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2008

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WORKING PAPER SERIES

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Printed and distributed by the Czech National Bank. Available at http://www.cnb.cz.

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Time Aggregation Bias in Discrete Time Models of Aggregate Duration Data

Michal Franta [*]

Abstract

The paper focuses on the dynamics of unemployment in the Czech Republic over the period 1992–2007. Unemployment dynamics are elaborated in terms of unemployment inflows and unemployment duration. The paper contributes to the literature dealing with discrete time models of aggregate unemployment duration data by accounting for time aggregation bias. Another innovation relates to the way we examine the impact of time-varying macroeconomic conditions on individual duration dependence and unemployment inflow composition. The estimation results suggest that both unobserved heterogeneity and individual duration dependence are present. The relative impact of the two factors on the aggregate duration dependence, however, changes over time. Next, seasonal effects on the individual hazard rate are detected. We do not find a significant role of macroeconomic influences. Finally, we demonstrate the profound influence of time aggregation of duration data on unemployment duration parameters for empirical data for France and the Czech Republic.

JEL Codes: J64, C41, E24.
Keywords: Duration dependence, time aggregation bias, unemployment, Unemployment duration.

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This work was supported by Czech National Bank Research Project No. E4/2007.

The views expressed are those of the author, and do not necessarily represent those of the affiliated institutions. I thank Daniel Münich, Jaap H. Abbring, Helene Turon, Kamil Galuščák and Tibor Zavadil for comments and suggestions.

Nontechnical Summary

The paper deals with the dynamics of unemployment in the Czech Republic over the period 1992-2007. The turnover in the pool of unemployed is examined in terms of unemployment inflows and unemployment duration. The analysis begins with a statistical decomposition of unemployment changes to assess the relative importance of unemployment inflows and duration. We show that variation of both inflow and average duration contributes to changes in unemployment in the Czech Republic. Then we examine unemployment inflows and unemployment duration in turn.

Unemployment inflows are analyzed in terms of the reason for leaving a job. We show that the shares of the various reasons for leaving a job among the newly unemployed change over time considerably. For instance, during the 1997–1999 recession the share of inflow into unemployment from employment due to redundancy increases, while quits for family and health reasons decrease.

Unemployment duration is studied by means of discrete time models of aggregate duration data. We estimate a non-parametric model enabling us to answer the question whether the observed decrease of the *aggregate* probability of leaving unemployment over the duration of unemployment is a consequence of the *individual* probability of leaving unemployment decreasing over the duration of unemployment or because of the increasing relative share of individuals with low re-employment probability in the pool of unemployed over the duration of unemployment. Estimation results suggest that both effects are present. Interestingly, the impact of the two factors changes over time. Furthermore, several semi-parametric extensions of the benchmark model are proposed. In addition, they allow for the assessment of the roles of effects of time of inflow into unemployment (cohort effects), and effects of time-varying macroeconomic conditions on individual probability of leaving unemployment. Estimates imply that the quality of entrants into unemployment depends on the season (quarter) of the inflow and is independent of time-varying macroeconomic influences.

The main contribution of the paper consists in that it explicitly accounts for time aggregation bias. Quarterly unemployment registry data usually report the unemployed as at *the last day* of the quarter. So, those who flow into unemployment during the quarter and leave unemployment before the end of the quarter are not covered by unemployment registry data on the unemployed in the first duration category (analogically for discrete time models based on monthly or yearly data). We assert that a standard approach that draws on reported quarterly data could yield misleading results regarding the individual duration dependence, unobserved heterogeneity, the dependence of the average quality of entrants into unemployment on the business cycle, and seasonal effects. In the literature so far, the time aggregation bias in discrete time models of aggregate duration data has not been accounted for. We demonstrate the profound influence of the time aggregation of duration data on unemployment duration parameters on empirical data for France and the Czech Republic.

1. Introduction

An analysis of the labor market based on stocks provides only an incomplete picture. A certain number of the employed, the unemployed, and non-participants can be a consequence of very distinct dynamic structures with different macroeconomic and policy implications. The same number of unemployed persons can reflect high turnover in unemployment on the one hand and a few entrants trapped in unemployment for a very long time on the other. To obtain a full description of the labor market, flows between labor market states should be taken into account.

The current paper deals with the dynamics of unemployment examined in terms of unemployment inflows and unemployment duration. Understanding the turnover in the pool of the unemployed sheds light on the origin of unemployment, on the proper way of conducting labor market policies, and on the wage pressures experienced in the economy.

The paper contributes mainly to the literature of discrete time models of aggregate duration data. First, it explicitly accounts for time aggregation bias. Quarterly unemployment registry data usually report the unemployed as at *the last day* of the quarter. So, those who flow into unemployment during the quarter and leave unemployment before the end of the quarter are not covered by unemployment registry data on the unemployed in the first duration category. Thus, a standard approach that draws on reported quarterly data could yield misleading results regarding the individual duration dependence and unobserved heterogeneity. Moreover, the number of unemployed persons not captured by the quarterly data depends on the business cycle. So, the model can detect a spurious dependence of the average quality of entrants into unemployment on the business cycle. Finally, if the number of unemployed persons ignored by the quarterly unemployment registry data depends on the season, then time aggregation could affect the estimate of seasonal effects.

In the literature so far, the time aggregation bias in discrete time models of aggregate duration data has not been accounted for. We demonstrate the profound influence of the time aggregation of duration data on unemployment duration parameters on empirical data for France and the Czech Republic. French data set is chosen to allow for a direct comparison with existing literature that is nowadays viewed as standard in the unemployment duration research. Czech data set is chosen to extend considerations about the time aggregation bias for emerging market economies.

The second contribution of this paper is the introduction of a novel approach to disentangling the effects of time-varying macroeconomic conditions on the unemployment inflow composition and individual duration dependence. Using dummy variables for different stages of the business cycle we avoid dependence of the parameters of interest on the particular business cycle indicator used.

Third, focusing on the Czech Republic over the period 1992–2007, the paper provides the first attempt to elaborate the situation of the unemployed using aggregate duration data models for countries that experienced transition from central planning to a market economy in the 1990s. Only a few studies based on micro data are available.[1] Several issues are worth analyzing in the context of a post-transition country. For example, the role of individual duration dependence and unobserved heterogeneity is not clear. The literature suggests that the impact of unemployment

[1] References are provided in the section discussing related literature.

duration on the individual probability of leaving unemployment may be caused, for example, by stigma effects and the presence of ranking in the recruitment process. Also, some supply side factors, such as deterioration of human capital over the time of unemployment and the effect of unemployment benefits, may play a role. The observed aggregate duration dependence may, however, stem from unobserved heterogeneity. The unemployed with high re-employment probabilities leave unemployment earlier and the average probability of finding a job in the pool of the unemployed diminishes over time. Knowledge of the importance of individual duration dependence and unobserved heterogeneity is crucial for the proper conduct of employment programs.[2]

A related issue is whether the role of individual duration dependence changes with time-varying macroeconomic conditions represented by the business cycle. There are two conflicting theoretical concepts underpinning the dependence of individual duration on the business cycle. First, the pool of the unemployed is not as competitive in booms as in recessions and even the long-term unemployed face a higher probability of finding a job during a boom (the ranking model of Blanchard and Diamond, 1994). This approach results in a weakening effect of duration on the individual hazard rate of the long-term unemployed during booms. Second, the long-term unemployed could be viewed as being of a low productivity type during booms and thus facing less employment opportunities (Lockwood, 1991). Consequently, the effect of duration of long-term unemployment is more profound in booms.

Within the broader economic context the unemployment dynamics are closely related to two macroeconomic concepts that are widely used in the modeling framework of central banks – the NAIRU and wage dynamics. Both concepts help us to understand the determination of wages and prices and consequently to assess inflationary pressures in the economy.

Campbell and Duca (2007) point out the link between changing average unemployment duration and changes in the NAIRU over time.[3] Abraham and Shimer (2001) and Llaudes (2005) discuss the effect of unemployment duration on the size of downward pressures on wages. The current paper provides results that can contribute to additional analysis dealing with the NAIRU and wage determination in the Czech Republic.

In this paper, we focus on the Czech Republic over the period 1992–2007. The Czech unemployment registry data are well suited for the analysis, since the quarterly data provide the numbers of the unemployed in quarterly duration categories and the monthly data contain inflows into unemployment. In addition, data are available a few days after the end of the quarter and are not subject to revisions.

We start with a statistical decomposition of unemployment changes to assess the relative importance of unemployment inflows and duration. Then we examine unemployment inflows and unemployment duration in turn.

[2] The basic policy question is whether employment programs should be focused on the long-term unemployed or whether the short-term unemployed should be scanned for individuals with bad individual characteristics. For the employment policy implications of different unemployment duration structures see the discussion in van den Berg and van Ours (1996).

[3] The changes in the NAIRU for the Czech Republic are estimated in Hurnik and Navratil (2004).

Unemployment inflows are discussed in terms of the reason for leaving a job. Unemployment duration is studied by means of discrete time models of aggregate duration data. We estimate a non-parametric model enabling us to distinguish individual duration dependence from unobserved heterogeneity. Furthermore, several semi-parametric extensions of the benchmark model are proposed. They allow for the assessment of the roles of individual duration dependence, unobserved heterogeneity, effects of time of inflow into unemployment (cohort effects), and effects of time-varying macroeconomic conditions on individual duration dependence.

The analysis suggests that changes in both unemployment inflows and average duration contribute to unemployment fluctuations. Regarding the inflows, the shares of the various reasons for leaving a job among the newly unemployed change over time considerably. Estimation results of duration models suggest that both unobserved heterogeneity and individual duration dependence contribute to the observed aggregate duration dependence. Moreover, the impact of the two factors changes over time. Next, the quality of entrants into unemployment depends on the season (quarter) of the inflow and is independent of time-varying macroeconomic influences. We also show that not accounting for the time aggregation in discrete time models of aggregate duration data result in biased estimates. In the case of the Czech Republic, for example, even the sign of the estimated coefficient capturing individual duration dependence changes. Unemployment registry data not adjusted for the very short-term unemployed lead to an estimated positive duration dependence. Data adjustment causes a switch to negative duration dependence.

The rest of the paper is as follows. In the next section the relevant literature is discussed. Then, the duration models of aggregate unemployment data are introduced. The unemployment data are described in Section 4. Section 5 focuses on a descriptive analysis of unemployment inflows and duration. Moreover, a statistical decomposition of unemployment changes is carried out. The time aggregation bias is examined in Section 6. The estimation results are reported in Section 7, and Section 8 concludes.

2. Related Literature

Regarding unemployment duration analysis, two basic approaches have been established in the literature. One branch of the research draws on individual (micro level) data using various specifications of hazard models. At the micro level, detailed information on individual characteristics can be exploited to examine the determinants of the duration of an individual unemployment spell. On the other hand, individual panel data usually cover a short time span and/or a limited area only, so they are not appropriate for examining the impacts of time-varying macroeconomic conditions. A survey of micro studies on unemployment duration analysis can be found in Machin and Manning (1999). Recent papers that incorporate the effects of the business cycle into proportional hazard models of micro duration data include Rosholm (2001) for Denmark and Verho (2005) for Finland.

The next strand of research focusing on unemployment duration deals with aggregate unemployment data categorized by the duration of unemployment spells. The aggregates usually cover a sufficiently long time span. However, in contrast to micro level studies, individual unemployment histories cannot be observed and attention has to be paid to the composition of inflows into unemployment to control for changes in inflow heterogeneity.

Recently, taking into account the achievements of duration analysis at the micro level, models of unemployment duration based on aggregate unemployment data have been set up. These models allow examination of the effect of macroeconomic conditions on unemployment duration. Their reliability, however, is considerably limited because of the many functional form assumptions they usually employ.

