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PALKANSAAJIEN TUTKIMUSLAITOS LABOUR INSTITUTE FOR ECONOMIC RESEARCH

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Tiivistelmä

1990-luvun alun lama synnytti Suomeen vakavan työttömyysongelman. Työttömien lukumäärä lisääntyi räjähdysmäisesti ja pitkäaikaistyöttömien osuus lähes kymmenkertaistui. Tässä työssä analysoidaan työttömyyden kestoon vaikuttavia taustatekijöitä käyttäen yksilöainestoa vuosilta 1987–2000. Aineisto koostuu laajasta satunnaisotoksesta työttömäksi jääneitä suomalaisia.

Keskeisenä kiinnostuksen kohteena ovat makrotaloudellisen tilanteen ja työttömien ihmisten ominaisuuksien muutoksien vaikutuksissa työttömyyden kestoon. Yleensä oletetaan, että laman aikana irtisanotuilla on huonommat ominaisuudet työllistymisen kannalta verrrattuna muihin aikoihin. Lisäksi työssä tutkitaan, miten suhdannevaihtelu vaikuttaa eri tyyppisiin ihmisiin ja muuttuvatko työttömyyden kestoon vaikuttavat tekijät aikavälillä. Myös kysymystä duraatioriippuvuudesta tarkastellaan. Duraatioriippuvuudella tarkoitetaan sitä, miten kulunut työttömyysjakson pituus vaikuttaa työllistymismahdollisuuteen. Useimmissa maissa vaikutus on negatiivinen. Duraatioriippuvuuden suuruus on olennaista työvoimapolitiikan suunnittelussa.

Työn analyysi tehdään verrannollisen hasardin mallilla, jossa perushasardi on määritelty ei-parametrisesti. Aluellista työttömyysastetta käytetään kuvaamaan makrotalouden tilaa. Erilliset mallit estimoidaan lyhyemmille aikaväleille, jotta voidaan tutkia muutoksia parametriarvoissa sekä ottaa huomioon ei-verrannolliset vaikutukset ajanjaksojen väleillä. Työttömien koostumuksen ja suhdannevaihtelun suhteellinen merkitys indentifioidaan Rosholmin (2001) lähestymistavan avulla.

Analyysin perusteella voidaan päätellä, että ajanjaksojen välillä on selvästi epäsymmetrisiä vaikutuksia. Perushasardin muoto muuttuu ja joidenkin yksilöitä kuvaavien parametrien arvoissa on trendejä. Tämä selittyy todennäköisesti laman seurauksena tapahtuneella talouden rakenteellisella muutoksella. Duraatioriippuvuus vaikuttaa olevan selvästi negatiivista, ja ihmisten erilaisuudella näyttää olevan vain vähäinen vaikutus perushasardiin. Analyysin perusteella työttömien valikointimalli (ranking model) ei saa tukea, koska työttömyysasteella ei ole vaikutusta perushasardin muotoon. Työttömien koostumuksen vaikutus osoittautuu merkitykselliseksi. Tuloksien perusteella näyttää yllättäen siltä, että koostumus muuttui työllistymisen kannalta paremmaksi laman aikana. Tämä voi selittyä jälleen laman vakavuudella, jos irtisanomiset kohdistuivat silloin satunnaisemmin ihmisiin muihin aikoihin verrattuna.

Avainsanat: työttömyys, kesto, suhdannevaihtelut

Abstract

The recession of the early 1990s caused a serious unemployment problem in Finland. The number of unemployed increased dramatically and the share of long-term unemployed became nearly tenfold. This study analyses the background of variation in unemployment duration using individual data from 1987 to 2000. The dataset consists of a large random sample of Finnish workers entering unemployment.

The main focus is on the relative contribution of macroeconomic conditions and compositional variation to unemployment duration. Generally, it is assumed that individuals who are laid off during a recession have weaker characteristics considering re-employment possibilities compared with other times. In addition, it is studied how the different type of people are influenced by the business cycle, and have the factors affecting unemployment duration changed during the period. Also the question of duration dependence is examined. Duration depedence means how the elapsed length of unemployment changes the possibility of employment. In most countries, the effect is negative. The magnitude of duration dependence is important for the design of the labor market policy.

The analysis is done using a proportional hazard model with a non-parametric specification for the baseline hazard. The regional unemployment rate is used to capture the macroeconomic conditions. Separate models are estimated for shorter time periods in order to study the changes in the parameter values as well as to take into account the non-proportional effects between the time periods. The relative effects of compositional and business cycle components are identified following Rosholm's (2001) approach.

Based on the analysis it is concluded that there are asymmetric effects between the periods. The shape of the baseline hazard changes and some individual parameters have trends in the effects. This is probably explained by the structural changes in the economy that took place due to the recession. There seems to be strong negative duration dependence and only a relatively small effect of heterogeneity on the baseline hazard. Evidence against the ranking model is found because the duration dependence is not affected by the level of unemployment. The effect of compositional variation is found to be important. The results suggest, surprisingly, that the characteristics of unemployed became better during the recession. Again, the severity of the recession might explain this if it caused workers to be laid off more randomly compared with other times.

Keywords: unemployment, duration, business cycle

Contents

1 Introduction

The economic development has been extraordinary in Finland during the past twenty years. The recession in the beginning of the 1990s was very deep and it had a huge impact on labor markets. The unemployment rate became fivefold and the proportion of long-term unemployment became almost tenfold in a couple of years. After the recovery started, the economy has done very well – the growth rate has been among the fastest in the EU. However, the large changes created a structural unemployment problem. The unemployment rate has declined only moderately and long-term unemployment has remained high.

Long-term unemployment is not only a Finnish problem. On the contrary, the proportion of long-term unemployment is not very high on European standards. This is partly due to the active labor market policy practiced in Finland. Anyhow, long-term unemployment is a very undesirable phenomenon. On individual level it causes poverty and affects both mental and physical well-being (see e.g. Machin & Manning 1999). On macroeconomic level it creates inefficiency to economy and a decrease in human capital.

The reasons affecting long-term unemployment are studied by analyzing the factors of unemployment duration. In an economic downturn both inflow to unemployment and the average duration usually increase. The changes in duration explain some of the rise in unemployment rate. Durations can increase due to several reasons. There is an extensive literature on the role of changes in the quality of individuals entering unemployment and macroeconomic conditions. However, this question has not been analyzed in depth on Finnish data. This is the first study on Finnish data where both the asymmetric and seasonal effects are addressed.

Another important aspect in the analysis of unemployment duration is duration dependence. It means the effect of elapsed unemployment time on possibilities to find a job. It is often thought that a long-term unemployed has a stigma of being a poor worker or, alternatively, that the individuals become passive. However, for some countries it has been suggested that there, in fact, is no negative duration dependence. For Finland, previous studies indicate that negative dependence exits (see e.g. Ollikainen 2003). Another interesting question is whether duration dependence varies in time and whether there are asymmetric effects, i.e. is the effect different in booms and recessions. There are only few studies that analyze this question using microlevel data and none of them is Finnish.

The objective of this study is to examine the variation in unemployment duration using Finnish microlevel data. The dataset is a random sample of 350 000 individuals from Statistics Finland's employment database. The data covers the period from 1987 to 2001 and it includes nearly all the unemployment spells together with an extensive set of individual variables. The main questions are: are there asymmetric effects between years, are there changes in duration dependence, how the different type of individuals are effected by the business cycle, and what is the contribution of compositional effect and the business cycle variation to unemployment duration. The dataset offers an excellent possibility to analyze these questions.

The analysis is done using an econometric duration model. Piecewise constant hazard models are estimated that allows a non-parametric specification of hazard rate. The question of the relative importance of macroeconomic conditions and compositional changes in the unemployment inflow is addressed using Rosholm's (2001) innovative approach. The regional unemployment rate is used as an indicator for the business cycle. It does not tell directly how many jobs are available for a person seeking a job but it describes the fraction of people competing among the vacancies.

In Finland the government has had an active role in reducing unemployment by means of active labor market policy (ALMP). Hence, there has been much interest in how effective the different policy actions are, and this subject has been studied extensively. In this work the focus is mainly on the determinants of employment probabilities. However, using this approach makes it possible to answer questions that are vitally important for the design of ALMP. For example, if duration dependence is strongly negative, the focus should be on preventing people from falling into long-term unemployment. On the other hand, it is possible that a certain type of people seem to have especially poor employment possibilities. Then the policy measures should concentrate in training those individuals.

There are some challenges in identifying the true duration dependence. The raw data in most countries, including Finland, exhibit negative duration dependence (Machin & Manning 1999). However, it is possible that duration dependence is caused by the heterogeneity of individuals. Some of the heterogeneity, like age and education, is easy to take into account but many of the characteristics affecting re-employment are hard to measure or not observable. These are called unobserved heterogeneity. For example, activity in job search and communication skills are rarely available variables in data. The heterogeneity bias is most conveniently presented using a hazard function, a central concept in duration analysis.

Let the $\lambda(t)$ denote the exit rate or hazard. It is the probability of employment at the given time t conditional on that unemployment has not ended before t. Duration dependence means that the exit rate from unemployment is a function of time. If $d\lambda(t)/dt > 0$, there is positive duration dependence, i.e. the exit rate increases the longer unemployment lasts. The more typical case is negative duration dependence, $d\lambda(t)/dt < 0$. Now, the negative bias in duration dependence caused by heterogeneity can be illustrated using a simple example. Let $\lambda_h > \lambda_l$ be the exit rates of high and low type people. As time passes, the high type people tend to find jobs more easily than the low type people. Therefore, at time t the average exit rate $\lambda(t)$ is lower than in the beginning. Thus, it seems that there is negative duration dependence unless heterogeneity is observed.

Duration models are regression models for hazard with explanatory variables. In unemployment duration analysis, the proportional hazard assumption is often utilized. It means that the effect of explanatory variables, or covariates as they are often called, is constant in time. With a rich dataset, it is possible to take into account the effect of unobserved heterogeneity using a random effect model. Recently, there has been an extensive research on non-parametric mixed proportional hazard models in order to answer the question whether duration dependence is true or spurious. The dataset in this study makes it possible to estimate such a model. However, in practice it seems hard to construct a robust mixed model with non-parametric baseline and parametric mixture distribution.

The structure of the paper is the following. First, there is a brief review of the recent economic development in Finland and unemployment problem in other countries. In the second section the methods of empirical analysis of microlevel data are discussed, a theoretical model, the basic search model, is presented and previous studies are reviewed. The dataset and the Finnish institutional framework are described in the third section.

The fourth section contains quite a long discussion on duration models. The purpose is to present the basic concepts to a reader who knows the basics of econometrics but is not familiar with duration analysis. The relation of the piecewise constant hazard model to accelerated life time models is elaborated since it justifies the estimation procedure used in the study. Also the concept of mixed proportional hazard model is presented.

The results of the analysis are presented in the fifth section. The estimation is done in multiple steps. Firstly, the proportionality assumption and the time invariance of parameters are studied. Then separated models are estimated on the basis of these results. Duration dependence and the decomposition of business cycle and compositional effects are analyzed with a slightly different parametrization of the model. Lastly, the results of experiments with mixed models are reported. The sixth section concludes.

1.1 Economic development in Finland

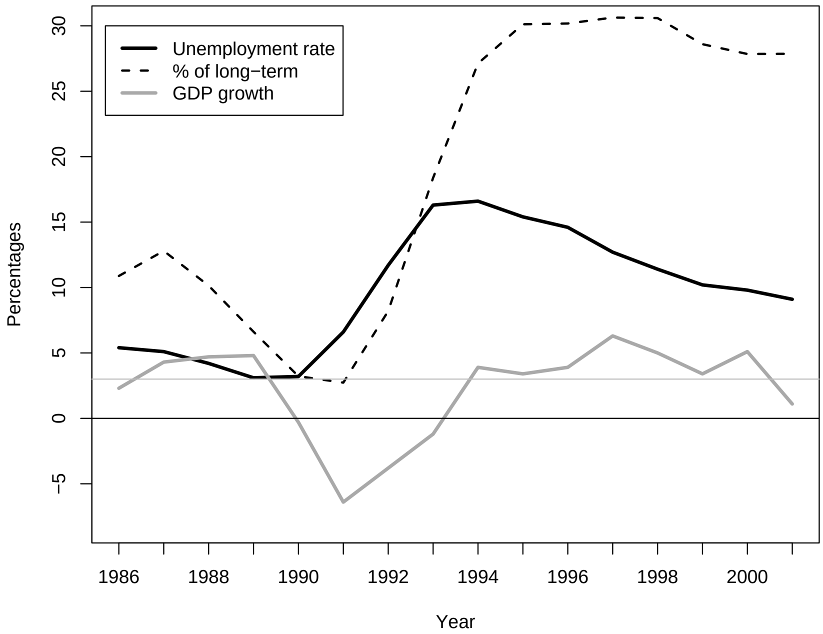

Figure 1: Unemployment rate, proportion of long-term unemployed and GDP growth in Finland (Finnish Labor Review 1/2002 and Statistics Finland).

The Finnish economy has been very volatile during the recent years. This variation is illustrated in Figure 1. The late 1980s was characterized by high economic growth and low unemployment. Especially the proportion of long-term[1] unemployment decreased which was mostly due to the government's decision to use ALMP to prevent people from falling to this category (see section 3.2). The boom turned to an economic crisis in 1990 and the unemployment rate started to rise dramatically. During the following years the proportion of long-term unemployed increased which reflects the fact that re-employment possibilities were weak during the recession. In 1993 the economy started to recover and the unemployment rate increased only slightly. During the next years, the GDP started to grow and the unemployment rate declined. However, the long-term unemployment share still increased. This can be seen as a result of a structural change in the economy: economic recovery took place only on some sectors of the economy and there was a growing number of people who had poor possibilities of employment. In the late 1990s the economy was again booming. The unemployment rate decreased steadily but the long-term unemployment share remained high. For more detailed discussion on Finnish economic development and unemployment, see Koskela & Uusitalo (2004).

1.2 Long-term unemployment in European countries

To see the Finnish unemployment problem in a larger picture, the unemployment rates and the share of long-term unemployment are plotted for several OECD countries in Figure 2. The figures are for the year 1995 which is a time of very high unemployment in Finland. It is seen that on European standards the share of long-term unemployment is not very high. On the other hand, in the US and Japan, the unemployment rate and

[1] An individual is defined as a long-term unemployed if the unemployment has lasted longer than 12 months.

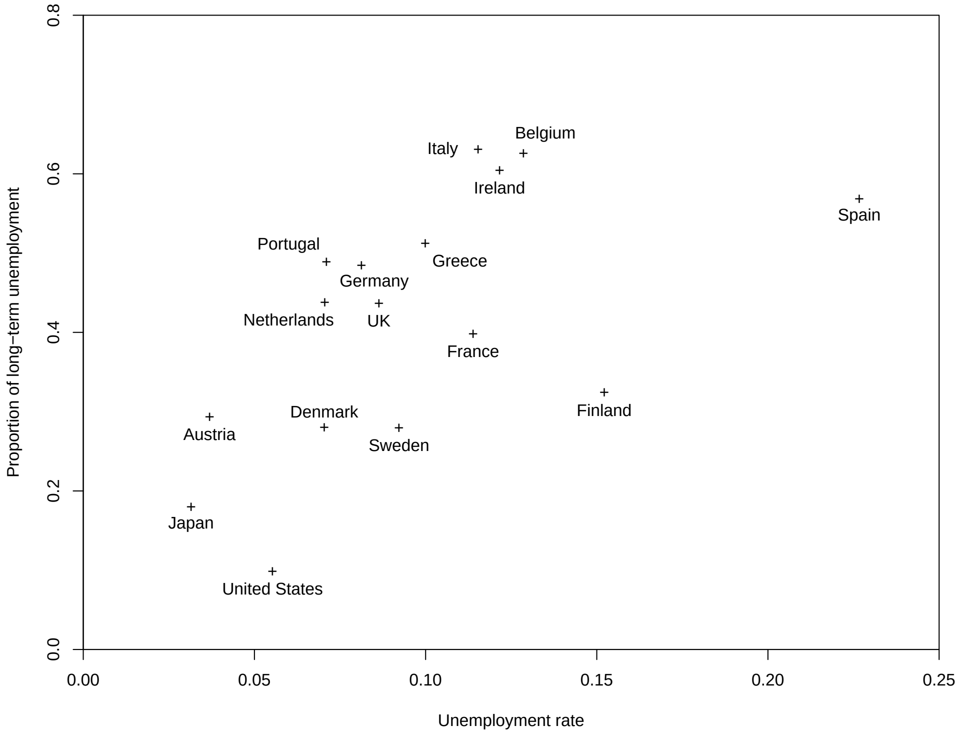

Figure 2: Long-term unemployment and unemployment rate in various OECD countries in 1995 (OECD database).

the share of long-term unemployment are on a much lower level. Austria and the Nordic welfare states with active labor market policies have a somewhat lower long-term unemployment share. The main difference is in the unemployment rate. The other European countries have a higher, some even twofold, share of long-term unemployment. Therefore, the questions analyzed in this study are relevant for the other European countries as well. For more discussion on the empirical aspect of the European long-term unemployment problem, see e.g. Machin & Manning (1999).

2 Empirical analysis of unemployment duration

The first empirical studies on unemployment duration were made using macro data. This is not surprising since unemployment has traditionally been analyzed from a macroeconomic point of view. The Walrasian theory provides only a little insight into reasons for unemployment. However, the microeconomic approach became more attractive as search theory was developed in the 1970s to describe the behavior of unemployed individuals.

The classical search model by McCall (1970) is a dynamic partial equilibrium model where wages and available vacancies are defined exogenously. As the approach became popular, the search theory was further developed. For example, the model was extended to study the effects of unemployment insurance (Mortensen 1977). At the same time, the development of computers and statistical methods made it easier to study individual unemployment duration data. There was an interest to study how well the search theory performs empirically, and variations in unemployment duration had importance for the welfare policy alone. A seminal study by Lancaster (1979) applied a proportional hazard model to economic duration data. Lancaster recognized that in economic data unobserved heterogeneity is likely to be a problem. He extended the model to a mixed proportional hazard model which is nowadays commonly used in the analysis of duration data (see van den Berg 2001).

The basic search model is briefly presented in Section 2.2. It provides some important concepts and predictions of unemployed individual's behavior. It is possible to do empirical analysis strictly based on a theoretical model. However, here the usefulness of this structural approach is limited considering the objectives of this study. Interpretation of results in a view of theoretical parameters would not be straightforward since the observed data is heavily affected by ALMP etc. and some important variables are not observed. It is not known whether an unemployed individual is really searching for a job and how many job offers are actually received. However, it is first discussed how in the analysis of individual unemployment duration data the macroeconomic conditions of economy can be taken into account. Lastly, a review of previous studies is presented.

2.1 Business cycle and unemployment

Business cycles are often regarded as being caused by exogenous shocks to the economy. For example, Layard, Nickell & Jackman (1991, p. 367) define three types of shocks: demand, technology and wage pressure shocks. The shocks move the economy away from the long-run equilibrium state and cause business cycles. The Phillips curve, a relation between inflation and unemployment, defines the equilibrium level of unemployment which is called the NAIRU (non-accelerating inflation rate of unemployment). Thus, the NAIRU defines the long-run equilibrium level for unemployment. However, the high persistence in European unemployment in the 1980s suggested that equilibrium unemployment may be path dependent. When there are rigidities in the wage setting, the shocks to economy may cause a durable effect on unemployment. This property is called the hysteresis effect. One explanation behind this theory is that long-term unemployed create only a little pressure on wages and therefore wages do not adjust which explains the persistence in unemployment (Blanchard & Summers 1987).

The high level of unemployment may be caused either by increased inflow to unemployment or longer average duration of unemployment. For example, the analysis of U.S. macro data indicates that both factors have an important impact on unemployment (Sider 1985). However, it is possible that differences in the average duration can be explained by heterogeneity among individuals entering unemployment (see e.g. Layard et al., p. 220–230). Thus, a micro level approach is required to answer this question.

From an empirical point of view, the question of persistence in unemployment is challenging. Firstly, the study of business cycles requires a relatively long time series. Unfortunately, microeconomic data are typically characterized by a short time dimension which has reduced the number of microeconomic studies on this subject (Dynarski & Sheffrin 1990). Moreover, there are requirements for the quality of data because of econometric problems, as it is discussed in Section 4.6.

There are several studies that analyze business cycles and unemployment duration empirically. However, only a few of them use as large individual datasets as this study. The setup and objectives of this study correspond closely to the work of Rosholm (2001). He analyzes Danish unemployed using a similar dataset as this study and uses an innovative approach in identifying a compositional and business cycle effect components of unemployment durations. Rosholm's idea is that it is possible to study the relative importance of individual covariates compared to macroeconomic variables using the predicted values of duration model.

In a regression model a seasonally adjusted national unemployment rate is used as a proxy for macroeconomic conditions together with annual dummies. Individual heterogeneity is modeled with an extensive set of covariates and a gamma mixture term. The baseline hazard is piecewise constant. Unemployment interactions are included with the baseline hazard and several covariates. The model is estimated separately for age groups and genders. The basic idea of the decomposition analysis is the following.

Firstly, predicted values from the model are calculated conditional on individual characteristics. Thus, the unemployment rate and annual dummies are kept on the baseline level. This gives expected durations for all observations that describe only the effect of individual characteristics. Then it is possible to calculate average durations for groups of individuals flowing to unemployment in calendar-time. Now, for example, a monthly or quarterly series of the average duration of unemployment starting at given time is obtained. It isolates the contribution of compositional variation to unemployment duration. Then it is possible to compare how closely the obtained values follow the shape of the observed duration curve.

Secondly, predicted values are calculated conditional on the national unemployment rate for an average person, i.e. a person with mean characteristics of the sample. This gives expected durations for the unemployment rate values in calendar-time. The obtained time series approximates the effect of macroeconomic conditions on unemployment duration. Finally, predicted values are calculated conditional on the contribution of annual dummies for the average person. This gives the residual calendar-time variation of unemployment duration.

2.2 Search theory

The basic idea of search models is that an unemployed worker is maximizing the present value of lifetime utility in the presence of imperfect information. The worker does not know the available jobs and wages, and therefore time is spent on searching a job which gives rise to market frictions. The framework is a partial equilibrium model where the wage and the vacancies are drawn from exogenous and stationary distributions.

The next presentation follows Mortensen (1986). The worker is assumed to be risk neutral and live forever. The instant utility equals income w, when employed, and outside option b when searching. Each period the worker receives a random number of wage offers drawn from a distribution $F(\cdot)$. Essentially, the worker faces an optimal stopping problem: searching is continued until the received wage offer is higher than the value of searching. This condition defines the reservation wage w^* which equals the value of searching. The following results are derived in Appendix A.

When it is assumed that job arrival rate λ follows a Poisson process and discount rate r is constant, an analytical solution for the reservation wage becomes

$$w^* - b = \frac{\lambda}{r} \left\{ \int_{w^*}^{\infty} [x - w^*] \, dF(x) \right\}. \tag{1}$$

The left side of the reservation wage equation 1 is the cost of rejecting an offer equal to the reservation wage. The right side gives the marginal return of continued search when w^* is offered.

The probability of drawing a higher offer than w^* equals $\Pr(w \geq w^*) = 1 - F(w^*)$. Now given the probability of receiving an offer, the instantaneous escape rate from unemployment is $\phi = \lambda[1 - F(w^*)]$. This gives rise to an exponential distribution of unemployment duration with expected length $E(T) = 1/\phi$. The main results of the model are given by the comparative statistics. Next, some key results are given for the rate parameter ϕ. The effects for the average duration have an inverse sign.

The model has no explicit parameter for the business cycle. However, the job offer rate is quite a natural indicator of economic activity. The effect of the change in the job offer rate is ambiguous:

$$\frac{\partial \phi}{\partial \lambda} \lesseqgtr 0 \;\Leftrightarrow\; [1 - F(w^*)] \lesseqgtr \lambda f(w^*) \frac{\partial w^*}{\partial \lambda}.$$

The intuition is that the escape rate from unemployment would increase with the job offer rate. Actually, a sufficient condition is a "log-concave" wage offer probability density function (Mortensen 1986). Then the probability of receiving a higher offer than the reservation wage dominates the indirect effect which comes from the rise in the reservation wage. The outside option b describes the value of both leisure time and unemployment benefit. A rise in the outside option decreases the escape rate. Also, it can be shown with a finite horizon model that if the worker has a liquidity constraint, for example a limited duration of unemployment benefit, it leads to a declining reservation wage (Mortensen 1986).

2.3 Extensions of search model

Search theory has been developed further since McCall's (1970) paper. For example, the survey of Mortensen (1986) presents an extension of the basic model to study job turnover where it is possible to search on the job and the search intensity is endogenous. The fact that search environment is often non-stationary in reality is studied by van den Berg (1990). However, perhaps the most important extension is to construct an equilibrium search model.

The basic search model has been criticized because it postulates an exogenous wage offer distribution. From a game theoretic point of view, an employer has no incentive to offer a higher wage than the reservation wage. Thus, at equilibrium the wage distribution would be concentrated at the reservation wage. To confront this problem, more advanced models were developed.

