigma}_j^{-1}$'s the GLS estimator and its standard errors can be computed rather easily from (A1) and (A2) even for very large unbalanced problems.

### II.A.2 Variance components

In practice $\mathbf{\Sigma}_j$'s depend upon unknown variances $\sigma_\varepsilon^2$, $\sigma_\xi^2$, and $\sigma_\omega^2$. These have to be estimated in the first step to make the GLS estimator operational. The consistent estimates of the variances can be obtained by equating the various sums of squared residuals to their expected values. From Searle (1961) we obtain

$$\begin{aligned}
\sum_{j=1}^{F} \sum_{k=1}^{c_j} \sum_{i=1}^{n_{jk}} E\left(u_{jki}^2\right) &= N\left(\sigma_\xi^2 + \sigma_\omega^2 + \sigma_\varepsilon^2\right), \\
\sum_{j=1}^{F} \sum_{k=1}^{c_j} n_{jk} E\left(\overline{u}_{jk\cdot}^2\right) &= N\left(\sigma_\xi^2 + \sigma_\omega^2\right) + C\sigma_\varepsilon^2, \\
\sum_{j=1}^{F} n_j E\left(\overline{u}_{j\cdot\cdot}^2\right) &= N\sigma_\xi^2 + k_{12}\sigma_\omega^2 + F\sigma_\varepsilon^2, \\
NE\left(\overline{u}_{\cdots}^2\right) &= k_1\sigma_\xi^2 + k_3\sigma_\omega^2 + \sigma_\varepsilon^2,
\end{aligned}$$

where the job, firm, and grand means of the residuals $u_{jki}$ are denoted with $\overline{u}_{jk\cdot}$, $\overline{u}_{j\cdot\cdot}$, and $\overline{u}_{\cdots}$ respectively; $N = \sum_{j=1}^{F} n_j$ is the sample size; $C = \sum_{j=1}^{F} c_j$ is the aggregate number of jobs; $k_{12} = \sum_{j=1}^{F} n_j^{-1} \left( \sum_{k=1}^{c_j} n_{jk}^2 \right)$; $k_1 = N^{-1} \sum_{j=1}^{F} n_j^2$; and $k_3 = N^{-1} \sum_{j=1}^{F} \sum_{k=1}^{c_j} n_{jk}^2$.

[24] Moreover, $e_j$ can be expressed as

$$e_j = 1 + n_j \frac{\sigma_\xi^2}{\sigma_\varepsilon^2} - \sum_{k=1}^{c_j} \frac{(n_{jk}\sigma_\xi\sigma_\omega)^2}{\sigma_\varepsilon^4 + n_{jk}\sigma_\varepsilon^2\sigma_\omega^2}$$

The expectations on the left-hand side of the equation system are estimated using

$$\widehat{E\left(u_{jki}^2\right)} = \widetilde{u}_{jki}^2, \qquad \widehat{E\left(\overline{u}_{jk\cdot}^2\right)} = \widetilde{\overline{u}}_{jk\cdot}^2, \qquad \widehat{E\left(\overline{u}_{j\cdot\cdot}^2\right)} = \widetilde{\overline{u}}_{j\cdot\cdot}^2, \qquad \widehat{E\left(\overline{u}_{\cdots}^2\right)} = \widetilde{\overline{u}}_{\cdots}^2 = 0$$

where $\widetilde{u}_{jki}$ denotes the OLS residual from the regression (II.10). By substituting these into the equation system and solving for the variance components, we obtain the following estimators:

$$\begin{aligned}
\widetilde{\sigma}_{\varepsilon}^2 &= \frac{1}{N-C}\left(\sum_{j=1}^{F}\sum_{k=1}^{c_j}\sum_{i=1}^{n_{jk}}\widetilde{u}_{jki}^2 - \sum_{j=1}^{F}\sum_{k=1}^{c_j} n_{jk}\widetilde{\overline{u}}_{jk\cdot}^2\right), \\
\widetilde{\sigma}_{\omega}^2 &= \frac{1}{N-k_{12}}\left(\sum_{j=1}^{F}\sum_{k=1}^{c_j} n_{jk}^2\widetilde{\overline{u}}_{jk\cdot}^2 - \sum_{j=1}^{F} n_j\widetilde{\overline{u}}_{j\cdot\cdot}^2 - (C-1)\,\widetilde{\sigma}_{\varepsilon}^2\right), \\
\widetilde{\sigma}_{\xi}^2 &= \frac{1}{N-k_1}\left(\sum_{j=1}^{F} n_j\widetilde{\overline{u}}_{j\cdot\cdot}^2 - (k_{12}-k_3)\,\widetilde{\sigma}_{\xi}^2 - (F-1)\,\widetilde{\sigma}_{\varepsilon}^2\right).
\end{aligned}$$

Using the estimated values of $\sigma_{\varepsilon}^2$, $\sigma_{\xi}^2$, and $\sigma_{\omega}^2$, we can construct estimates for the $\mathbf{\Sigma}_j$'s. In the second step the feasible GLS estimator of $\boldsymbol{\varphi}$ and its variance-covariance matrix are obtained from (A1) and (A2) computing the inversions using (A3).

There are several alternative methods available for estimating the variance components (see e.g. Baltagi et al., 2001). We adopted perhaps the simplest one here. However, by means of Monte Carlo simulations and empirical examples, the two-step GLS estimator has been found to be reasonably robust with respect to a particular choice of the method used in estimating the variance components (see Maddala and Mount, 1973, for the one-way error components models, and Baltagi et al., 2001, and Davis, 2002, for the nested error components models).

Table II.10: Wage regression results for technical and clerical workers

| | Model specification | | | | |
|---|---|---|---|---|---|
| | FE | OLS | RE | CRE1 | CRE2 |
| Intercept | | 1.6210 (.0065) [.1557] | 2.1733 (.0088) | 1.9896 (.0609) | 1.9827 (.0597) |
| **Individual regressors** | | | | | |
| Female | −.0283 (.0011) | −.0343 (.0036) [.0036] | −.0293 (.0015) | −.0283 (.0011) | −.0283 (.0011) |
| Schooling years | .0098 (.0003) | .0596 (.0004) [.0090] | .0191 (.0003) | .0098 (.0003) | .0098 (.0003) |
| Experience | .0061 (.0002) | .0090 (.0003) [.0010] | .0081 (.0002) | .0061 (.0002) | .0061 (.0002) |
| Experience$^2$/100 | −.0084 (.0004) | −.0076 (.0006) [.0023] | −.0110 (.0004) | −.0084 (.0004) | −.0084 (.0004) |
| $\sqrt{\text{Firm tenure}}$ | .0145 (.0004) | .0044 (.0006) [.0034] | .0130 (.0005) | .0145 (.0004) | .0145 (.0004) |
| **Job regressors** | | | | | |
| Fraction female | | −.1714 (.0032) [.0118] | −.1646 (.0026) | −.1463 (.0024) | −.0335 (.0021) |
| Mean schooling | | | | .0391 (.0007) | .0101 (.0006) |
| Mean experience | | | | .0096 (.0005) | .0009 (.0004) |
| Mean (experience)$^2$ /100 | | | | −.0123 (.0010) | −.0002 (.0008) |
| Technical | | | | .0447 (.0030) | .0629 (.0026) |
| Mean $\sqrt{\text{firm tenure}}$ | | | | −.0074 (.0010) | −.0141 (.0009) |
| Complexity level | | | | | .0666 (.0005) |
| Large city | | | | .0482 (.0033) | .0309 (.0025) |
| Log (job size) | | | | −.0131 (.0011) | −.0097 (.0008) |
| **Firm regressors** | | | | | |
| Fraction female | | −.0474 (.0042) [.0737] | −.1770 (.0133) | −.1545 (.0129) | −.1025 (.0128) |
| Mean schooling | | | | .0271 (.0040) | .0115 (.0041) |
| Mean experience | | | | −.0010 (.0030) | −.0036 (.0030) |
| Mean (experience)$^2$ /100 | | | | .0068 (.0064) | .0198 (.0064) |
| Fraction technical job | | | | .0398 (.0131) | .0312 (.0123) |
| Mean $\sqrt{\text{firm tenure}}$ | | | | −.0252 (.0030) | −.0225 (.0031) |
| Mean job complexity | | | | | .0433 (.0025) |
| Fraction jobs in large cities | | | | .0496 (.0051) | .0499 (.0051) |
| Worker mix | | | | .0314 (.0104) | .0274 (.0104) |
| Mean log (job size) | | | | −.0057 (.0049) | −.0097 (.0049) |
| Log (firm size) | | | | .0056 (.0026) | .0071 (.0026) |
| **Variance components** | | | | | |
| $\sigma_\varepsilon^2$ (individual error) | | | .0106 | .0064 | .0064 |
| $\sigma_\omega^2$ (job random effect) | | | .0111 | .0115 | .0052 |
| $\sigma_\xi^2$ (firm random effect) | | | .0121 | .0035 | .0043 |

Notes: FE is the fixed effects model with the heteroskedasticity-consistent standard errors in parentheses. For the OLS model the heteroskedasticity-consistent standard errors are in parentheses and standard errors robust to arbitrary heteroskedasticity and intrafirm correlation are in square brackets. RE, CRE1, and CRE2 are the (correlated) random effects models with the GLS standard errors in parentheses. All job regressors are measured in deviation from the firm mean. CRE1 and CRE2 models include 38 industry dummies. Number of observations is 71,504 in all regressions.

Table II.11: Gender wage gap decompositions for technical and clerical workers

| | Sample means | | | Contribution to the wage gap | | | | |
|---|---|---|---|---|---|---|---|---|
| | Men | Women | Diff. | FE | OLS | RE | CRE1 | CRE2 |
| **Individual regressors** | | | | | | | | |
| Female | .0000 | 1.0000 | −1.0000 | .0283 | .0343 | .0293 | .0283 | .0283 |
| Schooling years | 11.8415 | 11.5404 | .3012 | .0030 | .0180 | .0057 | .0030 | .0030 |
| Experience | 23.7720 | 23.2968 | .4753 | .0029 | .0043 | .0038 | .0029 | .0029 |
| Experience$^2$/100 | 6.7065 | 6.5161 | .1904 | −.0016 | −.0015 | −.0021 | −.0016 | −.0016 |
| $\sqrt{\text{Firm tenure}}$ | 3.4688 | 3.3031 | .1657 | .0024 | .0007 | .0022 | .0024 | .0024 |
| | | | | .0349 | .0558 | .0390 | .0349 | .0349 |
| **Job regressors** | | | | | | | | |
| Fraction female | −.2358 | .3074 | −.5432 | | .0931 | .0894 | .0795 | .0182 |
| Mean schooling | .0968 | −.1262 | .2230 | | | | .0087 | .0023 |
| Mean experience | .2190 | −.2855 | .5045 | | | | .0049 | .0004 |
| Mean (experience)$^2$ /100 | .1004 | −.1308 | .2312 | | | | −.0029 | .0000 |
| Technical | .0607 | −.0792 | .1399 | | | | .0063 | .0088 |
| Mean $\sqrt{\text{firm tenure}}$ | .0260 | −.0339 | .0599 | | | | −.0004 | −.0008 |
| Complexity level | .4808 | −.6269 | 1.1077 | | | | | .0738 |
| Large city | −.0042 | .0055 | −.0097 | | | | −.0005 | −.0003 |
| Log (job size) | .0846 | −.1103 | .1949 | | | | −.0026 | −.0019 |
| | | | | .1086 | .0931 | .0894 | .0930 | .1004 |
| **Firm regressors** | | | | | | | | |
| Fraction female | .3599 | .5308 | −.1710 | | .0081 | .0303 | .0264 | .0175 |
| Mean schooling | 11.7460 | 11.6645 | .0818 | | | | .0022 | .0009 |
| Mean experience | 23.6655 | 23.4357 | .2298 | | | | −.0002 | −.0008 |
| Mean (experience)$^2$ /100 | 6.6642 | 6.5713 | .0929 | | | | .0006 | .0008 |
| Fraction technical jobs | .2805 | .1701 | .1104 | | | | .0044 | .0034 |
| $\sqrt{\text{Mean firm tenure}}$ | 3.4145 | 3.3739 | .0406 | | | | −.0010 | −.0009 |
| Mean job complexity | 4.1964 | 4.2619 | −.0655 | | | | | −.0028 |
| Fraction jobs in large cities | .5217 | .5477 | −.0260 | | | | −.0013 | −.0013 |
| Worker mix | .6688 | .6710 | −.0022 | | | | −.0001 | −.0001 |
| Mean log (job size) | 2.7546 | 2.1469 | .6077 | | | | −.003 | −.0064 |
| Log (firm size) | 6.8983 | 6.6157 | .2826 | | | | .0016 | .0020 |
| Industry dummies | | | | | | | −.0078 | .0052 |
| | | | | .0136 | .0081 | .0303 | .0214 | .0176 |
| **Overall sum** | | | | .1570 | .1570 | .1587 | .1493 | .1529 |

Notes: The raw wage gap, as measured by the sex difference in mean log wages, is .1570. The first two columns report the samples means of all regressors among men and women; the third column gives the difference. The last five columns show the absolute contribution of each regressor obtained from various model specifications. The contributions are obtained by multiplying the coefficients in Table II.10 by the sex differences in sample means in Table II.11. The cumulative effect of each group of regressors is shown below the horizontal lines.

# Chapter III

# Extended UI Benefits and Labour Market Withdrawal of Older Workers via Unemployment

*In Finland the older unemployed can collect unemployment insurance benefits until retirement, while the entitlement period for younger groups is two years. In 1997 the eligibility age of persons benefiting from extended benefits was raised from 53 to 55. We consider layoff risks, unemployment durations, and exit states before and after the reform. In the duration analysis we apply a competing risks version of a split population model to account for multiple exit routes and the possibility that some of the elderly unemployed may not be active in the labour market due to pension rules. Since the reform the employed aged 53-54 have had a much lower risk of unemployment. We estimate that roughly half of unemployed workers with extended benefits are effectively withdrawn from the labour market. Those who remain active have a similar hazard rate to employment as individuals with the two-year entitlement period, but much lower hazard rates to non-participation and labour market programmes.*[1]

## 1 Introduction

Unemployment differences between the European countries and the United States have been the focus of much political and academic debate during the past couple of decades. In addition to higher levels of unemployment, the duration of unemployment spells is typically much longer in Europe than in the US (Machin and Manning, 1999). A high incidence of long-term unemployment among older workers and a tendency of workers to leave the labour force at ages several years below the official retirement age are common problems in Europe. The unemployment compensation system, with generous benefit levels and long entitlement periods, is often blamed for being responsible for much of the

[1] Results of this study can be found in Kyyrä and Ollikainen (2006) and Kyyrä and Wilke (2007).

European unemployment problem (e.g. Ljungqvist and Sargent, 1998). In many European countries, including Finland, Belgium, France, Germany, the Netherlands, Portugal, Spain, and United Kingdom, the entitlement periods are further extended for older workers and/or particular early retirement schemes are tailored for the elderly unemployed so that unemployment-related benefits effectively provide a particular pathway to early withdrawal from the labour market (Duval, 2003).

In Finland unemployment benefits, i.e. the basic unemployment allowance or earnings-related unemployment insurance benefits, can be received for a maximum of two years, but there is an exception for the older unemployed. Workers aged 55 (53 before 1997) or more at the time of job loss are allowed to collect unemployment benefits up to the age of 60, when they become eligible for the unemployment pension benefit. At the age of 65 the unemployment pension is transformed into the normal old-age pension. This route out of the labour market is widely known as the "unemployment tunnel". Since the level of unemployment pension benefits is comparable to that of UI benefits, this scheme effectively provides an indefinite period of UI benefits for older workers.

The unemployment tunnel (UT) scheme contributes to aggregate unemployment in two ways. First, the employers tend to target dismissals at the elderly workers, as a reasonable income level is fully secured for them. Rantala (2002) provides evidence that unemployment risk at least doubles at the eligibility age of the UT scheme. Secondly, without a risk of future cuts in the benefit level, the elderly unemployed are likely to be more passive in job search and more choosy in accepting job offers, leading to longer unemployment spells. In fact, many of those with extended UI benefits may not be searching for a new job at all. Not surprisingly, the older cohorts account for a large fraction of the aggregate unemployment rate. In 2000 one-third of the unemployed (including those on the unemployment pension) and two-thirds of the long-term unemployed were aged 56 and over (Koskela and Uusitalo, 2006).

In practice, the UT scheme facilitates the withdrawal of ageing workers from the labour market several years before the official retirement age of 65. This is in clear contrast with the government's goal to induce people to retire later. The effective retirement age in Finland is currently around 60, five years below the official retirement age. The Finnish pension system is built in such a way that the pensions of the retired are paid in large part by the current employees. As the Finnish population will age more rapidly than most of the other European populations over the next few decades,[2] the financing of future pensions has been a subject of increasing concern. As a result of financial pressure, several policy measures have been taken to discourage early retirement. These measures included an increase in the age threshold for the UT scheme: the eligibility age for the extended benefit entitlement period, followed by the unemployment pension at the age

[2]The old-age dependency ratio, i.e. the ratio of the population aged 65 and over to the population aged 20-64, is estimated to rise from the current level of 25% to over 40% by 2025, when Finland is expected to have the second highest dependency ratio among the OECD countries (OECD, 2004, pp. 18-20).

of 60, was increased from 53 to 55 in 1997. Consequently, the entitlement period of unemployment benefits for the age group 53-54 was effectively reduced to the maximum of two years, while the other age groups remained unaffected by the reform. We exploit this quasi-experimental setting to study how the incidence and duration of unemployment are affected by eligibility for extended UI benefits.

We employ high-quality panel data drawn from the records of the Employment Statistics database of Statistics Finland. This database includes information from several administrative registers, and it effectively covers the entire Finnish population. In the first stage we quantify the change in the inflow to unemployment resulting from the increase in the age threshold of the UT scheme. This effect turns out to be very strong. We find that disproportionate numbers of dismissals fall on employees who are old enough to be entitled to the extended UI period. Large employers, especially, tend to exploit this feature of the UI system to get rid of their elderly employees. There is also evidence of notable anticipation behaviour prior to the UT reform in 1997 and another reform in 1996.

In the second state we examine the effect of extended UI benefits on the labour market transitions of the elderly unemployed. This main part of the study contributes to the growing literature on the impact of maximum UI duration. The analysis of unemployment insurance has been the topic of several theoretical and empirical studies in recent years. In the empirical work the focus has been on estimating reduced-form duration models where the restrictions implied by structural job search models are not imposed. A typical problem in most empirical work has been the lack of variation in the maximum duration of UI benefits that can be regarded as independent of other factors determining unemployment duration (Atkinson and Micklewright, 1991; and Holmlund, 1998). A number of recent studies have exploited various policy changes in an attempt to overcome the endogeneity issue (e.g. Hunt, 1995; Winter-Ebmer, 1998; Bratberg and Vaage, 2000; Card and Levine, 2000; Carling et al., 2001; Røed and Zhang, 2003; Lalive and Zweimüller, 2004; Uusitalo and Moisala, 2003; and Lalive et al., 2006). In these studies escape rates from unemployment before and after the reform are compared within the group affected. A similar approach is taken in this study.

We use a sample of workers aged 50-54 who became unemployed between 1995 and 1998. Unemployment experiences of the group aged 53-54 are compared under two schemes: the extended UI entitlement period (pre-reform scheme) and the conventional UI period of two years (post-reform scheme). The younger group (aged 50-52) serves as a control group used to eliminate the business cycle effect. Since the unemployment spells can end through the taking of a job, withdrawal from the labour force, or participation in an active labour market programme (ALMP), competing risks are inherent in our data. As pointed out by Carling et al. (1996), the availability of various labour market programmes, in particular, may play an important role in mitigating the incentive effects of UI on the job-finding rate. A novel feature of our analysis is that we explicitly allow for some older workers, registered as unemployed job seekers, to effectively withdraw from job search and simply wait for access to early retirement. If this is the case, the standard duration models that assume all individuals are at risk of experiencing the event of interest are not applicable. Therefore, we apply a competing risks version of a split population duration model that is capable of accounting for this sort of heterogeneity, i.e. the possibility that some individuals do not consider all possible exit routes. The idea is to model simultaneously both the likelihood that the worker is still active in the labour market and the timing of exit to various end-states conditional on being active. This approach allows us to distinguish the participation decision from labour market behaviour in the case of continued search. We find that some half of those who are entitled to extended UI benefits are effectively withdrawn from the labour market.

The empirical analysis of UI has focused on detecting effects on the hazard rates. The cause-specific hazard function can be used to identify the effect of the UI scheme on the instantaneous transition rate to a particular destination at a given phase of the spell conditional on having not exited from unemployment to *any* destination. As a result, the employment hazard functions do not provide direct information about policy-relevant issues like changes in the overall or cumulative probability of employment, nor in the expected duration of unemployment. These are functions of all cause-specific hazard functions, each of which is subject to change in response to the change in the entitlement period. Therefore, we summarize our results from the competing risks analysis in terms of the cumulative incidence functions, which describe the probability of leaving unemployment to a particular destination by a given time. In this way we can assess to what extent the effect of the extended UI benefits on the probability of entering employment stems directly from a change in the employment hazard and indirectly from changes in other cause-specific hazard functions. This is the question of obvious interest because policy makers can also affect the employment probability indirectly, for example, by regulating the availability of labour market programmes over the course of the unemployment spell.

The plan of the paper is as follows. In the next section we discuss evaluation issues and existing empirical evidence about the importance of the length of the UI benefit entitlement period. Section 3 describes the Finnish unemployment compensation system and early retirement schemes, with an emphasis on the UT scheme. In Section 4 we give details of the data and report some descriptive statistics. Sections 5 and 6 discuss the econometric methods and report our estimation results for the layoff risk and transitions out of unemployment. The final section concludes.

## 2 UI duration in theory and practice

The analysis of unemployment insurance has been an active subject of both theoretical and empirical work for the past two or three decades. The key predictions of theory have found support from the microeconometric analysis of unemployment duration data. Here we briefly discuss the likely effects of maximum UI duration on exits out of unemployment among UI recipients, and give a selective survey of relevant empirical evidence. Needless to say, our focus is highly restrictive, as the existence of UI can affect labour market outcomes in a variety of ways that depend on the institutional features of the UI system under consideration.[3] In particular, we do not discuss here how the availability of extended benefits for the elderly affects the layoff risk of older workers. This is because such an effect depends also on other features of the social security system which, in the Finnish case, includes employers' liabilities for early retirement expenditures caused by their former employees.[4] Once the relevant part of the Finnish social security system is described in Section 3, we return to this issue.

## 2.1 Evaluation issues

In this section we raise the following issues that require particular attention when the effects of the length of the entitlement period among the unemployed are investigated. First, a flexible model specification should be adopted, as no a priori parametric restrictions for the effects of the entitlement period on the hazard functions can be derived from theoretical models. Second, some elderly unemployed with generous UI benefits may no longer be actively searching for a new job. Third, competing risks analysis is potentially very useful, especially when active labour market policy plays an important role, as in Finland. Finally, reliable analysis requires independent variation in the entitlement periods across individuals.

### Incentives of unemployed workers

Dynamic models of job search have shed light on the ways in which UI can affect unemployment duration through the reservation wage and search effort. Mortensen's (1977) model is the seminal contribution of this branch of the literature. In his model, eligibility for UI requires some previous work experience and UI benefits can be received for a fixed period. Workers are either employed or unemployed. When unemployed, the worker chooses optimal search effort and samples job offers from a known distribution of wage offers using the reservation wage strategy. When employed, the worker faces the risk of becoming unemployed. The transition rate from unemployment to employment increases with search effort (as the arrival rate of job offers increases) and decreases with the reservation wage (as the probability that a received offer is acceptable declines). As the unemployed worker approaches the time when UI benefits will expire, his search effort

[3] Atkinson and Micklewright (1991) and Holmlund (1998) discuss the topic in a wider context.

[4] When extended UI benefits are used to bridge the time until retirement, long-term unemployment provides effectively a particular pathway to early withdrawal from the labour market for some elderly workers. In the Finnish system employers are liable for a share of early retirement expenditures via partially experience-rated employer contributions, and these contributions differ between various early retirement schemes (and vary across employers of different size). As a consequence, it makes a clear difference for the employer whether its former employee ends up to unemployment pension via long-term unemployment or retires via some other early retirement scheme. It follows that the layoff risk of older workers is strongly affected by the availability of extended benefits for the elderly; see Sections 3.4., 4.2, and 5.

increases and the reservation wage decreases. After the exhaustion of UI benefits, the worker faces a stationary environment, and hence his search effort and reservation wage no longer change. The employment hazard therefore increases up to the point of benefit exhaustion and remains constant thereafter.[5]

The longer entitlement period increases not only the value of being unemployed but also the value of becoming employed with a given wage rate, as unemployment spells in the future will be better compensated for. The relative importance of this second effect, known as the "entitlement effect", increases as the day of benefit exhaustion comes closer. As a result, an increase in the maximum duration of UI benefits reduces the employment hazard over the forepart of the unemployment period but increases it close to and beyond the exhaustion point. In other words, the effect on the employment hazard is predicted to change over the course of the unemployment spell, potentially reversing its sign at some point. In the empirical analysis this possibility is sometimes ruled out a priori by imposing the restriction that changes in the length of the entitlement period may lead to level shifts in the underlying hazard function but cannot affect its shape (e.g. Hunt, 1995; and Lalive and Zweimüller, 2004). We do not impose such restrictions but allow the hazard functions of individuals covered by different UI schemes to be of different shape.

When behaviour of the older unemployed is of interest, Mortensen's (1977) assumption of a stationary environment is problematic. As pointed out by Lalive et al. (2006), the older unemployed may benefit less from a given search effort due to a shorter period of time to collect wages as they will retire in the near future in any case. This suggests that older workers may react stronger to an extension of the UI entitlement period, as was found in the study of Lalive et al. (2006). In general, the extent to which the length of the time horizon until retirement induces differences in search incentives between workers of different ages depends on the way how the level of future pension benefits is determined. A system where the benefits level is tied to the past wage level is likely to increase the reservation wage and depress the search effort among the older unemployed. The opposite may be true if the level of future pension benefits is an increasing function of the months worked at older ages, in which case the older unemployed have a high incentive to find a new job rapidly. Thus, the Mortensen's (1977) model gives a rather simplified picture of the relationship between the length of the entitlement period and job search for elderly workers.

Moreover, a particular characteristic of many European UI systems is that extended entitlement periods are made available for older workers. Consider a Finnish-type UI scheme where workers older than a certain age threshold at the time of job loss are entitled to an

[5] Mortensen derived a number of other predictions as well. First, the existence of UI benefits increases the transition rates of the unemployed who are not currently eligible for UI benefits. This is so because accepting a job offer qualifies for UI benefits in the future. Second, the time profile of the employment hazard among UI recipients depends on the replacement rate of UI benefits. An increase in the replacement rate increases both the value of search unemployment and the value of accepting a job offer, where the former becomes less important as the exhaustion time gets closer. As a consequence, the higher replacement rate is associated with a steeper hazard rate over the compensated part of the unemployment spell.

indefinite period of benefits. This scheme discourages job search among the unemployed entitled to the extension. In an extreme case an elderly unemployed worker with extended benefits may choose to withdraw from job search entirely, in which case the employment hazard is zero. In our application we take this possibility into account by using a split population duration model. Among younger workers who are not currently eligible for extended benefits, the age-dependent benefit extension increases the value of becoming employed with a given wage, and thereby the employment hazard, because employment qualifies for extended benefits in the future.

**Multiple exit routes**

Although Mortensen (1977) sophistically incorporates the key institutional features of UI into his model, some important aspects of the real-world labour market are abstracted away. The existence of large worker flows between unemployment, employment, inactivity, and various labour market programmes brings into question the extent to which the predictions of the two-state model are carried over to labour markets where workers can escape unemployment via various routes. Obviously, the generosity of unemployment compensation affects the attractiveness of participation in the labour market. Exhaustion of UI benefits in particular may encourage an unemployed worker to withdraw from the labour force rather than to accept lower wage offers. Moreover, the labour market policy in many countries, especially in the Nordic countries, involves a heavy stress on various labour market programmes. Such programmes are often targeted at the long-term unemployed who are at risk of benefit exhaustion. Participation may be associated with a rather high compensation level (e.g. relief work), may postpone the exhaustion day of UI benefits, or may even provide a way of regaining eligibility for UI. Using a search model, Carling et al. (1996) illustrate how the existence of labour market programmes can mitigate the incentive effects of fixed UI duration on the job-finding rate. If postponing the exhaustion day and regaining eligibility are important reasons for programme participation, we should expect much lower hazard rates for exits to such programmes among the older groups entitled to extended benefits.

In the case of multiple exit routes, the expected duration of the unemployment spell and the shape of the employment hazard are not the only questions of interest. From the policy point of view, the likelihood of escaping unemployment through a given route is an equally important question. The goal of policy makers is typically to induce the unemployed to find an acceptable job within a reasonable amount of time, transitions out of the labour force and into labour market programmes being less desired outcomes. The maximum duration of UI benefits is likely to affect all hazard rates, not only the employment hazard. This suggests that a proper way of analysing the role of the UI entitlement period requires a simultaneous account of all cause-specific hazards. We illustrate this point with a numerical example.

Suppose that when a transition out of unemployment occurs, it can be the result of an exit to employment ($e$), active labour market programme ($p$), or out of the labour force ($o$). The hazard function for destination $k \in \{e, p, o\}$ is denoted by $\theta_k(t)$. The cumulative distribution function (CDF) of unemployment duration is given by

$$F(t) \equiv \Pr(T \leq t) = 1 - \exp\left\{-\int_0^t \theta(u)du\right\},$$

where $\theta(u) \equiv \theta_e(u) + \theta_p(u) + \theta_o(u)$ denotes the overall hazard rate out of unemployment. The likelihood of entering employment within a short time interval $(t, t + dt]$ equals $\theta_e(t)\,[1 - F(t)]\,dt$, which depends on all cause-specific hazard functions through $F(t)$. It is important to recognize that a policy reform that causes a uniform increase in the employment hazard does not necessarily imply a higher cumulative or overall probability of employment. The cumulative incidence function (CIF) for destination $k \in \{e, p, o\}$ is defined as

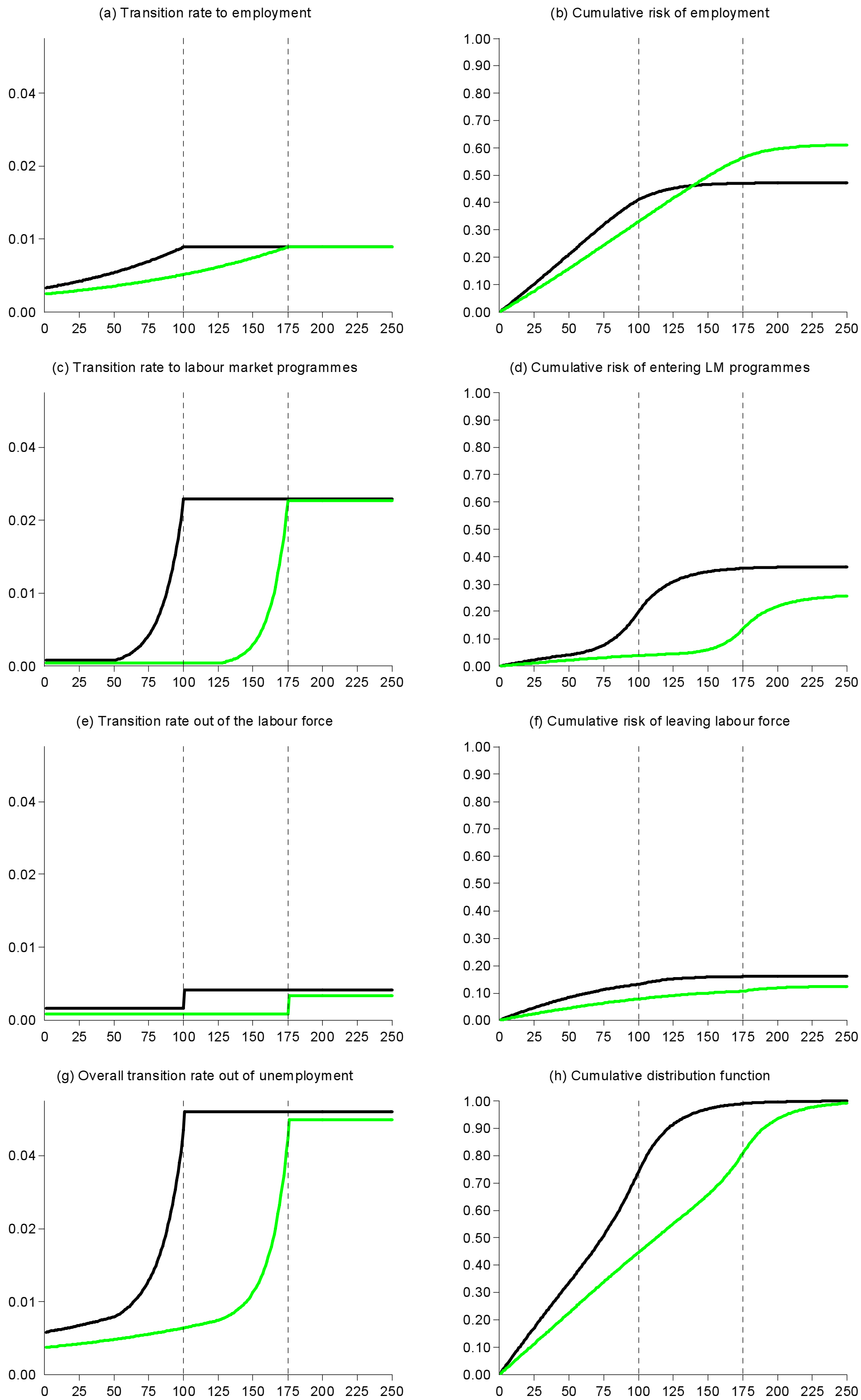
$$F_k(t) \equiv \Pr(T \leq t, K = k) = \int_0^t \theta_k(u)\,[1 - F(u)]\,du,$$

which gives the probability of entering state $k$ by time $t$ (see e.g. Gaynor et al., 1993). It is easy to see that $F(t) = F_e(t) + F_p(t) + F_o(t)$. Moreover, the probability of ever escaping unemployment to state $k$ is given by $\Pr(K = k) = \lim_{t\to\infty} F_k(t)$.

Consider two groups of the unemployed who are otherwise identical but differ in the length of the UI entitlement period. In the first group, UI benefits expire after 100 weeks of unemployment, and in the other group after 175 weeks. Hypothetical hazard functions under the two UI schemes are shown in Figure III.1. Although these hazard functions are not derived from any particular theoretical model, their shapes are intuitively reasonable and do not contradict the implications of the search models discussed above. The employment hazard increases up to the point of benefit exhaustion. The hazard rate for transitions to ALMPs is close to zero over the early stages of unemployment but begins to raise rapidly 50 weeks prior to the time when benefits will expire. There is a discrete upward shift in the hazard rate out of the labour force at the week followed by benefit exhaustion. The longer entitlement period leads to lower hazard rates for transitions to ALMPs and out of the labour force, with the level shifts occurring at a later point in the unemployment spell. The employment hazards under both UI regimes are assumed to converge at the same level. This is not strictly consistent with the prediction of Mortensen's model that the hazard rate associated with the longer UI entitlement period should end up at a higher level. The entitlement effect is neglected here to emphasize our main point.

The longer entitlement period is associated with a uniformly lower overall hazard rate (see Figure III.1g), which implies a longer average spell duration. Without information on the states occupied after unemployment, there is not much more to be said about the effects of the entitlement period length. In particular, we are unable to assess how the overall incidence of employment changes with the length of the entitlement period. One might guess that it must be lower in the case of the longer entitlement period. From Figure

Figure III.1: Entitlement period length and transitions out of unemployment (Note: Black lines correspond to the entitlement period of 100 weeks, and green/grey lines to that of 175 weeks)



III.1b we see that this may not be the case, however. The fraction of the unemployed who will eventually exit to employment is higher among those who are entitled to the longer benefit period. Since the employment hazard of this group never exceeds that of workers with the shorter entitlement period, this outcome is driven by discrepancies in the hazard rates out of the labour force and into ALMPs.

To summarize, competing risks analysis is potentially very useful in evaluating the effects of the length of the entitlement period. This is especially true in the cases where ALMPs play an important role, as in the Nordic countries. In addition, the cumulative incidence functions can be used to summarize information from all cause-specific hazard functions in a policy-relevant way.

**Variation in the entitlement period length**

Much of the empirical analysis of the potential UI duration has focused on detecting spikes in the transition rates around exhaustion time. The finding of an increasing exit rate to employment in the vicinity of UI benefit exhaustion is consistent with theory but has only a limited use from the policy point of view. It does not give much guidance as to how transition rates would change if the entitlement periods were subject to change. To address these questions, one needs some variation in the maximum length of UI benefits.[6] In an ideal setting one would have an inflow sample of unemployed workers who were randomly allocated into groups with varying lengths of UI entitlement periods. This sort of randomized data is not available anywhere, and therefore other sources of variation must be exploited in practice. The extent to which the available data provide variability in the benefit duration that is independent of unobserved determinants of unemployment duration is a crucial identification issue.

In many countries, the maximum entitlement length of UI benefits is partly determined by past work history (e.g. the US, Canada, and the Netherlands).[7] As a consequence, individuals with better track records in the labour market will be entitled to longer UI benefits periods. This suggests an endogeneity problem at the individual level if the past work history that determines the length of the entitlement period is related to unobserved characteristics that also affect the job-finding rate. Moreover, policy changes may cause changes in the entitlement periods across all UI recipients (e.g. US benefit extension programmes and reforms in Norway) or within some groups (e.g. reforms in Germany and Austria) over time. These policy changes are typically triggered by economic downturns, however. If the benefits are extended during periods of high unemployment, longer UI

[6] Even if the existence of a spike around benefit exhaustion were the only matter of interest, variation in the benefit duration would be useful to disentangle the exhaustion effects from the duration dependence.

[7] Where the entitlement period is the same for all UI recipients, the hazard rates have sometimes been compared between UI recipients and non-recipients (e.g. Carling et al., 1996). This is problematic, since workers who are not qualified for UI do not generally serve as a valid comparison group. Eligibility for UI benefit typically requires, among other things, previous work experience and hence non-recipients are often a highly selected group of labour market entrants and individuals with an unstable labour market history.

periods will be available at times when finding a new job is more difficult due to the demand constraint. This leads to an aggregate level endogeneity problem, which may be difficult to overcome unless a suitable control group unaffected by the reform is available to control for business cycle effects. If such a control group is available or the policy change is "exogenous" in the sense that it takes place over a period of stable economic conditions, the policy reforms are potentially very useful for identification purposes. In this study we exploit the UI reform which was not triggered by changing economic conditions and affected only a particular group of the elderly.

### 2.2 Empirical evidence

In the US the maximum duration of UI benefits varies for various reasons: the length of regular benefits varies across states, the entitlement period may depend on the individual's work history, and benefit periods are occasionally extended (at federal or state level) in respond to slackness in the labour market. Meyer (1990) and Katz and Meyer (1990) exploit these sources of variation for identification. They find that the hazard rate out of compensated unemployment increases sharply in the last few weeks of UI benefit eligibility. Moreover, when the benefit entitlement period is extended, the hazard rate also exhibits a peak around the time when benefits were previously expected to lapse. This finding may indicate that some firms recall their workers who are temporary laid-off at the time of the original benefit exhaustion according to a preplanned recall policy. In other words, during business downturns employers attempt to retain their skilled workers but forward part of the bill to the taxpayers via the UI system. Alternatively, some individuals eligible for extended benefits may fail to claim them because they are not aware of such a possibility or because they managed to arrange the start of a new job at the time when UI benefits were originally expected to run out. Furthermore, the simulations of Katz and Meyer (1990) suggest that a 13-week benefit extension (from 26 to 39 weeks) increases the mean spell duration of compensated unemployment by slightly over 2 weeks.

Card and Levine (2000) take advantage of a politically motivated programme that provided up to 13 weeks of extended benefits for those who exhausted their regular UI benefits in the state of New Jersey. The New Jersey Extended Benefit (NJEB) programme was in effect for a limited period of 6 months. Since the NJEB programme emerged as a result of a unique legislative episode that was unrelated to changes in economic conditions, it caused an exogenous change in the entitlement period. Card and Levine (2000) find only a small increase in the fraction of UI recipients who remained unemployed until the exhaustion of their regular benefits. The authors argue that such a moderate effect is attributable to the short-term nature of the NJEB programme, since many of those affected had been unemployed for a while before the programme was introduced. Their simulations suggest stronger long-term effects: Had the programme affected UI recipients from the beginning of their spell, the average duration of regular benefits would have increased by one week and the fraction exhausting the regular benefits would have risen by 7 percentage points.

The two major data limitations of these US studies are worth emphasizing. First, only unemployment spells covered by the UI system are observed. All spells ongoing at the time of benefit exhaustion are censored, and hence nothing can be said about the transition rate beyond the exhaustion point. Second, the data do not permit competing risks analysis because it is not possible to distinguish whether a completed spell ended through recall, the taking of a new job, withdrawal from the labour force, or exit to uncompensated unemployment. That is, what has been analysed is the overall rate out of compensated unemployment up to the point of benefit exhaustion.[8]

Consistent with the US evidence, Ham and Rea (1987) find the conditional probability of leaving unemployment through the finding of a new job to increase just prior to the exhaustion of UI benefits in Canada.[9] Lindeboom and Theeuwes (1993) provide evidence that the overall hazard rate out of unemployment increases sharply as the entitlement period comes to an end in the Netherlands.[10] By analysing the number of search contacts over the course of the unemployment spell, they conclude that the benefit exhaustion effect is mainly due to the declining reservation wage. Micklewright and Nagy (1999) recover a clear spike in the job-finding rate around the time of UI exhaustion in Hungary. They do not find evidence that the transition rate is strongly affected by the probability of being eligible for means-tested social assistance after UI exhaustion. Jenkins and García-Serrano (2004) detect only a moderate increase in the hazard to employment prior to the exhaustion of UI benefits in Spain. Somewhat surprisingly, longer entitlement periods appear to be associated with higher re-employment hazards (Figure 1, p. 255). While this observation was not discussed by the authors, it may be an indication of the endogeneity problem, since there was no clear exogenous variation in entitlement periods in the Spanish data. The length of the entitlement period was completely determined by the number of months for which contributions had been made over the 48-month period prior to unemployment.

Evidence on exhaustion effects from the Nordic countries, where benefit levels are higher, entitlement periods longer, and labour market programmes play a more important role, is less convincing. Carling et al. (1996) find only very weak evidence of an increase in the job-finding rate of UI recipients compared with that of non-recipients around the exhaustion time of UI benefits at 60 weeks in Sweden. There were no significant differences

[8] Katz and Meyer (1990) provide some indirect evidence that much of the observed effect of the potential duration of UI is expected to arise from differences in recall and job-finding hazards. Using complementary data from the Panel Study of Income Dynamics, they compare the distributions of unemployment spells between UI recipients and non-recipients. This source of data provides information on exit states and the eligibility status of UI benefits but lacks information on the benefit level and length of entitlement periods for UI recipients. Katz and Meyer (1990) find substantial peaks in both the empirical recall rate and the new job-finding rate around the durations when UI benefits are "likely to lapse" for UI recipients but not for non-recipients. These descriptive findings are consistent with a more formal analysis by Han and Hausman (1990) who apply a competing risks duration model to the same data.

[9] The length of the UI entitlement period is determined by the past work history and the local unemployment rate. The mean entitlement period in the data is 36 weeks.

[10] The length of the entitlement period depends on the past work history, the maximum duration being 26 weeks.

in the hazard rates out of the labour force between the two groups. By contrast, the transition rate to ALMPs among UI recipients increases sharply near the time of UI benefit exhaustion, being almost five times higher than the transition rate of non-recipients immediately after UI benefits have run out. These findings are intuitively reasonable in view of the fact that Swedish labour market policy involves a right to a temporary public job or training course for the unemployed whose benefits lapse.

In Norway, until 1991, UI benefits expired temporarily for 26 weeks after 80 weeks of continuous unemployment. This was then followed by a second covered 80-week unemployment period with somewhat reduced UI benefits.[11] As a response to increasing long-term unemployment, the intervening period without benefits was first shortened to 13 weeks in 1991 and one year later was abolished entirely. Bratberg and Vaage (2000) and Røed and Zhang (2003) document rises in the transition rate out of unemployment just prior to temporary and permanent benefit exhaustion. These effects are stronger for women than for men (Røed and Zhang, 2003). The reforms were followed by a drop in the employment hazard over the early stages of the unemployment spell but there is no evidence of increases in the employment hazard around benefit exhaustion (80 weeks) prior to the reforms, nor after the reforms (Bratberg and Vaage, 2000). Thus, the observed peaks in the overall hazard rate around (at least temporary) benefit exhaustion are due to the increasing outflow to other end-states than employment.

In the UK, the level of UI benefits does not depend on previous earnings but is a flat rate. If UI benefits expire, the individual can claim means-tested social assistance that is comparable to UI payments and potentially available for an indefinite period. Therefore, there is practically no fall in the level of unemployment compensation when the individual passes from UI benefits to social assistance. Stancanelli (1999) exploits this feature of the UK system in detecting benefit exhaustion effects. She compares hazard rates to full-time employment between those unemployed that should expect their benefits to exhaust and those whose benefit level is unlikely to change due to eligibility for social assistance.[12] Although a larger spike near the time of benefit exhaustion at 52 weeks exists for those whose benefits are going to expire, Stancanelli (1999) does not find statistically significant differences in the hazard functions for the two groups.

Hunt (1995) evaluates the impact of a series of UI entitlement extensions for older workers with much work experience in the former West Germany. These policy measures were motivated by concern about the increasing unemployment rate and long average spell duration of older workers. The number of additional months for UI benefits was tied to the amount of past work experience. As a result of an increase in the maximum UI duration

[11] UI benefits depend on past earnings and the system is universal covering all workers with earnings above a minimum level.

[12] Eligibility for social assistance depends on the level of household savings and spouse's earnings. Since household savings tend to be correlated with the work history of the unemployed individual, the same kind of endogeneity issues arise as in the UI systems where the length of the entitlement period is directly tied to past work history.

from 12 to 22 months, the hazard rates for workers aged 44 to 48 were found to fall by 46% for transitions to employment and by 63% for transitions out of the labour force. Among older workers between the ages of 49 and 57, only the hazard rate out of the labour force fell by 56% in response to an increase in the entitlement period from 12 to 32 months.