To avoid the restrictions inherent in parametric estimation, van den Berg and van Ours (1994, 1996) introduced a method of non-parametric estimation of duration models. Their model allows distinguishing between individual duration dependence and unobserved heterogeneity. In general, they find that unobserved heterogeneity plays a more important role than duration dependence in the US.[4] Abbring et al. (2001, 2002) extend the model of van den Berg and van Ours to estimate the effect of business cycles on unemployment incidence and duration in France and the US. Moreover, their model is able to identify the cohort effect, i.e., the dependence of the individual probability of leaving unemployment on the moment of inflow into unemployment. Turon (2003) modifies the preceding models to allow in addition for individual duration dependence dependent on the business cycle. She estimates the duration model using British quarterly data and finds the individual exit rate highly sensitive to the business cycle. Cohort effects are also examined in Cockx and Dejemeppe (2005) for Wallonia and in Dejemeppe (2005) for the whole of Belgium.

Empirical literature dealing with models of unemployment duration for the Czech Republic is rare. Terrell and Sorm (1999) and Ham et al. (1998) estimate a model at the micro level for the early transition period. Huitfeldt (1996) focuses on the aggregate level. However, he estimates average unemployment duration under the steady-state assumption for unemployment and he deals with the period covering the early transition only.[5] Next, Jurajda and Munich (2002) focus on long-term unemployment over the last decade. They also examine the basic characteristics of the short- and long-term unemployed. Finally, unemployment levels, flows into and out of unemployment, and the evolution of vacancies for Eastern European countries are examined in Munich and Svejnar (2007).

This paper extends the approaches used by the Czech National Bank for examination of wage dynamics – the wage curve and the matching function.

Regarding the wage curve, Galuscak and Munich (2003) show that the inverse relationship between the regional unemployment rate and the regional wage level is weakened by the presence of a high fraction of the long-term unemployed. Therefore, an understanding of the development of unemployment duration over time helps to refine the results based on the wage curve.

The matching function approach (Galuscak and Munich, 2007) relates the number of unemployed persons who have found a new job depending on the number of vacancies and the unemployment rate. Adding the aspect of unemployment duration leads to a more accurate assessment of the inflationary pressures on wages, since the long-term unemployed affect wages in a different manner then those unemployed temporarily. An attempt to incorporate the duration aspect into the matching function is made in Munich (2001).

[4] Mixed results on the roles of individual duration dependence and unobserved heterogeneity are found by van den Berg and van Ours (1994) for France, the Netherlands, and the United Kingdom.

[5] Sider (1985) shows that the steady-state assumption leads to misleading results in estimates of the average duration.

3. Models of Duration

In this section we introduce reduced form models of the individual hazard rate out of unemployment and derive a system of non-linear equations for the aggregate duration data. We work in a discrete time setting – the time period equals one quarter.

Model 1

Basically, we consider three models of individual duration. We start with the model introduced in van den Berg and van Ours (1994, 1996), which serves as a basis for all subsequent models of aggregate duration data.[6] The mixed proportional hazard model specification takes the following form:

$$h(t,d,v) = \psi_1(t)\psi_2(d)v\,, \tag{1}$$

where $h(t,d,v)$ denotes the probability that an individual leaves unemployment from a duration category d (given that he has been unemployed for d periods) and conditional on his unobservable characteristics v and calendar time t. Function $\psi_1(t)$ represents the calendar time dependence of the individual hazard rate and function $\psi_2(d)$ effect of duration of unemployment on the individual hazard rate. More precisely, $\psi_1(t)$ captures the effect of calendar time, which is the same for all individuals who are unemployed at calendar time t, and $\psi_2(d)$ captures the effect of duration, which is the same for all the unemployed with unemployment spells of d quarters, i.e., for those who entered unemployment d quarters back.

The term capturing individual unobserved characteristics, v, is distributed according to a distribution function $G(v)$ that satisfies the following conditions:

$$G_q(v) = G_{q-1}(v \cdot w_q)\,, \text{ where } \prod_{q=1}^{4} w_q = 1\,, \tag{2}$$

where q denotes the quarter of inflow into unemployment. Introducing the quarterly factors w_q allows us to distinguish the effects of the quarter (seasonal effects) from other calendar time effects (business cycle effects, secular trends).[7]

Model 2

Model 1 allows us to distinguish between individual duration dependence and unobserved heterogeneity. Succeeding versions of the model (e.g. Abbring et al., 2001, 2002, and Turon, 2003) extend the original framework by introducing terms allowing the individual duration dependence and heterogeneity distribution to be dependent on time-varying macroeconomic conditions. Following Turon (2003), the assumed form of the individual hazard takes the form:

$$h(t,d,v) = \psi_1(t)\psi_3(d,t)\psi_4(t-d)v\,. \tag{3}$$

[6] The formal definition of the model and a discussion of identification issues can be found in van den Berg and van Ours (1994, 1996) and Abbring (2001, 2002).

[7] Unobserved characteristics are introduced in this general way because only moments of the distribution appear in the resulting equations.

The model specification newly includes the effect of duration on individual hazard, $\psi_3(d,t)$, and a term reflecting the average quality of entrants into unemployment at the time of inflow, $\psi_4(t-d)$.

The inflow composition effect captured by the term $\psi_4(t-d)$ represents the effect on the individual hazard, which is the same for all the unemployed who entered unemployment at calendar time $t-d$ – the so-called cohort effect.[8] Model 2 is a parametric extension of the benchmark model. As in Turon (2003) we assume the following functional form for $\psi_4(t-d)$:[9]

$$\psi_4(t-d) = \lambda\left[bc(t-d)\right]^{\alpha}. \tag{4}$$

The function $bc(\cdot)$ denotes the business cycle indicator, which captures macroeconomic influences. So, depending on the particular business cycle indicator, the term $\psi_4(t-d)$ captures the inflow composition effect of business cycle frequency or the inflow composition effect of lower frequencies, e.g. the long-run effect of the economic transformation in the Czech Republic. The indicators used are discussed in the section Data. The cohort effect could be equivalently modeled using a more flexible functional specification in addition to the quarterly factors in formula (2). Such an approach is pursued in Abbring et al. (2002).

In contrast to Model 1, effect of duration on individual hazard ($\psi_3(d,t)$) is assumed to be dependent on time-varying macroeconomic conditions. The assumed specification follows Turon (2003):

$$\psi_3(d,t) = \prod_{j=1}^{d}\left[\eta_j^0 + \beta_j bc(t+1-j)\right], \quad d = 1,2,3.^{10} \tag{5}$$

Finally, the distribution of v satisfies the conditions stated in (2).

Several issues related to the introduction of time-varying macroeconomic dependencies into duration models in the manner of Turon (2003) are worth noting. First, the profile of individual duration dependence, represented by the ratios $\psi_3(d,t)/\psi_3(d-1,t-1)$, depends on the particular indicator of the business cycle. For Turon's model specification it holds that

$$\frac{\psi_3(d,t)}{\psi_3(d-1,t-1)} = \eta_d^0 + \beta_d bc(t). \tag{6}$$

In the system of estimation equations (see the derivation below and Appendix A) coefficient η_d^0 plays the role of an intercept. Therefore, η_d^0 depends on the mean of the business cycle indicator.

[8] In the context of countries in transition, the inflow composition effect also captures structural changes experienced by those economies, e.g. sudden inflows of the unemployed with a low re-employment probability related to declines in some sectors (the mining industry etc.).

[9] Similarly to Turon (2003) we also test another specification $\psi_4 = \lambda \cdot \exp\left[\alpha \cdot bc(t-d)\right]$.

[10] Since the individual duration dependence is described by the ratios of ψ_3 the functional specification takes the form of a product to enable the individual duration dependence to be described by a single number adjusted for the business cycle effect, i.e., $\eta_d^0 + \beta_d bc(t)$.

So, while coefficient β_d remains unaffected by the choice of business cycle indicator, we lose the straightforward interpretation of coefficient η_d^0 as the individual duration dependence.[11]

The second important issue relates to the term capturing cohort effects, ψ_4. Abbring et al. (2002) introduce a flexible specification of the inflow composition term, employing yearly dummies. Their approach, however, suffers in the case of the Czech unemployment duration data from the low number of observations that are used for the estimation of the yearly dummies. We observe only 16 average hazard rates of the unemployed entering unemployment in a particular year (4 quarters and 4 duration categories), which leads to 12 ratios of hazards entering the estimation. We, therefore, follow the parametric specification introduced in Turon (2003).

The interaction of the business cycle indicator with terms that are independent of the business cycle is resolved in the following Model 2'.

Model 2'

In Model 2' we change the specification of the functions ψ_3 and ψ_4 to avoid the problems we encounter in Model 2. We introduce dummy variables indicating two phases of the business cycle (recession, boom) in a similar manner as seasonality (effects of the quarter of inflow) is accounted for in Models 1 and 2. So, the individual hazard follows specification (3), with the term capturing the individual duration dependence defined as

$$\psi_3(d,t) = \prod_{j=1}^{d} \left[\eta_j^0 + \beta_j I(t) \right], \tag{7}$$

where $I(t) = 1$ in booms and 0 otherwise. The term capturing the inflow composition is defined as

$$\psi_4(t-d) = B_r I_r(t-d) + B_b I_b(t-d), \text{ with } B_b B_r = 1, \tag{8}$$

where $I_r(t-d)$ and $I_b(t-d)$ are indicators of recession (*r*) and boom (*b*) at the time of inflow, respectively.[12]

By restricting the range of the business cycle indicator values we confine our exploration to very simple effects of the time-varying macroeconomic conditions. On the other hand, the coefficients capturing the individual duration dependence are clearly defined. The construction of dummy variables I, I_r and I_b is discussed in the section dealing with the data.

The identification of Models 1–2' is discussed in detail in Abbring et al. (2001, 2002) and the use of dummies for phases of the business cycle to account for the cohort effect is suggested by van den Berg and van Ours (1994).

[11] Imposing the mean of the business cycle indicator to be equal to zero does not help, since the indicator enters the final system of non-linear equations also in the term capturing cohort effects.

[12] Note that the dummy variables I_r and I_b are complementary. The reason we include both in the formula is that the term ψ_4 has to be non-zero since it appears in the denominators in the system of estimation equations. For both parameters to be identified, we assume $B_b B_r = 1$ because we finally estimate only the ratios of the two parameters.

Derivation of estimation equations

In this section the system of equations is derived. We start with the individual hazard rate specification and we derive equations for aggregate hazards that can be computed from the unemployment registry data. Finally, we derive ratios of aggregate hazards that allow us to eliminate the term capturing calendar time effects, $\psi_1(t)$.

