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Empirical Essays on Unemployment, Inflation and Access to Human Capital

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Contents

Preface

This dissertation consists of three distinct topics within labor macroeconomics, applied microeconomics, and applied time-series econometrics. The first essay extends the standard methodology used in analyzing unemployment dynamics. The proposed extension is applied on empirical data for the Czech Republic and France. The second essay belongs to the field of the economics of education. It contributes to the discussion on the equal access to higher education. The theoretical (structural) model of an individual schooling decision is set up and the implied reduced form is estimated on a unique data set of all secondary school graduates in the Czech Republic in 1998. Finally, the third essay deals with the inflation dynamics. It draws on extensive research in the modeling of the inflation process in developed countries. Nevertheless, the focus is on developing countries where specific economic and consequently econometric issues have to be considered.

This dissertation is basically an empirical work. Theoretical considerations are, however, an inherent component of all essays and constitute an indispensable part of the contribution of the dissertation.

The first chapter deals with unemployment dynamics with the focus on an unemployment duration analysis. The duration analysis provides a lot of useful insights into the turnover of those unemployed. Unemployment duration is examined using individual-level or aggregate data. For the analysis of the impact of macroeconomic influences of frequencies close to the business cycle and lower, aggregate data are suitable since they usually cover time periods of several years.

In the late 1990s, a non-parametric approach for the estimation of discrete time models of aggregate duration data was introduced. The approach overcomes the problems that resulted from the parametric assumptions, and have estimates become more robust to the model specification. In the first essay, I show that estimates of the basic unemployment dynamic parameters (individual duration dependence, unobserved heterogeneity, seasonality, and the effect of the business cycle) produced by models of aggregate duration data are biased. The bias arises as a consequence of the duration data structure. An extended methodology based on the combination of duration data of different frequencies is proposed, and several models are estimated to demonstrate the high policy relevance of the more accurate approach to examining unemployment duration.

The second essay meets the current research in the economics of education at the point of research on the determinants of an individual schooling decision. The influence of the family, previous school, and environment is clearly theoretically motivated and empirically shown by many studies. Apart from the mentioned influences, the second essay focuses on the influence of a local university. In consequence, the essay answers the question whether the existence of a local university can be a source of the inequality when accessing higher education.

The crucial point that allows for an analysis is the unique data set, which consists of data on all secondary school graduates in the Czech Republic in 1998 that were eligible to enter higher education. The data set is combined with the data on all applicants to institutions providing higher education. From the theoretical point of view, the estimation of reduced form models resulting from the structural model is thoroughly discussed in the second essay.

The third essay deals with the persistence of inflation in the New EU Member States (NMS). There are several issues (e.g. structural breaks, the transition of the NMS economies, convergence) that make the problem of measuring inflation persistence in the NMS different from the standard approaches used for the developed countries.

The essay is a part of broader research that focuses on inflation persistence and the modeling of the inflation process in the NMS. The research started by a discussion on inflation persistence measures appropriate for the NMS and several measures were examined. These include standard parametric measures based on simple univariate models of inflation, univariate and multivariate unobserved component models, ARFIMA models, and the New Hybrid Phillips Curve.[1] It turns out that unobserved component models are flexible enough to describe the inflation process in the NMS. In addition, fractionally integrated processes are taken into consideration. Essay three is the final stage of the research where the most

[1] Details can be found in Franta, Saxa and Smidkova (2007), European Central Bank Working Paper No. 810.

promising models of the inflation process are employed to estimate the measures of the inflation persistence for all countries that joined the EU in 2004 and 2007.

To summarize, as a consequence of various research projects in which I have been involved, this dissertation covers three distinct areas of economic research. It provides new insights with the results highly relevant for policy makers (employment and educational policies) and central bankers (monetary policy).

Essay 1: Time Aggregation Bias in Discrete Time Models of Aggregate Duration Data

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 on 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 for macroeconomic influences. Finally, we demonstrate the profound influence of time aggregation of duration data on the unemployment duration parameters for the 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.

In the current paper, unemployment dynamics are 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 the unemployment registry data on. Thus, a standard approach that draws on reported quarterly data could yield misleading results regarding the individual duration dependence and the 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 the unemployment duration parameters for the empirical data for France and the Czech Republic.

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 the individual duration dependence. Using dummy variables for different stages of the business cycle, we avoid the 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 on 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.[2] 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 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 the 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.

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

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 relative importance of individual duration dependence and unobserved heterogeneity are crucial for the proper conduct of employment programs.[3]

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 face less employment opportunities (Lockwood, 1991). Consequently, the effect of the 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 the average unemployment duration and changes in the NAIRU over time.[4] Abraham and Shimer (2001) and Llaudes (2005) discuss the effect of unemployment duration on the size of the downward pressures on wages. The current paper provides results that can contribute to an additional analysis dealing with the NAIRU and wage determination in the Czech Republic.

Our analysis focuses 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.

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, the effects of time of inflow into unemployment

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

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

(cohort effects), and the 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. The 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 is carried out on unemployment changes. 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 the 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 impact of time-varying macroeconomic conditions. A survey of micro studies for 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 the aggregate unemployment data have been set up. These models allow for the 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 for the non-parametric estimation of duration models. Their model allows for the 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.[5] Abbring, van den Berg, and van Ours (2001, 2002) extend the model of van den Berg and van Ours to estimate the effect of business cycles on the 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 the 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.

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. They use monthly micro data and quarterly aggregate data. 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 a non-systematic character, and the assumption underlying the combination of micro and macro data need not be appropriate for the Czech Republic.

Empirical literature dealing with models of unemployment duration for the Czech Republic is rare. Terrell and Sorm (1999) and Ham, Švejnar, and Terrell (1998) estimate a model at the micro level for the early transition period. Huitfeldt (1996) focuses on the aggregate level. However, he estimates the average unemployment duration under the steady-state assumption for unemployment, and he deals with the period covering the early transition only.[6] 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 examining the 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 to 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

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[5] 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.

[6] Sider (1985) shows that the steady-state assumption leads to misleading results when estimating the average duration.

wages in a different manner than those unemployed temporarily. An attempt to incorporate the duration aspect into the matching function is made in Munich (2001).

3. Models of duration

In this section, we introduce the 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.[7] The mixed proportional hazard model specification takes the following form:

$$h(d \mid t, v) = \psi_1(t)\psi_2(d)v\,, \qquad (1)$$

where $h(d \mid t,v)$ 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 the 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. Both functions, $\psi_1(t)$ and $\psi_2(d)$, are assumed to be positive, and $\psi_1(t)$ is not constant. In addition, we assume

$$\Pr\left(0 \le h(d \mid t,v) \le 1\right) \text{ for every d and t.}$$[8]

The term capturing individual unobserved characteristics, *v*, does not change during unemployment and is distributed according to a distribution function $G(v)$ that satisfies the following conditions:

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

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).[9]

[7] 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).
[8] This condition ensures the existence of all moments of the distribution for the unobserved heterogeneity.
[9] Unobserved characteristics are introduced in this general way because only moments of the distribution appear in the resulting equations.

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 which allow 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:

$$h(d \mid t, v) = \psi_1(t)\psi_3(d,t)\psi_4(t-d)v. \qquad (3)$$

The model specification newly includes the effect of duration on individual hazard, $\psi_3(d,t)$, being dependent on the time-varying macroeconomic conditions 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 $t-d$ – known as the cohort effect.[10] Model 2 is a parametric extension of the benchmark model. As in Turon (2003), we assume the following functional form for $\psi_4(t-d)$:[11]

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

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, the 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):

$$\psi_3(d,t) = \prod_{j=1}^{d}\left[\eta_j^0 + \beta_j bc(t+1-j)\right], \quad d = 1,2,3\,.^{12} \qquad (5)$$

[10] 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 the declines in some sectors (the mining industry, etc.).

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

[12] 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., $\eta_d^0 + \beta_d bc(t)$.

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

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

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. So, while coefficient β_d remains unaffected by the choice of a business cycle indicator, we lose the straightforward interpretation of coefficient η_d^0 as the individual duration dependence.[13]

The second important issue relates to the term capturing cohort effects, ψ_4. Abbring et al. (2002) introduce a flexible specification for 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 the terms that are independent of the business cycle is resolved in the following Model 2'.

<u>Model 2'</u>

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 (the 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

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

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

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

[13] 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.

where $I_r(t-d)$ and $I_b(t-d)$ are indicators of recession (*r*) and boom (*b*) at the time of inflow, respectively.[14]

By restricting the range of 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.

To identify unobserved heterogeneity distribution in Models 2 and 2', we need to assume the existence of two cohorts of unemployed such that one cohort has higher mean hazards for all duration categories. In addition, we need to extend this assumption for cohorts entering the pool of unemployed in recession and boom.[15] Finally, note that 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).

Derivation of estimation equations

The unemployment registry data allow 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*:

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

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:

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

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,

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

[14] 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.

[15] The assumptions and the proof of the identification are formalized in Abbring et al. (2002) who prove that identification requires an additional normalization. In our case, we assume (2) and $B_b B_r = 1$.

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

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

Then, formulas for the ratios of average hazards $h(d\,|\,t)/h(0\,|\,t), d=1,2,3$ are derived, leading to the elimination of the term capturing the calendar time dependence.[16] 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).