Equilibrium search models require that one specifies more exactly how the wage distribution is determined and how the worker and the employer actually meet on the market. The standard equilibrium model is the Mortensen–Pissarides (1994) matching model. The idea is that workers and employers meet on the basis of matching process which is often assumed to be a Cobb-Douglas production function of unemployed and vacancies. A presentation of the matching functions is given in the survey by Petrongolo & Pissarides (2001). A general survey to theoretic search models is presented by Rogerson, Shimer & Wright (2005). Atkinson & Micklewright (1991) present a review of the empirical aspects of labor market analysis. They discuss the empirical evidence and practices of analyzing the effect of unemployment benefits.

In this study the focus is on the behavior of the job seekers and on the effect of business cycles. Thus, taking into account the aspect of firms will not be useful if it does not provide deeper insight into duration dependence or into the effect of macroeconomic conditions. Furthermore, Shimer (2005) argues that the Mortensen–Pissarides matching model cannot explain the business cycle variation of unemployment. However, another matching model presented by Blanchard & Diamond (1994) gives interesting implications. They assume that an employer is not hiring personnel randomly but prefers workers who have been unemployed least amount of time. This ranking behavior leads obviously to negative duration dependence. In addition, it follows that duration dependence is stronger the higher is the unemployment rate.

2.4 Empirical studies

There is a rich empirical literature on unemployment duration. Earlier the business cycle aspect of unemployment duration has been studied using macro data because large panel datasets have become available only recently. However, still many studies utilize macro data. Macro data does not suffer from the problems of survey data and it covers a long time span which is needed for the reliable estimation of business cycle effects (Abbring, van den Berg & van Ours 2002). After studies on macro data, micro data studies are reviewed. As it was mentioned earlier, there are no previous Finnish studies focusing on this subject. However, some of them provide an important insight and therefore the relevant Finnish studies are presented lastly.

Anther way to classify the literature is to consider the relation of estimated model to theoretical search models. The term structural estimation is used very broadly but generally it refers to a situation were the likelihood function of a model is derived using a theoretical model. Here the approach is strictly reduced form because the interest is not in the parameters of theoretical model. This is usually the case with studies focusing on the business cycle. An introduction to structural approach can be found, for example, in Wolpin (1995) or Devine & Kiefer (1991).

Studies on macro data

The majority of the empirical literature on unemployment duration and cyclical variability is based on the U.S. macro data. A selected sample of macro level studies is reviewed here. Sider (1985) analyzes a U.S. time-series from 1968 to 1982. He concludes that the aggregate unemployment duration is strongly countercyclical, i.e. decreasing when the aggregate unemployment is going down. To study the possible bias due to heterogeneity Baker (1992) uses U.S. data from the period 1980–1988. He has aggregate data for various demographic groups and finds that the composition effect is relatively small. This is against the expected result that duration would become longer because the proportion of job-losers, whose employment possibilities are weaker, increases during a recession in the U.S.

There are several studies that apply a method of estimating mixed proportional hazard (MPH) model on discrete aggregate outflow data. Thus, the data must contain information on how many individuals have been unemployed in a given category of durations. The main advantage of this approach is that van den Berg & van Ours (1994) find it possible to take into account the effect of unobserved heterogeneity non-parametrically. In a more recent study by Abbring et al. (2002) the method is further developed and extended to analyze business cycle effects. Naturally the interpretation of a heterogeneity term is different in a macroeconomic context than with individual data. However, a comparison of the results from an aggregate and individual analysis for the same population shows that macro and micro data are not in a serious conflict with each other (van den

Berg & van den Klaauw 2001).

Abbring et al. (2002) estimate separate MPH models for males and females on French data over the period 1982-1994. They conclude that unobserved heterogeneity explains negative duration dependence for the first 1.5 years of unemployment but beyond that duration dependence is true. In a recession the effect of negative duration dependence is found to be smaller than in a boom which is not in line with the ranking model. Results for females indicate a notable difference to men: durations are not countercyclical.

In a study by Cockx & Dejemeppe (2005), a similar MPH model is estimated on aggregate data for the early 1990s. The data consists of males from Wallonia, Belgium. They also find that negative duration dependence is largely due to heterogeneity. On contrary to the other studies, their result supports the ranking hypothesis.

Studies on micro data

The number of studies that analyze individual unemployment duration data using the proportional hazard model is vast (see e.g. survey by Machin & Manning 1999). However, there are only a few studies that study the effect of business cycles and some of them have data on relatively a short period.

An early study by Dynarski & Sheffrin (1990) applies Cox's proportional hazard model to U.S. data for period 1980–1982. They control for some demographic variables but do not allow for unobserved heterogeneity. Because the baseline hazard is not estimated, the picture of duration dependence is limited. However, they find that a rise in unemployment rate decreases hazard especially with long durations.

Imbens & Lynch (1993) analyze a larger U.S. dataset of young school leavers. The data is from 1978 to 1989 and the sample size is close to 5000 individuals. A strong negative duration dependence is found using Cox's model with no unobserved heterogeneity. A high unemployment rate has a positive effect on duration but, surprisingly, a smaller negative effect on long durations.

The Danish study by Rosholm (2001) uses a large register based sample, 1% sample of population, with many background variables from 1981 to 1990. He estimates a piecewise constant hazard model which is nowadays the standard model. The dataset contains multiple spells, and unobserved heterogeneity is taken into account using a gamma distribution. Rosholm observes positive duration dependence on long durations and that they are less negatively affected by the unemployment rate than short durations. Thus, there seems to be no evidence of ranking. He also finds that compositional effects have noticeable impact on duration.

Unemployment has been a serious problem in Spain. Bover, Arellano & Bentolila (2002) focus on both the effect of benefit duration and the effect of business cycle in their analysis. They estimate a MPH model for men on discrete monthly data from 1987 to 1994. Duration dependence is positive for the first 3 months and turns then negative. Obviously, the monthly data excludes short spells, which affects the results. Bover et al. use both GDP and sectoral unemployment as an indicator of business cycle. The business cycle has only a countercyclical effect but it does not affect especially on long durations.

Kalwij (2004) takes a slightly different aspect than the preceding studies when he analyzes the unemployment spells of a large sample of young men in the United Kingdom from 1983 to 1998. He focuses on the problem of repeated unemployment and studies the characteristics of the men who have stable employment. Based on simulations, he emphasizes the long-term benefits of ALMP that increase the employability of men because of a reduce in the probability of employment instability. Contrary to the previous results for the UK, Kalwij finds that not only duration but also inflow to unemployment is clearly affected by the business cycle. Duration dependence remains negative after controlling unobserved heterogeneity non-parametrically.

To summarize the results on empirical analysis, it seems evident that business cycles have countercyclical effect on unemployment duration. Thus, a more detailed analysis confirms the pattern observed at macrolevel and shows that compositional effects may have some role but do not dominate. Other results are found only for some special groups, like French females. On the other hand, the evidence on duration dependence is mixed. The results vary substantially between countries. It is not clear whether this is due to differences in labor markets or to the type of the dataset. Furthermore, the estimation results may be sensitive to the specification of unobserved heterogeneity.

Related Finnish studies

Statistics Finland provides an excellent dataset for analyzing unemployment durations in Finland. Since the early 1990s there has been a number of studies that use Finnish data but only some of them have analyzed longer periods and considered the effect of business cycles.

Data of unemployment spells ending in 1988, 1990 or 1992 is analyzed by Holm, Kyyrä & Rantala (1999). They focus on the question how the income affects the incentives of finding a job but they also consider the effect of the regional ratio of unemployed and vacancies. During this exceptional period, the economy turned from a boom to a deep recession. They estimate separate piecewise constant hazard models for different years and get a negative effect of the business cycle indicator on duration for 1988 but a positive effect later. The baseline hazards vary substantially. For 1988 data there is no as clear negative duration dependence as there is for 1990 data. For the last dataset the level of hazard rate drops radically and there seems to be no duration dependence. The results may be affected by the non-standard sampling procedure and unobserved heterogeneity.

Koskela & Uusitalo (2004) analyze the development of unemployment during the last decades and research the role of labor market institutions. As a part of study, they estimate a Weibull hazard model for the period 1987–2001. The data is based on the same dataset which is used in this study. The controlled background variables are age, education, gender and disability. The local unemployment rate and annual dummies are used as a business cycle indicator. The annual dummies show clear countercyclical pattern and the unemployment rate has a mild positive effect on duration. The Weibull coefficient indicates a strong negative duration dependence which declines notably when gamma heterogeneity is allowed. It must be kept in mind that the Weibull model makes a strong assumption of monotone duration dependence.

3 Data description

The dataset used in this study is based on a random sample drawn from the Employment Statistics database of Statistics Finland[2]. It is a representative sample of 350 000 individuals between 12 to 75 years of age living in Finland in 1997. The information in the data is combined from several official registers. The dataset is constructed as a yearly panel from 1987 to 2001. From the view point of this study, the most important information in the data is provided by the labor administration. The exact dates of individual labor market transitions are recorded. The information on job spells comes from the pension institutes.

The data contains some information on unemployment before 1987 but only spells starting after 1986 are used in order to avoid the problems of a stock sample (Wooldridge 2002, p. 694–703). Thus, the dataset is constructed using flow sampling and there is no left censoring. The last observations are at the end of 2001 which means that all the ongoing spells are censored at that time. Therefore, the spells starting after 1999 are excluded since for the later years no long spells are observed.

There are also over 200 other variables in the data including the demographic and socio-economic characteristics of individuals. Generally speaking the data provides an excellent possibility to study changes in the structure of unemployment: it contains a long time period, large sample size and it does not suffer from attrition.

As usual, there are some drawbacks in the dataset. Only one employment spell and one active labor market action of each type is recorded per year. In addition, only the first four unemployment spells of an individual are included. This causes a slight under representation of short spells. However, based on the data, the proportion of individuals with more than 4 spells is below 0.5%.

Since the official registers are not complete and contain errors, there is missing information. Approximately 6% of the unemployment spell end dates and 20% of the information on the new state are missing. Fortunately, it is possible to fix a major proportion of the missing data using other information in the dataset. After applying procedures described in Appendix B, the share of the missing dates is reduced below 1% and the share of missing states is 6%. However, the overall share of missing information remains above 10% since some of the states are encoded as 'other state or unknown'. Because the same fixing methods were applied to those spells, the exits to employment should be captured to a large degree. This is important because censoring at the time of employment is not random and it creates bias to estimates.

The objective is to study the duration of unemployment using as a long data period as possible. There have been notable institutional changes in the course of time which reduce the comparability of the results. Especially the reform concerning elderly people has had a major impact (see Kyyrä & Wilke 2004). To avoid these problems, the analysis is limited to individuals from 20 to 49 years. Also 663 individuals are removed from the data because missing covariate information. This leaves a dataset of 122 578 individuals and 471 674 unemployment spells.

Lastly, some of the background information is defined only for a subset of years which somewhat narrows the number of available covariates. Discussion on the covariate information and the exact definitions of the variables used in the study are presented in Appendix B.

[2]The Finnish name of the dataset is “Työvoimapoliittisten toimenpiteiden vaikuttavuusaineisto 1987–2001”.

3.1 Variables

The most important variable in the analysis is the indicator of business cycle. The previous studies have used several different measures. A usual choice is to use unemployment rate or its log-transformation (Dynarski & Sheffrin 1990, Imbens & Lynch 1993, Rosholm 2001). Also local or sectoral unemployment is a popular choice (Imbens & Lynch 1993, Bover et al. 2002, Koskela & Uusitalo 2004). Of course, the GDP is a natural alternative (Bover et al. 2002). Holm et al. (1999) use the logarithm of local vacancy-unemployment ratio.

In this study, the regional unemployment rate is used. It is available as a quarterly time series for 13 labor force districts. Its main advantage over the national series is that it takes into account the large differences in the economic development of the different areas of Finland. Also the seasonally adjusted GDP growth was considered but the preliminary results were not promising, probably due to a large quarterly fluctuation in the series. The number of vacancies is not used because the available data describes only openings at unemployment offices. In addition, an earlier Finnish study that used this variable found unexpected results[3].

Rosholm (2001) argues that the unadjusted unemployment rate may be dominated by seasonal fluctuations. Also Abbring et al. (2002) emphasis that seasonal effects should be taken into account in microeconometric analyzes. Therefore, quarterly dummies are used. Also following Rosholm, annual dummies are used to capture time trends that are not accounted for the variation in the unemployment rate. The annual dummies are used to denote the starting year of unemployment spells, whereas the value of unemployment rate and quarter indicator vary during the spells.

Because the neglected heterogeneity of individuals causes a negative bias on the hazard rate, it is important to include an extensive set of individual characteristics to model. The variables used in the analysis are gender, age, education, occupation, family type, native language, the type of living region and disability indicator. Some variables which are often used were not available in the data. Although, it is not in the focus of this study to analyze the effect of unemployment benefit, it is an important factor. At least an indicator for earnings related benefits would be beneficial. The age of children, work experience, wealth and spouse's income are defined only since 1991 onward. In addition, the labor market history of unemployed would be useful. Naturally, it can be derived to some extent using the data but it requires to shorten the analysis period. Since the data on the boom at the end of the 1980s is considered important, the time period is not reduced. However, when a mixed model is estimated, the labor market history variables are used.

3.2 Finnish labor market policy

Institutional features have a strong effect on individuals behavior during unemployment. The unemployment benefit system affects the incentives of searching and accepting a job, and a participation in active labor market program (ALMP) truncate the duration of unemployment spell. Next the Finnish system is presented briefly. For more details, see for example Heinonen et al. (2004) or Koskela & Uusitalo (2004).

The unemployment benefit system is a combination of basic daily allowance and earnings-related allowance with limited duration[4]. The basic allowance is 23 euros per day and it is paid for 5 days per week. It is possible to get an increase of a maximum 8 euros if an unemployed has dependent children. The duration of the basic allowance is

[3] Holm et al. (1999) find that the vacancy-unemployment ratio has a negative effect on the hazard during a recession.

[4] The following figures are for the year 2003.

unlimited but it is required that a person is willing to accept a job offer. It is possible to lose the benefit for 30 to 90 days if the person has resigned, refuses to accept a job or refuses to participate in an active labor market program.

To be entitled for the earnings-related allowance, an unemployed person is required to be a member of unemployment fund and to work for 10 months during the last two years[5]. The replacement ratio decreases with income. The share from previous earnings with the earnings-related allowance varies from almost 80% to below 40% with previous earnings from 1000 euros to 4000 euros, respectively. For the median income earner, the net replacement ratio is 64%. The duration of the earnings-related benefit is 500 days which are counted for 5 days per week. This means that the maximum length is close to two years.

There are some special rules considering young and elderly people. An unemployed person younger than 25 years is obliged to seek and participate in vocational education[6]. Otherwise a young person is not eligible for the basic allowance. Before 1997 people older than 53 years were entitled for the earnings-related allowance until the retirement age. In 1997 the age limit was raised to 55 years. This obviously influences the incentives of re-employment.

Since the 1970s the activation of unemployed has played an important role in Finnish labor market policy. The main objective has been to reduce frictions in the market by offering education and guidance in job search. Participation in labor market training increases the length of earnings-related allowance by 4 months. The share of labor force in training has varied from 1% to 2% in the 1990s.

Another form of ALMP is to offer subsidized jobs for individuals who have difficulties in finding a job. At the end of the 1980s there was an aim of achieving full employment and since 1988 there was a commitment to offer a subsidized job for long-term unemployed. For people younger than 20 years the time limit was 6 months. However, soon after the dramatic rise in unemployment rate it became impossible to offer a job for all and the commitment was abandoned gradually by 1993. However, due to this act in the late 1980s there were only a few long-term unemployed. The share of labor force in subsidized jobs rose from 1% to 2.5% between 1990 and 1997.

3.3 Descriptive analysis

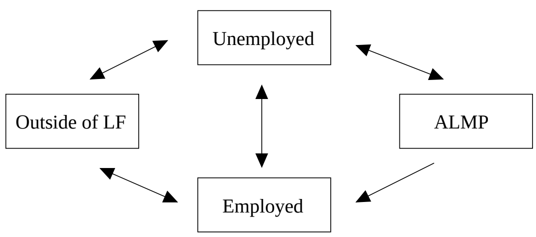

Figure 3: Individual's transitions in labor market.

The dataset can be described as event histories of individual labor market transitions. In Figure 3 it is illustrated how individual may move from one state to another. The state "Outside of labor force" includes e.g. children, students, housewives, disabled and elderly individuals. The unemployed people who participate in education or training

[5]The required number of months in work was raised from 6 to 10 months in 1997. In 2003, the time limits were changed again.

[6]This rule came into effect in 1996 with the age limit of 20 years. In 1997, the limit was increased to 25 years.

offered by the labor administration are in the state "ALMP". The focus of this study is in the transitions from unemployment to employment. Therefore, the movements from unemployment to other states than employment are treated as censored spells. The definition of employment is the following: a job is found independently or with the aid of the labor administration or when an individual is recalled to the previous work. A subsidized job offered by the labor administration is defined as participation to ALMP. The duration of unemployment is the difference between the end and start date of unemployment in the labor administration records.

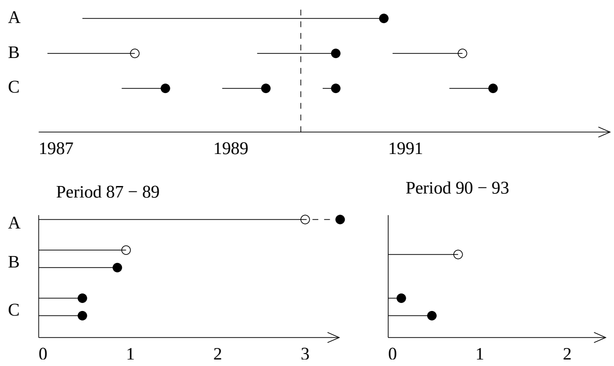

Figure 4: Longitudinal structure of the data. Lines with black dots are unemployment spells with exit to employment and white circles denote censoring.

The longitudinal structure of the data is illustrated in Figure 4. The dataset is split to four separate segments by the starting year of the spell. The motivation for this is discussed in Section 5.1. Loosely speaking the purpose is to group the same phases of the business cycle. The figure shows an example of how the spells are organized. The upper time scale presents the spells of three individuals in calendar-time. The lower time scale is the duration of a spell. Thus, all spells starting after the end of 1989 belong to the second segment. The spells of the first segment may continue to the year 1990. However, when the duration models are estimated all the spells are censored after three years of unemployment. The spells in the other segments are restricted in the respective manner.

Figure 5 presents the Loess[7] smoothed quarterly flow series calculated from the data. The inflow naturally follows the pattern of the national unemployment rate (see Figure 1). The outflow to any state from unemployment is lower than the inflow from 1990 to 1994. During this period, the unemployment rate grows over 10 percentage points. From 1995 onward the outflow is larger. The gap between the outflow and exits to employment starts to grow in 1990. This means that a larger proportion of the spells is censored during that time. A more detailed information on the exit states is shown in Table 1. The exit rates fall in the ends due to flow sampling.

The smoothed quarterly calculated duration of new unemployment spells is presented in Figure 6. Until 1990, the mean duration declines because of the boom in economy and the very active labor market policy (see previous chapter). After that, the mean duration increases from 100 to 290 days in 3 three years. The peak is in 1993 and then the mean duration declines steadily. The mean of the last few years is affected by censoring due to the end of follow-up. The gap between median and mean becomes more than threefold between 1990 and 1993 which means that also the dispersion of durations expands. The median duration of those who exit to employment is more stable. It only doubles during the recession. It should be noted that women's unemployment durations are generally shorter than men's, which is shown in Tables 6 and 7 (in Appendix B, p. 48–49).

[7] A newer version of Cleveland's (1979) Lowess smoother.

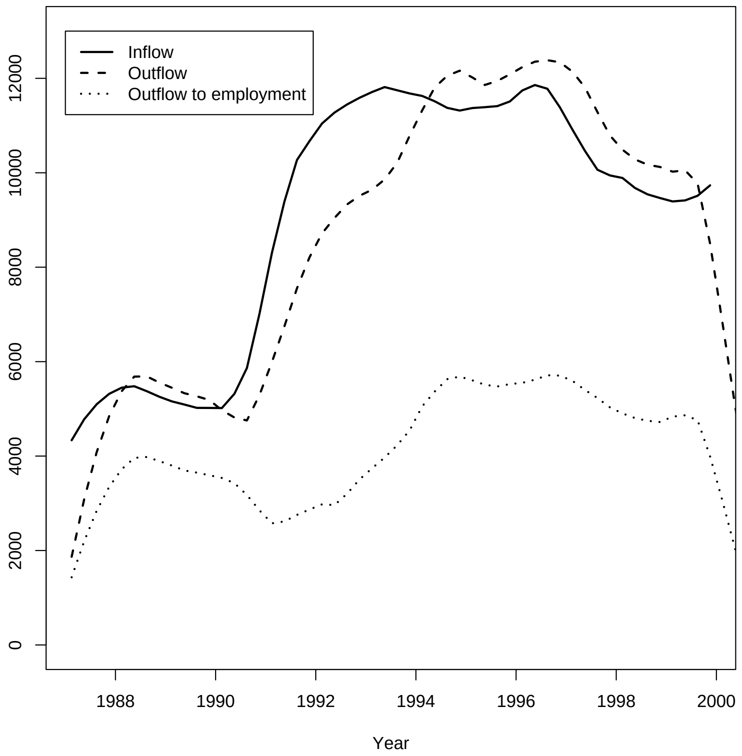

Figure 5: Smoothed inflow to unemployment and outflows.

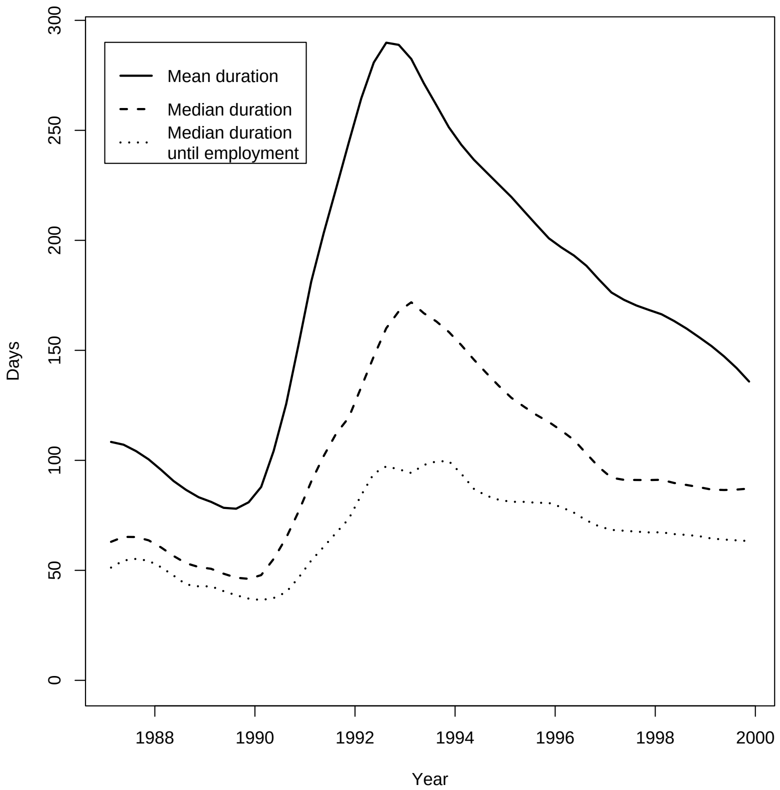

Figure 6: Smoothed unemployment duration of new spells.

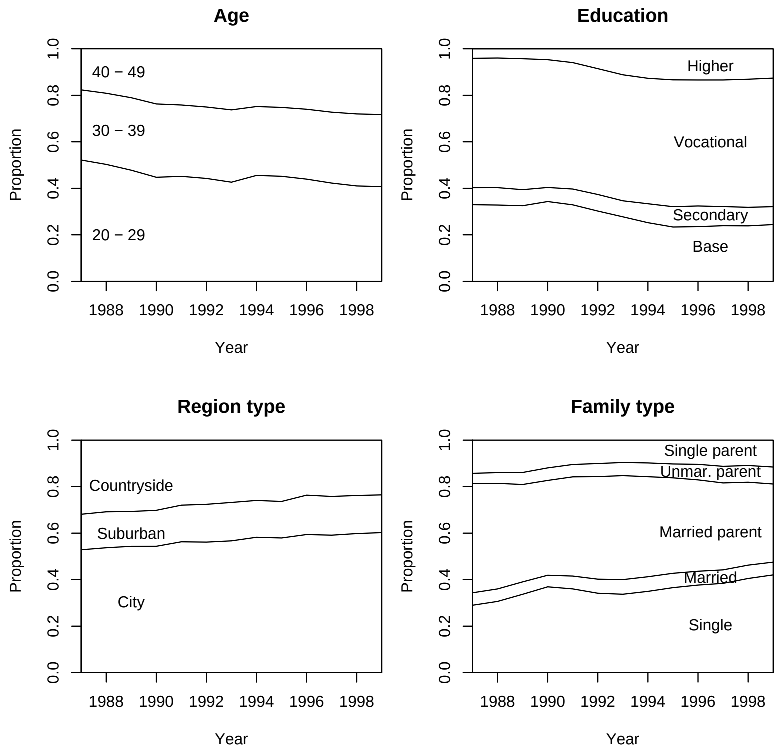

Figure 7: Variation in composition of inflow for selected variables.