The unemployment registry data allows us to compute the probability that an individual with the mean level of unobserved characteristics leaves unemployment from duration category *d* ($d \geq 0$) conditional on the time of entry into unemployment *t-d*:

$$h(t,d) = \frac{prob(D = d \mid \text{inflow at } t-d)}{prob(D \geq d \mid \text{inflow at } t-d)}, \tag{9a}$$

where, following van den Berg and van Ours (1996), we denote by *D* the random variable referring to unemployment duration and *d* realization of the random variable. In terms of individual probabilities, (9a) can be rewritten as:

$$h(t,d) = \frac{E_v\left[prob(D = d \mid \text{inflow at } t-d, v)\right]}{E_v\left[prob(D \geq d \mid \text{inflow at } t-d, v)\right]}. \tag{9b}$$

The expected value is taken relative to the distribution of unobserved characteristics at $t-d$, $G_{t-d}(v)$. The probabilities in (9b) can be expressed using individual hazard rates. For example,

$$prob(D = d \mid \text{inflow at } t-d, v) = h(t,d,v)\prod_{k=1}^{d}\left[1 - h(t-k, d-k, v)\right]. \tag{9c}$$

Substituting (9c) into (9b) and using the proportional hazard specification of Model 1 as in (1) we obtain:

$$h(t,d) = \frac{\psi_1(t)\psi_2(d)E_v\left[v\prod_{k=1}^{d}\left[1-\psi_1(t-k)\psi_2(d-k)v\right]\right]}{E_v\left[\prod_{k=1}^{d}\left[1-\psi_1(t-k)\psi_2(d-k)v\right]\right]} \quad \text{for } t = 1,2,...,T; d = 0,1,2,3. \tag{10}$$

Then, formulas for the ratios of average hazards $h(t,d)/h(t,0), d = 1,2,3$ are derived, leading to elimination of the term capturing the calendar time dependence.[13] Finally, we take logarithms of both sides of the derived equations and add disturbances that account for the specification error. The resulting system of three nonlinear equations is stated in Appendix A. Note that the system in Appendix A is derived for the general individual hazard specification (3).

[13] Note that the information on the calendar time dependence is in four average hazard rates only (for a particular quarter there are only four average hazard rates available). By removing calendar time factor $\psi_1(t)$ from the system of equations we need not estimate those parameters based on information from a few observations only.

The estimation equations obtained are of the following form:

$$\ln\left(\frac{h(t,d)}{h(t,0)}\right)=\ln\left(\prod_{j=1}^{d}\eta_j(t)\right)+\ln\left(\prod_{j=0}^{d-1}W_{t-j}\right)+\Omega\left(\gamma_2,...,\gamma_{d+1},\psi_4(\cdot),\eta_k(\cdot),W_l\right).$$

The time-varying coefficients $\eta_d(t)$ describe the shape of the individual duration dependence:

$$\eta_d(t)=\eta_d^0+\beta_d bc(t)=\frac{\psi_3(d,t)}{\psi_3(d-1,t-1)},\ \text{for } d=1,2,3. \tag{11}$$

If the impact of duration on the individual hazard rate diminishes over time ($\psi_3\left(d=0,t\right)>\psi_3\left(d=1,t+1\right)>...$), i.e., the probability of remaining in unemployment increases because of the length of the unemployment spell, then we refer to it as negative duration dependence and coefficient $\eta_d(t)<1$. Negative individual duration dependence can be a consequence of supply factors (deterioration of human capital, effects of unemployment benefits, etc.) and demand factors (stigma effects). The business cycle indicator in (11) reflects the impact of time-varying macroeconomic conditions on the individual duration dependence.

In the Model 1 specification, the individual duration dependence is not time dependent, i.e., $\eta_d=\psi_2(d)/\psi_2(d-1)$. In Model 2', where the indicator $bc(t)$ is replaced by the dummy variable for booms, the coefficient η_d^0 represents the individual duration dependence during recessions and $\eta_d^0+\beta_d$ represents that during booms. If the Blanchard and Diamond (1994) concept is in place, the effect of duration is weakened during booms and $\beta_d<0$. Lockwood (1991) implies the opposite effect of a boom and $\beta_d>0$.

Coefficients γ_i characterize the distribution of unobserved heterogeneity, $G(v)$:

$$\gamma_i=\frac{E_v\left\{v^i\right\}}{\left[E_v\left\{v\right\}\right]^i},\ \text{for } i=2,3,4.$$

We assume that $E_v\left\{v\right\}=1$. So, the coefficients γ_i are normalized moments of the heterogeneity distribution. Unobserved heterogeneity is present in the pool of unemployment entrants if $\text{var}(v)>0$, i.e., $\gamma_2>1$. Furthermore, van den Berg and van Ours (1996) suggest specification tests applicable to Models 1, 2, and 2'. The following restrictions for the coefficients representing unobserved heterogeneity must hold to ensure the existence of distribution $G(v)$ with a finite number of points of support:

$$\gamma_2\geq 1, \tag{12a}$$

$$\gamma_3\geq\gamma_2^2, \tag{12b}$$

$$\gamma_2\gamma_4-\gamma_3^2-\gamma_4-\gamma_2^3+2\gamma_2\gamma_3\geq 0. \tag{12c}$$

If the unobserved characteristics *v* vary over individuals, then those with a higher level of *v* leave unemployment earlier than those with a low level of *v* (in a particular quarter *t* from duration category *d*). Consequently, the aggregate hazard rates decrease for higher duration categories.

The quarterly inflow effect on the heterogeneity distribution W_t is defined as:

$$W_t = \sum_{q \in \{1,2,3,4\}} w_q I_{t,q} \ ,$$

where $I_{t,q}$ is an indicator of a particular quarter (i.e., $I_{t,q} = 1$ if *t* equals a particular quarter) and w_q are quarterly factors satisfying the condition stated in (2). According to whether the value of w_q is lower or higher than 1, the number of new entrants into unemployment systematically decreases or increases with respect to other quarters.

Finally, in Model 2', the term capturing the cohort effect, ψ_4, includes coefficients B_b and B_r, representing the effect of macroeconomic conditions on the inflow composition. The hypothesis that during recessions a proportionally higher fraction of the unemployed with a low re-employment probability enters unemployment than in booms is introduced in Darby et al. (1985).[14] Such hypothesis implies $B_b > 1$ and $B_r < 1$. In the Model 2 specification, the inflow composition effect is captured by $\psi_4(t-d)$, defined in (4). Positive values of coefficient α imply pro-cyclicality of inflows in terms of the re-employment probabilities of unemployment entrants.

The system of nonlinear equations in Appendix A is estimated by non-linear seemingly unrelated regression as in van den Berg and van Ours (1994, 1996). We assume that the errors are correlated across equations and uncorrelated over time.

4. Data

There are two different sources of quarterly unemployment data for the Czech Republic – survey data (LFS – Labor Force Survey) and registry data (UR – Unemployment Registry).

The LFS is survey of the population that is collected by the Czech Statistical Office following the ILO definition of unemployment, i.e., a) an individual is without work (not in paid employment or self-employment), b) currently available for work, and c) seeking work. The LFS data also contains various individual characteristics that help us to assess the composition of inflows into unemployment, e.g. the reason for leaving the last job.

The UR data set is collected by district labor offices and covers the period 1992:1–2007:1. It contains all the unemployed that are registered at a labor office. Registering is a necessary condition for receiving unemployment and numerous social benefits in the Czech Republic.

Note that the two data sets define unemployment somewhat differently. Since we attempt to combine information from the two data sets, we compare the total level of unemployment reported by each of them in Appendix B.

[14] See also Baker (1992) for an examination of this hypothesis employing US data.

Model 2 employs various indicators of the business cycle to capture time-varying macroeconomic conditions – the deseasonalized and detrended unemployment rate, the tightness of the labor market (the ratio of the number of vacancies to the number of the unemployed), and the balances of the confidence indicator for industry. The confidence indicator is constructed by the Czech Statistical Office and is based on the expected development of the economy as revealed by firms' managements.[15] The confidence indicator is supposed to capture the effects of macroeconomic conditions related to transition.

The dummy variables describing recessions and booms in Model 2' are constructed using the business cycle indicators from Model 2. Booms are periods when the relevant indicator is above trend and recessions are periods when it is below trend.

In Section 6 French registry data are employed. We combine aggregate quarterly unemployment duration data used in Abbring et al. (2002) with quarterly data on inflows into the unemployment. To enable the comparison of our estimates with those in Abbring et al. (2002) we consider the same period i.e. 1983:1–1994:4. The data set of French quarterly data on duration and inflows was kindly provided by Jaap H. Abbring.

5. Descriptive Analysis

In this section we decompose changes in unemployment into changes in unemployment inflows and outflows. The aim of this exercise is to show that unemployment changes are not predominantly driven either by inflow or by outflow changes.[16] Analysis of unemployment dynamics in the Czech Republic should, therefore, include both inflows and outflows.

The reason why we carry out the unemployment decomposition in levels is that using rates for explaining changes in unemployment can be problematic. First, the inflow rate and outflow rate are normalized by the number of employed and unemployed persons, respectively. Thus, changes in rates are not directly comparable. Second, since the outflow rate is normalized by the number of the unemployed, which depends on the inflow, movement in the outflow rate can be caused by movement in inflow with the level of outflow being constant.

The demonstration of the important role of inflow and outflow changes in unemployment fluctuations is followed by a descriptive analysis of inflows and outflows. Survey data are employed for a simple inflow analysis based on examining the reasons for leaving the last job of the newly unemployed. The analysis of outflows is built on an examination of unemployment duration. Note that the inverse of the outflow rate equals the average duration of the unemployment spell.

[15] See details at http://www.czso.cz/eng/redakce.nsf/i/business_cycle_surveys.

[16] An extensive discussion on the measurement of contributions of changes in inflow and outflow rates to the unemployment cyclical variation is currently under way. See, for example, Shimer (2007), Fujita and Ramey (2007), and Elsby et al. (2007).

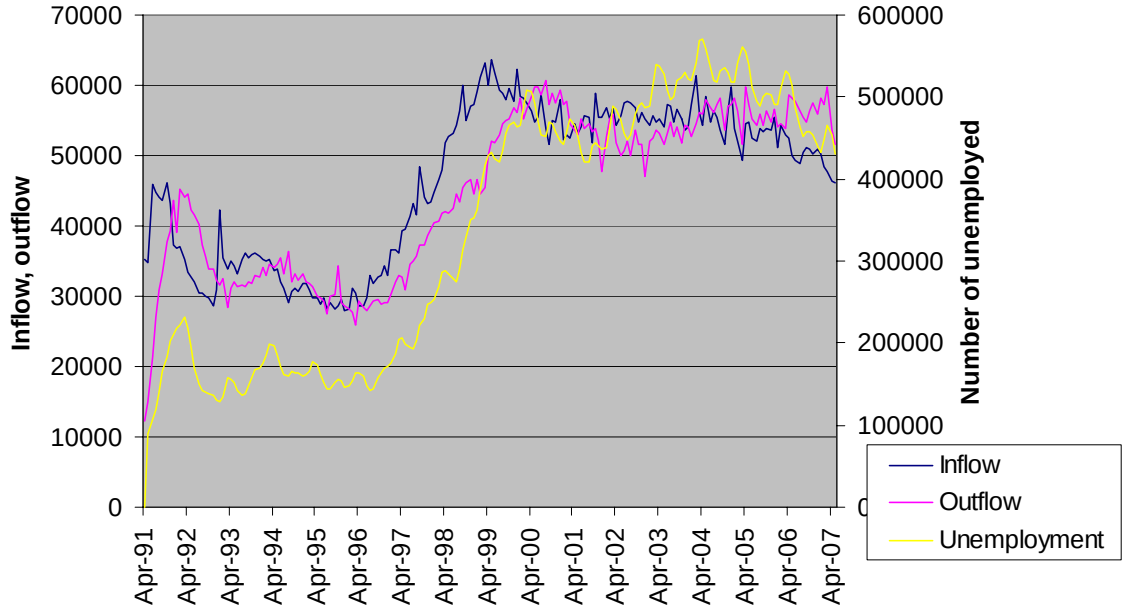
Statistical decomposition of unemployment changes

We start with a statistical decomposition of unemployment changes based on the accounting identity:

$$\Delta U_t \equiv Inflow_t - Outflow_t , \tag{13}$$

so that the observed number of unemployed persons is the cumulative sum of net inflows plus the initial number of unemployed persons.

Figure 1: Unemployment Inflow and Outflow (monthly) – levels



Note: Time series are seasonally adjusted. Source: Czech UR data.