A reform similar to the German case took place in Austria around the turn of the 1990s. The reform was a response to a privatization process of nationalized firms that led to mass layoffs due to plant closures and downsizing especially in the steel industry (Winter-Ebmer, 1998, and Lalive and Zweimüller, 2004). The maximum entitlement period of UI benefits was raised from 30 or 52 to 209 weeks for workers aged 50 or more with experience above a certain threshold living in certain regions of the country. In terms of pre-reform labour market conditions, the counties selected for the extended benefit periods were similar to other counties but characterized by a larger employment share in the steel industry and hence expected to be hit by a negative demand shock. Winter-Ebmer (1998) finds a decrease in the exit rate to a new job for men, but no notable effects on transitions to recall employment, retirement, or non-participation for either gender.[13] The resulting increase of 5 weeks in men's unemployment duration is very low, given the substantial increase in the maximum benefit duration. Lalive and Zweimüller (2004) exploit variation in the programme eligibility across regions and over time in an attempt to account for policy endogeneity. They conclude that the increase in the UI entitlement period from 30 to 209 weeks declined men's transition rate to employment by 17%.

The focus of Finnish empirical literature has been on the effects of benefit levels (e.g. Kettunen, 1993, Lilja, 1993, Kyyrä, 1999, Holm et al., 1999). There are no studies with an emphasis on the role of the entitlement period length. In the late 1980s the Finnish UI system included a cut in the level of UI benefits. Within the period from April 1987 to July 1989, UI benefits were reduced by 12.5% after 40 weeks of unemployment (and finally expired after 100 weeks). Exploiting the removal of the cut in 1989, Uusitalo and Moisala (2003) find an increase of some 8% in the employment hazard when the cut kicks in, but this effect was not statistically significant. Empirical hazard rates for UI recipients aged 52 or less reported in Koskela and Uusitalo (2006) exhibit no peaks for transitions to employment, but a level shift at one year that is followed by an additional peak after two years for transitions to labour market programmes. These descriptive observations are in line with evidence from Sweden and Norway. The absence of significant increases in the employment hazard around the exhaustion of UI benefits in the Nordic countries is perhaps attributed to relatively long entitlement periods, the availability of welfare payments after UI benefit exhaustion, and easy access to active labour market programmes.

[13] A fully parametric Weibull model was adopted, so that all hazard functions were restricted to being constant, monotonically increasing, or monotonically decreasing.

# 3 The Institutional Framework

We shall discuss the features of the Finnish social security system during the second half of the 1990s, i.e. around the time of our empirical analysis. It should be stressed that the Finnish system has been subject to continuous changes over the years. A more complete description of the regulations and current reforms affecting early retirement is provided by OECD (2004).

## 3.1 The unemployment compensation system

The Finnish compensation system distinguishes between the basic unemployment allowance, earnings-related unemployment insurance (UI) benefit, and labour market support. The earnings-related UI benefit is received by workers who have been working and contributing insurance payments to an unemployment fund for at least 10 months during the two years prior to unemployment.[14] Those who fulfil the employment criteria of having worked at least 10 months but do not belong to any unemployment fund are eligible only for the basic allowance (which amounts to 115 euros per week in 2003). The replacement rate for the earnings-related UI benefit declines with the level of former earnings, the gross and net replacement rates for a worker with median earnings being 55% and 64% respectively (Koskela and Uusitalo, 2003). The basic allowance and UI benefit can be received for a maximum of two years, i.e. 500 working days, but an exception is made for the elderly (see below). Workers who do not meet the employment criteria or whose entitlement period has been exhausted can claim labour market support, which is viewed as a minimum income for the long-term unemployed and those entering the labour market. The maximum benefit level for labour market support equals the basic unemployment allowance, but it is means-tested against household income.

## 3.2 Early retirement schemes and the unemployment tunnel

Disability and unemployment pensions are the major pathways of early withdrawal from the labour market.[15] The disability pension is payable to people between the ages of 16 and 65 who are unable to support themselves by regular work due to deteriorated health. Although receipt of disability pension is conditional on a medical assessment, almost one-fifth of all people aged 55 to 64 were on a disability pension in 2001 (Rantala and Romppanen, 2004). Compared with most other OECD countries, the incidence of disability among older people seems to be particularly high in Finland (OECD, 2004, p. 58). The disability pension provides a benefit level close to normal old-age pension benefits, which may partly explain its popularity. The unemployment pension is payable to a

[14] The unemployment funds are closely related to labour unions. The fund membership is voluntary, and workers can join the fund without joining the union.

[15] Other early retirement schemes include early old-age pension, individual early retirement, part-time pension, and farmers' pensions. These schemes are of less importance and are not discussed here. See OECD (2004) for a more complete description of the Finnish pension system.

person aged between 60 and 64 who has been unemployed and has collected unemployment benefits for at least two years. The compensation level of the unemployment pension is close to other early retirement schemes and usually exceeds the level of UI benefit.[16] At the age of 65 unemployment and disability pensions are transformed into normal old-age pensions.

The unemployed who turn 57 (55 before 1997) during their initial two-year period of unemployment benefit entitlement are allowed to collect unemployment benefits up until the age of 60. Thus an unemployed person at least 55 years and 1 month of age (53 years and 1 month or over before 1997) at the beginning of the unemployment spell has an option to collect unemployment benefits up to the entry into the unemployment pension scheme, which will be subsequently followed by a normal old-age pension. This combination of the extended unemployment benefit entitlement period and the unemployment pension has become known as the "unemployment tunnel" (UT).

There have been two reforms in the UT scheme that are relevant for our analysis. The first one ("1996 reform") cut benefit levels for various early retirement schemes, including unemployment pensions.[17] The reduced benefit levels apply to workers who start collecting early pension benefits in 1996 or later. This law was enacted by the parliament in September 1995. There was, however, a peculiar protection clause in the law: all workers born before 1943 who were unemployed on the first working day of 1996 remain covered by the old rules in case of early retirement (regardless of the day the early retirement event takes places in the future). As we shall see, the anticipation of the law change caused an excess inflow to unemployment at the end of 1995 among elderly workers who benefited from the protection clause. Although this reform is not of our interest, we need to take it into account in our research design.

Another reform ("1997 reform") raised the age threshold for the extended benefit period from 55 to 57. This reform was passed as a law by the parliament in September 1996, and it came into effect on January 1st 1997. However, according to a protection clause, the former threshold was applied to workers born before 1944 who were unemployed on January 1st 1997 if they either resigned from their job or were made redundant before June 1996. As a result, individuals aged 53-54 becoming unemployed before June 1996 were eligible for the extension, but those becoming unemployed in 1997 no longer were. Because of the period of notice which can be 6 months at maximum, workers aged 53-54 who entered unemployment in 1996 between June and December may or may not be

[16] The compensation levels of UI benefits and unemployment pensions are determined by previous earnings over the periods of different lengths. The UI benefits tend to be higher for workers with a steeply increasing earnings profile before job loss. Rantala (2003) finds that transitions from unemployment to the unemployment pension were followed by an average increase of 16 percent in the gross compensation level in 1996 and 1997.

[17] The accrual rate for projected pensionable service was decreased from 1.5% per year to 1.2% per year while aged under 60 and to 0.8% per year while aged 60 to 65. (Projected pensionable service is the time period from the pension contingency to the age of 65. The projected pensionable service increases the amount of pension, since it is calculated as if the person had continued working until the age of 65. A pension accrues according to a lower accrual rate, however.)

eligible for the extension, depending on the exact timing of resignation or dismissal.

The aim of this 1997 reform package was to cut unemployment expenditures, to improve employment incentives among the unemployed, and to close certain loopholes in the system. The unemployment pension scheme was perceived as a loophole, given that some companies had exploited the existing system when downsizing and it had turned into a somewhat generally acceptable early retirement scheme. Hence, the government wanted to phase the system out.[18] Since there is no reason to believe that the age threshold was raised in response to a change in relative labour market conditions for the older workers, our analysis should not be subject to endogenous policy bias.

### 3.3 Active labour market programmes

Although finding suitable employment for the unemployed is the main goal of policy makers we should bear in mind that in the Finnish case active labour market programmes are a significant route out of unemployment and, thus, cannot be ignored. However, the elderly unemployed were not specifically targeted with active measures during the 1990s, since unemployment among them was not foreseen as the most acute problem. In general, participation in ALMPs tends to be lowest in the oldest cohorts, ranging from some 25% of all unemployed in the youngest cohorts to some 17% in the eldest cohorts (Aho, 2005).

The programmes are offered to the unemployed by the employment office, but an unemployed individual can also apply for these measures unprompted.[19] During the placement period in subsidised employment a participant receives the prevailing market wage set in collective agreements. Subsidised employment contracts in the private sector are expected to be continuous and may thus result in the unemployed individual renewing eligibility for earnings-related benefits by fulfilling the 10 months' time-at-work condition. Job placements in the public sector tend to be fixed-term and shorter by nature (often 6 months) and, thus, a single such period does not usually suffice to renew eligibility.[20] During participation in labour market training the participants receive a sum equalling their unemployment compensation together with a daily allowance for maintenance and possibly for accommodation. The training period neither consumes nor accumulates the UI entitlement period left.

While for some unemployed people ALMPs may truly be a way of obtaining contacts and skills leading to a secure job, there is also the possibility that others simply comply to participate in order to prolong the exhaustion of benefits or to regain foregone eligibility. If the latter should apply, the older individuals entitled to extended UI benefits have little

[18] The age threshold for the extended period of unemployment benefits was raised by two additional years in 2005. Over the period 2009-2014 the unemployment pension scheme will be gradually abolished and replaced with additional unemployment benefit days for the elderly until the age of 65.

[19] Should an unemployed individual refuse to participate in these measures without a valid reason if such a measure is offered to him, he will be deprived of unemployment compensation for a period of 60 days.

[20] According to Virjo et al. (2006) in 1996 and 1998 some 15 percent of all the unemployed were receiving earnings-related benefits owing at least in part to participation in the programmes.

incentive to participate in these programmes, and we might also expect this to show up in our results.

### 3.4 Incentives

Large numbers of older workers have been found to withdraw from the labour market several years before the normal retirement age. This finding is related to the elements of the Finnish social security system that induce firms to focus workforce reductions on older workers on the one hand, and discourage the elderly unemployed from returning to work on the other hand. Consider the supply side first. As those who are eligible for the extended entitlement period cannot lose their unemployment benefits, they may be less active in searching for employment opportunities and claim higher wages. There are also doubts that the employment authorities may not forward job offers that arrive at the public employment offices to the oldest applicants. Accepting a low wage job can reduce future old-age pension benefits, which may increase the wage claims of the older unemployed. It may also be difficult to find wage offers close to the previous wage level, as post-unemployment wages are generally clearly below the average wage level (see Holm et al., 1999). Overall, financial incentives to return to employment are rather poor for the elderly unemployed.

For the employer, keeping elderly workers can be a risky business. Employers are liable for a large fraction of early retirement expenditures via partially experience-rated employer contributions. Experience-rating is not applied to firms with fewer than 50 employees, but larger firms have to pay a given proportion of the early pension benefit stream received by their former employees. This cost share is determined as a linear function of firm size. In the case of the unemployment pension, firms with over 300 employees pay a maximum amount of one-half of the overall cost, whereas medium-sized firms with 51-300 employees pay a lower share. A different scale is applied to the disability pension, in which case the former employer pays 0% (firms with fewer than 50 employees) to 100% (firms with more 1000 employees) of the early pension expenditures. In practice, the cost share of the disability pension exceeds that of the unemployment pension for firms with more than 500 employees.[21] The opposite is true for firms with 51 to 500 employees, while it does not make any difference for smaller firms.

It is worth emphasizing that costs incurred by the employer can cumulate over several years until the former employee reaches the age of 65 and transfers to an old-age pension. Once again, there is a difference between the two schemes: unemployment pension costs cannot be realised until the former employee turns 60 but disability pension costs may emerge much earlier. For example, a worker laid off at age 55 must remain unemployed for five years before he or she can enter the unemployment pension. Since the employer is not liable for unemployment benefits received by its former employees, the UT scheme may be a financially attractive option to get rid of elderly employees with a high disability risk

[21] The experience-ratings of the two early pension schemes were harmonized in 2000.

also for medium-sized firms which have to pay a higher share of unemployment pension expenditures than disability pension expenditures.

It is evident that early retirement can become costly for the former employer, especially in the case of a large firm. Discrepancies in experience-rating and timing of early retirement costs between disability and unemployment pensions may encourage economically distressed firms to lay off older workers. In doing so, the firm avoids the risk of incurring disability pension costs later, i.e. the risk that is rather high in the light of official statistics. Moreover, the fear of future early retirement cost may induce firms to discriminate against older job applicants in recruitment.[22]

# 4 Data and descriptive statistics

## 4.1 The Employment Statistics database

Our data were drawn from the records of the Employment Statistics (ES) database of Statistics Finland. Since 1987 the ES database has been updated regularly by merging information from over 20 administrative registers through the use of unique personality identity numbers. The ES database effectively covers all people with permanent residence in Finland, and its information content is extensive. Along with standard socio-demographic background variables, the database includes detailed information on annual income (from the tax authorities), job spells (from the pension institutes), unemployment spells and participation in labour market programmes (from the employment offices). With this source of data one can basically follow the entire Finnish population over time and across different labour market states. This sort of comprehensive data is available for economic research mainly in the Nordic countries, where collection and maintenance of large-scale administrative registers, with unique identification information, has a long tradition. When our samples were drawn the records of the ES database were available for the period 1988-2000.

## 4.2 The incidence of unemployment

The UT scheme is of less importance in the public sector, where employers have weaker financial incentives for age discrimination and workers with a long employment history gain from a high level of job security. In the following analysis we therefore consider private sector workers only. Our analysis focuses on the second-half of the 1990s which was a time of stable economic growth and high unemployment. The Finnish economy was hit by a severe depression in the early 1990s. The GNP contracted three years in a row (1991-1993), and at the worst, in 1991 the GNP decreased by over 7%. According to the

[22] Age-dependent social security contributions further raise the costs of older workers compared with prime-age workers. In 2003, the contribution paid by the employer on top of the wage received by the worker varied from 19.3 to 38.4 percent, being an increasing function of firm size and the worker's age (OECD, 2004, p. 82).

Labour Force Survey the unemployment rate increased from 3.2% to 16.6% between 1990 and 1994, even though masses of people were removed from the unemployment register and directed to labour market programmes. The depression was followed by a period of strong and stable economic growth. The average growth rate of GNP was above 4% between 1994 and 2000. The unemployment rate declined approximately by one percentage point each year over this period, reaching 9.8% in 2000.

Figure III.2 displays the risk of becoming unemployed by age and year in the private sector. The unemployment risk corresponds to a proportion of workers who were continuously employed over the past year but who became unemployed or participated in a labour market programme during the current year.[23] This group of workers is eligible for unemployment benefits in the case of job loss, and hence exposed to the UT scheme. These workers are also very likely to be members of unemployment funds, and thereby eligible for earnings-related UI benefits.

Before the 1997 reform those who were 53 or older at the beginning of their unemployment period were eligible for the extended period of unemployment benefits, owing to the UT scheme. In 1994, 1995, and 1996 the likelihood of unemployment jumped at the age of 53, increasing thereafter smoothly up to the age of 58. In each year the unemployment risk starts to decline at around the age of 60, suggesting that the oldest workers can leave the labour market through other early retirement schemes. At the beginning of 1997 the age threshold for the UT scheme was raised by two years (for those who resigned from their job or were made redundant after May 1996). As a result, the unemployment risk as a function of age shifted forward by two years in 1997 and 1998 compared with the earlier years. In particular, the risk of unemployment in the age group 53-54 dropped to a level roughly identical to that of younger groups. This clearly indicates that the sharp level shift in the unemployment risk after a given age cannot be a coincidence but is driven by the UT scheme. Moreover, the inflow to unemployment among workers aged 53 and 54 is much higher in 1996 than in 1994 and 1995. This suggests that some employees who were eligible for extended UI benefits in 1996 but lost their eligibility temporarily as a result of the increase in the age threshold in 1997 entered unemployment in 1996 in anticipation of the law change.

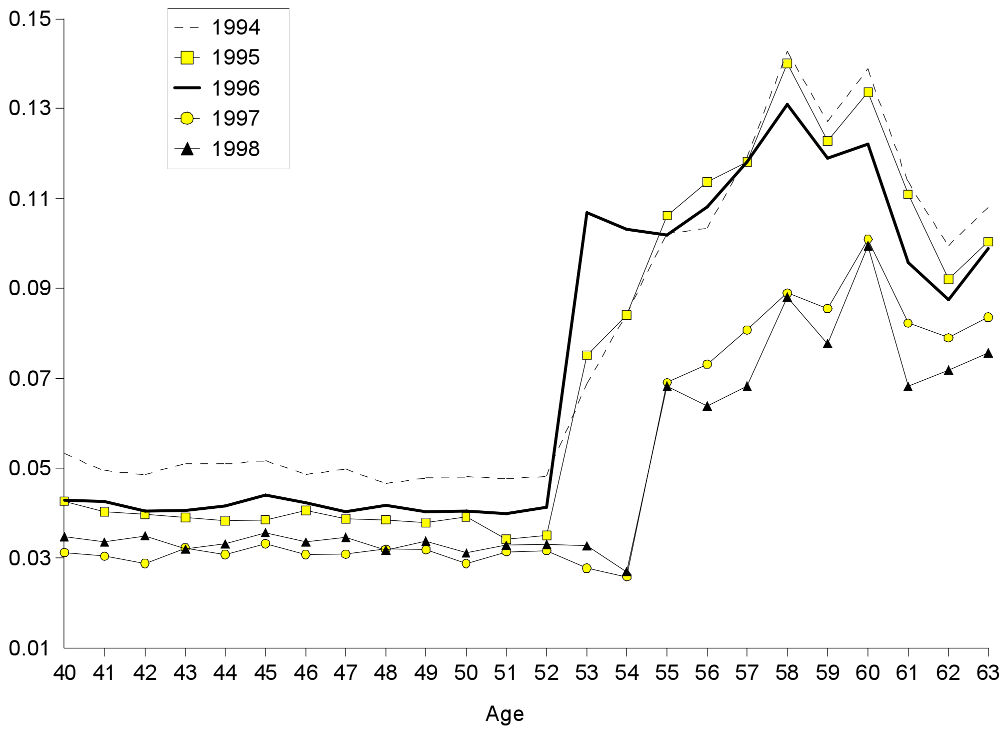
A third noteworthy pattern in Figure III.2 is a clear decrease in the incidence of unemployment among workers aged 55 and over after the 1997 reform. This is partly illusory, however, as the annual unemployment risks of older groups in 1995 and 1996

[23] More specifically, the risk of unemployment in year $t$ for $k$ years old workers is computed as

$$1-\prod_{m=1}^{12}\left[1-p_{t,m}(k)\right],$$

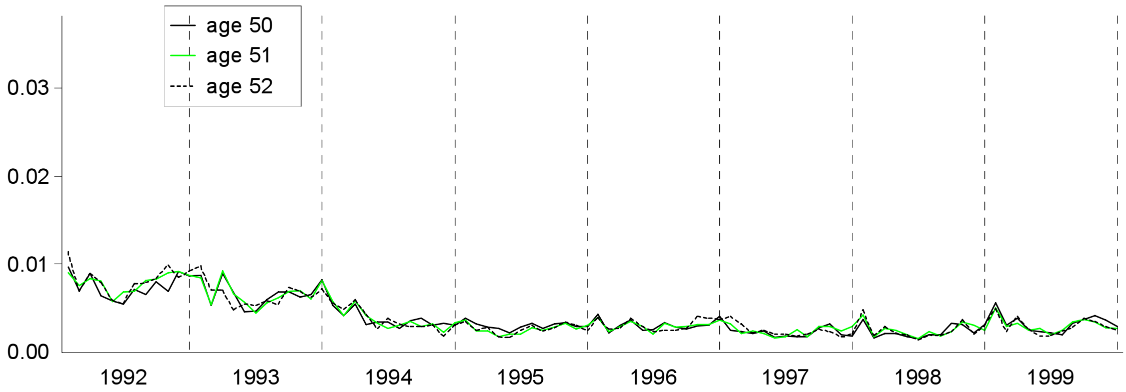
where $p_{t,m}(k)$ is the monthly layoff rate among workers aged $k$ at the end of month $m$ in year $t$, which is defined as the ratio of workers unemployed (and those participating in labour market programmes) at the end of month $m$ who were employed from the beginning of year $t-1$ to the end of month $m-1$ in year $t$ to otherwise equal workers but who were still employed at the end of month $m$. Data on the entire population of private sector employees were used for calculations.

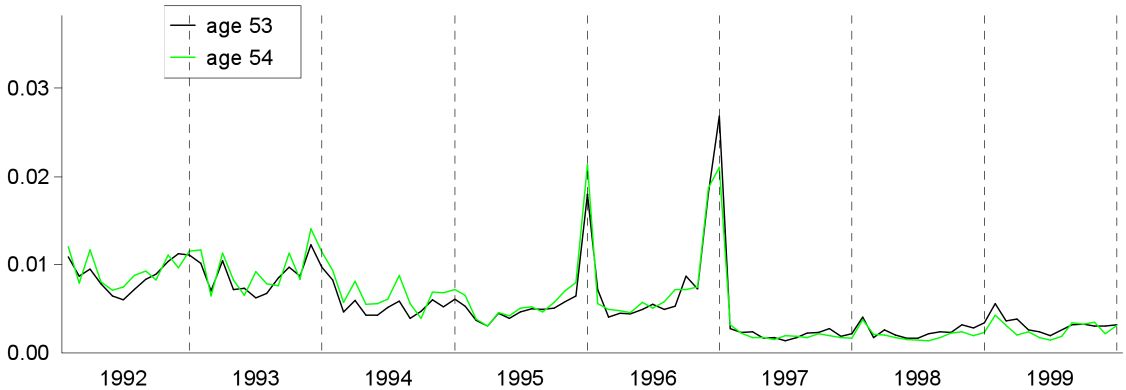
Figure III.2: Annual unemployment risk by age and year in the private sector (Source: the authors' calculations from the ES database)

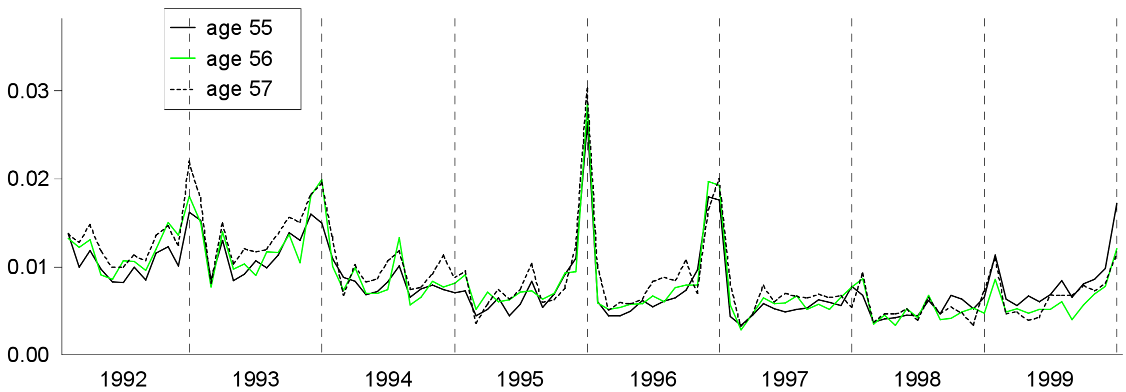



are inflated by the anticipation effects of the two distinct UT reforms. The presence of anticipation effects can be seen from Figure III.3. The inflow to unemployment increases sharply among workers aged 53 or over (i.e. those born before 1943 who were covered by the protection clause of the 1996 reform) at the end of 1995, while there is no evidence of peaks for younger groups. An even larger increase in the unemployment risk occurs at the end of the next year for workers aged 53 and 54 who were affected by the 1997 increase in the age threshold for the UT scheme. This is consistent with the anticipation hypothesis of the 1997 reform. Surprisingly, the unemployment inflow also increases, though less strongly, among older workers who remain unaffected by the 1997 reform. There is no obvious explanation for this phenomenon. This "shadow effect" may arise from uncertainty about the forthcoming reform if firms and employees were aware that the age threshold will increase but did not know by how much. This may be the case here, as the exploitation of the prior age threshold required that the dismissal or resignation took place several months before the law was enacted by the parliament in September 1996. When interpreting the results one should note that the majority of the elderly workers who entered unemployment in the late 1996 were likely to be covered by the protection clause of the 1997 reform because of 6 months' notice for workers with long job tenure.

Figure III.3: Monthly unemployment risk by age in the private sector (Note: Vertical lines correspond to Decembers. Source: the authors' calculations from the ES database.)



Compared with 1998, the inflow rate in 1997 is lower for younger groups but higher for older groups (see Figure III.2). In 1998 the lower age limit for part-time pensions was reduced from 58 to 56. Workers on part-time pension remain employed but work less than five days per week or do a reduced number of hours per day. If employers view part-time pensions as an alternative way of adjusting working hours in the case of older employees, this reform may partly explain the decline in the unemployment risk among the older groups in 1998.

Older workers who are eligible for extended UI benefits are clearly much more likely to become unemployed than their younger co-workers. It is hard to explain this phenomenon with a simple supply or demand side story alone. In most cases, unemployment causes, along with a social stigma, a notable cut in both gross and net income. Therefore, a claim that elderly workers are flowing into long-term unemployment of their own free will does not sound very convincing. Moreover, it seems economically irrational for employers to lay off disproportionate numbers of workers who have just passed the age limit of the UT scheme. Such workers yield a liability to the firm for the unemployment pension expenditure. The firm could easily avoid this liability by laying off employees that are a few years younger. In the case of a large firm (with more than 500 employees), which aims to minimise the risk of disability pension expenditures, targeting dismissals at the elderly group of workers may have some economic reasoning. This is so because large firms must pay a higher cost share of disability pensions than of unemployment pensions. But this does not explain why layoffs tend to fall on the elderly employees in firms of all sizes (see Rantala, 2002, and Section 5 below).

One possibility is that the dismissals of older people, whose income levels are secured through the UT scheme or some other early retirement scheme, have an implicit approval from the general public and, to some extent, from the older people themselves. For example, some elderly people may agree to accept a lower income level in favour of much more leisure time. This view is formalised in a study by Hakola and Uusitalo (2001). Building on the work of Arnott et al. (1998) and Hutchens (1999), they lay out an optimal contract model of early retirement for Finland. In their model the dismissals of elderly employees are determined via an optimization problem where both the employer and employee are involved. An optimal contract specifies wages, firing rules, and severance payments so as to maximise the sum of expected utilities of the employer and employee. Within this framework a partially experience-rated unemployment pension system subsidizes effectively the dismissals of the elderly employees. This encourages firms to target dismissals at their older employees, which subsequently increases early retirement. In other words, if a firm cares about the welfare of its employees, it organises workforce reductions so that losses to the employees are minimised, which means that those who are eligible for the extended UI period are displaced in the first place. Hakola and Uusitalo also show that a number of predictions of their theoretical model are in accordance with empirical regularities observed in the Finnish micro data.

### 4.3 The sample of the elderly unemployed

In the subsequent analysis of unemployment durations, we focus on private sector workers aged 50-54 becoming unemployed between 1995 and 1998, having been continuously employed for at least one calendar year prior to the year of job loss, and being thus likely eligible for earnings-related UI benefits. We further restrict the sample by including only those with UI benefits higher than 14 euros per day,[24] which corresponds to the amount of basic unemployment allowance at the time. For each worker in the data we observe the length of the unemployment spell (in days), exit destination, and a set of control variables. All unemployment spells that continue beyond the end of 2000 are treated as censored.

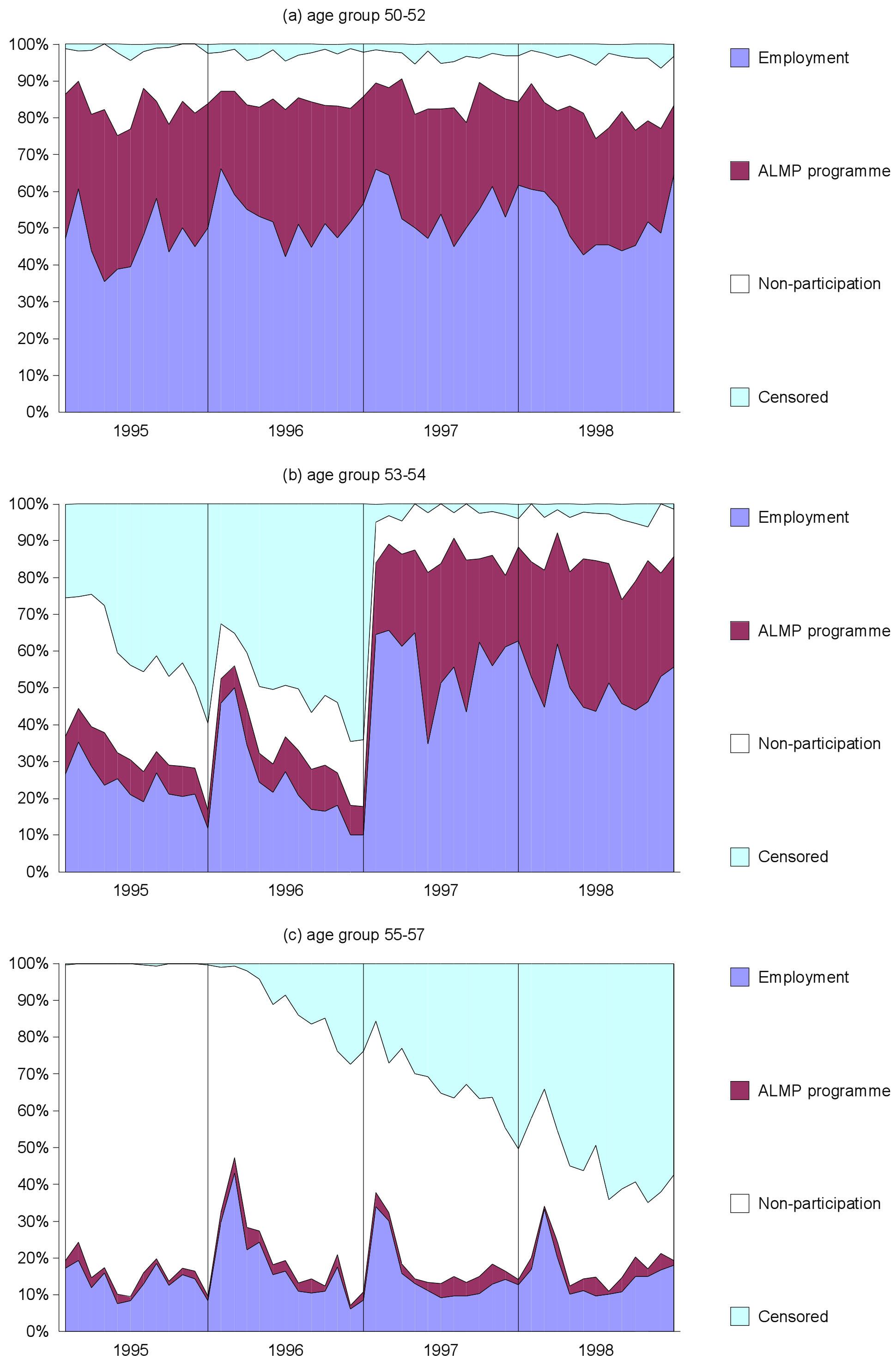
The age threshold for the newly unemployed to be eligible for the extended UI benefit was increased from 53 to 55 years in 1997. This effectively reduced the unlimited entitlement period to two years among the group aged 53-54 at the time of job loss, providing a quasi-experimental setting for studying the relationship between the length of the UI entitlement period and transitions out of unemployment. We allocate workers to groups on the basis of their age at the beginning of the unemployment spell and the time they entered unemployment. Workers aged 53-54 who entered unemployment in 1995 or 1996 are referred to as the *treatment* group since their behaviour is affected by eligibility for the extended UI benefits. Workers aged 53-54 who became unemployed in 1997 or 1998 serve as the *comparison* group. Apart from eligibility for the extended UI benefits and the timing of unemployment entry, this group is assumed to be highly similar to the treatment group. Workers aged 50-52 are labelled as the *control* group, as they are used to identify the business cycle effect.

Figure III.4 shows the distribution of post-unemployment destination states by age group and the month of unemployment entry. For comparison purposes, we include also workers aged 55-57 which were eligible for extended benefits in all years. The unemployed in the youngest group typically exit to employment or labour market programmes. For this group the distribution of different exit events has remained stable over time. Workers between the ages of 55 and 57 rarely find a new job, and they do not participate in labour market programmes. For this group, when the destination state is observed, it is most likely to be retirement (i.e. non-participation). A high degree of censoring for the spells that started in 1997 or 1998 further implies that many retirements occur after the end of the observation period. The distribution of destination states for the age group 53-54 closely resembles that for the age group 50-52 in the 1997 and 1998 inflows. However, roughly one-half of the unemployment spells of workers aged 53-54 that started in 1995 or 1996 had not terminated by the end of 2000. This indicates very long periods of unemployment for this group prior to the increase in the age threshold of the UT scheme.

Among the two older groups, the degree of censoring is particularly high and the share of exits to employment low for the spells that started at the end of 1995 and 1996 while

[24] And less than 75 euros per day.

Figure III.4: Post-unemployment destination by age and the month of unemployment entry, percent (Note: Vertical lines correspond to Decembers)



the opposite is true for the spells that started in the early 1996 and early 1997. There is no similar variation over time for the age group 50-52.[25] This further highlights the selection issues arising from anticipation of the two distinct UT reforms: the elderly employees who expected to start a long spell of unemployment in the early 1996 or 1997 (i.e. those who believed to benefit from extended UI benefits and/or unemployment pension) tend to advance their unemployment entry in order to benefit from the prior rules. To identify the effects of eligibility for extended benefits in the absence of anticipation and selection issues, we exclude the following groups from the duration analysis:

- *All individuals who entered unemployment between October 1995 and January 5th 1996.* Anticipation of the 1996 reform led to the excess inflow to unemployment at the end of 1995 among workers aged 53 and over owing to the protection clause of the law (see Figure III.3). These workers are nonrandomly selected with respect to their re-employment prospects, as implied by the increase in the share of censored spells and the decline in the share of spells ending in employment particularly in December 1995 in Figure III.4. Individuals aged 50-52 who became unemployed in the same period are excluded to keep the seasonal composition of the 1995 inflow identical for both age groups.

- *All individuals who entered unemployment between June 1996 and December 1996.* The eligibility status is not clear for workers aged 53 or 54 who became unemployed during this time interval as it depends on the day of resignation or dismissal which is not known. Most of these workers are likely to be eligible for the UT scheme due to the period of notice but we cannot be sure. In addition there is an obvious selection problem at the end of 1996 due to the anticipation of the 1997 reform (see Figures III.3 and III.4), which we avoid by focusing on individuals entering unemployment before June. It should be noted that the first half of 1996 for the age group 53-54 may still be subject to another selection issue due to the anticipation of the earlier reform. The high share of exits to employment among the spells that started in the early 1996 imply that some of those who expected to retire via the UT scheme and who would have become unemployed in the first half of 1996 in the absence of the 1996 reform did so already in 1995 in order to benefit from the old rules. For this reason the 1996 inflow sample of the age groups 53-54 remains problematic, which we should keep in mind.

- *Individuals born in 1942 or 1943 who entered unemployment in 1997-1998 at age 53*

[25] As pointed out in Section 2.1, the age-dependent benefit extension may affect also job search incentives of the unemployed who are not currently entitled to extended benefits. In particular, those who are only slightly below the age threshold may be able to qualify themselves for extended benefits by accepting a short-term job or participating in ALMPs. This suggests that the 1997 reform may have had an indirect effect also on workers aged 52 at the time of job loss. However, we find only a marginal change in exit behaviour of the 52-years-old after the 1997 reform compared with younger workers, and excluding them from the control group does not change our results.

*or 54.* In 1996 the 1942 and 1943 birth cohorts were 53 years old, and thereby eligible for extended benefits, but they lost their eligibility briefly on January 1st 1997 as a result of the increase in the age threshold. Those who expected to experience a long spell of unemployment starting in 1997 or 1998 had an incentive to enter unemployment already in 1996. This claim is supported by the excess inflow to unemployment among workers aged 53-54 at the end of 1996 (see Figure III.3). As a consequence, individuals born in 1942 or 1943 who became unemployed after the 1997 reform are likely to be a selected group in terms of skills and motivation. By excluding these workers, we effectively restrict the age group 53-54 entering unemployment in 1997-1998 to those who were born between 1944 and 1945. These workers were not eligible for extended benefits in 1996, and hence were not able to gain from the protection clause of the 1997 reform.

These excluded groups were chosen on the basis of the timing of the law changes, the details of the protection clauses, and our first impression of the timing of anticipation effects. It is not clear at which time employers and employees actually became aware of the forthcoming law changes. For example, the observed increases in the unemployment risk at the end of 1996 for the older groups show that anticipatory decisions were made well before the law change was enacted by the parliament. In Section 5 we assess the validity of the included groups in more detail.

Sample statistics by age group and by year of entering unemployment are shown in Table III.1. The average duration of an unemployment spell is roughly one year for the 50 to 52-year-olds entering unemployment in 1995 – 1998, as well as for the 53 to 54-year-olds entering unemployment in 1997 and 1998, but it is much longer for the older cohort entering unemployment in 1995 and 1996. When considering only completed spells eventually ending in employment, differences between the groups diminish drastically. This, according to our view, indicates that a large fraction of the older age group entering unemployment in 1995 or 1996 is not actually searching for a job but is instead passively waiting for access to retirement.

Given the age structure of our sample, it is not surprising to find that most of the individuals are married, nor that only a small share have a dependent child in the family. Overall, the differences in mean individual characteristics among the groups remain small. The occupational distribution in both age groups is fairly similar across entering years. Not surprisingly, the elderly unemployed are rather poorly educated on average. Roughly half of the sample were previously unemployed in the 1990s. This is a rather large fraction despite the fact that the early 1990s was a period of sky-high unemployment. On the other hand, almost half of the sample have stayed with the same employer at least for the previous four years. There is practically no difference in the average level of earnings-related unemployment benefits received by the different groups.

The excluded spells of the older group (not reported) are longer on average than the spells included in the 1995 and 1996 inflow samples. This is consistent with the likely

Table III.1: Sample statistics by age and time of entering unemployment

| | 1995 Jan to Sep | | 1996 Jan to May | | 1997/1998 Jan to Dec | |
|---|---|---|---|---|---|---|
| | 50-52 | 53-54 | 50-52 | 53-54 | 50-52 | 53-54 |
| Unempl. duration, days | 368 | 1252 | 290 | 968 | 284 | 299 |
| | (382) | (866) | (350) | (767) | (291) | (265) |
| Duration to employment | 190 | 215 | 151 | 144 | 151 | 155 |
| | (214) | (279) | (175) | (187) | (176) | (164) |
| Female | .475 | .553 | .394 | .455 | .434 | .476 |
| Married | .687 | .724 | .700 | .712 | .685 | .677 |
| Female × married | .304 | .388 | .259 | .301 | .295 | .314 |
| Dependent child | .218 | .099 | .195 | .098 | .205 | .100 |
| Swedish-speaking | .061 | .045 | .051 | .043 | .040 | .062 |
| Post-secondary education | .083 | .049 | .061 | .055 | .059 | .049 |
| *Occupation:* | | | | | | |
| Commercial | .183 | .157 | .131 | .154 | .156 | .180 |
| Technical | .083 | .071 | .081 | .065 | .078 | .070 |
| Humanist | .022 | .021 | .020 | .015 | .021 | .029 |
| Health care | .019 | .014 | .016 | .017 | .020 | .020 |
| Clerical | .188 | .261 | .149 | .158 | .151 | .157 |
| Agricultural | .026 | .011 | .076 | .046 | .016 | .021 |
| Transportation | .053 | .057 | .061 | .060 | .065 | .061 |
| Industrial | .324 | .315 | .382 | .396 | .395 | .371 |
| Services | .092 | .091 | .078 | .077 | .092 | .085 |
| Not classified | .009 | .003 | .005 | .012 | .006 | .006 |
| *Firm size:* | | | | | | |
| 50 employees or less | .435 | .297 | .474 | .390 | .470 | .473 |
| 51-500 employees | .293 | .313 | .253 | .293 | .270 | .271 |
| Over 500 employees | .272 | .390 | .272 | .317 | .260 | .256 |
| Tenure ≥ 4 years | .460 | .497 | .437 | .450 | .437 | .457 |
| Unemployed in early 1990s | .383 | .287 | .570 | .510 | .549 | .518 |
| Past recall in early 1990s | .076 | .062 | .186 | .158 | .176 | .157 |
| Ln (UI benefits) | 3.30 | 3.31 | 3.32 | 3.32 | 3.30 | 3.28 |
| | (.33) | (.27) | (.34) | (.28) | (.33) | (.33) |
| Number of observations | 935 | 1046 | 837 | 584 | 2939 | 657 |

Notes: Sample standard deviations for continuous variables are in parentheses. The spells of those born in 1942 or 1943 for 53-54 years old are excluded from 1997/1998 data.

effects of anticipation behaviour, though the business cycle may play a role as well. Among workers aged 53-54 entering unemployment in 1997 or 1998, the excluded individuals (i.e. those born in 1942 or 1943) have marginally shorter spells than those included in the analysis. Also this finding is in line with the expected selectivity effects.

Almost one-half of workers aged 50-52 were employed by small firms with 50 employees or less and a quarter by large firms with more than 500 employees before unemployment. These shares do not exhibit variation over time, and the differences between the included and excluded groups are minor. The size distribution of the past employer for the age group 53-54 is quite different in 1995 and 1996 but almost identical to the size distribution for the younger group in 1997-1998. Evidently, individuals old enough for the extended benefit period tend to become unemployed from larger firms than their younger counter-

Table III.2: Risk set and observed exits by duration intervals

| | Treatment group[1)] | | | | Control and comparison groups[2)] | | | |
|---|---|---|---|---|---|---|---|---|
| | Exits to | | | Risk | Exits to | | | Risk |
| Interval | Emp | ALMP | Out | set | Emp | ALMP | Out | set |
| (0,2] months | 150 | 10 | 23 | 1630 | 1041 | 117 | 100 | 5368 |
| (2,4] months | 121 | 7 | 20 | 1447 | 674 | 118 | 98 | 4110 |
| (4,6] months | 41 | 10 | 15 | 1299 | 387 | 103 | 64 | 3220 |
| (6,8] months | 25 | 16 | 11 | 1233 | 202 | 123 | 48 | 2666 |
| (8,10] months | 32 | 6 | 14 | 1181 | 129 | 97 | 49 | 2293 |
| (10,12] months | 9 | 9 | 10 | 1129 | 107 | 121 | 49 | 2018 |
| (12,14] months | 13 | 3 | 21 | 1101 | 55 | 160 | 43 | 1741 |
| (14,16] months | 9 | 6 | 10 | 1064 | 63 | 159 | 43 | 1483 |
| (16,18] months | 12 | 9 | 8 | 1039 | 51 | 128 | 31 | 1218 |
| (18,20] months | 11 | 5 | 9 | 1010 | 37 | 98 | 35 | 1008 |
| (20,22] months | 2 | 6 | 8 | 985 | 27 | 99 | 43 | 838 |
| (22,24] months | 4 | 4 | 6 | 969 | 28 | 86 | 37 | 669 |
| (24,30] months | 8 | 17 | 20 | 955 | 44 | 162 | 56 | 518 |
| (30,36] months | 2 | 4 | 14 | 910 | 8 | 31 | 20 | 221 |
| (36,48] months | 3 | 8 | 33 | 890 | 4 | 12 | 21 | 135 |
| (48,60] months | 2 | 4 | 34 | 846 | 1 | 4 | 3 | 49 |
| (60,63] months | 0 | 0 | 42 | 547 | 0 | 1 | 0 | 18 |
| (63,$\infty$] months | 1 | 0 | 111 | 502 | 0 | 1 | 0 | 17 |
| Sum | 445 | 124 | 409 | | 2858 | 1620 | 740 | |
| (%) | (27.3) | (7.6) | (25.1) | | (53.2) | (30.2) | (13.8) | |

1) Individuals aged 53-54 becoming unemployed in 1995 or 1996. 2) Individuals aged 50-52 becoming unemployed in 1995-1998 and individuals aged 53-54 in 1997-1998.

parts. Compared with the included workers, a higher share of the excluded workers in the older group entering unemployment in 1995 or 1996 were employed by large firms (not reported). This suggests that large employers were responsible for much of the excess inflow to unemployment at the end of 1995 and 1996.

Table III.2 shows the numbers of individuals at risk of exiting unemployment and observed exits to different destinations by each duration interval for our treatment group (those with extended UI benefits) and the pooled control and comparison group (all those with the fixed two-year entitlement period). Only 60% of the individuals in our treatment group exit unemployment during the observation period, while almost everyone from the control and comparison groups do exit. Moreover, the distribution of end-states is quite different in the two groups. Given the large share of individuals in the treatment group who are still unemployed at the end of the observation period of 5 to 6 years of length, it seems clear that many of those with extended UI benefits are no longer active in the labour market. Ervasti (2003) studies preferences for job search using a survey of 970 unemployed workers.[26] According to their search activity he classifies the unemployed into four groups, where the most passive group consists of those who do not look for a new job, nor even wish to return to employment. Members of this group are rather old, i.e. entitled to extended

[26] The survey was subject to a large response bias.

UI benefits, receiving high UI benefits, having high reservation wages, and suffering from deteriorated health. Consequently, accounting for this considerably lower level of activity does appear necessary here for the treatment group. This will be accomplished by using the split population model described below.

# 5 Flow from employment to unemployment

It has become evident that the unemployment inflow of the elderly employed changed sharply in response to the increase in the age threshold for the UT scheme in 1997. From Figures III.2 and III.3 it is difficult to distinguish the "pure" effects of the 1997 reform from changes in the business cycle and the anticipation effects of the two distinct reforms. Therefore, we elaborate this issue further by modelling the likelihood of becoming unemployed over various periods. By identifying the timing of the anticipation effects, we also validate our choices of treatment, comparison, and control groups for the duration analysis.