The changes in the composition of unemployment are a possible explanation for the cyclical variation of unemployment. The detailed characteristics of unemployment spells for the data segments are presented in Tables 6 and 7 (p. 48–49). In Figure 7 the yearly shares of important groups are shown. In 1987 half of the individuals entering unemployment are under 30 years. Their share drops and the share of older than 40 years grows gradually by 10 percentage points. Also the proportion of individuals with base education declines while higher education becomes more common among the unemployed. The fraction of the unemployed living in a city rises and the share of the unemployed in densely populated areas grows slightly. Lastly, the share of single individuals is increasing while the fraction of married with children is decreasing. There are some differences in shares between men and women but the trends are similar.

Variation in the occupation of unemployed by year is shown in Figure 8. The shares are given by gender since there are large differences. For men, the most common occupation among unemployed is the industrial sector. During the period, generally, the share of other occupations increases slightly. Between 1990 and 1992 the proportion of technical occupation grows while the other sector diminishes. The largest sectors for unemployed women are health care, services and clerical. During the period the share of health care and humanistic grows and the share of services and industrial decreases. The changes take place one year later than for men.

Table 1 presents outflow from unemployment to different states. The reason of ending unemployment varies substantially between years. During the late 1980s over half of the people exit to employment. In 1991 the share has dropped to a quarter and then it stabilizes a little bit below 40%. Already in 1990 there is a 10% increase in the number of exits to ALMP. Next year the share is close to 30% where it remains. Also, the exits to outside of labor force become more frequent. In recalls there is a large peak in 1993. The share of exits to unknown state varies from 8% to 31%. A considerable effort is placed

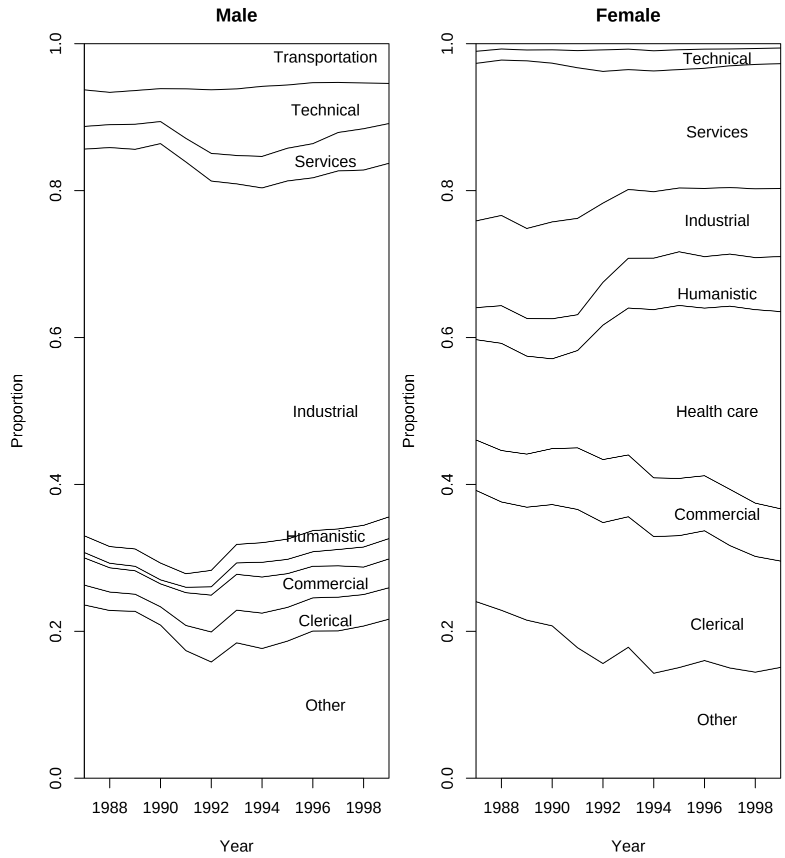

Figure 8: Variation in composition of inflow for occupation.

in checking that there are no employment cases among unknown states (see Appendix B). This is important since censoring at the time of employment causes bias to a hazard estimate. It can be seen from Tables 6 and 7 (p. 48–49) that the share of exits to employment is similar for men and women in the first data segments but in the later segments the share is larger for men.

	ALMP	Employed	Out of LF	Recall	Unknown	Total
1987	9.40	64.70	9.00	2.00	14.90	19960
1988	7.90	61.70	8.20	8.30	13.90	21590
1989	7.80	61.50	8.50	8.10	14.10	20365
1990	17.60	47.80	7.20	8.00	19.30	22761
1991	29.30	28.60	7.40	3.70	31.00	39371
1992	30.00	28.70	11.00	5.10	25.20	45705
1993	31.50	31.20	13.00	10.10	14.10	47249
1994	31.10	41.50	13.70	5.50	8.20	45706
1995	32.20	42.20	12.90	5.10	7.70	45658
1996	32.40	42.70	12.30	4.60	8.00	47382
1997	32.60	42.70	12.30	4.70	7.70	40393
1998	30.20	43.60	11.40	4.50	10.40	38468
1999	25.70	44.00	11.20	4.90	14.30	37066
Total	27.10	41.90	11.10	5.60	14.20	471674

Table 1: Outflow from unemployment in percentages by starting year and reason.

4 Duration Models

Longitudinal data on individual labor market histories consists of transitions between different states. Here the focus is in transitions from unemployment to employment. Consider an unemployment spell and let a random variable $T \geq 0$ denote the duration until employment. Usually there is also a positive probability that an individual participates in ALMP or moves out of labor force. Denote this duration with T_c. Since it is possible that some other event occur before employment or the follow-up length of data is shorter than the duration, the observed variable is $\min\{T, T_c, t_{end}\}$ where t_{end} is a fixed length of the follow-up.

If an exit from unemployment is not observed, i.e. $\min\{T, T_c, t_{end}\} < T$, it is said that the unemployment spell is censored. Censoring is classified in several ways. Left censoring means that the beginning of the unemployment spell is not observed. This is the case, for example, when labor market histories are observed from 1987 onward but some people have been unemployed before that and continue to be unemployed during the follow-up period. When an unemployment spell last longer than $\min\{T, T_c, t_{end}\}$, it is called right censored. The data used in this study is obtained using flow sampling and therefore it is only subject to right censoring. Another way to categorize censoring is to consider its mechanism. If it is plausible to assume that censoring is not dependent on the length of the follow-up or other factors in the model, random censoring can be assumed.

These special properties of duration data give rise to a class of models which are referred to as duration models. It appears that a natural way to present duration data is to use the concept of hazard function. Before introducing the basic concepts and duration models, a short discussion of the background is informative.

Duration analysis means practically the same as survival analysis. The term survival analysis relates to the fact that transition data was first analyzed in medical, industrial reliability and demographic context. There an observed event is usually illness, death or failure of a machine which is the origin of the term hazard. The textbooks normally use examples from medical studies (see Cox & Oakes 1984 or Kalbfleisch & Prentice 2002). The more complex models of transition data are derived using the theory of counting processes (see Fleming & Harrington 1991 or Andersen et al. 1993). It is needed, for example, in proving the asymptotic properties of extended Cox's model with time dependent covariates or recurrent events.

However, in economic applications there are often slight differences in the form of the data compared, for example, with medical applications. The labor market history of an individual may consist of multiple unemployment spells. In survival analysis these are often viewed as consecutive, i.e. recurrent events in time. In the case of unemployment, the focus is on the hazard rate and therefore it is more practical to view the spells parallel. It means that spells are not compared with each other in calendar-time but in duration. Therefore, to apply the standard analysis methods, it is necessary to assume multiple spells as independent observations (Devine & Kiefer 1991, p. 44). From a statistical point of view this not always justified. A random effect model allows making a weaker assumption that spells are independent conditional on unobserved characteristics (see Lancaster 1990, van den Berg 2001). Unfortunately, the estimation of a mixed model is not always straightforward.

4.1 Hazard function

In continuous time, the hazard function is formally defined

$$\lambda(t) = \lim_{dt \to 0+} \frac{\Pr(t \leq T < t + dt | T \geq t)}{dt},$$

where the random variable T is the time of exit. Thus, the hazard is the conditional probability of employment given that an individual is still unemployed. Denote the cumulative distribution function of T by $F(t) = \Pr(T < t)$ and the survivor function by $S(t) = 1 - F(t) = \Pr(t \geq T)$ which describes the probability of being still unemployed after time t. Now a useful relation can be derived for the hazard and survivor functions. Using the definition of the conditional probability and the fact that $f(t) = -dS(t)/dt$ gives

$$\lambda(t) = \frac{f(t)}{S(t)} = \frac{-d \log S(t)}{dt}. \tag{2}$$

Further, integrating both sides and using condition $S(0) = 1$ results

$$S(t) = \exp(-\int_0^t \lambda(s)ds) = \exp(-\Lambda(t)), \tag{3}$$

where $\Lambda(t)$ is the cumulative hazard function. The cumulative hazard or equally survivor function is often more convenient when representing empirical distributions since the hazard function takes zero value on many intervals.

The simplest type of hazard function gives rise to an exponent distribution. A constant hazard, $\lambda(t) = \lambda$, $\forall t \geq 0$, means that the underlying process for T is memoryless: the probability of exit in the next interval is not affected by the length of previous intervals. Using Equation 3 and a constant hazard, gives $F(t) = 1 - \exp(-\lambda t)$, which is the cumulative distribution function of the exponential distribution.

To represent duration dependence, a more general distribution is needed. Commonly used Weibull distribution is a generalization of exponential distribution which allows monotonically increasing or decreasing hazard. Its hazard function is defined by $\lambda(t) = \gamma \alpha t^{\alpha - 1}$ where α is a parameter for duration dependence.

4.2 Models for hazard

When the data contains a non-homogeneous sample of individuals, there are explanatory variables which hazard depends on. Let x be a vector of covariates. The most popular the econometric specification for hazard model uses the proportional hazard assumption

$$\lambda(t; x) = \lambda_0(t)\phi(x), \tag{4}$$

where $\lambda_0 > 0$ is called a baseline hazard and $\phi(\cdot) > 0$ is a function specifying the effects of covariates. The baseline gives the shape of the hazard for all individuals. The effect of covariates is proportional in a sense that only the level of the hazard is affected, not the shape. It is possible that $\phi(\cdot)$ depends also on t which means that at least some of the covariates vary in time. Here the notation simplified but the case of time-depended covariates is discussed in Section 4.4. Using the usual specification $\phi(x) = \exp(x'\beta)$ and taking logarithms gives a linear model

$$\log(\lambda) = \log(\lambda_0) + x'\beta,$$

which equals the classic model developed by Cox (1972). Thus, $\log \lambda_0$ is the intercept of the model and β gives the marginal effects.

The proportional hazard model includes the Weibull model as a special case. By choosing $\lambda_0(t) = \alpha t^{\alpha - 1}$, the Weibull model is obtained. Further, with the restriction $\alpha = 1$, it reduces to the exponential model. The Weibull model is also a member of accelerated failure time models (see Appendix C). Accelerated failure time models are a general class of parametric log-linear models for T. Other common parametric specifications are, for example, lognormal, gamma and logistic distributions (see e.g. Kalbfleisch & Prentice

2002). However, with these specifications, the model is no longer a proportional hazard model.

Generally, accelerated failure time models provide a flexible modeling of duration dependence but it has been argued that they are unsatisfactory from an econometric point of view since they do not focus on the individual hazard as the parameters of interest (van den Berg 2001). Hence, the proportional hazard specification is often used in unemployment duration analysis.

When modeling duration data, parametric models are rarely adequate in applied work. For example, the hazard rate of duration data is often not monotonic and requires a more flexible specification than Weibull model. Cox's partial likelihood method requires no specification for the baseline hazard λ_0 (Cox 1972). However, as the baseline hazard is not estimated in Cox's method, some other approach is usually adopted in unemployment duration applications[8].

The piecewise constant hazard model has become a popular choice (Wooldridge 2002, p. 709–710). It defines the hazard function separately for each interval $m = 1, \ldots, M$, as

$$\lambda(t; x) = \lambda_m \phi(x), \qquad a_{m-1} \leq t < a_m, \tag{5}$$

where $a_0 = 0$ and a_m is the end point of each interval. The piecewise constant specification implies that duration distribution is discontinuous but it does not cause any serious problems. When the number of intervals is increased, piecewise constant specification becomes a non-parametric hazard estimator (Baker & Melino 2000). Therefore, the piecewise constant model is very flexible and with a large number of observations the shape of the hazard can be estimated accurately.

4.3 Mixed proportional hazard model

In economic data unobserved heterogeneity is often present. As demonstrated in Section 1, the presence of unobserved heterogeneity creates a negative bias to the estimated hazard. If some of the variables are omitted from the model, this can be taken into account using a mixed model. Also errors in recorded durations or covariates give rise to a mixture distribution (Lancaster 1990, p. 58–62). Usually the mixture term v enters the hazard function multiplicatively as

$$\lambda(t; x) = \lambda_0(t)\phi(x)v.$$

It is also assumed that v is independent of the observed covariates, starting times and the censoring times of spells (Wooldridge 2002, p. 703–706). The distribution of v is often specified parametrically but a non-parametric approach is also possible. Typical parametric choices are gamma and lognormal distributions. However, there are more general families of mixture distributions that would be preferable in a theoretic sense. Therefore, in economic applications estimation methods for non-parametric specifications of the mixture term have been suggested (Heckman & Singer 1984). Unfortunately, there are problems related to the estimation of mixed models, especially with non-parametric mixture distribution, which are discussed in Section 4.6.

Next a specific case of unobserved heterogeneity is considered. It is assumed that there are several observations from individuals belonging to the same group $i = 1, \ldots, n$. There is independence between groups and individuals within a group share a common value of the mixture term v_i. Then there is positive dependence between exit times for the

[8]In some earlier applications, Cox's model is used to analyze the effect of business cycle (Dynarski & Sheffrin 1990, Imbens & Lynch 1993). In those duration dependence is modeled using some function of elapsed duration as a time dependent covariate.

same value of i. If all share the same value and v has no variation, it implies independence between observations (Hougaard 2000, p. 215–218). This kind of a setting is referred to as shared frailty in statistical literature and is used when there are, for example, repeated measurements. In the context of unemployment durations, it can be assumed that the spells of a single individual share the common mixture term v_i. If the mixture term captures the unobserved heterogeneity between individuals, it takes care of two problems: creates dependence between individuals in the same group and removes bias from the hazard function[9].

4.4 Inference in parametric models

Parametric duration models can be estimated using standard maximum likelihood methods. Of course, some special attention must be given to censoring. In the case of random right censorship, a spell censored at t contributes $S(t;\beta)$, i.e. the probability of survival beyond t. The contribution of a spell ending with employment at t is $f(t;\beta)$. Hence, the full likelihood of $i = 1,\dots,n$ spells, conditional on the covariates is

$$L(\beta) \propto \prod_{i=1}^{n} f(t_i;\beta,x_i)^{\delta_i} S(t_i;\beta,x_i)^{1-\delta_i},$$

where δ_i is an indicator variable taking value 0 for censored spells (Kalbfleisch & Prentice 2002, p. 52–57). In the exponential regression, the likelihood function becomes

$$L(\beta) = \prod_{i=1}^{n} \exp(\delta_i x_i'\beta)\exp(-\exp(x_i'\beta t_i)),$$

which can easily be seen from the results derived in Appendix C.

Since the exponential model is a special case of the Weibull model, it is therefore also an accelerated failure time model. It has a close relation to generalized linear models, especially to Poisson regression. For example, the piecewise constant model can be fitted as a Poisson regression model with some care in parametrization. Further, the parametric duration models can be fitted using iteratively reweighted least square formulation (Therneau 1999).

Because the model is log-linear, the parameters of the model are often interpreted in the form $\exp(\beta)$ which gives the hazard or risk ratio, i.e. the impact of covariate on the baseline hazard. If $\beta < 0$ (> 0), then $\exp(\beta) < 1$ (> 1) and the hazard rate decreases (increases). For example, when $\exp(\beta) = 2$, the hazard rate is double compared to the baseline group. Naturally, $\beta = 0$ and $\exp(\beta) = 1$ stand for no effect.

In practice, covariates are often time-dependent, i.e. functions of time. In many cases there are good reasons to suspect that the hazard function is affected by the current value of the covariate instead of its value at the beginning of the spell. A time dependent covariate can be easily incorporated into the model if the stochastic process of covariate is a predictable process (van den Berg 2001). The concept relates to the assumption of weak exogeneity in time series analysis. The counting process literature contains a more precise exposition of the definitions by the use of measure theory (see Fleming & Harrington 1991 or Andersen et al. 1993).

Kalbfleisch & Prentice (2002) define two general classes of time-dependent covariates. An external covariate is an output of stochastic process that does not depend on the parameters of duration of the spell under study. Thus, the regional unemployment rate is an external covariate if the area is big enough so that the unemployment rate is not

[9] The data used in this study could be also modeled as recurrent event data. Then the individual spells would not be considered parallel but consecutive.

affected by the employment of single individual. Also time-dependent covariates which are deterministic or fixed covariates are external.

An internal covariate is an output of the stochastic process that is generated by the individual under study. This corresponds to a situation where the individual has inside information about the future realization of the covariate, i.e. stochastic process is no longer predictable. For example, an individual may expect a baby which affects the hazard rate but it is not observable to the researcher. In the case of external covariates, the standard tools of duration analysis can be applied. The internal covariates must be handled differently but no further emphasis is placed on this discussion since most of the covariates in this study are fixed and the time-dependent covariates are evidently also external.

4.5 Model diagnostics

The central assumption of the proportional hazard model is, as its name suggests, the proportionality of covariate effects β. Consider two covariates x_i and x_j, then ratio of the hazards $\lambda(t;x_i)/\lambda(t;x_j)$ should be independent of t with all $i \neq j$. Now assume that a single covariate has two values 1 and 0. From proportionality it follows that the ratio of cumulative hazard functions of two groups should be $\Lambda_1(t)/\Lambda_0(t) = \beta t$. Descriptive graphical methods can be used to check the validity of proportionality assumption. Plotting the non-parametric Nelson–Aalen estimators of cumulative hazard should produce lines that diverge with a constant multiplier in time. Alternatively, it is possible to plot log-cumulative hazards against a logarithmic time scale which should produce lines with a constant distance. A drawback of this technique is that the variance of Nelson–Aalen estimator increases in time (Kalbfleisch & Prentice 2002, p. 14–26). Of course, this is natural since the number of observations decline but it makes it harder to interpret the results.

In normal distribution models, residuals are commonly evaluated in order to check the assumptions of the model. For duration data, residual analysis is more complicated because of binary dependent variable and censoring. The Cox–Snell residuals are often used with parametric regression[10]. For observation i, the residual is defined as

$$\hat{r}_i = \hat{\Lambda}(t_i)\exp(x_i'\hat{\beta}),$$

where $\hat{\Lambda}$ is a cumulative hazard estimator of baseline hazard and $\hat{\beta}$ is a vector of estimated parameter values (Kalbfleisch & Prentice 2002, p. 119–128). If the model is appropriate, the residuals should be from a censored exponential sample. Then the survival curve estimates based on residuals should yield approximately a straight line with slope -1 when plotted on a log scale. However, it is not clear how close the distribution is to the unit exponential distribution in small samples (Andersen et al. 1993, p. 555–556). In addition, it should be noted that it is not apparent what kind of departures one would expect to see in residuals if the model is incorrect, and fitting many free parameters to the data may lead to misleadingly good approximations (Kalbfleisch & Prentice 2002, p. 119–128).

4.6 Estimation of mixed proportional hazard model

From a theoretical perspective, the mixed proportional hazard (MPH) model is very appealing. In practice, empirical application of the MPH model is often difficult and there are concerns about the robustness of results. In statistical literature the analysis methods

[10]There are also other, more advanced, definitions of residuals. Because function for calculating residuals had be coded to implement it in piecewise constant hazard setting, only Cox–Snell residuals are used in this study.

for parametric mixture models are well established (see Hougaard 2000). However, the data in unemployment duration analysis has somewhat different properties than in the cases discussed in textbooks. For example, when the data constitutes of twins, there are always two observations for unobserved characteristics. In unemployment duration analysis, many individuals experience only one unemployment spell and, therefore, it is not clear how the random effect term can be identified.

It turns out that in a proportional hazard setting, it is possible to identify the mixture distribution even with single spell data, at least in theory. There is an extensive literature on this subject (van den Berg 2001). Heckman & Singer (1984) derive identification results and a consistent non-parametric maximum likelihood estimator for a class of MPH models with the baseline hazard belonging to a known parametric family. This result is generalized by Horowitz (1999) who provides non-parametric estimators for the MPH model for both the mixture distribution and the baseline hazard. They are only assumed to satisfy certain smoothness conditions. The practical performance of this estimator is still a topic of future research.

Although, the identification results for single spell data do exits, generally more information is required for robust estimation (van den Berg 2001). For example, Baker & Melino (2000) examine the performance of a non-parametric estimator. They note that there seems to be a trade-off between relaxing the assumptions on mixture distribution and the flexibility of baseline hazard distribution, i.e. the number of intervals in the piecewise constant case.

Thus, strong prior information on the functional form or multiple spells is needed. Van den Berg (2001) points out that multiple spell data is particularly sensitive to censoring. Let $t_1$and t_2 be exit times of spells following each other in calendar-time. Now, when the random effect v is large, t_1 will be short on average. If the follow-up has a fixed length, t_2 will often be censored at a high duration since it starts early. Thus, the censoring is not independent. On the other hand, if t_1 is long, it is possible that t_2 is not observed at all. Therefore, it is important to have a long follow-up period to avoid this problem.

In this study, non-parametric estimation of the mixture distribution is not attempted. There are several reasons for that. Firstly, it would require the construction of estimation routines. They are not available in software packages or on the Internet. Secondly, it seems hard to get robust estimates even with parametric mixture distributions. Moreover, the estimation procedure must be very efficient to fit the model for a large dataset like in this study. As it is discussed in Therneau, Grambsch & Pankratz (2003), the full information matrix of mixed model has $(n + p)^2$ elements, where n is the number of individuals and p is the number of normal parameters. Thus, when estimating with a large dataset, a very efficient algorithm is needed.

The large number of parameters is a problem with parametric models as well. Fortunately, Therneau et al. (2003) have developed a sparse method that saves over 95% of memory space in estimation. The use of this algorithm allows fitting the piecewise constant hazard model with different parametric mixture distribution using penalized likelihood estimator[11]. In addition, Abbring & van den Berg (2003) show that a large class of hazard models with proportional mixture distributions converge, often rapidly, to a gamma mixture distribution. This justifies the common use of gamma distribution.

[11]This estimator is available for S language (Therneau 1999).

5 Estimation results

In order to study various question, the empirical analysis practical to do in several stages. In the first stage, the objective is to validate the assumption of proportional hazard rate and to study the variation of covariate effects over calendar-time. The proportionality of the covariates is checked using cumulative hazard plots. Descriptive yearly models are estimated to examine changes in the parameter values. Secondly, on the basis of the first stage analysis the dataset is split to eight different segments and separate models are estimated. The model fit is checked using Cox–Snell residual plots.

Next duration dependence is studied. Restricted models are estimated to evaluate the impact of individual covariates on the baseline hazard. This gives some indication of the magnitude of the bias caused by neglected heterogeneity. Then the model is extended to allow the shape of baseline hazard to change when unemployment varies. This is a test for the ranking hypothesis. In the fourth stage, the model is extended to study the business cycle effects more rigorously. Following Rosholm's approach (2001), compositional and outflow effects' impact on the variation of unemployment duration are identified. Lastly, a model with gamma unobserved heterogeneity is studied.

All the estimated models are of the piecewise constant hazard form with log linear covariate effects (see Section 4.2). Denoting the baseline, individual and business cycle parameters with α, β and γ, respectively, the model can be expressed

$$\lambda(t; x) = \exp(d_p(t)'\alpha) \exp(x'\beta + d_b(t)'\gamma), \tag{6}$$

where the first term is the baseline and the second gives the effect of covariates. The hazard and some covariates depend on t which denotes the duration of spell from the beginning of unemployment. $d_p(t)$ is a 14 dimensional vector of time-dependent dummies which indicate $m = 1, \ldots, 14$ intervals[12]. The first two intervals are 30 days and the next 11 intervals are 60 days. The last interval is a residual piece which starts from 720 days and ends at 1095 days. $d_b(t)$ is a vector of time-dependent quarter dummies, regional unemployment rate and fixed annual dummies which indicate the starting year of unemployment[13].

In the analysis all the unemployment spells are treated as independent observations, except when mixed models are estimated. This is clearly a deficiency. However, it is a standard assumption in unemployment duration analysis. Generally, correlation between observations increases the standard errors of estimates. Therefore, to take this into account, 1% significance level is used.