Figure 1 reports monthly inflows into and outflows from unemployment during the period April 1991 – May 2007. The difference between them indicates whether the number of unemployed persons in a particular period changes because of a change in inflow, a change in outflow, or both. So, for example, the growth of unemployment in 1997 was primarily caused by higher inflows, not by lower outflows.

Figure 1 also suggests an interesting empirical regularity – outflows that closely follow inflows with a lag of approximately a year. Regression of outflows on inflows lagged by 12 periods (months) shows that more than 90% of the variation in outflow is explained by the lagged inflow. A similar lag between inflow and outflow is observable, for example, in the UK (Burgess and Turon, 2005). Duration analysis should help to explain this phenomenon.[17]

[17] Note that for Slovakia, for example, such regularity is not present.

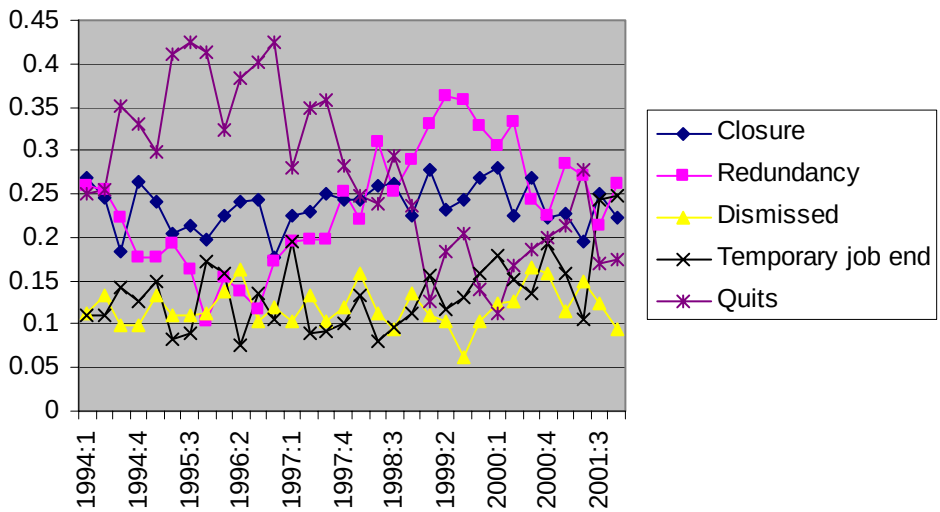
Unemployment inflows

Entrants into unemployment come from out of the labor market (OLM) or from employment (E). Inflows from OLM have a lower share than inflows from employment. Gottvald (2005), based on the Czech LFS data, shows that the transition probability from employment to unemployment is approximately two times higher than transition from OLM to unemployment during the period 1993–2000 and even higher during the 1997–1999 recession. So, since the transition probabilities are normalized by the number of individuals in OLM and in employment, the level of the flow from OLM is even less important. We focus on inflows from employment only.

Regarding the unemployment inflows from employment, the LFS data set provides information on the reason for leaving the last job. The next two figures report the shares of selected reasons for leaving a job for those entering unemployment in a particular quarter. Figure 2 covers the period 1994–2001 and Figure 3 the period 2002–2006, when the classification of the reasons for leaving a job changed toward a more aggregated classification.

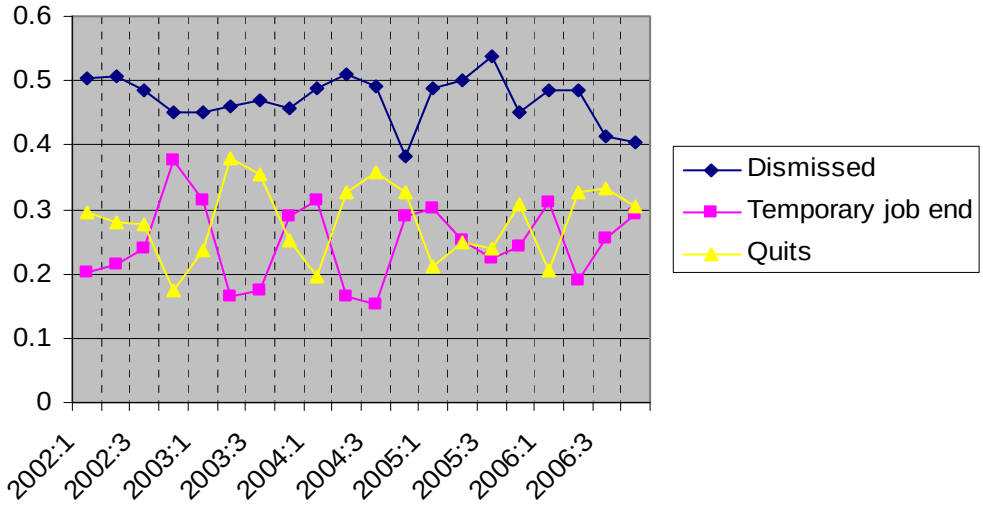
Figure 2 indicates that during the 1997–1999 recession the share of inflow into unemployment from employment due to redundancy increases, while quits for family and health reasons decrease. Interestingly, the number of all the unemployed caused by the closure of an enterprise has not changed much. Due to the high level of aggregation of the reasons for leaving a job in Figure 3 (e.g. the category of dismissed workers now aggregates redundancy, closure, and dismissed workers from the previous classification), the shares do not exhibit trends, but a strong seasonal pattern for all the reasons can be observed.

Figure 2: Shares of Selected Reasons for Leaving a Job of the Newly Unemployed, Czech Republic, 1994–2001



Source: Own calculations based on the Czech LFS.

Figure 3: Shares of Selected Reasons for Leaving a Job of the Newly Unemployed, Czech Republic, 2002–2006



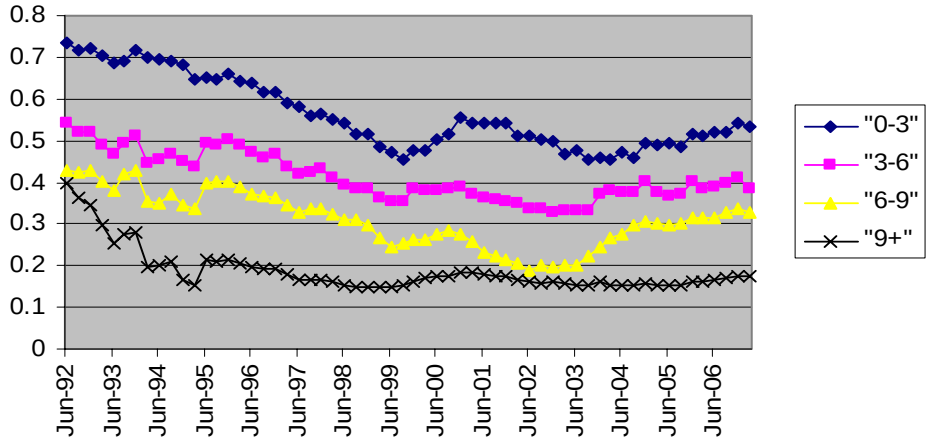
Source: Own calculations based on the Czech LFS.

<u>Unemployment duration</u>

The duration analysis is built upon aggregate hazard rates out of unemployment $h(t,d)$, i.e., the average probability that an individual unemployed for *d* quarters in period *t* leaves unemployment from duration category *d*. The registry data categorizes the number of unemployed persons into four basic duration categories according to quarters. So, the first duration category "0–3" contains the unemployed that have been unemployed for less than 3 months (*d*=0) at the end of a quarter. Similarly, the other duration categories are "3–6" (*d*=1), "6–9" (*d*=2), and "9+" months (*d*=3).

The following figures show empirical hazard rates computed from the unemployment registry data. Decreasing hazard rates in all duration categories over time can be observed. At the end of the time period considered we can see a slight upsurge. Furthermore, the hazard rates decrease with duration category, i.e., the hazards exhibit negative aggregate duration dependence. Econometric analysis provides an explanation of whether the decreasing aggregate hazard rate over the duration categories is a consequence of individual duration dependence, unobserved heterogeneity, or both.

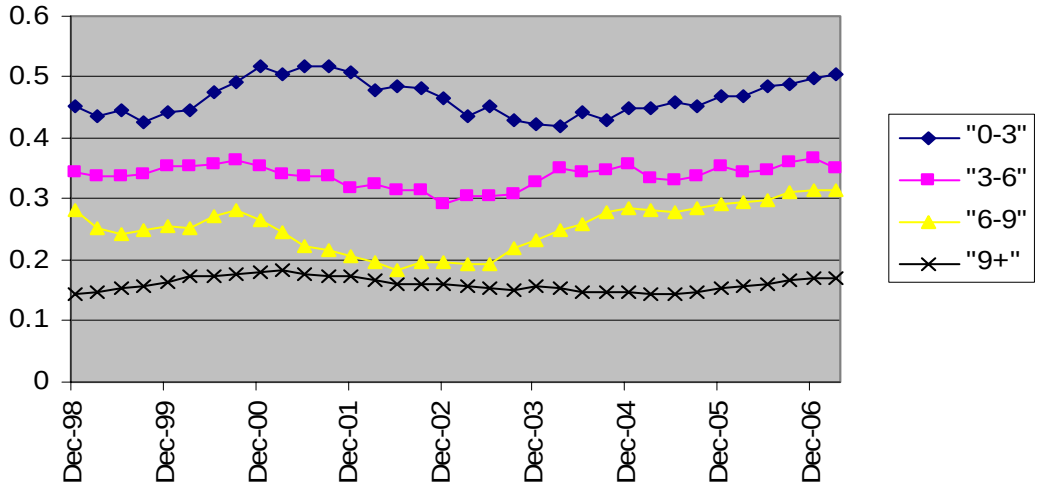
Figure 4: Hazard Rates by Duration Category, moving average of 5 observations, whole population



Source: Own calculations based on UR data set.

Hazard rates categorized by gender exhibit similar patterns in terms of aggregate duration dependence (see Figure 5, which reports female hazards). Duration data by genders are available since 1998:4 only. The probability of leaving unemployment is slightly higher for men than for women for all duration categories.[18]

Figure 5: Hazard Rates by Duration Category, moving average of 5 observations, women



Source: Own calculations based on UR data set.

6. Time Aggregation Bias

At the end of each quarter, labor offices publish the number of registered unemployed in each duration category *as at the last day* of a given quarter. Therefore, those who leave unemployment in the quarter of their inflow are not reported by the quarterly statistics. We denote this group of the unemployed with very short unemployment spells as the omitted unemployed (OU).[19]

The OU group influences the aggregate hazard rate out of the "0–3" months duration category. Neglecting the OU, the hazard computed as the simple outflow rate out of the "0–3" months duration category, i.e.,

$$\frac{u(t,"0-3")-u(t+1,"3-6")}{u(t,"0-3")}, \tag{14}$$

is lower than the hazard defined by equation (9a), which takes the OU into account.[20] Note that $u(t,d)$ denotes the number of unemployed persons in duration category *d* in quarter *t*. Also note

[18] The average hazard rate for duration category "0–3" is 0.47 for women vs. 0.53 for men, that for duration category "3–6" is 0.34 vs. 0.40, that for category "6–9" is 0.25 vs. 0.27, and finally that for duration category "9+" is 0.16 vs. 0.20. The averages are computed over the period 1998:4–2007:1.