Since the entire private sector is covered by the ES database, we have observations on the employees of a large number of plants (and firms). We model the probability that a worker aged $s$ who is working in plant $k$ becomes unemployed during the period under consideration as

$$p_{ks}(\mathbf{x}) = \frac{\exp(\gamma_k + \alpha_s + \mathbf{x}'\boldsymbol{\beta})}{1 + \exp(\gamma_k + \alpha_s + \mathbf{x}'\boldsymbol{\beta})}, \tag{III.1}$$

where $\gamma_k$ is the fixed plant effect, $\alpha_s$ is the age effect, and $\mathbf{x}$ is a vector of individual-specific control variables.[27] We include all workers between the ages of 50 and 63 who were employed over the past year in the analysis. Workers aged 50 serve as a reference category, and hence $\alpha_{50} \equiv 0$ is imposed as a normalisation. We estimate separate logit models for different periods. Under the assumption that changes in macroeconomic conditions affect all age groups similarly, significant differences in the age pattern of the unemployment risk between two periods are attributed to factors other than the business cycle, such as the anticipation and permanent effects of the UT reforms.

For each period we estimate two models: one for employees of small firms with less than 50 employees and another for employees of larger firms.[28] Small firms should have weaker, if any, incentives for age discrimination because the experience-rating of early retirement schemes is applied only to larger firms.[29] We apply the conditional maximum likelihood

[27] Age is measured at the end of the year under consideration. The control variables $\mathbf{x}$ include education, firm tenure, its square, gender, marital status and its interaction with gender, a dummy for a dependent child in the family and its interaction with gender, a dummy for those who speak Swedish as their native language, a dummy for recipients of capital income, a dummy for those with taxable wealth, and a dummy for debts. Information on income, wealth, and debts refers to the previous year.

[28] It may be confusing that we split the data by firm size but allocate workers to plants in the estimations. The distinction between plants and firms is relevant only for large firms with multiple plants. However, if we replace the fixed plant effects with the fixed firm effects, few very large firms will lead to numerical problems in the estimation step.

[29] In addition, a large employer has a wider range of possibilities in targeting dismissals at workers of particular ages than a small firm with only a few employees.

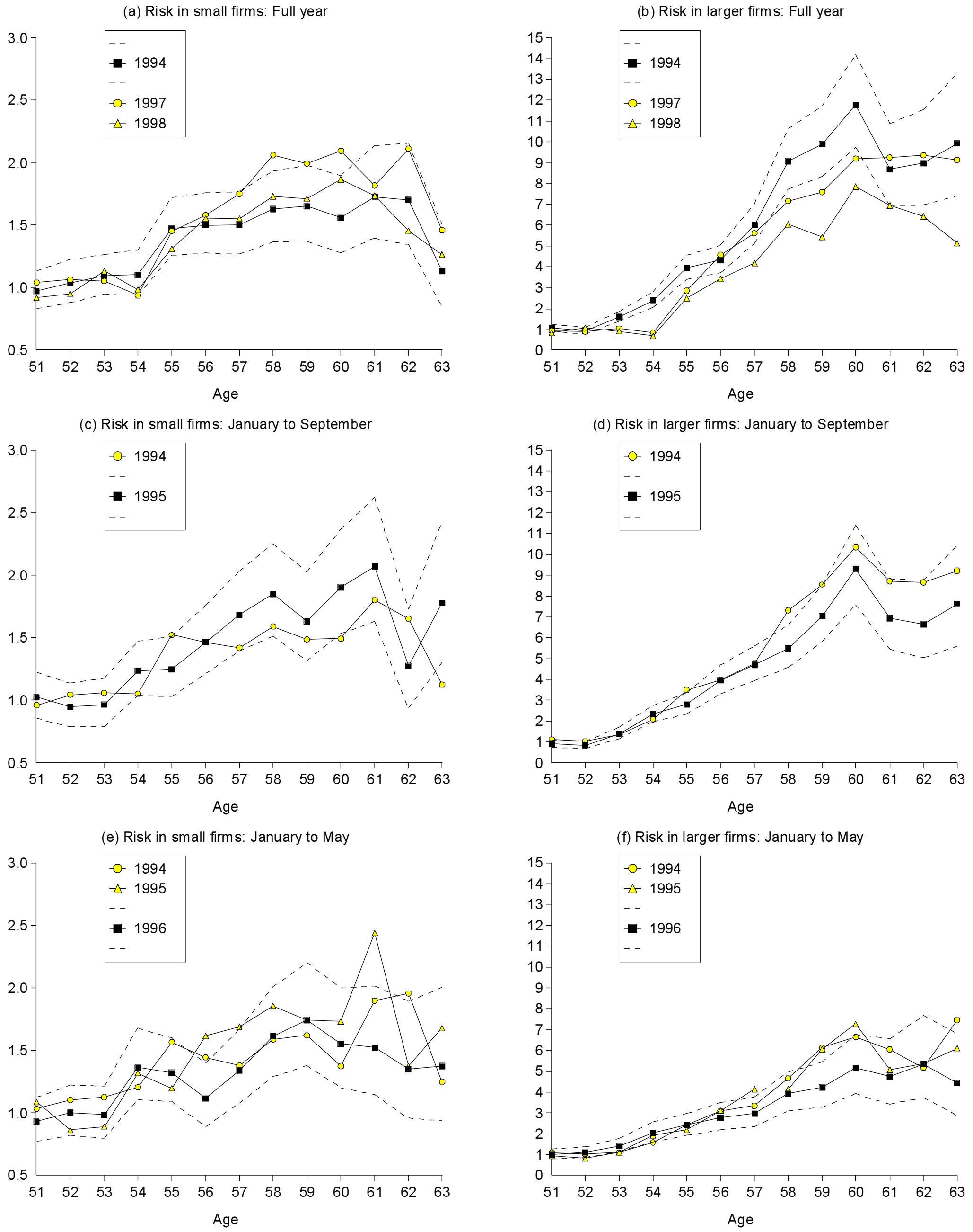
method (i.e. the fixed effects logit model) to estimate $\alpha_{51}, \alpha_{52}, ..., \alpha_{63}$ and $\boldsymbol{\beta}$ for the employees of large firms. Since the fixed plant effects drop out of the conditional likelihood function, no assumptions about how the unobserved plant effects are related to age and control variables are needed. A particular feature of the approach is that observations on the employees of a given plant do not contribute to the conditional likelihood function if either none or all of the plant's employees became unemployed during the period. This is the case for most small plants which cannot have many employees between the ages of 50 and 63. As a result, the fixed effects method is a less appealing choice for modelling the unemployment risk in small firms (unless one is willing to throw away over 90% of observations). In the case of the employees of small firms we therefore replace the fixed plant effects with a set of industry and regional dummies and apply the standard logit model (but adjust the covariance matrix for within-plant correlation). We represent our results for the age effects in terms of odds ratios. The odds of becoming unemployed is defined as $p_{ks}(\mathbf{x})/\left[1 - p_{ks}(\mathbf{x})\right]$. The odds ratio for age group $s \in [51, 63]$ is given by $e^{\alpha_s}$, and it gives the proportional effect on the odds of becoming unemployed compared with the reference worker aged 50.[30]

The odds ratios for workers between the ages of 51 and 63 in three different years are shown in Figures III.5a and III.5b. We have chosen 1994 as a reference period for the pre-reform time since it is supposed to be free of all anticipation issues. We have also added the 95% confidence band for this year. Among the employees of large firms the odds of becoming unemployed starts to increase smoothly at the age of 53 in 1994. This increase occurs more sharply two years later in the post-reform periods. Since the reform in 1997 workers aged 53 and 54 have not been at a higher risk of unemployment than the reference workers aged 50. Overall the older employees of large firms have a substantially higher risk of becoming unemployed than their younger co-workers. As expected, the risk of unemployment does not depend so much on age in small firms, though it is significantly higher for the elderly employees also in this case. Among the employees of small firms the higher risk applies only to workers aged 55 and over in all years, and hence no significant differences are observed for those aged 53 or 54 in 1994.

Small declines in the odds ratio for 54-years-old workers in 1997 in Figures III.5a and III.5b are consistent with the hypothesis that the entry to unemployment for some workers who lost their eligibility for the UT scheme was advanced in anticipation of the 1997 reform. However, these declines are not statistically significant at the 5% level and similar declines occur also in 1998 (workers who turned 54 in 1998 were not eligible for the UT scheme in 1997). Compared with 1994, the odds ratios for workers aged 55 and over who are

[30] For example, $e^{\alpha_{55}} = 1.7$ would imply that the odds of becoming unemployed is 70 percent higher for a 55-year-old worker than for a 50-year-old worker who is identical in terms of characteristics $x$ and who is working in the same plant (or in the same industry and region in the case of workers employed by a small firm). Note that the effect of age on the odds of becoming unemployed does not depend on the other explanatory variables and the unknown plant-specific effects (which cannot be estimated consistently without further assumptions).

Figure III.5: Odds ratios of becoming unemployed from logit models compared with a reference worker aged 50



working in large firms are roughly at the same level in 1997 (with a few exceptions) and lower in 1998. The age pattern for the employees of small firms looks rather similar across all years. So there are no notable changes in the relative risk of unemployment among the older groups not directly affected by the reform in 1997 (i.e. those aged 55 or more), and hence the overall inflow of the elderly employees to unemployment also decreased. The additional declines in the unemployment risk for those aged 55 and over in 1998 remain a puzzle, but reasons like the increased use of part-time pension or social pressure may play a role here.

In the duration analysis we aim to solve the selection problems arising from the anticipation of the UT reforms by excluding certain inflow months of 1995 and 1996 from the data. To test the validity of this solution we compare the age patterns of the unemployment risk over the selected subperiods of 1995 and 1996 with the corresponding subperiods of 1994 which are not subject to any selection issues. Figures III.5c and III.5d show the age patterns of the unemployment risk over the first three quarters of 1994 and 1995. The 1994 curve lies within the 95% confidence band for the 1995 curve with a few exceptions. Marginally significant differences occur at the ages of 55 and 58. These differences, however, cannot be attributed to the anticipation of the 1996 reform which should lead to a *higher* risk of unemployment for workers aged 53 and over in 1995 than in 1994. We therefore conclude that the anticipation of the 1996 reform caused the excess inflow to unemployment among workers covered by the protection clause only in the last quarter of 1995 (see also Figure III.3), and thereby workers aged 53-54 who entered unemployment in 1995 by the end of September serves as an anticipation-free group for the duration analysis.

In Section 4.2 we found a sharp increase in the unemployment risk at the end of 1995 among the groups covered by the protection clause of the 1996 reform. If a large fraction of workers who entered unemployment at that time would have become unemployed in 1996 in the absence of the reform, we should see a decline in the unemployment risk in the early 1996 which would then imply a selection problem for our 1996 inflow sample. Indeed, some differences appear in Figures III.5e and III.5f, which show the age profiles of the odds of becoming unemployed in 1994, 1995, and 1996 by the end of May, along with the 95% confidence band for the 1996 curve. The odds ratio for workers older than 55 is occasionally significantly lower in 1996 than in 1994 and 1995. But there are no statistically significant differences at the ages of 53 and 54. Therefore, on the basis of unemployment risk, workers aged 53-54 who entered unemployment in 1996 by the end of May seem to be another valid group for the duration analysis. This conclusion should be treated with caution, however, as it is in contrast with evidence in Figure III.4 where the distribution of exit states implies a possibility of a selection problem for this group.

# 6 Unemployment duration analysis

We need to be aware of several complications in the empirical analysis of duration data. First, the unemployment spells start at different points in time, and, in particular, workers aged 53-54 under different UI schemes enter unemployment in different years. We need to find a way to separate the changes in the hazard function owing to different UI schemes from the effects of changing macro-economic conditions. For purposes of identifying the effects of the business cycle, we adopt a difference-in-differences type of setting where workers aged 50-52 serve as a control group. Second, prior survey evidence and our descriptive analysis suggest that a notable fraction of workers with extended UI benefits are passive and effectively withdrawn from the labour market. This issue is taken into account by allowing the transition probabilities to employment and ALMPs to be zero for some individuals in this group.

## 6.1 The split population model

Consider a worker who loses his job and becomes unemployed at time $\tau$. The worker is followed until the termination of the unemployment spell or the end of the observation period $\overline{\tau}$ (i.e. the last day of 2000). The duration of the unemployment spell $T$ is continuous. If a transition out of unemployment occurs within the observation period, it will be followed by employment ($e$), participation in an ALMP ($p$), or withdrawal from the labour market ($o$). The unemployment spell is right-censored if it continues beyond the observation period, in which case we know only that $T > \overline{\tau} - \tau$. We allow for a possibility that the worker chooses to withdraw from active labour market behaviour, in which case he does not look for employment, nor is he willing to participate in ALMPs. Instead he is passively waiting for an opportunity to escape the labour force via some early retirement scheme. For simplicity, we assume this choice is made at the moment of entering unemployment. We denote $\varepsilon = 1$ if the worker is still active, and $\varepsilon = 0$ otherwise. The value of this latent choice variable is not directly observed. The time path of explanatory variables for the hazard functions from $\tau$ to $\tau + t$ is denoted by $\mathbf{X}(t, \tau)$. This set includes variables that are either fixed, change with spell duration $t$ (unemployment benefits), or change with calendar time $\tau + t$ (calendar-time dummies and local unemployment rate). The subset of variables that also affect the probability distribution of $\varepsilon$ is denoted with $\mathbf{z}$.

The conditional hazard rates at spell duration $t$ to employment and ALMPs are multiplicative in $\varepsilon$ :

$$\theta_k(t\,|\mathbf{X}(t,\tau),\varepsilon) = \theta_k(t\,|\mathbf{X}(t,\tau))\,\varepsilon, \qquad k \in \{e,p\}\,.$$

We assume that the worker is not active with probability $p(\mathbf{z}) = \Pr(\varepsilon = 0\,|\mathbf{z})$ , in which case $\theta_k(t\,|\mathbf{X}(t,\tau),\varepsilon = 0) = 0$ for $k \in \{e,p\}$ . The transition rate out of the labour force is independent of $\varepsilon$, so that

$$\theta_o(t\,|\mathbf{X}(t,\tau),\varepsilon) = \theta_o(t\,|\mathbf{X}(t,\tau))\,.$$

The survivor function conditional on $\mathbf{X}(t,\tau)$ and $\varepsilon$ is given by

$$\begin{aligned} S(t\,|\mathbf{X}(t,\tau),\varepsilon) &= \exp\left\{-\varepsilon\int_0^t \theta_e(u\,|\mathbf{X}(u,\tau))\,du - \varepsilon\int_0^t \theta_p(u\,|\mathbf{X}(u,\tau))\,du \right. \\ &\quad \left. - \int_0^t \theta_o(u\,|\mathbf{X}(u,\tau))\,du\right\}. \end{aligned} \tag{III.2}$$

Since the value of $\varepsilon$ is observed only in some cases, we cannot always condition on it. By taking the expected value of $S(t\,|\mathbf{X}(t,\tau),\varepsilon)$ with respect to $\varepsilon$, we obtain

$$\begin{aligned} S(t\,|\mathbf{X}(t,\tau)) &= [1-p(\mathbf{z})]\exp\left\{-\int_0^t \sum_j \theta_j(u\,|\mathbf{X}(u,\tau))\,du\right\} \\ &\quad + p(\mathbf{z})\exp\left\{-\int_0^t \theta_o(u\,|\mathbf{X}(u,\tau))\,du\right\}, \end{aligned} \tag{III.3}$$

where $\sum_j$ denotes the sum over all the three possible exit destinations.

If a transition to employment or to an ALMP occurred at spell duration $t$, the values of both $\varepsilon$ and $T$ are observed along with the destination state. The likelihood contribution in this case is given by

$$[1-p(\mathbf{z})]\,\theta_k(t\,|\mathbf{X}(t,\tau))\,S(t\,|\mathbf{X}(t,\tau),\varepsilon=1)\,, \qquad k\in\{e,p\}\,.$$

When the unemployment spell ended via withdrawal from the labour force at spell duration $t$, we observe the spell length but not the value of $\varepsilon$, and hence the likelihood contribution is

$$\theta_o(t\,|\mathbf{X}(t,\tau))\,S(t\,|\mathbf{X}(t,\tau))\,.$$

If the unemployment spell is still in progress at time $\overline{\tau}$, the value of $\varepsilon$ remains unobserved and all we know is that $T>\overline{\tau}-\tau$. The likelihood contribution in this censored case is

$$S(\overline{\tau}-\tau\,|\mathbf{X}(t,\tau))\,.$$

Putting these pieces together, we obtain the log-likelihood of the model:

$$\begin{aligned} \mathcal{L} &= \sum_i\sum_j d_{ij}\ln\theta_j(t_i\,|\mathbf{X}_i(t_i,\tau_i)) + \sum_i (1-d_{ie}-d_{ip})\ln S(t_i\,|\mathbf{X}_i(t_i,\tau_i)) \\ &\quad + \sum_i (d_{ie}+d_{ip})\left[\ln[1-p(\mathbf{z}_i)] + \ln S(t_i\,|\mathbf{X}_i(t_i,\tau_i),\varepsilon_i=1)\right], \end{aligned} \tag{III.4}$$

where $\sum_i$ denotes the sum over all individuals in the sample; $\sum_j$ denotes the sum over all the three possible exit destinations; $d_{ij}=1$ if individual $i$ exited to destination $j\in\{e,p,o\}$, and $d_{ij}=0$ otherwise; and for censored observations $t_i=\overline{\tau}-\tau_i$ and $\sum_j d_{ij}=0$. The log-likelihood function (III.4) is maximised with respect to the unknown determinants of $\theta_e(\cdot)$, $\theta_p(\cdot)$, $\theta_o(\cdot)$, and $p(\cdot)$.

## 6.2 Parametrization

We adopt a step-function approximation to the cause-specific hazard functions in a continuous time framework. Compared with the grouped data analysis, this specification is equally flexible but also allows us to exploit the variation in the observed durations between the spells that fall into the same time interval. The time axis for the length of unemployment spells is divided into $M$ intervals as $(c_{m-1}, c_m]$, $m = 1, 2, ..., M$, with $c_0 \equiv 0$ and $c_M \equiv \infty$. Although any duration dependence can be approximated arbitrarily closely by increasing the number of time intervals, this is not possible in practice because of a finite sample size. The number and length of the time intervals used are chosen on the basis of observed exits out of unemployment in the data. We set the length of the first 12 intervals to two months. These are followed by two intervals of six months, two intervals of twelve months, one interval of three months, and the open-ended interval (see Table III.2). We have to impose some group-specific restrictions on the shape of hazard functions on the basis of observations available for estimation.

We assume the following hazard function for destination $k \in \{e, p, o\}$ at spell duration $t \in (c_{m-1}, c_m]$:

$$\theta_k(t\,|\mathbf{X}(t,\tau)) = \exp\left\{\lambda_k^m + \eta_k^m D + \alpha_k G_{50-52} + \gamma_k Y_{53-54\times 96} + \mathbf{x}_m' \boldsymbol{\beta}_k\right\},$$

where $D$ is the dummy variable for the entitlement period of two years (i.e. 53-54 years old who entered unemployment in 1997-1998 and 50-52 years old in all entry years), $G_{50-52}$ is the dummy variable for workers aged 50-52, $Y_{53-54\times 96}$ is the dummy variable for workers aged 53-54 whose unemployment started in 1996, and $\mathbf{x}_m$ is a vector of other covariate values for the $m$th duration interval. The hazard functions are constant within each interval but vary across intervals owing to time-varying parameters ($\lambda_k^m$ and $\eta_k^m$) and time-varying covariates (included in $\mathbf{x}_m$). The time-varying covariates include unemployment compensation, local unemployment rate, and year and quarter dummies. Among individuals under the conventional UI scheme UI benefits lapse after 24 months of unemployment and are followed by labour market support. The local unemployment rate, year dummies, and quarter dummies are related to calendar time, not to the elapsed duration of unemployment. These variables control for changing labour demand conditions over time and across regions.[31]

For destination $k$ the shape of the hazard function for the treatment group (53-54 years old in 1995 and 1996) is modelled with a set of dummy variables for the log baseline hazard function, $\lambda_k^m$, $m = 1, 2, ..., M$. Given a relatively small number of observed exits for this group (see Table III.2), we need to impose some equality constraints on $\lambda_k^m$ for subsequent intervals. Within the treatment group the hazard function is allowed to differ

[31] The local unemployment rate is computed as the average of monthly rates. The quarter/year dummy takes a value of one if the midpoint of the duration interval is located on that quarter/year. For the open-ended interval 3 months from the beginning of the period is used as a reference point instead of the midpoint, which is not well-defined.

by a proportional factor of $e^{\gamma_k}$ between workers who entered unemployment in 1995 and 1996. These two groups are covered by different rules for computing unemployment pension benefits. The pattern of duration dependence for the comparison group (53-54 years old who entered unemployment in 1997 and 1998) is very close to that of the control group (50-52 years old). This is not very surprising, given that the age difference is so small and they all are covered by the same UI scheme. Consequently, the hazard functions between these groups are allowed to differ only by a proportional shift factor of $e^{\alpha_k}$.

The likelihood of choosing passivity, $p(\mathbf{z})$, varies with characteristics $\mathbf{z}$. On the basis of descriptive evidence, we assume that all workers with a fixed entitlement of two years are active, and hence $p(\mathbf{z}) = 0$ is imposed for them. Following Schmidt and Witte (1989) and Pudney and Thomas (1995) among others, we assume the logistic distribution for $\varepsilon$ within the treatment group:

$$p(\mathbf{z}) = \begin{cases} 0, & \text{if } D = 1, \\ \dfrac{\exp\{\mathbf{z}'\boldsymbol{\delta}\}}{1+\exp\{\mathbf{z}'\boldsymbol{\delta}\}}, & \text{if } D = 0, \end{cases}$$

where $\mathbf{z}$ includes a constant.

We will consider the standard competing risks model as a benchmark for our duration analysis. The model outlined above is reduced to the standard competing risks model with piecewise constant hazards if one imposes $p(\mathbf{z}) = 0$ for all individuals in the data. In this case the log-likelihood function (III.4) factorizes into separate components for the parameters of each destination, and hence the estimation may be done in three steps.

## 6.3 Cumulative incidence functions

In our model there is a variety of channels through which the extended UI benefits can affect the flows of workers out of unemployment to employment, ALMPs, and non-participation. The cause-specific hazard functions are affected by extended UI benefits in two ways. First, the cause-specific hazard functions of the treatment group can be of a different shape. The hazard rates to destination $k$ in the $m$th interval differ by the proportional factor $e^{\eta_k^m}$ between workers who are otherwise identical but are covered by the two different UI schemes. Since $\eta_k^m$ are allowed to vary freely across the intervals, this amounts to estimating separate baseline hazard functions for the treatment and comparison groups.[32] Second, unlike the other groups, workers aged 53-54 who entered

[32]The flexible specification for the effect of the entitlement period on the hazard functions is adopted because economic theory does not impose simple parametric restrictions. In the two-state search model of Mortensen (1977), for example, an increase in the maximum duration of UI benefits reduces the employment hazard over the forepart of the unemployment period but increases it close to and beyond the exhaustion point. In other words, the effect on the employment hazard is predicted to change over the course of the unemployment spell, potentially reversing its sign at some point. In the empirical analysis this possibility is sometimes ruled out a priori by imposing the restriction that changes in the length of the entitlement period may lead to level shifts in the underlying hazard function but cannot affect its shape (e.g. Hunt, 1995; and Lalive and Zweimüller, 2004). Moreover, economic theory provides little guidance on the expected responses in the hazard rates to ALMPs and non-participation.

unemployment in 1995 or 1996 do not lose their UI benefits after 24 months. This results in a different time pattern for the unemployment compensation variable that is included in $\mathbf{x}_m$, the effect of which comes on top of the difference in the baseline hazard functions for long-duration spells. It should be stressed that these entitlement period effects on the hazard functions are conditional on workers being active (i.e. conditional on $\varepsilon = 1$). There is an additional disincentive effect via the choice of labour market withdrawal: some of those with extended UI benefits may be discouraged and choose to withdraw from active labour market behaviour entirely. This effect can be heterogeneous, and it is measured with $p(\mathbf{z})$.

To summarize all these potential effects in a coherent way, we will calculate the marginal cumulative incidence and distribution functions for different groups. The cumulative incidence function (CIF) for destination $k \in \{e, p, o\}$ at spell-duration $t \in (c_{m-1}, c_m]$ conditional on $\mathbf{X}(t, \tau)$ and $\varepsilon$ is defined as

$$F_k(t\,|\mathbf{X}(t,\tau),\varepsilon) = \int_0^t \theta_k(u\,|\mathbf{X}(u,\tau),\varepsilon)\, S(u\,|\mathbf{X}(u,\tau),\varepsilon)\, du, \tag{III.5}$$

and it equals the probability that the individual has entered destination $k$ by spell duration $t$. Note that $F_k(t\,|\mathbf{X}(t,\tau), \varepsilon = 0) = 0$ for $k \in \{e, p\}$ and $F_o(t\,|\mathbf{X}(t,\tau), \varepsilon = 0) = 1 - S(t\,|\mathbf{X}(t,\tau), \varepsilon = 0)$.

The marginal CIF gives the predicted fraction of workers who have escaped from unemployment through a particular exit route by a given duration time. The marginal cumulative distribution function (CDF), which equals the sum of marginal CIFs for all exit destinations, gives the predicted share of those who have left unemployment by a given duration time for any reason. The estimated fractions of individuals who have escaped unemployment by spell duration $t$ through employment and ALMPs are obtained as

$$\widehat{F}_k(t) = \frac{1}{N}\sum_{i=1}^{N} [1 - \widehat{p}(\mathbf{z}_i)]\, \widehat{F}_k(t\,|\mathbf{X}_i(t,\tau_i), \varepsilon_i = 1)\,, \qquad k \in \{e, p\}\,,$$

where $i$ indexes individuals and $N$ denotes the group size at time $t = 0$. The estimated fraction of the workers who have left the labour force by spell duration $t$ is

$$\widehat{F}_o(t) = \frac{1}{N}\sum_{i=1}^{N} \Big( [1 - \widehat{p}(\mathbf{z}_i)]\, \widehat{F}_o(t\,|\mathbf{X}_i(t,\tau_i), \varepsilon_i = 1) + \widehat{p}(\mathbf{z}_i) \Big[1 - \widehat{S}(t\,|\mathbf{X}_i(t,\tau_i), \varepsilon_i = 0)\Big] \Big)\,.$$

In other words, we first calculate the estimates of CIFs for each individual at various points in duration time, conditional on the time path of the individual's covariate values up until that point. Then we obtain the group-specific estimates of the marginal CIFs by taking averages over individual estimates within the groups. The marginal CDF at spell duration $t$ can be estimated as $\widehat{F}(t) = \sum_k \widehat{F}_k(t) = 1 - \widehat{S}(t)$, where the marginal survivor function is

$$\widehat{S}\,(t) = \frac{1}{N}\sum_{i=1}^{N} \Big( [1 - \widehat{p}(\mathbf{z}_i)]\, \widehat{S}(t\,|\mathbf{X}_i(t,\tau_i), \varepsilon_i = 1) + \widehat{p}(\mathbf{z}_i) \widehat{S}(t\,|\mathbf{X}_i(t,\tau_i), \varepsilon_i = 0) \Big)\,.$$

In the conventional competing risks specification we simply have $\widehat{p}(\mathbf{z}_i) = 0$ and $\varepsilon_i = 1$ for all individuals.

### 6.4 Discussion

One can think of the model outlined above as a special case of a multiplicative frailty (or unobserved heterogeneity) model (Sy and Taylor, 2000). As a frailty variable, $\varepsilon$ has a probability distribution with two mass points at known values. Unlike in the standard frailty models, $\varepsilon$ is not entirely unobservable, since it is observed for individuals who exited to employment or ALMPs, and its distribution can depend on the same observed characteristics as the hazard functions do. This class of duration models was introduced by Farewell (1977). The models are known as mixture or cure models in statistics, and split population or mover-stayer models in econometrics (Schmidt and Witte, 1989; and Abbring, 2002). Applications in labour economics include Yamaguchi (1992), Swaim and Podgursky (1994), Pudney and Thomas (1995), Addison and Portugal (2003), Ollikainen (2003), and Mavromaras and Orme (2004). Our specification departs from the existing literature in that the same $\varepsilon$ enters multiplicatively in the two distinct cause-specific hazard functions and does so only for a particular subgroup of the population.

Farewell (1982) emphasizes that the split population models should not be applied indiscriminately. There must be strong evidence of a subgroup not at the risk of experiencing the event of interest. A feature of the model that the same covariates can affect the choice of withdrawal from labour market behaviour and exit rates out of unemployment allows additional flexibility in modelling, but opens up the possibility of over-parametrization (Sy and Taylor, 2000). Identifiability of the model generally requires a long observation period and a sufficiently large number of uncensored observations. In our application descriptive findings along with indirect survey results give convincing evidence of the existence of a group of the elderly unemployed who are no longer engaged in labour market activities. Having a follow-up period of 5-6 years, we should also be able to detect this group.

The focus of the econometric analysis of UI has been on detecting effects on the employment hazard or the overall hazard out of unemployment. However, the effect of UI on the employment hazard may be less relevant from a policy perspective than its effects on the likelihood of leaving unemployment via employment by a given time. The employment effect of a policy change in the UI system that affects the employment hazard may be reinforced or attenuated by changes in hazard rates out of the labour force and to ALMPs. As a consequence, a policy change with a strong effect on the employment hazard may have a negligible or even opposite effect on the probability that the unemployment spell will end with employment. Alternatively, a policy change with no effect on the employment hazard may still have a significant effect on the likelihood of finding a job due to indirect effects via competing hazards. Thus it may be hazardous to focus on estimating reform effects on the employment hazard only by treating individuals who exit to other destinations than employment as censored observations. We believe that an appropriate way of evaluating employment effects requires simultaneous account of all cause-specific hazards, and the cumulative incidence functions provide a useful way of summarizing the results of competing risks analysis in a coherent and policy-relevant way. Although the cumulative incidence approach has enjoyed popularity in the medical treatment literature (e.g. Pepe, 1991; Gaynor et al., 1993; and Satagopan et al., 2004),[33] it has attracted surprisingly little attention in economic applications.

### 6.5 Hazard function estimates

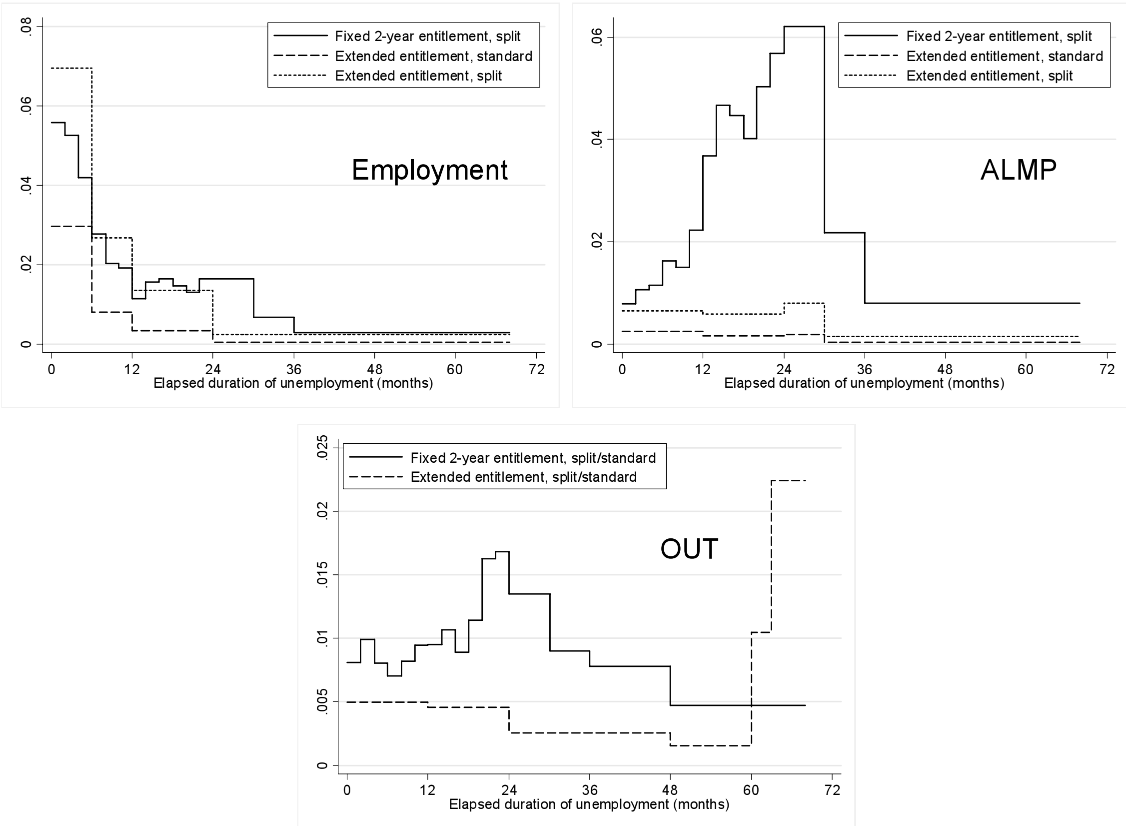
The hazard function estimates of the standard competing risks and split population specifications are presented in Figure III.6 and Tables III.3 and III.4. The hazard functions are depicted for a reference person,[34] and the estimates obtained from the split population specification are conditional on searching (i.e. $\varepsilon = 1$). The baseline parameters ($\lambda_k$) not reported in the tables determine the shape of the cause-specific hazards for the treatment group with extended UI benefits in Figure III.6. The time-varying coefficients ($\eta_k$) for individuals with the fixed two-year-entitlement period measure the difference between the hazard functions for the treatment and comparison groups, and the statistical significance thereof. The hazard functions for transitions to employment and ALMPs obtained from both specifications are plotted for a reference person with extended UI benefits. The corresponding hazard functions under the fixed entitlement period are roughly identical between the specifications, and hence only the hazard function estimate from the split population model is shown in Figure III.6. Since both specifications produce identical estimates for the transition rate out of the labour force (see discussion in the Appendix and parameter estimates in Tables III.3 and III.4), the two hazard functions in the last graph are common to both models.

Under the two-year entitlement period the employment hazard exhibits considerable negative duration dependence. By the time the unemployment period has lasted for 6 months the employment hazard is more than halved. We find only a slight benefit-exhaustion-related upturn in the hazard for employment at 22-30 months, whereas most of the benefit-exhaustion-related exits are directed towards ALMPs. The hazard function for transitions to ALMPs peaks considerably both at one year and, even more so, at two years of continuous unemployment. These findings are in line with evidence from Norway (Bratberg and Vaage, 2000; and Røed and Zhang, 2003) and Sweden (Carling et al., 1996). The transition rate out of the labour force is fairly steady and low overall, peaking slightly

[33] In clinical studies, it is common to compare nonparametric estimates of the cumulative incidence functions. In the presence of covariates, Fine and Gray (1999) and Fine (1999) propose semiparametric methods for directly estimating the cumulative incidence functions rather than combining estimates of the cause-specific hazard functions.

[34] The reference individual is married, lives in a region with the local unemployment rate of 20 per cent (slightly below the sample mean), and receives UI benefits equal to the mean benefits for the 53-54-year-olds (log of UI benefits = 3.3162). Other dummy variables are set to zero. Under the fixed entitlement period, the UI benefits of the reference individual are assumed to drop after 2 years of unemployment to the level of basic allowance (log of UI benefits = 2.6529).

Figure III.6: Cause-specific hazard functions for a reference person under two different UI schemes




around the time of benefit exhaustion.

The employment hazard of the worker with extended UI benefits obtained from the standard competing risks model declines with the elapsed duration, being significantly lower than the hazard of the worker with the fixed entitlement period (see time-varying coefficients and their standard errors in Table III.3). However, the most dramatic discrepancies between the UI schemes are found for the transition rates to ALMPs. The hazard function of the treatment group for transitions to ALMPs obtained from the standard competing risks model lies flat at a very low level. The transition rate out of the labour force among workers with extended benefits is also low and flat until it peaks at the very end of the observation period when the individuals start to exit via the unemployment pension scheme.

Our estimates of the labour market withdrawal probability from the split population model suggest that some half of the workers with extended UI benefits are inactive, having zero hazard rates to employment and ALMPs (see the next section). Hence, hazard estimates for the treatment group obtained from the standard competing risks specification are subject to bias, owing to a particular type of unobserved heterogeneity problem. The

Table III.3: Results of the standard competing risks specification

| | Hazard function for transitions to | | | | | |
|---|---|---|---|---|---|---|
| | Employment | | ALMPs | | Non-particip. | |
| *Time-varying coefficient for 2-year entitlement period:* | | | | | | |
| Interval (0,2] months | 0.634 | (0.110) | 1.150 | (0.198) | 0.491 | (0.201) |
| Interval (2,4] months | 0.580 | (0.112) | 1.457 | (0.198) | 0.691 | (0.202) |
| Interval (4,6] months | 0.361 | (0.118) | 1.544 | (0.201) | 0.481 | (0.216) |
| Interval (6,8] months | 1.258 | (0.162) | 1.891 | (0.198) | 0.347 | (0.230) |
| Interval (8,10] months | 0.946 | (0.171) | 1.808 | (0.205) | 0.495 | (0.231) |
| Interval (10,12] months | 0.889 | (0.176) | 2.207 | (0.201) | 0.639 | (0.234) |
| Interval (12,14] months | 1.235 | (0.210) | 3.177 | (0.218) | 0.730 | (0.243) |
| Interval (14,16] months | 1.569 | (0.205) | 3.418 | (0.219) | 0.849 | (0.245) |
| Interval (16,18] months | 1.609 | (0.215) | 3.372 | (0.223) | 0.663 | (0.265) |
| Interval (18,20] months | 1.508 | (0.232) | 3.267 | (0.229) | 0.916 | (0.260) |
| Interval (20,22] months | 1.372 | (0.254) | 3.494 | (0.230) | 1.270 | (0.253) |
| Interval (22,24] months | 1.610 | (0.252) | 3.614 | (0.235) | 1.305 | (0.264) |
| Interval (24,30] months | 3.120 | (0.304) | 5.025 | (0.285) | 1.847 | (0.245) |
| Interval (30,36] months | 2.231 | (0.443) | 5.738 | (0.328) | 1.442 | (0.310) |
| Interval (36,48] months | 1.387 | (0.521) | 4.734 | (0.364) | 1.300 | (0.286) |
| Interval (48,60] months | 1.387 | (0.521) | 4.734 | (0.364) | 1.300 | (0.286) |
| Interval (60,63] months | 1.387 | (0.521) | 4.734 | (0.364) | −0.623 | (0.329) |
| Interval (63,$\infty$] months | 1.387 | (0.521) | 4.734 | (0.364) | −1.383 | (0.306) |
| Age 50-52 | 0.117 | (0.063) | −0.233 | (0.077) | 0.135 | (0.119) |
| Female | −0.170 | (0.071) | 0.672 | (0.093) | −0.006 | (0.102) |
| Married | 0.363 | (0.050) | 0.172 | (0.086) | −0.109 | (0.092) |
| Female × married | −0.368 | (0.081) | 0.021 | (0.108) | 0.149 | (0.122) |
| Dependent child | 0.155 | (0.045) | 0.062 | (0.067) | −0.032 | (0.091) |
| Swedish-speaking | 0.204 | (0.082) | −0.049 | (0.122) | 0.136 | (0.141) |
| Tenure $\geq$ 4 years | −0.172 | (0.037) | −0.126 | (0.049) | 0.064 | (0.060) |
| Unemployed in early 1990s | 0.312 | (0.042) | 0.146 | (0.053) | 0.065 | (0.067) |
| Past recall in early 1990s | 0.709 | (0.047) | −0.291 | (0.126) | 0.089 | (0.127) |
| *Occupation: (ref. commercial)* | | | | | | |
| Technical | 0.302 | (0.081) | −0.131 | (0.109) | −0.179 | (0.147) |
| Humanist | 0.071 | (0.140) | −0.107 | (0.161) | −0.163 | (0.217) |
| Health care | 0.708 | (0.127) | −0.071 | (0.200) | 0.101 | (0.253) |
| Clerical | −0.050 | (0.074) | 0.079 | (0.073) | 0.059 | (0.096) |
| Agricultural | 0.685 | (0.102) | 0.140 | (0.275) | 0.162 | (0.282) |
| Transportation | 0.239 | (0.086) | −0.177 | (0.136) | 0.306 | (0.130) |
| Industrial | 0.383 | (0.060) | −0.204 | (0.073) | −0.092 | (0.091) |
| Services | −0.037 | (0.084) | −0.068 | (0.090) | 0.015 | (0.114) |
| Not classified | −0.231 | (0.264) | 0.332 | (0.295) | 0.606 | (0.299) |
| Year 1996 x age 53-54 | 0.043 | (0.106) | −0.168 | (0.199) | 0.095 | (0.136) |
| *Time-varying covariates:* | | | | | | |
| Ln (UI benefits) | −0.735 | (0.064) | 2.155 | (0.093) | 0.271 | (0.125) |
| Ln (local unemployment rate) | 0.076 | (0.080) | 0.205 | (0.096) | 0.027 | (0.119) |
| Quarter 2 | 0.268 | (0.047) | −0.323 | (0.072) | 0.179 | (0.091) |
| Quarter 3 | −0.066 | (0.056) | −0.197 | (0.072) | 0.079 | (0.094) |
| Quarter 4 | −0.201 | (0.058) | 0.012 | (0.070) | 0.206 | (0.094) |
| Year 1996 | 0.183 | (0.067) | 0.117 | (0.127) | −0.224 | (0.132) |
| Year 1997 | 0.241 | (0.070) | 0.397 | (0.129) | −0.213 | (0.143) |
| Year 1998 | 0.210 | (0.069) | 0.306 | (0.129) | −0.129 | (0.141) |
| Year 1999 | 0.199 | (0.087) | 0.365 | (0.138) | 0.161 | (0.158) |
| Year 2000 | −0.235 | (0.180) | 0.395 | (0.161) | 0.667 | (0.193) |

Notes: Number of observations is 6,998. Standard errors are in parentheses. Estimates of the baseline hazards not reported.

Table III.4: Results of the split population specification

| | Hazard function for transitions to | | | | | |
|---|---|---|---|---|---|---|
| | Employment | | ALMPs | | Non-particip. | |
| *Time-varying coefficient for 2-year entitlement period:* | | | | | | |
| Interval (0,2] months | −0.220 | (0.152) | 0.174 | (0.235) | 0.491 | (0.201) |
| Interval (2,4] months | −0.282 | (0.154) | 0.480 | (0.235) | 0.691 | (0.202) |
| Interval (4,6] months | −0.508 | (0.159) | 0.565 | (0.239) | 0.481 | (0.217) |
| Interval (6,8] months | 0.035 | (0.235) | 0.910 | (0.236) | 0.347 | (0.230) |
| Interval (8,10] months | −0.276 | (0.239) | 0.824 | (0.242) | 0.495 | (0.232) |
| Interval (10,12] months | −0.335 | (0.243) | 1.221 | (0.240) | 0.639 | (0.235) |
| Interval (12,14] months | −0.179 | (0.294) | 1.839 | (0.288) | 0.730 | (0.243) |
| Interval (14,16] months | 0.151 | (0.293) | 2.078 | (0.289) | 0.849 | (0.245) |
| Interval (16,18] months | 0.189 | (0.300) | 2.031 | (0.292) | 0.663 | (0.265) |
| Interval (18,20] months | 0.089 | (0.314) | 1.926 | (0.296) | 0.916 | (0.260) |
| Interval (20,22] months | −0.044 | (0.326) | 2.151 | (0.297) | 1.270 | (0.253) |
| Interval (22,24] months | 0.196 | (0.327) | 2.273 | (0.301) | 1.305 | (0.264) |
| Interval (24,30] months | 1.481 | (0.419) | 3.440 | (0.377) | 1.847 | (0.245) |
| Interval (30,36] months | 0.595 | (0.529) | 4.039 | (0.438) | 1.442 | (0.310) |
| Interval (36,48] months | −0.264 | (0.597) | 3.036 | (0.465) | 1.300 | (0.286) |
| Interval (48,60] months | −0.264 | (0.597) | 3.036 | (0.465) | 1.300 | (0.286) |
| Interval (60,63] months | −0.264 | (0.597) | 3.036 | (0.465) | −0.623 | (0.329) |
| Interval (63,$\infty$] months | −0.264 | (0.597) | 3.036 | (0.465) | −1.383 | (0.306) |
| Age 50-52 | 0.124 | (0.063) | −0.228 | (0.077) | 0.135 | (0.119) |
| Female | −0.155 | (0.074) | 0.692 | (0.095) | −0.006 | (0.116) |
| Married | 0.394 | (0.052) | 0.196 | (0.088) | −0.109 | (0.097) |
| Female × married | −0.350 | (0.085) | 0.010 | (0.112) | 0.149 | (0.134) |
| Dependent child | 0.135 | (0.046) | 0.055 | (0.067) | −0.032 | (0.091) |
| Swedish-speaking | 0.198 | (0.084) | −0.060 | (0.124) | 0.136 | (0.141) |
| Tenure $\geq$ 4 years | −0.156 | (0.039) | −0.124 | (0.050) | 0.064 | (0.060) |
| Unemployed in early 1990s | 0.291 | (0.044) | 0.143 | (0.054) | 0.065 | (0.067) |
| Past recall in early 1990s | 0.682 | (0.049) | −0.312 | (0.126) | 0.089 | (0.127) |
| *Occupation: (ref. commercial)* | | | | | | |
| Technical | 0.278 | (0.084) | −0.140 | (0.110) | −0.179 | (0.148) |
| Humanist | 0.009 | (0.151) | −0.140 | (0.163) | −0.163 | (0.217) |
| Health care | 0.666 | (0.131) | −0.099 | (0.202) | 0.101 | (0.253) |
| Clerical | −0.086 | (0.077) | 0.053 | (0.074) | 0.059 | (0.096) |
| Agricultural | 0.629 | (0.106) | 0.134 | (0.277) | 0.162 | (0.283) |
| Transportation | 0.264 | (0.089) | −0.151 | (0.137) | 0.306 | (0.131) |
| Industrial | 0.381 | (0.062) | −0.198 | (0.074) | −0.092 | (0.091) |
| Services | −0.082 | (0.088) | −0.100 | (0.091) | 0.015 | (0.115) |
| Not classified | −0.284 | (0.272) | 0.282 | (0.298) | 0.606 | (0.299) |
| Year 1996 x age 53-54 | −0.255 | (0.171) | −0.379 | (0.270) | 0.095 | (0.136) |
| *Time-varying covariates:* | | | | | | |
| Ln (UI benefits) | −0.695 | (0.064) | 2.096 | (0.093) | 0.271 | (0.126) |
| Ln (local unemployment rate) | 0.094 | (0.082) | 0.217 | (0.097) | 0.027 | (0.122) |
| Quarter 2 | 0.274 | (0.047) | −0.321 | (0.072) | 0.179 | (0.091) |
| Quarter 3 | −0.038 | (0.056) | −0.199 | (0.072) | 0.079 | (0.094) |
| Quarter 4 | −0.176 | (0.058) | 0.018 | (0.071) | 0.206 | (0.094) |
| Year 1996 | 0.214 | (0.069) | 0.145 | (0.129) | −0.224 | (0.132) |
| Year 1997 | 0.267 | (0.071) | 0.430 | (0.131) | −0.213 | (0.143) |
| Year 1998 | 0.239 | (0.070) | 0.333 | (0.131) | −0.129 | (0.141) |
| Year 1999 | 0.241 | (0.088) | 0.395 | (0.139) | 0.161 | (0.158) |
| Year 2000 | −0.185 | (0.181) | 0.429 | (0.162) | 0.667 | (0.193) |

Notes: Number of observations is 6,998. Standard errors are in parentheses. Estimates of the baseline hazards not reported.

split population model takes this issue explicitly into account, and yields the hazard estimates for a reference worker with extended benefits who is still actively looking for a new job and considers ALMPs as a possible way of escaping unemployment. Not surprisingly, the hazard functions of the treatment group for transitions to employment and ALMPs conditional on being active are higher compared with the estimates from the conventional competing risks specification. The employment hazard for the treatment group exhibits negative duration dependence, being rather close to the estimated hazard for the comparison group. The difference between the employment hazard under fixed and extended entitlement is statistically significant at the conventional risk levels only between 4-6 and 24-30 months of unemployment (see Table III.4). In other words, workers with extended UI benefits choosing to continue job search exit to employment at a similar rate as otherwise identical workers with a fixed period of UI benefits. By contrast, active individuals within the treatment group have very low transition rates to ALMPs compared with the comparison group. As a general remark, the transition rates out of unemployment under the two different UI schemes are of a different shape here. Restricting the effects of the length of the UI entitlement period to a proportional shift alone would, at least in our case, be far too constraining (for such a priori restrictions see e.g. Hunt, 1995, and Winter-Ebmer, 1998).