The estimation equations obtained are of the following form:

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

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 the 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 the remaining in unemployment increases because of the length of the unemployment spell, then we refer to it as negative duration dependence and the 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)

[16] 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 the 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.

ranking concept is in place, the effect of the 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, $G(v)$:

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

We assume that $E_v\{v\} = 1$. 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 that result from the normalization assumption. The following restrictions for the coefficients representing the unobserved heterogeneity must hold to ensure the existence of distribution $G(v)$ with positive 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 quality 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. Darby, Haltiwanger, and Plant (1985) introduce the hypothesis that during recessions, a proportionally higher fraction of the unemployed with a low re-employment probability enters unemployment than in booms.[17] Such a 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 the coefficient α imply pro-cyclicality of inflows in terms of the re-employment probabilities of the unemployment entrants.

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

The system of nonlinear equations in Appendix A is estimated by a 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 the registry data (UR – Unemployment Registry).

The LFS is a survey of the population that is collected by the Czech Statistical Office following the ILO definition of unemployment, which is a) an individual is without work (not in paid employment or self-employment); b) the individual is currently available for work; and c) the individual is seeking work. The LFS data also contain 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 the information from the two data sets, we compare the total level of unemployment reported by each of them in Appendix B.

Model 2 employs various indicators of the business cycle to capture time-varying macroeconomic conditions: the de-seasonalized and de-trended 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' management.[18] 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.

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.[19] Analysis of unemployment dynamics in the Czech Republic should, therefore, include both inflows and outflows.

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

[19] 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, Michaels, and Solon (2007).

The reason why we carry out the unemployment decomposition in levels is that it can be problematic to use rates for explaining changes in unemployment. First, the inflow and outflow rates 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 a 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 of the newly unemployed for leaving the last job. 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.

Statistical decomposition of unemployment changes

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

$$\Delta U_t \equiv Inflow_t - Outflow_t\,, \qquad (13)$$

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

Figure 1 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. The 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). A duration analysis should help to explain this phenomenon.[20]

[20] Note that for Slovakia, for example, such regularity is not present. From a supply side, the lag probably reflects a benefit structure.

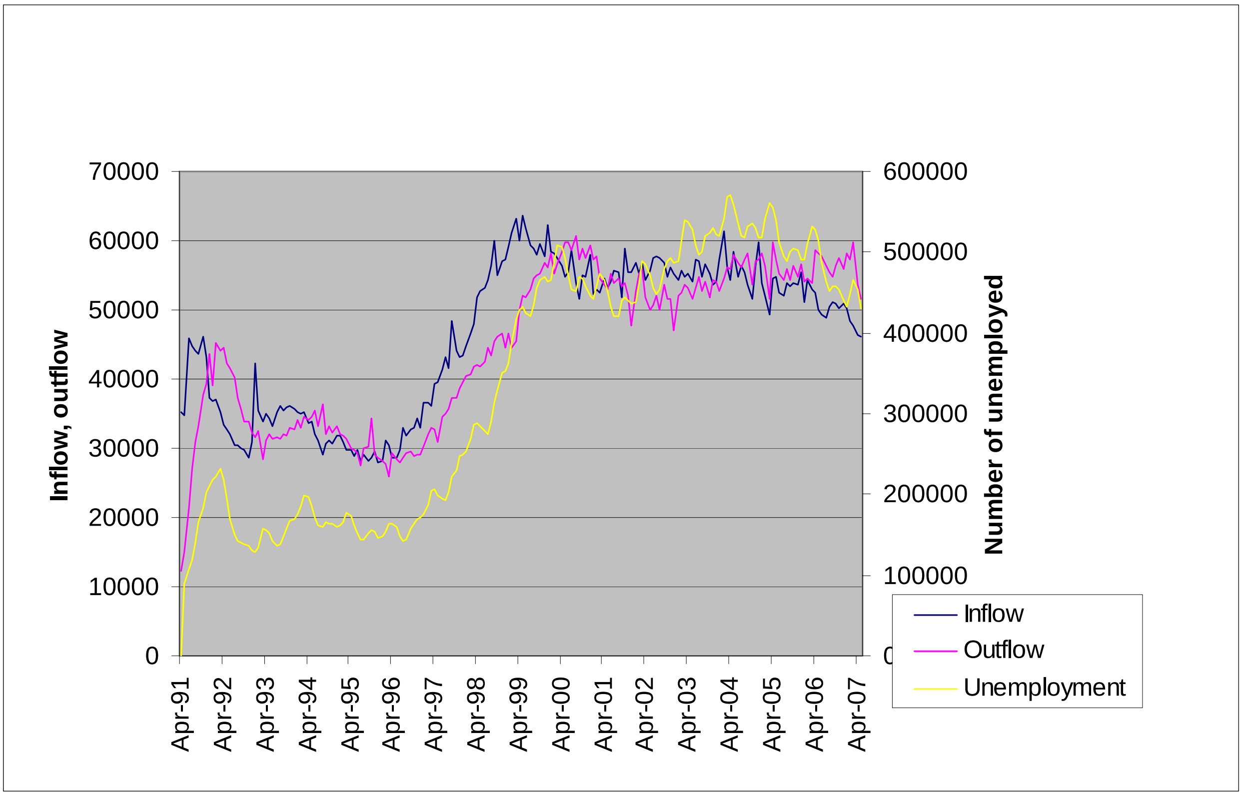

Figure 1: Unemployment inflow and outflow (monthly) – levels.
Note: Time series are seasonally adjusted. Source: Czech UR data.

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. The transition probabilities are normalized by the number of individuals in OLM and in employment. For the Czech Republic, the two normalizing constants are comparable. Available data, however, allow us the examination of 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 quitting 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.

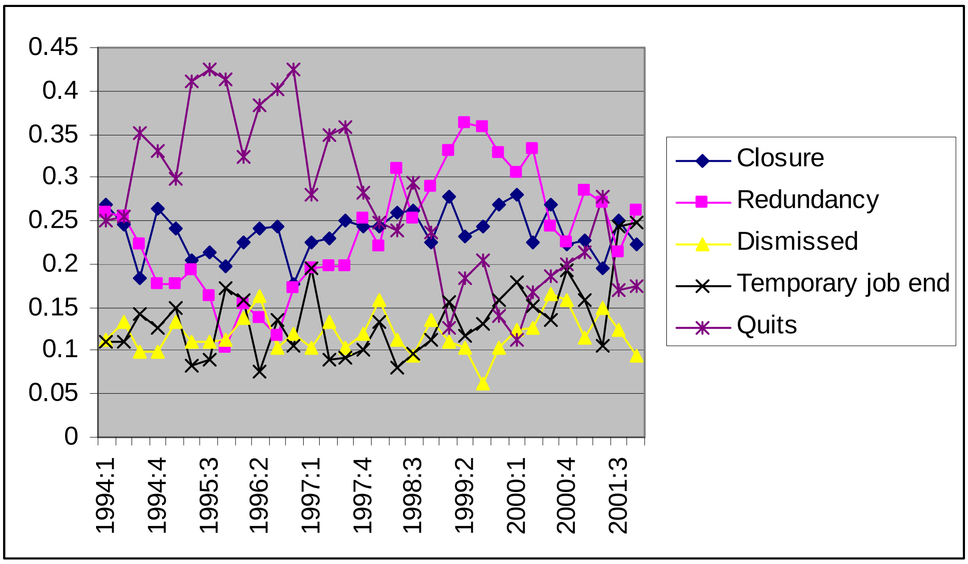

Figure 2: Shares of selected reasons of the newly unemployed for leaving a job, the Czech Republic, 1994–2001.
Source: Author's calculations based on the Czech LFS.

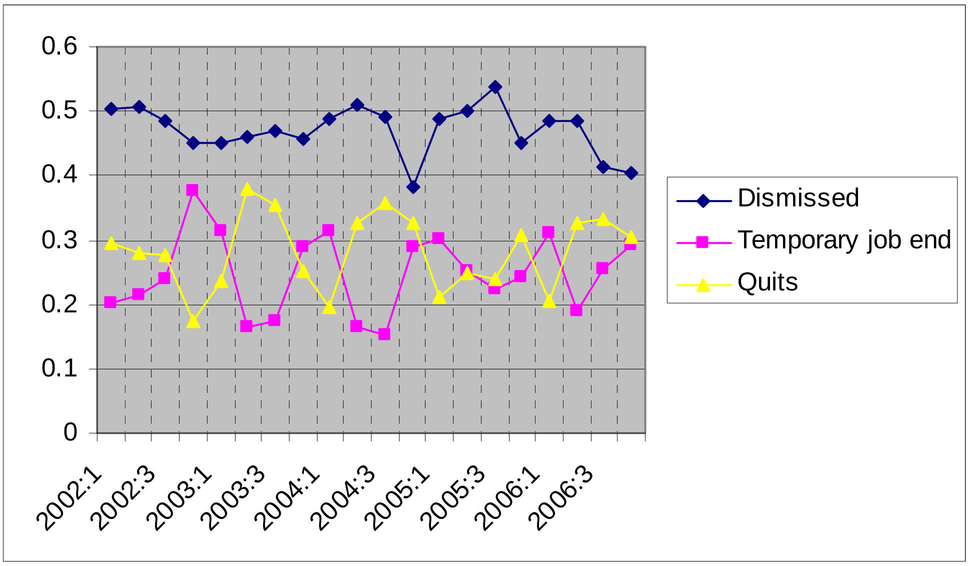

Figure 3: Shares of selected reasons of the newly unemployed for leaving a job, the Czech Republic, 2002–2006.
Source: Author's calculations based on the Czech LFS.