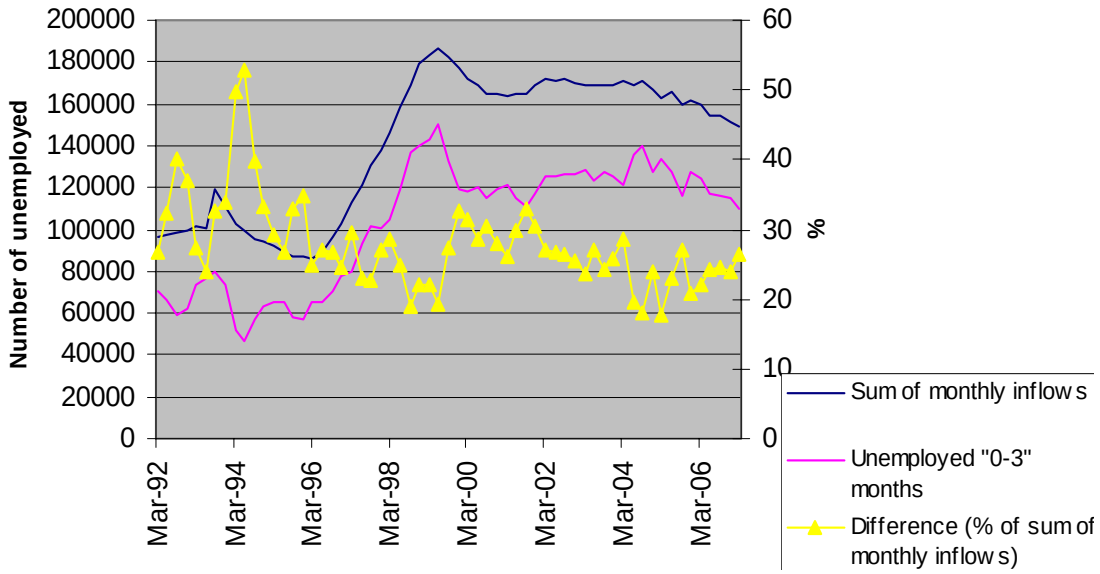
[19] In some countries, unemployment exits have to last for three months in order to be recorded and the OU group is empty (e.g. in Belgium, see Cockx and Dejemeppe, 2005). Nevertheless, for most countries the OU group is non-negligible (e.g. France, the UK, and the Czech Republic).

[20] The hazard rate defined in (14) is lower than the hazards defined in (9a) because the simple outflow rate takes the outflow from duration category "0–3" in quarter *t+1* only. The hazards in (9a) add the outflow that happens also in quarter *t*.

that the literature dealing with models of aggregate duration data employs the simple outflow rates defined as in (14).[21]

Nevertheless, the number of the OU can be easily disentangled from monthly statistics if available: the sum of monthly unemployment inflows during the three months constituting a quarter minus the unemployed reported in duration category "0–3" months in the quarterly data. The next graph shows the sum of monthly unemployment inflows in a quarter, the number of unemployed persons in duration category "0–3" at the end of the quarter, and the difference between the two numbers as a share of inflows in 3 months.

Figure 6: Quarterly Inflows, number of unemployed persons in duration category "0–3" months, difference



Note: Time series are seasonally adjusted.
Source: Czech quarterly and monthly UR data.

The average difference between the total quarterly inflows and the number of unemployed persons reported in duration category "0–3" is approximately 32,000 before 1997 and more than 42,000 after the economic downturn in 1997–1999. So, around one third of the unemployed with a spell of less than 3 months are not captured by the quarterly unemployment registry data. Furthermore, the difference is not constant over time and exhibits a seasonal pattern.

Omitting the OU group results in upward bias of the coefficient capturing the individual duration dependence from the first to the second quarter, η_1, because systematically lower individual hazard rates out of duration category "0–3" lead to lower terms $\psi_2(0)$ and $\psi_3(0,t)$. If some kind of stigma effect is present, i.e., firms treat, for example, those unemployed for less than two months differently than those unemployed for longer spells, then models of aggregate quarterly duration data cannot detect the stigma effect reflected by negative individual duration dependence, since a lot of non-stigmatized unemployed persons do not appear in the quarterly data. So, time aggregation can result in bias leading to wrong conclusions and misleading policy

[21] Other concepts related to the elaboration of unemployment dynamics, however, take the time aggregation issue into account. Aggregation bias in the matching function approach is discussed, for example, in Galuscak and Munich (2007).

recommendations. Since the hazard rates $h(t,0)$ enter the right-hand side of each equation of the estimation system, ignoring the OU affects the estimates of the other coefficients as well.

The upward bias in the individual duration dependence could be avoided by employing models based on micro level (individual) data and thus by tracing individuals over their whole unemployment spell. Micro data, however, do not usually cover a sufficiently long time span for examining the effects of time-varying macroeconomic conditions.[22]

In addition to the bias in the individual duration dependence estimates, the change in the number of the OU affects the estimates of the term controlling for the inflow composition ($\psi_4(t-d)$) and the compositional inflow effect of a season. Since the number of the OU differs over time, as shown in Figure 6, the estimation results of the model employing simple outflow rates lead to spurious dependence of the average quality of unemployment inflow on time-varying macroeconomic conditions. In booms, the unemployed with a high hazard rate face a lower probability of being reported by the quarterly data than in recessions. Therefore, the counter-cyclicality of the average quality of unemployment entrants could be a consequence of time aggregation bias. Indeed, strong counter-cyclicality is found, for example, in Turon (2003), who employs quarterly data. Abbring et al. (2001) use monthly data and find pro-cyclicality of the inflow composition. The OU group is negligible (or zero if it takes a month to leave the unemployment registry) in the monthly data relative to the quarterly data. The effect of time aggregation should, therefore, be stronger in the case of the quarterly data. Finally, Cockx and Dejemeppe (2005) detect acyclicality for prime aged workers using quarterly data for Wallonia (Belgium), where it takes three months to leave the pool of the unemployed, i.e., the problem of time aggregation is not present. Similarly to the spurious cohort effect, seasonality in the number of the OU could lead to wrong conclusions about the effects of season on the inflow composition.

To verify the above theoretical considerations on the effects of time aggregation in discrete time models of aggregate duration data, we estimate Model 1 both with and without the OU group. We take the data set of French aggregate quarterly unemployment duration data used in Abbring et al. (2002).[23] First, we estimate Model 1 using the same hazard rates as in Abbring et al. (2002). The hazard rates are constructed as in equation (14) and cover the period 1983:1–1994:4.

Both Model 1 and the model in Abbring et al. (2002) detect a non-monotonic profile of the individual duration dependence for both sexes – see the estimation results in Table 1.[24] Second, since the French unemployment registry data include information on monthly inflows we compute hazard rates that take into account the OU group and estimate Model 1 again. Table 2 shows that

[22] Van den Berg and van der Klaauw (2001) combine micro and macro unemployment data in order to exploit the advantages of the respective data sources. Using monthly micro data and quarterly aggregate data they weaken the effect of time aggregation bias. However, they assume that the micro data represents samples of aggregate quarterly hazard rates differing by a zero mean random error. As shown in Appendix 2, the difference between the survey (micro) and administrative (macro) unemployment data can have non-systematic character and the assumption underlying the combination of micro and macro data need not be appropriate for the Czech Republic.

[23] The data set was kindly provided by Jaap H. Abbring.

[24] The differences in the estimation results are due to the fact that Abbring et al. (2001) estimate a slightly different model with yearly and seasonal dummies to capture time-varying macroeconomic influences.

including the OU changes the estimates toward monotonic (and strictly negative for men) individual duration dependence.

Table 1: Individual Duration Dependence in Model 1 and Abbring et al. (2002) by sex, French data without OU, 1983:1–1994:4

	Model 1		Abbring et al. (2002)	
	Women	Men	Women	Men
η_1	1.14	1.06	1.17	1.08
η_2	1.01	0.99	0.89	0.91
η_3	1.07	1.00	1.03	0.96

Source: Own computations and Abbring et al. (2002).

Table 2: Individual Duration Dependence in Model 1 by sex, French data with and without OU, 1983:1–1994:4

	Hazards with OU		Hazards without OU	
	Women	Men	Women	Men
η_1	0.64	0.65	1.14	1.06
η_2	0.90	0.92	1.01	0.99
η_3	1.01	0.95	1.07	1.00

We demonstrated that ignoring the OU in models of aggregate duration data leads to a conclusion of non-negative individual duration dependence. So, the implication that the aggregate negative duration dependence is caused by unobserved heterogeneity is misleading. Taking into account the OU suggests negative individual duration dependence. For the Czech Republic, the effect of time aggregation is demonstrated in the section dealing with the estimation results.

Finally, it is worth noting that time aggregation bias is not a problem of simple measurement error. Abbring et al. (2002) accounts for the measurement error (e.g. administrative errors) by assuming that the real number of the unemployed in duration category *d* at calendar time *t* equals the observed number multiplied by the normally distributed disturbance with zero mean:

$$\tilde{U}(d,t) = U(d,t)\varepsilon_{d,t} .$$

However, time aggregation bias represents a systematic change in the number of the unemployed. Therefore, the problem of bias is not resolved by accounting for the simple form of the measurement error.

7. Estimation Results

In this section, the estimation results for the Czech Republic are presented. We start with the results for the whole period 1992:2–2007:1 and model specifications 1, 2, and 2'. The estimation period is then restricted based on the results of the specification tests. Then we deal with men and women separately. Finally, the effects of time aggregation for the Czech Republic are demonstrated.

The estimation results of Models 1, 2, and 2' for all the unemployed and the period 1992:2–2007:1 are reported in Table 1. The hazard rates are computed taking into account the OU group. In general, the estimated coefficients for the three model specifications are not statistically different. Therefore, in what follows we focus mainly on the most general model specification of Model 2'.

Table 3: Estimation Results of Models 1, 2, 2', whole population, period 1992:2–2007:1

		Model 1	Model 2	Model 2'
Individual duration dependence	η_1	**0.79**	**0.79**	**0.78**
		0.03	0.02	0.03
	η_2	**0.71**	**0.72**	**0.69**
		0.03	0.03	0.03
	η_3	**0.59**	**0.64**	**0.59**
		0.02	0.03	0.03
Effect of time-varying macroeconomic conditions on individual duration dependence	β_1	-	**0.17**	0.03
		-	0.08	0.02
	β_2	-	0.11	0.04
		-	0.13	0.03
	β_3	-	**-0.28**	-0.01
		-	0.10	0.03
Unobserved heterogeneity	γ_2	**1.05**	**1.08**	**1.05**
		0.02	0.02	0.02
	γ_3	**1.23**	**1.29**	**1.22**
		0.07	0.08	0.07
	γ_4	**1.64**	**1.64**	**1.61**
		0.22	0.22	0.22
Seasonal inflow effect	w_1	**1.03**	**1.04**	**1.04**
		0.02	0.02	0.02
	w_2	0.99	0.97	0.98
		0.02	0.02	0.02
	w_3	1.01	1.02	1.01
		0.02	0.02	0.02
	w_4	**0.97**	0.98	**0.97**
		0.02	0.02	0.02
Effect of time-varying macroeconomic conditions on inflow composition (cohort effect)	α	-	-0.03	-
		-	0.03	-
	B_b	-	-	1.02
		-	-	0.01
	B_r	-	-	0.98
		-	-	0.01

Note: Standard errors reported below the coefficient estimate. Bold indicates coefficients significantly different from 1 (all sections except Effect of macroeconomic conditions on individual duration dependence, where bold indicates coefficients different from zero). 95% level of significance considered. Tightness of the labor market as a business cycle indicator is used for Model 2.