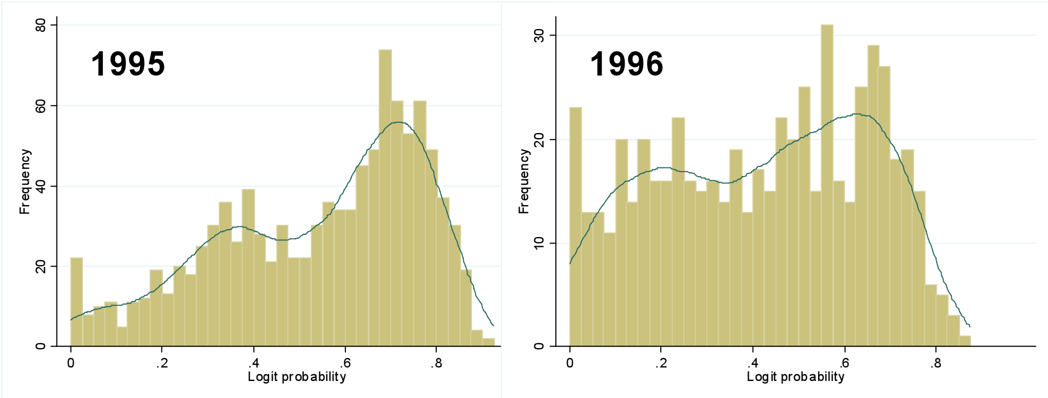
The coefficient estimates for the background characteristics in Tables III.3 and III.4 are in line, and hence we will only discuss the estimates of the split population specification. The findings are fairly conventional, indicating that women have a lower employment hazard and a higher hazard rate for transitions to active labour market programmes. Married people have higher transition rates both to employment and ALMPs. Individuals with dependent children also have a higher employment hazard, as do people speaking Swedish as their first language. The coefficients of occupational variables indicate differences in the transition rate to employment across different sectors.

There is evidence of both quarterly and yearly variation in transition rates to all end-states. The time-dependent regional unemployment rate has a significant positive effect on the transition rate to ALMPs. This merely points out the strong regional aspect of the labour market policy practised in Finland. As discussed in Lilja (1992) and Ollikainen (2003), a higher than average proportion of individuals participating in active labour market programmes comes from regions with a high unemployment to vacancies ratio. As expected, the amount of unemployment benefits has a negative effect on the hazard rate for transitions to employment. This is generally viewed as a result of the individual's higher leeway in being selective about his employment. High unemployment benefits substantially increase the transition rate to ALMPs, as well.

### 6.6 Likelihood of labour market withdrawal

As expected on the basis of descriptive analysis, we find evidence of a large subgroup of workers with extended UI benefits who are no longer actively engaged in job search. Figure

Figure III.7: Distributions of labour market withdrawal probabilities by year of entry to unemployment (Epanechnikov kernel)




III.7 shows the distributions of labour market withdrawal probabilities (i.e. the probability of $\varepsilon = 0$) across individuals with extended benefits by year of entry to unemployment. The mean probability of being inactive in our treatment group is .54 among those becoming unemployed in 1995 and .42 among those becoming unemployed in 1996. Thus, roughly half of the unemployed eligible for extended UI benefits are at no point interested in finding a way out of unemployment via employment or ALMPs, but instead are just passively waiting for retirement. The finding of such high overall withdrawal probabilities corroborates the necessity of implementing the split population model here.

Moreover, there is a lot of variation in the withdrawal probabilities across individuals. In addition to the evident variation within each year, there might also be some difference in the activity levels of the groups between years. However, looking at the logit coefficients in Table III.5 we find that, in fact, the dummy for 1996 is statistically insignificant, indicating that the observed yearly differences in the withdrawal probabilities are attributed to differences in the observed characteristics of the unemployed individuals. It appears that personal characteristics such as gender, being married or having dependent children do not significantly affect the decision of whether or not to search. Factors related to the individual's employment history turn out to be much more important. In all occupations individuals tend to be less likely discouraged than in the reference group, commercial work, although many of these differences are not statistically significant. The inflection point for the quadratic effect of unemployment benefits is 31 euros per day. Since two-thirds of individuals in the treatment group are receiving benefits lower than this, a small increase in UI benefits would discourage most of the people from searching for a new job.

According to our previous findings, the unemployment risk of those elderly workers who are eligible for extended UI benefits is much higher than that of other older workers, and particularly high in the case of employers with more than 50 employees. When forced to downsize, companies tend to target their dismissals on the elderly, some of whom may

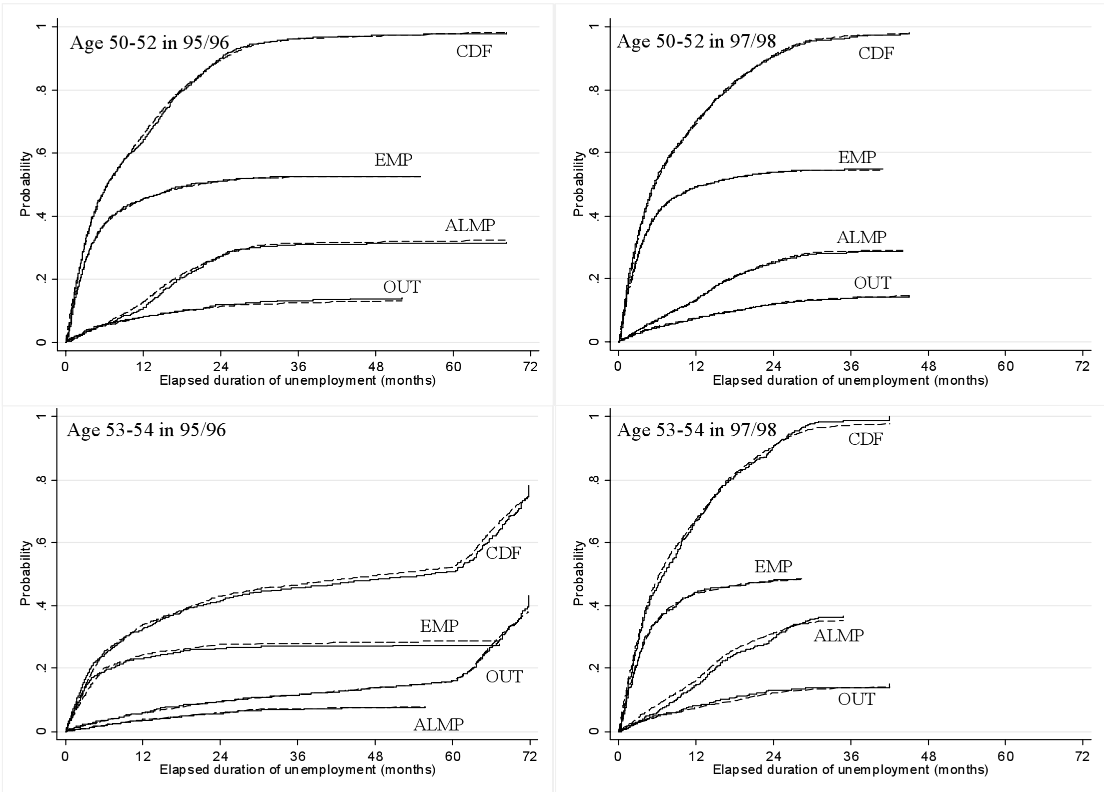
Table III.5: Determinants of the labour market withdrawal probability in the split population model

| | Logit coefficient | | Marginal Effect |
|---|---|---|---|
| Year 1996 | −0.295 | (0.257) | −0.058 |
| Female | 0.254 | (0.360) | 0.050 |
| Married | 0.447 | (0.305) | 0.087 |
| Female × married | 0.103 | (0.388) | 0.020 |
| Dependent child | −0.475 | (0.265) | −0.093 |
| Swedish-speaking | −0.101 | (0.402) | −0.020 |
| Tenure ≥ 4 years | 0.224 | (0.163) | 0.044 |
| Unemployed in early 1990s | −0.170 | (0.188) | −0.033 |
| Past recall in early 1990s | −0.796 | (0.308) | −0.156 |
| *Occupation: (ref. commercial)* | | | |
| Technical | −0.848 | (0.384) | −0.166 |
| Humanist | −0.947 | (0.733) | −0.185 |
| Health care | −1.304 | (0.642) | −0.255 |
| Clerical | −0.680 | (0.289) | −0.133 |
| Agricultural | −1.955 | (0.655) | −0.382 |
| Transportation | −0.008 | (0.414) | −0.002 |
| Industrial | −0.628 | (0.261) | −0.123 |
| Services | −0.523 | (0.413) | −0.102 |
| Not classified | −1.347 | (1.564) | −0.263 |
| *Firm size: (ref. ≤ 50 employees)* | | | |
| 51-500 employees | 1.031 | (0.236) | 0.202 |
| Over 500 employees | 1.264 | (0.246) | 0.247 |
| Ln (local unemployment rate) | −0.042 | (0.409) | −0.008 |
| (UI benefits) / 10 | 5.064 | (1.035) | 0.990 |
| (UI benefits)2 / 100 | −0.817 | (0.175) | −0.160 |
| Constant | −7.963 | (1.782) | |

Notes: Standard errors of logit coefficients are in parentheses. Marginal effects are computed by taking the average of individual-specific effects.

quite willingly retire via the unemployment tunnel scheme. In a tough situation this is the most easily approved line of action by the general public, and hence least damaging for the firms' reputation, as the income level for the elderly is well secured by the unemployment tunnel scheme. Moreover, firms with more than 50 employees are liable for a fraction of early retirement expenditures via partially experience-rated employer contributions. The largest firms with more than 500 employees are obliged to pay a higher cost share of disability pensions than of unemployment pensions. As a consequence, directing the elderly employees in the UT scheme may be economically rational, especially for large companies, as in this way they escape the potential disability pension expenditures of these employees. Of course, the employers have an incentive to get rid of workers with the highest risk of disability in the first place. Such workers may also be more likely to become passive in the case of job loss. This is consistent with our result that individuals laid off from medium-sized or large firms are much more likely to withdraw from job search than those laid off from small firms with no more than 50 employees. Moreover, the estimated withdrawal probability is highest for the employees of the largest firms.

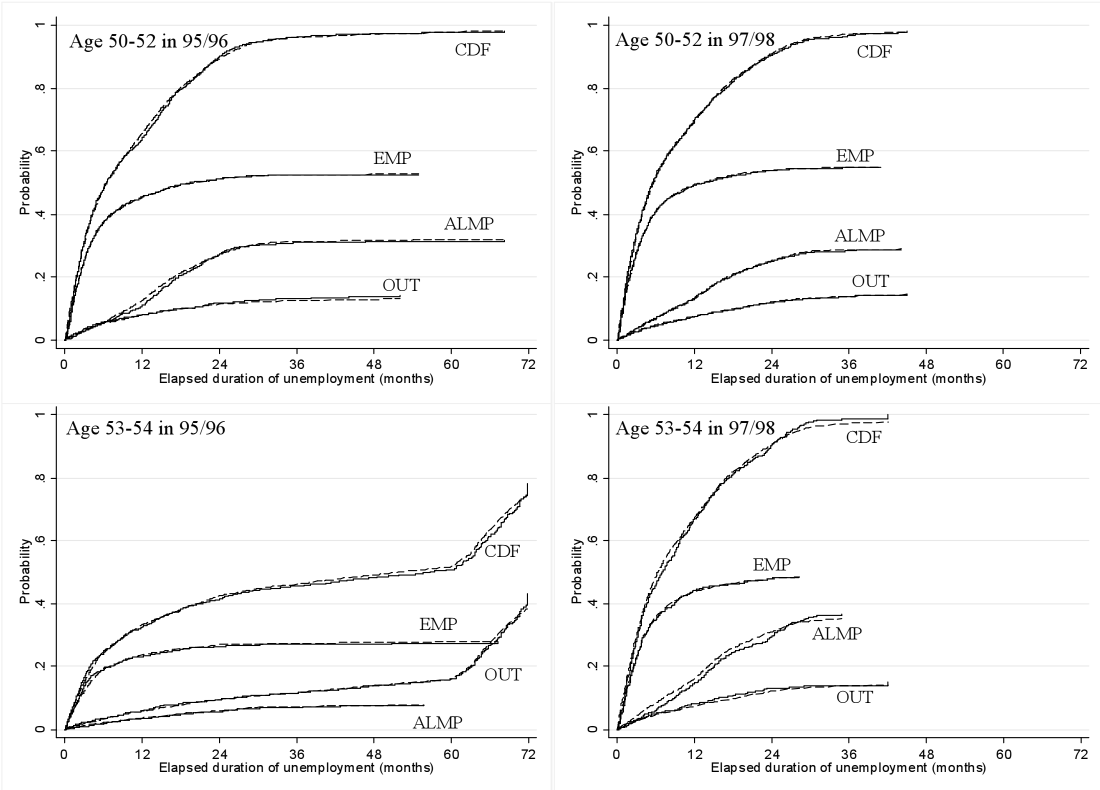
Figure III.8: Cumulative incidence and distribution functions from standard duration model by age and entry year of unemployment (Note: Solid lines are nonparametric estimates, and the dashed ones are the fitted curves from the model)




## 6.7 Cumulative incidence function estimates

We found evidence of a large fraction of inactive workers within the treatment group and notable differences in the cause-specific hazard functions between the groups. To summarize these results, we calculate the marginal cumulative incidence and distribution functions for different groups defined by age category and time of entry to unemployment. In Figures III.8 and III.9 the solid lines depict the nonparametric estimates given by the data and the dashed ones depict the estimates of our models. A comparison of the predictions obtained from our model with the corresponding nonparametric estimates provides a simple procedure for assessing the goodness of fit. The cumulative incidence and distribution function estimates from the standard competing risks specification and from the split population specification are roughly identical in all the other groups except for the treatment group. Even there, the fit of the split population model is only marginally better compared to the standard duration model. Hence, the contribution of our paper lies not in claiming the split population model to be superbly better in obtaining an accurate fit in case of this particular data set, but in stating that with the split population model

Figure III.9: Cumulative incidence and distribution functions from split population model by age and entry year of unemployment (Note: Solid lines are nonparametric estimates, and the dashed ones are the fitted curves from the model)




we can dig deeper into the reasons behind the phenomenon we are observing.

We find that the treatment group, as such, is very different from the other three groups, with considerably lower cumulative probabilities of exiting to employment and ALMPs. The cumulative incidence of employment by 12 months is some 45 to 50% in the control and comparison groups, but only 25% in the treatment group. In the control groups the overall probability of employment eventually converges up to 55% and in the comparison group to 50%, while in the treatment group this figure is less than 30%. Also, very few people in the treatment group eventually escape unemployment through ALMPs, while the cumulative probability of participation in such programmes in the control and comparison groups converges even up to 35%. As discussed in Section 3.3, if the unemployed participate in ALMPs simply in order to prolong the exhaustion of benefits or to regain eligibility, then the individuals in our treatment group have little incentive to participate, which appears to be the case here. Overall, the percentage of the unemployed eventually leaving unemployment in the group with extended benefit duration converges to only some 50% by duration of 60 months, after which it converges further to 75% due to retirement.

### 6.8 Simulating the effects of indefinite UI benefits

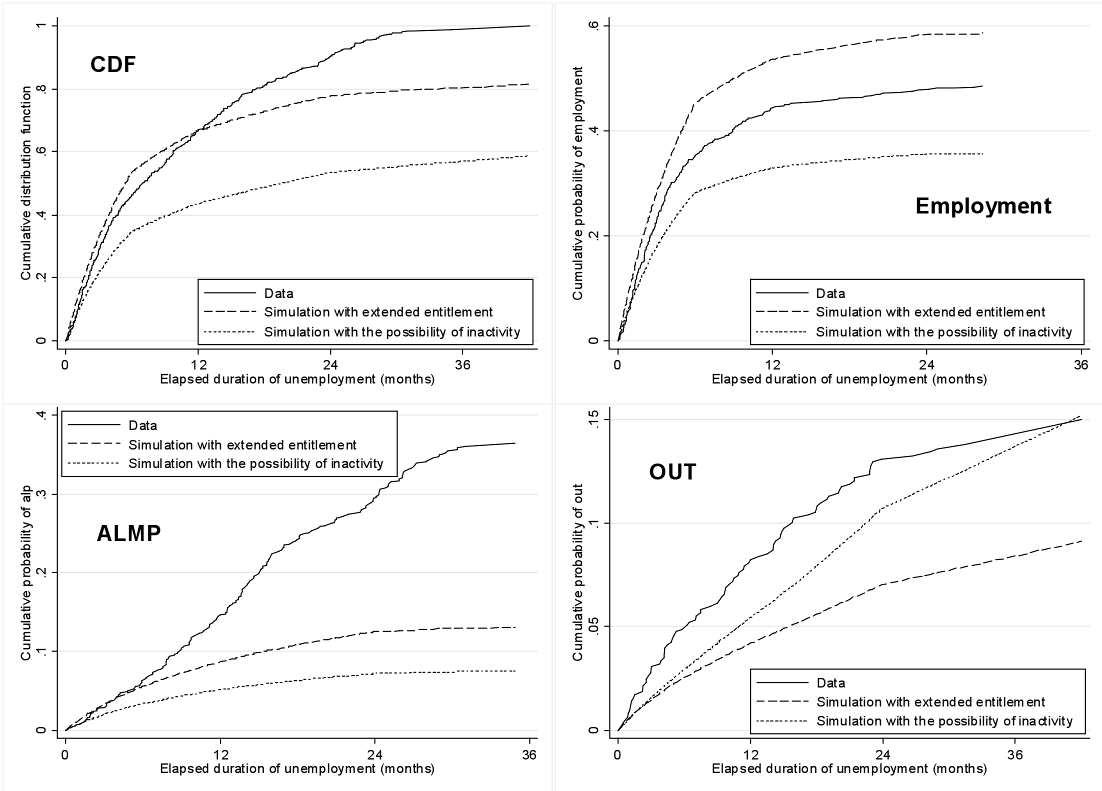
Eligibility for extended UI benefits was removed from workers aged 53 and 54 in 1997. As we have already seen, such a sharp change in the UI scheme has had a strong effect on the unemployment experiences of those who were affected. In this section we address this issue further by simulating the hypothetical effects of extended UI benefits on workers aged 53-54 who entered unemployment in 1997 or in 1998. In other words, we ask how this group of the unemployed would have behaved, had they been eligible for the extended benefits. We emphasize that our simulation exercise does not tell much about the overall effect of the 1997 reform, since it also had a strong impact on the inflow to unemployment. In the absence of the reform there would have been more 53-54-year-old employees becoming unemployed between 1997 and 1998. That is, our results apply only to the group of workers who lost their jobs and became unemployed in the world where the reform actually took place. Using the parameter estimates from the split population model we are able to separately identify the effects of extended UI benefits on the participation choice and conditional cumulative probabilities of exits to employment, ALMPs, and non-participation.

In Figure III.10 we illustrate the results of this experiment by plotting the cumulative distribution and incidence functions (1) for the observed data, i.e. individuals 53-54 entering unemployment in 1997 or 1998,[35] (2) for the same group in the hypothetical case of being eligible for the extended UI entitlement, but assuming that all individuals remain active (i.e. by setting $\varepsilon = 1$ for all), and (3) in this same hypothetical situation, but allowing individuals to withdraw from the labour market with the estimated probabilities. These simulations were performed separately for each individual in the data, and the averages of fitted curves over all individuals are plotted in Figure III.10.

We begin with a comparison of actual outcomes and hypothetical outcomes when all workers with extended UI benefits are assumed to remain active. In the real-world data the cumulative distribution function converges to 1, but among the active population with extended entitlement it converges to some .8, i.e. 20% of the active unemployed are predicted to remain unemployed secured by the extension. The probability of employment in the actual sample with fixed 2-year UI entitlement converges to 50%, but allowing for the extended entitlement it, in fact, approaches 60% when all individuals are assumed to remain active. This results from the drastically low transition rates to ALMPs and non-participation among the extension-entitled population. In the real-world data exits to ALMPs account for a notable part of all exits, as some 36% of all unemployment spells eventually end with a transition to such programmes. Adding extended entitlement, it would only be about 13%. The probability of exiting the labour force altogether converges to 15% in the real data, but if we should allow for extended entitlement the incidence of exiting would decline to 9%. Hence, among the active unemployed the entitlement

[35] These are simply the nonparametric estimates.

Figure III.10: Simulated marginal cumulative distribution and incidence functions under different UI schemes




extension effectively increases the probability of employment by 10 percentage points, but due to the otherwise low transitions rates, the probability of remaining unemployed is also higher for them.

If we consider the population with the extended entitlement and allow for the possibility of inactivity, the predicted cumulative probability of exiting from any cause by the end of the observation period is only some 60%. The probability of employment decreases by 15 percentage points compared with the real-world case with fixed entitlement, converging eventually to 35%. Allowing for the possibility of inactivity for the extension-entitled population results in the probability of participation in ALMPs decreasing further to 7%, while the probability of withdrawing from the labour market returns to the level of the real-world case.

Overall, our simulation exercise illustrates that consideration of the end-state specific hazard functions does not give a full picture of the underlying phenomena. In this particular case, the employment hazard functions reveal hardly any statistically significant difference in the case of the fixed two-year UI entitlement and the extended entitlement among the active population (Figure III.6). This might falsely lead us to conclude that, after conditioning on remaining active, the extension of the entitlement period has no effect on the probability of exiting to employment. Looking at our simulated cumulative incidence functions we do, however, find that among the active extension-entitled population the cumulative probability of employment is actually *higher* due to the lower hazards for transitions to ALMPs and non-participation. This result is reversed once we allow some of those with extended UI benefits to choose inactivity. To summarize, via our simulation exercise we are able to say, that had this UI entitlement extension from two years to indefinite been applied to the same cohort becoming unemployed in 1997 or 1998, it would have resulted in a 15% decrease in their employment probability.

## 7 Concluding remarks

We analysed the effects of the two-year increase in the eligibility age of extended UI benefits on the incidence and duration of unemployment among elderly workers. We found that disproportionate numbers of dismissals fall on the group of older workers who are eligible for extended benefits in the case of unemployment. Large employers, especially, seem to actively exploit the unemployment tunnel scheme to get rid of their elderly employees. This kind of a culture of early labour market withdrawal is in sharp contrast with the original idea of the experience-rating of early retirement schemes, which was to encourage employers to invest in working conditions and preventive measures to reduce the disability and layoff risks of their older employees. We found evidence of notable anticipation behaviour prior to the UT reforms in 1997 and 1996. This suggests that social security reforms should be implemented without delay after the political decisions have been made. As a result of the 1997 reform, the layoff risk of 53-54 years old employees of large firms reduced to a level identical to that of their younger co-workers.

In the duration analysis we took advantage of the UI reform in 1997 to identify the impact of the extended UI duration within the difference-in-differences framework. The possibility that some older unemployed people may be discouraged from labour market activities was accounted for by using the competing risks specification of the split population duration model. We found no evidence of large increases in the employment hazard around the time of benefit exhaustion for those workers with the entitlement period of two years. By contrast, the hazard rates for labour market programmes and non-participation exhibit large increases as the time of benefit exhaustion approaches. These findings are in line with evidence from other Nordic countries.

Our results suggest that as many as half of the elderly unemployed entitled to extended UI benefits choose to withdraw from the labour market, remaining passive until early retirement. The likelihood of labour market withdrawal varies with occupation, the level of UI benefits, and the size of the past employer. There are no notable discrepancies in the employment hazards between active workers with extended UI benefits and those with the entitlement period of two years. However, active workers with extended UI benefits have much lower transition rates to labour market programmes and non-participation (prior to access to early retirement). As a consequence, compared with those who will lose their benefits after two years of unemployment, active workers entitled to extended UI benefits are more likely to enter employment but also more likely to still be unemployed 36 months after entry to unemployment.

Without doubt, the combination of extended UI benefits and an early retirement scheme serves as a popular pathway to labour market withdrawal several years prior to the normal old-age pension. The reform in 1997 reduced unemployment among the older workers, and it may therefore be viewed as a success story. On the other hand, the poor employment prospects of elderly workers can be attributed to the Finnish social security system that encourages employers for age discrimination and older unemployed to withdraw from the labour market. Therefore, a more cynical observer might see the 1997 reform as a partial correction of the self-inflicted catastrophe rather than a success story. The lessons of the Finnish reform may be useful to other OECD countries with similar schemes for the elderly which have not yet enacted all required changes of the social security and unemployment insurance systems in order to challenge the ageing of their societies. Our results show that early retirement via long-term unemployment can be effectively reduced by abolishing the extended unemployment benefit periods of the elderly used to bridge the time until the normal old-age pension.

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## III.A Nonparametric estimators

Let $t_1 < t_2 < \cdots < t_M$ be the observed durations of completed unemployment spells in the data. Denote the number of individuals who exit unemployment to destination $k \in \{e, p, o\}$ at spell duration $t_j$ with $d_{kj}$. The Kaplan-Meier estimate of the survivor function is

$$\widehat{S}(t) = \prod_{j|t_j \leq t} \left(1 - \frac{d_j}{n_j}\right),$$

where $d_j = d_{ej} + d_{pj} + d_{oj}$ is the total number of exits and $n_j$ is the number of individuals at risk at spell duration $t_j$. The estimate of the cumulative incidence function for destination $k$ is given by

$$\widehat{F}_k(t) = \prod_{j|t_j \leq t} \frac{d_{kj}}{n_j} \widehat{S}(t_{j-1}),$$

see for example Gaynor et al. (1993). It can be verified that $\widehat{F}_e(t) + \widehat{F}_p(t) + \widehat{F}_o(t) = 1 - \widehat{S}(t)$.

## III.B Survivor functions

For ease of exposition, we denote the hazard rate for destination $k$ at spell duration $t \in (c_{m-1}, c_m]$ as $\theta_k(\mathbf{x}_m) \equiv \theta_k(t\,|\mathbf{X}(t,\tau))$, where $\mathbf{x}_m$ is a vector of covariate values in the $m$th duration interval. The overall hazard rate is denoted with $\theta(\mathbf{x}_m) = \theta_e(\mathbf{x}_m) + \theta_p(\mathbf{x}_m) + \theta_o(\mathbf{x}_m)$.

The survivor function at spell duration $t \in (c_{m-1}, c_m]$ is given by

$$S(t\,|\mathbf{X}(t,\tau)) = [1 - p(\mathbf{z})]\, S(t\,|\mathbf{X}(t,\tau), \varepsilon = 1) + p(\mathbf{z}) S(t\,|\mathbf{X}(t,\tau), \varepsilon = 0),$$

where

$$\begin{aligned} S(t\,|\mathbf{X}(t,\tau), \varepsilon = 1) &= \exp\left\{ -\int_0^t \sum\nolimits_k \theta_k(u\,|\mathbf{X}(u,\tau))\, du \right\} \\ &= \exp\left\{ -\sum_{j=1}^{m-1} \int_{c_{j-1}}^{c_j} \theta(\mathbf{x}_j) du - \int_{c_{m-1}}^{t} \theta(\mathbf{x}_m) du \right\} \\ &= \left[ \prod_{j=1}^{m-1} \exp\left\{ -\theta(\mathbf{x}_j)\,(c_j - c_{j-1}) \right\} \right] \exp\left\{ -\theta(\mathbf{x}_m)\,(t - c_{m-1}) \right\}, \end{aligned}$$

and

$$S(t\,|\mathbf{X}(t,\tau), \varepsilon = 0) = \left[ \prod_{j=1}^{m-1} \exp\left\{ -\theta_o(\mathbf{x}_j)\,(c_j - c_{j-1}) \right\} \right] \exp\left\{ -\theta_o(\mathbf{x}_m)\,(t - c_{m-1}) \right\}.$$

## III.C Cumulative incidence functions

The cumulative incidence function for destination $k$ at spell duration $t \in (c_{m-1}, c_m]$

$$F_k(t\,|\mathbf{X}(t,\tau)) = [1 - p(\mathbf{z})]\, F_k(t\,|\mathbf{X}(t,\tau), \varepsilon = 1) + p(\mathbf{z}) F_k(t\,|\mathbf{X}(t,\tau), \varepsilon = 0)\,,$$

where

$$\begin{aligned}
F_k(t\,|\mathbf{X}(t,\tau), \varepsilon = 1) &= \int_{\mathbf{0}}^{t} \theta_k(u\,|\mathbf{X}(u,\tau))\, S(u\,|\mathbf{X}(u,\tau), \varepsilon = 1)\, du \\
&= \sum_{j=1}^{m-1} \int_{c_{j-1}}^{c_j} \theta_k(\mathbf{x}_j) S(u\,|\cdot)\, du + \int_{c_{m-1}}^{t} \theta_k(\mathbf{x}_m) S(u\,|\cdot)\, du \\
&= \sum_{j=1}^{m-1} \theta_k(\mathbf{x}_j) S(c_{j-1}\,|\cdot) \int_{c_{j-1}}^{c_j} \exp\left\{-\theta(\mathbf{x}_j)\,(u - c_{j-1})\right\} du \\
&\quad + \theta_k(\mathbf{x}_m) S(c_{m-1}\,|\cdot) \int_{c_{m-1}}^{t} \exp\left\{-\theta(\mathbf{x}_m)\,(u - c_{m-1})\right\} du \\
&= \sum_{j=1}^{m-1} \frac{\theta_k(\mathbf{x}_j) S(c_{j-1}\,|\cdot)}{\theta(\mathbf{x}_j)} \left[1 - \exp\left\{-\theta(\mathbf{x}_j)\,(c_j - c_{j-1})\right\}\right] \\
&\quad + \frac{\theta_k(\mathbf{x}_m) S(c_{m-1}\,|\cdot)}{\theta(\mathbf{x}_m)} \left[1 - \exp\left\{-\theta(\mathbf{x}_m)\,(t - c_{m-1})\right\}\right] \\
&= \sum_{j=1}^{m-1} \frac{\theta_k(\mathbf{x}_j)}{\theta(\mathbf{x}_j)} \left[S(c_{j-1}\,|\cdot) - S(c_j\,|\cdot)\right] + \frac{\theta_k(\mathbf{x}_m)}{\theta(\mathbf{x}_m)} \left[S(c_{m-1}\,|\cdot) - S(t\,|\cdot)\right],
\end{aligned}$$

with $S(c_{\mathbf{0}}\,|\cdot) \equiv 1$, and

$$F_k(t\,|\mathbf{X}(t,\tau), \varepsilon = 0) = 0, \qquad k \in \{e, p\}\,,$$

and

$$F_o(t\,|\mathbf{X}(t,\tau), \varepsilon = 0) = 1 - S(t\,|\mathbf{X}(t,\tau), \varepsilon = 0)\,.$$

## III.D The log-likelihood function

For ease of exposition, the conditioning covariates, $\mathbf{X}(t,\tau)$, are suppressed from the following expressions. Denote the cumulative hazard function for destination $k \in \{e, p, o\}$ at spell duration $t \in (c_{m-1}, c_m]$ with

$$\Lambda_k(t) \equiv -\sum_{j=1}^{m-1} \theta_k(\mathbf{x}_j)\,(c_j - c_{j-1}) - \theta_k(\mathbf{x}_m)\,(t - c_{m-1})\,.$$

We can write

$$\ln S(t\,|\varepsilon = 1) = -\sum_j \Lambda_j(t),$$

where $\sum_j$ denotes the sum over all the three exit destinations. For an individual in the treatment group with $p(\mathbf{z}) > 0$ we have

$$\begin{aligned}
\ln S(t) &= \ln\left(\left[1-p(\mathbf{z})\right]e^{-\sum_j \Lambda_j(t)} + p(\mathbf{z})e^{-\Lambda_o(t)}\right) \\
&= \ln\left(e^{-\sum_j \Lambda_j(t)} + e^{\mathbf{z}'\boldsymbol{\delta}-\Lambda_o(t)}\right) - \ln\left(1+e^{\mathbf{z}'\boldsymbol{\delta}}\right) \\
&= \ln\left(e^{-\Lambda_e(t)-\Lambda_p(t)} + e^{\mathbf{z}'\boldsymbol{\delta}}\right) - \Lambda_o(t) - \ln\left(1+e^{\mathbf{z}'\boldsymbol{\delta}}\right).
\end{aligned}$$

By substituting these expressions into (III.4), we find that the contribution of individual $i$ to the log-likelihood function is

$$\begin{aligned}
\mathcal{L}_i &= \sum_j d_{ij}\ln\theta_j(t_i) - (d_{ie}+d_{ip})\left[\ln\left(1+e^{\mathbf{z}_i'\boldsymbol{\delta}}\right) + \sum\nolimits_j \Lambda_j(t)\right] \\
&\quad + (1-d_{ie}-d_{ip})\left[\ln\left(e^{-\Lambda_e(t_i)-\Lambda_p(t_i)} + e^{\mathbf{z}_i'\boldsymbol{\delta}}\right) - \Lambda_o(t_i) - \ln\left(1+e^{\mathbf{z}_i'\boldsymbol{\delta}}\right)\right] \\
&= \sum_j d_{ij}\ln\theta_j(t_i) - \Lambda_o(t_i) - \ln\left(1+e^{\mathbf{z}_i'\boldsymbol{\delta}}\right) - (d_{ie}+d_{ip})\left[\Lambda_e(t_i)+\Lambda_p(t_i)\right] \\
&\quad + (1-d_{ie}-d_{ip})\ln\left(e^{-\Lambda_e(t_i)-\Lambda_p(t_i)} + e^{\mathbf{z}_i'\boldsymbol{\delta}}\right),
\end{aligned}$$

if he belongs to the treatment group, and

$$\mathcal{L}_i = \sum_j d_{ij}\ln\theta_j(t_i) - \sum\nolimits_j \Lambda_j(t)$$

otherwise. These expressions can be combined:

$$\begin{aligned}
\mathcal{L}_i &= \sum_j d_{ij}\ln\theta_j(t_i) - \Lambda_o(t_i) - \left[1-q_i+q_i\left(d_{ie}+d_{ip}\right)\right]\left[\Lambda_e(t_i)+\Lambda_p(t_i)\right] \\
&\quad + q_i\left[(1-d_{ie}-d_{ip})\ln\left(e^{-\Lambda_e(t_i)-\Lambda_p(t_i)} + e^{\mathbf{z}_i'\boldsymbol{\delta}}\right) - \ln\left(1+e^{\mathbf{z}_i'\boldsymbol{\delta}}\right)\right],
\end{aligned}$$

where $q_i = 1$ if individual $i$ belongs to the treatment group, and $q_i = 0$ otherwise.

The structure of the log-likelihood function implies that the ML estimators of the parameters of the non-participation hazard are statistically independent of all other parameters of the model (since the matrix of the second derivatives of the log-likelihood function is block diagonal). As a consequence, the estimation of the conventional competing risks and split population specifications will lead to identical parameter estimates for the hazard function for transitions out of the labour force.

# Chapter IV

# Estimating Equilibrium Search Models from Finnish Data

*Empirical equilibrium search models have attracted a growing interest in recent years. Estimation of such models has not been completely successful, however. This has led researchers to develop more sophisticated versions of the models in an attempt to get a better fit to the data. This study investigates whether various proposed specifications of the Burdett-Mortensen model are able to explain the labour market histories observed in Finnish panel data. We begin with a pure search model in which all wage dispersion results from search frictions. Then we proceed to more complex specifications by introducing measurement error in wages and unobserved employer heterogeneity.*

## 1 Introduction

The focus of *partial* job search models is on the behaviour of workers in the labour market where it takes time to locate alternative job opportunities. In such models the optimal search strategy of workers is typically characterized by the reservation wage but the wage offer distribution the workers face when searching is taken as exogenously given. The analysis of partial job search models has been the focus of much empirical work and such models have proved to be able to explain many stylized facts of the labour market (see Devine and Kiefer, 1991, Wolpin, 1995, and Rogerson et al., 2005, for surveys). However, in ignoring the demand side of the story the partial job search approach rules out the analysis of several important issues. Among the issues which cannot be analysed within the partial framework are all those which are related to wage determination, firm behaviour, interactions between worker and firm behaviour as well as the effects of policy reforms which affect wages (Bontemps et al., 1999).

In *equilibrium* models of job search labour market phenomena are modelled as the outcome of optimal choices by both sides of the labour market. When firms are assumed to take the search behaviour of workers and wages set by other firms into account when setting wages, the wage offer distribution emerges as a part of the equilibrium solution. The endogeneity of the wage offer distribution makes the equilibrium search approach a useful framework for analysing different labour market issues. In recent years the equilibrium search models have attracted a growing interest in the theoretical and empirical literature (see Mortensen and Pissarides, 1999, Van den Berg, 1999, Rogerson et al., 2005, and Eckstein and Van den Berg, 2007, for surveys). Estimation of such models in particular has proved to be quite a tricky task.

The first empirical application of equilibrium search theory is Eckstein and Wolpin's (1990) empirical analysis of the model of Albrecht and Axell (1984). In the Albrecht-Axell model only unemployed workers are searching for jobs, and a worker who accepts a job is expected to hold it as long as he remains in the labour market. In this setting each wage offer in the market must be equal to the reservation wage of some group of searching workers as a higher wage for a given type of workers would not attract any more workers from that group. When workers are homogeneous, all firms offer a single wage equal to the common reservation wage of the unemployed, and the Diamond's (1971) paradoxical monopsony solution emerges. Wage dispersion in the Albrecht-Axell model can arise only in the presence of exogenous worker heterogeneity. Therefore Eckstein and Wolpin (1990) assume that workers differ from each others according to their value of non-market time. Since the computational complexity of the equilibrium solution increases rapidly with the number of different types, only a small number of worker types could be considered in practice. This results in a discrete distribution of wage offers with only a few support points and, as a consequence, Eckstein and Wolpin (1990) find a poor fit to the wage data.

In the equilibrium search model of Burdett and Mortensen (1998) (see also Burdett, 1990, and Mortensen, 1990) workers are searching both on and off the job. For workers jobs are identical apart from the wage associated with them, so employed workers are willing to move into higher-paying jobs whenever the opportunity arises. The fact that the current wage serves as the reservation wage for employed workers extends the range of reservation wages. For the wage-setting firms this means that the labour supply curve is upward-sloping. By offering a higher wage the firm makes a lower profit per worker but attracts more workers from other firms and retains them longer as high-paid workers are less likely to receive an acceptable offer elsewhere. It follows that the equilibrium distribution of wage offers is dispersed even when all workers and firms are respectively identical.[1] Thus persistent wage differentials across identical workers can exist as an equilibrium outcome in the labour market characterized by search frictions in the form of time it takes to find trading partners. This main prediction of the model is consistent with empirical evidence on the existence of considerable wage differentials which cannot be explained by worker and job characteristics (see e.g. Bowlus et al., 1995). Other strong predictions concerning

[1] Bunzel et al. (2001) refer to the homogeneous version of the Burdett-Mortensen model as a 'pure' equilibrium search model because no heterogeneity is needed on either side of the labour market to produce a dispersed wage offer distribution.

the relationship between wages, job durations and firm sizes follow from this simple model as well. Since many of these predictions are consistent with empirical observations and since search on the job is by now regarded to be an important source of wage dispersion, much of research effort has been directed to estimating equilibrium search models that builds on the framework of Burdett and Mortensen (1998). However, in the absence of exogenous worker and firm heterogeneity, the equilibrium distribution of wages generated by the Burdett-Mortensen model has an increasing density over its whole support. This contradicts the shape of wage densities usually observed in the data. So, the simplest version of the model is unable to explain the *shape* of the wage distribution.

There are many attempts to get the Burdett-Mortensen model more consistent with the wage data. The simplest way to proceed is to introduce *between-market* heterogeneity by assuming that the labour market is composed of a large number of segments which differ from each others according to observable characteristics of workers and jobs, like education, age and industry. Assuming workers and firms to be identical within the segments one can then apply the homogeneous model separately to each segment of the labour market (see Kiefer and Neumann, 1993, Van den Berg and Ridder, 1998, and Bunzel et al., 2001). Stratifying the data in this way is, however, unlikely to be sufficient to obtain a good fit to the wage data. This is because the empirical wage distributions do not usually exhibit increasing densities even within narrowly defined worker categories.

An *ad hoc* way of accounting for the discrepancy between the empirical and theoretical wage distributions within the segments is to assume that the wage data are subject to measurement error (Christensen and Kiefer, 1994*a*). In this case the underlying theoretical model remains unchanged, but the estimation procedure must deal with a more complex measurement process. With an appropriate distribution for the measurement error, the discrepancy between the empirical and theoretical distributions can be attributed to the presence of measurement error in wages. On the other hand, workers and jobs are likely to be different within the narrowly defined labour market segments as well. In this regard a more sophisticated approach is to introduce *within-market* heterogeneity in terms of unobserved differences across workers and/or firms operating in the same market. With an exception of Bontemps et al. (1999), the empirical applications of the Burdett-Mortensen model have focused entirely on allowing for employer heterogeneity rather than worker heterogeneity. This is mainly due to the difficulties of accounting for heterogeneity simultaneously on both sides of the market,[2] whereas employer heterogeneity is expected to be a more important source of wage dispersion.

A theoretical extension of the Burdett-Mortensen model which allows for a discrete

[2] Bontemps et al. (1999) estimate a version of the Burdett-Mortensen model with a continuous distribution for labour productivity (across firms) as well as for the value of non-market time (across workers). However, this makes the model intractable which enforces them to restrict the arrival rate of wage offers to be the same for unemployed and employed workers. This is a problematic assumption as the empirical evidence supports the view that unemployed workers receive wage offers more frequently (see for example our empirical results below).

distribution of productivity across firms is outlined in Mortensen (1990) and in Burdett and Mortensen (1998). Bowlus et al. (1995) develop an estimation method which is able to deal with the ill-behaved likelihood function of this extension. Bontemps et al. (1999, 2000) introduce an alternative version of the Burdett-Mortensen model which allows for a continuous productivity distribution. They also propose a structural nonparametric estimation procedure for the model that does not restrict the productivity distribution to belong to any parametric family. Both approaches have advantages and disadvantages regarding computational complexity and interpretation of the results. A discrete distribution of productivity has been adopted in the empirical studies by Bowlus et al. (1995, 2001), Bowlus (1997) and Bunzel et al. (2001), whereas Van den Berg and Van Vuuren (2000) and Bontemps et al. (1999, 2000) have favoured the continuous specification in their applications.

It is worth emphasizing that the alternative ways of introducing extra wage variation into the Burdett-Mortensen model can lead to an equally good statistical fit to the data. This raises some issues regarding the empirical inference. Though the fundamental structure of the model remains unchanged, the source and interpretation of observed wage differentials depend upon the underlying assumptions of measurement error and productivity heterogeneity. Since the additional sources of wage variation are not directly observable by definition, it is generally difficult to distinguish between them. This suggests that one may be able to attribute some fraction of wage dispersion arbitrarily either to unobserved productivity or to the measurement error in the wage data. Moreover, the estimates of the fundamental parameters, such as the layoff rate and arrival rates of wage offers which are common to all extensions, are potentially sensitive with respect to the specification used.

We explore these issues by comparing the results obtained from the various extensions of the Burdett-Mortensen model proposed in the literature. All variants of the model are estimated using maximum likelihood from a sample of workers who entered unemployment in Finland during 1992. In the analysis we distinguish between separate segments of the labour market by stratifying the data according to education, sex and age. All structural parameters of the model are allowed to vary freely across the different segments. We begin with the homogeneous version of the model which is then followed by the estimation of specifications involving the measurement error in wages and unobserved employer heterogeneity within the labour market segments. The estimation results are discussed and compared across the model specifications as well as across the worker groups. Our analysis is closely related to the study by Bunzel et al. (2001) in which the results obtained from different equilibrium search models are compared. However, our set of equilibrium search models to be compared is wider and we apply the models to the Finnish data instead of the Danish data.