5.1 Descriptive analysis

The non-parametric Nelson–Aalen estimator for cumulative hazard provides an easy way to study the effects of covariates and, especially, the validity of proportionality assumption. In Figure 9 is the hazard of employment by the starting year of unemployment and gender. It clearly shows that the shape of the hazard is very different between years and is not even close to proportional. The group of three higher hazard rates is the years at the end of the 1980s. The coarse steps at the end of line means that there are only few observations left. Thus, less emphasis should be placed for those parts. The cumulative hazard of genders is higher before 200 days but lower later for women. Thus, this suggests

[12] The idea is to provide a flexible shape for the hazard function that can take account all the interesting, perhaps non-monotonic, changes. For Finnish data, previous studies have used, for example, 14 monthly intervals (Holm et al. 1999) and 10 intervals of length 100 days (Ollikainen 2003).

[13] For estimation technical reasons, the time-dependent variables are allowed to change value only between intervals.

that there is a need for separate models[14].

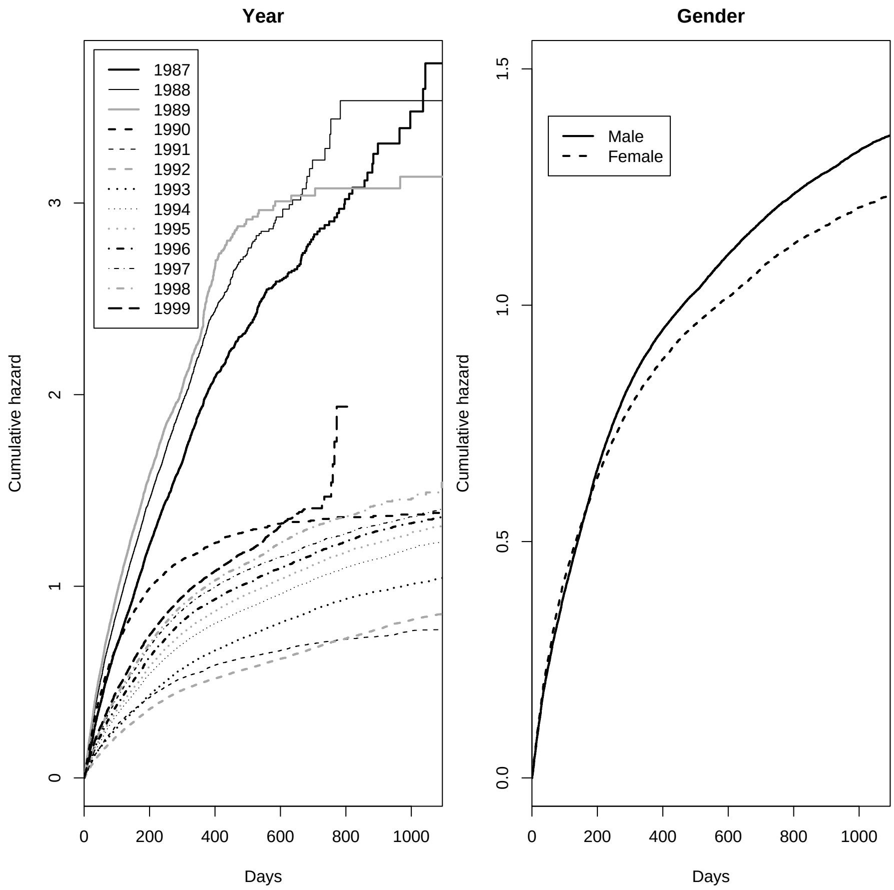

Figure 9: Cumulative hazard of employment by starting year of unemployment and gender.

Appendix D (p. 54–55) presents cumulative hazard plots for the other covariates by gender. It seems that age, native language, region type and disability have quite nice proportional effects. Education and family type have some groups that exhibit non-proportional effects, mainly for women. However, the deviations take place at long durations. On the other hand, some occupations indicate a violation of proportionality for men more clearly than for women. Altogether, these variables are clearly less problematic than the starting year of unemployment and gender.

Next the model (6) is estimated for every year and both genders separately. Thus, the data is split by the starting year of unemployment. This is done to find a suitable grouping such that the baseline hazards within every group are proportional. The proportionality between years is an important property, especially since the focus in this study is in the form of hazard.

The figures of scaled baseline hazards are presented in Appendix D (p. 56). The hazards are grouped in such a way that the years within a group are as similar as possible. Furthermore, the phase of business cycle is taken roughly into account which, of course, reflects basically the same underlying phenomenon. The first period is the boom of 1987–1989 and the second is the recession of 1990–1992. The shape of the hazard in 1990 is

[14] It is possible that there are compositional differences in the groups which might explain the non-proportionality, especially for genders. However, since there is a large number of variables, the checking of all the subgroups is very troublesome.

much closer to later years than earlier years[15]. The third period is from 1993 to 1995 which is the time of recovery. Lastly, the boom of the late 1990s is from 1996 to 1999.

The first group from 1987 to 1989 is the most divergent. Also the variation inside the group is large and negative duration dependence is less clear. The share of long-term unemployment is low during this period and therefore the estimates are not very precise for long durations. The second group from 1990 to 1992 is more uniform and the hazards are quite proportional. The last two groups look very close to each other and it would be possible to join them on the basis of yearly models. Nonetheless, this setup makes it possible to compare for differences.

The effects of covariates are presented in Table 8 (p. 53). For some covariates there are clear time trends while the changes for the other seem to be more random. There are substantial differences between the estimates for men and women. Generally, the effect of higher education has become more positive. For men, this is also true for vocational education. In addition, the relative position of married becomes better. The effect of age is less negative after 1992 and the effect of other language changes more negative. The variation in the occupation effects is more or less random. The effect of health care and commercial sectors between 1991 and 1994 seems to be more positive. The fact that men's and women's estimates differ and that there are some trends in the effects gives further support for the need of separate models.

5.2 Basic model

On the basis of descriptive analysis, eight separate models are estimated: both men's and women's models for periods 87–89, 90–92, 93–95 and 96–99[16]. The estimates of β and γ are presented in Tables 2 and 3. The baseline hazards are illustrated later in Figures 10 and 11 (for complete output, see p. 9–10). The models are referred to by the corresponding time periods. The baseline group in the models is a healthy single 20–29 years old living in a city with basic schooling, 'other' occupation and Finnish as the native language. The formal tests for the differences between years are reported in Appendix D (p. 59).

The men's results in Table 2 show a negative effect for age which becomes milder during the time period. The effect of education changes. In 87–89 secondary schooling is better than vocational and higher education is not significantly better than basic education. In 90–92 the effect of higher education is largest and later vocational education becomes better than secondary schooling. This is due to the fact that in later periods the people with higher education experience an increase in the number of spells while the duration increases only little compared to people with base education. This might be due to the fact that unemployed with higher education in 87–89 are a very selected and small group.

Also the effect of occupation varies in time. Clerical occupation has a negative or insignificant effect whereas commercial has a positive or no effect. Health care, industrial and transition sectors have all strong positive effects. Also service sector has a strong positive effect in 90–92 but a milder effect at other times. Humanistic occupation becomes positive in 90–92 and technical in 93–95.

Being married rises the hazard and being unmarried with a child has a milder positive effect. The effect of being a single parent is negative or none. The Swedish-speaking minority have a high hazard while people with 'other' native language have a very low

[15]This holds also for the year 1993 but not as clearly. It should be noted that it is logical to combine borderline cases to a later period because the spells starting in a given year continue to later years.

[16]Also Holm et al. (1999) adopt a same kind of strategy. They estimate separate models on Finnish data for years 1988, 1990 and 1992. Rosholm (2001) finds no asymmetric effects between years but he estimates separate models for genders and age groups.

	87–89		90–92		93–96		96–99	
(Intercept)	0.01	**	0.01	**	0	**	0	**
ageg30–39	0.79	**	0.84	**	1.02		0.94	**
ageg40–49	0.73	**	0.76	**	0.93	**	0.85	**
edusec	1.3	**	1.32	**	1.17	**	1.15	**
eduvoc	1.16	**	1.26	**	1.25	**	1.32	**
eduhigh	1.04		1.39	**	1.57	**	1.65	**
occcler	0.87	**	0.94		0.93	*	0.88	**
occcom	0.97		1.19	**	1.09	**	0.97	
occheal	1.17		1.91	**	1.71	**	1.43	**
occhum	0.95		1.38	**	1.31	**	1.08	*
occind	1.26	**	1.14	**	1.38	**	1.38	**
occserv	1.12	**	1.25	**	1.14	**	1.08	**
occtech	1.05		1.03		1.16	**	1.18	**
occtran	1.24	**	1.44	**	1.51	**	1.44	**
famtmar	1.29	**	1.41	**	1.38	**	1.53	**
famtmar.par	1.29	**	1.33	**	1.4	**	1.45	**
famtunmar.par	1.19	**	1.13	**	1.3	**	1.39	**
famtsingle.par	1.04		0.93	**	0.96		0.99	
langswedish	0.96		1.2	**	1.25	**	1.19	**
langother	0.86		0.66	**	0.45	**	0.42	**
urbsuburb	1.12	**	1.16	**	1.16	**	1.18	**
urbcountry	1.1	**	1.13	**	1.16	**	1.17	**
dis	0.56	**	0.5	**	0.45	**	0.52	**
reg.ur	0.97	**	1.01	**	0.99	**	0.98	**
quartII	1.47	**	1.33	**	1.23	**	1.34	**
quartIII	1.31	**	1.24	**	0.95	**	1.04	*
quartIV	0.81	**	0.89	**	0.78	**	0.74	**
year2	1.26	**	0.39	**	1.2	**	1.08	**
year3	1.35	**	0.36	**	1.3	**	1.08	**
year4							1.11	**

Table 2: Hazard ratios of the basic models for men (* = $p < 0.05$, ** = $p < 0.01$).

hazard from 90–92 onward. Living outside cities has a positive effect, and being disabled has a large impact, it halves the hazard.

The effect of regional unemployment rate varies. During the period of low unemployment in 87–89 it is quite strongly negative. When the unemployment rises in 90–92 the effect, surprisingly, turns positive. Then it turns negative again. This peculiar result is further studied in Section 5.4 by allowing interaction effects for different groups. The second quarter of the year is the best time for employment. It is the time when the summer season starts and schools end. From the data it is seen that especially young people have averagely short unemployment spells in the second quarter. The third quarter has a positive effect except in 93–95, and the last quarter has a negative effect.

The results for women, in Table 3, have some notable differences compared to men. The negative effect of age is not as evident. The effect of education changes in a similar way as for men but higher and secondary education have a more positive effect. The differences in occupation ratios are somewhat dissimilar which reflects the different positioning in the labor market. Clerical, commercial and service sectors have more positive effects. The hazard at health care sector is almost double and humanistic occupation also has a very high hazard in 93–95. On the other hand, industrial and technical sectors have lower hazards compared to men.

As expected, the family type affects quite differently for women. Being married has a positive effect only in 96–99. Having a dependent child clearly reduces the hazard. This

	87–89		90–92		93–96		96–99	
(Intercept)	0.01	**	0.01	**	0	**	0.01	**
ageg30–39	0.84	**	0.78	**	0.89	**	0.89	**
ageg40–49	0.85	**	0.75	**	0.91	**	0.89	**
edusec	1.46	**	1.37	**	1.29	**	1.32	**
eduvoc	1.21	**	1.37	**	1.33	**	1.44	**
eduhigh	1.22	**	1.81	**	1.79	**	1.9	**
occcler	1.27	**	1.2	**	1.21	**	1.17	**
occcom	1.33	**	1.35	**	1.39	**	1.32	**
occheal	1.78	**	1.87	**	1.95	**	1.77	**
occhum	1.17	**	1.37	**	1.86	**	1.64	**
occind	1.22	**	1.09	**	1.21	**	1.16	**
occserv	1.44	**	1.41	**	1.48	**	1.38	**
occtech	1.05		0.8	**	1.09		1.12	**
occtran	1.33	**	1.27	**	1.39	**	1.4	**
famtmar	0.93	*	0.98		1		1.1	**
famtmar.par	0.87	**	0.9	**	0.91	**	1	
famtunmar.par	0.66	**	0.71	**	0.69	**	0.8	**
famtsingle.par	0.81	**	0.75	**	0.75	**	0.76	**
langswedish	0.96		1.07		1.2	**	1.15	**
langother	0.68	**	0.48	**	0.43	**	0.4	**
urbsuburb	1.03		1.08	**	1.08	**	1.09	**
urbcountry	1.01		1.07	**	1.12	**	1.11	**
dis	0.54	**	0.57	**	0.5	**	0.53	**
reg.ur	0.98	**	0.99	**	0.98	**	0.96	**
quartII	1.09	**	1.04		0.97		1.01	
quartIII	1.01		1.16	**	1		1.1	**
quartIV	0.8	**	0.95	*	0.95	**	0.97	*
year2	1.16	**	0.42	**	1.19	**	1.01	
year3	1.31	**	0.33	**	1.24	**	1.02	
year4							1.06	**

Table 3: Hazard ratios of the basic models for women (* = $p < 0.05$, ** = $p < 0.01$).

reflects women's weaker labor market attachment. Language, region type and disability have a relatively similar effect as for men except living outside a city has less a positive impact. The regional unemployment effect does not alter as much as for men. Lastly, it should be noted that seasonal variation is less important.

The qualitative results of the covariate effects are similar to the results of previous studies on Finnish Data. For example, also Koskela & Uusitalo (2004) find a negative age effect and a positive education effect. Other studies analyze shorter time periods[17]. Generally, also the results for occupation, family status and region type are found to be the same (see Ollikainen (2003) for the results of the year 1997). Only Holm et al. (1999) study the effects of covariates in time. They have quite a different set-up and their analysis period is 1988–1992. However, they observe a positive trend in the effect higher education as well.

Graphical model diagnostics is presented in Appendix D (p. 60). The Cox–Snell residuals are plotted for all the observations. The deviations from the unit exponential line are largest for the 90–92 models. For the 87–89 models there are only few observations for the bigger deviations which is seen from the coarse steps in the lines. With some caution it could be concluded that the models fit better for men than for women. The 93—95 and 96–99 models show a very good fit which is not surprising since the economic

[17]Other Finnish studies, except the ones mentioned earlier, that include duration analysis on data from the period 1987–2001 are, for example, Pyy (1994) and Tuomala (2002).

development in that period is more homogeneous than in the earlier period. However, one must keep in mind the qualitative limitations of Cox–Snell residuals discussed in Section 4.5.

5.3 Duration dependence

To assess the impact of heterogeneity on duration dependence, the model (6) is estimated without individual covariates, i.e. restricting $\beta = 0$. By comparing the full model and the reduced model gives some indication of the bias caused by neglected heterogeneity. Figures 10 and 11 present the scaled baseline hazards for men and women, respectively. Overall, there is clear negative duration dependence. The differences between solid and dotted lines are relatively small. It means that the heterogeneity bias in hazard, caused by omitted variables is minor. Unfortunately, this tells only little about the magnitude of bias caused by unobserved variables. The question of unobserved heterogeneity is studied later in Section 5.5.

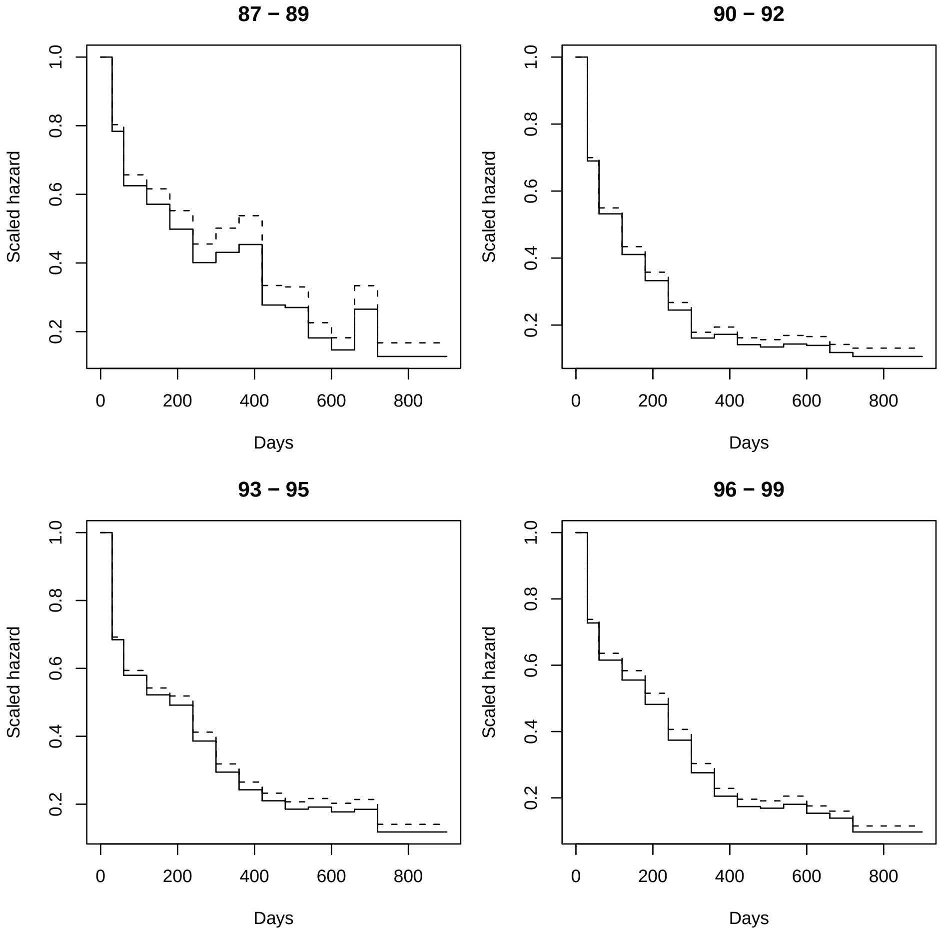

Figure 10: Scaled baseline hazard of the basic model (solid line) and the restricted model (dotted line) for men.

The scaled baseline hazard drops sharply to around 0.6 during the first 100 days of unemployment. After that it continues to fall but there are differences between years. In 87–89 the relative hazard remains above 0.4 until 420 days. During this period the labor administration offered subsidized jobs to all long-term unemployed which probably also explains the higher exit rate to normal jobs around 365 days. Then the hazard falls

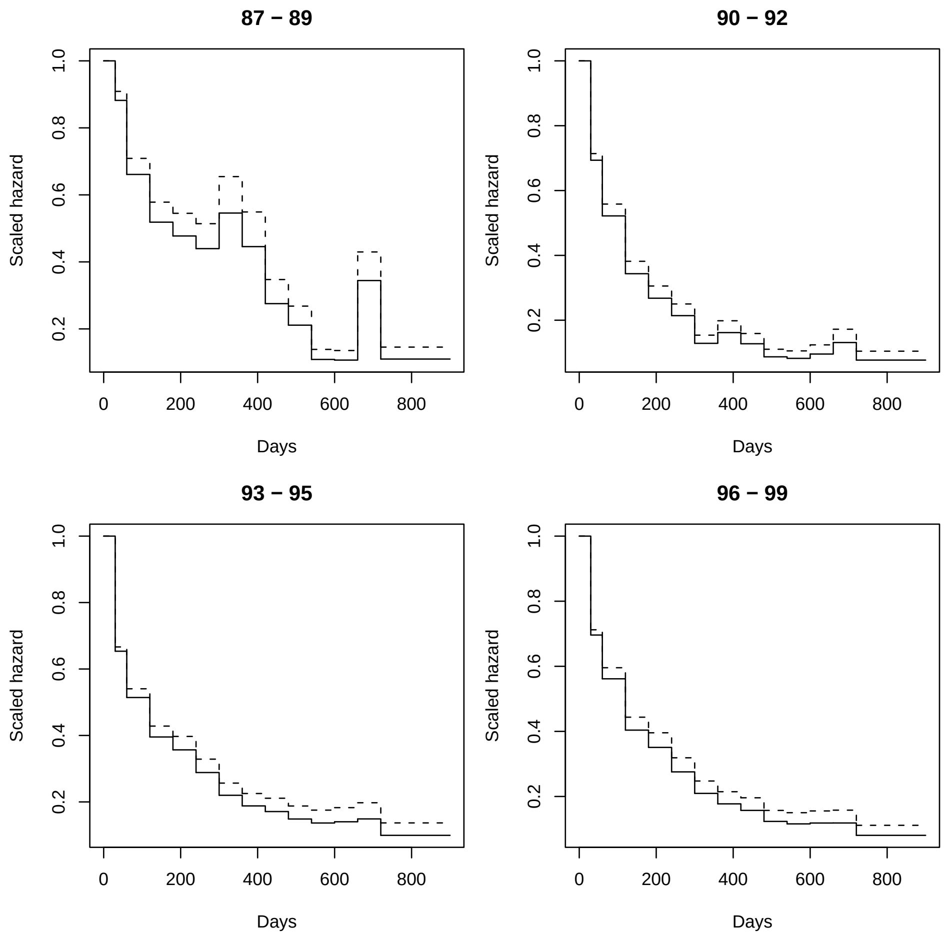

Figure 11: Scaled baseline hazard of the basic model (solid line) and the restricted model (dotted line) for women.

further below 0.2 but there is a spike at 700 days which corresponds to the expiration date of earning-related unemployment benefits. The rise in the hazard is especially strong for women. However, the confidence intervals are quite wide for long durations because the number of long-term unemployment is low (see Tables 9 and 10, p. 57–58). According to the search model, this is because of increased incentives to accept a job offer. However, a more likely explanation is that a large number of individuals exit to ALMP at that time, especially since the pattern is not evident in the later periods. For the later periods the hazard rates look quite similar. In 90–92 the drop in the hazard is steeper than later. The spikes in the hazard rate are not as large as in the first period.

Next the model is extended by including interaction terms with the baseline hazard and unemployment. This formulation makes it possible to test whether the duration dependence is stronger during a downturn of the economy. The results are shown in Appendix D (p. 61). The hazards are calculated for the baseline group at 10% regional unemployment level. Therefore, the levels of hazard are comparable only for the baseline group. The significance of unemployment effect on 5% level is denoted by stars in the top of the figures[18]. The first character from the left stands for the overall effect and the rest stand for the change in the shape of the hazard. Thus, the effect on the shape is not significant in any of the models. With this parametrization the overall effect is not significant for women's 90–92 model and for the 93–95 models.

[18]The null hypothesis is that the interaction term with the overall effect is different from zero.

The basic search model with exhausting unemployment benefits suggests positive duration dependence (see Section 2.2). With some extra assumptions it implies that the exit rate decreases when the job offer decreases. Hence, the results are in line with the latter but not with the former prediction. One theoretical explanation for negative duration dependence is provided by the ranking model. In addition to negative duration dependence, it predicts that duration dependence should be stronger the higher is the unemployment rate. The result does not support this hypothesis since there is no significant change in the shape of the baseline hazard.

The previous evidence on ranking hypothesis, i.e. that duration dependence varies with business cycle, is mixed. Rosholm (2001) rejects the hypothesis using a similar inspection as here. Abbring et al. (2002) reject ranking behavior using macro data. On the other hand, Cockx & Dejemeppe (2005) find support for the hypothesis using the same kind of data as Abbring et al. However, it must be noted that there is no unambiguous way to form the test. In addition, it must be assumed that unobserved heterogeneity is correctly taken account when testing the ranking hypothesis. Here it is only assumed that the heterogeneity bias is relatively small.

5.4 Decomposition of effects

Here the objective is to answer the question: to what extent does the compositional changes of inflow explain the variation in unemployment duration. The relative importance of compositional effects and macroeconomic conditions can be assessed using Rosholm's approach presented in Section 2.1. Here the role of unemployment rate as a proxy for the business cycle is central. In the basic model the effect of regional unemployment is unexpected which rises the question whether there are interaction effects in different groups. Therefore, the basic model is extended to allow interaction between the key covariates. The interaction terms with the baseline hazard are left out since none of them is significant. The baseline hazard is estimated on 10% unemployment rate level which is the average national rate between 1987 and 1999.

Men's results are shown in Table 4. Only hazard ratios of the interacted covariates are reported because the other coefficients are essentially at the same level as in the basic model (for complete output, see Appendix D, p. 62–63). Many of the interaction terms are significant. This affects regional unemployment's effect on the baseline group which becomes more negative in all the periods except in 93–95 where it turns insignificant. The effects of other interacted variables change depending on the difference between the current unemployment rate and the average rate. If the average rate is higher than the rate in the period, the direct effect rises when there is a positive interaction term. Thus, these results do not change the previous interpretations but merely show if there is dependency on unemployment.

Older people seem to have higher hazards when the unemployment rate is increasing. A possible explanation is that age acts as a proxy for work experience in the model. Thus, if in a downturn firms do not want to use resources to educate new people, it would explain the observed result. The same pattern is seen in the unemployment rates of the young people which rose much more during the 1990s recession compared to the whole population. In addition, more educated people seem to have a lower hazard when unemployment is high in some later periods.

Many of the occupations have a lower hazard when unemployment is high after 1993. The exceptions are the following. The hazard of humanistic occupation shows an interestingly large positive dependence on unemployment in 87–89. In 93–95 it has a negative dependency. Technical sector performs better when unemployment is high in 90–92 and worse later. Transportation sector has a negative dependency in 96–99 and health care sector has no dependency.