We observe a strong negative individual duration dependence over all the duration categories considered (coefficients $\eta_d, d = 1,2,3$ are significantly lower than 1). Moreover, the decrease is more profound as the duration category increases. So, the probability of finding a job decreases with increasing duration and the decrease accelerates during the year when an individual is unemployed. As discussed above, this could be a consequence of, for example, a deterioration of human capital (supply side) or some kind of stigma effects (demand side).[25] Since the coefficients β_d are statistically insignificant, the individual duration dependence does not change with the time-varying macroeconomic conditions represented by the dummy variables for phases of the business cycle.[26]

The third panel of Table 3 shows that unobserved heterogeneity is also present ($\gamma_2 > 1$). So, the observed aggregate duration dependence (Figures 4 and 5) is caused by both individual duration dependence and unobserved heterogeneity.

We also detect a seasonal effect of the inflow composition – coefficients w_1 and w_4 are statistically different from 1 (fourth panel of Table 3). So, those entering unemployment in the first quarter (January–March) are on average of higher quality (on average more successful in finding a new job and leaving a particular duration category) than those entering unemployment in the preceding quarter (October–December). In Figures 2 and 3, a strong seasonal pattern can be observed for the share of the newly unemployed who terminate their job because of family reasons (pregnancy, maternity leave, serious disease of a family member, etc.) and health reasons. The share is regularly lowest in the first quarters of the year. If we assume that the population leaving employment for family and health reasons exhibits low hazards on average, its under-representation in the group of fresh unemployment entrants indicates that this group of the unemployed has higher re-employment probabilities.

Finally note that no effect of time-varying macroeconomic conditions on the inflow composition is detected, i.e., the coefficients on the dummies for boom B_b and recession B_r are not statistically different from 1. The use of several business cycle indicators (Model 2) and dummy variables (Model 2') that we introduced in the section Data leaves the results unchanged. So, the cohort effect driven by macroeconomic conditions is not present.

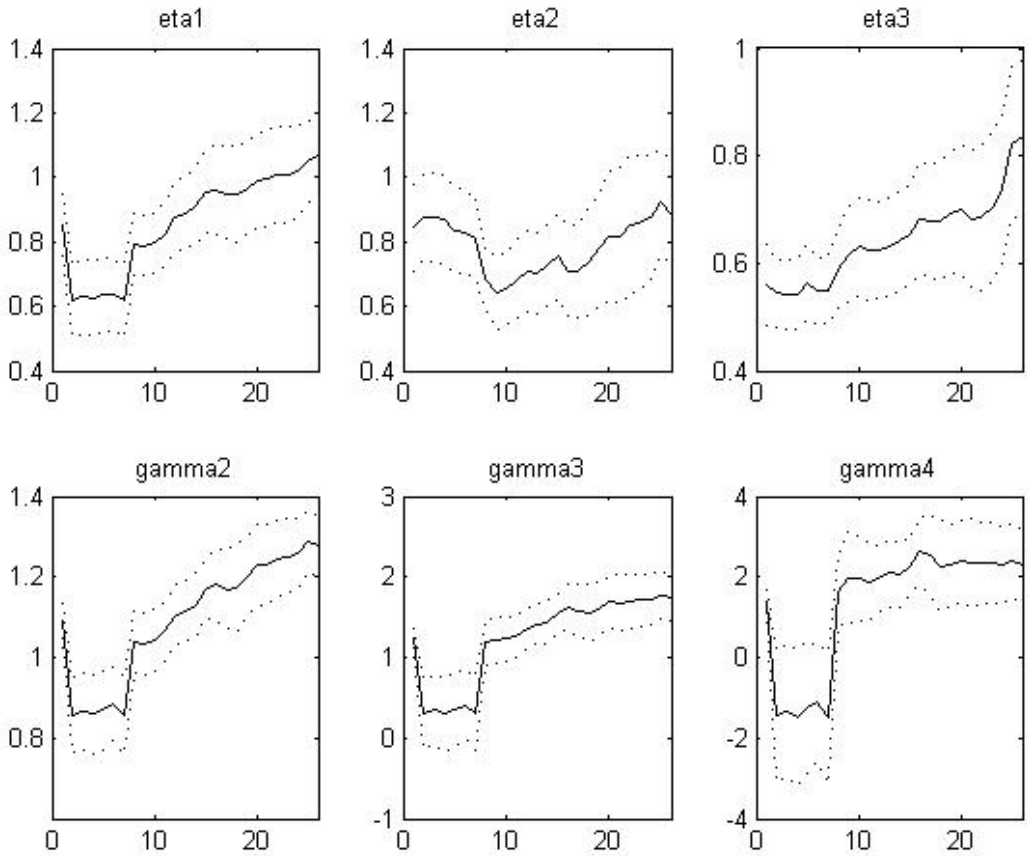
We conduct the specification tests introduced in (12a)–(12c). The first two restrictions (12a) and (12b) cannot be rejected at all conventional significance levels for all duration models. The same is not true for the third restriction (12c). Residual analysis suggests a positive correlation between the residuals across equations in a particular period. The autocorrelation test (Durbin-Watson) does not detect any problem with residual autocorrelation. The data fit is very good (based on the pseudo-R^2 measure).

[25] The negative duration dependence may also be, on the supply side, a consequence of decreasing motivation to search for a new job. On the effects of taxes and benefits on the unemployed and labor market flows in the Czech Republic, see Galuscak and Pavel (2007).

[26] The effect of time-varying macroeconomic conditions on individual duration dependence is detected by Model 2. It follows that during booms the negative individual duration dependence is not so strong for the unemployed in their first and second quarters of unemployment. On the other hand, the negative duration dependence is stronger in booms for those with unemployment spells of three and four quarters. So, Lockwood's (1991) concept of viewing the long-term unemployed as low productivity types during booms by hiring firms occurs in the Czech Republic.

Regarding parameter stability (which is examined for countries that have experienced structural changes) we estimate Model 2' over a rolling window of 32 observations. The resulting 26 values for the selected parameters and the 95% confidence intervals are shown in the following figures.[27]

Figure 7: Evolution of Parameters Estimated Over a Rolling Window of 32 Observations



The figures indicate parameter instability for almost all the parameters displayed. Furthermore, the figures suggest evolution of the coefficients over time. For example, the strong negative individual duration dependence from the first to second quarter of unemployment is weakening over time according to the first panel of Figure 7.[28] In general, we observe a falling impact of individual duration dependence and higher unobserved heterogeneity (an increase in parameter γ_2, reflecting the variance of the heterogeneity distribution). So, the source of observed negative aggregate duration dependence shifts towards the unobserved heterogeneity which is the case in continental Europe and the US. In the UK, the aggregate duration dependence stems mainly from the individual duration dependence.

[27] We report the series for parameters that exhibit significant changes or are of main interest in this study.

[28] One could, for example, relate the switch from negative to neutral (positive) individual duration dependence from the first to second quarter of unemployment to the evolution of the system of unemployment benefits in the Czech Republic, which is often viewed as being not sufficiently motivating for job search in recent years.

If the parameter instability of coefficients γ_i is considered with respect to the specification tests stated in (12a)–(12c), the problems are detected at the beginning of the sample period. The estimate of γ_2 is significantly lower than one for the first 10 values. There is no distribution function with positive support with such moment.[29] The specification problems could be a consequence of outliers in the hazard rates in 1994. So, we estimate Model 2' on sub-sample 1995:1–2007:1. The results are reported in Table 4.

Table 4: Estimation Results of Model 2', all unemployed, period 1995:1–2007:1

Individual duration dependence			
η_1	η_2	η_3	
0.87	**0.69**	**0.60**	
0.04	0.05	0.04	
Effect of time-varying macroeconomic conditions on individual duration dependence			
β_1	β_2	β_3	
-0.05	0.05	0.01	
0.03	0.04	0.04	
Unobserved heterogeneity			
γ_2	γ_3	γ_4	
1.09	**1.36**	**1.97**	
0.03	0.09	0.32	
Seasonal inflow effect			
w_1	w_2	w_3	w_4
1.04	0.99	1.02	**0.95**
0.02	0.02	0.02	0.01
Effect of time-varying macroeconomic conditions on inflow (cohort effect)			
B_b	B_r		
0.99	1.01		
0.01	0.01		

Note: Standard errors reported below the coefficient estimate. Bold indicates coefficients significantly different from 1 (all sections except Effect of macroeconomic conditions on individual duration dependence, where bold indicates coefficients different from zero). 95% level of significance considered.

The coefficients change in the direction suggested by Figure 7, with an increasing role of unobserved heterogeneity and a decreasing role of individual duration dependence. The interpretation, however, does not change qualitatively.

The next table reports the results separately for men and women. Since the data categorized by sex are available only since 1998, we focus on sub-period 1998:4–2007:1.

[29] Note that γ_i are normalized *i*th moments of the distribution and we assume the mean of the distribution to equal 1. So, γ_2 less than 1 implies a negative variance of the distribution.

Table 5: Estimation Results of Model 2' by sex, period 1998:4–2007:1

Individual duration dependence							
Men			Women				
η_1	η_2	η_3	η_1	η_2	η_3		
1.17	0.98	**0.71**	1.00	0.92	**0.80**		
0.07	0.10	0.14	0.08	0.10	0.06		
Effect of time-varying macroeconomic conditions on individual duration dependence							
Men			Women				
β_1	β_2	β_3	β_1	β_2	β_3		
0.00	0.14	0.01	0.06	0.06	-0.08		
0.05	0.07	0.13	0.04	0.07	0.06		
Unobserved heterogeneity							
Men			Women				
γ_2	γ_3	γ_4	γ_2	γ_3	γ_4		
1.31	**1.87**	**2.77**	**1.35**	**2.06**	**3.30**		
0.03	0.07	0.19	0.05	0.18	0.55		
Seasonal inflow effect							
Men				Women			
w_1	w_2	w_3	w_4	w_1	w_2	w_3	w_4
1.00	**0.90**	**1.23**	**0.91**	**1.12**	0.98	**1.06**	**0.86**
0.04	0.03	0.05	0.03	0.03	0.02	0.03	0.02
Effect of time-varying macroeconomic conditions on inflow (cohort effect)							
Men		Women					
B_b	B_r	B_b	B_r				
1.00	1.00	1.02	0.98				
0.03	0.03	0.02	0.02				

Note: Standard errors reported below the coefficient estimate. Bold indicates coefficients significantly different from 1 (all sections except Effect of macroeconomic conditions on individual duration dependence, where bold indicates coefficients different from zero). 95% level of significance considered.

In general, the estimated coefficients do not differ between men and women. The only exception is the positive individual duration dependence from the first to second quarter of unemployment for men and the neutral individual duration dependence for women for that duration category. The magnitudes of the coefficients are in accordance with the results for the population of all the unemployed as they are involved in the rolling window estimation.[30]

Time aggregation bias

In this subsection, we briefly discuss the effect of time aggregation for the Czech Republic similarly to the case of France in the previous section. In addition to the estimation results that are implied by the hazards where the OU are taken into account, we estimate Models 1, 2, and 2' for the hazards neglecting the OU. The data fit of the models employing hazards without the OU is worse than that of the models based on hazards with the OU. Also, the residual autocorrelation tests perform worse in the case of hazards without the OU. The results are shown in Table 6.

[30] The length of the period we focus on in the case of men and women is close to the 32 observations window and thus the results for both men and women relate approximately to the last point of the graphs in Figure 7.