The results of the paper are useful in a variety of ways. First, a comparison of the fit of different extensions is informative on what aspects of the theory and empirical specification are likely to be important to obtain an acceptable fit to the Finnish data. Second, by investigating variation in the parameter estimates across the model specifications, we can test how robust the estimates of the fundamental parameters are with respect to different ways of deviating from the homogenous version of the model. Third, our results are informative about the relationship between unemployment durations, job durations and wages in the Finnish labour market. This information can be used to evaluate the degree of wage differentials attributable to differences in search behaviour and labour productivity across the worker groups.

The rest of the paper is organized as follows. In the next section the concepts of the equilibrium search theory are described. Section 3 discusses the data and provides some summary statistics. Empirical specifications and estimation results are discussed in Section 4. The final section concludes.

# 2 Equilibrium search theory

In this section we briefly describe equilibrium search theory along the lines of Burdett and Mortensen (1998) and Bontemps et al. (2000). We begin with a pure search model in which all jobs are equally productive and all workers are identical. Then we introduce employer heterogeneity in the model but retain the assumption of homogeneity of the worker population throughout the paper.

## 2.1 Equilibrium search with identical agents

### Worker behaviour

The supply side of the labour market is populated by a continuum of *ex ante* identical workers. Behaviour of workers is characterised with the standard job search model with search on the job. In particular workers are assumed to be risk-neutral agents who are maximising the expected present value of future income stream with infinite horizon. Each worker in the labour market is either employed or unemployed. Events the worker faces in the labour market arrive with random time intervals. Each worker is facing a known distribution of wage offers $F$ with associated jobs, from which he randomly samples wage offers both on and off the job. Wage offers arrive at the Poisson rate $\lambda_0$ when unemployed and at the Poisson rate $\lambda_1$ when employed. Unemployed workers search for an acceptable job and employed workers for a better job. Jobs are destroyed at the Poisson rate $\delta$, in which case the worker who holds the job is laid off and becomes unemployed.

Given this framework, the present value of being unemployed, $V$, solves the continuous time asset pricing equation

$$\rho V = b + \lambda_0 \left( E_F \left( \max \left\{ W\left(\widetilde{w}\right), V \right\} \right) - V \right), \tag{IV.1}$$

where $\rho$ is the common discount rate, $W(w)$ is the present value of a job paying wage $w$, and $b$ is the value of non-market time, including unemployment benefits net of search costs. The expectation above is taken over the support of $F$, and the tilde above $w$ refers to a random draw from $F$. The equation (IV.1) simply states that the opportunity cost of unemployment, the left-hand side of (IV.1), is equal to the sum of the value of non-market time and the expected capital gain of finding an acceptable job, the right-hand side of (IV.1). Analogously, the present value of being employed at wage $w$, $W(w)$, solves

$$\rho W(w) = w + \lambda_1 \left( E_F \left( \max \left\{ W\left(\widetilde{w}\right), W(w) \right\} \right) - W(w) \right) + \delta \left( V - W(w) \right), \tag{IV.2}$$

which consists of the current wage, the likelihood and value of receiving an alternative job offer, and the likelihood and value of becoming unemployed. Note that the utility flow of an employed worker is assumed to be equal to his current wage.

Since $W(w)$ increases with $w$ and $V$ is independent of it, there exists a reservation wage $r$ such that $W(r) = V$. By virtue of (IV.1) and (IV.2), it then holds that

$$\begin{aligned} r &= b + (\lambda_0 - \lambda_1) \left( E_F \left( \max \left\{ W\left(\widetilde{w}\right), V \right\} \right) - V \right) \\ &= b + (\lambda_0 - \lambda_1) \int_r^h \left( W(z) - V \right) dF(z), \end{aligned} \tag{IV.3}$$

where $h$ is the upper bound of the support of $F$. To put this expression into a more convenient form, we integrate by parts to obtain

$$\begin{aligned} r &= b + (\lambda_0 - \lambda_1) \int_r^h \left[ 1 - F(z) \right] dW(z) \\ &= b + (\lambda_0 - \lambda_1) \int_r^h \frac{1 - F(z)}{\rho + \delta + \lambda_1 \left[ 1 - F(z) \right]} dz. \end{aligned} \tag{IV.4}$$

Following Burdett and Mortensen (1998), we focus on the limiting case of zero discounting and set $\rho = 0$. This allows us to rewrite (IV.4) in the simpler form:

$$r = b + (\kappa_0 - \kappa_1) \int_r^h \frac{1 - F(z)}{1 + \kappa_1 \left[ 1 - F(z) \right]} dz, \tag{IV.5}$$

where $\kappa_0 = \lambda_0 / \delta$ and $\kappa_1 = \lambda_1 / \delta$. This equation defines the reservation wage $r$ as a function of the structural parameters of the model.

From (IV.5) one can see how the possibility of search on the job affects the optimal search strategy of an unemployed worker. If wage offers arrive more frequently when unemployed than when employed $(\lambda_0 > \lambda_1)$, the reservation wage $r$ exceeds the value of non-market time $b$. In that case it is more rewarding to search while unemployed and the worker rejects wage offers in the interval $(b, r)$, even though this causes a utility loss in the short run. When the arrival rate is independent of employment status $(\lambda_0 = \lambda_1)$, the worker is indifferent between searching while employed and while unemployed. Any job that compensates for the foregone value of non-market time is acceptable in this case and thus $r = b$. If search on the job is not possible $(\lambda_1 = 0)$, the expression in (IV.5) reduces to the standard optimization condition.

#### Firm behaviour

The demand side of the labour market consists of a continuum of *ex ante* identical firms. The firms are assumed to use only labour inputs in production. Each worker generates a flow of revenue $p$ to his employer. We assume that $p$ is independent of the size of the workforce and refer to $p$ as the (labour) productivity of the firm. The firm sets its wage so as to maximise the expected steady-state profit flow taking the optimal search behaviour of workers and wages set by other firms as given. To attract workers the firm posts wage offers, among which workers randomly search using a uniform sampling scheme. Contrary to the competitive setting, the presence of search frictions in the labour market generates dynamic monopsony power for wage-setting firms. As workers cannot find a higher-paying job instantaneously, firms can offer wages strictly smaller than marginal labour productivity.

The expected profit flow of a firm paying wage $w$ in a steady state is given by

$$\pi(p, w) = (p - w)\, l(w), \tag{IV.6}$$

where $l(w)$ is the expected size of the workforce (associated with a given $F$). The firm would employ as many workers as possible to maximise its profit flow as long as $p > w$. Since the current wage serves as the reservation wage for employed workers, the number of workers available to the firm in equilibrium increases with the wage offered, i.e. the labour supply curve the firm is facing with is upward-sloping. The firm takes the function $l$ as given and offers a wage that maximises its expected steady-state profit flow. Obviously, a firm never offers a wage above $p$ as the profits would be negative, nor it offers a wage less than $r$ as such a wage would not attract any workers. The optimal wage offer of a firm with productivity $p$ is a point in a set $K_p$ of wages that maximise the expected steady-state profits,

$$K_p = \arg\max_{w} \left\{ \pi(p, w) \,|r \leq w \leq p \right\}. \tag{IV.7}$$

When $K_p$ is not a singleton the firm is indifferent between alternative wage strategies.

Equally productive firms must receive the same expected profit flow in equilibrium. This does not mean that wage offers need to be equal, however. A firm paying a higher wage makes a lower profit per worker but makes it up in volume as the higher wage attracts more workers from other firms and enables the firm to retain them for a longer time. It follows that some firms choose to offer low wages with a cost of high labour turnover, while others pay higher wages and experience lower labour turnover. Due to this trade-off between the wage offered and labour turnover, the same expected profit level can be attained by paying different wages.

#### Steady-state outcomes

Denote the fixed size of the labour force with $m$ and the steady-state number of unemployed workers with $u$. In a short time interval $dt$ a fraction $\delta dt$ of employed workers, $m - u$, lose their jobs and become unemployed, so the flow from employment into unemployment is $\delta(m-u)\,dt$. The corresponding flow out of unemployment into employment is given by $\lambda_0 u dt$.[3] In a steady state the flows into and out of unemployment are equal which implies that the steady-state unemployment rate is

$$\frac{u}{m} = \frac{\delta}{\delta + \lambda_0} = \frac{1}{1+\kappa_0}. \tag{IV.8}$$

Using an analogous argument we can derive the steady-state *earnings* distribution $G$, the cross-section wage distribution of currently employed workers, associated with a given wage offer distribution $F$. Given the initial allocation of workers to firms, the number of workers employed at a wage no greater than $w$ is given by $G(w)(m-u)$. The flow out of jobs paying $w$ or less in a short time interval $dt$ is $\delta G(w)(m-u)dt + \lambda_1 [1-F(w)]\, G(w)(m-u)dt$, while the flow into such jobs is $\lambda_0 F(w) u dt$. The outflow is equal to the number of workers who lose their jobs due to a demand shock plus the number of those who receive an offer greater than $w$. The inflow consists of those unemployed who receive an offer no greater than $w$. By equating these flows, we find the following steady-state relationship between the wage offer and earnings distribution:

$$G(w) = \frac{F(w)}{\delta + \lambda_1 [1-F(w)]} \cdot \frac{\lambda_0 u}{m-u} = \frac{F(w)}{1+\kappa_1 [1-F(w)]} \tag{IV.9}$$

for all $w$ on the common support of $F$ and $G$. Since workers tend to move up the wage range over time, the earnings distribution lies to the right of the wage offer distribution, or more formally, $G$ first-order stochastically dominates $F$ as $F(w) - G(w) \geq 0$ for all $w$ and $\kappa_1 \geq 0$. The discrepancy between the earnings and wage offer distributions depends on $\kappa_1$ which is equal to the expected number of wage offers during a spell of *employment* (which may consist of several consecutive job spells) and can be thought of as a relative measure of competition among firms for workers.

Let us consider next the labour turnover of a firm which offers wage $w$ in the support of $F$. In a short time interval $dt$ a fraction $\delta dt$ of firm's employees are laid off and a fraction $\lambda_1 [1-F(w)]\, dt$ quits for a higher-paying job, so the outflow of employees is $(\delta + \lambda_1 [1-F(w)])\, l(w) dt$. Provided that the size of the firm population is normalized to one and contacts are made randomly, the inflow of workers to the firm is $[\lambda_0 u + \lambda_1 G(w)(m-u)]\, dt$, the number of hires from unemployment plus the number of hires from lower-paying firms. In a steady state the inflow and outflow are expected to be equal which implies that the expected size of the workforce of the firm offering wage $w$ can be expressed as

$$l(w) = \frac{\lambda_0 u + \lambda_1 G(w)(m-u)}{\delta + \lambda_1 [1-F(w)]} = \frac{\kappa_0 (1+\kappa_1)\, m}{(1+\kappa_0)(1+\kappa_1 [1-F(w)])^2}. \tag{IV.10}$$

Obviously $l$ is increasing in $w$ and continuous where $F$ is continuous. Note that no assumptions on the shape of $F$ have been made so far. Since workers quit and are hired

[3] More generally, the flow out of unemployment is $\lambda_0 [1-F(r)]\, udt$ but we know that in equilibrium $F(r) = 0$ because firms offering a wage below $r$ do not attract any workers and cannot therefore survive.

and laid off at random intervals, the workforce of the firm is a random variable, varying around its expected value $l$ over time. As a consequence, also the profit flow is a random variable.

Burdett and Mortensen (1998) prove that there exists a unique non-cooperative equilibrium which consists of a triple $(r, F, \overline{\pi})$, such that $(i)$ $r$ satisfies (IV.5) given $F$ and $(ii)$ each $w$ on the support of $F$ maximises $\pi(p, w)$, yielding the expected steady-state profit flow equal to $\overline{\pi}$.[4] Furthermore, they show that the equilibrium solutions for $F$ and $G$ are absolutely continuous with the common support $[r, h]$.[5]

Since the expected profit flow is $\overline{\pi}$ across all firms in equilibrium, it holds in particular that $\pi(r) = \overline{\pi} = \pi(w)$ for all $w$ on the support of $F$. Taking this together with (IV.10) gives the equilibrium wage offer distribution[6]

$$F(w) = \frac{1+\kappa_1}{\kappa_1}\left(1 - \sqrt{\frac{p-w}{p-r}}\right), \quad w \in [r, h], \tag{IV.11}$$

with the associated density

$$f(w) = \frac{1+\kappa_1}{2\kappa_1\sqrt{(p-r)(p-w)}}, \quad w \in [r, h]. \tag{IV.12}$$

Moreover, by substituting (IV.11) into (IV.5) and recognising that $F(h) = 1$, we can write the bounds of support of $F$ as

$$r = \alpha b + (1-\alpha)\,p, \tag{IV.13}$$

$$h = \beta b + (1-\beta)\,p, \tag{IV.14}$$

where the weights are given by

$$\alpha = \frac{(1+\kappa_1)^2}{(1+\kappa_1)^2 + (\kappa_0 - \kappa_1)\,\kappa_1}, \tag{IV.15}$$

$$\beta = \frac{1}{(1+\kappa_1)^2 + (\kappa_0 - \kappa_1)\,\kappa_1}. \tag{IV.16}$$

In other words, both the support and functional form of the wage offer distribution depends only on the structural parameters of the model.[7] The fact that $h$ is a weighed average of

[4] Trivial solutions are ruled out by making the natural assumptions that $\infty > p > b$ and $\infty > \kappa_i > 0$ for $i = 0, 1$.

[5] To see that there cannot be mass points in the equilibrium wage distributions, suppose that there is a mass point at $w^* \in [r, h]$. This induces the firm offering $w^*$ to increase its offer slightly to increase its steady-state workforce substantially at the cost of only a second-order decrease in the profit per worker. It follows that a wage offer equal to a mass point cannot be profit-maximising for any firm. Secondly, to illustrate that there cannot be gaps in the support $[r, h]$, let us suppose that no firm offers a wage on the interval $(\underline{w}, \overline{w}) \subset [r, h]$. This cannot be the case in equilibrium as the firm offering wage $\overline{w}$ could increase its profits by reducing its wage offer to $\underline{w}$. The same argument implies that the firms offering the lowest wage in the market must offer a wage equal to $r$.

[6] The associated equilibrium solutions for the earnings distribution follows directly from the steady-state relationship outlined in (IV.9).

[7] Obviously, $\beta = \alpha/(1+\kappa_1)^2$ which implies that $0 < \beta < \alpha < 1$ for $\kappa_1 > 0$, so $h > r$ provided that $p > b$.

$b$ and $p$ further implies that the highest wage offered in the market is strictly smaller than $p$.

The main outcome of equilibrium search theory with on-the-job search is that wages are dispersed in equilibrium even when all workers and firms are respectively identical. When the arrival rates of job offers, $\lambda_0$ and $\lambda_1$, tend to infinity, the equilibrium earnings distribution $G$ converges to a mass point at $p$, and both the steady-state unemployment rate and the equilibrium profit rate tends to zero. Thus the competitive solution emerges as a limiting case when search frictions disappear. As a second extreme, if only unemployed workers receive offers ($0 < \lambda_0 < \infty$ and $\lambda_1 = 0$), the firms cannot increase their workforce by offering higher wages. Thus all firms offer the same wage equal to $r$ which in turn converges to $b$. In this case the equilibrium earnings distribution $G$ limits to a mass point at $b$, and the Diamond's (1971) paradoxical monopsony solution emerges. Moreover, all employment would be uniformly distributed across the firms as $l(w) = m - u$ by virtue of (IV.10) and (IV.8).

Other strong predictions follow from the simple model outlined above. Firstly, workers with longer employment history are predicted to be more likely to be located at the upper end of the wage distribution. This is because wage growth in the model results from job-to-job transitions. Secondly, the model implies a positive relationship between the size of workforce and the wage paid by the firm. Firms offering higher wages grow at a larger size because a higher wage attracts more workers to a firm from other firms and reduces the quit rate, $\lambda_1 [1 - F(w)]$. These results are driven by on-the-job search.

An interesting prediction of the model is that a change in the unemployment benefit $b$ does not affect equilibrium unemployment as long as $b < p$. For example, an increase in $b$ increases the reservation wage $r$ by virtue of (IV.5). However, to retain a positive workforce, firms offering wages below the new value of $r$ must react by increasing their wage offers which in turn affects the wage offers of other firms. The net result is that the exit rate out of unemployment and thus the unemployment level remain unchanged. Using a similar reasoning one can see that a decrease in $b$ does not affect unemployment either.

## 2.2 Employer heterogeneity

The model of the previous section makes several predictions which can be expected to be consistent with empirical data. However, a closer look at (IV.12) reveals that the density of the wage offer distribution (and, consequently, that of the earnings distribution) is strictly increasing and convex on its whole support. This contradicts with the shape of wage distributions usually observed in the data as empirical wage densities are typically unimodal and skewed with a long right tail. This calls to doubt whether the simple equilibrium search model with identical agents can provide an acceptable fit to the wage data. To make the model more realistic, we extend the basic model by allowing for employer heterogeneity. In the first case we introduce heterogeneity assuming a discrete distribution for productivity across firms along the lines of Mortensen (1990) and Burdett and Mortensen (1998). This is followed by an extension of Bontemps et al. (2000) which allows for continuous productivity dispersion.

**A finite number of firm types**

Assume that there are $q$ types of firms which differ in their labour productivity such that $p_1 < p_2 < ... < p_q$. Let $\gamma_i$ be the fraction of firms with productivity $p_i$ or less. Keeping all other aspects of the model unchanged, Mortensen (1990) and Burdett and Mortensen (1998) show that the equilibrium solution in this case results in a complete segmentation of the wage offer range among firm types. Optimal wage setting implies that the wage offered increases with productivity and that all firms of type $i$ offer wages on the interval $[\underline{w}_i, \overline{w}_i)$, where the bounds of intervals are such that $\overline{w}_i = \underline{w}_{i+1}$ for $i = 1, 2, ..., q-1$. In addition, the lowest wage offered is equal to the reservation wage, so that $\underline{w}_1 = r$. We also define that $\overline{w}_q = h$ in order to be consistent with our previous notation.

In equilibrium all firms of given type must have the same expected profit flow, so that $(p_i - w)\, l(w) = (p_i - \underline{w}_i)\, l(\underline{w}_i)$, where $l(w)$ is as defined in (IV.10), holds for all firms with productivity $p_i$ offering a wage on the interval $[\underline{w}_i, \overline{w}_i)$. This implies the following equilibrium distribution of wage offers:

$$F(w) = \frac{1+\kappa_1}{\kappa_1}\left(1 - \frac{1+\kappa_1\left(1-\gamma_{i-1}\right)}{1+\kappa_1}\sqrt{\frac{p_i - w}{p_i - \underline{w}_i}}\right), \quad w \in [\underline{w}_i, \overline{w}_i), \tag{IV.17}$$

with the associated density

$$f(w) = \frac{1+\kappa_1\left(1-\gamma_{i-1}\right)}{2\kappa_1\sqrt{(p_i - w)\,(p_i - \underline{w}_i)}}, \quad w \in [\underline{w}_i, \overline{w}_i), \tag{IV.18}$$

where $\gamma_i = F(\overline{w}_i)$, with the convention that $\gamma_0 = 0$. As shown in Mortensen (1990) and in Burdett and Mortensen (1998), an equilibrium is characterized by $(r, F, \overline{\pi}_1, ..., \overline{\pi}_q)$, where $(i)$ $r$ is the common reservation wage satisfying (IV.5), $(ii)$ $F$ is the wage offer distribution given in (IV.17) and $(iii)$ $\overline{\pi}_i = (p_i - w)\, l(w)$ is the expected steady-state profit flow of firms with productivity $p_i$ offering wages on the interval $[\underline{w}_i, \overline{w}_i)$, $i = 1, 2, ..., q$. In general, when there are $q$ types of firms, the resulting distribution of wage offers $F$ is absolutely continuous with the support $[r, h]$ and has $q-1$ "kinks" corresponding to the wage cuts $(\overline{w}_1, \overline{w}_2, ..., \overline{w}_{q-1})$.[8]

Recall from the previous section that the equilibrium wage distributions have increasing densities over their whole support when all jobs are equally productive. This property is at odds with the long flat right tail commonly observed in the wage data. In contrast, the model of this section with productivity heterogeneity implies that the wage density $f$ is

[8] Van den Berg (2003) points out that there may exist other equilibria characterized by a different reservation wage and a different number of active firm types. This possibility arises from the two-way relationship between the reservation wage of the unemployed and minimum productivity level in use. In other words, the reservation wage affects the minimum level of profitable productivity and vice versa.

discontinuous at the wage cuts, between which it exhibits locally increasing patterns. This theoretical distribution can take the functional form able to mimic the shape observed in the data. Moreover, since more productive firms offer higher wages, they attract more workers, face lower quit rates and, consequently, are larger on average. High productivity firms make also more profit on average in equilibrium than less productive firms.

**A continuum of firm types**

Bontemps et al. (2000) (see also Bontemps et al., 1999, and Burdett and Mortensen, 1998) propose an alternative extension of the Burdett-Mortensen model which allows for continuous productivity dispersion. For this specification we suppose that productivity $p$ is continuously distributed across *active* firms according to the distribution function $\Gamma$, with support $\left[\underline{p}, \overline{p}\right]$, where $\underline{p} \geq r$.[9] Bontemps et al. (2000) show that only one wage offer can be profit-maximizing for each firm (that is, the set $K_p$ of profit-maximizing wages for a firm with productivity $p$ is a singleton) and the optimal wage offer increases with productivity. It follows that there exists a direct map between the productivity distribution $\Gamma$ and wage offer distribution $F$:

$$F(K(p)) = \Gamma(p), \tag{IV.19}$$

where $K(p)$ denotes the wage offered by firms with productivity $p$ and $K$ is an increasing and continuous function. Stated differently, the fraction of offers no higher than $K(p)$ equals the fraction of firms with productivity $p$ or less.

Given that $K$ is strictly increasing in $p$, firms with the lowest productivity $\underline{p}$ must offer a wage equal to the reservation wage $r$ and the highest wage in the market is offered by firms with the highest productivity $\overline{p}$. Since the wage offer is unique for any $p$ in the interior of $\Gamma$, the optimal wage offer $w = K(p)$ solves the first-order condition $\partial\pi\left(p, w\right)/\partial w = 0$, where the expected profit function is $\pi(p, w) = (p - w)\, l\left(w\right)$ and $l\left(w\right)$ is as defined in (IV.10). For given $F$ and $p$ this condition writes as

$$2\kappa_1 f(w)\left(p - w\right) - \left(1 + \kappa_1\left[1 - F(w)\right]\right) = 0, \tag{IV.20}$$

and the associated second-order condition can be expressed as

$$f'(w)\left(1 + \kappa_1\left[1 - F(w)\right]\right) - \kappa_1 f(w)^2 < 0, \tag{IV.21}$$

[9] The number of active firms in the market can be viewed to be endogenous in this setting. To see this, suppose that there are $N_0$ firms willing to participate in the market, across which productivity is distributed according to the distribution function $\Gamma_0$, with the lower and upper bound of support $\underline{p}_0$ and $\overline{p}$ respectively. However, only firms making a non-negative profit are active and hence participating in the market. The distribution of productivity across these firms is obviously $\Gamma(p) = \Gamma_0\left(p\,|p \geq r\right)$, where the threshold value for participation is the reservation wage $r$. Stated differently, only those firms which are able to pay at least $r$ can participate in the market. If the reservation wage is high enough to drop some firms out of the market (i.e. when $r > \underline{p}_0$), the measure of active firms in the market is $N_0\left[1 - \Gamma_0(r)\right]$ (this figure is normalized to one in the text to be consistent with our previous analysis). See Bontemps et al. (2000) for further discussion.

provided that $w = K(p) \geq r$. The first-order condition (IV.20) gives an implicit function of the wage offer of a firm with productivity $p$ given $\kappa_1$ and the distribution of wages offered by other firms.

From (IV.19) it follows that $\gamma(p) = f(K(p))K'(p)$, where $\gamma$ denotes the productivity density associated with $\Gamma$. Using this we can rewrite (IV.20) as

$$K'(p) = \frac{2\kappa_1\gamma(p)}{1+\kappa_1\left[1-\Gamma(p)\right]}\left(p-K(p)\right). \tag{IV.22}$$

This differential equation with the boundary condition $K(\underline{p}) = r$ imply the following optimal wage policy:

$$K(p) = p - \left(1+\kappa_1\left[1-\Gamma(p)\right]\right)^2 \int_r^p \frac{dz}{\left(1+\kappa_1\left[1-\Gamma(z)\right]\right)^2}. \tag{IV.23}$$

By substituting $r$ from (IV.5) into (IV.23), we can express $K(p)$ in terms of the structural parameters $(b, \lambda_0, \lambda_1, \delta, p, \Gamma)$.

Given $\Gamma$ an equilibrium is characterized by $(r, F)$, where $(i)$ the common reservation wage $r$ satisfies (IV.5) and $(ii)$ the wage offer distribution the workers face while searching $F$ is given by (IV.19) and (IV.23).[10] As before the equilibrium distribution of wage offers $F$ is absolutely continuous over its support $[r, h]$. Neither $K$ nor $F$ has a closed-form expression in general. Despite this the model outlined above makes some strong restrictions on the shape of the wage distributions, excluding certain shapes for $F$ and $G$. Bontemps et al. (2000) show that the set of wage offer distributions that can be generated by the model is characterized by the following conditions:[11] $(i)$ the upper bound of support of $F$ is finite (i.e. $h < \infty$), $(ii)$ the density $f$ has a high peak at the lowest wage if and only if the lowest wage equals the lower bound of the support of the productivity distribution (i.e. if $r = \underline{p}$), and $(iii)$ for given $\kappa_1$, $f(w)\left(1+\kappa_1\left[1-F(w)\right]\right)$ decreases over the whole support of $F$ (that is, the second-order condition (IV.21) holds).[12] These conditions impose testable restrictions which can be used as a specification test in the empirical analysis of the model.

In ruling out wage distributions with unbounded support the first condition implies that firms with high productivity may have very high monopsony power and, consequently, receive very high profits.[13] The second condition reflects the fact that if the reservation wage is high enough it destroys monopsony power of firms located at the lower end of the productivity distribution. Since the wage offers of these firms must lie in a narrow interval

[10] To be specific, there can be a single equilibrium, multiple equilibria or equilibrium may not exist at all, depending on the values of structural parameters of the model. Bontemps et al. (2000) point out that it is in general hard to differentiate between alternative cases. In the text we arbitrarily assume that the unique equilibrium exists.

[11] Bontemps et al. (2000) derive the corresponding conditions for the earnings distribution $G$ as well. Since $F$ and $G$ are directly related through (IV.9), as imposed by the equilibrium flow conditions, we focus here on the conditions for $F$ only.

[12] Note that $f(w)\left(1+\kappa_1\left[1-F(w)\right]\right)$ is constant for the homogeneous version of the Burdett-Mortensen model.

[13] The expected steady-state profit flow is convex in productivity, suggesting a high degree of monopsony power for high-productivity firms.

between the reservation wage and their productivity, there is a congestion at the lowest wages, resulting in a peak. In contrast, when the lower bound of productivity support exceeds the reservation wage notably, low-productivity firms can also choose their wages from a wide range. In such a case a wage offer equal to a mass point cannot be profit-maximizing for any firm. The third condition imposes the restriction how steeply $f$ can increase for given $\kappa_1$. Where the density $f$ is decreasing the condition is obviously met regardless of the value of $\kappa_1$. For large $\kappa_1$ the condition allows $f$ to increase quite steeply, but for small $\kappa_1$ the condition is violated even if $f$ increases only slightly.

When productivity is dispersed across firms, the shape of $F$ obviously depends on the shape of $\Gamma$. However, whereas $\kappa_1 > 0$ is necessary and sufficient for wage dispersion, it should be noted that productivity dispersion is neither necessary nor sufficient for wage dispersion. In the presence of productivity differentials the degree of wage dispersion may be decomposed into two parts: one which is due to search frictions analogously to the homogeneous case and another which results from variation in productivity across firms. In particular it can be shown that the equilibrium of the homogeneous version of the Burdett-Mortensen models emerges as a limiting case when the degree of productivity dispersion goes to zero (see Bontemps et al., 2000, for details).

# 3 Data

Christensen and Kiefer (1997) discuss data requirements for identification of the structural parameters of the Burdett-Mortensen model. They show that the model can be estimated from data on individual labour market histories where at least some of the workers are observed with both unemployment duration and job duration with the associated wage. Empirical analysis of this study is based on a sample of individuals drawn from the worker data of the Integrated Panel of Finnish Companies and Workers (the IP data).[14] Underlying source of information on workers in the IP data is the Employment Statistics (ES) database of Statistics Finland. The ES database is a longitudinal database which combines information from over 20 administrative registers. Since 1987 the ES database has been updated regularly, and it covers effectively all people with a permanent residence in Finland.

Each individual in the ES database who holds a job at the last week of the year is associated to his or her employer with a company and establishment identifier. The worker panel of the IP data covers all people from the ES database with an identifier of the private-sector employer at least in one of the years between 1988 and 1996. As a result, the underlying worker panel covers practically *all* persons who have been employed in the private sector during the period 1988-1996 (at least at the end of one year). The total number of persons in the IP data is slightly below two million. For these people a set of

[14] A detailed description of the IP data is given in Korkeamäki and Kyyrä (2000). More recently, the Finnish Longitudinal Employer-Employee data (FLEED) have replaced the IP data.

variables, collected by combining the annual records of the ES database, is available over the period 1988-1996.

In this paper we focus on a certain subsample of the worker panel of the IP data. As a first step we select all individuals between the ages of 16 and 65 who entered unemployment during 1992. In choosing a sample of unemployed workers we follow the practice of Bowlus et al. (2001) and Bunzel et al. (2001).[15] We exclude workers who have been self-employed as well as those have been employed by the public sector or non-profit organization during the period 1990-1996. These groups are excluded as the underlying model does not describe their labour market experiences.

For all individuals selected in the sample, we record the duration of the unemployment spell ($d$) and information on whether unemployment ended because of finding a job ($c_d = 0$) or for some other reason ($c_d = 1$).[16] Unemployment spells not followed by a job are treated as right-censored in the empirical analysis. This may occur due to a drop out of the labour force, participation in the active labour market programme or the spell continuing beyond the observation period. It should be stressed that we treat unemployment spells ended in a job placement programme as right-censored as well. Thus we make a difference between finding a job from the open labour market and becoming employed by labour administrative measures.

For those workers who found a job, we further record the accepted wage ($w$) and the duration of the subsequent job spell ($j$) along with the reason for termination. The wage rate is computed using information on annual earnings and the days worked. A job spell may end in a layoff ($a = 0$, $c_j = 0$), a quit ($a = 1$, $c_j = 0$) or be right-censored ($c_j = 1$). Job spells followed by unemployment are classified to be ended in a layoff, whereas job spells consecutively followed by another job spell with a new employer are interpreted to be ended in a quit for a better job. We identify changes in employer by comparing establishment identifiers attached to workers on the basis of the employer. Job spells terminated due to a drop out of the labour force and those continuing beyond the observation period are treated as right-censored. All durations are measured in months, and wages are converted into monthly rates to match the duration measures.

Recall that our theoretical model is concerned with the population of homogeneous workers. While all workers are different in practice, we cannot allow the parameters to be different for each individual as the model will be of no use at all in such a case. Instead we assume that the labour market consists of a large number of segments, each

[15] A few points concerning the sampling scheme should be stressed. First, the sample drawn from the inflow of unemployment is not a representative sample of the labour force but workers with poor employment prospects are likely to be over represented. But as we wish explain differences in post-unemployment wages a flow sample is a natural choice and, under the assumptions of the theory, it does not make any difference whether we use a stock or flow sample. Second, the sampled workers are followed from 1992 to 1996, which is the period following a deep recession and is, consequently, characterised by a record high unemployment level (see discussion in the text). However, this sub-period exhibits the most stable labour market conditions in the period 1988-1996 potentially available for the analysis.

[16] If the worker has several unemployment spells started in 1992, we choose the first one.

of which forms a single market of its own. These segments are assumed to differ from each others according to observed characteristics of workers. To deal with this kind of heterogeneity, the model can be applied separately to each group of workers, allowing for all parameters to vary freely across the groups. This approach corresponds to controlling observed heterogeneity with a complete set of discrete regressors (Christensen and Kiefer, 1994*a*). To pursue this approach, we stratify the data by education, sex and age. We categorize education as follows: lower vocational education or less (11 years or less), upper vocational education (12-13 years), lower university (a Bachelor degree or the lowest level of university education, 13-15 years), and upper university (a Master degree or higher, 16 years or more). The age groups considered are: 16-21 years, 22-30 years, 31-50 years, and 51-65 years. As only few workers with lower or upper university education are aged below 22 or above 50, we combine the two lowest age groups as well as the two highest age groups for these education groups.

As some of the estimation procedures used are sensitive to outliers in the wage data, some concern needs to be taken with our wage measures. Since the monthly wages are computed from annual earnings without information on hours worked, the wage data can be expected to contain some measurement error. To deal with outliers in the wage data, we first require that all wages must be at least 80% of the lowest salary grade of the central government, after which we trim the lowest and highest 3% of wage observations in each subgroup.

Table IV.1 gives some descriptive statistics for the worker groups to be analysed. The number of observations in the underlying group ($N$) is given in the first column of the table. Since the computational burden of the estimation method for the model with a discrete distribution of productivity increases rapidly with the sample size and the number of firm types, the maximum size of the estimation sample is restricted to 3,000 observations. Thus, where $N$ exceeds 3,000 we have drawn a random subsample of 3,000 workers from the underlying group (after trimming the wage data). All sample statistics in the table are computed from this subsample, describing the sample to be used in the estimations.

It is worth emphasizing that the period under investigation is exceptional one. An overheating period of the Finnish economy in the last years of the 1980s was followed by a deep recession in the early 1990s. The annual change in the GDP was negative during the period 1991-1993, and in the worst year, 1991, the GDP decreased by over 7%. According to the Labour Force Survey, the unemployment rate rose from 3.2% in 1990 to over 16% in 1993, remaining at the level beyond 14.5% until 1996. Thus, labour market experiences of the sampled workers thus took place in a period of record high and stable unemployment. We should keep this in mind when interpreting the results.

From the first column of the table it appears that the size of the underlying worker group is much lower for highly educated groups. This does not reflect only the education structure of the labour force but also a lower incidence of unemployment among more educated workers. The fact that the period under investigation is characterized by high

Table IV.1: Summary statistics

| | $N$ | $\overline{w}$ | $w_{\min}$ | $w_{\max}$ | $\overline{d}$ | $c_d$ | $\overline{j}$ | $c_j$ | $a$ |
|---|---|---|---|---|---|---|---|---|---|
| Lower vocational and less | | | | | | | | | |
| Men, 16-21 | 17,051 | 7,819 | 4,625 | 16,713 | 7.56 | .78 | 12.54 | .32 | .20 |
| Men, 22-30 | 40,145 | 9,526 | 4,845 | 23,464 | 10.49 | .58 | 12.28 | .20 | .22 |
| Men, 31-50 | 73,142 | 10,483 | 5,067 | 26,669 | 11.58 | .57 | 12.52 | .22 | .20 |
| Men, 51-65 | 20,129 | 10,320 | 4,940 | 27,002 | 16.43 | .73 | 9.94 | .20 | .19 |
| Women, 16-21 | 7,604 | 7,071 | 4,546 | 18,325 | 7.07 | .80 | 12.24 | .33 | .17 |
| Women, 22-30 | 13,721 | 7,638 | 4,607 | 18,858 | 10.06 | .71 | 14.63 | .31 | .22 |
| Women, 31-50 | 31,212 | 7,932 | 4,685 | 18,172 | 11.94 | .66 | 16.71 | .29 | .14 |
| Women, 51-65 | 13,724 | 7,871 | 4,647 | 17,741 | 19.17 | .79 | 13.95 | .22 | .10 |
| Upper vocational | | | | | | | | | |
| Men, 16-21 | 9,544 | 7,843 | 4,659 | 15,324 | 5.83 | .78 | 11.91 | .41 | .27 |
| Men, 22-30 | 11,233 | 9,298 | 4,834 | 22,003 | 8.81 | .57 | 14.92 | .28 | .27 |
| Men, 31-50 | 8,993 | 11,742 | 5,278 | 28,770 | 11.22 | .60 | 17.82 | .31 | .22 |
| Men, 51-65 | 1,811 | 13,645 | 5,724 | 27,963 | 18.08 | .79 | 14.02 | .30 | .12 |
| Women, 16-21 | 6,769 | 6,919 | 4,535 | 14,799 | 5.41 | .73 | 11.45 | .37 | .25 |
| Women, 22-30 | 11,002 | 7,734 | 4,680 | 16,232 | 7.51 | .60 | 15.72 | .31 | .26 |
| Women, 31-50 | 6,273 | 9,298 | 4,837 | 22,809 | 10.35 | .65 | 17.60 | .32 | .23 |
| Women, 51-65 | 695 | 10,284 | 5,028 | 23,591 | 18.98 | .82 | 13.98 | .26 | .07 |
| Lower university | | | | | | | | | |
| Men, 16-30 | 5,042 | 10,531 | 5,185 | 23,859 | 7.36 | .59 | 17.77 | .35 | .28 |
| Men, 31-65 | 4,495 | 13,755 | 5,338 | 37,047 | 9.28 | .54 | 18.88 | .34 | .24 |
| Women, 16-30 | 1,831 | 8,541 | 4,725 | 16,842 | 6.55 | .56 | 17.31 | .36 | .32 |
| Women, 31-65 | 1,512 | 11,241 | 4,938 | 28,597 | 10.83 | .61 | 17.97 | .36 | .25 |
| Upper university | | | | | | | | | |
| Men, 16-30 | 502 | 12,883 | 5,636 | 27,255 | 7.21 | .47 | 20.87 | .35 | .55 |
| Men, 31-65 | 1,321 | 17,874 | 5,667 | 53,488 | 12.12 | .56 | 22.18 | .38 | .32 |
| Women, 16-30 | 526 | 11,756 | 5,683 | 34,397 | 6.33 | .51 | 18.09 | .40 | .38 |
| Women, 31-65 | 543 | 12,887 | 4,831 | 34,092 | 10.32 | .59 | 16.64 | .34 | .32 |

Notes: $N$ is the number of observations in the underlying population from which the estimation sample was drawn. $\overline{w}$ is the average accepted wage (FIM) in the estimation sample. $w_{\min}$ and $w_{\max}$ are the minimum and maximum of observed wages (FIM) in the estimation sample respectively. $\overline{d}$ and $\overline{j}$ are the average durations of unemployment and job spells respectively. $c_d$ is the share of censored unemployment spells, and $c_j$ is the share of censored job spells in the estimation sample. $a$ is the share of uncensored job spells ending in a quit for a better job.

unemployment levels is reflected to the figures in the table. Unemployment durations are relatively long with a high rate of censoring, and most of subsequent job spells ended in a layoff.

Unemployment duration increases with age and is exceptionally high among low educated workers aged over 50. There are no clear differences in the average duration of unemployment by sex. The rate of censoring in the unemployment data is found to be very high. It is also worth emphasizing that the average duration of censored spells is over two times higher than that of uncensored spells (not shown in the table). This is because long-duration spells of unemployment are often terminated by labour administrative measures. This explains partly the higher censoring rates for the groups with the longest unemployment durations. Young job seekers are often regarded as a special target group of the labour administrative measures, resulting in a relatively high censoring rate for workers aged under 22. There are no large differences in job duration across age groups.

Highly educated workers experience slightly longer job spells and are more likely to quit for a better job. Compared to unemployment spells, job spells are longer on average and the rate of censoring in the job duration data is much lower.

Wages increase with age at least up until the interval 31-50 years of age. There are no clear wage differentials between workers at the two lowest levels of education, whereas higher education yields slightly higher return. Despite the trimming procedure there are still wage observations which are relatively low compared to minimum requirements, reflecting some measurement problems in the wage data. Empirical wage densities for each worker group are shown in Figures IV.1 to IV.3 in the Appendix, where the thick solid lines represent the kernel density estimates obtained using Gaussian kernels with the bandwidth chosen by a rule of thumb. Other lines depict the predicted densities obtained from the different specifications of the equilibrium search model and they will be discussed later on. The empirical wage densities are generally unimodal and skewed with a long right tail.

# 4 Empirical application

We have derived the explicit solutions for the equilibrium wage offer distribution with and without employer heterogeneity. From the assumptions underlying the theoretical model it is straightforward to derive distributions for unemployment and job durations as well. Knowledge about these distributions allows us to write down the likelihood functions for various specifications of the model. In the next section we derive the general form of the likelihood function without specifying the functional form for the wage offer distribution. In the subsequent sections we will then discuss the estimation of various specifications of the model and report the results.

## 4.1 The log-likelihood function

The structural parameters of interest to be estimated are $(\lambda_0, \lambda_1, \delta, r)$ with a scalar $p$ for the homogeneous model, the set $(p_1, p_2, ..., p_q)$ of productivity terms for the model with a discrete distribution of productivity, and $\Gamma$ for the model with a continuous distribution of productivity. With these parameter estimates in hand, we can obtain an estimate for $b$ using (IV.5).[17] Since our data were drawn from the inflow of unemployment, we observe a spell of unemployment along with the post-unemployment destination for each individual in the data. For those whose unemployment ended in a new job we further observe the wage rate accepted as well as the duration of the subsequent job along with the reason for termination. Since we do not have complete information on all observations, the possibility of censored observations on unemployment and job durations is explicitly accounted for using censoring indicators $c_d$ and $c_j$.

[17] It can be argued that $b$ is the 'deep' structural parameter of the model rather than $r$, which follows implicitly from the optimal search strategy of unemployed workers. However, this distinction does not make any difference in practice due to the one-to-one relationship between $b$ and $r$ outlined in (IV.5).

The likelihood contribution from an individual who is unemployed for $d$ periods, accepts then a job with an associated wage $w$, keeps that jobs for $j$ periods until he gets laid off ($a = 0$) or finds another job ($a = 1$) has a general form

$$\ell = \varphi(d)\left[f(w)\phi(j, a\,|w)\right]^{1-c_d}, \tag{IV.24}$$

where $\varphi$ is the density function of unemployment duration, $f$ is the density of the wage offer distribution and $\phi$ is the density function of job duration and destination conditional on the accepted wage $w$. The censoring indicator for unemployment duration $c_d$ takes a value of zero if the unemployment spell is followed by a new job, and a value of one otherwise.

Since job offers arrive at the Poisson rate $\lambda_0$ and all offers are acceptable to the unemployed in equilibrium, unemployment duration $d$ is exponentially distributed with intensity parameter $\lambda_0$, so

$$\varphi(d) = \lambda_0^{1-c_d}e^{-\lambda_0 d}. \tag{IV.25}$$

As workers search randomly among employers using a uniform sampling scheme, the wage offers are random draws from the equilibrium wage offer distribution $F$. To derive the conditional distribution of job duration $j$ and destination $a$, we can use the standard competing risks framework for exponential duration models. Recall that layoffs occur at the Poisson rate $\delta$ and alternative offers arrive at the Poisson rate $\lambda_1$. Since only wage offers exceeding the current wage will be accepted, the actual quit rate is $\lambda_1(1-F(w))$, the probability of receiving an offer times the probability that the received offer is acceptable given the current wage $w$. Conditional on the current wage $w$, the job duration $j$ has an exponential distribution with intensity parameter $\delta + \lambda_1(1-F(w))$. Exit from this job into unemployment occurs with probability $\delta/\left[\delta + \lambda_1(1-F(w))\right]$ and exit into a higher-paying job with probability $\lambda_1(1-F(w))\,/\left[\delta + \lambda_1(1-F(w))\right]$. Putting these together yields

$$\phi(j, a\,|w) = \left[(1-a)\delta + a\lambda_1(1-F(w))\right]^{1-c_j} e^{-(\delta+\lambda_1[1-F(w)])j}. \tag{IV.26}$$

Substituting (IV.25) and (IV.26) into (IV.24) and taking logarithm gives the individual contribution to the log-likelihood function

$$\begin{aligned}\log \ell \;&=\; (1-c_d)(1-c_j)\ln\left[(1-a)\delta + a\lambda_1(1-F(w))\right] - \lambda_0 d \\ &\quad + (1-c_j)\left(\ln\lambda_0 + \ln f(w) - (\delta + \lambda_1[1-F(w)])\,j\right).\end{aligned} \tag{IV.27}$$

Estimations of different specifications of the Burdett-Mortensen model will all be based on (IV.27), the only difference between the specifications being the functional form assumed for $F$ and $f$.[18] Recall that the shape of the equilibrium wage offer distribution generally

[18] Christensen and Kiefer (1997) show that identification of all structural parameters of the model does not necessarily require information on whether the job spell ends in a quit or layoff, i.e. observations on $a$ are not crucial for identification. The separate identification of $\lambda_1$ and $\delta$ even without knowledge of $a$ follows from the fact that the conditional job hazard decreases with $w$. A higher wage does not affect the layoff rate but implies a lower quit rate and the extent of this effect depends on $\lambda_1$.

does not depend on $\lambda_0$. This observation taken together with (IV.27) suggests that $\lambda_0$ is identified from the unemployment duration data only. It follows that the estimator of $\lambda_0$ is stochastically independent of all other parameters of the model, being robust with respect to different model specifications.

## 4.2 Identical workers and firms

We begin our empirical analysis with the simplest specification of the model with homogeneous workers and firms. Equilibrium solutions for $F$ and $f$ are given by (IV.11) and (IV.12) respectively. Substituting these expressions into (IV.27) and summing over the observations gives the log-likelihood function in terms of $(\lambda_0, \lambda_1, \delta, p, r)$. The properties of the maximum likelihood estimators are not standard in this case, however. This is due to the dependence of the support of $F$ on the unknown parameters of the model. Kiefer and Neumann (1993) show that one can simplify the estimation problem considerably by reparametrizing the model from $(\lambda_0, \lambda_1, \delta, p, r)$ to $(\lambda_0, \lambda_1, \delta, h, r)$ and using order statistics to estimate the bounds of the support of $F$. To pursue this route, we solve the system (IV.13) and (IV.14) for $p$ and $b$ to obtain

$$p = \frac{\beta}{\beta-\alpha}r + \frac{\alpha}{\alpha-\beta}h, \tag{IV.28}$$

$$b = \frac{\beta-1}{\beta-\alpha}r + \frac{\alpha-1}{\alpha-\beta}h, \tag{IV.29}$$

where $\alpha$ and $\beta$ are given by (IV.15) and (IV.16) respectively. Using (IV.28) to substitute $p$ out of the expressions for $F$ and $f$, we can rewrite the log-likelihood function in terms of $(\lambda_0, \lambda_1, \delta, r, h)$.