	87–89		90–92		93–95		96–99	
ageg30–39	0.91	*	0.85	**	0.85	**	0.85	**
ageg40–49	0.86	**	0.78	**	0.72	**	0.75	**
edusec	1.44	**	1.28	**	1.2	**	1.21	**
eduvoc	1.17	**	1.26	**	1.32	**	1.35	**
eduhigh	1.07		1.41	**	1.59	**	1.71	**
occcler	0.83		0.94		1.24	**	0.98	
occcom	1.1		1.21	**	1.28	**	1.06	
occheal	1.12		1.94	**	1.57	**	1.47	**
occhum	1.53	**	1.4	**	1.6	**	1.13	**
occind	1.15	**	1.16	**	1.73	**	1.44	**
occserv	1.1		1.26	**	1.5	**	1.19	**
occtech	0.93		1.03		1.48	**	1.28	**
occtran	1.18		1.46	**	1.59	**	1.57	**
reg.ur	0.96	**	0.99	*	1		0.97	**
ageg30–39:reg.ur	1.03	**	1.02	**	1.03	**	1.03	**
ageg40–49:reg.ur	1.03	**	1.02	**	1.04	**	1.04	**
edusec:reg.ur	1.02		0.98	**	1		0.98	**
eduvoc:reg.ur	1		1		0.99	*	0.99	**
eduhigh:reg.ur	1		1.01		1		0.99	*
occcler:reg.ur	0.99		1		0.96	**	0.96	**
occcom:reg.ur	1.02		1.01		0.98	*	0.97	**
occheal:reg.ur	0.99		1.02		1.02		1	
occhum:reg.ur	1.08	**	1		0.97	*	0.99	
occind:reg.ur	0.98		1.01		0.97	**	0.99	*
occserv:reg.ur	1		1		0.96	**	0.97	**
occtech:reg.ur	0.98		1.02	**	0.96	**	0.98	**
occtran:reg.ur	0.99		1.01		0.99		0.97	**

Table 4: Hazard ratios of the interaction models for men (* = $p < 0.05$, ** = $p < 0.01$).

In Table 5 is presented the results for women. It is seen that the effect of regional unemployment on the baseline group becomes stronger for women as well. Age does not have as large positive dependency on unemployment as for men. Nonetheless, it is significant for over 40 years old from 1990 and also for over 30 years old from 1993 onward. Secondary schooling raises the hazard in 87–89 when unemployment increases and higher education rises the hazard from 1990 onward. Hence, the effect is the opposite to that for men.

In women's model, the interaction terms of occupation are more commonly positive in the earlier periods compared to men. In 87–89 this is the case on health care and service sectors and in 90–92 on commercial, health care, humanistic and technical sectors. Here again humanistic occupation has a large positive interaction coefficient. In 96–99 the dependency turns negative for clerical, commercial, health care, humanistic, services and technical sectors. Thus, the change from positive to negative dependency takes place later for women than for men.

The contribution of individual characteristics to unemployment duration is illustrated in Figure 12. The expected values conditional on individual specific covariates are calculated for unemployment inflow[19]. Thus, the effect of unemployment is held constant

[19]This means that predicted values of the presented model are calculated for all the observations, i.e. for inflow to unemployment. When predictions are calculated conditional on a subset of the explanatory variables, the remaining variables are held constant at the baseline level. To obtain average expected duration for individuals with different characteristics, quarterly averages are calculated for inflow, which gives a time series. In practice, the calculation of predicted values from the piecewise constant hazard model is relatively easy. Nonetheless, since the piecewise constant hazard model is not presented in

	87–89		90–92		93–95		96–99	
ageg30–39	0.89	*	0.79	**	0.78	**	0.86	**
ageg40–49	0.85	*	0.76	**	0.73	**	0.85	**
edusec	1.87	**	1.39	**	1.21	**	1.3	**
eduvoc	1.28	**	1.39	**	1.4	**	1.43	**
eduhigh	1.46	*	1.88	**	1.59	**	1.8	**
occcler	1.17		1.21	**	1.26	**	1.22	**
occcom	1.46	**	1.4	**	1.31	**	1.33	**
occheal	2.4	**	1.9	**	1.84	**	1.84	**
occhum	1.22		1.53	**	1.74	**	1.74	**
occind	1.21	*	1.09	*	1.23	**	1.18	**
occserv	1.75	**	1.43	**	1.35	**	1.42	**
occtech	1.06		0.84	**	1.04		1.19	**
occtran	1.94	*	1.3	**	1.21		1.35	**
reg.ur	0.95	**	0.97	**	0.96	**	0.95	**
ageg30–39:reg.ur	1.01		1.01		1.02	**	1.02	**
ageg40–49:reg.ur	1		1.01	*	1.04	**	1.02	**
edusec:reg.ur	1.05	**	1.01		1.01		1.01	
eduvoc:reg.ur	1.01		1.01		0.99		1.01	
eduhigh:reg.ur	1.03		1.03	**	1.02	**	1.03	**
occcler:reg.ur	0.99		1		1		0.98	**
occcom:reg.ur	1.02		1.02	**	1.01		1	
occheal:reg.ur	1.06	**	1.01	*	1.01		0.98	**
occhum:reg.ur	1.01		1.05	**	1.01		0.97	**
occind:reg.ur	1		1		1		0.99	
occserv:reg.ur	1.04	**	1.01		1.02		0.99	*
occtech:reg.ur	1		1.03	*	1.01		0.97	**
occtran:reg.ur	1.07		1.01		1.03		1.03	

Table 5: Hazard ratios of the interaction models for women (* = p < 0.05, ** = p < 0.01).

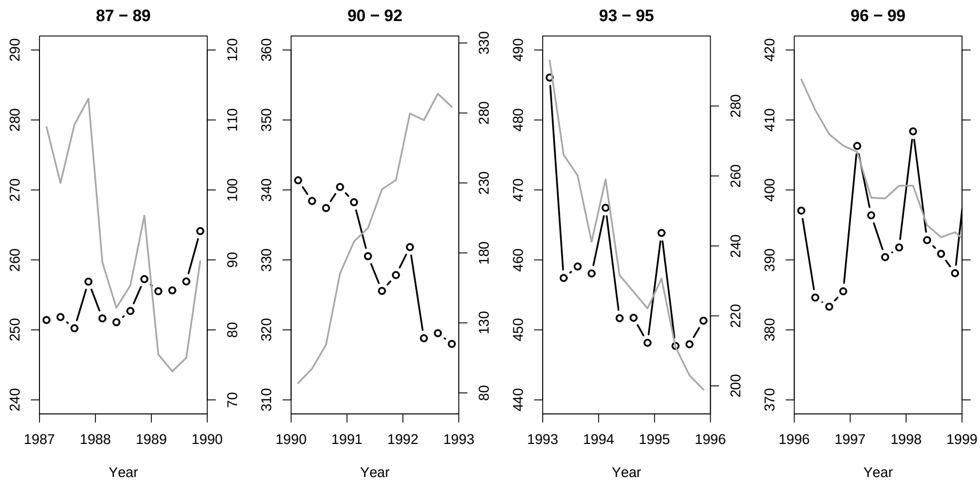

Figure 12: Compositional influence on unemployment duration (black line) and observed duration (gray line). The left axis shows the predicted duration in days and the right axis shows the observed average duration of inflow.

textbooks, the expression for the expectation is derived in Appendix C. Using the obtained result, it is straightforward to construct a function for calculating predictions.

at 10% level and the annual and seasonal dummies are kept on the baseline level. The average duration for genders are weighted with their relative shares in the periods. Separate figures are drawn for the periods because of illustrative reasons. The predicted values have large discontinuities between periods. The technical explanation is that the values present explained variation around the mean of every period. The expected values conditional on a subset of variables may have the opposite trend to observed values as the average durations are heavily affected by the other sources of variation as well. In addition, the scales are set different for the predicted and observed durations to make the figures more informative. The values diverge mainly because the observed duration spells do not necessarily end with employment and, therefore, the mean is a downward biased estimator of the true average. Also the share of censored spells varies between the periods (see Tables 6 and 7, p. 48–49), which also makes the comparison of periods harder.

In the first period from 1987 to 1989, the predicted values have an upward trend. This means that the quality[20] of those becoming unemployed becomes lower during the period. This is the opposite what the observed durations show. The commitment to offer subsidized jobs for long-term unemployed affects negatively the observed duration. It seems that the compositional changes explain some of the seasonal variation. For this period, the observed durations show peaks for the people entering unemployment at the end of the year which is partly captured by predictions.

The second period 1990–1992 is the time of a huge increase in the unemployment durations. Therefore, the scale is five time bigger for the observed values. Again, the trend of the predicted values is different. Now the quality of new unemployed becomes better. This supports the hypothesis that layoffs during the recession focus more randomly on the employed which causes more qualified workers to enter unemployment. Now the individuals entering unemployment in the first period seem to have worse characteristics.

In 1993–1995, the predicted values have the same trend as the observed values. The scale is now double for the observed values. Thus, the quality of new unemployed still becomes better. The explained seasonal variation peaks clearly at the first quarter and it explains the observed variation quite well (keeping in mind the different scales).

The last period from 1996 to 1999 has only a slight positive trend in the predicted values. This is in line with the first period where the same pattern is seen. The observed duration has a double scale and it declines. The seasonal variation dominates and individuals entering unemployment in the first quarter still have the worst characteristics.

Figure 13 presents the effect of unemployment rate on duration. Expected values are calculated for an average person in each sample conditional on the national unemployment rate. The unemployment rate is held constant during the spell which over-predicts the duration in a recession and under-predicts it in a boom[21]. The axis for the observed values is moved but not scaled. It is seen that the model predicts the trends quite well except for the second period. Only a moderate rising trend is seen for 1990–1992. Since the compositional variation has a larger effect in 1993–1995, the unemployment effect has a steeper trend than the observed values at that time. In the last period the predicted values have a right trend but they are dominated by seasonal variation. Thus, a seasonally adjusted unemployment rate would probably improve results, at least for this period.

The residual calendar-time variation of unemployment duration is shown in Figure 14. Here the expected values are calculated conditional on annual and seasonal dummies. The seasonal dummies are kept constant during the spell, which over-predicts their effect. The trend line of predictions shows that in the first and the third period the contribution

[20]Here quality refers to the average composition of unemployed individuals in the sense of their possibilities to find a job. Obviously, the purpose is not to make an ethical judgment.

[21]This is done for simplicity since it is easier to calculate the expected values for constant covariates. Rosholm (2001) follows the same strategy.

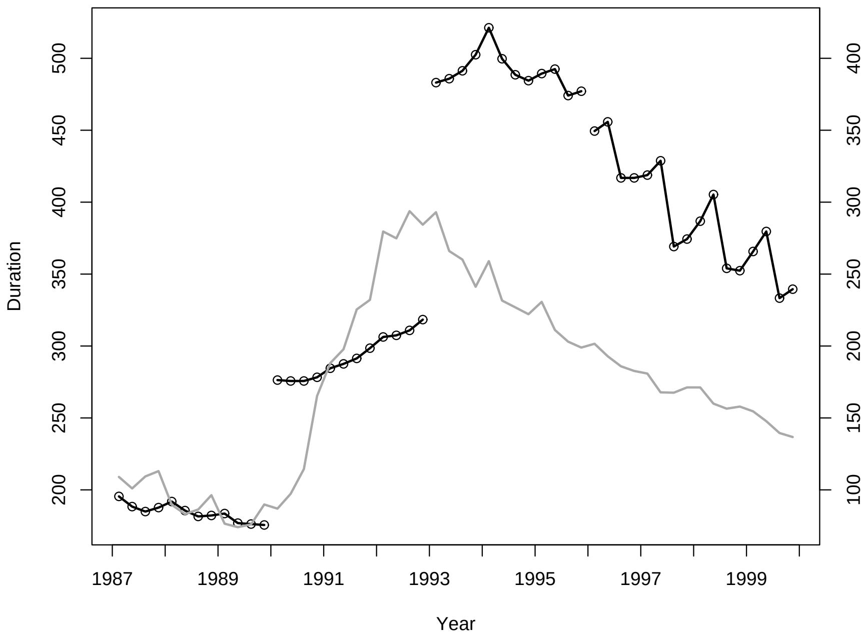

Figure 13: Effect of aggregate unemployment on duration (black line) and the observed duration (gray line). The left axis is duration in days for predicted values, the right is for observed values.

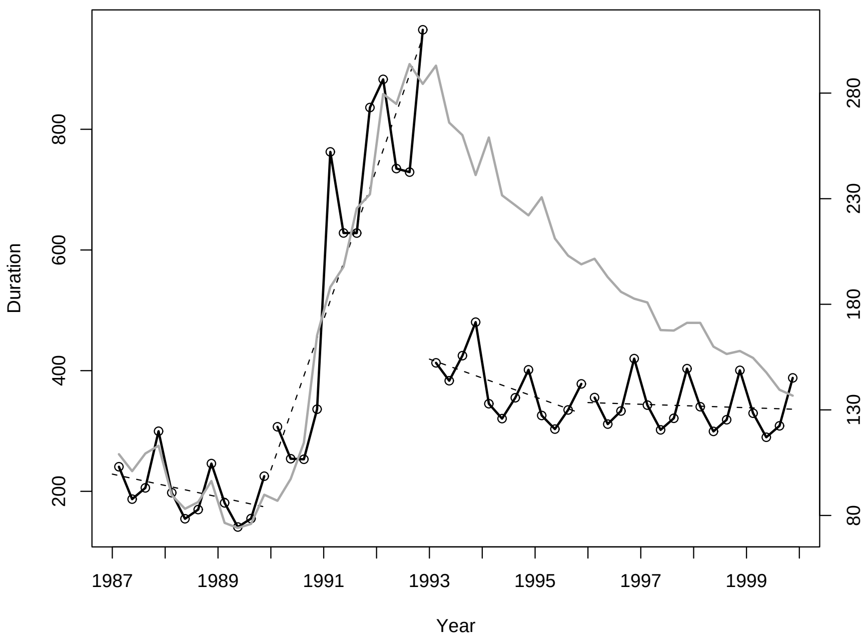

Figure 14: Residual effects on unemployment duration (black line), trend of predicted values (dotted line) and observed duration (gray line). The left axis is duration in days for predicted values, the right is for observed values.

is moderate and in the last period it is none-existent. However, the big increase during the recession is captured nearly completely by residual effects. The observed variation is presented on a heavily transformed scale.

5.5 Model with unobserved heterogeneity

In order to study the effect of unobserved heterogeneity on duration dependence, the model is extended to allow for shared gamma heterogeneity. Generally, there is no theoretical justification why heterogeneity would be gamma distributed. Usually, it is chosen for computational reasons. However, Abbring & van den Berg (2003) show that, in fact, a large class heterogeneity distributions converge to the gamma distribution.

When gamma heterogeneity is included in the basic model, the obtained results do not seem to be robust. Therefore, several different estimation experiments are conducted. One obvious limitation in the data is that 38–54%, depending on the group, of the individuals experience only a single unemployment spell in the periods (see Figure 17, p. 52). The number of spells per person is important since it provides the identification of shared frailty term in practice[22]. The number of spells increases at the end of the 1990s. Therefore, a model is estimated for the years 1994–1999 to increase the number of multiple spells. In this period, the baseline hazard and the effect of covariates are quite similar.

Since the objective of analysis is no longer to compare different periods, it is possible to extend the analysis and include new covariates to describe the labor market histories of individuals. The purpose is to control as large part of observed heterogeneity as possible. An indicator for the length of previous unemployment is added as well as a variable describing previous state before unemployment (see Appendix B). These all turn out to be significant covariates and they also decrease the influence of the other covariates (see Table 14, p. 64).

The mixed model is very computation intensive. To be able to estimate the model, random samples of 15 000 individuals are analyzed, i.e. over 40 000 spells for both genders. The estimation is done using penalized regression which allows, for example, an exact gamma mixture and approximative lognormal mixture distributions (Therneau 1999). A more general method is to use EM-algorithm but it is slow and not available in software packages.

Figure 15 presents the baseline hazards of model with and without shared gamma heterogeneity for men and women. To study the robustness of the results, the models are estimated using five different random samples. As expected, the model without mixture term gives nearly identical results for different samples. Thus, only the results of the first sample are shown. As in Section 5.2, including more variables, describing labor market history, affects only little duration dependence.

When gamma heterogeneity is allowed, the shape of hazard changes notably. Unfortunately, the results are quite different between samples. In some samples, negative duration dependence disappears almost completely whereas in other samples it disappears only for short durations. The reason affecting this is that the estimated variance of gamma heterogeneity distribution varies from 0.5 to 2 for both men and women.

Hence, it seems that the analysis of longer time period does not give more robust results. A possible explanation is that there are too many parameters in the model even the sample size is very large. In order to find a solution, the number of parameters is reduced. A small model with only 6 intervals for the baseline hazard and no individual covariates together with several larger models was tested. These experiments did not provide better results. It is possible that gamma heterogeneity assumption is not suitable for this data. Next natural step would be to test how a non-parametric mass point distribution would work. Because of estimation technical reasons, discussed in Section 4.6, it remains to be studied later.

[22]In the ideal situation there would be no censoring and every individual would experience at least two spells. Of course, in the case of unemployment data this is not a very likely scenario. There are individuals who do not find a job during the follow-up and, therefore, experience only one censored spell.

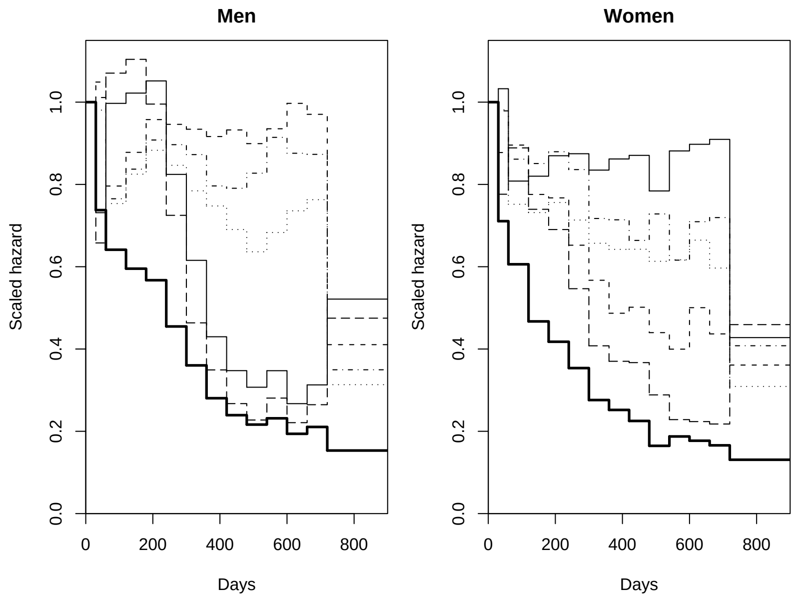

Figure 15: Scaled baseline hazards of gamma mixture models for men and women. The bold line stands for the model without a mixture term. The 5 thin lines stand for the results of the mixed model on different samples.

It is not possible to conclude on the basis of this analysis what is the true duration dependence. Allowing for gamma heterogeneity seems to remove at least some of the duration dependence. On the other hand, removing variables that describe the observed heterogeneity indicates{ a less dramatic change in the shape of hazard. Therefore, it is likely that there exists true negative duration dependence. At least a pattern of positive duration dependence, as reported by Rosholm (2001) for Denmark, seems to be ruled out.

6 Conclusions

This is the first study on Finnish data where the variation in unemployment duration and the business cycle is examined explicitly. None of the previous studies has analyzed individual unemployment durations taking into account the asymmetric effects, macroeconomic conditions and seasonal variation. In addition, the changes in the effects of covariates and duration dependence over time are assessed, and the compositional effects of cyclical variations in the inflow to unemployment and the outflow effects are identified using Rosholm's (2001) innovative approach.

The descriptive analysis indicated that it is not possible to analyze the whole time period using a proportional hazard model because otherwise the proportionality assumption is violated. Therefore, eight separate models are estimated for genders and for the unemployment spells starting in the following time periods: 1987–1989, 1990–1992, 1993–1995 and 1996–1999. The differences in the parameter estimates between years are evident. The shapes of the hazard rates change and the relative positions of different groups vary. This is probably due to the large structural change in the economy which took place during the recession in the beginning of the 1990s. In addition, the share of people participating in active labor market programs has varied. Thus, there seems to be a strong indication of asymmetric effects which should be taken into account in future empirical work as well.

Some interesting changes in the individual parameters are observed. Age has a negative effect but older people seem to have a relatively better position when the unemployment rate is higher. Thus, unemployed young people are more vulnerable to the business cycle variation. This is possibly explained by their lack of work experience. This finding is more evident for men than for women. There is a quite large increase in the positive effect of higher education during the period. This is explained by a larger relative rise in the number of unemployment spells for the people with higher education than for the people with basic schooling. At the same time, their unemployment durations increase less. This is true for women especially.

Based on the analysis, there is strong negative duration dependence. After the period 1987–1989 the hazard rate drops more quickly to a lower level. This is in line with the previous Finnish studies which, however, have analyzed only shorter time periods. When the model is estimated without the individual covariates, duration dependence changes only little. This suggests that the negative bias caused by the neglected heterogeneity is not very large. Higher unemployment rate does not affect the shape of the hazard. Thus, there is an evidence against the ranking hypothesis.

However, it should be noted that the above results on duration dependence are obtained without allowing for unobserved heterogeneity in the model. A mixed proportional hazard model with gamma heterogeneity was estimated but the results were not robust. Further work is needed to obtain reliable estimates. As discussed in Section 2.4, the evidence is mixed in other studies that take unobserved heterogeneity into account.

Since the time period is analyzed in four parts, the results of decomposition analysis are not as easy to interpret as in Rosholm's study. He did not find any asymmetric effects for the Danish data covering the period 1981–1990. Nonetheless, according to the analysis there seems to be a notable compositional variation. This is in line with Rosholm's results but also unimportant inflow effects has been found (van den Berg & van den Klaauw 2001). During the recession, the characteristics of those becoming unemployed becomes better. Thus, the result suggests that workers were laid off more randomly during the recession than during the time of good economic development. This is the opposite to Rosholm's result and what is generally expected. However, considering the severity of the economic crises in the early 1990s, the explanation is quite plausible. It should also be mentioned that, interestingly, the inflow effect explains some of the seasonal variation in the observed unemployment duration.

The business cycle indicator explains the variations in the trends of observed unemployment quite well for all the periods except 1990–1992. During that time, the observed unemployment duration experienced a huge increase. The change is captured almost entirely by the residual calendar-time effects. On the other periods, the contribution of the annual and seasonal variables is reasonably small. For some reason, the unemployment rate captures a part of the seasonal variation in the last period. Therefore, the seasonally adjusted unemployment rate might be more suitable for the analysis.

In future research it would be interesting to study models with unobserved heterogeneity more rigorously. The dataset used in this study is very good for this purpose. It has a large sample size and a long time period. Hence, it includes many people with multiple unemployment spells. In addition to gamma mixtures, non-parametric mixture distributions could be studied.

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A Derivation of search model

Mortensen's (1986) presentation of search model starts from a discrete time optimal stopping problem. Let the time interval be presented by a sequence of periods with length h. On each period, a worker receives a random number n of wage offers. The number of offers is drawn from distribution $q(n,h)$. The received offers are compared and, naturally, only the highest offer is considered. Denote the cumulative distribution of wage offers by $F(\cdot)$ and the cumulative distribution of the highest offer $w = \max[w_1, \ldots, w_n]$ by $G(w,n)$.

It is assumed that the worker is risk neutral and lives forever. Since the wage offers arrive randomly, the knowledge of market is imperfect. Therefore, time is spent on searching which gives rise to market frictions. As the environment is assumed to be stationary, Bellman's principle can be applied to solve the optimization problem.

Let $W(w)$ represent the present value of stopping which means accepting the best wage offer received on the current period. Denote the expected value of searching during the next period by $V(\Omega)$. The information set is constant over time, i.e. $\Omega(t) = \Omega(t+h)$, meaning that the sequence of offers is assumed to be identically and independently distributed and the worker does not learn anything.

Searching is continued until a wage offer w is received such that $W(w) \geq V$. Thus, the offer must be higher than the expected value of continued search. In a stationary environment, a unique value w^* exists for which $W(w^*) = V$. This value is called the reservation wage, and it is optimal to stop searching when an offer $w \geq w^*$ is received.

The Bellman equation of the maximization problem is

$$V = bh + \beta(h)\left[\sum_{n=0}^{\infty} g(n,h)\int_0^{\infty} \max[V, W(x)]dG(x|n)\right], \tag{7}$$

where b is the outside option[23] and $\beta(h)$ is the discount rate function. To obtain an analytical solution, the functional forms must be specified. A natural assumption is that the number of job offers follows a Poisson process, which means that the offers arrive independently with a constant rate λ. With period length h, the probability function of receiving n offers is $g(n,h) = e^{-\lambda h}(\lambda h)^n/n!$. The discount rate r is assumed to be constant over time, i.e. $\beta(h) = e^{-rh}$.