Table 6: Time Aggregation Bias – different estimation results for hazards with and without OU, 1995:1–2007:1, all unemployed

Hazard:		Model 1 W/out OU	Model 1 With OU	Model 2 W/out OU	Model 2 With OU	Model 2' W/out OU	Model 2' With OU
Individual duration dependence	η_1	**1.26**	**0.83**	**1.26**	**0.85**	**1.33**	**0.87**
		0.05	0.04	0.05	0.03	0.07	0.04
	η_2	**0.80**	**0.74**	**0.78**	**0.78**	**0.74**	**0.69**
		0.04	0.04	0.05	0.04	0.05	0.05
	η_3	**0.65**	**0.60**	**0.67**	**0.70**	**0.70**	**0.60**
		0.02	0.02	0.03	0.03	0.04	0.04
Effect of time-varying macroeconomic conditions on individual duration dependence	β_1	-	-	-0.02	**0.44**	-0.08	-0.05
		-	-	0.18	0.14	0.05	0.03
	β_2	-	-	0.15	0.35	0.08	0.05
		-	-	0.15	0.20	0.04	0.04
	β_3	-	-	-0.16	**-0.23**	-0.07	0.01
		-	-	0.12	0.11	0.04	0.04
Unobserved heterogeneity	γ_2	**1.25**	**1.09**	**1.24**	**1.18**	**1.27**	**1.09**
		0.04	0.03	0.06	0.03	0.05	0.03
	γ_3	**1.96**	**1.31**	**1.86**	**1.53**	**2.03**	**1.36**
		0.14	0.10	0.22	0.10	0.15	0.09
	γ_4	**3.68**	**1.80**	**3.28**	**2.09**	**3.97**	**1.97**
		0.37	0.32	0.58	0.25	0.39	0.32
Seasonal inflow effect	w_1	0.96	**1.04**	0.96	**1.05**	0.96	**1.04**
		0.02	0.02	0.02	0.02	0.02	0.02
	w_2	1.01	0.99	0.99	**0.96**	1.00	0.99
		0.02	0.02	0.03	0.02	0.02	0.02
	w_3	1.04	1.02	1.05	**1.06**	1.04	1.02
		0.02	0.02	0.03	0.02	0.02	0.02
	w_4	1.00	**0.95**	1.00	**0.94**	0.99	**0.95**
		0.02	0.01	0.02	0.01	0.02	0.01
Effect of time-varying macroeconomic conditions on inflow composition (cohort effect)	α	-	-	**-0.43**	-0.23	-	-
		-	-	0.17	0.13	-	-
	B_b	-	-	-	-	1.00	0.99
		-	-	-	-	0.01	0.01
	B_r	-	-	-	-	1.00	1.01
		-	-	-	-	0.01	0.01

Note: Standard errors reported below the coefficient estimate. Bold indicates coefficients significantly different from 1 (all sections except Effect of macroeconomic conditions on individual duration dependence, where bold indicates coefficients different from zero). 95% level of significance considered. Tightness of the labor market as a business cycle indicator is used for Model 2.

Table 6 demonstrates almost all the wrong results that could be caused by time aggregation in discrete time models of aggregate duration data. First, ignoring the OU results in reporting a positive ($\eta_1 > 1$) instead of negative ($\eta_1 < 1$) individual duration dependence for the first two duration categories, as one can observe from the first row of the table. As a consequence, models

based on the hazards without the OU provide higher estimates of unobserved heterogeneity (γ_2), since both data sets have to explain the same observed negative aggregate duration dependence.

Second, ignoring the OU in the hazard rates can also cause non-detection of the effect of season on the quality of the inflow into unemployment, especially when the seasonal inflow effects are driven by those who leave unemployment before the end of their first quarter of unemployment. Table 6 shows that models employing the hazards with the OU do not detect seasonality in inflow composition, while models with the OU hazards do.[31]

Finally, the effect of time-varying macroeconomic conditions on the inflow composition is detected by Model 2 using hazards neglecting the OU. The negative coefficient α suggests that in booms the quality of unemployment entrants decreases. Based on the hazards with the OU, such effect is not statistically significant. As we discussed in the previous section, this is a result of the fact that data ignoring the OU do not capture the high quality unemployed, who leave unemployment before the end of quarter more probably in booms than in recessions.

To assess the possible biases caused by the time aggregation, Table 7 reports the average percentage share of the unemployed that are unemployed for less than one month in selected countries for the year 2004. The table suggests how severe the problem of time aggregation bias can be regarding other countries. The share of the very short-term unemployed relates to the number of those who are not depicted by quarterly data if collected as at *the last day* of the quarter. Table 7 shows that the Czech Republic belongs to the group of countries with a low share of the very short-term unemployed. Therefore, the problem of biased results is even more profound for other countries.

Table 7: Share of Unemployed with Duration Less than 1 Month (%), 2004

Czech Republic	5.0
Hungary	5.3
Poland	6.5
Slovakia	6.1
EU15	7.2
OECD	14.7
United States	33.1
Japan	16.9

Source: OECD Statistics.
http://www.oecd.org/document/15/0,3343,fr_21571361_33915056_38938959_1_1_1_1,00.html

[31] Indeed, the time series of the number of unemployed persons in the duration category "0–3" months without the OU exhibit lower seasonality that the time series capturing the OU group.

8. Conclusions

In this paper, the unemployment dynamics in the Czech Republic over the period 1992–2007 are explored through aggregate unemployment duration data analysis. We exploit the existence of data on monthly inflows into unemployment and, contrary to previous studies, we are able to account for time aggregation bias. The bias is caused by the fact that a fraction of the very short-term unemployed do not appear in the unemployment registry quarterly data on the number of unemployed persons in the duration category of less than 3 months. We show that ignoring this group of the unemployed leads to upward bias in individual duration dependence, spurious counter-cyclicality of the average quality of entrants into unemployment, and spurious seasonal effects, and show the presence of these biases on empirical data for France and the Czech Republic.

The estimation results suggest that the coefficients describing unemployment duration change over time significantly. We observe a high impact of negative individual duration dependence in the 1990s in the Czech Republic. At the beginning of the 2000s the impact of individual duration dependence is dampened and unobserved heterogeneity strengthens its role. So, the source of the observed negative aggregate duration dependence shifts from individual duration dependence toward unobserved heterogeneity, approaching the situation experienced by the Western European countries (except the UK).

In general, we do not detect significant influences of time-varying macroeconomic conditions on unemployment duration (on individual duration dependence and inflow composition). There are two possible reasons underlying such a conclusion. First, there really are no significant effects of macroeconomic conditions of business cycle frequency on outflows. Second, our indicators of the time-varying macroeconomic conditions do not capture the evolution of the economy sufficiently to uncover links between the macroeconomic conditions and unemployment duration. The models of aggregate duration data employed in this paper can detect effects of time-varying conditions of a frequency equal to the frequency of the chosen indicators. Secular trends, for example, are eliminated in the system of estimation equations.

On the other hand, analysis of the reason for leaving a job for the newly unemployed suggests a link between the time-varying macroeconomic conditions and the shares of reasons for job termination (a decrease in quits from a job and an increase in terminations due to redundancy during the 1997–1999 recession). However, this link is difficult to examine further because of the new highly aggregated classification of the reasons for leaving a job used in the Czech LFS data since 2002.

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Appendix A: Estimation Equations

In this section we state the system of equations for the ratios of aggregate hazard rates. The system of equations is an extension of the system introduced in van den Berg and van Ours (1994). The extension concerns the possibility of variation in inflow composition and individual duration dependence.

1st equation:

$$\ln\left(\frac{h(t,1)}{h(t,0)}\right) = \ln\left(\eta_1(t)\right) + \ln\left(W_t\right) + \ln\left(\frac{\psi_4(t-1)}{\psi_4(t)}\right) +$$
$$+\ln\left(1-\gamma_2 h(t-1,0)\right) - \ln\left(1-h(t-1,0)\right) + \varepsilon_t^1$$

2nd equation:

$$\ln\left(\frac{h(t,2)}{h(t,0)}\right) = \ln\left(\eta_1(t)\eta_2(t)\right) + \ln\left(W_t W_{t-1}\right) + \ln\left(\frac{\psi_4(t-2)}{\psi_4(t)}\right) +$$
$$+\ln\left(\begin{array}{l} 1-\eta_1(t-1)\gamma_2 W_{t-1}\dfrac{\psi_4(t-2)}{\psi_4(t-1)}h(t-1,0) - \\ -\gamma_2 h(t-2,0) + \eta_1(t-1)\gamma_3 W_{t-1}\dfrac{\psi_4(t-2)}{\psi_4(t-1)}h(t-1,0)h(t-2,0) \end{array}\right)$$
$$-\ln\left(\begin{array}{l} 1-\eta_1(t-1)W_{t-1}\dfrac{\psi_4(t-2)}{\psi_4(t-1)}h(t-1,0) - \\ -h(t-2,0) + \eta_1(t-1)\gamma_2 W_{t-1}\dfrac{\psi_4(t-2)}{\psi_4(t-1)}h(t-1,0)h(t-2,0) \end{array}\right) + \varepsilon_t^2$$

3rd equation:

$$\ln\left(\frac{h(t,3)}{h(t,0)}\right)=\ln\left(\eta_1(t)\eta_2(t)\eta_3(t)\right)+\ln\left(W_tW_{t-1}W_{t-2}\right)+\ln\left(\frac{\psi_4(t-3)}{\psi_4(t)}\right)+$$

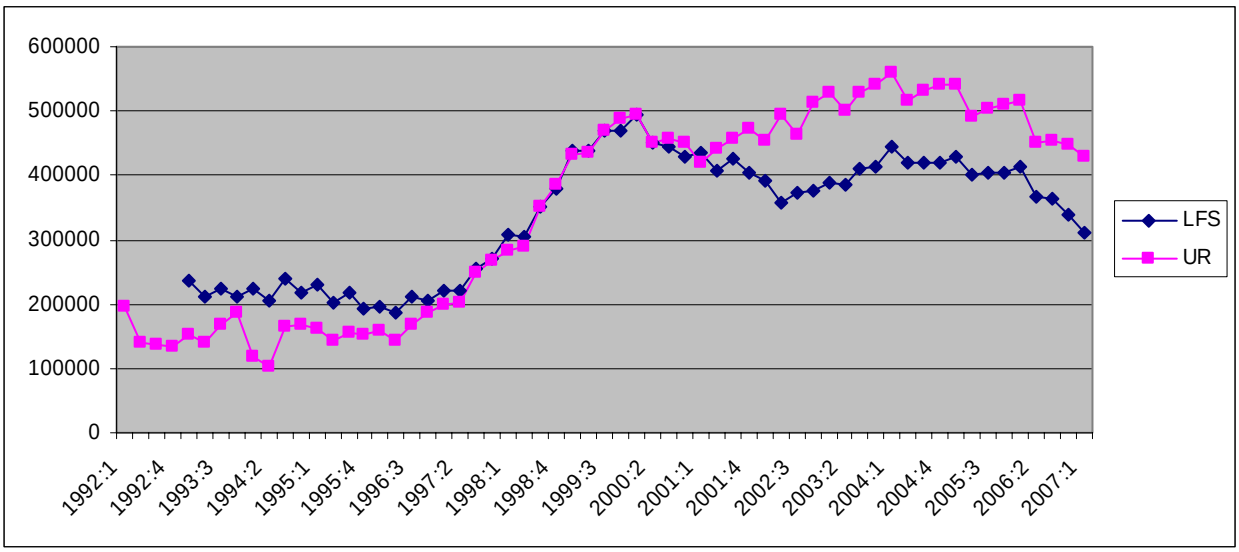
$$+\ln\left(\begin{array}{l}
1-\eta_1(t-1)\eta_2(t-1)\gamma_2W_{t-1}W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-1)}h(t-1,0)- \\
-\gamma_2h(t-3,0)+\eta_1(t-1)\eta_2(t-1)\gamma_3W_{t-1}W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-1)}h(t-1,0)h(t-3,0) \\
-\eta_1(t-2)\gamma_2W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-2)}h(t-2,0)+\eta_1(t-2)\gamma_3W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-2)}h(t-2,0)h(t-3,0) \\
+\eta_1(t-1)\eta_1(t-2)\eta_2(t-1)\gamma_3W_{t-1}W_{t-2}^2\dfrac{\left[\psi_4(t-3)\right]^2}{\psi_4(t-1)\psi_4(t-2)}h(t-1,0)h(t-2,0) \\
-\eta_1(t-1)\eta_1(t-2)\eta_2(t-1)\gamma_4W_{t-1}W_{t-2}^2\dfrac{\left[\psi_4(t-3)\right]^2}{\psi_4(t-1)\psi_4(t-2)}h(t-1,0)h(t-2,0)h(t-3,0)
\end{array}\right)$$