Following Kiefer and Neumann (1993), we estimate $r$ and $h$ using the sample minimum and maximum respectively. In the second step the frictional parameters are estimated by maximizing the likelihood function with respect to $(\lambda_0, \lambda_1, \delta)$ conditional on the estimates of $(r, h)$. Due to the properties of order statistics, the estimates of $(r, h)$ are superconsistent, converging to their true values at a rate faster than $\sqrt{n}$, where $n$ is the sample size. This suggests that ignoring variation in the estimates of $(r, h)$ does not affect asymptotic inference about $(\lambda_0, \lambda_1, \delta)$, and therefore we can treat $(r, h)$ as fixed in the maximum likelihood estimation of the frictional parameters, even though they are not exogenous (see Christensen and Kiefer, 1994*b*). Given the consistent estimates of $(\lambda_0, \lambda_1, \delta, r, h)$, we can estimate $p$ and $b$ using (IV.28) and (IV.29) and compute their standard errors using the delta method (see Bunzel et al., 2001, for details).

Order statistics estimates of $(r, h)$ for each group can be found from Table IV.1, where they correspond to the minimum and maximum accepted wage (i.e. $\widehat{r} = w_{\min}$ and $\widehat{h} = w_{\max}$). Estimates of other parameters of the model are presented in Table IV.2. It is found that $\lambda_0$ is uniformly higher than $\lambda_1$, suggesting that wage offers arrive more frequently when unemployed than when employed. This corresponds to the case where the reservation

Table IV.2: Estimation results with identical agents

| | $\lambda_0$ | $\lambda_1$ | $\delta$ | $p$ | $b$ |
|---|---|---|---|---|---|
| Lower vocational and less | | | | | |
| Men, 16-21 | .0285 (.0011) | .0099 (.0011) | .0470 (.0024) | 42,697 (3,271) | 2,461 (229) |
| Men, 22-30 | .0399 (.0011) | .0130 (.0009) | .0547 (.0018) | 58,533 (2,844) | 754 (279) |
| Men, 31-50 | .0375 (.0010) | .0117 (.0008) | .0531 (.0018) | 70,946 (3,629) | 332 (312) |
| Men, 51-65 | .0166 (.0006) | .0138 (.0013) | .0701 (.0029) | 78,136 (5,373) | 4,532 (205) |
| Women, 16-21 | .0282 (.0012) | .0070 (.0009) | .0486 (.0025) | 62,871 (6,164) | 1,753 (257) |
| Women, 22-30 | .0292 (.0010) | .0082 (.0007) | .0401 (.0017) | 50,235 (3,240) | 1,228 (264) |
| Women, 31-50 | .0286 (.0009) | .0051 (.0005) | .0384 (.0015) | 65,841 (5,314) | 811 (238) |
| Women, 51-65 | .0109 (.0004) | .0054 (.0008) | .0519 (.0024) | 78,050 (9,152) | 3,988 (114) |
| Upper vocational | | | | | |
| Men, 16-21 | .0385 (.0015) | .0128 (.0013) | .0405 (.0022) | 29,884 (1,751) | 1,740 (298) |
| Men, 22-30 | .0494 (.0014) | .0118 (.0008) | .0390 (.0014) | 46,673 (1,950) | −2,358 (416) |
| Men, 31-50 | .0353 (.0010) | .0080 (.0006) | .0327 (.0012) | 71,490 (3,825) | −3,464 (535) |
| Men, 51-65 | .0116 (.0006) | .0071 (.0013) | .0454 (.0029) | 94,126 (13,130) | 4,687 (342) |
| Women, 16-21 | .0505 (.0018) | .0113 (.0010) | .0458 (.0022) | 33,238 (1,982) | 635 (291) |
| Women, 22-30 | .0534 (.0015) | .0106 (.0007) | .0357 (.0013) | 33,173 (1,426) | −1,366 (346) |
| Women, 31-50 | .0335 (.0010) | .0079 (.0006) | .0324 (.0013) | 55,604 (3,089) | −1,489 (419) |
| Women, 51-65 | .0095 (.0009) | .0035 (.0014) | .0506 (.0055) | 152,083 (55,257) | 3,970 (337) |
| Lower university | | | | | |
| Men, 16-30 | .0562 (.0016) | .0096 (.0007) | .0296 (.0011) | 48,443 (2,054) | −7,453 (697) |
| Men, 31-65 | .0495 (.0013) | .0075 (.0005) | .0292 (.0010) | 91,523 (4,474) | −14,893 (1,031) |
| Women, 16-30 | .0675 (.0025) | .0119 (.0010) | .0284 (.0014) | 28,814 (1,272) | −5,081 (705) |
| Women, 31-65 | .0357 (.0015) | .0080 (.0009) | .0293 (.0017) | 66,729 (4,988) | −4,881 (895) |
| Upper university | | | | | |
| Men, 16-30 | .0735 (.0047) | .0180 (.0020) | .0184 (.0018) | 34,727 (1,350) | −16,266 (2,945) |
| Men, 31-65 | .0363 (.0016) | .0078 (.0008) | .0218 (.0013) | 110,639 (7,135) | −20,876 (2,368) |
| Women, 16-30 | .0770 (.0050) | .0102 (.0015) | .0249 (.0023) | 63,666 (5,355) | −26,298 (3,901) |
| Women, 31-65 | .0395 (.0027) | .0123 (.0019) | .0310 (.0029) | 64,873 (6,069) | −5,850 (1,781) |

Notes: Standard errors are in parentheses.

wage $r$ exceeds the value of non-market time $b$. Moreover, as $\delta$ is uniformly higher than $\lambda_1$, jobs are more likely to end in a layoff than in a quit for a better job.

Ignoring workers aged below 22, $\lambda_0$ decreases with age, being exceptionally low for less educated workers aged over 50. Moreover, $\lambda_0$ increases with education, though not uniformly. In contrast, $\lambda_1$ does not exhibit any clear patterns with respect to education nor with respect to age. Less educated women aged over 50 have the lowest chances of finding a job when unemployed, but women with university education tend to receive more offers than their male counterparts when unemployed. Layoff rate $\delta$ decreases with education but there is little difference by sex. Workers aged below 22 and those aged over 50 are more likely to be laid off than other workers.

Productivity $p$ increases with age and is often higher for men than women with some exceptions. Young workers with upper vocational education are found to be less productive than their less educated counterparts. Otherwise productivity differentials across education groups do not exhibit very clear insight. The value of non-market time $b$ appears to be positive among workers with the lowest level of education. For more educated groups

$b$ is typically negative, being more negative for higher education levels. Negativity of $b$ reflects the need to interpret this parameter not only a function of unemployment benefits but also of search costs and perhaps even of the disutility of unemployment (Bunzel et al., 2001). There is also a tendency for $b$ to be lower for women than men among less educated workers aged below 22 and over 50, while the reverse is true among workers between 22 and 50.

Overall all structural parameters of the model are estimated accurately and their estimates allow for a meaningful economic interpretation. The fit to the wage data is less satisfactory, however. This is illustrated in Figures IV.1 to IV.3 in the Appendix where empirical wage distributions and predicted wage offer distributions obtained from the different specifications of the model are shown. The predicted theoretical density for the pure homogeneity model is computed by inserting the parameter estimates into (IV.12). While the empirical (kernel) densities are unimodal and skewed with a long right tail, the equilibrium search model with identical agents restricts the predicted densities to be increasing and convex over the whole support. Such a shape is obviously not supported by the data. The predicted densities are flat over their whole support, leading to a poor fit to the wage data in all worker groups.

Recall that our data do not contain information on working time. This with some inaccuracies in the available wage data suggests that our wage variables are subjected to measurement error. The existence of measurement error in wages may partly explain the clear discrepancy between the empirical and theoretical wage distributions. The estimates of the structural parameters of the model can be expected to be affected by measurement errors as well. Note that the order statistics estimators of $(r, h)$ are clearly sensitive to measurement error. Moreover, the dependence of $(r, h)$ on other parameters of the model implies that the maximum likelihood estimates of frictional parameters $(\lambda_1, \delta)$ are also affected by measurement error in wage data (Van den Berg and Ridder, 1993). Taking the possibility of measurement error in wages explicitly into account may hence improve the performance of maximum likelihood estimation.

To deal with measurement errors, we assume that the wage observation in the data, say $x$, is the product of the true unobserved wage $w$ and an error term $\varepsilon$, so that $x = w \cdot \varepsilon$. The multiplicative measurement error is assumed to be independently and identically distributed across individuals and to be independent of all other variables in the model. Following Christensen and Kiefer (1994*a*) and Bunzel et al. (2001), we assume that $\varepsilon$ has a Pearson Type V distribution with unit mean, variance $\sigma^2$ and density

$$g_\varepsilon(\varepsilon) = \frac{\left(1+\sigma^{-2}\right)^{2+\sigma^{-2}}}{\widetilde{\Gamma}\left(2+\sigma^{-2}\right) \cdot \varepsilon^{3+\sigma^{-2}}} \exp\left(-\frac{1+\sigma^{-2}}{\varepsilon}\right), \tag{IV.30}$$

where $\widetilde{\Gamma}$ denotes the gamma function. A consequence of allowing for the measurement error is that we need to add an integral for each wage observation in the individual likelihood

Table IV.3: Estimation results with identical agents and measurement error in wages

| | $\lambda_0$ | $\lambda_1$ | $\delta$ | $p$ | $b$ | $\sigma$ |
|---|---|---|---|---|---|---|
| Low voc. & less | | | | | | |
| Men, 16-21 | .0285 (.0011) | .0236 (.0027) | .0437 (.0023) | 9,278 (920) | 7,052 (454) | .3012 (.0114) |
| Men, 22-30 | .0399 (.0011) | .0317 (.0024) | .0508 (.0018) | 11,915 (848) | 8,121 (475) | .3417 (.0108) |
| Men, 31-50 | .0375 (.0010) | .0291 (.0022) | .0495 (.0017) | 11,329 (996) | 9,995 (545) | .3739 (.0100) |
| Men, 51-65 | .0166 (.0006) | .0339 (.0033) | .0658 (.0028) | 14,336 (1,499) | 8,855 (517) | .3743 (.0173) |
| Women, 16-21 | – | – | – | – | – | – |
| Women, 22-30 | – | – | – | – | – | – |
| Women, 31-50 | .0286 (.0009) | .0122 (.0013) | .0366 (.0015) | 8,013 (1,022) | 7,849 (420) | .2700 (.0069) |
| Women, 51-65 | .0109 (.0004) | .0124 (.0018) | .0502 (.0024) | 11,457 (1,793) | 7,026 (391) | .2883 (.0123) |
| Upper vocational | | | | | | |
| Men, 16-21 | .0385 (.0015) | .0300 (.0031) | .0363 (.0021) | 10,900 (660) | 5,611 (409) | .2294 (.0183) |
| Men, 22-30 | .0494 (.0014) | .0286 (.0020) | .0353 (.0013) | 10,682 (635) | 8,056 (540) | .3320 (.0091) |
| Men, 31-50 | .0353 (.0010) | .0189 (.0015) | .0301 (.0012) | 16,688 (1,268) | 8,244 (889) | .3549 (.0170) |
| Men, 51-65 | .0116 (.0006) | .0133 (.0025) | .0439 (.0029) | 34,816 (4,476) | 8,013 (652) | .2657 (.0327) |
| Women, 16-21 | .0505 (.0018) | .0301 (.0029) | .0412 (.0021) | 7,436 (479) | 6,464 (364) | .2594 (.0076) |
| Women, 22-30 | – | – | – | – | – | – |
| Women, 31-50 | – | – | – | – | – | – |
| Women, 51-65 | .0095 (.0009) | .0075 (.0031) | .0496 (.0054) | 40,043 (13,510) | 5,802 (674) | .2217 (.0516) |
| Lower university | | | | | | |
| Men, 16-30 | .0562 (.0016) | .0228 (.0016) | .0264 (.0011) | 15,660 (612) | 4,556 (607) | .2506 (.0151) |
| Men, 31-65 | .0495 (.0013) | .0183 (.0013) | .0265 (.0010) | 22,672 (1,127) | 4,951 (1,007) | .3550 (.0201) |
| Women, 16-30 | .0675 (.0025) | .0267 (.0024) | .0251 (.0014) | 9,190 (570) | 7,545 (827) | .3018 (.0103) |
| Women, 31-65 | .0357 (.0015) | .0195 (.0022) | .0265 (.0016) | 13,554 (1,640) | 9,305 (1,332) | .3832 (.0188) |
| Upper university | | | | | | |
| Men, 16-30 | .0735 (.0047) | .0431 (.0047) | .0140 (.0016) | 17,131 (528) | 2,864 (1,355) | .2071 (.0210) |
| Men, 31-65 | .0363 (.0016) | .0197 (.0020) | .0189 (.0012) | 27,896 (1,760) | 6,656 (1,901) | .4462 (.0388) |
| Women, 16-30 | .0770 (.0050) | .0294 (.0044) | .0205 (.0022) | 12,490 (1,350) | 9,911 (2,646) | .3409 (.0206) |
| Women, 31-65 | .0395 (.0027) | .0305 (.0050) | .0271 (.0028) | 19,978 (1,861) | 6,219 (1,642) | .4045 (.0604) |

Notes: Standard errors are in parentheses

contribution. Formally, we replace (IV.24) by

$$\ell = \varphi(d)\left(\int_{x/h}^{x/r} \phi\left(j, a \left| \frac{x}{\varepsilon}\right.\right) f\left(\frac{x}{\varepsilon}\right)\frac{1}{\varepsilon} g_{\varepsilon}(\varepsilon)d\varepsilon\right)^{1-c_d}, \tag{IV.31}$$

where $\varphi$, $\phi$ and $f$ are as given in the previous section, and $1/\varepsilon$ is the Jacobian of the transformation between the true and observed wages given the error term. In this case we do not use order statistics for $(r, h)$ but estimate them simultaneously with $(\lambda_0, \lambda_1, \delta, \sigma)$ by maximizing the likelihood function based on (IV.31), in which the integral must be evaluated numerically in each iteration.[19] With the estimates of $(\lambda_0, \lambda_1, \delta, r, h)$ in hand, the estimates of $(p, b)$ can be computed using (IV.28) and (IV.29) as before.

Estimation results for the homogeneous model with measurement error in wages are reported in Table IV.3. The results are missing for four groups of low-educated women as the estimates of $r$ and $h$ converged to the same value in their cases. Compared to the previous results, $\lambda_1$ is now uniformly much higher and $\delta$ uniformly slightly lower, while $\lambda_0$

[19] Note that the presence of measurement errors makes the support of the distribution of observed wages independent of the unknown parameters, so the maximum likelihood estimation is standard in this case.

is of course not affect by the introduction of measurement errors. Among workers with an upper university degree $\lambda_1$ now exceeds $\delta$, while the reverse still holds for other groups. Moreover $p$ is uniformly lower and $b$ uniformly higher than previously. The presence of measurement errors in the wage data suggests that a range of wage offers is narrower than previously, so less variation in $p$ and $b$ is required to explain the observations in the data. The estimates of $r$ and $h$ are generally very close to each other, resulting in a small difference between $p$ and $b$. As another implication, dispersion in the sequence of wages that the worker can earn over time is predicted to be quite narrow.

From Figures IV.1 to IV.3 in the Appendix we see that the measurement error specification results in a good fit to the wage data.[20] Both tails are captured quite nicely and the mode point is very close. Because allowing for the measurement error in the wages improves the model's fit to the wage data crucially, one can expect that the estimates of frictional parameters are more appropriate as well. On the other hand, the fact that measurement errors account for such a large part of the observed wage variation can be viewed as a failure of the model as it implies that the theory is unable to explain wage dispersion within the labour market segments. Provided the clear contrast between the theoretical and empirical wage distributions, it is obvious that a large degree of measurement error is required to 'explain' the divergent shapes of the distributions.

### 4.3 Discrete productivity dispersion

Next we consider the extended model with a discrete distribution of productivity. Here we do not allow for measurement error in wages, so comparisons with the homogeneous version of the model can be done in a straightforward manner. The individual contribution to the likelihood function is still given by (IV.27), the only difference compared to the homogeneous case without measurement errors being that $F$ and $f$ are now given by (IV.17) and (IV.18) respectively. In addition to the previous problem that the bounds of the support of $F$ depend on unknown parameters, estimation is further complicated by the fact that the likelihood function is not differentiable at the wage cut points $(\overline{w}_1, ..., \overline{w}_{q-1})$. An estimation method which can deal with these complications has been developed by Bowlus et al. (1995).

Once again it is convenient to reparametrize the model in a similar fashion as was done in the homogeneous case. Evaluating (IV.17) at $w = \overline{w}_i$ and solving for $p_i$ gives the following relationship between the productivity terms, wage cuts and the fractions of firm types:

$$p_i = \frac{1}{1-\mu_i^2}\overline{w}_i - \frac{\mu_i^2}{1-\mu_i^2}\underline{w}_i, \quad i = 1, 2, ..., q, \tag{IV.32}$$

[20]The predicted densities for *observed* wages in the figures are obtained by inserting the parameter estimates into

$$\int_{x/h}^{x/r} f\left(\frac{x}{\varepsilon}\right)\frac{1}{\varepsilon}g_\varepsilon(\varepsilon)d\varepsilon.$$

where

$$\mu_i = \frac{1 + \kappa_1 (1 - \gamma_i)}{1 + \kappa_1 \left(1 - \gamma_{i-1}\right)} \in (0,1), \quad i = 1, 2, ..., q. \tag{IV.33}$$

Substituting $p_i$'s out of (IV.17) and (IV.18) using (IV.32) allows us to write the likelihood function in terms of $\left(\lambda_0, \lambda_1, \delta, r, h, \overline{w}_1, ..., \overline{w}_{q-1}, \gamma_1, ..., \gamma_{q-1}\right)$. Since there are kinks at the wage cuts in $F$, the density $f$ and hence the likelihood function is discontinuous at these points.

Bowlus et al. (1995) show that the maximum likelihood estimates of wage cuts $(\overline{w}_1, ..., \overline{w}_{q-1})$ come from the set of observed wages. As in the homogenous case, we use order statistics to estimate $(r, h)$. Conditional on these estimates, the likelihood function can be maximized using an iterative procedure with two steps in each iteration. In the first step the likelihood function is maximized with respect to $(\overline{w}_1, ..., \overline{w}_{q-1})$ holding $(r, h, \lambda_0, \lambda_1, \delta)$ fixed, using simulated annealing which randomly searches over the possible wage cut combinations according an optimal stopping rule.[21] Given the estimates of $(\overline{w}_1, ..., \overline{w}_{q-1})$, the corresponding discontinuity points in the wage offer distribution $\left(\gamma_1, ..., \gamma_{q-1}\right)$ are estimated by observed frequencies in the wage data. In the second step the likelihood function is maximized with respect to $(\lambda_0, \lambda_1, \delta)$ conditional on $\left(r, h, \overline{w}_1, ..., \overline{w}_{q-1}, \gamma_1, ..., \gamma_{q-1}\right)$. Since this part of the maximization problem is smooth, standard maximum likelihood algorithms can be applied. These two steps are then iterated until convergence occurs.

In addition to the order statistics estimators for $(r, h)$, the maximum likelihood estimators of the wage cuts in the wage offer distribution $(\overline{w}_1, ..., \overline{w}_{q-1})$ also converge to their true value at a rate faster than $\sqrt{n}$. It follows that they are asymptotically independent of the maximum likelihood estimator of $(\lambda_0, \lambda_1, \delta)$ and the theory of local cuts by Christensen and Kiefer (1994*b*) justifies conditioning on them in the second step of the procedure. The iterative separate maximization can be shown to lead to a joint maximum of the likelihood function on convergence.

There is no formal test for choosing a value of $q$, the number of firm types. However, the authors of this estimation technique argue that the likelihood ratio test of one value of $q$ against another based on the standard $\chi^2$-criterion can be expected to work reasonably well in practice. This is so even though the exact distribution of the test statistics is not known due to non-regular estimation procedure. Thus, we choose the number of firm types by comparing two times the improvement in the log-likelihood function with each additional firm type to the $\chi^2_{.05}$ critical value.[22] Once the other parameters of the model are estimated, unobserved heterogeneity terms $(p_1, ..., p_q)$ can be estimated using (IV.32)

[21] For simulated annealing, see for example Goffe et al. (1994) and Bowlus et al. (1995).

[22] A Monte Carlo evidence of Bowlus et al. (2001) indicates a tendency towards overfitting the number of heterogeneity types using this criterion. However, they further find that choosing a value of $q$ greater than the true value has only a minor effect on the estimates of $(\lambda_1, \delta)$, while the order statistics estimators of $(r, h)$ and the ML estimator of $\lambda_0$ are obviously unaffected by the value of $q$ chosen.

Table IV.4: Estimation results with discrete productivity dispersion

| | $\lambda_0$ | $\lambda_1$ | $\delta$ | $q$ | $\overline{p}$ | $b$ |
|---|---|---|---|---|---|---|
| Lower vocational and less | | | | | | |
| Men, 16-21 | .0285 (.0011) | .0219 (.0023) | .0444 (.0023) | 5 | 21,539 | 4,266 |
| Men, 22-30 | .0399 (.0011) | .0288 (.0019) | .0507 (.0018) | 6 | 28,438 | 4,049 |
| Men, 31-50 | .0375 (.0010) | .0234 (.0016) | .0499 (.0017) | 5 | 36,920 | 3,761 |
| Men, 51-65 | .0166 (.0006) | .0298 (.0026) | .0662 (.0028) | 6 | 37,507 | 5,793 |
| Women, 16-21 | .0282 (.0012) | .0166 (.0020) | .0464 (.0025) | 4 | 27,227 | 4,069 |
| Women, 22-30 | .0292 (.0010) | .0193 (.0017) | .0370 (.0017) | 6 | 22,808 | 3,971 |
| Women, 31-50 | .0286 (.0009) | .0123 (.0012) | .0365 (.0015) | 6 | 29,556 | 3,465 |
| Women, 51-65 | .0109 (.0004) | .0122 (.0017) | .0503 (.0024) | 4 | 36,217 | 4,715 |
| Upper vocational | | | | | | |
| Men, 16-21 | .0358 (.0015) | .0254 (.0024) | .0373 (.0021) | 4 | 17,497 | 3,827 |
| Men, 22-30 | .0494 (.0014) | .0254 (.0016) | .0353 (.0013) | 4 | 23,945 | 2,491 |
| Men, 31-50 | .0353 (.0010) | .0181 (.0013) | .0301 (.0012) | 5 | 35,160 | 2,320 |
| Men, 51-65 | .0116 (.0006) | .0133 (.0023) | .0439 (.0029) | 3 | 53,937 | 5,972 |
| Women, 16-21 | .0505 (.0018) | .0276 (.0024) | .0420 (.0021) | 5 | 15,697 | 3,636 |
| Women, 22-30 | .0534 (.0015) | .0230 (.0015) | .0323 (.0013) | 6 | 17,499 | 2,547 |
| Women, 31-50 | .0335 (.0010) | .0174 (.0013) | .0298 (.0013) | 4 | 27,277 | 2,913 |
| Women, 51-65 | .0095 (.0009) | .0072 (.0029) | .0498 (.0054) | 2 | 77,089 | 4,798 |
| Lower university | | | | | | |
| Men, 16-30 | .0562 (.0016) | .0213 (.0014) | .0267 (.0011) | 5 | 25,167 | 275 |
| Men, 31-65 | .0495 (.0013) | .0180 (.0012) | .0266 (.0010) | 6 | 41,202 | −1,758 |
| Women, 16-30 | .0675 (.0025) | .0245 (.0019) | .0250 (.0014) | 6 | 16,807 | 373 |
| Women, 31-65 | .0357 (.0015) | .0205 (.0021) | .0263 (.0016) | 6 | 29,217 | 2,460 |
| Upper university | | | | | | |
| Men, 16-30 | .0735 (.0047) | .0410 (.0043) | .0138 (.0016) | 5 | 19,919 | −863 |
| Men, 31-65 | .0363 (.0015) | .0208 (.0020) | .0188 (.0012) | 6 | 45,053 | −584 |
| Women, 16-30 | .0770 (.0050) | .0257 (.0033) | .0206 (.0022) | 5 | 26,853 | −3,965 |
| Women, 31-65 | .0395 (.0027) | .0265 (.0039) | .0275 (.0028) | 5 | 33,265 | 2,109 |

Notes: Standard errors are in parentheses. $q$ is the number of firm types and $\overline{p} = \sum_{i=1}^{q} (\gamma_i - \gamma_{i-1}) p_i$ is the average productivity across firms.

and (IV.33),[23] and an estimate of $b$ can be obtained using

$$b = r - \frac{\lambda_0 - \lambda_1}{\lambda_1} \sum_{i=1}^{q} (p_i - \underline{w}_i) \left(1 - \mu_i^2 - \frac{2\delta (1 - \mu_i)}{\delta + \lambda_1 (1 - \gamma_{i-1})}\right), \qquad \text{(IV.34)}$$

which follows from the substitution of (IV.17) into (IV.5).

Order statistics estimates for $(r, h) \equiv (\underline{w}_1, \overline{w}_q)$ can be found from Table IV.1 as previously. Other parameter estimates are shown in Tables IV.4 to IV.6. Estimates of the frictional parameters $(\lambda_1, \delta)$ are generally very close to the estimates obtained from the homogeneous model with measurement error in wages. Compared to the corresponding estimates from the measurement error specification, there is a tendency for $\lambda_1$ to be slightly smaller while $\delta$ does not exhibit any systematic differences. Overall the differences in these estimates are so moderate that one can draw basically the same conclusions con-

[23] It is worth noting that in this model all wage differentials that cannot be explained by differences in the frictional parameters are attributed to productivity differences. Thus the productivity parameters may capture also other sources of wage dispersion than pure productivity differences (Bowlus, 1997).

Table IV.5: Estimation results with discrete productivity dispersion, continued

| | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ |
|---|---|---|---|---|---|---|
| Lower vocational and less | | | | | | |
| Men, 16-21 | 13,643 | 30,392 | 40,487 | 44,072 | 108,892 | |
| Men, 22-30 | 17,295 | 17,190 | 19,007 | 24,177 | 41,443 | 136,864 |
| Men, 31-50 | 22,671 | 37,564 | 47,012 | 56,809 | 148,293 | |
| Men, 51-65 | 20,879 | 26,750 | 35,892 | 40,360 | 62,652 | 211,517 |
| Women, 16-21 | 11,969 | 33,784 | 114,231 | 679,097 | | |
| Women, 22-30 | 12,354 | 17,426 | 25,163 | 42,016 | 47,827 | 125,113 |
| Women, 31-50 | 16,398 | 17,708 | 24,134 | 28,632 | 45,129 | 162,682 |
| Women, 51-65 | 19,360 | 43,418 | 123,891 | 540,357 | | |
| Upper vocational | | | | | | |
| Men, 16-21 | 13,375 | 19,258 | 26,360 | 62,415 | | |
| Men, 22-30 | 15,146 | 21,668 | 27,620 | 75,768 | | |
| Men, 31-50 | 22,338 | 27,545 | 30,704 | 41,592 | 100,363 | |
| Men, 51-65 | 38,261 | 72,673 | 141,549 | | | |
| Women, 16-21 | 9,757 | 15,158 | 29,653 | 39,350 | 87,954 | |
| Women, 22-30 | 11,946 | 13,236 | 16,207 | 26,410 | 56,156 | 56,535 |
| Women, 31-50 | 16,759 | 26,769 | 48,668 | 195,431 | | |
| Women, 51-65 | 49,328 | 152,647 | 721,354 | | | |
| Lower university | | | | | | |
| Men, 16-30 | 18,213 | 20,020 | 24,891 | 35,263 | 113,867 | |
| Men, 31-65 | 25,616 | 45,985 | 48,888 | 83,992 | 156,640 | 446,879 |
| Women, 16-30 | 12,812 | 13,507 | 14,208 | 17,024 | 22,032 | 41,729 |
| Women, 31-65 | 17,605 | 25,184 | 30,545 | 44,957 | 59,843 | 127,858 |
| Upper university | | | | | | |
| Men, 16-30 | 16,589 | 16,960 | 19,525 | 21,083 | 40,111 | |
| Men, 31-65 | 26,719 | 28,891 | 31,640 | 44,102 | 58,421 | 168,181 |
| Women, 16-30 | 17,355 | 18,697 | 25,678 | 50,459 | 151,310 | |
| Women, 31-65 | 22,495 | 26,773 | 34,878 | 40,743 | 95,614 | |

Notes: All $p_i$'s are statistically significant at the 5 per cent level.

cerning the frictional parameters from this model and from the homogeneous model with the measurement error.

To get an idea of productivity differences, the average productivity across the firms is computed and shown in Table IV.4. Conditional on the education level, the average productivity $\overline{p}$ tends to increase with age. Except for workers aged over 50, there is a tendency for $\overline{p}$ to be lower for workers with upper vocational education than for those with lower vocational education. Overall these differences across the worker groups are in line with the findings from the homogeneous model, even though the absolute values of productivity estimates are quite different. Namely, the average productivity estimates $\overline{p}$ are approximately only half of the corresponding productivity estimates obtained from the homogeneity model without measurement error but are clearly higher than the estimates from the measurement error specification. Furthermore, it turns out that the value of non-market time $b$ is typically positive, though there are few groups for which $b$ takes a negative value. Differences in $b$ with respect to education and age are similar to those observed in the case of the homogeneous model.

Table IV.6: Estimation results with discrete productivity dispersion, continued

| | $\overline{w}_1$ | $\overline{w}_2$ | $\overline{w}_3$ | $\overline{w}_4$ | $\overline{w}_5$ | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ | $\gamma_4$ | $\gamma_5$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Lower voc. & less | | | | | | | | | | |
| Men, 16-21 | 8,700 | 10,704 | 11,755 | 12,511 | | .7857 | .8917 | .9297 | .9543 | |
| Men, 22-30 | 9,768 | 10,008 | 10,273 | 11,889 | 15,874 | .6143 | .6493 | .6807 | .8053 | .9420 |
| Men, 31-50 | 12,458 | 14,803 | 15,684 | 16,329 | | .7477 | .8620 | .8933 | .9110 | |
| Men, 51-65 | 11,330 | 11,478 | 12,988 | 13,132 | 18,042 | .7283 | .7403 | .8183 | .8247 | .9467 |
| Women, 16-21 | 7,352 | 9,303 | 14,857 | | | .8027 | .9153 | .9927 | | |
| Women, 22-30 | 7,913 | 8,150 | 10,445 | 11,352 | 12,211 | .7080 | .7357 | .8880 | .9173 | .9410 |
| Women, 31-50 | 8,270 | 8,647 | 9,378 | 9,629 | 12,102 | .6623 | .7290 | .8063 | .8270 | .9383 |
| Women, 51-65 | 8,849 | 11,177 | 13,265 | | | .7947 | .9433 | .9823 | | |
| Upper vocational | | | | | | | | | | |
| Men, 16-21 | 9,379 | 10,197 | 11,728 | | | .7967 | .8673 | .9450 | | |
| Men, 22-30 | 9,563 | 10,242 | 14,532 | | | .6310 | .6810 | .9067 | | |
| Men, 31-50 | 12,429 | 13,539 | 14,280 | 17,680 | | .6340 | .7100 | .7527 | .8757 | |
| Men, 51-65 | 16,607 | 19,303 | | | | .7914 | .8767 | | | |
| Women, 16-21 | 7,118 | 8,296 | 10,438 | 10,646 | | .7297 | .8663 | .9517 | .9573 | |
| Women, 22-30 | 8,074 | 8,349 | 9,603 | 11,238 | 11,580 | .6483 | .6957 | .8377 | .9157 | .9213 |
| Women, 31-50 | 10,213 | 11,963 | 18,128 | | | .7013 | .8103 | .9770 | | |
| Women, 51-65 | 13,736 | 17,585 | | | | .8653 | .9686 | | | |
| Lower university | | | | | | | | | | |
| Men, 16-30 | 12,405 | 12,811 | 13,030 | 17,481 | | .7490 | .7897 | .8030 | .9563 | |
| Men, 31-65 | 15,407 | 21,470 | 21,528 | 25,153 | 31,672 | .7200 | .9040 | .9057 | .9520 | .9903 |
| Women, 16-30 | 8,763 | 8,951 | 9,742 | 10,257 | 12,828 | .5913 | .6199 | .7297 | .7763 | .9206 |
| Women, 31-65 | 10,846 | 13,638 | 14,769 | 15,852 | 21,243 | .6153 | .7864 | .8373 | .8635 | .9533 |
| Upper university | | | | | | | | | | |
| Men, 16-30 | 12,846 | 14,301 | 16,066 | 17,204 | | .5553 | .7085 | .8255 | .8872 | |
| Men, 31-65 | 16,284 | 17,287 | 19,185 | 23,020 | 29,622 | .5637 | .6181 | .7062 | .8022 | .9103 |
| Women, 16-30 | 13,065 | 13,086 | 16,651 | 22,223 | | .7102 | .7122 | .8796 | .9592 | |
| Women, 31-65 | 13,888 | 15,327 | 17,958 | 21,768 | | .6160 | .6979 | .7914 | .9006 | |

Estimates of productivity parameters, wage cuts and their weights are shown in Tables IV.5 and IV.6. Individual productivity values and wage cuts, say $p_i$ and $\overline{w}_i$, exhibit increasing patterns with respect to age among groups with university education while the picture is less clear for less educated workers. Of course, these kinds of comparisons are complicated by the fact that the number of firm types $q$ varies across the groups. Given the shape of the empirical wage distribution, it is not very surprising that the bulk of firms is found to be low productivity ones. Firms with the lowest level of productivity represent over half of all firms in each submarket as $\gamma_1 > .5$ holds for all worker groups. Some productivity terms take very high values in some groups of workers, though their relative weights are very low (see the associated $\gamma_i$'s).

In Figures IV.1 to IV.3 in the Appendix the estimated density functions of the model with discrete productivity dispersion are characterized by discontinuous jumps at the estimated wage cuts $(\overline{w}_1, ..., \overline{w}_{q-1})$, between which the densities exhibit locally increasing patterns. It turns out that the model with discrete productivity dispersion is able to capture the shape of the wage distribution quite well but has some difficulties with the both tails of the distribution. In particular the estimated density has generally the left tail which is too fat compared to the observed wage distribution. As a result, the model has problems also to match the mode point accurately. These failures are not unique to the Finnish data but appear in the previous empirical applications of the same model as well (see Bowlus et al., 1995, Bowlus, 1997, Bunzel et al., 2001, and Bowlus et al., 2001). Additionally, there are difficulties in explaining wage observations at the upper end of the distribution which is often thin, covering wide ranges. Adding more firm types serves as a way of obtaining a more accurate fit to the right tail of the distribution. The estimation procedure aims to attach different firm types to each of these observations, leading to implausibly high productivity values sometimes. However, these high productivity values have only a minor overall effect as their weights are very low (in terms of the associated values of $\gamma_i$'s).

It should be stressed that the trimming procedure applied to the wage data is related to the number of heterogeneity terms needed to match the right hand tail of the wage distribution. Indeed by trimming a higher fraction of wage values from the upper end of the distribution leads to a smaller choice of $q$, with the highest productivity parameters $p_i$ being in a more reasonable range and the associated values of $\gamma_i$ being well below one. Changing the upper value of trimming has of course a direct effect on the estimate of $h$. A brief sensitivity analysis done with the different trimming thresholds suggests that the parameters and conclusions of interest are reasonably robust, however.

### 4.4 Continuous productivity dispersion

Next we turn our attention to the version of the model with a continuous productivity distribution. The individual likelihood contribution has the same general form as previously defined in (IV.27) but the equilibrium distribution of wage offers is now given by $F(w) = \Gamma\left(K^{-1}(p)\right)$. This is a highly nonlinear function of unknown parameters and does not have a closed-form expression in general, suggesting that the standard maximum likelihood estimation could be very cumbersome. The first point to note is that the integrals within the expressions for $F$ and $f$ must be evaluated numerically in each iteration. An additional difficulty follows from the fact that the productivity distribution $\Gamma$ is not generated by the model but it must be taken as exogenously given. This is not a problem as such but, as argued by Bontemps et al. (2000), the most well-known parametric specifications for $\Gamma$ are unlikely to generate the wage offer distribution consistent with the shape usually observed in the wage data.

For these difficulties Bontemps et al. (2000) propose a flexible estimation procedure which does not restrict $\Gamma$ to belong in any parametric family. This estimation method consists of three steps. The first step of the procedure is to estimate $F$ and $f$ from the wage data using some nonparametric procedure. In the second step the likelihood function is maximized with respect to $(\lambda_0, \lambda_1, \delta)$ conditional on the nonparametric estimates of $F$

and $f$. As the final step $p = K^{-1}(w)$ and $\gamma(p)$ are estimated using[24]

$$K^{-1}(w) = w + \frac{1+\kappa_1 [1 - F(w)]}{2\kappa_1 f(w)}, \tag{IV.35}$$

$$\gamma(p) = \frac{2\kappa_1 f(w)^3}{\kappa_1 f(w)^2 - f'(w)\left(1+\kappa_1 [1 - F(w)]\right)}, \tag{IV.36}$$

where $F$, $f$ and $f'$ are replaced by their nonparametric estimates from the first step and $\kappa_1 = \lambda_1/\delta$ by its maximum likelihood estimate from the second step.[25] To estimate the wage offer density $f$, we apply the standard Gaussian kernel density estimator and choose the bandwidth by a rule of thumb that minimizes the mean integrated square error. Corresponding estimates of $F$ and $f'$ are then obtained by integration and differentiation of the kernel density estimate. Standard errors are finally obtained by bootstrapping the whole estimation procedure outlined above.[26]

It is worth emphasizing that the application of the kernel density techniques to the wage data does not impose any restrictions on the shape of equilibrium wage distributions. Conditional on the nonparametric estimates of $F$ and $f$, the likelihood function estimated in the second step relies only on assumptions about the behaviour of individual workers who are taking the wage offer distribution as given. In other words, the assumptions about the wage-setting strategies of firms do not affect the estimation of frictional parameters $(\lambda_0, \lambda_1, \delta)$. Only the third step of the estimation procedure exploits the part of the model which describes firm behaviour (that is, the first-order condition of firm's problem). Bontemps et al. (2000) emphasize that the estimates of the frictional parameters can be expected to be consistent under a wide range of assumptions on the demand side of the story. This class of models includes, among others, the specifications of equilibrium search models outlined and estimated in the previous sections. Finally, it should be stressed that the estimation method of Bontemps et al. (2000) is very simple in computational respect. Substitution of the kernel estimates in the likelihood function circumvents the need for numerical integrations, while the third step does not require even iterations. This a clear advantage compared to the estimation procedure of Bowlus et al. (1995) for the case of discrete productivity dispersion.

[24] The first equation is simply the first-order condition (IV.20) solved for $p = K^{-1}(w)$. The second equation can be found by differentiating the first equation with respect to $w$ and noting that $\left(K^{-1}\right)'(w) = f(w)/\gamma(p)$ by virtue of the relationship $F(w) = \Gamma\left(K^{-1}(w)\right)$.

[25] Obviously, the final step requires the denominator of (IV.36) to be positive. Note that this condition is equivalent to the second-order condition of the firm's problem outlined in (IV.21) or, in other words, that $f(w)\left(1+\kappa_1 [1 - F(w)]\right)$ decreases over the support of $F$.

[26] Our estimation procedure differs slightly from that used by Bontemps, et al. (2000) because of the different sampling scheme. Contrary to the inflow sample of unemployment, Bontemps, et al. (2000) use a sample from the French Labour Force Survey drawn from the stock of employed and unemployed workers. Consequently, wage observations in their data come from $G$, not from $F$ as in our data. As such they estimate $G$ (instead of $F$) using a nonparametric procedure and then recover the associated $F$ using the equilibrium flow relationship. They also replace (IV.35) and (IV.36) by the corresponding equations expressing $p$ and $\gamma$ as functions of $G$, $g$, $g'$ and $\kappa_1$, where $g$ is the density of the earnings distribution and $g'$ its derivative.

Table IV.7: Estimation results with continuous productivity dispersion

| | $\lambda_0$ | $\lambda_1$ | $\delta$ | $\overline{p}$ |
|---|---|---|---|---|
| Lower vocational and less | | | | |
| Men, 16-21 | .0285 (.0009) | .0234 (.0029) | .0437 (.0034) | 20,921 |
| Men, 22-30 | .0399 (.0014) | .0291 (.0021) | .0508 (.0026) | 28,443 |
| Men, 31-50 | .0375 (.0016) | .0254 (.0022) | .0495 (.0025) | 34,973 |
| Men, 51-65 | .0166 (.0007) | .0298 (.0030) | .0658 (.0040) | 36,894 |
| Women, 16-21 | .0282 (.0010) | .0179 (.0025) | .0454 (.0032) | 25,973 |
| Women, 22-30 | .0292 (.0010) | .0194 (.0019) | .0368 (.0022) | 22,520 |
| Women, 31-50 | .0286 (.0011) | .0118 (.0011) | .0366 (.0019) | 30,019 |
| Women, 51-65 | .0109 (.0006) | .0117 (.0016) | .0502 (.0034) | 38,504 |
| Upper vocational | | | | |
| Men, 16-21 | .0385 (.0014) | .0293 (.0026) | .0362 (.0029) | 16,134 |
| Men, 22-30 | .0494 (.0017) | .0262 (.0020) | .0352 (.0019) | 23,465 |
| Men, 31-50 | .0353 (.0012) | .0183 (.0014) | .0301 (.0018) | 33,879 |
| Men, 51-65 | .0116 (.0006) | .0129 (.0026) | .0440 (.0043) | 56,461 |
| Women, 16-21 | .0505 (.0023) | .0280 (.0026) | .0412 (.0029) | 15,990 |
| Women, 22-30 | .0534 (.0019) | .0232 (.0017) | .0322 (.0017) | 17,573 |
| Women, 31-50 | .0335 (.0013) | .0184 (.0015) | .0296 (.0016) | 26,052 |
| Women, 51-65 | .0095 (.0012) | .0077 (.0034) | .0495 (.0075) | 71,444 |
| Lower university | | | | |
| Men, 16-30 | .0562 (.0018) | .0224 (.0014) | .0264 (.0014) | 24,535 |
| Men, 31-65 | .0495 (.0018) | .0174 (.0011) | .0266 (.0013) | 42,881 |
| Women, 16-30 | .0675 (.0026) | .0245 (.0025) | .0251 (.0018) | 16,971 |
| Women, 31-65 | .0357 (.0015) | .0185 (.0020) | .0265 (.0020) | 31,605 |
| Upper university | | | | |
| Men, 16-30 | .0735 (.0067) | .0384 (.0054) | .0139 (.0021) | 20,448 |
| Men, 31-65 | .0363 (.0018) | .0189 (.0018) | .0190 (.0016) | 48,668 |
| Women, 16-30 | .0770 (.0051) | .0271 (.0042) | .0204 (.0026) | 24,157 |
| Women, 31-65 | .0395 (.0031) | .0294 (.0051) | .0272 (.0035) | 30,916 |

Notes: Standard errors are in parentheses. $\overline{p}$ is the average productivity over workers who found a job.

The estimates of the frictional parameters are given in Table IV.7, whereas the kernel estimates of $f$ are shown in Figures IV.1 to IV.3 in the Appendix. It appears that $\lambda_1$ is generally very close to the estimates obtained from the homogeneous model with measurement error and from the model with discrete productivity dispersion while $\delta$ is almost identical. Since the estimates of $(\lambda_0, \lambda_1, \delta)$ in this setting can be expected to be robust with respect to different mechanisms determining the wage distributions, we can conclude that all specifications of the Burdett-Mortensen model generating an acceptable fit to the wage data produce appropriate estimates for the frictional parameters. This suggests that to the extent we are concerned with the estimation of frictional parameters it is not so important whether the deviations from the theoretical distribution predicted by the homogeneous model are explained by measurement error or by employer heterogeneity as long as the shape of the wage distribution is captured by the specification. This is essentially the same result as found by Bunzel et al. (2001) with the Danish data.

The average productivity values in the last column are computed by taking the average over workers entering employment based on (IV.35). However, the estimated relationship between the wage offer and productivity is not consistent with the theory. The condition that $f(w)\,(1+\kappa_1\,[1-F(w)])$ decreases everywhere is violated for small wages in all worker groups. In other words, the model fails to capture a steeply increasing wage density observed at the lower end of the wage distribution. Recall that the model with a discrete distribution of productivity also fails to explain the shape of the left tail of the wage distribution.

The increasing pattern of $f(w)\,(1+\kappa_1\,[1-F(w)])$ on small wages implies that the relationship $K(p)$ is downward-sloping for small values of $p$. This suggests the wages offered by some less productive firms are not optimal as they could increase their profits by reducing their wages. A binding minimum wage is an obvious candidate to explain this failure of the model, as it may prevent low paying firms from lowering their wages further. As pointed out by Van den Berg and Van Vuuren (2000), omitted worker heterogeneity may also provide an explanation. To see this, suppose that workers within a given labour market segment are heterogeneous with respect to their value of non-market time (this heterogeneity may result, for example, from differences in unemployment benefits or in the value of leisure). In this case workers will apply different reservation wages when searching from unemployment. Thus a firm which lowers its wage offer may become unattractive for some groups of workers. The firms should take this effect into account when setting wages which may explain the failure of the theoretical model at the lower end of the wage distribution.