Subtracting $\beta(h)V$ from both sides of Equation 7 and dividing it by h gives:

$$\frac{(1-\beta(h))}{h}V = b + \beta(h)\left[\sum_{n=0}^{\infty}\frac{g(n,h)}{h}\int_0^{\infty}\max[V, W(x)]dG(x|n) - \frac{V}{h}\right].$$

To obtain the continuous time analogue of the result, the limit $h \to 0$ is taken. Applying l'Hôpital's rule, the left side becomes:

$$\lim_{h\to 0}\left[\frac{1-e^{-rh}}{h}\right]V = \lim_{h\to 0}\frac{re^{-rh}}{1}V = rV.$$

Next it is assumed that the limit exists for $\beta(h)$ and for the sum expression. The former limit is $\lim_{h\to 0}\beta(h) = \lim_{h\to 0} e^{-rh} = 1$ and the latter can be decomposed as follows:

$$\begin{aligned} & \lim_{h\to 0} \quad \sum_{n=0}^{\infty}\frac{g(n,h)}{h}\int_0^{\infty}\max[V, W(x)]dG(x|n) - \sum_{n=0}^{\infty}\frac{g(n,h)}{h}V \\ = & \lim_{h\to 0} \quad \left\{\frac{g(0,h)}{h}\int_0^{\infty}\max[0, W(x)-V]dG(x|0) + \right. \end{aligned}$$

[23]Mortensen (1986) separates the value of not working and the cost of searching. The results are otherwise equivalent but the formulation of participation constraint becomes slightly simpler.

$$\frac{g(1,h)}{h}\int_0^\infty \max[0,W(x)-V]dG(x|1)+$$
$$\left.\sum_{n=2}^\infty \frac{g(n,h)}{h}\int_0^\infty \max[0,W(x)-V]dG(x|n)\right\}.$$

In the no offer case $n=0$, $\max[0,W(x)-V]=0$. Further, the Poisson specification results

$$\lim_{h\to 0} e^{-\lambda h}\frac{(\lambda h)^n}{hn!}=\frac{\lambda^n}{n!}\lim_{h\to 0} e^{-\lambda h}h^{n-1}=\begin{cases}\lambda, & \text{if } n=1\\ 0 & \text{if } \geq 2.\end{cases}$$

Now combining the obtained results gives:

$$rV=-b+\lambda\int_0^\infty \max[0,W(x)-V]dF(x)$$

The equation can be interpreted so that the "income" of searching equals to the outside option and the expected present value of difference between a wage offer and stopping the search.

The present value of future earnings when wage x is accepted is $W(x)=\int_0^\infty xe^{-rh}dh = x/r$. Then using the definition of the reservation wage $w^*=rV$ gives:

$$w^*-b=\lambda\left\{\int_0^{w^*}\max\left[0,\frac{x}{r}-\frac{w^*}{r}\right]dF(x)+\int_{w^*}^\infty \max\left[0,\frac{x}{r}-\frac{w^*}{r}\right]dF(x)\right\},$$

which simplifies to Equation 1 because the first integral equals zero.

Comparative statistics

To ease the derivation, manipulate Equation 1 and define an implicit function $\Phi(w^*,b,r,\lambda_j)=0$, such that

$$\Phi(w^*,b,r,\lambda_j)\equiv w^*-b-\frac{\lambda_j}{r}\left\{\int_{w^*}^\infty [x-w^*]\,dF(x)\right\}.$$

Next, the following partial derivatives are calculated: Φ_{w^*}, Φ_b and Φ_{λ_j}.

$$\begin{aligned}\Phi_{w^*} &= 1-\tfrac{\lambda_j}{r}\tfrac{\partial}{\partial w^*}\left\{\textstyle\int_{w^*}^\infty [x-w^*]\,dF(x)\right\}\\ &= 1-\tfrac{\lambda_j}{r}\textstyle\int_{w^*}^\infty -1dF(x)\\ &= 1+\tfrac{\lambda_j}{r}[1-F(w^*)]>0,\end{aligned}$$

where the second line is obtained by Leibniz' rule. The effect of the outside option is simply $\Phi_b=-1<0$ and the effect of the job offer rate is

$$\Phi_{\lambda_j}=-\frac{1}{r}\left\{\int_{w^*}^\infty [x-w^*]\,dF(x)\right\}<0.$$

Thus, it follows that $\partial w^*/\partial b=-\Phi_b/\Phi_{w^*}>0$ and $\partial w^*/\partial\lambda_j=-\Phi_{\lambda_j}/\Phi_{w^*}>0$. As expected, the reservation wage rises as the outside option or the job offer rate increase.

The outside option has only a negative indirect effect on the escape rate from unemployment

$$\frac{\partial\phi}{\partial b}=-\lambda_j f(w^*)\frac{\partial w^*}{\partial b}<0.$$

The job offer rate has a positive direct effect and a negative indirect effect. Hence, the overall effect remains ambiguous

$$\frac{\partial\phi}{\partial\lambda_j}=[1-F(w^*)]-\lambda_j f(w^*)\frac{\partial w^*}{\partial\lambda_j}.$$

B Construction of dataset and variables

The dataset provided by Statistics Finland is originally in a form of yearly panel data. It has 350 000 rows each representing one individual. The yearly collected variables are bound together as columns, and the last two characters of variables' names denote the corresponding year.

The key variables describing four unemployment spells for each year are $tyalk1, \ldots, tyalk4$ and $tylop1, \ldots, tylop4$ and $tjpsy1, \ldots, tjpsy4$ which give the start date, the end date and the new state, respectively. The variable giving the last spell of the year is also used but it rarely gives additional information. The dates in the data are character strings in the form 'yymmdd' standing for year, month and day. For some variables, the character strings are corrupted but practically all of the problems can be fixed using simple routines.

A more problematic aspect of the data is that is that approximately 6% of the end dates of the spells and 18% of the new states are missing. Hopefully, the information is missing randomly in which case the unknown end dates could be simply removed. However, the missing new states are not harmless as censoring at the time of event (i.e. employment) causes bias to the hazard estimate. Further, the proportion of missing states is quite large. In addition, some of the existing information is encoded as 'other reason' meaning practically missing information.

In the dataset, there is some information about periods of active labor market programs (ALMP) and employment for each year. There are also variables describing the activity at the end of each year ($ptoim1$, $tyok1$). These variables are used first to find the end date for spells and then to infer the new state.

Finding end dates and missing states

The ALMP and work periods are matched to start dates if they begin before the next unemployment spell. The ALMP periods are preferred to the work periods because they include more reliable information[24]. Some of the work periods have only the starting month recorded. These were set to start in the 15th day of month. If the obtained end dates are further than 365 days from the start date of the spells, the information is considered too uncertain.

For the remaining cases, the end state of year information is used in the following way. It is traced how many subsequent years a person is defined as unemployed taking into account information on the next unemployment spell. The spells are censored at the end of the year unemployment is still known to continue. For example, if a person remains unemployed at the end of second year but is out of labor force at the end of third year, the spell is censored at the end of second year because the exact date of moving out of labor force is not known. All these censored spells are restricted to be at most three years long since it is the maximum duration in the models.

After the end dates are set there is a large number of spells without new state information. The missing new states are simply fixed by matching first the ALMP periods and then the work periods to the end dates using within two weeks criteria. In addition, the work periods are also matched if the period starts in the same month. This is done to take into account different practices used in employment contracts. Using these procedures the proportion of missing states is reduced to 6% and the proportion of missing end dates is reduced to 1%.

[24]Work periods come from the registers of pension institutes. Originally the information is provided by employers and it is subject to inconsistent recording procedures.

Refining spells

Generally, the data on unemployment spells is messy. The same unemployment spell often has multiple records. This results in a number of contradictions in the data which must be removed. Typical examples are overlapping spells and altering end or start dates. Firstly, the spells with no end date after the applying the preceding procedures, the spells with not positive duration and the spells within another spells are removed. Then the overlapping spells and the spells within 20 days are joined. It is often used practice to combine spells close to each other because most of these breaks originate from administrative reasons.

Individual specific variables

age Age in years at the beginning of unemployment. Classified to 3 groups: 21–30, 31–40, 41–50.

edu The highest degree earned at the time unemployment starts according to Statistics Finland classification. Classified to 4 groups: base (comprehensive school), yo (secondary school) and vocational education and higher degree.

occ Occupational classification according to the labor administration, see the table below.

famt Type of the family: other (single or unmarried couple), married couple with children, married couple, unmarried couple with children or single parent.

lang Native language: Finnish, Swedish or other.

urb Classification of the living municipality: city, densely populated area or countryside.

dis Indicator whether a person is defined mentally or physically disabled by the labor administration. The 1997 data is used for the period of missing 1998–1999 information.

Class	Description of occupation classification
other	Unclassified work together with agriculture and forestry, also students.
cler	Administrative, clerical and ADP work.
com	Commercial workers like advertising people and sales clerks.
heal	Health sector and social workers.
hum	Humanistic workers and other academics and artists.
ind	Construction, industrial and graphical industry workers. E.g. mining, construction, textile work, metalwork, mechanical, electricity, wood, printing, ceramic, warehouse work, food, chemical and paper industry.
serv	Service workers like firemen, policemen, security guards, military workers, restaurant and hotel workers, etc.
tech	Technical and biology related workers, like engineers, biologists, farming and forest advisers or researchers.
tran	Transition work which includes also mailing services.

	1987–1989	1990–1992	1993–1995	1996–1999
Duration (mean)	93.90	241.10	249.20	177.50
Employed %	69.40	37.30	48.20	51.60
Age 20–29 %	48.60	44.30	44.80	43.60
Age 30–39 %	31.60	31.00	29.60	29.40
Age 40–49 %	19.80	24.70	25.60	27.10
Edu base %	35.40	33.40	28.30	28.60
Edu sec %	5.90	5.90	7.50	8.10
Edu voc %	55.00	54.50	54.50	54.60
Edu high %	3.70	6.10	9.60	8.60
Occ other %	23.00	17.50	18.20	20.60
Occ cler %	2.50	3.50	4.60	4.40
Occ com %	3.40	4.40	4.80	4.10
Occ heal %	0.70	0.90	1.80	2.40
Occ hum %	2.30	2.10	2.60	2.90
Occ ind %	53.80	55.00	48.70	48.30
Occ serv %	3.20	3.40	4.20	5.20
Occ tech %	4.60	7.10	9.10	6.80
Occ tran %	6.40	6.20	5.90	5.30
Famt single %	36.50	38.00	37.40	44.80
Famt mar %	4.20	4.60	5.10	4.40
Famt mar.par %	42.30	43.00	43.60	35.50
Famt unmar.par %	4.70	5.60	6.10	7.10
Famt single.par %	12.40	8.70	7.90	8.30
Lang finnish %	97.50	95.80	94.30	94.00
Lang swedish %	2.00	2.80	3.30	2.70
Lang other %	0.50	1.40	2.30	3.30
Urb city %	52.30	54.40	55.60	58.00
Urb suburb %	14.70	15.90	16.20	16.60
Urb country %	32.90	29.70	28.20	25.40
Dis %	5.50	4.30	3.70	4.50
N persons	17806	20651	14179	10421
N spells	33789	63401	72950	79013

Table 6: Descriptive statistics for men.

Calendar-time and time-dependent variables

quarter Quarter of year. Included as a time-dependent covariate.

year Starting year of unemployment.

reg.ur Regional unemployment rate in percentages by labor force district according to the Statistics Finland classification. It has 13 regions which have changed slightly during the years. In the models the unemployment rate is included as a difference from the average rate in the period 1987–1999 which is 10%.

The time series of regional unemployment rates are shown in Figure 16. The definition of the unemployment changed in 1997 because of the adoption of the EU standards. The series by the old definition is for the period 1987–1996 and by the new definition for the period 1995–2001. The overlapping period was used to adjust the unemployment rate from 1987 to 1994. The adjustment was done using a linear model (R-squared 0.97).

	1987–1989	1990–1992	1993–1995	1996–1999
Duration (mean)	90.00	198.70	220.80	159.40
Employed %	68.00	38.80	41.80	44.40
Age 20–29 %	51.80	45.20	44.10	40.70
Age 30–39 %	29.50	30.70	30.70	31.80
Age 40–49 %	18.70	24.10	25.30	27.50
Edu base %	29.60	30.10	22.30	19.40
Edu sec %	8.90	8.00	8.40	8.30
Edu voc %	57.00	54.20	53.90	54.80
Edu high %	4.60	7.70	15.50	17.40
Occ other %	22.80	17.50	15.70	15.20
Occ cler %	15.10	18.50	18.10	16.20
Occ com %	7.00	8.30	8.10	7.40
Occ heal %	13.90	15.20	22.20	25.10
Occ hum %	4.90	5.40	7.00	7.20
Occ ind %	12.10	12.10	9.00	9.20
Occ serv %	21.80	19.60	16.30	16.70
Occ tech %	1.50	2.50	2.70	2.30
Occ tran %	0.90	0.90	0.80	0.70
Famt single %	24.70	31.70	32.50	34.60
Famt mar %	6.80	7.00	7.60	7.00
Famt mar.par %	47.70	42.60	42.30	37.80
Famt unmar.par %	4.80	5.30	5.60	7.10
Famt single.par %	16.10	13.30	12.10	13.60
Lang finnish %	97.30	95.60	94.40	93.90
Lang swedish %	2.10	2.80	3.50	3.00
Lang other %	0.60	1.60	2.10	3.10
Urb city %	55.20	57.90	59.80	61.20
Urb suburb %	15.90	15.90	15.80	16.50
Urb country %	28.90	26.20	24.30	22.30
Dis %	7.20	7.10	5.20	5.90
N persons	16389	16354	15331	11447
N spells	28126	44436	65663	84296

Table 7: Descriptive statistics for women.

Labor market history variables

These variables are used only in the analysis presented in Section 5.5. The previous state variables are not complete due to limitations in data. The data includes only work periods defined by variables *ptoim*1, *tyok*1 and one ALMP period of each type for every year.

l.hist Indicator whether an individual has been unemployed more than 6 months during the last 12 months. This describes a long previous unemployment.

s.hist Indicator whether and individual has been unemployed less than 14 days during last 3 months. This describes a frequent but short unemployment. The variable is not correlated with l.hist.

p.wrk Indicator for exit from a work within last 2 months.

p.edu Indicator for exit from an ALMP education within last 2 months.

p.sij Indicator for exit from an ALMP job within last 2 months.

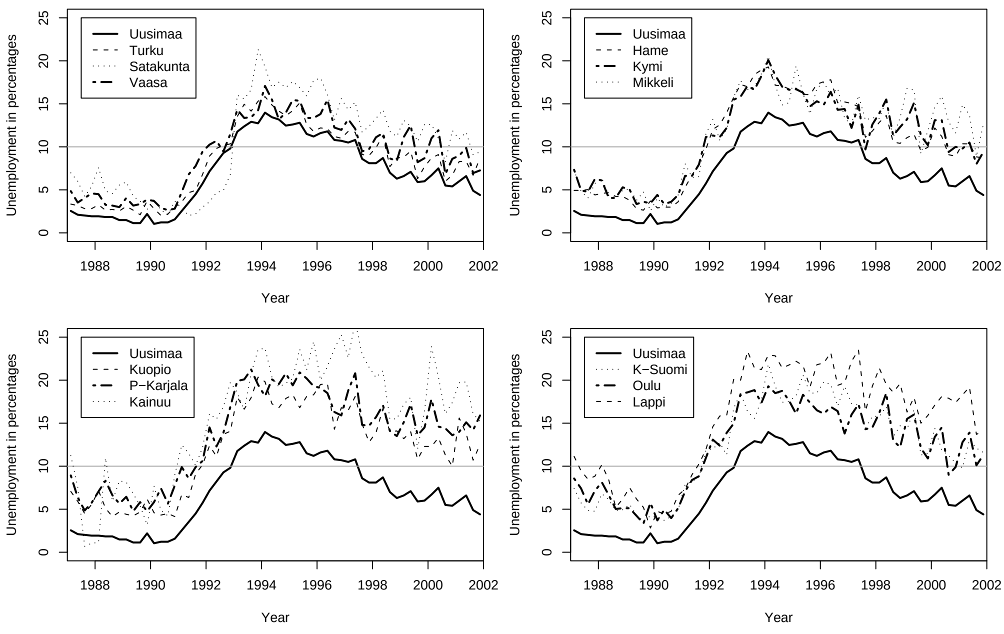

Figure 16: Regional unemployment rates.

C Some details of duration model

Weibull model

The Weibull model with covariates is $\lambda(t) = \alpha t^{\alpha-1}\exp(x'\beta)$. Denote $\mu = \exp(x\beta)$ to simplify notation. The survivor function is obtained from the relation 3

$$S(t) = \exp(-\int_0^t \alpha s^{\alpha-1}\mu ds) = \exp(-\mu t^{\alpha}).$$

Equation 2 gives the density function of Weibull model

$$f(t) = \mu\alpha t^{\alpha-1}\exp(-\mu t^{\alpha}).$$

Next it is shown how the Weibull model can be estimated in the framework of accelerated failure time models. Take a following monotonic transformation of random variable $S = \mu T^{\alpha}$. Thus, it gives

$$\left|\frac{dt}{ds}\right| = \frac{1}{\mu\alpha}\left(\frac{s}{\mu}\right)^{\frac{1}{\alpha}-1}$$

and the density function becomes

$$\begin{aligned} f_S(s) &= f_T(t(s))\left|\tfrac{dt}{ds}\right| \\ &= \left(\tfrac{s}{\mu}\right)^{\frac{\alpha-1}{\alpha}}\left(\tfrac{s}{\mu}\right)^{\frac{1-\alpha}{\alpha}}\exp\left(-\mu\left[\left(\tfrac{s}{\mu}\right)^{1/\alpha}\right]^{\alpha}\right), \\ &= \exp(-s) \end{aligned}$$

which is the density function of the unit exponential distribution. Consequently, $\log s$ has the type I extreme value distribution[25], i.e. $\log\mu t^{\alpha} \sim \varepsilon$. This gives an accelerated failure time model

$$\log t = -\frac{x'\beta}{\alpha} + \frac{\varepsilon}{\alpha}.$$

[25] This is seen by taking another transformation of random variable. Let $R = \log S$. Hence, $f_R(r) = f_S(\exp(r))\,|\exp(r)| = \exp(r - \exp(r))$ which is the type I smallest extreme value distribution with location 0 and scale 1.

Expected duration of unemployment

It is relatively straightforward to compute the expected duration in a piecewise constant hazard rate model. However, the piecewise constant model is not presented in standard textbooks. Therefore, the predicted values are derived here following Rosholm's (2001) presentation.

Consider a proportional hazard model with piecewise constant hazard $\lambda(t) = \lambda_m \exp(x'\beta)$ where $m = 1, \ldots, M$ and the related splitting times are $\theta_0, \ldots, \theta_M$. The cumulative hazard function up to i'th interval is defined

$$\Lambda_i = \int_0^{\theta_i} \lambda(t)dt = \sum_{m=1}^{i} \int_{\theta_{m-1}}^{\theta_m} \lambda_m \exp(x'\beta)dt.$$

Thus, the covariates enter the cumulative hazard proportionally as in the case of hazard. Hence, it follows that the following notation can be simplified by assuming that there are no covariates.

The expectation of duration can be calculated using the moment generating function

$$M(s) = \int_{-\infty}^{\infty} e^{st} f(t)dt.$$

The first derivative of M, if it exists, evaluated at $s = 0$ gives the expectation. The density function of exponential distribution is easily derived using the relations presented in Section 4.2, $f(t) = \lambda e^{-\lambda t}$. It is useful to note that in a piecewise constant case

$$e^{-\lambda(t)t} = e^{-\int_0^t \lambda(t)ds} = e^{-(\int_0^{\theta_{m-1}} \lambda(t)ds + \int_{\theta_{m-1}}^t \lambda(t)ds)} = e^{-(\Lambda_{m-1}+\lambda_m[t-\theta_{m-1}])},$$

when $\theta_{m-1} \leq t \leq \theta_m$. Now, substituting the piecewise constant $f(t)$ to the moment generating function gives

$$M(s) = \sum_{m=1}^{M} \int_{\theta_{m-1}}^{\theta_m} e^{st} f(t)dt = \sum_{m=1}^{M} \int_{\theta_{m-1}}^{\theta_m} e^{st} \lambda_m e^{-(\Lambda_{m-1}+\lambda_m[t-\theta_{m-1}])}dt.$$

Solving the integral and observing that $\Lambda_i = \Lambda_{i-1} + \lambda_i(\theta_i - \theta_{i-1})$ simplify the expression

$$M(s) = \sum_{m=1}^{M} \frac{\lambda_m}{s - \lambda_m}(e^{s\theta_m - \Lambda_m} - e^{s\theta_{m-1}-\Lambda_{m-1}}).$$

The first derivative of the moment generating function is

$$\begin{aligned} M'(s) \quad = \quad & \textstyle\sum_{m=1}^{M} \frac{-\lambda_m}{(s-\lambda_m)^2}(e^{s\theta_m-\Lambda_m} - e^{s\theta_{m-1}-\Lambda_{m-1}}) + \\ & \textstyle\sum_{m=1}^{M} \frac{\lambda_m}{s-\lambda_m}(\theta_m e^{s\theta_m-\Lambda_m} - \theta_{m-1}e^{s\theta_{m-1}-\Lambda_{m-1}}), \end{aligned}$$

and evaluating it at $s = 0$ gives the expected duration

$$\begin{aligned} E(T) \quad &= \quad \textstyle\sum_{m=1}^{M} \frac{-1}{\lambda_m}(e^{-\Lambda_m} - e^{-\Lambda_{m-1}}) + \sum_{m=1}^{M}(\theta_m e^{-\Lambda_m} - \theta_{m-1}e^{-\Lambda_{m-1}}) \\ &= \quad \textstyle\sum_{m=1}^{M} \frac{1}{\lambda_m}(e^{-\Lambda_{m-1}} - e^{-\Lambda_m}). \end{aligned}$$

The second sum disappears because the terms in the middle cancel and $\theta_0 = 0$ and $S(\infty) = 0$. Using the relation 3 and the definition of survival function gives $e^{-\Lambda_{m-1}} - e^{-\Lambda_m} = S_{m-1} - S_m = \Pr(\theta_m \leq T < \theta_{m-1})$.

Finally, an intuitive result is obtained, namely that the expected duration in a piecewise constant exponential distribution case is the weighted average of the expectations of M pieces

$$E(T) = \sum_{m=1}^{M} \frac{\Pr(\theta_m \leq T < \theta_{m-1})}{\lambda_m}.$$

D Estimation results

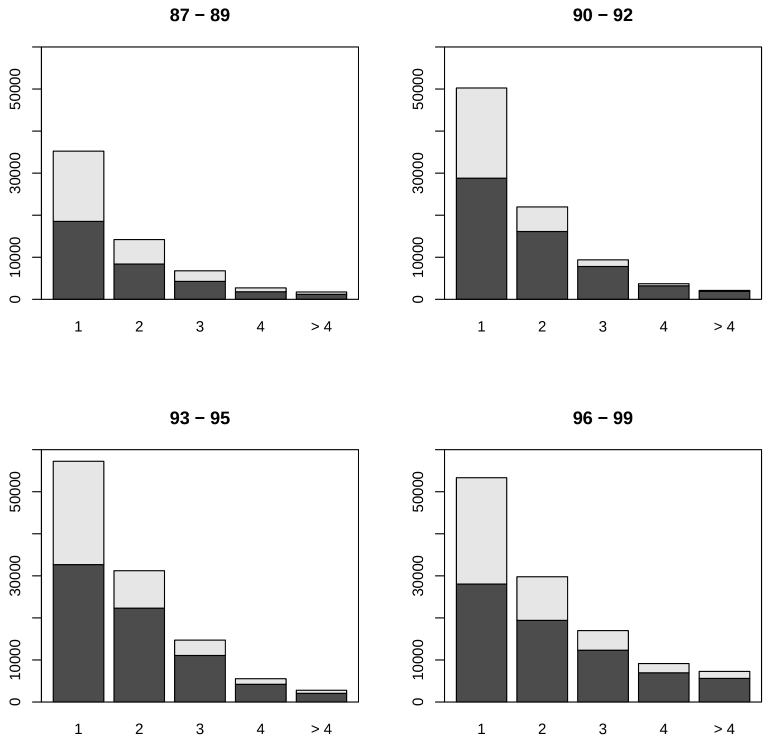

Figure 17: Number of spells on the periods. Dark part of bars stands for spells ending with employment.