Unemployment duration

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 categorize the number of unemployed persons into five 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 at the end of a quarter. Similarly, the other duration categories are "3–6", "6–9", "9+", and "12+" months.

The numbers of unemployed in duration categories are used to compute the aggregate hazard rates (see Figure 4 and 5). 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 the duration category, i.e., the hazards exhibit negative aggregate duration dependence. An econometric analysis provides an explanation for whether the decreasing aggregate hazard rate over the duration categories is a consequence of the individual duration dependence, the unobserved heterogeneity, or both.

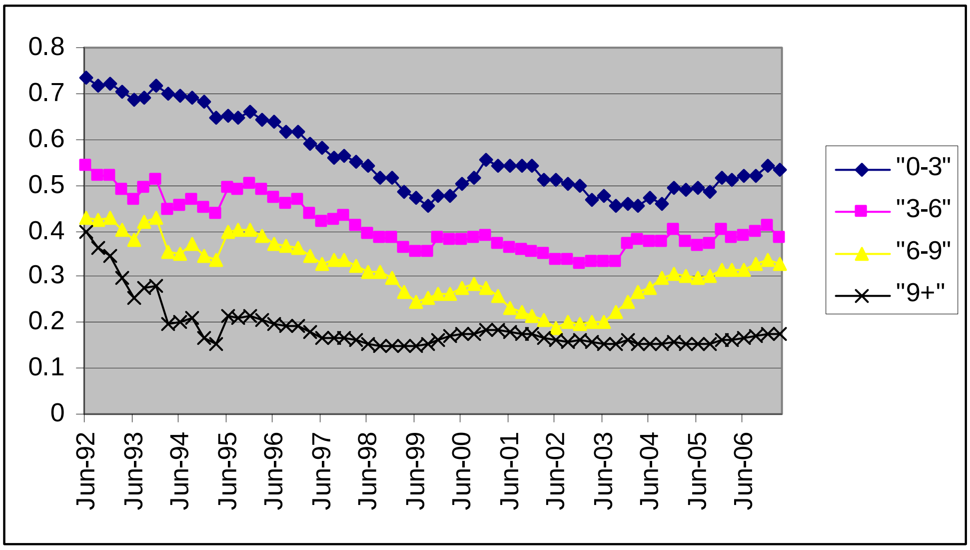

Figure 4: Hazard rates by duration category – moving average of 5 observations, whole population. Source: Author's calculations based on the UR data set.

Hazard rates categorized by gender exhibit similar patterns in terms of aggregate duration dependence (see Figure 5, which reports female hazards). Duration data by gender are available from 1998:4 only. The probability of leaving unemployment is slightly higher for men than for women for all duration categories.[21]

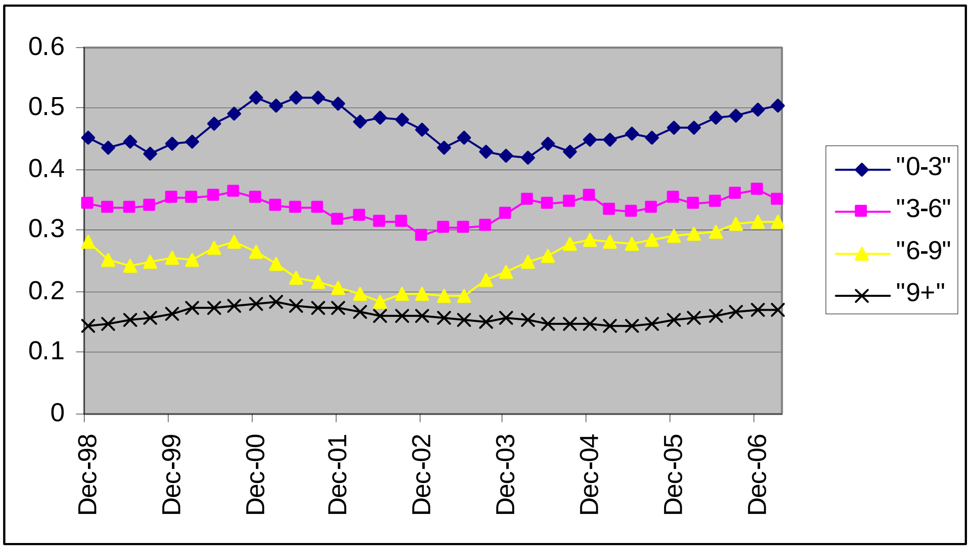

Figure 5: Hazard rates by duration category – moving average of 5 observations, women. Source: Author's calculations based on the UR data set.

[21] The average hazard rate for the 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.

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 who have very short unemployment spells as the omitted unemployed (OU).[22]

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.,

$$\frac{u(t,"0-3")-u(t+1,"3-6")}{u(t,"0-3")}, \qquad (15)$$

is lower than the hazard defined by equation (9a), which takes the OU into account.[23] Note that $u(t,d)$ denotes the number of unemployed persons in duration category d in quarter t. Also note that the literature dealing with models of aggregate duration data employs the simple outflow rates defined as in (15).[24]

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 the monthly unemployment inflows in a quarter, the number of unemployed persons in the 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.

[22] 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).

[23] The hazard rate defined in (15) 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 occurs also in quarter *t*.

[24] 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).

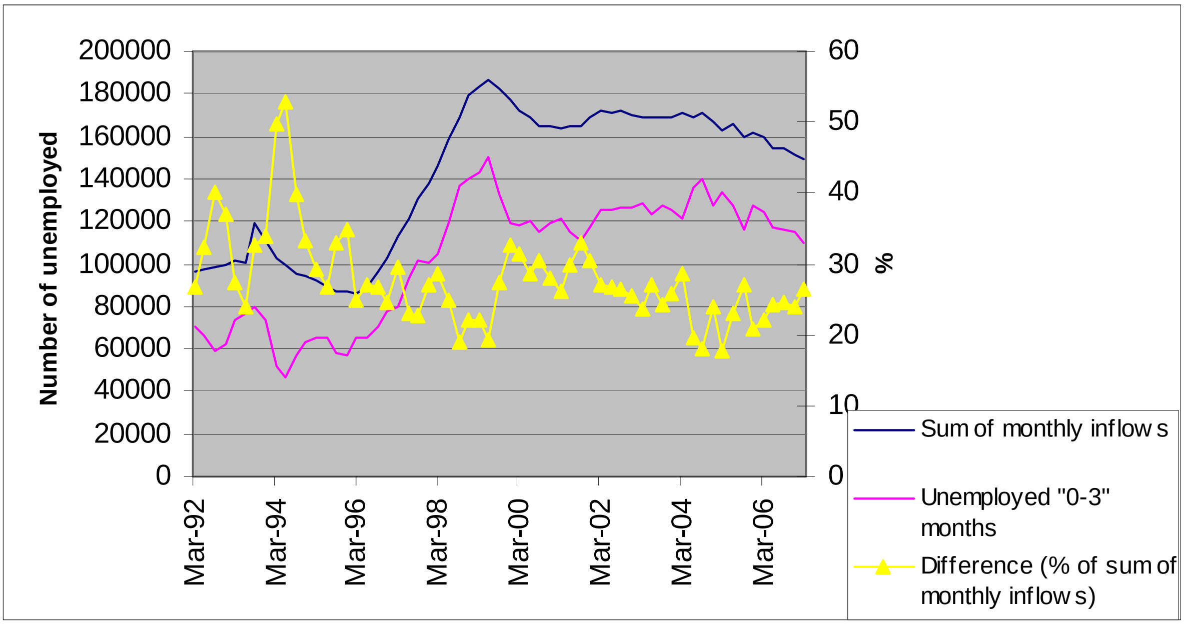

Figure 6: Quarterly inflows, the number of unemployed persons in duration category “0–3” months, and the difference.
Note: Time series are seasonally adjusted.
Source: Czech quarterly and monthly UR data.

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 is 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 an 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 the duration category “0–3” lead to the 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 a 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 a bias leading to wrong conclusions and misleading policy recommendations. Since the hazard rates $h(0\,|\,t)$ enter the right-hand side of each equation of the estimation system, ignoring the OU affects the estimates of the other coefficients as well.

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 a-cyclicality 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).[25] First, we estimate Model 1 using the same hazard rates as in Abbring et al. (2002). The hazard rates are constructed as in equation (15) 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.[26] 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 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: Author's 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

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

[26] 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.

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:

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

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. In what follows, we focus mainly on the Model 2' specification.

Table 3. Estimation results of Models 1, 2, 2', all unemployed, 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, for example, a consequence of a deterioration of human capital (supply side) or some kind of stigma effects (demand side).[27] 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 the phases of the business cycle.[28]

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.

[27] 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).

[28] 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.

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 of, on average, 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).[29] 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).