## 5 Conclusion

This paper has provided quite an extensive structural empirical analysis of various specifications of the Burdett-Mortensen model. We found that, in the absence of measurement error in wages, the equilibrium search model with identical agents does not fit to the wage data. This failure is due to the prediction of the theory that the equilibrium wage offer distribution has an increasing density everywhere which is at odds with the wage data. Introduction of the measurement error in wages or employer heterogeneity in terms of labour productivity across firms provides a way of making the model more flexible. These extended versions of the basic model proved to give a much better fit to the wage data. The frictional parameters of the model, i.e. the layoff rate and arrival rates of job offers, were found to be fairly robust across the model specifications which fit to the wage data. Stated differently, it does not make much difference for the estimates of the frictional parameters whether the wage distribution is matched by allowing for the measurement error in wages or unobserved productivity differences. However, the estimates of the other parameters – the value of non-market time and productivity terms – vary across the different specifications to a large extent.

In the case of the homogeneous model with the measurement error in wages almost all wage dispersion was attributed to the measurement error. This indicates that the model without (unobserved) worker or employer heterogeneity cannot explain the observed wage variation. Although the equilibrium models with employer heterogeneity match the overall shape of the wage distributions relatively well, they do have problems in explaining the shape of the left tail of the wage distribution, and in particular the testable theoretical conditions implied by the model with continuous productivity dispersion were rejected in the empirical analysis. Of course, one can expect that incorporating employer heterogeneity and measurement error into the same model provides a way of capturing the shape of the lower end of the wage distribution as well. On the other hand, unobserved heterogeneity and measurement errors allowed for in a sufficiently flexible form can be used to 'explain' any discrepancy between the theory and data.

One may call into question whether introducing more unobservables in the empirical analysis of equilibrium search models stands for any progress. As long as the shape of empirical wage distributions has to be captured mainly by unobservables, we cannot be very satisfied with our empirical applications. Since the equilibrium search theory is a story about joint behaviour of workers and firms, it may be hard to make significant progress in the empirical analysis of such models without data on both sides of the market. Indeed, the increasing availability of matched worker-firm data provides a natural way to proceed. With such data one may, for example, estimate the distribution of labour productivity from firm records rather than infer it indirectly from the wage distribution. In general, the matched worker-firm data contain more information for estimation and testing of existing models as well as make the estimation of more general models feasible (see Postel-Vinay and Robin, 2002, and Christensen et al., 2005) .

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Figure IV.1: Wage offer densities for workers with lower vocational education or less

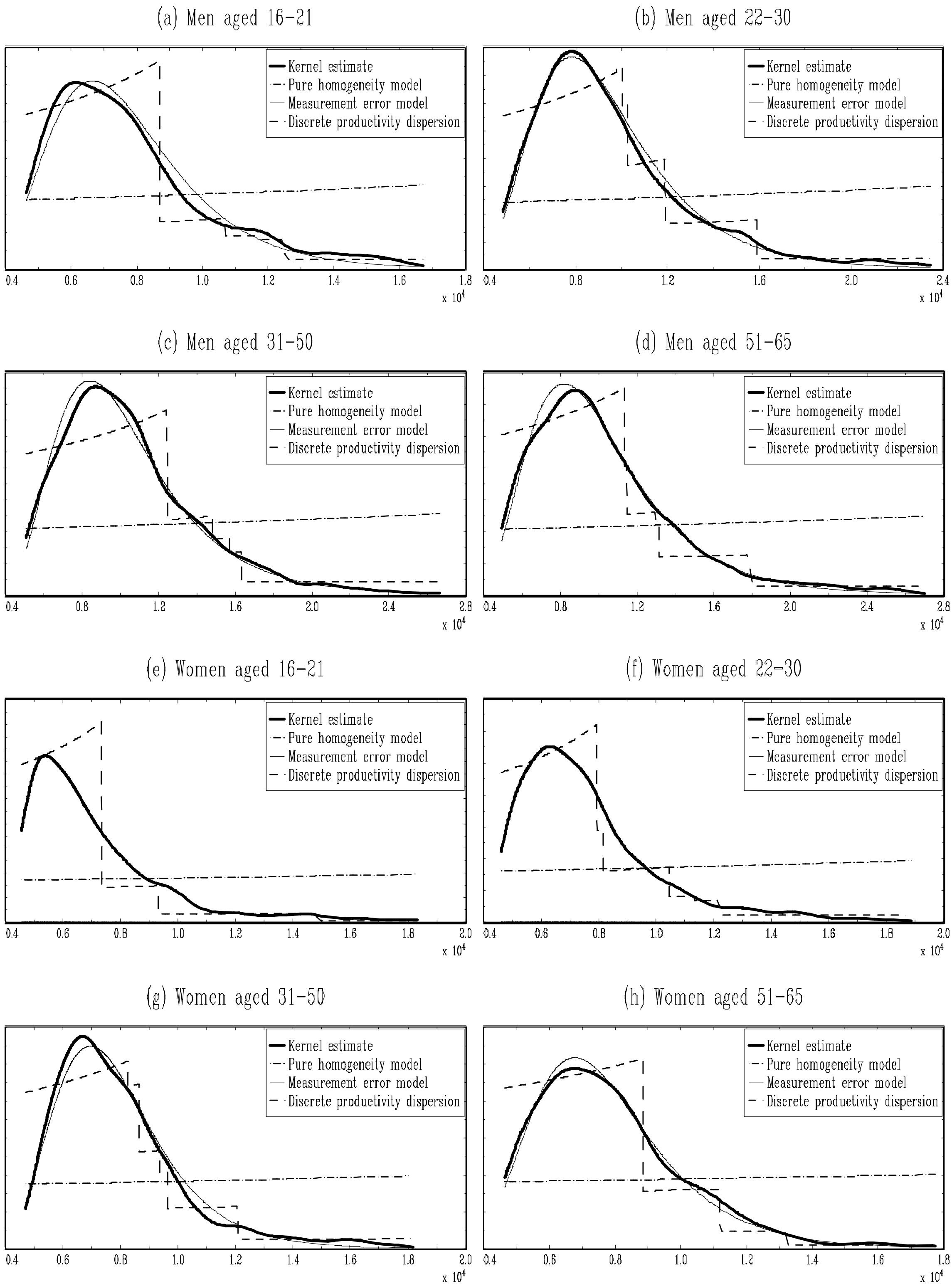


Figure IV.2: Wage offer densities for workers with upper vocational education

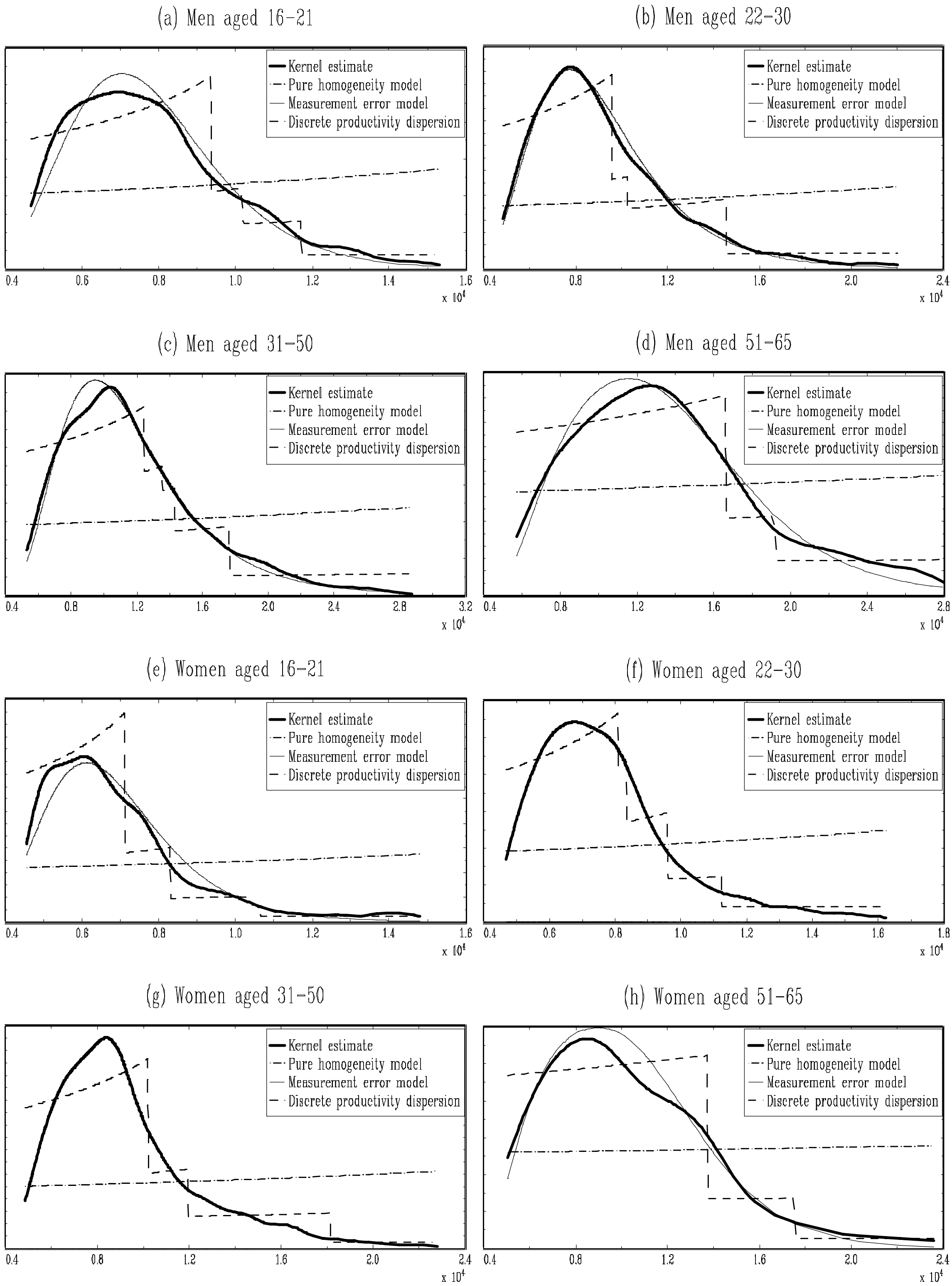
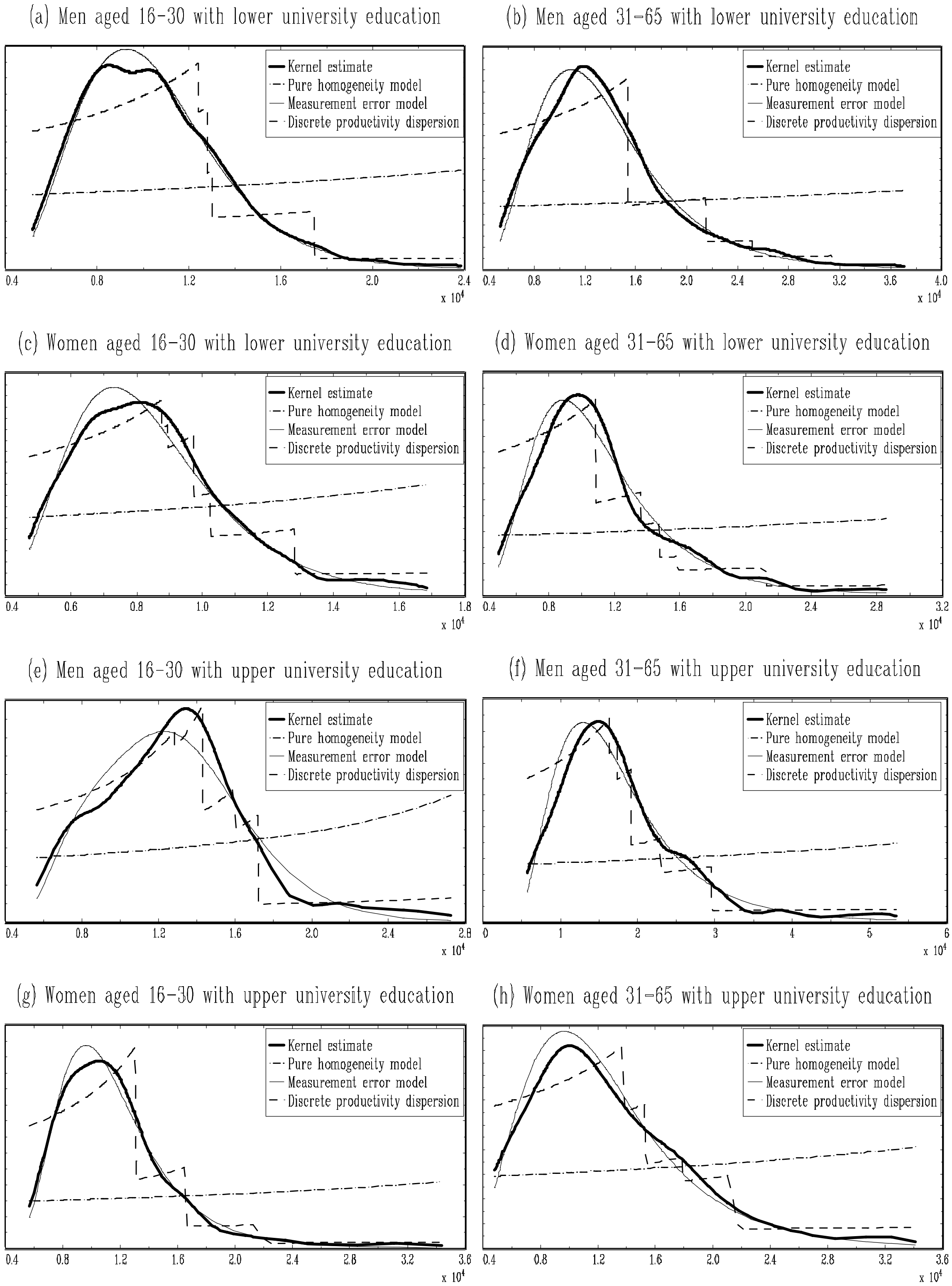


Figure IV.3: Wage offer densities for workers with university education



# Chapter V

# Marginal Effects for Competing Risks Models with Piecewise Constant Hazards

*In the competing risks context the effect of a covariate on the hazard function for a particular cause may be very different from its effect on the likelihood of exiting from that cause. The latter probability is a function of all cause-specific hazards, and thereby potentially affected by indirect effects via hazards for competing causes. We consider the effects of covariates on the cumulative probability of exiting from a particular cause. These "marginal effects" are decomposed into direct effects via the hazard of interest and indirect effects via the hazards for competing causes. For the piecewise constant hazard specification we derive simple closed-form expressions for the marginal effects that can be easily computed from the standard hazard functions estimates. We argue that the marginal effects provide a useful and coherent way of summarizing the results of competing risks analysis. This point is illustrated with an empirical application of unemployment duration data.*

## 1 Introduction

Competing risks arise in the analysis of duration data on individuals subject to leave the initial state from one of several competing causes. For example, a person may leave unemployment by taking a job, by withdrawing from the labour force, or by participating in a labour market programme. The conventional approach involves the specification and estimation of hazard functions for exits from competing causes. The cause-specific hazard function can be used to examine the effects of covariates on the instantaneous exit rate from a particular cause conditional on not having exited from any cause previously. It does not, however, provide direct information about the cumulative or overall probability of exit due to a particular cause since these are functions of all cause-specific hazards. In general, the effect of a covariate on the hazard function for a particular cause can be very different from its effect on the likelihood of exiting from that cause by a given time (Gray, 1988). This latter probability, described by the cumulative incidence function, is often of primary interest.

For example, the goal of policy-makers may be to induce the unemployed to find an acceptable job within a reasonable amount of time, while transitions out of the labour force and into labour market programmes are viewed as less desired outcomes. The effects of policy variables, such as benefit levels or the maximum length of entitlement periods, on the hazard rate to employment may be less interesting from a policy perspective than their effects on the likelihood of leaving unemployment for employment by a given time. The employment effect of a policy change that affects the employment hazard may be reinforced or attenuated by changes in hazard rates out of the labour force and to labour market programmes. As a consequence, a policy change with a strong effect on the employment hazard may have a negligible or even inverse effect on the probability that the unemployment spell will end with employment. Alternatively, a policy change with no effect on the employment hazard may still have a significant effect on the likelihood of exiting to employment due to indirect effects via the competing hazards. If one focuses on estimating the reform effects only on the employment hazard, the overall employment effect of the reform is not identified. An appropriate way of evaluating employment effects in the presence of competing risks calls for a simultaneous account of all cause-specific hazards.

An alternative approach is to directly compare the cumulative probabilities of employment between different groups. Estimation of the cumulative incidence functions has a long tradition in the statistical analysis of medical trials (see for example Pepe, 1991, Gaynor et al., 1993, or Satagopan et al., 2004). This literature has, however, relied heavily on nonparametric estimators, which may be less useful in economic applications where randomized experiments are rare and hence the need to account for heterogeneity is more important. Recently, some semiparametric methods for estimating the effects of covariates on the cumulative incidence function have been developed (see Fine, 1999, and Fine and Gray, 1999). However, the effect of a covariate on the cumulative incidence function does not generally identify the effects on the underlying cause-specific hazards. This may limit the usefulness of these methods in economic applications where the hazard function specification is often dictated by some theoretical model (Van den Berg, 2001). Therefore, in economic applications where the cumulative cause-specific exit probabilities are of interest, it may be advisable to obtain estimates of the cumulative incidence functions and covariate effects on these by combining the estimates of cause-specific hazard functions from the first step. This approach is taken in this study. It preserves a direct link to the hazard function specification which has been the focal point of econometric duration analysis but facilitates the interpretation of covariates effects.

To be more specific, we consider the effects of covariates on the cumulative probability of exiting from a particular cause by a given time. These "marginal effects" provide us with a complementary way of summarizing the results of cause-specific hazard estimates. This is analogous to the common practice of reporting marginal effects in the context of qualitative response models, such as multinominal logit and ordered probit models. Just as in the context of qualitative response models, the marginal effects in the competing risks model provide a clear probabilistic interpretation for covariate effects and eliminate much of the risk of confusion about the interpretation of the results.

In general, the cumulative incidence function and marginal effects are not available in closed form. We consider a class of semiparametric competing risks models with piecewise constant hazard functions. For this class there exist simple analytical expressions for the cumulative incidence functions and marginal effects, which can be easily computed using the standard hazard estimates. We decompose the marginal effects into direct effects via the hazard of interest and indirect effects via the hazards for competing causes. To what extent the effect of a covariate on the cumulative incidence function stems from a change in a particular hazard function may be of particular interest. For example, in assessing the effect of unemployment benefits on the likelihood of finding a job, the indirect effect via the hazard rate into labour market programmes may be particularly interesting from a policy perspective, as the eligibility rules for such programmes are under the direct control of the employment authorities.

In the next section we discuss the marginal effects in the competing risks context with an emphasis on a special case of the piecewise constant hazard specification. This is followed by an empirical illustration in Section 3. We estimate a competing risks model of unemployment duration with distinct hazards for exits to employment, labour market programmes, and out of the labour force using a sample of unemployed workers drawn from Finnish register data. We find clear differences, both in quantitative and qualitative terms, between the effects of covariates on cause-specific hazards and their effects on the associated cumulative incidence functions. In addition, by examining the distributions of marginal effects across individuals, we illustrate how marginal effects may work in the opposite directions for different subgroups. Some extensions of the modelling approach are discussed in Section 4. This is followed by concluding remarks about the usability of marginal effects as a way of summarizing the results of competing risks analysis.

# 2 Econometric methods

## 2.1 Basic concepts

Let $T$ be the (continuous) time until exit out of the initial state from one of $K$ possible causes. The hazard function for cause $k$ at time $t$, conditional on a vector of covariates $\mathbf{x}$, is defined as

$$\theta_k(t\,|\mathbf{x}) = \lim_{dt\to\mathbf{0}} \frac{\Pr(t \leq T < t + dt, K = k\,|T \geq t, \mathbf{X} = \mathbf{x})}{dt}. \tag{V.1}$$

The survivor function is

$$S(t\,|\mathbf{x}) \equiv \Pr(T > t\,|\mathbf{X} = \mathbf{x}) = \exp\left\{-\sum\nolimits_{k=1}^{K} \Lambda_k(t\,|\mathbf{x})\right\}, \tag{V.2}$$

where $\Lambda_k(t\,|\mathbf{x}) \equiv \int_0^t \theta_k(u\,|\mathbf{x})\,du$ denotes the integrated hazard for cause $k$. The likelihood of exiting from cause $k$ during a short interval $[t, t + dt)$ is $\theta_k(t\,|\mathbf{x})\,S(t\,|\mathbf{x})\,dt$. In other words, one must not have exited from any cause by time $t$, the probability of which is $S(t\,|\mathbf{x})$, to subsequently exit from cause $k$ during $[t, t + dt)$, the probability of which is $\theta_k(t\,|\mathbf{x})\,dt$. The likelihood of exiting due to cause $k$ by time $t$ is

$$F_k(t\,|\mathbf{x}) \equiv \Pr(T \leq t, K = k\,|\mathbf{X} = \mathbf{x}) = \int_0^t \theta_k(u\,|\mathbf{x})\,S(u\,|\mathbf{x})\,du, \tag{V.3}$$

(see e.g. Kalbfleisch and Prentice, 2002, p. 252). The likelihood of ever exiting from cause $k$ emerges as a limiting case: $\Pr(K = k\,|\mathbf{X} = \mathbf{x}) = \lim_{t\to\infty} F_k(t\,|\mathbf{x})$.[1] We refer to $F_k(t\,|\mathbf{x})$ as the cumulative incidence function but it is also known as the cause-specific failure probability and sub-distribution function.

Obviously, $F_k(t\,|\mathbf{x})$ depends on all hazard rates via $S(u\,|\mathbf{x})$. The marginal effect of a continuous covariate, say $x_i$, on $F_k(t\,|\mathbf{x})$ can be decomposed as

$$\frac{\partial F_k(t\,|\mathbf{x})}{\partial x_i} = \frac{\partial^2 F_k(t\,|\mathbf{x})}{\partial\theta_k \partial x_i} + \sum_{j\neq k} \frac{\partial^2 F_k(t\,|\mathbf{x})}{\partial\theta_j \partial x_i}, \tag{V.4}$$

where

$$\frac{\partial^2 F_k(t\,|\mathbf{x})}{\partial\theta_k \partial x_i} = \int_0^t \left(\frac{\partial\theta_k(u\,|\mathbf{x})}{\partial x_i} - \theta_k(u\,|\mathbf{x})\,\frac{\partial\Lambda_k(u\,|\mathbf{x})}{\partial x_i}\right) S(u\,|\mathbf{x})\,du \tag{V.5}$$

denotes the direct effect via the hazard function for cause $k$ and

$$\frac{\partial^2 F_k(t\,|\mathbf{x})}{\partial\theta_j \partial x_i} = -\int_0^t \theta_k(u\,|\mathbf{x})\,S(u\,|\mathbf{x})\,\frac{\partial\Lambda_j(u\,|\mathbf{x})}{\partial x_i}du \tag{V.6}$$

denotes the indirect effect via the hazard for cause $j \neq k$.

The formulas above apply to continuous covariates but may be used as approximations for dummy variables as well. Alternatively, one can compute the marginal effect for a dummy variable, $x_i$, as $F_k(t\,|\mathbf{x}_i^*, x_i = 1) - F_k(t\,|\mathbf{x}_i^*, x_i = 0)$, where $\mathbf{x}_i^*$ denotes a vector of all other covariates.[2] The direct effect via the hazard of cause $k$ can obtained by computing this difference but restricting the effect of $x_i$ to zero in hazards for causes $j \neq k$ when computing $F_k(t\,|\mathbf{x}_i^*, x_i = 1)$. The indirect effects can be obtained in a similar fashion. In this case the sum of direct and indirect effects does not generally equal the overall marginal effect. However, the difference is found to be reasonably small at least in our empirical application.

If a covariate has a positive effect on $\theta_k(t'\,|\mathbf{x})$ for all $t' \leq t$, its direct effect on $F_k(t\,|\mathbf{x})$ is positive. The indirect effect via the hazard for cause $j \neq k$ evaluated at time $t$ is positive

[1] One can easily verify that $\sum_{k=1}^{K} F_k(t\,|\mathbf{x}) = 1 - S(t\,|\mathbf{x})$ and $\sum_{k=1}^{K} \Pr(K = k\,|\mathbf{X} = \mathbf{x}) = 1$.

[2] If $x_i$ is a discrete variable with several categories that is measured in deviation from some proper reference value (e.g. sample mean), the same formula applies directly.

(negative) if the covariate has a negative (positive) effect on $\theta_j(t'|\mathbf{x})$ for all $t' \leq t$. With $\theta_k(t'|\mathbf{x})$ held constant for all $t' \leq t$, the negative effect on the hazard for cause $j \neq k$ increases the likelihood of surviving up to $t' \leq t$, and hence the individual is more likely to be at risk of exiting from cause $k$ at each $t' \leq t$. In sum, the marginal effect of $x_i$ on $F_k(t|\mathbf{x})$ is positive if the covariate increases $\theta_k(t|\mathbf{x})$ and decreases or has no effect on $\theta_j(t|\mathbf{x})$ for all $j \neq k$ up to time $t$. When the direct effect and some of the indirect effects work in opposite directions, i.e. when the covariate affects the cause-specific hazards in the same direction, the marginal effect is generally ambiguous, depending on the shapes of the hazard functions, the relative magnitude of the covariate effects, and the values of the conditioning covariates.

Only in some special cases can we deduce the sign of a covariate effect on the cumulative incidence function directly from the hazard parameters. Consider the following proportional risks model:

$$\theta_k(t|\mathbf{x}) = \lambda(t)\, e^{\gamma_k + \mathbf{x}'\boldsymbol{\beta}_k}, \qquad k = 1, 2, ..., K,$$

in which the covariates have proportional effects on the baseline hazard $\lambda(t)$ and the cause-specific hazards are proportional to each other over time (and for uniqueness let $\gamma_1 = 0$).[3] Denote $\Lambda(t) \equiv \int_0^t \lambda(u)\, du$. From (V.3) we find that $F_k(t|\mathbf{x}) = \Pi_k(\mathbf{x})\,[1 - S(t|\mathbf{x})]$, where

$$S(t|\mathbf{x}) = \exp\left\{-\Lambda(t) \sum\nolimits_{j=1}^{K} e^{\gamma_j + \mathbf{x}'\boldsymbol{\beta}_j}\right\}$$

is the survivor function and

$$\Pi_k(\mathbf{x}) = \frac{e^{\gamma_k + \mathbf{x}'\boldsymbol{\beta}_k}}{\sum_{j=1}^{K} e^{\gamma_j + \mathbf{x}'\boldsymbol{\beta}_j}}$$

denotes the likelihood that the exit will eventually be from cause $k$, which is of the familiar multinominal logit form. Let $\beta_{ki}$ be the coefficient of $x_i$ in the hazard for cause $k$. If $\beta_{ki} > \beta_{ji} \geq 0$ for all $j \neq k$, both $\Pi_k(\mathbf{x})$ and $1 - S(t|\mathbf{x})$ increase with $x_i$, and thereby $x_i$ has a positive effect on $F_k(t|\mathbf{x})$ for any choice of $\mathbf{x}$ and $\lambda$.[4] The effect of $x_i$ on the overall probability of exit due to cause $k$, $\Pi_k(\mathbf{x})$, is positive if $\beta_{ki} > \beta_{ji}$ for all $j \neq k$. These results and the particularly simple form of $F_k(t|\mathbf{x})$ follow from the proportional risks assumption, which is rather restrictive. In particular, the restriction that the cause-specific hazards are proportional over time implies that $K$ and $T$ are statistically independent.

When the baseline hazards are not proportional over time, it is difficult to draw any insight about the effect of the covariate $i$ on $F_k(t|\mathbf{x})$ from the hazard coefficients except in the trivial case where $\beta_{ki}$ has the opposite sign compared with $\beta_{ji}$ for all $j \neq k$. Then the only way to proceed is to compute the marginal effect of interest explicitly. This may be computationally demanding, however, since the cumulative incidence function and the marginal effects may not have closed-form expressions. This problem arises, for example,

[3] See Gaynor et al. (1993) for the discussion of a similar example.

[4] One can easily verify that $\partial\Pi_k(\mathbf{x})/\partial x_i = \Pi_k(\mathbf{x}) \sum_{j \neq k} \left(\beta_{ki} - \beta_{ji}\right) \Pi_j(\mathbf{x})$ and $\partial\left[1 - S(t|\mathbf{x})\right]/\partial x_i = S(t|\mathbf{x})\,\Lambda(t) \sum_j \beta_{ji} e^{\gamma_j + \mathbf{x}'\boldsymbol{\beta}_j}$.

in the context of the simple parametric specifications of the Weibull and Log-Logistic hazards. Thomas (1996), for example, simulates the marginal effects for a competing risks Weibull model by evaluating the probability of exiting due to a given cause at various values of covariates using numerical methods to compute the integral in (V.3).[5]

It should be stressed that a good fit of $F_k(t\,|\mathbf{x})$ from the hazard estimates requires that all cause-specific hazards are appropriately specified. This suggests that the proportional risks model, even in the absence of parametric restrictions on the shape of the common baseline hazard, and fully parametric hazard specifications are likely to be too restrictive for most applications. The piecewise constant hazard specification provides a more attractive alternative, at least for two reasons. First, without parametric restrictions on the shape of the hazard functions, it is very flexible, which is crucial for obtaining an accurate fit of the cumulative incidence function. Second, besides being very flexible, the specification results in simple closed-form solutions for the cumulative incidence function and marginal effects.

## 2.2 Piecewise constant hazard specification

Suppose the time axis is divided into $M$ intervals $(c_{m-1}, c_m]$, $m = 1, 2, ..., M$, with $c_0 \equiv 0$ and $c_M \equiv \infty$. The hazard function for exit from cause $k$ at time $t \in (c_{m-1}, c_m]$ is parametrized as

$$\theta_k(t\,|\mathbf{x}) \equiv \theta_k^m(\mathbf{x}) = e^{\alpha_k^h + \mathbf{x}'\boldsymbol{\beta}_k}, \tag{V.7}$$

where $e^{\alpha_k^h}$ equals the cause-specific hazard in interval $m$ for a reference individual with $\mathbf{x} = \mathbf{0}$ (i.e. baseline hazard). The hazard functions are constant within each interval but can vary across intervals. Any duration dependence can be approximated arbitrarily closely by increasing the number of time intervals. The integrated hazard for cause $k$ at time $t \in (c_{m-1}, c_m]$ is given by

$$\begin{aligned} \Lambda_k(t\,|\mathbf{x}) &= \sum_{h=1}^{m-1} \int_{c_{h-1}}^{c_h} \theta_k^h(\mathbf{x})du + \int_{c_{m-1}}^{t} \theta_k^m(\mathbf{x})du \\ &= \sum_{h=1}^{m-1} e^{\alpha_k^h + \mathbf{x}'\boldsymbol{\beta}_k} \Delta c_h + e^{\alpha_k^m + \mathbf{x}'\boldsymbol{\beta}_k} \left(t - c_{m-1}\right), \end{aligned} \tag{V.8}$$

where $\Delta c_h \equiv c_h - c_{h-1}$.

We can express the cumulative probability of exiting from cause $k$ by time $t \in (c_{m-1}, c_m]$

[5] Andrews et al. (2002) summarize their results from a competing risks proportional hazard model in terms of the effects of covariates on the probability of exit due to cause $k$ conditional on exiting at time $t$. This conditional exit probability equals the ratio of hazard $k$ to the overall hazard at time $t$. They justify their approach by pointing out that these effects are computationally much easier to obtain than covariates effects on the likelihood of eventually exiting from cause $k$. This is true, but the approaches are quite different. If the latter effects are of interest, computing only the former effects does not help.

as

$$
\begin{aligned}
F_k(t\,|\mathbf{x}) &= \sum_{h=1}^{m-1} \int_{c_{h-1}}^{c_h} \theta_k^h(\mathbf{x}) S(u\,|\mathbf{x})\,du + \int_{c_{m-1}}^{t} \theta_k^m(\mathbf{x}) S(u\,|\mathbf{x})\,du \\
&= \sum_{h=1}^{m-1} P_k(\Delta c_h\,|\mathbf{x}) + P_k(t - c_{m-1}\,|\mathbf{x})\,, \qquad \text{(V.9)}
\end{aligned}
$$

where

$$P_k(\Delta c_h\,|\mathbf{x}) \equiv \pi_k^h(\mathbf{x})\left[S(c_{h-1}\,|\mathbf{x}) - S(c_h\,|\mathbf{x})\right]$$

denotes the probability of exiting during interval $h$ from cause $k$, which equals the product of the overall probability of exiting during interval $h$, $S(c_{h-1}\,|\mathbf{x}) - S(c_h\,|\mathbf{x})$, and the probability that the exit is from cause $k$ conditional on exiting,

$$\pi_k^h(\mathbf{x}) \equiv \frac{\theta_k^h(\mathbf{x})}{\sum_{j=1}^{K} \theta_j^h(\mathbf{x})}.$$

Thus $F_k(t\,|\mathbf{x})$ can be computed as the sum of the survivor functions weighted by the ratio of interval-specific hazards.

The marginal effect of a continuous variable, $x_i$, at time $t \in (c_{m-1}, c_m]$ is computed as

$$\frac{\partial F_k(t\,|\mathbf{x})}{\partial x_i} = \sum_{h=1}^{m-1} \frac{\partial P_k(\Delta c_h\,|\mathbf{x})}{\partial x_i} + \frac{\partial P_k(t - c_{m-1}\,|\mathbf{x})}{\partial x_i}, \qquad \text{(V.10)}$$

where

$$
\begin{aligned}
\frac{\partial P_k(\Delta c_h\,|\mathbf{x})}{\partial x_i} &= \pi_k^h(\mathbf{x})\left[S(c_{h-1}\,|\mathbf{x}) - S(c_h\,|\mathbf{x})\right] \sum_{j \neq k} \pi_j^h(\mathbf{x}) \left(\beta_{ki} - \beta_{ji}\right) \qquad \text{(V.11)} \\
&\quad + \pi_k^h(\mathbf{x}) \sum_{j} \left[S(c_h\,|\mathbf{x})\,\Lambda_j(c_h\,|\mathbf{x}) - S(c_{h-1}\,|\mathbf{x})\,\Lambda_j(c_{h-1}\,|\mathbf{x})\right] \beta_{ji},
\end{aligned}
$$

which equals the sum of the direct effect via hazard $k$

$$
\begin{aligned}
\frac{\partial^2 P_k(\Delta c_h\,|\mathbf{x})}{\partial \theta_k \partial x_i} &= \pi_k^h(\mathbf{x})\left[1 - \pi_k^h(\mathbf{x})\right]\left[S(c_{h-1}\,|\mathbf{x}) - S(c_h\,|\mathbf{x})\right] \beta_{ki} \\
&\quad + \pi_k^h(\mathbf{x})\left[S(c_h\,|\mathbf{x})\,\Lambda_k(c_h\,|\mathbf{x}) - S(c_{h-1}\,|\mathbf{x})\,\Lambda_k(c_{h-1}\,|\mathbf{x})\right] \beta_{ki},
\end{aligned}
$$

and the indirect effects via hazards $j \neq k$

$$
\begin{aligned}
\frac{\partial^2 P_k(\Delta c_h\,|\mathbf{x})}{\partial \theta_j \partial x_i} &= -\pi_k^h(\mathbf{x})\pi_j^h(\mathbf{x})\left[S(c_{h-1}\,|\mathbf{x}) - S(c_h\,|\mathbf{x})\right] \beta_{ji} \\
&\quad + \pi_k^h(\mathbf{x})\left[S(c_h\,|\mathbf{x})\,\Lambda_j(c_h\,|\mathbf{x}) - S(c_{h-1}\,|\mathbf{x})\,\Lambda_j(c_{h-1}\,|\mathbf{x})\right] \beta_{ji}.
\end{aligned}
$$

Since the right-hand side of (V.11) does not include anything more than the sums and products of survivor functions, hazard functions, and coefficients, the marginal effects of continuous covariates can be easily computed from the standard hazard function estimates. The marginal effects for discrete covariates are even simpler to obtain. We just take the difference in $F_k(t\,|\mathbf{x})$ evaluated at two different values of the covariate of interest, holding all other covariates constant. The direct and indirect effects via a particular hazard can be obtained by allowing the covariate of interest to change only in that hazard.

## 2.3 Estimation and statistical inference

The maximum likelihood estimation of unknown hazard function parameters is straightforward. Consider an individual $l$ with characteristics $\mathbf{x}_l$ who left the initial state at time $t_l \in (c_{m-1}, c_m]$. Let $d_{kl} = 1$ if the exit was due to cause $k$, and $d_{kl} = 0$ otherwise. If the spell is censored, $\sum_{k=1}^{K} d_{kl} = 0$. The contribution of this observation to the log-likelihood function is given by

$$\begin{aligned} \mathcal{L}_l &= \sum_{k=1}^{K} d_{kl} \ln \theta_k(t_l \,|\mathbf{x}_l) + \ln S(t_l \,|\mathbf{x}_l) \\ &= \sum_{k=1}^{K} \left( d_{kl} \left(\alpha_k^m + \mathbf{x}_l'\boldsymbol{\beta}_k\right) - \sum_{h=1}^{m-1} e^{\alpha_k^h + \mathbf{x}_l'\boldsymbol{\beta}_k} \Delta c_h - e^{\alpha_k^m + \mathbf{x}_l'\boldsymbol{\beta}_k} \left(t_l - c_{m-1}\right) \right). \end{aligned} \quad \text{(V.12)}$$

The log-likelihood function of the model is maximized with respect to $\boldsymbol{\phi} = (\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, ..., \boldsymbol{\phi}_K)$, where $\boldsymbol{\phi}_k = (\alpha_k^1, \alpha_k^2, ...., \alpha_k^M, \boldsymbol{\beta}_k)$. Since $\partial^2 \mathcal{L}_l / \partial \boldsymbol{\phi}_j \partial \boldsymbol{\phi}_k' = \mathbf{0}$ for all $j \neq k$, the ML estimators of $\boldsymbol{\phi}_j$ and $\boldsymbol{\phi}_k$ are statistically independent for all $j \neq k$, a common property of independent risks duration models. The asymptotic distribution of the ML estimator $\widehat{\boldsymbol{\phi}}$ is $N(\boldsymbol{\phi}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ is the block-diagonal matrix of the covariance matrixes of $\boldsymbol{\phi}_j$, $j = 1, 2, ..., K$.

Given the properties of the ML estimator $\widehat{\boldsymbol{\phi}}$, we can derive asymptotic distributions for the estimators of the cumulative incidence functions and marginal effects using the delta method. The asymptotic distribution of $\widehat{F}_k(t\,|\mathbf{x})$ is given by

$$\sqrt{n}\left[\widehat{F}_k(t\,|\mathbf{x}) - F_k(t\,|\mathbf{x})\right] \overset{as}{\to} N\left(0, \sum_{j=1}^{K} \left(\frac{\partial F_k(t\,|\mathbf{x})}{\partial \boldsymbol{\phi}_j'}\right) \boldsymbol{\Sigma}_j \left(\frac{\partial F_k(t\,|\mathbf{x})}{\partial \boldsymbol{\phi}_j}\right)\right), \quad \text{(V.13)}$$

where $n$ is the sample size and $\boldsymbol{\Sigma}_j$ is the covariance matrix of $\boldsymbol{\phi}_j$. Let $\widehat{\boldsymbol{\delta}}_k(t\,|\mathbf{x})$ be the vector of estimators for the marginal effects of both continuous and discrete covariates with respect to $F_k(t\,|\mathbf{x})$. Its asymptotic distribution is given by

$$\sqrt{n}\left[\widehat{\boldsymbol{\delta}}_k(t\,|\mathbf{x}) - \boldsymbol{\delta}_k(t\,|\mathbf{x})\right] \overset{as}{\to} N\left(0, \sum_{j=1}^{K} \left(\frac{\partial \boldsymbol{\delta}_k(t\,|\mathbf{x})}{\partial \boldsymbol{\phi}_j'}\right) \boldsymbol{\Sigma}_j \left(\frac{\partial \boldsymbol{\delta}_k(t\,|\mathbf{x})}{\partial \boldsymbol{\phi}_j}\right)\right). \quad \text{(V.14)}$$

The additive structures of the variance in (V.13) and the covariance matrix in (V.14) result from the block-diagonality of $\boldsymbol{\Sigma}$.

To summarize, we first obtain the ML estimate of $\boldsymbol{\phi}$ by maximising the log-likelihood function based on (V.12). In the second stage we compute the estimates of cumulative incidence functions and marginal effects at $\widehat{\boldsymbol{\phi}}$. The standard errors and confidence intervals of these two-step estimators are obtained from (V.13) and (V.14) by replacing $\boldsymbol{\Sigma}_j$'s with their ML estimates and evaluating the derivatives of $F_k(t\,|\mathbf{x})$ and $\boldsymbol{\delta}_k(t\,|\mathbf{x})$ numerically at $\widehat{\boldsymbol{\phi}}$.[6] In the empirical application we report $\boldsymbol{\delta}_k(t\,|\mathbf{x})$ at the sample mean of $\mathbf{x}$. We also examine the distribution of marginal effects over observations. To assess the fit of the model, one may contrast the nonparametric estimate of $F_k(t)$ with the model's estimate of the marginal cumulative incidence function, $n^{-1}\sum_{l=1}^{n} \widehat{F}_k(t\,|\mathbf{x}_l)$.

[6] One can derive the analytical expression for $\partial \boldsymbol{\delta}_k(t\,|\mathbf{x}) / \partial \boldsymbol{\phi}_j$ but it is rather messy.

# 3 Empirical application

## 3.1 Data

Our data come from the records of the Employment Statistics database of Statistics Finland. This database merges information from over 20 administrative registers for all people with permanent residence in Finland. Along with standard socio-demographic background variables, the database includes detailed information on annual income (from the tax authorities), job spells (from the pension institutes), unemployment spells and participation in labour market programmes (from the employment offices). Our sample includes workers aged 25 to 50 who lost their private-sector job and entered unemployment in 1998, having been employed for the past year. Workers who have been working and contributing insurance payments to an unemployment fund for at least 10 months during the two years prior to unemployment are eligible for earnings-related UI benefits, which can be collected for the maximum duration of two years. We focus on this group by excluding workers whose unemployment benefits do not exceed 14 euros per day, which equals the maximum level of the basic allowance. In addition, observations with the replacement rate above one or unemployment benefits exceeding 100 euros per day are excluded, due to likely errors in income variables.

For each worker we observe the length of the unemployment spell in days, exit destination, and a number of background variables. An unemployment spell may end owing to one of three causes: a person returns to work, enters a labour market programme (relief work or training course), or withdraws from the labour force. Those whose exit destination is not known are assumed to be withdrawn from the labour force, which is likely the case, as activities outside the labour force are not well documented in the data. All unemployment spells that continued beyond the end of 2000 are recorded as censored.

Table V.1 reports the sample means of the explanatory variables used in the analysis. The sample deviations are given in parentheses for non-dummy variables. Some 40% of individuals are female and roughly half are married. The average age is slightly below 38. Commercial, clerical, and industrial work are the most typical occupations among the unemployed. Over 70% of individuals were unemployed previously in the 1990s. This high fraction is explained by the fact that the early 1990s was a time of record high unemployment in Finland. The mean replacement rate, the ratio of UI benefits to earnings in 1997, is 0.49, which seems rather meaningful, as the gross replacement rate for a worker with median earnings is 0.55 (Koskela and Uusitalo, 2006). In the empirical analysis the continuous and discrete covariates are measured in deviation from the sample mean.

We divide the time axis, i.e. the duration of unemployment, into intervals of one to two months on the basis of observations available for estimation. The frequency of observed exits from different causes over time is shown in Table V.2. It appears that 61% of the unemployment spells eventually ended in employment, 27% in labour market programmes, and 11% in withdrawal from the labour force. Less than 2% of the unemployment spells

Table V.1: Definition of variables and sample statistics

| | Mean (Std.dev.) | Description |
|---|---|---|
| Married | 0.4781 | *1 if married, 0 otherwise* |
| Female | 0.4185 | *1 if female, 0 otherwise* |
| Dependent child | 0.4353 | *1 if there is a child under age 17 in the family, 0 otherwise* |
| Swedish | 0.0316 | *1 if person speaks Swedish as native language, 0 otherwise* |
| Past unemployment | 0.7273 | *1 if person experienced unemployment in the early 1990s, 0 otherwise* |
| Past recall | 0.1904 | *1 if person experienced a temporary layoff in the early 1990s, 0 otherwise* |
| Tenure | 2.6270 (2.4466) | *Tenure with the last employer in years* |
| Age | 37.6472 (7.3811) | *Age in years* |
| Occupation: | | *Occupation reported to employment authorities* |
| Commercial work | 0.1191 | |
| Technical | 0.0640 | |
| Sociological work | 0.0323 | *Teacher, lawyer, humanist* |
| Health care | 0.0389 | |
| Clerical work | 0.1230 | |
| Agricultural work | 0.0230 | *Forest work, farming, fishing* |
| Transportation | 0.0604 | |
| Industrial work | 0.4215 | |
| Service work | 0.1050 | |
| Not classified | 0.0128 | |
| Wealth | 5886 (16157) | *Taxable wealth in 1997, in euros* |
| Capital Income | 279 (2554) | *Capital income in 1997, in euros* |
| Debt | 10243 (15206) | *Debts in 1997, in euros* |
| Replacement rate | 0.4887 (0.1421) | *UI benefits / Earnings in 1997* |

were still in progress at the end of 2000 and hence treated as censored.