$$-\ln\left(\begin{array}{l}
1-\eta_1(t-1)\eta_2(t-1)W_{t-1}W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-1)}h(t-1,0)- \\
-h(t-3,0)+\eta_1(t-1)\eta_2(t-1)\gamma_2W_{t-1}W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-1)}h(t-1,0)h(t-3,0) \\
-\eta_1(t-2)W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-2)}h(t-2,0)+\eta_1(t-2)\gamma_2W_{t-2}\dfrac{\psi_4(t-3)}{\psi_4(t-2)}h(t-2,0)h(t-3,0) \\
+\eta_1(t-1)\eta_1(t-2)\eta_2(t-1)\gamma_2W_{t-1}W_{t-2}^2\dfrac{\left[\psi_4(t-3)\right]^2}{\psi_4(t-1)\psi_4(t-2)}h(t-1,0)h(t-2,0) \\
-\eta_1(t-1)\eta_1(t-2)\eta_2(t-1)\gamma_3W_{t-1}W_{t-2}^2\dfrac{\left[\psi_4(t-3)\right]^2}{\psi_4(t-1)\psi_4(t-2)}h(t-1,0)h(t-2,0)h(t-3,0)
\end{array}\right)+\varepsilon_t^3$$

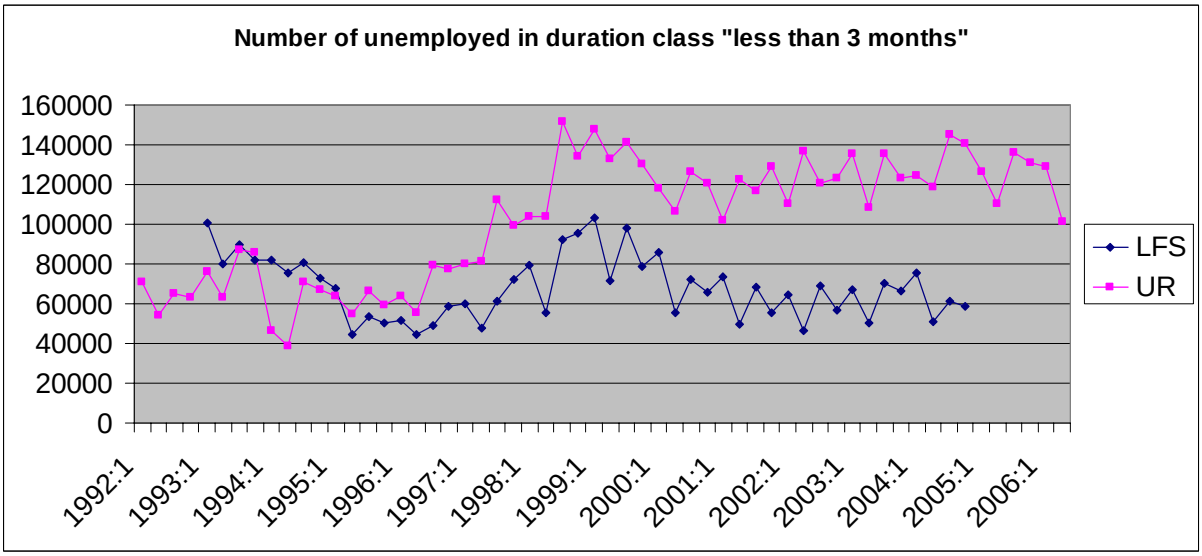
Appendix B: Descriptive Analysis of Differences between Labor Force Survey (LFS) and Unemployment Registry (UR) Data

The comparison of the level of unemployment reported by the LFS and UR data sets is captured by Figure B1. We observe that UR unemployment was lower than LFS unemployment in the period 1992–1997. Subsequently, the two measures attained similar levels, and finally UR unemployment has been higher than LFS unemployment since 2001.[32]

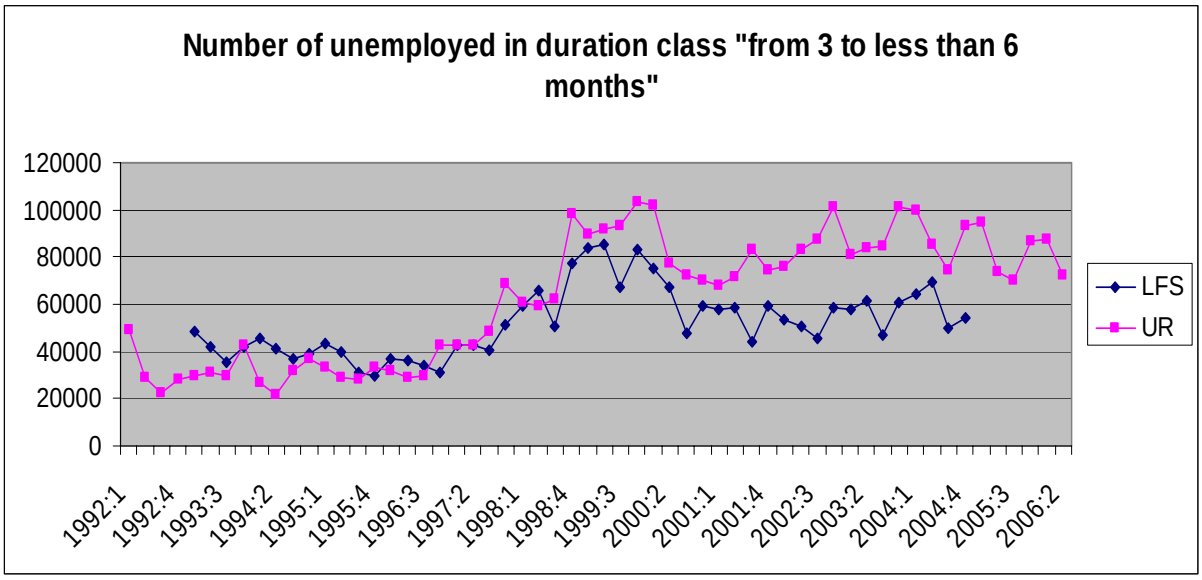
Figure B1: Number of Unemployed Reported by the LFS and UR Data Sets, Czech Republic, 1992:1–2007:1

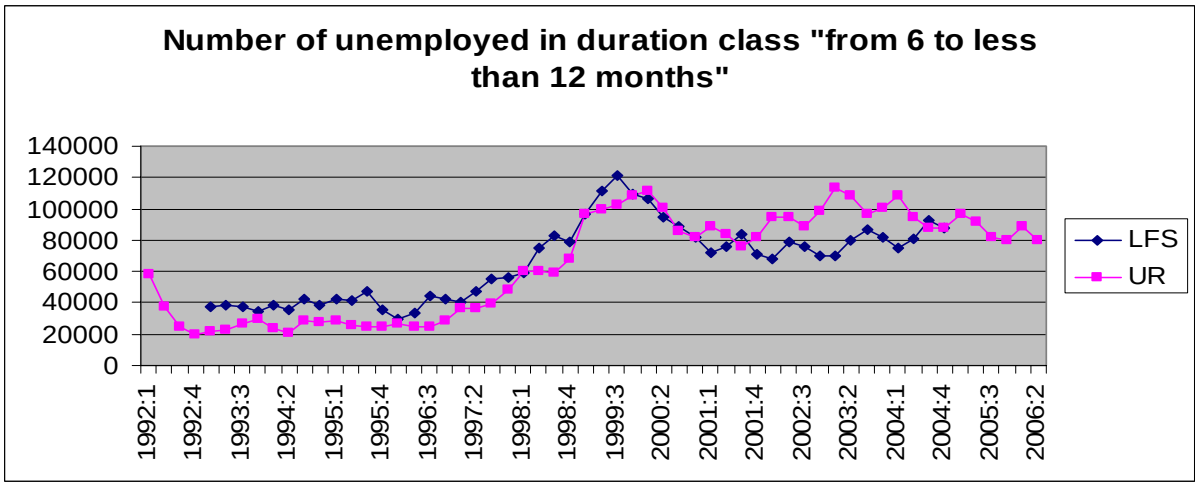


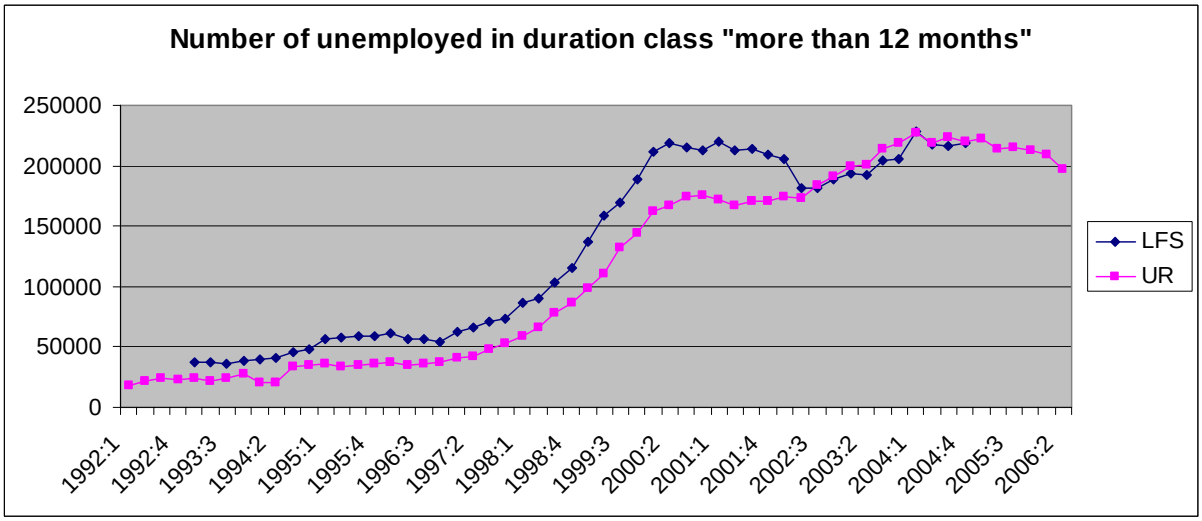
The following figures report the numbers of unemployed persons in different duration categories according to the LFS and UR data sets.



[32] The described differences are statistically significant. Computation of the 95% confidence intervals for the values reported by the LFS data set suggests that the relative magnitude of the two series does not change even when confidence bounds are taken into account.







The figures suggest that all duration classes contribute to the rise in the number of unemployed persons in the UR data over the LFS data. The moment of switch of the number of UR unemployed from below to above the LFS unemployed shifts over time with respect to the duration class we consider.

There are a lot of possible explanations of why the two data sets differ in the numbers of unemployed persons – it takes time between losing a job (LFS) and registering at a labor office (UR) (Munich and Jurajda, 2002), people start to register at labor offices even if they move to another job and they stay unemployed for a few months only, some of the unemployed work even though they are registered at a labor office and therefore they do not appear in the LFS as unemployed, etc. Nevertheless, it is beyond the scope of the paper to identify the source of the different numbers in the survey and unemployment registry data.

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ISSN 1803-7070