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.[30]

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[29] Van den Berge and van Ours (1996) discuss a possible reason for the rejection of the specification test e.g. a wrong assumption of the individual hazard being of multiplicative form in its variables. Models estimated on sub-samples pass the specification test.

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

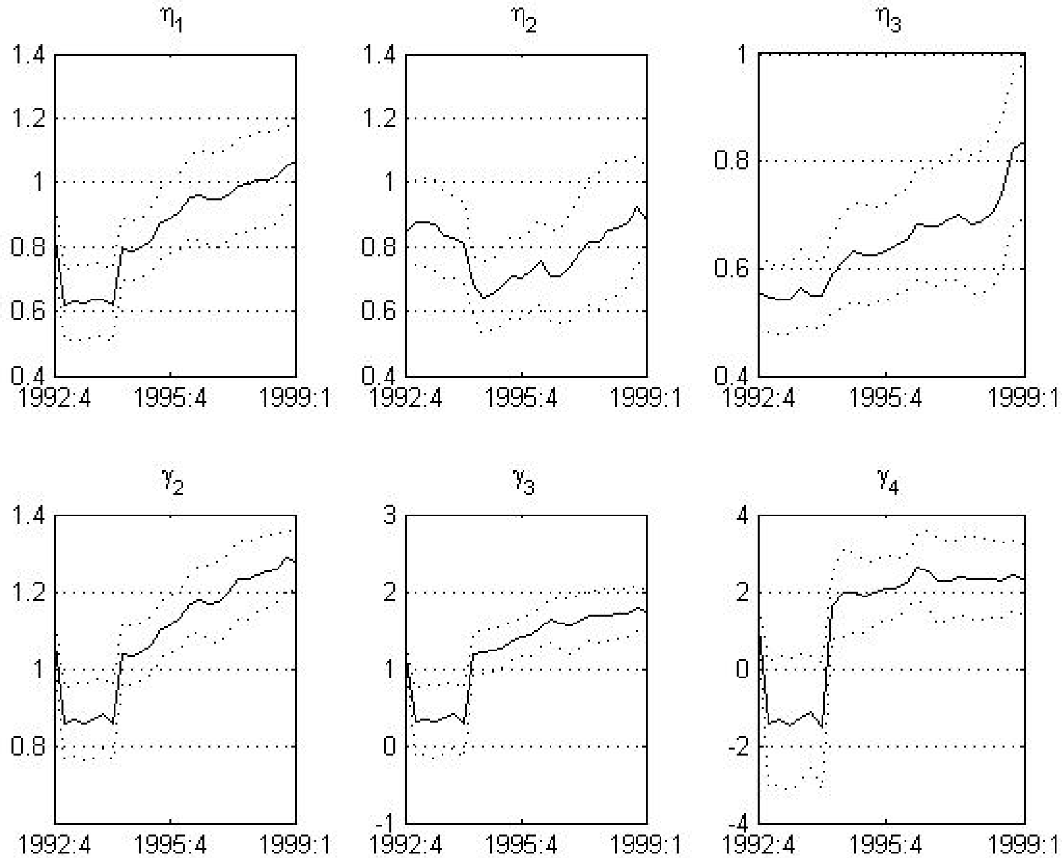

Figure 7: Evolution of parameters estimated over a rolling window of 32 observations.

The figures indicate parameter instability for almost all the parameters displayed. Furthermore, the figures suggest an 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.[31] In general, we observe a falling impact of individual duration dependence and a 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.

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 a moment.[32] The specification problems

[31] One could, for example, relate the switch from negative to neutral (positive) individual duration dependence from the first to the 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 searching in recent years.

[32] 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.

could be a consequence of outliers in the hazard rates in 1994. So, we estimate Model 2' on the 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. Specification tests are satisfied.

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

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 the second quarter of unemployment for men and the neutral individual duration dependence for women for that duration category. Since the pooled sample enables us to estimate the model using longer data spans, we stick to the pooled sample. Finally, note that 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.[33]

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. Specification tests are passed for both types of hazards. The results are shown in Table 6.

[33] 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.

		Model 1		Model 2		Model 2'	
Hazard:		W/out OU	With OU	W/out OU	With OU	W/out OU	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 the 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.[34]

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 an 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 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

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

[34] Indeed, the time series of the number of unemployed persons in the duration category “0–3” months without the OU exhibit lower seasonality than the time series capturing the OU group.

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 an upward bias in individual duration dependence, a 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 21st century 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 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 the 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 the 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, an 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 those quitting 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:

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

2nd equation:

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

3rd equation:

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

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

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

Appendix B: A descriptive analysis of differences between the LFS and the 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.[35]

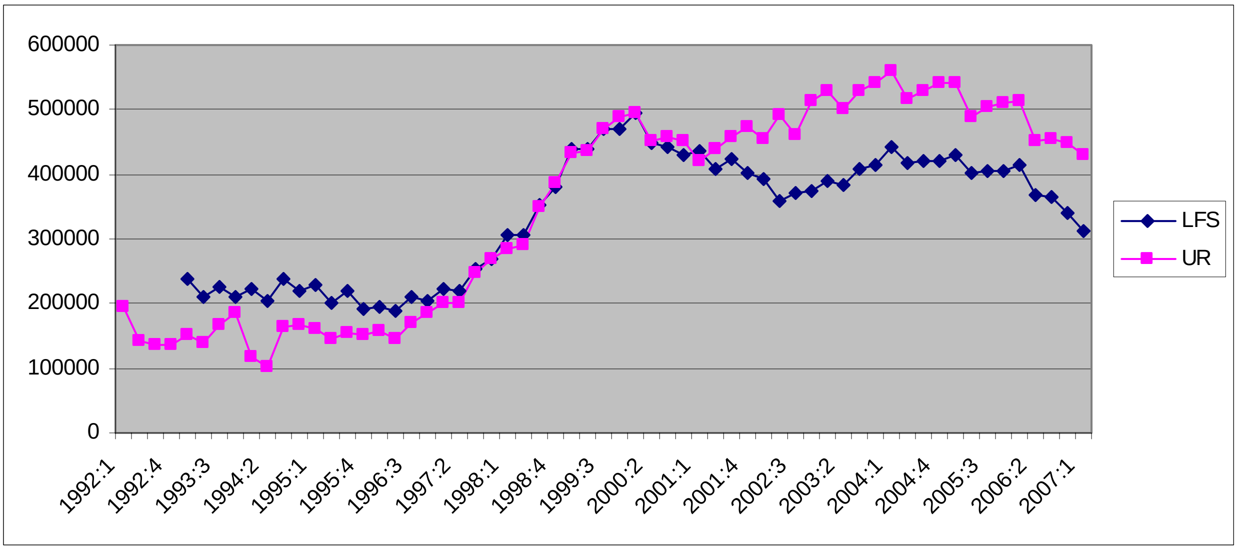
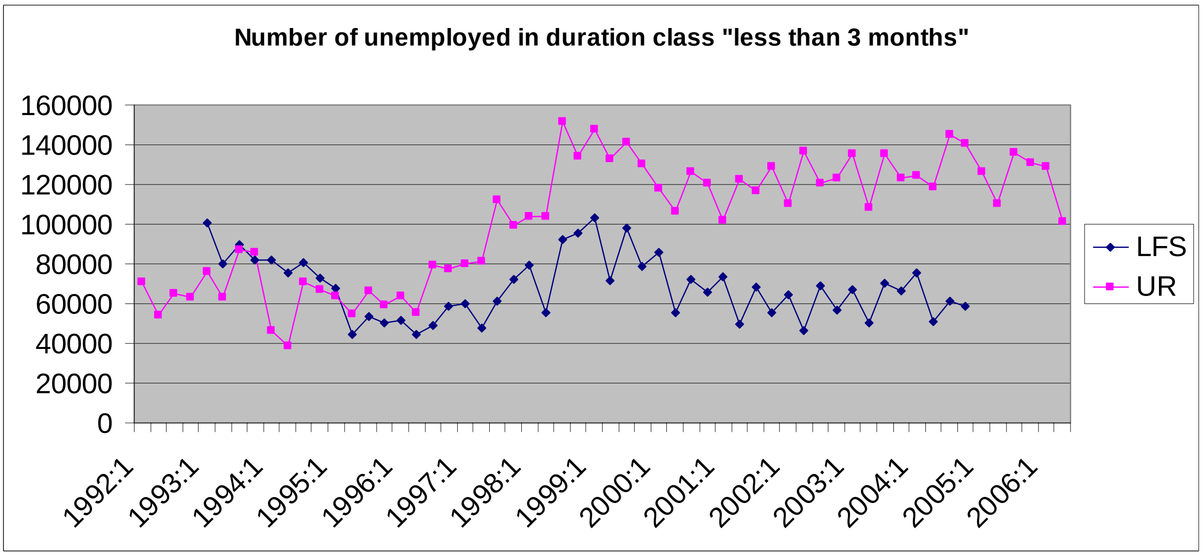
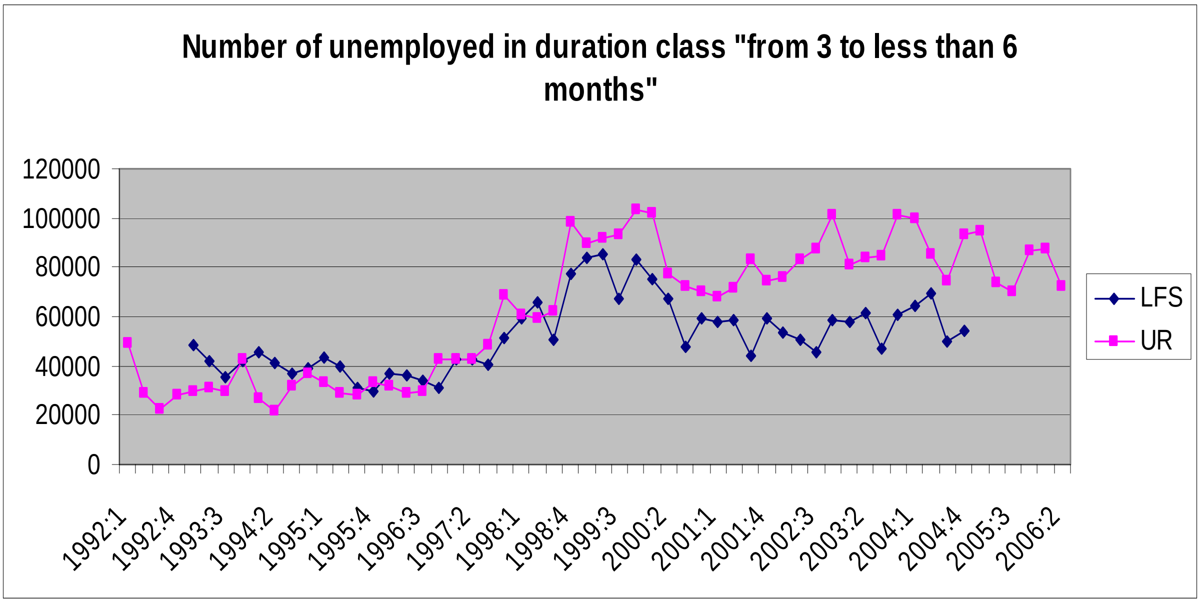