Men	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
ageg30–39	0.77	0.80	0.80	0.81	0.76	0.94	1.08	0.99	1.01	1.02	0.95	0.90	0.86
ageg40–49	0.72	0.74	0.73	0.76	0.71	0.83	0.98	0.90	0.92	0.89	0.87	0.82	0.81
edusec	1.31	1.27	1.34	1.47	1.28	1.29	1.06	1.25	1.18	1.16	1.21	1.07	1.13
eduvoc	1.13	1.14	1.23	1.23	1.31	1.23	1.23	1.27	1.25	1.23	1.35	1.38	1.35
eduhigh	0.96	0.95	1.20	1.15	1.42	1.49	1.45	1.65	1.64	1.56	1.67	1.73	1.68
occcler	0.94	0.83	0.83	0.92	0.90	0.99	1.02	0.93	0.84	0.87	0.86	0.85	0.95
occcom	1.03	0.90	0.98	1.03	1.22	1.28	1.24	1.09	0.94	0.95	0.89	0.98	1.08
occheal	1.26	1.05	1.18	1.42	1.96	2.22	2.22	1.67	1.40	1.54	1.23	1.37	1.61
occhum	1.13	1.00	0.79	1.11	1.56	1.48	1.62	1.15	1.22	1.08	1.19	1.04	1.00
occind	1.22	1.29	1.25	1.13	1.06	1.27	1.45	1.39	1.30	1.33	1.41	1.35	1.47
occserv	1.17	1.16	1.04	1.18	1.33	1.30	1.36	1.14	0.98	1.00	1.12	1.12	1.08
occtech	1.15	0.98	1.03	0.92	1.03	1.14	1.19	1.18	1.09	1.14	1.17	1.18	1.26
occtran	1.19	1.26	1.25	1.33	1.48	1.55	1.65	1.49	1.38	1.35	1.38	1.51	1.56
famtmar	1.26	1.37	1.24	1.39	1.40	1.49	1.45	1.38	1.34	1.53	1.46	1.65	1.48
famtmar.par	1.26	1.34	1.26	1.24	1.36	1.40	1.45	1.38	1.38	1.42	1.44	1.48	1.47
famtunmar.par	1.22	1.24	1.13	1.08	1.19	1.13	1.32	1.28	1.31	1.33	1.39	1.49	1.36
famtsingle.par	1.05	1.05	1.04	0.96	0.94	0.89	1.02	0.92	0.95	0.95	1.05	1.00	1.00
langswedish	1.07	1.03	0.79	1.01	1.20	1.29	1.25	1.25	1.24	1.17	1.19	1.17	1.24
langother	0.72	1.03	0.84	0.77	0.73	0.60	0.39	0.46	0.47	0.38	0.40	0.43	0.46
urbsuburb	1.19	1.16	1.03	1.13	1.12	1.25	1.17	1.16	1.18	1.21	1.16	1.14	1.21
urbcountry	1.10	1.16	1.06	1.13	1.11	1.19	1.23	1.14	1.14	1.20	1.13	1.17	1.20
dis	0.59	0.56	0.54	0.52	0.51	0.46	0.39	0.43	0.51	0.52	0.46	0.52	0.59
reg.ur	0.98	0.96	0.97	0.92	1.00	1.03	1.00	0.98	0.98	0.98	0.98	0.98	0.97
quartII	1.60	1.52	1.29	1.41	1.36	1.28	1.16	1.23	1.35	1.33	1.31	1.44	1.28
quartIII	1.23	1.39	1.29	1.39	1.28	1.07	0.86	1.01	0.97	1.01	1.04	1.07	1.01
quartIV	0.72	0.88	0.82	0.59	1.11	0.98	0.75	0.80	0.78	0.76	0.71	0.76	0.73
Women	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
ageg30–39	0.80	0.85	0.86	0.79	0.79	0.77	0.93	0.86	0.90	0.91	0.87	0.91	0.88
ageg40–49	0.87	0.84	0.84	0.75	0.72	0.78	1.04	0.90	0.84	0.89	0.92	0.91	0.85
edusec	1.52	1.47	1.39	1.26	1.43	1.46	1.17	1.37	1.28	1.39	1.32	1.25	1.30
eduvoc	1.27	1.17	1.20	1.22	1.46	1.46	1.26	1.40	1.36	1.41	1.49	1.39	1.49
eduhigh	1.38	1.18	1.14	1.18	2.12	2.03	1.84	1.87	1.72	1.82	2.03	1.85	1.90
occcler	1.27	1.20	1.34	1.24	1.18	1.19	1.41	1.10	1.14	1.11	1.17	1.20	1.22
occcom	1.29	1.33	1.37	1.27	1.33	1.45	1.64	1.20	1.33	1.30	1.32	1.28	1.41
occheal	1.86	1.74	1.73	1.71	1.84	1.99	2.20	1.84	1.79	1.77	1.70	1.72	1.90
occhum	1.14	1.18	1.18	1.20	1.26	1.78	2.22	1.68	1.70	1.64	1.65	1.59	1.68
occind	1.21	1.17	1.30	1.16	0.94	1.16	1.39	1.19	1.05	1.08	1.23	1.16	1.18
occserv	1.41	1.48	1.42	1.37	1.36	1.49	1.78	1.29	1.39	1.34	1.34	1.42	1.42
occtech	1.00	1.02	1.14	0.72	0.71	0.96	1.22	0.99	1.03	1.15	1.01	1.11	1.20
occtran	1.39	1.44	1.22	1.39	1.22	1.20	1.64	1.35	1.16	1.72	1.73	1.04	1.02
famtmar	0.90	0.97	0.92	0.96	1.04	0.95	0.94	1.03	1.02	1.00	1.15	1.20	1.08
famtmar.par	0.84	0.87	0.89	0.97	0.85	0.88	0.88	0.93	0.92	0.92	1.03	1.06	1.00
famtunmar.par	0.59	0.67	0.71	0.73	0.72	0.69	0.73	0.65	0.71	0.78	0.82	0.80	0.81
famtsingle.par	0.78	0.80	0.85	0.81	0.77	0.69	0.70	0.76	0.77	0.76	0.78	0.76	0.74
langswedish	1.12	0.91	0.88	0.85	1.02	1.27	1.20	1.27	1.15	1.17	1.14	1.13	1.13
langother	0.61	0.69	0.71	0.49	0.54	0.44	0.36	0.48	0.44	0.40	0.33	0.40	0.49
urbsuburb	1.03	1.07	1.00	1.10	1.02	1.14	1.03	1.11	1.11	1.14	1.02	1.06	1.13
urbcountry	1.00	1.03	1.01	1.12	1.01	1.11	1.12	1.09	1.13	1.11	1.13	1.06	1.14
dis	0.54	0.55	0.52	0.61	0.56	0.52	0.43	0.50	0.55	0.46	0.51	0.53	0.63
reg.ur	0.97	0.99	0.98	0.93	0.99	1.00	0.99	0.98	0.97	0.97	0.97	0.96	0.95
quartII	1.12	1.11	1.06	1.03	1.02	1.08	0.99	0.95	0.98	1.03	1.08	0.97	0.94
quartIII	0.90	1.02	1.12	1.19	1.11	1.14	0.99	0.99	1.00	1.09	1.11	1.12	1.06
quartIV	0.76	0.78	0.86	0.73	1.03	1.09	0.98	0.95	0.92	1.04	0.93	0.92	0.97

Table 8: Risk ratios of yearly models for men (above) and women (below).

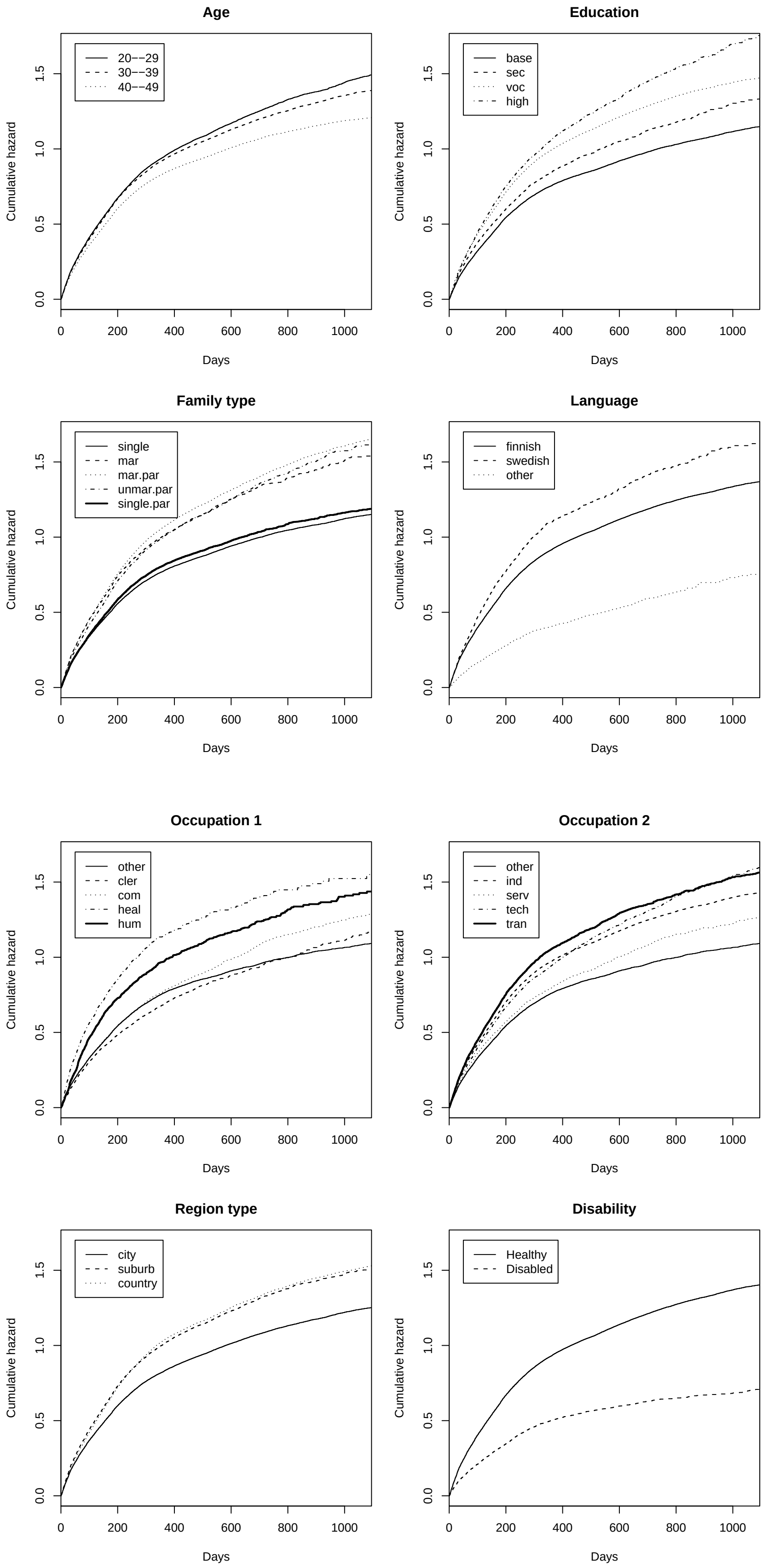

Figure 18: Nelson–Aalen cumulative hazard estimates for men.

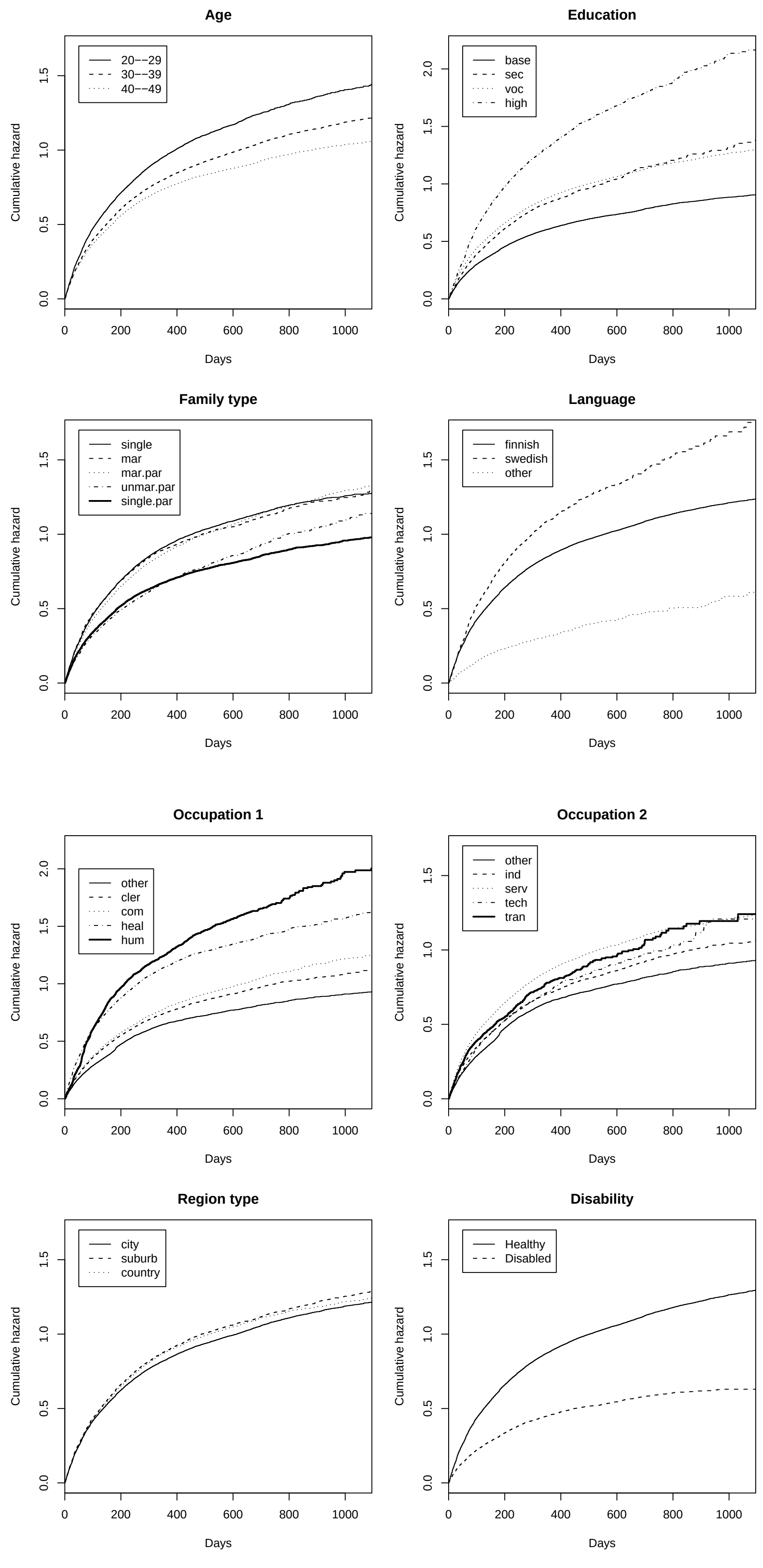

Figure 19: Nelson–Aalen cumulative hazard estimates for women.

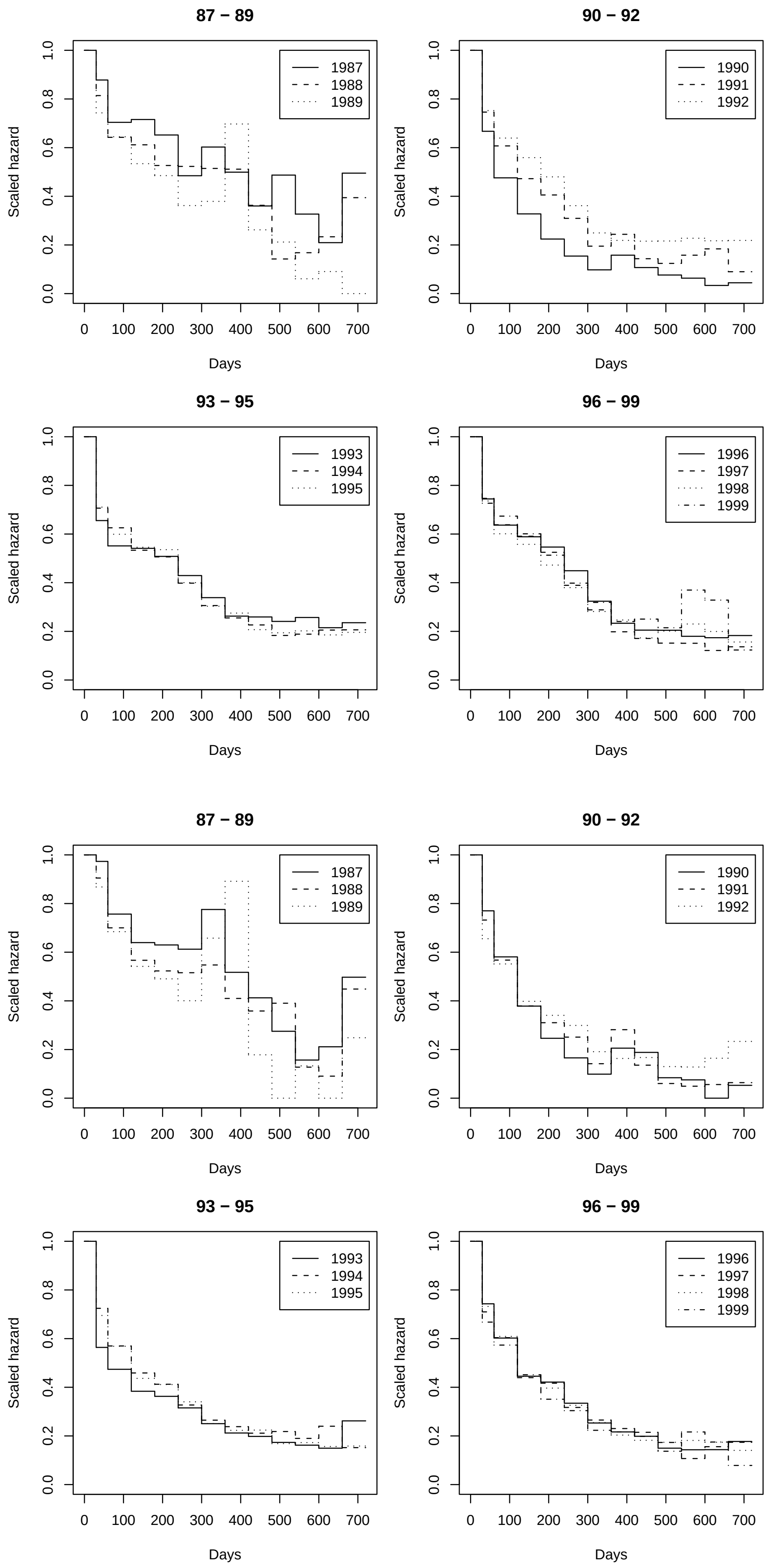

Figure 20: Scaled baseline hazards of the yearly models for men (above) and women (below).

	87–89		90–92		93–95		96–99	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
(Intercept)	−4.974	0.034	−5.293	0.03	−6.016	0.041	−5.563	0.032
piece2	−0.219	0.018	−0.357	0.02	−0.368	0.018	−0.304	0.016
piece3	−0.42	0.018	−0.598	0.019	−0.521	0.016	−0.453	0.014
piece4	−0.484	0.023	−0.834	0.023	−0.612	0.018	−0.539	0.017
piece5	−0.593	0.03	−1.028	0.028	−0.656	0.02	−0.663	0.02
piece6	−0.787	0.042	−1.319	0.034	−0.886	0.024	−0.9	0.024
piece7	−0.69	0.053	−1.723	0.044	−1.144	0.03	−1.192	0.031
piece8	−0.62	0.071	−1.639	0.049	−1.327	0.035	−1.476	0.04
piece9	−1.096	0.113	−1.82	0.062	−1.459	0.041	−1.63	0.048
piece10	−1.108	0.141	−1.855	0.069	−1.575	0.048	−1.656	0.054
piece11	−1.487	0.219	−1.778	0.073	−1.529	0.052	−1.583	0.059
piece12	−1.703	0.302	−1.798	0.08	−1.596	0.06	−1.74	0.072
piece13	−1.097	0.278	−1.951	0.094	−1.542	0.065	−1.833	0.084
piece14	−1.788	0.25	−2.031	0.053	−1.961	0.043	−2.161	0.058
ageg30–39	−0.235	0.015	−0.179	0.016	0.023	0.013	−0.064	0.012
ageg40–49	−0.315	0.018	−0.269	0.017	−0.074	0.014	−0.16	0.013
edusec	0.259	0.032	0.281	0.031	0.161	0.026	0.14	0.024
eduvoc	0.152	0.015	0.229	0.016	0.22	0.013	0.277	0.012
eduhigh	0.036	0.042	0.326	0.035	0.452	0.026	0.5	0.025
occcler	−0.145	0.046	−0.065	0.042	−0.075	0.032	−0.124	0.03
occcom	−0.032	0.04	0.177	0.036	0.084	0.03	−0.03	0.03
occheal	0.154	0.084	0.648	0.065	0.534	0.042	0.359	0.035
occhum	−0.048	0.05	0.324	0.048	0.272	0.038	0.076	0.035
occind	0.229	0.018	0.134	0.021	0.323	0.018	0.325	0.017
occserv	0.11	0.041	0.22	0.04	0.133	0.032	0.075	0.027
occtech	0.05	0.037	0.032	0.036	0.15	0.028	0.167	0.028
occtran	0.214	0.03	0.368	0.03	0.412	0.026	0.361	0.025
famtmar	0.255	0.033	0.346	0.032	0.325	0.025	0.424	0.024
famtmar.par	0.252	0.015	0.283	0.015	0.336	0.012	0.372	0.012
famtunmar.par	0.174	0.032	0.123	0.03	0.261	0.023	0.326	0.019
famtsingle.par	0.043	0.022	−0.077	0.026	−0.039	0.022	−0.005	0.02
langswedish	−0.039	0.048	0.184	0.037	0.22	0.028	0.174	0.029
langother	−0.146	0.096	−0.412	0.072	−0.809	0.052	−0.879	0.039
urbsuburb	0.111	0.019	0.149	0.019	0.152	0.015	0.164	0.014
urbcountry	0.095	0.015	0.119	0.016	0.15	0.013	0.16	0.013
dis	−0.586	0.033	−0.692	0.041	−0.81	0.038	−0.662	0.029
reg.ur	−0.029	0.004	0.007	0.002	−0.013	0.002	−0.023	0.002
quartII	0.384	0.018	0.285	0.019	0.211	0.014	0.291	0.013
quartIII	0.267	0.019	0.217	0.019	−0.055	0.015	0.035	0.014
quartIV	−0.215	0.019	−0.117	0.019	−0.25	0.016	−0.298	0.015
year2	0.233	0.016	−0.943	0.019	0.185	0.013	0.074	0.014
year3	0.3	0.017	−1.02	0.026	0.263	0.013	0.077	0.014
year4							0.105	0.015

Table 9: Coefficients of the basic model for men.

	87–89 Coef.	S.E.	90–92 Coef.	S.E.	93–95 Coef.	S.E.	96–99 Coef.	S.E.
(Intercept)	−4.784	0.04	−4.766	0.036	−5.757	0.048	−5.295	0.037
piece2	−0.095	0.019	−0.337	0.022	−0.406	0.019	−0.339	0.015
piece3	−0.344	0.02	−0.583	0.022	−0.615	0.018	−0.518	0.015
piece4	−0.548	0.027	−0.963	0.029	−0.848	0.021	−0.813	0.018
piece5	−0.607	0.035	−1.186	0.036	−0.924	0.024	−0.927	0.022
piece6	−0.666	0.047	−1.386	0.043	−1.113	0.029	−1.143	0.027
piece7	−0.424	0.057	−1.872	0.059	−1.36	0.035	−1.396	0.035
piece8	−0.6	0.092	−1.618	0.066	−1.491	0.042	−1.539	0.043
piece9	−1.057	0.157	−1.839	0.088	−1.555	0.051	−1.63	0.053
piece10	−1.317	0.224	−2.203	0.12	−1.673	0.062	−1.851	0.07
piece11	−1.974	0.378	−2.25	0.137	−1.741	0.073	−1.896	0.083
piece12	−1.999	0.447	−2.088	0.138	−1.699	0.082	−1.861	0.094
piece13	−0.845	0.317	−1.759	0.129	−1.622	0.09	−1.845	0.107
piece14	−1.926	0.378	−2.259	0.089	−1.989	0.063	−2.194	0.079
ageg30–39	−0.178	0.018	−0.249	0.019	−0.115	0.015	−0.114	0.013
ageg40–49	−0.164	0.021	−0.29	0.021	−0.089	0.016	−0.115	0.014
edusec	0.376	0.03	0.316	0.033	0.257	0.029	0.281	0.026
eduvoc	0.191	0.018	0.313	0.02	0.288	0.017	0.367	0.016
eduhigh	0.199	0.043	0.595	0.034	0.581	0.023	0.64	0.02
occcler	0.237	0.026	0.182	0.029	0.194	0.025	0.157	0.023
occcom	0.284	0.032	0.302	0.034	0.328	0.029	0.28	0.027
occheal	0.574	0.026	0.624	0.029	0.669	0.024	0.57	0.022
occhum	0.161	0.044	0.316	0.041	0.621	0.03	0.492	0.027
occind	0.202	0.028	0.086	0.033	0.192	0.029	0.149	0.026
occserv	0.364	0.024	0.34	0.028	0.392	0.025	0.32	0.023
occtech	0.05	0.063	−0.224	0.06	0.083	0.044	0.111	0.04
occtran	0.289	0.077	0.236	0.084	0.327	0.069	0.334	0.064
famtmar	−0.072	0.031	−0.018	0.032	0	0.024	0.096	0.021
famtmar.par	−0.142	0.018	−0.109	0.019	−0.094	0.015	−0.001	0.013
famtunmar.par	−0.421	0.039	−0.346	0.039	−0.368	0.03	−0.219	0.023
famtsingle.par	−0.207	0.024	−0.29	0.026	−0.292	0.022	−0.274	0.018
langswedish	−0.038	0.05	0.072	0.044	0.182	0.03	0.136	0.027
langother	−0.389	0.109	−0.731	0.094	−0.851	0.065	−0.907	0.043
urbsuburb	0.034	0.021	0.081	0.022	0.081	0.017	0.083	0.015
urbcountry	0.013	0.017	0.065	0.019	0.109	0.015	0.104	0.014
dis	−0.622	0.033	−0.556	0.036	−0.697	0.036	−0.643	0.028
reg.ur	−0.021	0.004	−0.013	0.003	−0.019	0.002	−0.04	0.002
quartII	0.089	0.021	0.044	0.023	−0.032	0.018	0.005	0.016
quartIII	0.015	0.021	0.151	0.022	−0.002	0.017	0.092	0.015
quartIV	−0.223	0.021	−0.047	0.022	−0.052	0.018	−0.034	0.015
year2	0.148	0.018	−0.864	0.022	0.177	0.015	0.006	0.015
year3	0.268	0.019	−1.119	0.031	0.218	0.015	0.02	0.015
year4							0.055	0.016

Table 10: Coefficients of the basic model for women.