### 3.2 Results

Cause-specific hazards, evaluated at the sample mean of the covariates, are shown in Figure V.1. Over the first months of unemployment the employment hazard is very high but decreases steeply and crosses the hazard for labour market programmes at 12 months, remaining approximately constant thereafter. The hazard rate for labour market programmes increases slowly over the first 12 months and exhibits level shifts at around one and two years of unemployment. After 18 months of unemployment, a transition to a labour market programme is the most likely way of escaping unemployment. Transitions out of the labour force seem to be relatively rare. The hazard rate for labour market withdrawal starts at a very low level but increases somewhat as unemployment is prolonged. A number of studies have found that the hazard rates out of unemployment increase just prior

Table V.2: Exits to different states and risk set by duration interval

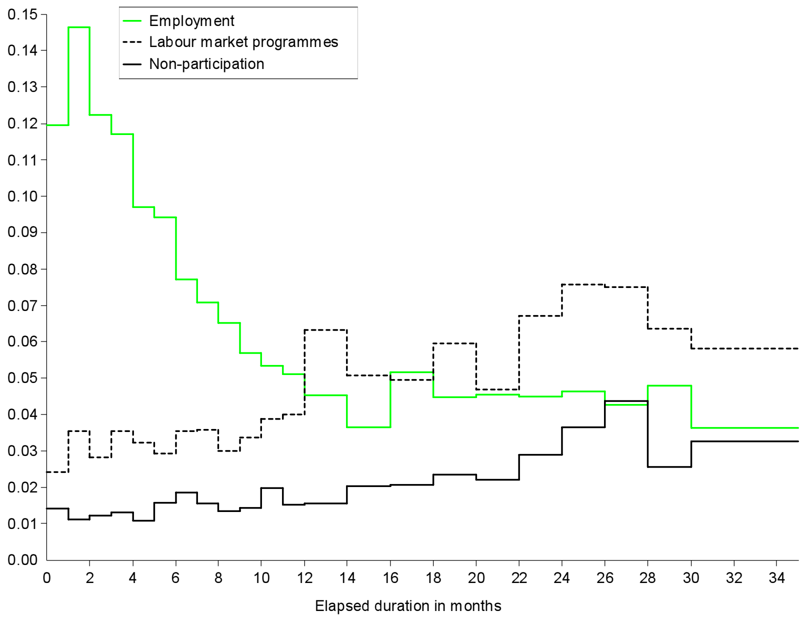
| Time Interval | Exits to Work | Exits to Labour market progr. | Exits to Outside labour force | Risk set |
|---|---|---|---|---|
| $(0, 1]$ | 1721 | 329 | 189 | 13501 |
| $(1, 2]$ | 1613 | 401 | 122 | 11262 |
| $(2, 3]$ | 1063 | 269 | 112 | 9126 |
| $(3, 4]$ | 824 | 286 | 101 | 7682 |
| $(4, 5]$ | 563 | 221 | 71 | 6471 |
| $(5, 6]$ | 469 | 176 | 90 | 5616 |
| $(6, 7]$ | 326 | 184 | 92 | 4881 |
| $(7, 8]$ | 260 | 164 | 68 | 4279 |
| $(8, 9]$ | 212 | 121 | 52 | 3787 |
| $(9, 10]$ | 166 | 121 | 50 | 3402 |
| $(10, 11]$ | 140 | 124 | 61 | 3065 |
| $(11, 12]$ | 120 | 114 | 42 | 2740 |
| $(12, 14]$ | 177 | 299 | 72 | 2464 |
| $(14, 16]$ | 112 | 187 | 73 | 1916 |
| $(16, 18]$ | 126 | 142 | 59 | 1544 |
| $(18, 20]$ | 86 | 131 | 52 | 1217 |
| $(20, 22]$ | 69 | 80 | 38 | 948 |
| $(22, 24]$ | 54 | 89 | 39 | 761 |
| $(24, 26]$ | 39 | 71 | 35 | 577 |
| $(26, 28]$ | 23 | 45 | 27 | 386 |
| $(28, 30]$ | 16 | 24 | 10 | 248 |
| $(30, \infty)$ | 13 | 24 | 14 | 158 |
| Sum | 8192 | 3602 | 1469 | |
| (%) | (60.7) | (26.7) | (10.9) | |

Notes: Risk set is the number of spells in progress at the beginning of the time interval.

to the exhaustion of UI benefits. We find no evidence of spikes in the employment hazard and only a moderate level shift in the hazard for labour market programmes around two years of unemployment when UI benefits lapse. Although someone might have expected a larger increase in the employment hazard close to benefit exhaustion, these findings are consistent with previous evidence for the Nordic countries, where active labour market policy has an important role by international standards (e.g. Carling et al., 1996, and Koskela and Uusitalo, 2006)

Figure V.2 depicts the marginal distribution function and marginal cumulative incidence functions for each cause of exit. These curves were computed by averaging the estimates of individual level curves. If the corresponding non-parametric estimates are added to the same graph, they will be basically identical to the marginal curves obtained from our model, implying a good fit of the model. The cumulative incidence function for employment increases steeply over the first 12 months of unemployment, remaining almost unchanged for the rest of the period. The likelihood of escaping unemployment eventually to employment is close to 60%. The cumulative incidence of participating in labour market programmes and that of withdrawing from the labour force increase more

Figure V.1: Cause-specific hazards evaluated at the sample mean of covariates

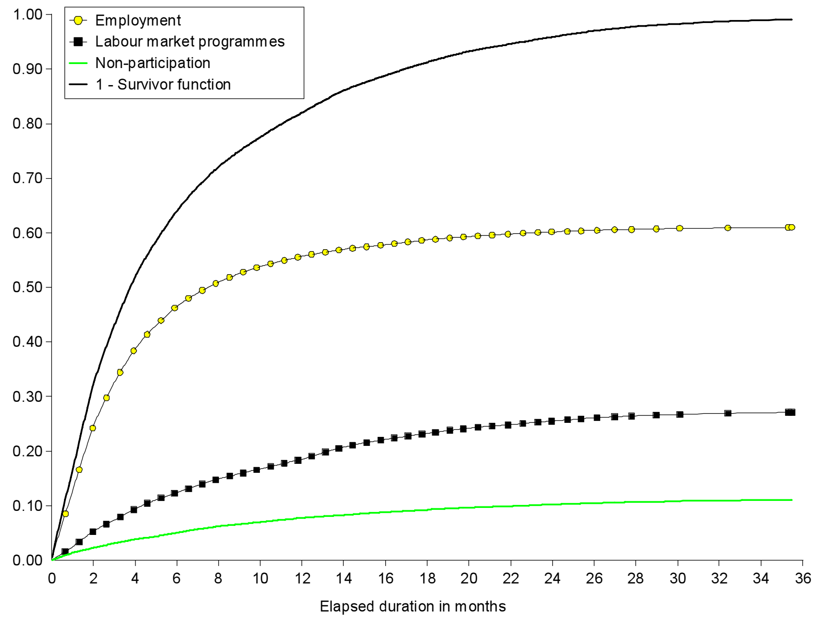



smoothly over a longer period. The unemployed are estimated to leave unemployment via labour market programmes with a probability of 25%t on average, while the likelihood of labour force withdrawal is some 10%.

The estimated hazard coefficients for covariates are given in Table V.3. Table V.4 reports the marginal effects at the sample mean of covariates, decomposed into direct and indirect effects, on the overall probability of exiting from a given cause. Evolution of the overall marginal effects over the observation period is shown in Figures V.3, V.4, and V.5 in the Appendix. We do not report the marginal effects for the occupational dummies in order to reduce the reported numbers. The marginal effects of continuous variables (wealth, capital income, debt, and the replacement rate) are based on derivatives and those of discrete variables were obtained by taking the differences. Age, tenure, and the continuous variables are measured in deviation from their sample mean. As a result, the marginal effects of age and tenure correspond to one year's increase from their mean values. For discrete covariates we also report the sum of partial effects in the last column, since the partial effects do not total the overall effect in their case. Since these sums are very close to the overall marginal effects in each case, decomposing the overall marginal effects of discrete covariates into the partial marginal effects seems reasonable as well.

A comparison of Table V.3 and Panel A of Table V.4 suggests that the effects of covariates on the employment hazard are very similar to their overall marginal effects on the overall incidence of employment. Covariates with statistically significant hazard effects are associated with the significant effects of the same sign on the overall probability of

Figure V.2: Marginal cumulative incidence functions




employment. The only exception is the amount of debt, which increases the employment hazard significantly but has no significant effect on the overall incidence of employment. This can be understood by noting that the debts also increase the hazard for labour market programmes. The relative importance of this indirect effect increases over time as a transition to employment becomes less likely compared with a transition to a labour market programme (see Figure V.1). As a result, the effect of debts increases the likelihood of finding a job within two years of unemployment but loses its significancy since then (see Figure V.3).

From Table V.3 we observe that the hazard rate to employment is 20% lower for women than men (because $e^{-\mathbf{0.2195}} \approx 0.80$). But this observation does not tell us how much less likely women's unemployment spells will end with employment. To answer this question we must take into account women's higher hazard rates for labour market programmes and out of the labour force. We see from Table V.4 that the likelihood of leaving unemployment via employment is 10.1 percentage points lower for women. This gender gap would shrink to 6.7 percentage points in the absence of sex differences in the hazards for labour market programmes and labour market withdrawal. Turning to the incentive issues, it is interesting to note that the effects of the replacement rate on the hazards for employment and labour market programmes are of the same magnitude but in opposite directions. The former effect contributes more to the likelihood of exiting from various causes, as the employment hazard is higher for most of the time and especially in the early phases of unemployment. A ten percentage points increase in the replacement

Table V.3: Coefficients of covariates for cause-specific hazard functions

| | Employment | | Labour market programmes | | Outside labour force | |
|---|---|---|---|---|---|---|
| Married | 0.1830 | (0.0253)*** | −0.0235 | (0.0371) | 0.0292 | (0.0584) |
| Female | −0.2195 | (0.0280)*** | 0.1627 | (0.0397)*** | 0.2986 | (0.0620)*** |
| Dependent child | 0.1512 | (0.0247)*** | 0.0923 | (0.0366)** | −0.2459 | (0.0593)*** |
| Swedish | 0.0451 | (0.0646) | 0.1266 | (0.0933) | 0.1608 | (0.1420) |
| Past unemployment | 0.3195 | (0.0297)*** | 0.0427 | (0.0388) | −0.0830 | (0.0607) |
| Past recall | 0.5199 | (0.0276)*** | −0.2600 | (0.0607)*** | −0.0655 | (0.0910) |
| Tenure | −0.0321 | (0.0050)*** | 0.0011 | (0.0071) | −0.0307 | (0.0113)*** |
| Age | −0.0146 | (0.0017)*** | −0.0082 | (0.0026)*** | −0.0242 | (0.0040)*** |
| Occupation: | | | | | | |
| Technical | 0.1698 | (0.0572)*** | 0.2390 | (0.0794)*** | −0.0307 | (0.1454) |
| Sociological work | 0.3074 | (0.0727)*** | 0.0081 | (0.1033) | 0.4425 | (0.1426)*** |
| Health care | 0.3581 | (0.0688)*** | 0.0493 | (0.0901) | 0.2916 | (0.1404)** |
| Clerical work | 0.0175 | (0.0514) | 0.1911 | (0.0569)*** | 0.1326 | (0.0982) |
| Agricultural work | 0.6916 | (0.0748)*** | −0.2328 | (0.1588) | 0.3214 | (0.2064) |
| Transportation | 0.2328 | (0.0581)*** | −0.1915 | (0.0880)** | 0.1782 | (0.1300) |
| Industrial work | 0.3617 | (0.0414)*** | −0.1635 | (0.0534)*** | −0.0139 | (0.0885) |
| Service work | 0.2273 | (0.0510)*** | −0.1644 | (0.0642)** | 0.2780 | (0.0980)*** |
| Not classified | −0.3619 | (0.1295)*** | −0.3143 | (0.1405)** | 0.5233 | (0.1665)*** |
| ln Wealth | 0.0194 | (0.0028)*** | 0.0127 | (0.0043)*** | 0.0018 | (0.0070) |
| ln Capital income | 0.0011 | (0.0053) | 0.0102 | (0.0080) | 0.0315 | (0.0123)** |
| ln Debt | 0.0101 | (0.0027)*** | 0.0137 | (0.0040)*** | −0.0008 | (0.0063) |
| Replacement rate | −1.8561 | (0.0930)*** | 1.8543 | (0.1290)*** | 0.1609 | (0.2141) |

Notes: The number of observations is 13,501. The mean log-likelihood is −3.54322. The reference occupation is commercial work. Age, tenure, and income variables are measured in deviation from their sample mean. The standard errors in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively.

rate would lead to a decline of 7.9 percentage points in the employment probability, of which 5.7 percentage points is attributable to the decrease in the employment hazard.

In terms of the sign or statistical significance there are no notable differences between the effects of covariates on the employment hazard and their marginal effects on the cumulative likelihood of employment. In other words, the indirect effects via the hazards for labour market programmes and labour market withdrawal play a relatively small role. This is what one should expect, as the employment hazard is quantitatively the most important one and some 60% of individuals eventually escape from unemployment to employment. By the same way of reasoning, we should expect the indirect effects via competing hazards to account for a larger part of the overall marginal effects on the incidence functions for the two other exit causes.

Being married or having experienced a spell of unemployment in the past have no significant effects on the hazard rate for labour market programmes in Table V.3. However, these covariates significantly affect the likelihood of exiting via labour market programmes (see the overall marginal effects in Panel B of Table V.4). In both cases the significant overall marginal effect stems from a strong indirect effect via the employment hazard. The opposite pattern is found for the dummy of a dependent child. Having a child under

Table V.4: Marginal effects for the overall probability of exiting from a given cause

| | Partial effect via hazard function for | | | Overall marginal effect | Std. Err. | Sum of partial effects |
|---|---|---|---|---|---|---|
| | Empl. | LMP | Out | | | |
| **Panel A: Likelihood of finding a job** | | | | | | |
| Married | 0.0562 | 0.0028 | −0.0014 | 0.0574 | $(0.0093)^{***}$ | 0.0575 |
| Female | −0.0673 | −0.0193 | −0.0154 | −0.1011 | $(0.0102)^{***}$ | −0.1020 |
| Dependent child | 0.0464 | −0.0105 | 0.0123 | 0.0475 | $(0.0091)^{***}$ | 0.0482 |
| Swedish | 0.0138 | −0.0150 | −0.0084 | −0.0089 | (0.0237) | −0.0096 |
| Past unemployment | 0.0989 | −0.0048 | 0.0042 | 0.0982 | $(0.0107)^{***}$ | 0.0983 |
| Past recall | 0.1526 | 0.0293 | 0.0031 | 0.1816 | $(0.0103)^{***}$ | 0.1849 |
| Tenure | −0.0099 | −0.0001 | 0.0015 | −0.0085 | $(0.0018)^{***}$ | −0.0085 |
| Age | −0.0045 | 0.0010 | 0.0012 | −0.0024 | $(0.0006)^{***}$ | −0.0024 |
| ln Wealth | 0.0060 | −0.0015 | −0.0001 | 0.0044 | $(0.0011)^{***}$ | |
| ln Capital income | 0.0003 | −0.0012 | −0.0015 | −0.0024 | (0.0020) | |
| ln Debt | 0.0031 | −0.0016 | 0.0000 | 0.0016 | (0.0010) | |
| Replacement rate | −0.5706 | −0.2150 | −0.0079 | −0.7935 | $(0.0340)^{***}$ | |
| **Panel B: Likelihood of entering labour market programmes** | | | | | | |
| Married | −0.0397 | −0.0039 | −0.0014 | −0.0444 | $(0.0084)^{***}$ | −0.0451 |
| Female | 0.0479 | 0.0252 | −0.0113 | 0.0603 | $(0.0093)^{***}$ | 0.0619 |
| Dependent child | −0.0311 | 0.0153 | 0.0114 | −0.0076 | (0.0083) | −0.0044 |
| Swedish | −0.0097 | 0.0207 | −0.0072 | 0.0037 | (0.0215) | 0.0038 |
| Past unemployment | −0.0674 | 0.0075 | 0.0048 | −0.0577 | $(0.0097)^{***}$ | −0.0551 |
| Past recall | −0.1085 | −0.0428 | 0.0032 | −0.1388 | $(0.0092)^{***}$ | −0.1481 |
| Tenure | 0.0069 | 0.0002 | 0.0013 | 0.0085 | $(0.0017)^{***}$ | 0.0084 |
| Age | 0.0032 | −0.0013 | 0.0010 | 0.0029 | $(0.0006)^{***}$ | 0.0029 |
| ln Wealth | −0.0042 | 0.0020 | −0.0001 | −0.0022 | $(0.0010)^{**}$ | |
| ln Capital income | −0.0002 | 0.0016 | −0.0014 | 0.0000 | (0.0018) | |
| ln Debt | −0.0022 | 0.0022 | 0.0000 | 0.0001 | (0.0009) | |
| Replacement rate | 0.4004 | 0.2984 | −0.0069 | 0.6920 | $(0.0302)^{***}$ | |
| **Panel C: Likelihood of labour market withdrawal** | | | | | | |
| Married | −0.0164 | 0.0012 | 0.0028 | −0.0130 | $(0.0061)^{**}$ | −0.0124 |
| Female | 0.0194 | −0.0059 | 0.0266 | 0.0408 | $(0.0068)^{***}$ | 0.0401 |
| Dependent child | −0.0153 | −0.0048 | −0.0237 | −0.0399 | $(0.0059)^{***}$ | −0.0438 |
| Swedish | −0.0041 | −0.0057 | 0.0156 | 0.0051 | (0.0155) | 0.0058 |
| Past unemployment | −0.0315 | −0.0027 | −0.0091 | −0.0405 | $(0.0073)^{***}$ | −0.0432 |
| Past recall | −0.0440 | 0.0135 | −0.0063 | −0.0428 | $(0.0070)^{***}$ | −0.0368 |
| Tenure | 0.0030 | 0.0000 | −0.0028 | 0.0000 | (0.0012) | 0.0001 |
| Age | 0.0013 | 0.0004 | −0.0022 | −0.0005 | (0.0004) | −0.0005 |
| ln Wealth | −0.0018 | −0.0006 | 0.0002 | −0.0022 | $(0.0007)^{***}$ | |
| ln Capital income | −0.0001 | −0.0005 | 0.0029 | 0.0023 | $(0.0013)^{*}$ | |
| ln Debt | −0.0009 | −0.0006 | −0.0001 | −0.0016 | $(0.0007)^{**}$ | |
| Replacement rate | 0.1701 | −0.0834 | 0.0148 | 0.1016 | $(0.0221)^{***}$ | |

Notes: The marginal effects are evaluated at the sample mean of covariates, and computed using partial derivatives for continuous variables and using differences for discrete variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. The last column shows the sum of partial effects for discrete variables. The marginal effects for the occupational dummies are not reported.

age 17 in the family increases the hazard for labour market programmes significantly but does not significantly affect the likelihood of leaving unemployment via such programmes. In two cases the indirect effects are strong enough to turn the overall marginal effect in the opposite direction from that of the direct effect. One year's increase in age increases the hazard for labour market programmes but decreases the likelihood that the worker will eventually escape from unemployment via such a programme. Although both effects are quantitatively very small, they are statistically significant at the conventional risk level. Also, the amount of taxable wealth has opposite effects on the hazard and incidence functions for labour market programmes.

From Panel C of Table V.4 we see that amounts of taxable wealth and debts, having experienced unemployment or a recall in the past, being married, and the replacement rate all significantly affect the likelihood of labour market withdrawal, but none of these variables have statistically significant effects on the hazard rate out of the labour force. By contrast, age and capital income have statistically significant effects on the hazard rate out of the labour force, while their overall effects on the likelihood of leaving the labour force do not differ from zero at the 5% risk level.

Since the spell of unemployment must eventually end in one way or another, the sum of the marginal effects on the likelihood of exiting from different causes must equal zero in Table V.4. For example, a ten percentage increase in the replacement rate is predicted to raise the flow to labour market programmes by 6.9 percentage points and the flow out of the labour force by one percentage point. These increases occur at the expense of a decline of 7.9 percentage points in the flow out of unemployment to employment. When we look at changes in the cumulative incidence functions by the end of some limited time period, say by one year, the sum of the marginal effects need not be zero, as the expected duration of the spell can change as well.

The size of the marginal effect of a covariate depends on the values of all covariates, and hence the marginal effects vary across individuals in the sample. This is illustrated in Table V.5, where the distributions of marginal effects on the overall likelihood of exiting from competing causes are shown. Marginal effects on the overall incidence of employment in Panel A exhibit a considerable amount of variation across individuals but always have the same sign for all individuals. This is not the case for marginal effects on the overall probabilities of entering labour market programmes and labour market withdrawal. Panels B and C show that for many covariates the sign of the marginal effect differs between different individuals. For example, an increase in the replacement rate is predicted to encourage some individuals to stay in the labour market but will induce some others to withdraw from the labour force.

Obviously it is possible that the marginal effect of a covariate does not differ significantly from zero when evaluated at the sample mean of covariates but takes large positive and/or negative values when evaluated at some other values of covariates. Therefore a policy variable of interest may have no effect on average but still have a strong effect within

Table V.5: Distributions of marginal effects for the overall probability of exiting from a given cause

| | Min | P5 | Q1 | Median | Q3 | P95 | Max | Mean |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Likelihood of finding a job** | | | | | | | | |
| Married | 0.0071 | 0.0249 | 0.0450 | 0.0533 | 0.0569 | 0.0586 | 0.0600 | 0.0491 |
| Female | −0.1088 | −0.1033 | −0.1004 | −0.0961 | −0.0842 | −0.0535 | −0.0188 | −0.0896 |
| Dependent child | 0.0080 | 0.0212 | 0.0365 | 0.0429 | 0.0470 | 0.0524 | 0.0648 | 0.0407 |
| Swedish | −0.0133 | −0.0101 | −0.0089 | −0.0082 | −0.0073 | −0.0053 | −0.0027 | −0.0080 |
| Past unemployment | 0.0145 | 0.0492 | 0.0799 | 0.0916 | 0.0968 | 0.0999 | 0.1059 | 0.0855 |
| Past recall | 0.0362 | 0.0960 | 0.1447 | 0.1740 | 0.1880 | 0.1940 | 0.1983 | 0.1625 |
| Tenure | −0.0094 | −0.0089 | −0.0084 | −0.0078 | −0.0066 | −0.0035 | −0.0006 | −0.0072 |
| Age | −0.0028 | −0.0025 | −0.0023 | −0.0021 | −0.0018 | −0.0008 | 0.0000 | −0.0020 |
| ln Wealth | 0.0004 | 0.0018 | 0.0034 | 0.0040 | 0.0043 | 0.0046 | 0.0052 | 0.0037 |
| ln Capital income | −0.0037 | −0.0028 | −0.0024 | −0.0022 | −0.0019 | −0.0012 | −0.0005 | −0.0021 |
| ln Debt | 0.0001 | 0.0006 | 0.0011 | 0.0014 | 0.0016 | 0.0018 | 0.0024 | 0.0013 |
| Replacement rate | −0.8624 | −0.8184 | −0.7848 | −0.7347 | −0.6247 | −0.3452 | −0.0970 | −0.6795 |
| **Panel B: Likelihood of entering labour market programmes** | | | | | | | | |
| Married | −0.0549 | −0.0499 | −0.0454 | −0.0410 | −0.0336 | −0.0176 | −0.0040 | −0.0384 |
| Female | −0.0035 | 0.0282 | 0.0450 | 0.0536 | 0.0606 | 0.0691 | 0.0796 | 0.0519 |
| Dependent child | −0.0181 | −0.0129 | −0.0097 | −0.0059 | 0.0023 | 0.0162 | 0.0542 | −0.0028 |
| Swedish | −0.0042 | 0.0007 | 0.0024 | 0.0032 | 0.0039 | 0.0049 | 0.0075 | 0.0031 |
| Past unemployment | −0.0773 | −0.0658 | −0.0571 | −0.0502 | −0.0416 | −0.0260 | −0.0059 | −0.0487 |
| Past recall | −0.1840 | −0.1662 | −0.1495 | −0.1309 | −0.1045 | −0.0662 | −0.0209 | −0.1251 |
| Tenure | 0.0006 | 0.0031 | 0.0065 | 0.0083 | 0.0092 | 0.0096 | 0.0099 | 0.0076 |
| Age | 0.0002 | 0.0009 | 0.0021 | 0.0029 | 0.0033 | 0.0035 | 0.0037 | 0.0026 |
| ln Wealth | −0.0031 | −0.0026 | −0.0021 | −0.0018 | −0.0014 | −0.0007 | 0.0010 | −0.0017 |
| ln Capital income | −0.0035 | −0.0014 | −0.0005 | 0.0000 | 0.0003 | 0.0005 | 0.0008 | −0.0002 |
| ln Debt | −0.0004 | −0.0002 | −0.0001 | 0.0001 | 0.0005 | 0.0011 | 0.0025 | 0.0002 |
| Replacement rate | 0.0594 | 0.2645 | 0.5298 | 0.6627 | 0.7256 | 0.7784 | 0.8484 | 0.6087 |
| **Panel C: Likelihood of labour market withdrawal** | | | | | | | | |
| Married | −0.0308 | −0.0184 | −0.0138 | −0.0106 | −0.0076 | −0.0035 | 0.0034 | −0.0107 |
| Female | 0.0083 | 0.0203 | 0.0297 | 0.0374 | 0.0450 | 0.0565 | 0.0835 | 0.0377 |
| Dependent child | −0.0833 | −0.0587 | −0.0476 | −0.0384 | −0.0286 | −0.0148 | −0.0060 | −0.0379 |
| Swedish | 0.0013 | 0.0026 | 0.0039 | 0.0049 | 0.0059 | 0.0077 | 0.0112 | 0.0050 |
| Past unemployment | −0.0814 | −0.0555 | −0.0441 | −0.0367 | −0.0290 | −0.0190 | −0.0068 | −0.0368 |
| Past recall | −0.1011 | −0.0611 | −0.0458 | −0.0370 | −0.0277 | −0.0166 | 0.0093 | −0.0374 |
| Tenure | −0.0050 | −0.0022 | −0.0009 | 0.0000 | 0.0004 | 0.0008 | 0.0019 | −0.0003 |
| Age | −0.0027 | −0.0015 | −0.0009 | −0.0005 | −0.0002 | −0.0001 | 0.0000 | −0.0006 |
| ln Wealth | −0.0045 | −0.0031 | −0.0025 | −0.0020 | −0.0015 | −0.0008 | −0.0002 | −0.0020 |
| ln Capital income | 0.0003 | 0.0009 | 0.0016 | 0.0023 | 0.0029 | 0.0036 | 0.0050 | 0.0023 |
| ln Debt | −0.0036 | −0.0025 | −0.0020 | −0.0016 | −0.0011 | −0.0005 | −0.0001 | −0.0015 |
| Replacement rate | −0.2217 | −0.0602 | 0.0358 | 0.0803 | 0.1162 | 0.1658 | 0.3021 | 0.0708 |

some subgroup. In the treatment analysis it may be of considerable interest to examine the variation in the treatment effect on the likelihood of exiting from a given cause across individuals and to detect subgroups who respond in different ways.

The last column of Table V.5 reports the sample means of marginal effects over individuals. Compared with the overall marginal effects in Table V.4, these are qualitatively equivalent and quantitatively rather similar. However, there are such differences that we cannot argue that it would not matter at all whether the marginal effects were computed at the sample mean of covariates or as the sample mean of individual-specific marginal effects.

# 4 Some extensions

We have considered the marginal effects associated with the proportional effects of time-invariant covariates on the cause-specific hazard functions in the absence of unmeasured heterogeneity. Computation of marginal effects can be modified in a straightforward way for the piecewise constant hazard models with time-varying covariates, a more general form of covariate effects, and unobserved heterogeneity.

## 4.1 Time-varying covariates

In the presence of exogenous time-varying covariates (Lancaster, 1990, p. 28), we can define hazard functions and various exit probabilities conditional on the time path of covariates from the beginning of the spell to the current point of time. If the time-varying covariates are constant within the duration intervals but vary across the intervals, only minor notational changes to the previous analysis are required. Let $\mathbf{x}_m$ be the vector of covariate values for interval $m$ (which may also include the past values of covariates). We replace $\mathbf{x}$ with $\mathbf{x}_m$ in the hazard function specification (V.7). As a consequence, the integrated hazard, survivor, and cumulative incidence functions at time $t \in (c_{m-1}, c_m]$ will depend on $\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_m$. Given these changes, the cumulative incidence functions and marginal effects can be computed as before from (V.9), (V.10), and (V.11). The cumulative incidence function now gives the probability of exiting from a particular cause by a given time conditional on the time path of covariates up to that point. The marginal effect of a time-varying continuous covariate describes a change in this probability resulting from a marginal change in the time path of the covariate. For a discrete covariate one may compute the difference in the cumulative incidence functions associated with two alternative time paths of the covariate, holding other covariates fixed at some prespecified values.

## 4.2 Time-varying coefficients

The assumption that all covariates have proportional effects on the underlying cause-specific hazards is rather restrictive. This can be relaxed by introducing time-varying coefficients. Denote the vector of coefficients for hazard $k$ in interval $m$ with $\boldsymbol{\beta}_k^m$, where some of the coefficients may vary across intervals. In this case $\boldsymbol{\beta}_k^m$ replaces $\boldsymbol{\beta}_k$ in the hazard specification (V.7), so that the integrated hazard, survivor, and cumulative incidence functions at time $t \in (c_{m-1}, c_m]$ will be functions of $\boldsymbol{\beta}_k^1, \boldsymbol{\beta}_k^2, ..., \boldsymbol{\beta}_k^m$, $k = 1, 2, ...., K$. After these modifications, the cumulative incidence function can be computed as before from (V.9). The marginal effect of a continuous covariate $i$ with a time-varying coefficient is obtained by substituting

$$\begin{aligned}\frac{\partial P_k(\Delta c_h \,|\mathbf{x})}{\partial x_i} &= \pi_k^h(\mathbf{x}) \left[S(c_{h-1} \,|\mathbf{x}) - S(c_h \,|\mathbf{x})\right] \sum_{j \neq k} \pi_j^h(\mathbf{x}) \left(\beta_{ki}^h - \beta_{ji}^h\right) \\ &\quad + \pi_k^h(\mathbf{x}) \sum_j \left[ S(c_h \,|\mathbf{x}) \sum_{s=1}^{h} \theta_j^s(\mathbf{x}) \Delta c_s \beta_{ji}^s - S(c_{h-1} \,|\mathbf{x}) \sum_{s=1}^{h-1} \theta_j^s(\mathbf{x}) \Delta c_s \beta_{ji}^s \right],\end{aligned}$$

into (V.10). The marginal effects of discrete covariates with time-varying coefficients are obtained by computing the difference in the cumulative incidence functions.

## 4.3 Unobserved heterogeneity

Not all relevant covariates may be observed in the available data. A common approach to deal with this issue is to introduce multiplicative individual-specific random effects into the hazard functions. Assume that the effect of all unmeasured factors on the hazard for cause $k$ is captured by a scalar variable $\varepsilon_k$, which is unobserved, time-invariant, and independent of $\mathbf{x}$. The hazard function for exit from cause $k$ at time $t \in (c_{m-1}, c_m]$ conditional on $\mathbf{x}$ and $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_K)$ is

$$\theta_k(t \,|\mathbf{x}, \boldsymbol{\varepsilon}) = \varepsilon_k \left(e^{\alpha_k^h + \mathbf{x}'\boldsymbol{\beta}_k}\right) = e^{\alpha_k^h + \widetilde{\mathbf{x}}'\widetilde{\boldsymbol{\beta}}_k}.$$

where $\widetilde{\mathbf{x}} \equiv (1, \mathbf{x})$ and $\widetilde{\boldsymbol{\beta}}_k \equiv (\ln \varepsilon_k, \boldsymbol{\beta}_k)$. With this reparametrization, it is easy to see that $F_k(t \,|\mathbf{x}, \boldsymbol{\varepsilon})$ has an expression similar to $F_k(t \,|\mathbf{x})$ in the absence of unobserved heterogeneity. In a special case of a discrete distribution for $\boldsymbol{\varepsilon}$ we can further integrate $\boldsymbol{\varepsilon}$ out as $F_k(t \,|\mathbf{x}) = \sum_q \Pr(\boldsymbol{\varepsilon} = \boldsymbol{\varepsilon}^q) \, F_k(t \,|\mathbf{x}, \boldsymbol{\varepsilon}^q)$, where the sum is over all possible realizations of $\boldsymbol{\varepsilon}$, resulting in a closed-form expression for $F_k(t \,|\mathbf{x})$ and, hence, for marginal effects. It is worth emphasising that incorporating unobserved heterogeneity in this way leads to a very general model. First, as the number of points of support increases, the discrete distribution can approximate any distribution of $\boldsymbol{\varepsilon}$, even if the true underlying distribution were continuous (Van den Berg, 2001). Second, the unobserved heterogeneity terms $\varepsilon_k$ can be correlated across $k$.

Thus one can compute the marginal effects in a rather straightforward manner for dependent competing risks models with unobserved heterogeneity of the unknown form. Although the marginal effects would be readily available in the second step, the identification and estimation of such a general model is another issue (see Heckman and Honoré, 1989, and Abbring and Van den Berg, 2003, for the identifiability of dependent risks models). The parameters of the heterogeneity distribution – the number of points of support, their location, and associated probabilities – must be estimated along with other parameters. This can be a difficult task even if we assume independence between the unobserved heterogeneity components across the cause-specific hazards (see e.g. Baker and Melino, 2000). Usually either the hazard function or the heterogeneity distribution is characterized by a parametric form to minimize numerical difficulties (e.g. Heckman and Singer, 1984, Meyer, 1990, and Han and Hausman, 1990). Under the piecewise constant hazard specification with the discrete distribution of unobserved heterogeneity, this may imply that only a few steps in the baseline hazards could be allowed for in empirical analysis.

## 5 Conclusions

This paper has aimed to highlight the potential benefits of marginal effects as a way of summarizing the results of competing risks analysis. The marginal effects, the effects of covariates on the cumulative incidence function, are directly interpretable in terms of probabilities that are likely to be of interest in many applications. We derived analytical solutions for the marginal effects in the context of the piecewise constant hazard model. In the empirical application the marginal effects were contrasted with the standard hazard function estimates obtained from the competing risks model of unemployment duration. This exercise illustrated some issues that require attention when the researcher is interested in the likelihood of exiting from a particular cause.

First, our findings confirm the old claim that the effect of the covariate on the hazard function for a particular cause can differ substantially from its effect on the corresponding cumulative incidence function. These two effects were found to work in opposite directions in many cases. Such a difference is driven by the indirect effects via the competing hazards. One can expect a potentially more important role for the indirect effects in cases where the level of the hazard function for the cause of primary interest is relatively low compared with the competing hazards. Therefore, when exits due to the cause of primary interest are relatively rare, one should pay particular attention to indirect effects via the competing hazards. Testing the effect of a covariate on the cause-specific hazard and testing its effect on the likelihood of exiting from that cause are, of course, two different issues. If the latter effect is of interest, one should not focus on the cause-specific hazard function only but look at the marginal effects on the cumulative incidence function as well. The relative importance of partial effects via different hazards can be seen by decomposing the marginal effect into direct and indirect effects.

Second, a considerable amount of variation existed in marginal effects across individuals and, in many cases, the marginal effects worked in opposite directions for different subgroups. This degree of heterogeneity took place under the standard proportional hazard specification, where all covariates were assumed to have homogeneous proportional effects on the underlying cause-specific hazards. By exploring the distribution of marginal effects one can study heterogeneity in responses across individuals. This may be of considerable interest in the evaluation of treatment effects on the likelihood of exiting via a particular route in the presence of competing risks.

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Figure V.3: Marginal effects with 95% confidence bands for the cumulative incidence function for employment

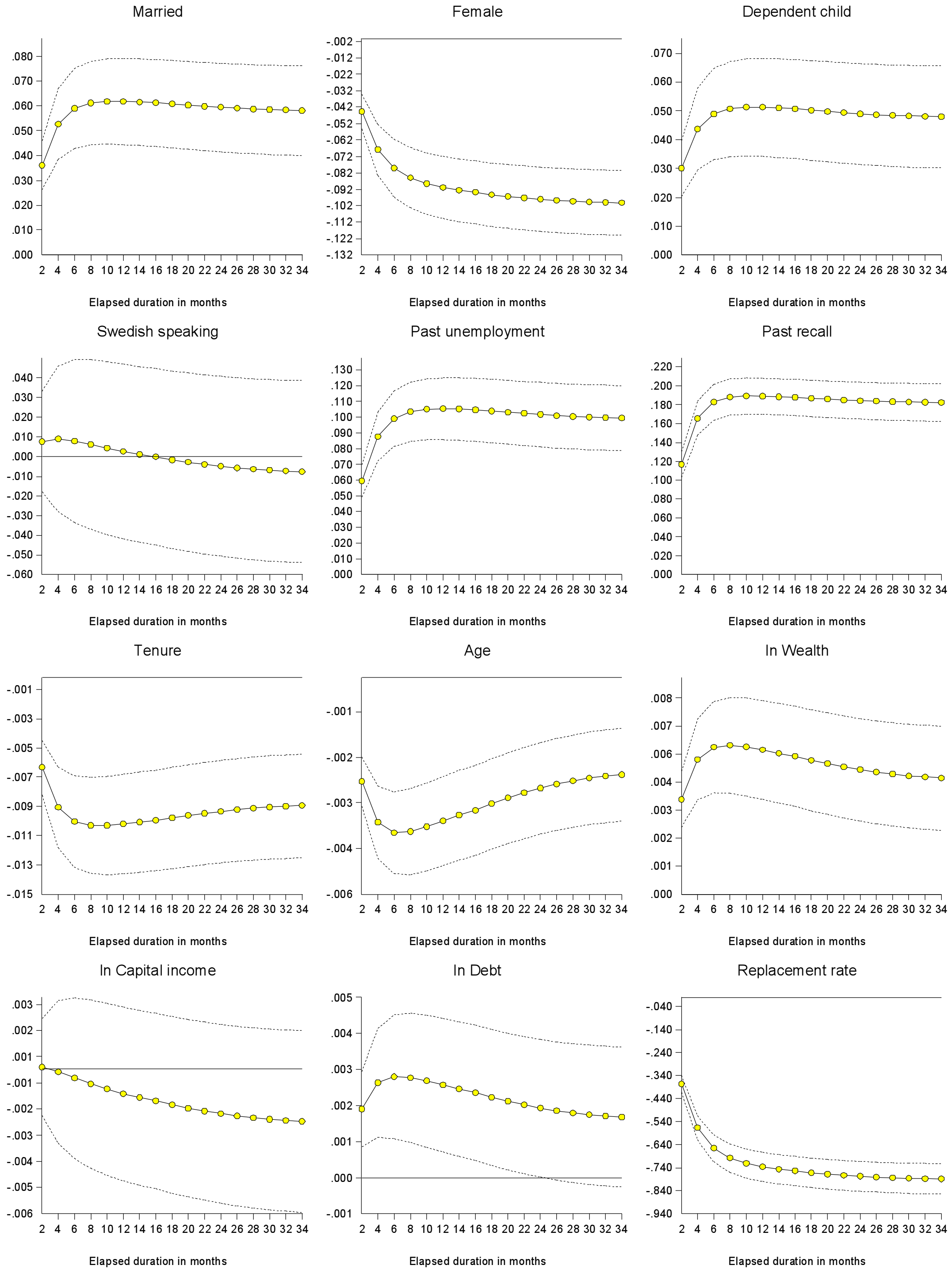


Figure V.4: Marginal effects with 95% confidence bands for the cumulative incidence function for labour market programmes

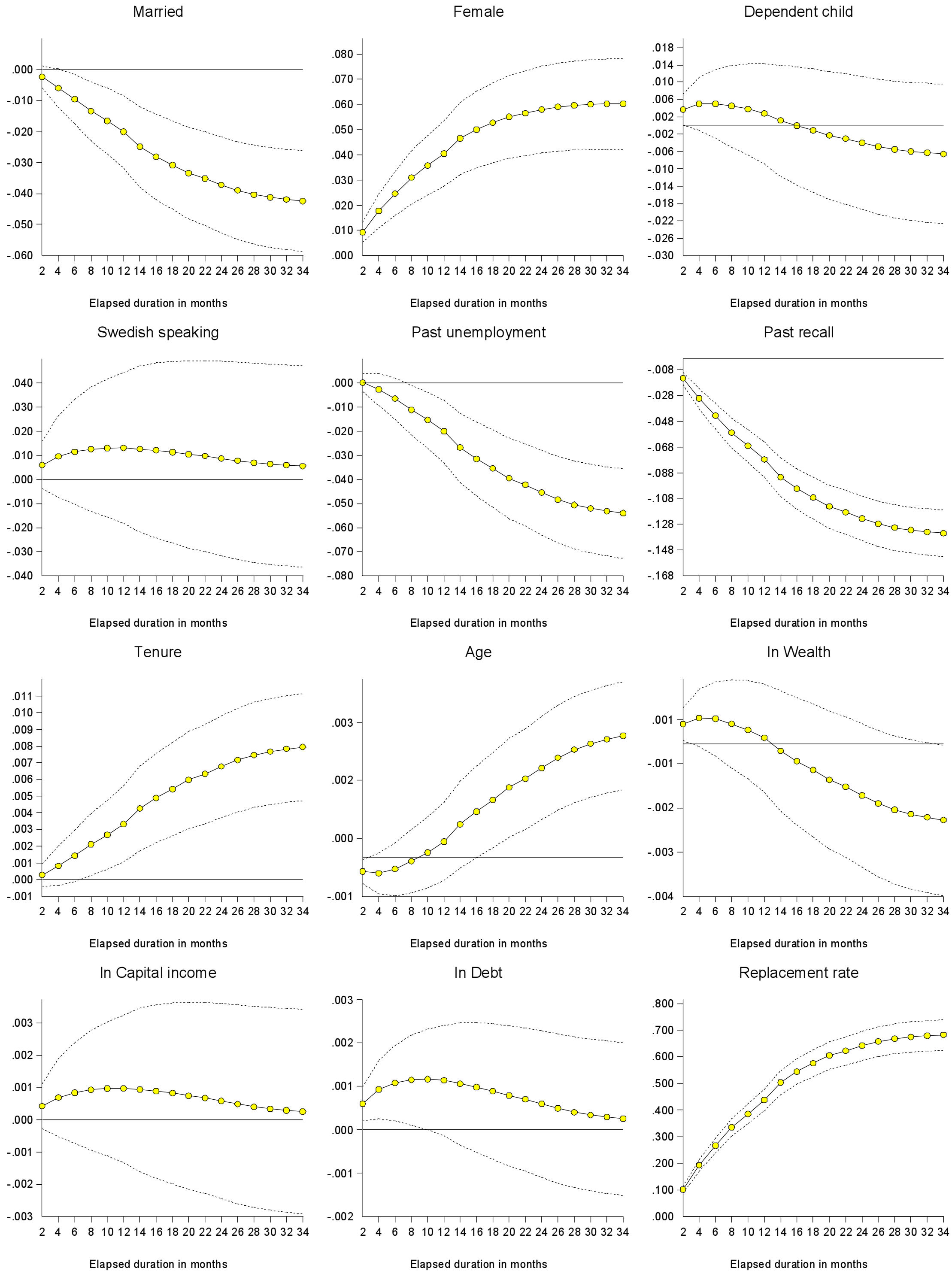
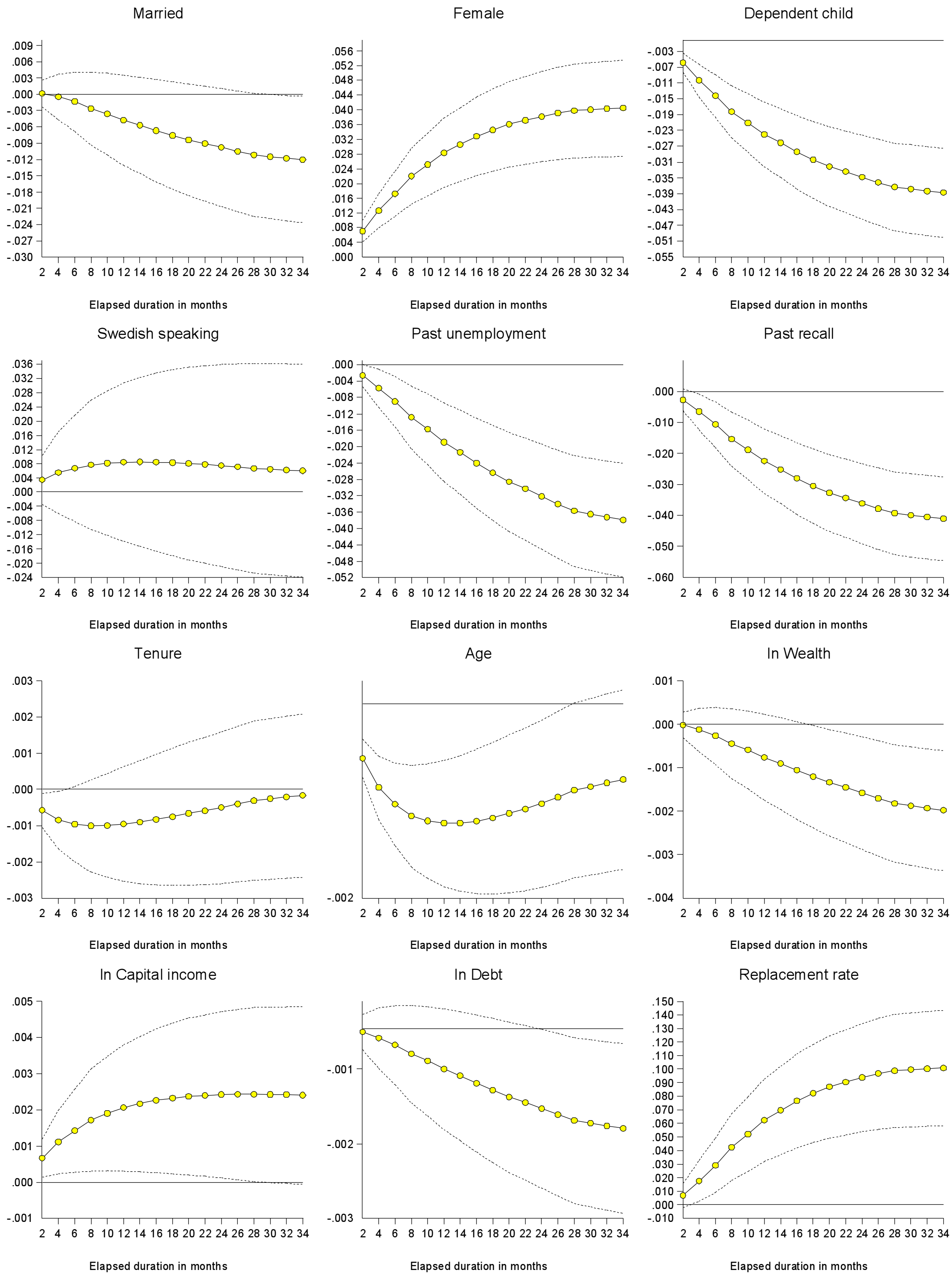


Figure V.5: Marginal effects with 95% confidence bands for the cumulative incidence function for labour market withdrawal



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