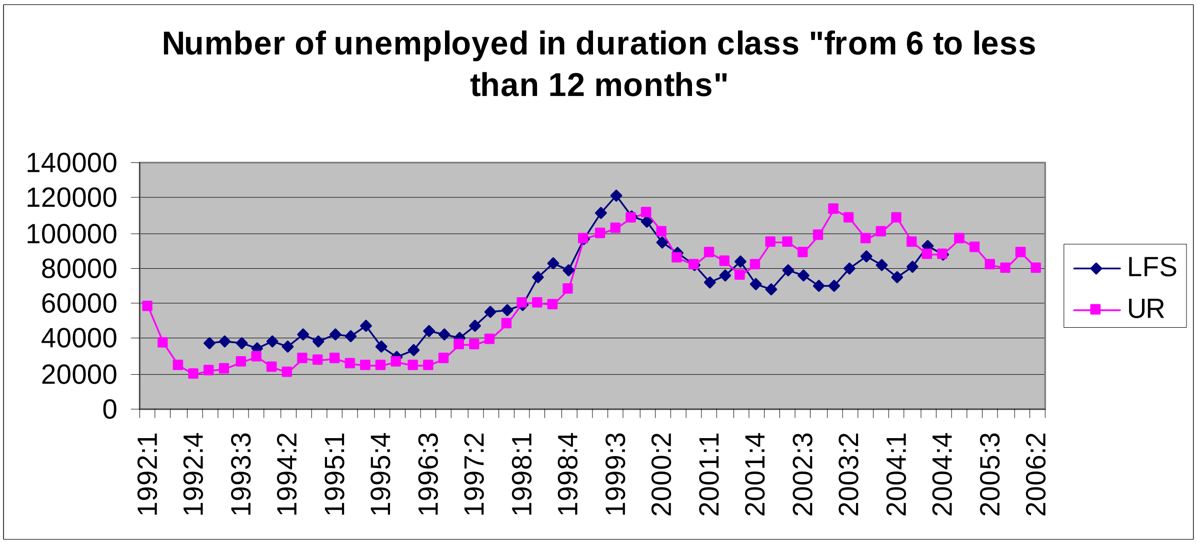
Figure B1: Number of unemployed reported by the LFS and UR data sets, Czech Republic, 1992:1–2007:1.

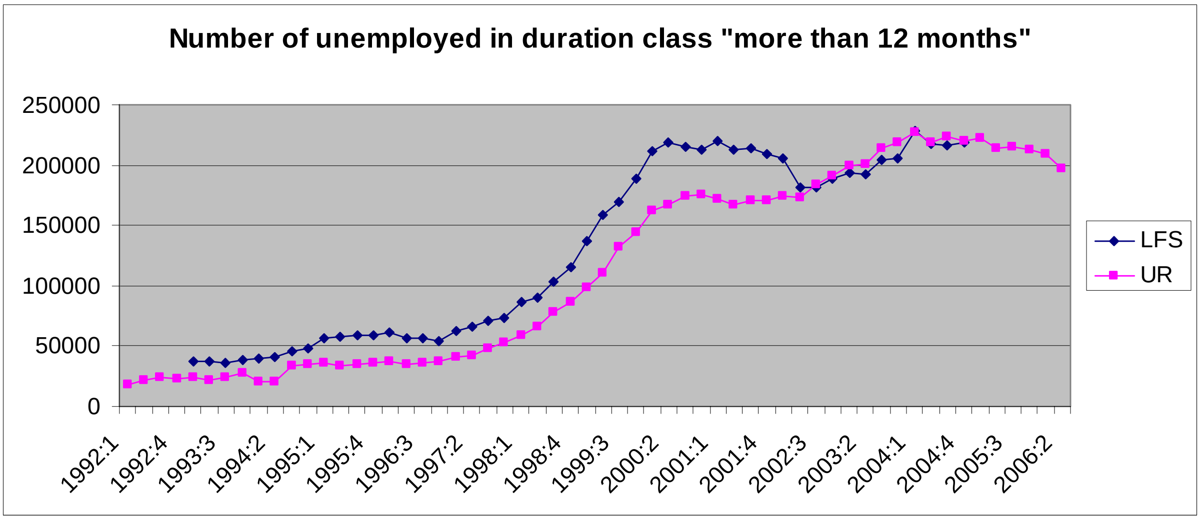
The following figures report the numbers of unemployed persons in different duration categories according to the LFS and UR data sets.



[35] The described differences are statistically significant. A 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.


Number of unemployed in duration class "from 3 to less than 6 months"
LFS
UR
120000
100000
80000
60000
40000
20000
0
1992:1
1992:4
1993:3
1994:2
1995:1
1995:4
1996:3
1997:2
1998:1
1998:4
1999:3
2000:2
2001:1
2001:4
2002:3
2003:2
2004:1
2004:4
2005:3
2006:2


Number of unemployed in duration class "from 6 to less than 12 months"
LFS
UR
140000
120000
100000
80000
60000
40000
20000
0
1992:1
1992:4
1993:3
1994:2
1995:1
1995:4
1996:3
1997:2
1998:1
1998:4
1999:3
2000:2
2001:1
2001:4
2002:3
2003:2
2004:1
2004:4
2005:3
2006:2


Number of unemployed in duration class "more than 12 months"
LFS
UR
250000
200000
150000
100000
50000
0
1992:1
1992:4
1993:3
1994:2
1995:1
1995:4
1996:3
1997:2
1998:1
1998:4
1999:3
2000:2
2001:1
2001:4
2002:3
2003:2
2004:1
2004:4
2005:3
2006:2

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 for 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. Nevertheless, it is beyond the scope of this paper to identify the sources of the different numbers in the survey and unemployment registry data.

Essay 2: Unequal Access to Higher Education in the Czech Republic

(A joint work with Martin Guzi)

Abstract

The Czech Republic exhibits high geographical variation of both human capital and universities. We examine a potential source of human capital spatial disparities: the unequal access to tertiary education caused by the absence/presence of a local university. We model both a secondary school graduate's decision whether to apply to a university and a university's decision about admission. Two possible sources of unequal access to university study are distinguished: cost savings and informational advantages for those residing close to a university. Estimation results suggest that the local neighborhood having a highly educated population, rather than the presence of a university *per se*, has a positive effect on a secondary school graduate's decision to apply. Moreover, we find that heterogenous information plays a significant role in admission to university.

1. Introduction

A growing interest in the various consequences of human capital geographical distribution can be noticed in the recent economic literature. Research focuses mainly on productivity spillovers, regional economic and population growth, and regional unemployment.[36] In general, significant effects of human capital spatial disparities have been found. The impact of the unequal spatial distribution of human capital can be even more pronounced in post-transition countries since they exhibit a higher geographical variation of the tertiary-educated population than countries in Western Europe.[37]

Given the importance of private and social returns to human capital and the implications of its geographical distribution especially in post-transition countries, a natural question arises: What determines the spatial distribution of human capital? In this paper, we deal with a fundamental source of human capital: university education.[38] So, we examine the differences in the shares of a tertiary-educated population across regions.

The literature distinguishes three principal determinants of the geographical distribution of the tertiary-educated population: a general migration of the tertiary-educated population,[39] a post-university migration of graduates,[40] and unequal access to tertiary education. We examine the third potential reason, exploring the determinants of access to university study. Moreover, we focus on the unequal access to tertiary education caused by the absence/presence of a local university. We ask whether individuals living close to a university are more likely to continue with tertiary education and why.