Men	87 vs 90	87 vs 93	87 vs 96	90 vs 93	90 vs 96	93 vs 96
ageg30–39	**	**	**	**	**	**
ageg40–49		**	**	**	**	**
edusec		**	**	**	**	
eduvoc	**	**	**		**	**
eduhigh	**	**	**	**	**	
occcler						
occcom	**	**		**	**	**
occheal	**	**	**		**	**
occhum	**	**	**		**	**
occind	**	**	**	**	**	
occserv					**	
occtech		**	**	**	**	
occtran	**	**	**			
famtmar	**		**		**	**
famtmar.par		**	**	**	**	**
famtunmar.par		**	**	**	**	**
famtsingle.par	**	**			**	
langswedish	**	**	**			
langother	**	**	**	**	**	
urbsuburb			**			
urbcountry		**	**		**	
dis	**	**		**		**
reg.ur	**	**		**	**	**
quartII	**	**	**	**		**
quartIII		**	**	**	**	**
quartIV	**		**	**	**	**
Women	87 vs 90	87 vs 93	87 vs 96	90 vs 93	90 vs 96	93 vs 96
ageg30–39	**	**	**	**	**	
ageg40–49	**	**	**	**	**	
edusec		**	**			
eduvoc	**	**	**		**	**
eduhigh	**	**	**			
occcler			**			
occcom						
occheal		**				**
occhum	**	**	**	**	**	**
occind	**			**		
occserv						**
occtech	**			**	**	
occtran						
famtmar			**		**	**
famtmar.par		**	**		**	**
famtunmar.par			**		**	**
famtsingle.par	**	**	**			
langswedish		**	**	**		
langother	**	**	**			
urbsuburb						
urbcountry	**	**	**			
dis				**		
reg.ur			**		**	**
quartII		**	**	**		
quartIII	**		**	**	**	**
quartIV	**	**	**			

Table 11: Z-test of time invariance of coefficients for men's (above) and women's (below) model (* $p<0.05$, ** $p<0.01$).

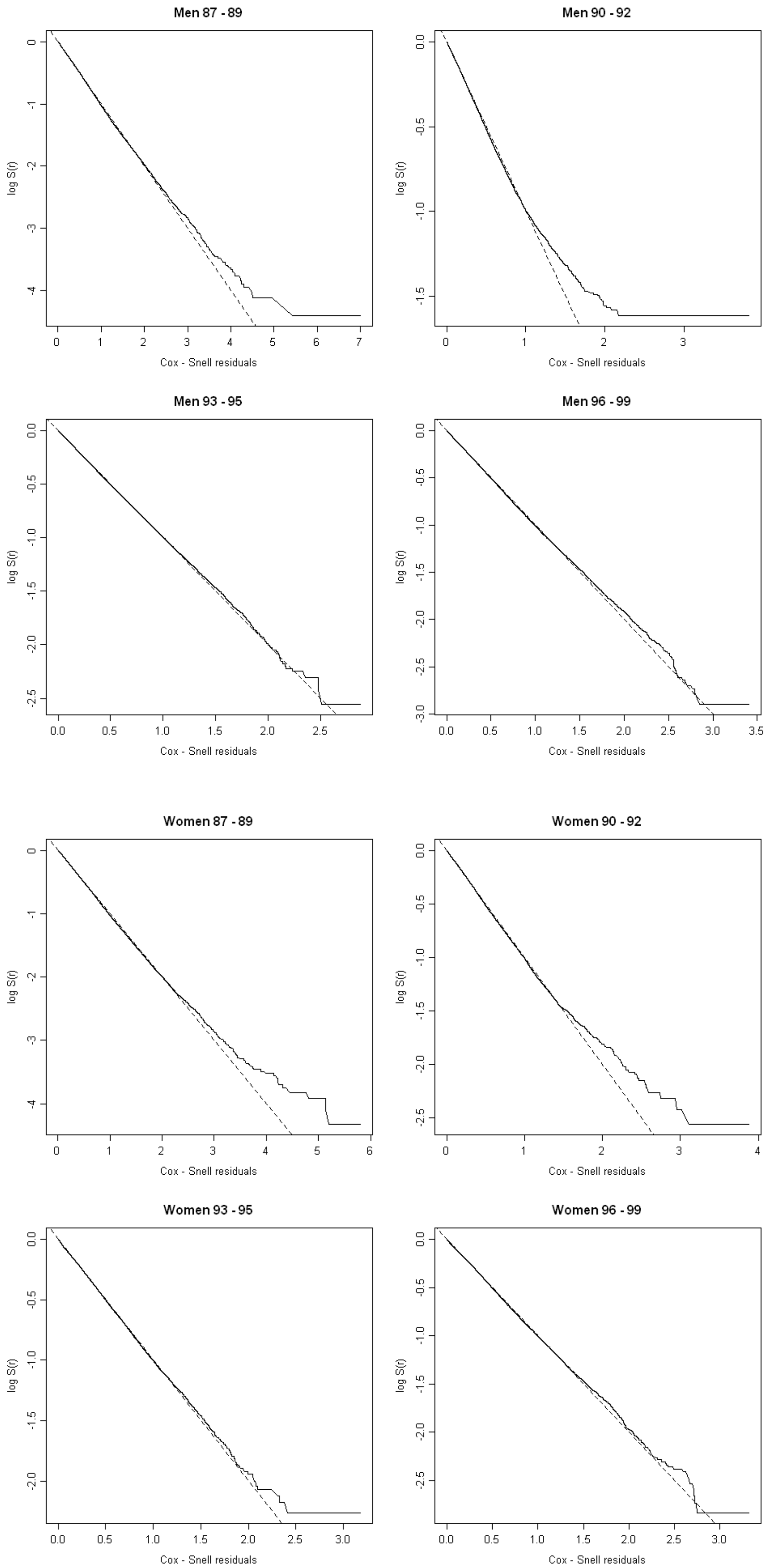

Figure 21: Cox–Snell residual plots of models for men (above) and women (below).

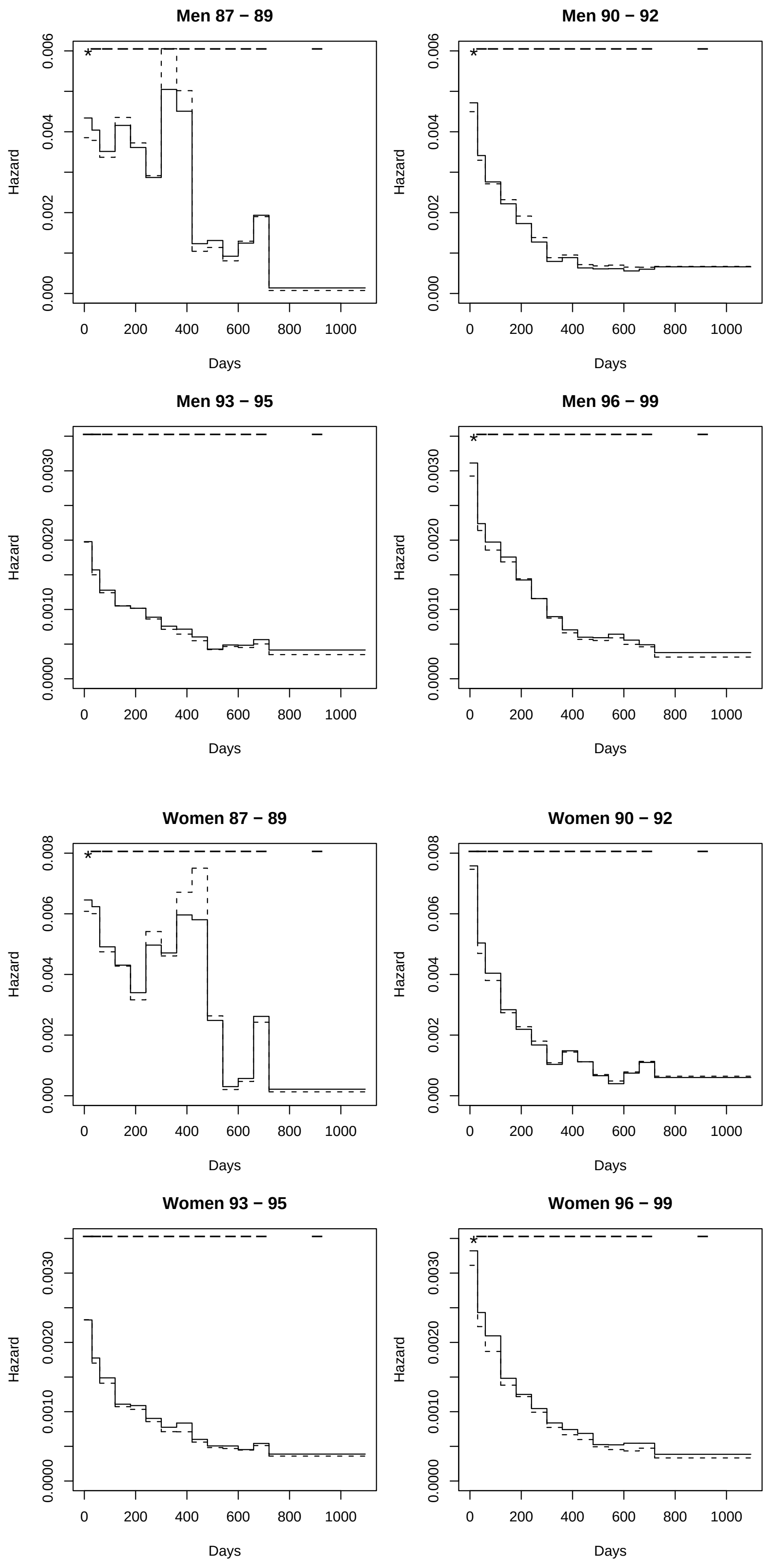

Figure 22: Baseline hazard of interaction models for men and women. The dotted line presents the effect of 2 percentage points increase in regional unemployment rate.

	87–89 Coef.	S.E.	90–92 Coef.	S.E.	93–95 Coef.	S.E.	96–99 Coef.	S.E.
(Intercept)	−5.307	0.056	−5.255	0.034	−6.232	0.045	−5.795	0.026
piece2	−0.218	0.018	−0.355	0.02	−0.367	0.018	−0.304	0.016
piece3	−0.418	0.018	−0.594	0.019	−0.52	0.016	−0.454	0.014
piece4	−0.481	0.023	−0.829	0.023	−0.61	0.018	−0.539	0.017
piece5	−0.59	0.03	−1.021	0.028	−0.654	0.02	−0.663	0.02
piece6	−0.783	0.042	−1.314	0.034	−0.883	0.024	−0.898	0.024
piece7	−0.686	0.053	−1.719	0.044	−1.14	0.03	−1.188	0.031
piece8	−0.615	0.071	−1.638	0.049	−1.323	0.035	−1.471	0.04
piece9	−1.09	0.113	−1.823	0.062	−1.456	0.041	−1.625	0.048
piece10	−1.101	0.141	−1.861	0.069	−1.57	0.048	−1.649	0.054
piece11	−1.484	0.219	−1.787	0.073	−1.524	0.052	−1.577	0.059
piece12	−1.705	0.302	−1.807	0.08	−1.588	0.06	−1.731	0.072
piece13	−1.105	0.278	−1.961	0.094	−1.532	0.065	−1.822	0.084
piece14	−1.815	0.251	−2.043	0.053	−1.947	0.043	−2.149	0.058
ageg30–39	−0.094	0.044	−0.162	0.016	−0.163	0.03	−0.165	0.015
ageg40–49	−0.15	0.053	−0.251	0.017	−0.328	0.032	−0.287	0.016
edusec	0.366	0.096	0.248	0.034	0.181	0.056	0.192	0.028
eduvoc	0.16	0.044	0.228	0.016	0.275	0.03	0.3	0.015
eduhigh	0.069	0.144	0.345	0.036	0.465	0.056	0.537	0.028
occcler	−0.191	0.155	−0.058	0.043	0.217	0.068	−0.016	0.035
occcom	0.095	0.129	0.194	0.036	0.248	0.068	0.056	0.035
occheal	0.113	0.298	0.661	0.065	0.453	0.096	0.386	0.043
occhum	0.424	0.152	0.336	0.05	0.468	0.082	0.126	0.04
occind	0.143	0.05	0.144	0.021	0.55	0.042	0.367	0.022
occserv	0.096	0.132	0.233	0.04	0.408	0.067	0.172	0.032
occtech	−0.074	0.113	0.034	0.036	0.392	0.063	0.247	0.035
occtran	0.163	0.086	0.382	0.031	0.465	0.06	0.451	0.031
famtmar	0.256	0.033	0.345	0.032	0.328	0.025	0.427	0.024
famtmar.par	0.252	0.015	0.281	0.015	0.336	0.012	0.373	0.012
famtunmar.par	0.176	0.032	0.122	0.03	0.263	0.023	0.326	0.019
famtsingle.par	0.042	0.022	−0.079	0.026	−0.04	0.022	−0.008	0.02
langswedish	−0.031	0.048	0.187	0.037	0.222	0.029	0.162	0.029
langother	−0.146	0.096	−0.411	0.072	−0.795	0.052	−0.875	0.039
urbsuburb	0.109	0.019	0.151	0.019	0.149	0.015	0.165	0.014
urbcountry	0.092	0.015	0.121	0.016	0.145	0.013	0.153	0.013
dis1	−0.583	0.033	−0.694	0.041	−0.806	0.038	−0.658	0.029
reg.ur	−0.036	0.009	−0.011	0.005	−0.003	0.006	−0.026	0.004
quartII	0.382	0.018	0.285	0.019	0.211	0.014	0.295	0.013
quartIII	0.265	0.019	0.217	0.019	−0.055	0.015	0.035	0.014
quartIV	−0.217	0.019	−0.116	0.019	−0.25	0.016	−0.297	0.015
year2	0.232	0.016	−0.94	0.019	0.183	0.013	0.072	0.014
year3	0.299	0.017	−1.015	0.026	0.261	0.013	0.074	0.014
year4							0.102	0.015
ageg30–39:reg.ur	0.026	0.008	0.02	0.003	0.029	0.004	0.033	0.003
ageg40–49:reg.ur	0.03	0.009	0.021	0.004	0.04	0.005	0.04	0.003
edusec:reg.ur	0.019	0.016	−0.021	0.007	−0.002	0.009	−0.021	0.006
eduvoc:reg.ur	0.001	0.008	−0.001	0.003	−0.009	0.004	−0.01	0.003
eduhigh:reg.ur	0.004	0.023	0.012	0.007	−0.001	0.009	−0.015	0.006
occcler:reg.ur	−0.009	0.025	0.002	0.009	−0.045	0.01	−0.038	0.008
occcom:reg.ur	0.02	0.021	0.015	0.007	−0.023	0.01	−0.028	0.008
occheal:reg.ur	−0.009	0.05	0.017	0.013	0.016	0.013	−0.003	0.009
occhum:reg.ur	0.075	0.025	0.004	0.01	−0.029	0.012	−0.012	0.009
occind:reg.ur	−0.017	0.009	0.005	0.004	−0.033	0.006	−0.009	0.004
occserv:reg.ur	−0.003	0.022	0.004	0.008	−0.043	0.01	−0.031	0.007
occtech:reg.ur	−0.022	0.019	0.019	0.007	−0.036	0.009	−0.019	0.007
occtran:reg.ur	−0.01	0.015	0.01	0.006	−0.006	0.008	−0.026	0.006

Table 12: Coefficients of the extended model for men.

	87–89		90–92		93–95		96–99	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
(Intercept)	−5.173	0.073	−4.942	0.041	−5.804	0.055	−5.677	0.03
piece2	−0.095	0.019	−0.335	0.022	−0.405	0.019	−0.339	0.015
piece3	−0.343	0.02	−0.581	0.022	−0.614	0.018	−0.518	0.015
piece4	−0.545	0.027	−0.96	0.029	−0.846	0.021	−0.812	0.018
piece5	−0.604	0.035	−1.182	0.036	−0.921	0.024	−0.926	0.022
piece6	−0.665	0.047	−1.382	0.043	−1.11	0.029	−1.141	0.027
piece7	−0.424	0.057	−1.867	0.059	−1.357	0.035	−1.394	0.035
piece8	−0.601	0.092	−1.614	0.066	−1.487	0.042	−1.536	0.043
piece9	−1.057	0.157	−1.836	0.089	−1.551	0.051	−1.627	0.053
piece10	−1.314	0.224	−2.201	0.12	−1.668	0.062	−1.848	0.07
piece11	−1.973	0.378	−2.247	0.137	−1.736	0.073	−1.892	0.083
piece12	−1.997	0.448	−2.081	0.138	−1.693	0.082	−1.857	0.094
piece13	−0.837	0.317	−1.75	0.129	−1.613	0.09	−1.84	0.107
piece14	−1.884	0.378	−2.24	0.089	−1.975	0.063	−2.19	0.079
ageg30–39	−0.118	0.054	−0.234	0.02	−0.246	0.034	−0.152	0.015
ageg40–49	−0.163	0.066	−0.271	0.022	−0.31	0.037	−0.167	0.016
edusec	0.628	0.097	0.33	0.036	0.187	0.061	0.263	0.029
eduvoc	0.248	0.057	0.328	0.021	0.334	0.038	0.359	0.018
eduhigh	0.38	0.151	0.63	0.034	0.467	0.05	0.587	0.023
occcler	0.16	0.086	0.192	0.031	0.23	0.056	0.2	0.027
occcom	0.382	0.105	0.337	0.036	0.271	0.066	0.288	0.031
occheal	0.874	0.081	0.64	0.031	0.61	0.054	0.609	0.026
occhum	0.202	0.142	0.425	0.043	0.553	0.066	0.555	0.031
occind	0.189	0.093	0.083	0.036	0.208	0.068	0.167	0.031
occserv	0.562	0.075	0.357	0.03	0.3	0.057	0.353	0.027
occtech	0.063	0.197	−0.175	0.062	0.036	0.097	0.178	0.047
occtran	0.66	0.273	0.26	0.09	0.188	0.149	0.301	0.073
famtmar	−0.072	0.031	−0.017	0.032	−0.003	0.024	0.096	0.021
famtmar.par	−0.142	0.018	−0.11	0.019	−0.094	0.015	−0.001	0.013
famtunmar.par	−0.42	0.039	−0.343	0.039	−0.363	0.03	−0.216	0.023
famtsingle.par	−0.208	0.024	−0.293	0.026	−0.292	0.022	−0.272	0.018
langswedish	−0.034	0.05	0.076	0.044	0.181	0.03	0.137	0.027
langother	−0.408	0.109	−0.727	0.094	−0.848	0.065	−0.9	0.043
urbsuburb	0.034	0.021	0.083	0.022	0.081	0.017	0.084	0.015
urbcountry	0.013	0.017	0.066	0.019	0.109	0.015	0.104	0.014
dis1	−0.622	0.033	−0.559	0.036	−0.698	0.036	−0.643	0.028
reg.ur	−0.053	0.012	−0.034	0.006	−0.043	0.008	−0.047	0.006
quartII	0.088	0.021	0.05	0.023	−0.034	0.018	0.006	0.016
quartIII	0.017	0.021	0.154	0.022	−0.004	0.017	0.092	0.015
quartIV	−0.222	0.021	−0.047	0.022	−0.053	0.018	−0.034	0.015
year2	0.148	0.018	−0.858	0.022	0.176	0.015	0.005	0.015
year3	0.267	0.019	−1.12	0.031	0.217	0.015	0.018	0.015
year4							0.054	0.016
ageg30–39:reg.ur	0.011	0.009	0.006	0.004	0.022	0.005	0.017	0.003
ageg40–49:reg.ur	0	0.011	0.011	0.004	0.036	0.005	0.023	0.004
edusec:reg.ur	0.044	0.016	0.006	0.007	0.013	0.01	0.009	0.007
eduvoc:reg.ur	0.01	0.01	0.007	0.004	−0.007	0.006	0.005	0.004
eduhigh:reg.ur	0.03	0.024	0.031	0.007	0.02	0.008	0.027	0.006
occcler:reg.ur	−0.013	0.015	0.002	0.006	−0.005	0.008	−0.017	0.006
occcom:reg.ur	0.018	0.018	0.019	0.007	0.01	0.01	−0.001	0.007
occheal:reg.ur	0.055	0.014	0.012	0.006	0.01	0.008	−0.017	0.006
occhum:reg.ur	0.008	0.023	0.047	0.009	0.013	0.01	−0.03	0.007
occind:reg.ur	−0.002	0.016	−0.001	0.007	−0.002	0.01	−0.007	0.007
occserv:reg.ur	0.036	0.013	0.008	0.006	0.015	0.008	−0.014	0.006
occtech:reg.ur	0.003	0.032	0.029	0.012	0.009	0.015	−0.03	0.011
occtran:reg.ur	0.066	0.046	0.012	0.019	0.025	0.023	0.027	0.018

Table 13: Coefficients of the extended model for women.

	Men		Women	
	Coef.	S.E.	Coef.	S.E.
(Intercept)	−5.734	0.051	−5.423	0.059
piece2	−0.304	0.022	−0.341	0.022
piece3	−0.444	0.02	−0.501	0.021
piece4	−0.519	0.023	−0.761	0.026
piece5	−0.567	0.027	−0.873	0.031
piece6	−0.788	0.033	−1.039	0.038
piece7	−1.021	0.041	−1.287	0.047
piece8	−1.271	0.051	−1.379	0.057
piece9	−1.43	0.062	−1.491	0.07
piece10	−1.531	0.073	−1.804	0.096
piece11	−1.463	0.079	−1.674	0.104
piece12	−1.64	0.097	−1.731	0.122
piece13	−1.558	0.104	−1.797	0.144
piece14	−1.876	0.069	−2.033	0.1
l.hist	−0.364	0.019	−0.243	0.023
s.hist	0.179	0.015	0.116	0.017
p.wrk	−0.247	0.018	−0.175	0.018
p.edu	−0.596	0.031	−0.482	0.032
p.sij	−0.894	0.027	−0.629	0.026
ageg30–39	−0.012	0.017	−0.065	0.019
ageg40–49	−0.127	0.018	−0.015	0.02
edusec	0.102	0.034	0.258	0.037
eduvoc	0.242	0.017	0.332	0.023
eduhigh	0.426	0.034	0.556	0.029
occcler	−0.038	0.043	0.18	0.033
occcom	0.013	0.041	0.271	0.038
occheal	0.344	0.049	0.568	0.032
occhum	0.175	0.048	0.51	0.039
occind	0.365	0.024	0.2	0.037
occserv	0.115	0.039	0.354	0.033
occtech	0.174	0.038	0.076	0.059
occtran	0.395	0.035	0.315	0.086
famtmar	0.264	0.034	0.106	0.029
famtmar.par	0.313	0.016	−0.086	0.019
famtunmar.par	0.247	0.028	−0.377	0.034
famtsingle.par	−0.065	0.029	−0.332	0.027
langswedish	0.157	0.039	0.164	0.039
langother	−0.753	0.057	−0.873	0.066
urbsuburb	0.156	0.019	0.124	0.021
urbcountry	0.157	0.018	0.107	0.019
dis	−0.498	0.04	−0.573	0.041
reg.ur	−0.014	0.002	−0.029	0.003
quartII	0.325	0.019	0.002	0.022
quartIII	0.063	0.02	0.111	0.021
quartIV	−0.234	0.021	−0.028	0.022
factor(sdt.year)1995	0.055	0.023	0.045	0.025
factor(sdt.year)1996	0.185	0.023	0.064	0.026
factor(sdt.year)1997	0.277	0.025	0.144	0.027
factor(sdt.year)1998	0.187	0.026	0.1	0.029
factor(sdt.year)1999	0.233	0.027	0.171	0.03

Table 14: Coefficients of the model with labor market history variables for men and women (the first sample).