[36] Productivity spillovers are discussed in Moretti (2004) and Lange and Topel (2006). The link between the local level of human capital and regional economic and population growth is examined, for example, in Glaeser, Scheinkman, and Schleifer (1995) and Kaldewei and Walz (2001). Regional unemployment is discussed in Overman and Puga (2002) for developed countries and in Jurajda and Terrell (2008) for post-transition countries.
[37] See Table 1 that reports the coefficient of the variation of the tertiary-educated population share for selected post-transition and western European countries.
[38] Human capital can be acquired via education, training, experience, or medical treatment (Becker 1964).
[39] See Giannetti (2002, 2003).
[40] See Bound, Groen, Kezdi, and Turner (2004) and Makovec (2005).

Basically, we consider two ways how the local university affects a secondary school graduate in the admission process.[41] First, students living near a university face a cheaper option for obtaining tertiary education. They can continue to live with their parents, saving on rent and moving costs, as opposed to graduates residing away from a university.[42] Second, secondary school graduates residing close to a university can be better informed about the admission process, university study, job prospects related to a university degree, and the local university's open days. The second reason, based on heterogenous information, is realized through various channels: information provided by secondary schools, face-to-face contacts with university students, the possibility to use university facilities during secondary school study, among others. In general, secondary school students living near a university can benefit from the university environment they live in and consequently can be at more of an advantage in the admission process.[43]

Our goal is to detect the presence of the two mentioned causes of unequal access to tertiary education and assess their relative importance. The identification is possible due to a unique data set. It enables us to scrutinize the process of entrance to a university in detail; we distinguish two stages—application and admission. So, our research goes beyond the existing studies that usually deal with university enrollees only.

We conduct an analysis for the Czech Republic, a country with a high geographical variation of its tertiary-educated population, which is typical for post-transition countries (Table 1). Graph 1 depicts the distribution of the tertiary-educated population by district (NUTS4-level) in the Czech Republic for 1991 and 2001. This implies that

[41] Note that we elaborate the effect of a local university on the demand for tertiary education. The supply of tertiary education has remained unchanged since the 1960s, when the current system of universities was established in the Czech Republic.
[42] Matějů (2007) presents the results of an income and expenditure survey of university students (Eurostudent 2005). According to this survey, 40% of university students live with their parents. Moreover, expenditures for transportation and accommodation account for the one-third of total student expenditures. So, attending a local university represents a large savings.
[43] In general, the two reasons are a) the set of factors that affect performance on the admission test and influence the decision on an application and b) the set of factors that do not affect performance on the admission test but influence the decision on application. The related economic literature discussed in the next section points out the access to information as a prominent representative of the first set and the costs of study as a prominent representative of the second set. Therefore, in the paper, we consider only these two reasons instead of a broadly defined set of factors.

the population with a university degree is concentrated mainly in a few areas. There were two districts with 15% and 17% of university degree holders in 1991 (23% and 25% in 2001). The vast majority of districts, however, report only 5% of university graduates in 1991 (10% in 2001). Moreover, Graph 2 suggests that the highest increase in the tertiary-educated population during 1991–2001 occurred in regions (NUTS3-level) already endowed with a high portion of a tertiary-educated population. There are two possible explanations: either the highly educated population has migrated towards the highly educated regions or secondary school graduates living far from a university have faced worse prospects regarding university study.

The Czech Republic experiences not only the heterogenous spatial distribution of the tertiary-educated population but also highly unequal spatial distribution of universities. According to the Czech Institute for Information on Education (2002), 94% of public university departments are concentrated in 13% of districts. In terms of enrolled students, the problem of the unequal distribution of the sources of tertiary education is even more obvious. The majority (over 70%) of all university students enrolled in the academic year 1997/98 attended universities located in three districts only (Prague, Brno, and Ostrava).[44]

We exploit the high spatial variation in the number of institutions providing tertiary education to estimate the effect of a local university on a prospective university applicant. We set up a structural model of the post-secondary schooling decision: whether the secondary school graduate applies to a university or not. We estimate the reduced form of the model and discuss the relationship between the reduced form model parameters and the structural parameters. Estimation results suggest that study costs do not drive a graduate's application decision. Rather there is a positive effect of the district's characteristics, represented by the share of the tertiary-educated population in the district, on the prospective applicant. The impact is larger for a graduate from a specialized secondary school than from a gymnasium. Moreover, we observe different application strategies followed by applicants from districts with and without a local university.

[44] Note that the three districts account for 18.5% of population in the Czech Republic.

Next, we discuss a model of admission (conditional on application). The econometric analysis reveals that applicants are, in terms of their admission probabilities, positively affected by the presence of a local university. Moreover, we find that the influence of a local university is "program specific", i.e., a local university brings an advantage to applicants applying to programs provided by the local university even if they apply to that program in a non-local university. So, living close to any university need not necessarily help in the admission process but living near the "right" university helps. We also briefly discuss the nature of information flows that underlie the positive effects of local universities.

The identification of the source of unequal access to a university is of high policy relevance. If secondary school graduates are constrained by the cost of study, then policies should support those living far from a university. On the other hand, if the source lies in the distance-dependent distribution of information, policies should expand tertiary education to other regions or improve the access to information for disadvantaged graduates.

The structure of the paper is the following. In the next section, we discuss the research dealing with the effects of local universities and the post-secondary schooling decision. We also describe the schooling system and the admission process to a university in the Czech Republic. Section 3 introduces the reduced form models of applying and admission. In Section 4, we introduce the data set employed, point out its uniqueness, and carry out a preliminary analysis. We also discuss the variables entering our econometric analysis. Estimation results are reported in Section 5. The structural and reduced form models of applying and the model of being admitted (conditional on application) are introduced in Appendices A, B, and C. Graphs and Tables can be found at the end of the paper in Appendix D.

2. Literature review

The analysis carried out in this paper connects two branches of economic research: the research focusing on the various effects of a university presence (or its proximity) and the research exploring the determinants of the post-secondary schooling decision. Models of the post-secondary schooling decision usually do not take into account the effects of local universities or the distance to the nearest university.

The research on the effects of university presence is mainly focused on regional and individual economic outcomes: local productivity and output (Andersson, Quilgey, and Wilhelmsson, 2001) and the local labor market (Beeson and Montgomery 1993). University proximity is used as a source of exogenous variation in educational attainment in studies on the returns to education (Card 1995; Card 1999).

The effect of a local university on the prospective university applicant is considered in Do (2004), Frenette (2002, 2003), Sá, Florax, and Rietveld (2004) and Eliasson (2006). All of these authors recognize the effect of the lower cost of study for the population living near a university and in general find that those living near a university participate in university study more often. In addition, Do (2004) takes into account a "knowledge spillover" that influences the choice of the quality of university where a university applicant enrolls. He finds that the quality of the university in which the applicant enrolls is positively linked to the quality of a local university. Frenette (2002) also mentions that the dependence of the probability to enroll on the distance to the nearest university could be caused by fact that "students in outlying areas simply don't see the benefits from a university education since fewer people hold a degree" (p. 23). The research approach he employs, however, cannot distinguish between these two determinants of behavior dependent on the distance to the nearest university.

Regarding the post-secondary schooling decision there are three main theoretical approaches established in the literature. First, human capital theory views the decision on taking another period of schooling as an investment decision (Becker 1964; structural model in Willis and Rosen 1979). An individual compares the present value of future benefits based on expected future earnings with the costs related to continuing education. Another approach assumes that education is also a consumption good and the decision on post-secondary education is a current consumption choice (e.g. Gullason 1989). Finally, the third approach views schooling as an indicator of an individual's capabilities that has nothing to do with the individual's productivity.

Therefore, the decision on post-secondary education reflects the individual's willingness to provide the signal (Spence 1973). The structural model of application derived in Appendix A is based on the human capital approach.

Long (2004), Sá et al. (2004), Whitehead, Raffan, and Deany (2006), and Brooks (2002) represent recent empirical studies on the determinants of the post-secondary schooling decision. Individual capabilities, a student's socio-economic background, the characteristics of universities, the regional economic conditions, and local social interactions are found to be influential for the outcome of secondary school graduates' decision processes. Brooks (2002) focused on these determinants from the point of view of the information they convey, discussing possible inequalities among students. She points out, for example, the important role of interactions with current university students in the prospective applicant's decision process. Details on the determinants of the post-secondary schooling decision are introduced in Appendix A, where we derive an economic model.

2.1 The Czech educational system

In this section, we describe the educational system in the Czech Republic *circa* 1998. Primary education lasts nine years. Afterwards students apply to various types of secondary school depending on their future career plans and ability. The lower level of secondary education involves two years of vocational education. The higher level of secondary education takes four years and comprises three types of schools: (i) the vocational, (ii) the technical, and (iii) the general academic high schools known as gymnasiums.[45]

The tertiary level of education is provided solely by universities. The admission process to a university is a sequential process: first the student decides where to apply, then the university decides who to admit, and then the student decides where to enroll. In the first step, the student carries out a simultaneous decision whether to apply to a

[45] Gymnasiums and specialized schools correspond to the ISCED level 3A, while vocational schools to the ISCED level 3C.

university and where. In order to apply, the student must hold a final general exam credential known as the *maturita* from secondary school. The maturita exam is a comprehensive examination that comprises Czech language and an additional two or three subjects chosen by the student. However, the examinations are not standardized and therefore universities do not take into account the performance on the maturita exam during the admission process. All gymnasiums and 95 percent of specialized secondary school programs, but only 12 percent of vocational school programs, lead to the *maturita* and the possibility of university admission. Vocational programs finishing with a maturita exam represent only a small minority of all vocational programs; therefore, we exclude them from the analysis. In 1998, 60 percent of secondary school students finished with the *maturita* and thus were eligible to apply for tertiary education.

In 1998, there were 111 university departments in 23 universities in the Czech Republic. Universities provide education in 41 program specializations.[46] Altogether there were 225 different university programs available in 1998. Government-owned universities did not charge tuition and only performance stipends were in place. A law to accredit private universities in the Czech Republic was passed in 1999; therefore, they do not enter our analysis. Finally, a system of support for university students was in operation in 1998 in the Czech Republic. It involves, for example, the possibility of living in dormitories for those residing out of the commuting distance from a university, meal tickets, and public transportation discounts. The system was intended to lower the study costs especially for those living far from the university in which they were enrolled.

Each university charged a fee for each application, which is not a limiting factor, but it made applicants ration their decisions. The number of applications per person is not limited and on average applicants sent two applications. Some university programs were highly over-subscribed.[47]

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[46] The classification of program specialization corresponds to the two-digit JKOV classification (Unified Classification of Study Fields) refer to http://www.czso.cz/csu/klasifik.nsf/i/vazba_klasifikace_na_byvalou_jkov (in Czech).
[47] In 1998, the probability of admission to psychology programs was only 5% and 10% to law programs.

Students sent applications to preferred university programs, and all of them were invited to participate in the admission tests. The decision on admission was solely on the side of the university and was based on the performance on admission tests and/or oral interviews. Universities did not take into account the applicant's residence. In 1998, about 50 percent of graduates who applied to a university were admitted to at least one program. If the applicant succeeded in admission to several university programs,[48] he chose where to enroll.

3. Models

As described in the previous section, the admission process to a university is comprised of the graduate's decision on applying to the program, the university's decision on admission, and the applicant's decision on enrollment.

The derivation of a structural model of the application decision and its reduced form is discussed in Appendix A. The reduced form model takes the following form

$$Apply_{icd} = \alpha_0 + \alpha I_{icd} + \beta C_{cd} + \varphi R_d + \delta d_d + \sum_{j=1}^{8(7)} \mu_j SD_{icd}^j + \varepsilon_{icd}, \qquad (1)$$

where $Apply_{icd}$ is a dummy variable that indicates whether a graduate i from secondary school class c and district d applies to a university. In addition, we control for individual characteristics (vector I_{icd}); class (secondary school) characteristics (vector C_{cd}); and regional (district) characteristics (vector R_d). The coefficient on the dummy variable d_d is our primary interest. The dummy equals 1 if a graduate resides within commuting distance to the nearest university and 0 otherwise. Finally, the set of eight (seven for technical secondary schools) dummy variables SD_{icd} accounts for subjects taken at the maturita exam for gymnasiums and the field of study in technical secondary schools. The set of variables included on the right-hand side is a compromise between data availability and variables suggested by research on the post-secondary

[48] 27 percent of those admitted were admitted to two programs in 1998, 9% to 3 programs.

schooling decision discussed in the literature review and in Appendix A. Variables are described in detail in Section 4.

The dummy variable indicating the presence of a local university d_d in (1) captures both of the effects of a local university on the prospective applicant: the lower costs of study and heterogenous information. However in the application regression, we cannot distinguish these two effects. We resolve the problem in the admission regression where the applicant's potential cost of study does not play any role, and the coefficient on the local university dummy captures the effect of heterogenous information only.[49]

A non-zero coefficient on the local university dummy variable in the admission regression equation (on the pool of applicants) reveals whether those living near a university are at an advantage in the admission process because of an information spread within the university neighborhood. To examine the nature of heterogeneous information in detail, we add an additional dummy variable f_j that identifies applicants according to whether they live close to a university offering the program to which they apply. So, f_j equals one if an applicant applies to a program that is provided by a local university even if the applicant applies to that program at other (possibly non-local) universities.

So, we divide all the applications into three sub-groups. We distinguish applications by applicants living far from any university ($d_d = 0$, $f_j = 0$); applicants living near a university that does not provide the applicants' preferred program ($d_d = 1$, $f_j = 0$); and applicants living near a university providing the applicants' preferred program ($d_d = 1$, $f_j = 1$).

[49] Note that information affecting the decision on applying and information providing an advantage in the admission test (and/or oral interview) need not necessarily be of the same nature. Therefore, by econometric analysis, we identify whether the heterogenous information, along with the costs of study, play a role in the application decision and whether heterogenous information affects admission to university. Then, based on an assumption about the common nature of heterogenous information, we can discuss the relative roles of costs of study and heterogenous information in the application decision.

The estimated coefficients on the two dummy variables indicate whether either proximity to any university or proximity to a university with the desired program can provide an advantage in the admission process at any other university.[50]

Our baseline specification of the model of admission (conditional on application) derived in Appendix C is

$$Admitted_{icd}^{j} = \beta_0 + \alpha I_{icd} + \beta C_{cd} + \varphi R_d + \delta_1 d_d + \delta_2 f_j + \rho F_j + \upsilon_{icd}^{j}, \qquad (2)$$

where $Admitted_{icd}^{j}$ is a dummy variable that indicates whether application i has successfully passed through the admission procedure at a program j (conditional on applying).[51] We control for individual characteristics (I_{icd}), secondary school (class) characteristics (C_{cd}), and district characteristics (R_d). Finally, the admission regression equation includes the vector of university characteristics F_j that control for university-specific characteristics relevant to the admission process—the self-selectivity of applicants and differences in admission tests (see the discussion in Appendix C).

4. Data

Our empirical analysis is based on the following two data sets collected by the Institute for Information on Education (IIE) in 1998: (i) the data set of all university applicants (Uchazec) and (ii) the data set of all secondary school graduates (Maturant). Additional district descriptions are taken from the Czech Statistical Office.

The database *Uchazec* contains data on all individuals who applied to universities in 1998. Specifically, it provides information on all applications sent to universities for a given year together with the results from the admission process. The data allow the distinguishing of applications sent to a university by program specialization. The

[50] So we ask, for example, whether an applicant residing near a university providing medical programs is more informed and thus advantaged in the admission test to a medical program than an applicant living near a university that does not provide medical programs or another applicant living far from a university.
[51] The unit of observation is an application. In the case of the application decision regression the unit of observation is a secondary school graduate.

database *Maturant* is the result of a project that tested all graduates at every secondary school that finishes with the maturita exam in the Czech Republic in 1998. The database provides data on student characteristics, performance, and subjects taken at the maturita exam. The graduate's performance is measured by the average test score computed from four tests taken in Czech, one foreign language, mathematics and study aptitude, and this variable is called the composite score. We merged the database *Maturant* to *Uchazec* on an individual basis to obtain a set of information on the cohort of secondary school graduates finishing their study with the maturita exam in 1998 augmented with the graduates' revealed preferences for tertiary education. Due to missing or incorrect identification numbers, only 84.2% of individuals in *Maturant* is usable and potentially can be matched with the respective data in *Uchazec*. The uniqueness of the resulting data set allows us to provide a detailed analysis of graduates' education track depending on university accessibility.

In estimating models (1) and (2), we employ the following variables. Vector I_{icd} includes individual characteristics: a female dummy, a dummy if born before 1980, a composite score rank,[52] the level of parental education, and a dummy for computer ownership. Computer ownership is included as a proxy for the missing information on family income. We distinguish the three levels of parental education (i) basic or vocational (reference category); (ii) secondary; and (iii) tertiary; the highest level of the two parents is taken. Vector C_{cd} includes class (secondary school) characteristics: class size, composite score class average, and a private secondary school indicator.

For regression equation (1), vector R_d consists of the district (NUTS4-level) unemployment rate and the regional (NUTS3-level) GDP growth in 1998. For both regression equations (1) and (2), vector R_d includes the share of the tertiary-educated population in the district[53] and the relative excess demand for gymnasiums in the district. The relative excess demand for gymnasiums in a district is computed as the demand for gymnasium seats predicted using the share of tertiary-educated population

[52] The composite score rank expresses the rank of each graduate in the whole cohort of graduates, comparing their composite scores. The variable is normalized so that a rank of 100 is the best graduate and the rank of 0 the worst.
[53] Data on the tertiary-educated population are taken from the Census 2001.

in a district, a university presence dummy, and the share of seats at gymnasiums taken by 6- and 8-year gymnasium programs subtracted by the supply of gymnasium seats (relative to all secondary school seats in a district).[54] Basically, relative excess demand serves as a proxy for the average level of non-cognitive skills for secondary school graduates.[55] A high district relative excess demand for gymnasiums implies that students entering gymnasiums exhibit on average a higher level of non-cognitive skills in comparison with districts with low relative excess demand.[56] Specialized secondary schools are often viewed as the second best option—those not admitted to gymnasiums enter specialized secondary schools. Thus, districts with high relative excess demand for gymnasiums are assumed to exhibit a high level of non-cognitive skill even for students of specialized secondary schools. So, in the econometric analysis we control for individual cognitive skills using the composite score of an individual and for non-cognitive skills incorporating relative excess demand for gymnasiums in a district.

The set of dummies SD_{icd} denotes subjects taken at the maturita exam for gymnasiums (mathematics, biology, physics, chemistry, history, geography, social sciences, and foreign language) and the field of secondary school for specialized secondary schools (agriculture, manufacturing, light manufacturing, health care, social sciences, art, and business as a reference category).

The dummy variable d_d equals 1 if a graduate resides within commuting distance of the nearest university. We have collected data on travel time between the district capital of a graduate's secondary school and the nearest university. [57] We determine the district of a graduate's residence based on the address of her secondary school because the data do not provide any information about a graduate's residence.[58] The travel time threshold

[54] The computation procedure for relative excess demand for the districts in the Czech Republic is introduced and thoroughly discussed in Drnakova (2006). She kindly provided us with data for 2002/2003; earlier data are not available.

[55] The effect of non-cognitive skills on various outcomes is discussed in Heckman, Stixrud, and Urzua (2006).

[56] Non-cognitive skills involve e.g. motivation, persistence. We presume that a higher level of non-cognitive skills helps in admission to the secondary level of education.

[57] The information about traveling time is computed using the software Kilometrovnik taken from the webpage www.tranis.cz. We compute the time taken for a car to drive from all 76 district capitals to each of the 11 university centers.

[58] The sources of heterogenous information considered are related to the secondary school location rather than place of residence. Our data confirms that more than 90% of students attend gymnasium in their

for the dummy variable d_d is set to 30 minutes. It is important to note that the travel time is computed for travel by car and that travel within cities (from home to university) is not considered. The same journey by bus or train usually takes a longer time. We illustrate this by Graph 3, which depicts the kernel density of commuting time by public transportation for secondary school graduates as of 2007. Moreover, additional time is needed for inner city travel, so the overall commuting time (door to door) is higher. Therefore, we consider the threshold of 30 minutes as reasonable. Graph 4 shows the map of the Czech Republic with marked districts within commuting distance to the nearest university.[59]

The vector of university program characteristics F_j includes variables that control for differences in admission tests over university programs, for the self-selectivity of applicants and for differences in excess demand for particular programs. As discussed in Appendix C, we employ the following variables: dummy variables for university departments, program specializations, and university programs. Further, we include a marginal composite score variable that is defined as the lowest composite score of the applicant who succeeds in the admission process (assuming that the university admits entirely according to the applicant's composite score).

4.1 Descriptive analysis

In this section, we describe the population of secondary school graduates and university applicants. We also inspect the application strategies of secondary school graduates in terms of the chosen university programs and the admission probabilities of the chosen programs.

Table 2 provides a basic summary of the characteristics of gymnasium and specialized secondary school graduates and applicants to university in 1998. Graduates and applicants are further divided according to their residence type, i.e. whether a university

district of residence. In the analysis, we use the secondary school's district instead of the place of residence.

[59] We admit that such a procedure of construction of time distance can be a source of measurement error.

exists within commuting distance (local university) or not (no local university). It follows that more than 90% of gymnasium graduates choose to apply to university, and approximately two-thirds of them are admitted regardless of the location. The corresponding figures for specialized secondary schools are 50% and 40%.

The considerable difference between gymnasiums and specialized secondary schools in the shares of applicants (and of those being admitted conditional on application) has two origins. First, study programs at gymnasiums are intended to prepare students for university study. Gymnasium graduates, therefore, generally perform better on admission tests than applicants from specialized secondary schools. Second, the difference is also supported by the sorting process at the level of entry to a secondary school. Students enter a gymnasium presuming they will continue their study at a university and therefore the population entering the secondary level of education is sorted according to interest in (and ability for) tertiary education. So, we expect different behavior of graduates regarding the entrance into the tertiary level of education for the two types of secondary school, and thus, we carry out separate analyses for gymnasiums and specialized secondary schools.

Table 2 also indicates a decreasing pattern in the shares of applicants and those being admitted (conditional on application) when comparing graduates with and without a local university. For example, 53% of graduates from specialized secondary schools living near a local university apply in comparison with 47% of those living far away. Restricting our attention to admission, we observe a lower share of admission for applicants living far from a university than the share for those living near a university (0.36 vs. 0.41 for specialized secondary schools and 0.64 vs. 0.66 for gymnasiums). The admission decision does not depend on the level of potential study cost, and therefore, heterogenous information can be a reason for admission shares depending on the distance to the nearest university. The reported differences in admission shares, however, need not prove the presence of heterogenous information since the shares are not conditional on other characteristics. Differences can result also from the differences in ability, socio-economic background, etc. for the two residence types. Note that a worse socio-economic background (parental education, computer ownership) and a lower level of observable cognitive skills (composite score) appear for those graduates and applicants living far from a university (see Table 2). The effect of heterogenous information and other observable characteristics is examined by the econometric analysis in Section 5.

Application strategies—program specializations

The costs of study and heterogenous information can influence not only the decision about applying but also the choice of university programs. Examining the differences in the applicants' revealed preferences for university programs according to residence type can shed some light on the effect of a local university on the secondary school graduate's application decision.

Table 3 presents the shares of applicants who apply to one program specialization only (not necessarily at one university). Lower study costs affect the choice of the programs of applicants with local university who apply locally. To filter out the study cost effect and to examine the effect of heterogenous information, we focus on those applying to a non-local university(ies) only (i.e. applicants with a local university applying to a non-local university only and applicants without a local university). All applicants in this subgroup face high potential costs of university study. Applicants living near a university tend to stick to one program specialization more than those living far away (28% vs. 20% of applicants from gymnasiums). The difference is even higher for specialized secondary school graduates (63% vs. 53%). The result suggests that applicants from a university neighborhood are better informed about university programs and thus have a more concrete idea about what to study. The reason could also be that applicants living far from a university prefer programs that demand broader knowledge so they can also apply to related programs. The preferences for various programs are explored in Tables 4a and 4b.[60]

Table 4a shows that some programs are demanded more by applicants living far from a university (e.g. Education, Technical Chemistry) and some by applicants living near a university (e.g. Theory and History of Art, Philosophy, Engineering). The total share of applicants without a local university is 0.45 for applicants from gymnasiums and 0.46

[60] Note that all the results presented in this section are unconditional.

for applicants from specialized secondary schools. The column *Difference I* in Table 4a indicates the difference between the total share of applicants without a local university and the share of applicants without a local university for a particular program. So, positive figures suggest more than the average share of applicants from locations without universities and vice versa. The table also provides the number of programs and districts where it is possible to study a particular program together with the probability of admission to that program.

In Table 4a, we compare the preferences of all applicants and applicants applying to a non-local university(ies) only. Similarly to previous paragraphs, we argue here that the second group of applicants faces the same (high) potential costs of study and therefore heterogenous information as a reason for differences can be identified. According to Table 4a, the variation of differences decreases markedly when we focus on applicants that apply only to non-local universities (see columns *Difference I* and *Difference II*). Therefore, the revealed preferences for university programs are affected by the costs of study and consequently by programs provided by local universities.

Table 4b provides a comparison of cognitive skills (composite scores) and non-cognitive skills (relative excess demand for gymnasiums in a district) of applicants to selected programs by residence type and by the location of the university to which they apply. It follows that gymnasium graduates living near a university and applying only non-locally are, in the terms of the composite scores, smarter than their colleagues who apply only locally. Interestingly, the opposite is true in the case of specialized secondary school graduates.

Furthermore, the table suggests that the relation between the composite scores of applicants living near a university and applying only locally and those living far from a university relates to differences in the revealed preferences of applicants (column *Difference I*). Programs demanded relatively more by those without local university (positive numbers in column *Difference I*) are demanded more on average by smarter graduates who live far in comparison with those living near a university (higher composite score for applicants from locations without a university than the score for applicants applying locally only) and vice versa. This result suggests different perceptions of various programs from different groups of graduates.

Finally, Table 4b implies that applicants residing far from a university exhibit a higher district level of non-cognitive skills for almost all programs. Therefore, applicants living far from a university are on average more motivated and persistent than those living near a university. Again, this could be a result of information heterogeneity.

Application strategies—probability of admission

Table 5 suggests that the average applicant applying only to a local university faces a higher probability of being admitted than an average applicant living far from a university (the difference is around 2% for applicants from gymnasiums and 5% from specialized secondary schools). This result holds even if we condition on cognitive skills (composite score) and the district level of non-cognitive skills (relative excess demand for gymnasiums in a district).[61] The different strategies regarding the probabilities of admission correspond to the different strategies with respect to university programs discussed in the previous sub-section.

5. Estimation results

Our empirical analysis proceeds in two steps. First, we explore whether individuals residing in close proximity to a university are more likely to apply to any university, and we discuss the main determinants that influence the application decision. In the second step, we estimate the probability of admission conditional on application.

We start estimating the reduced form model of applying to a university (1) separately for gymnasium and secondary school graduates. We estimate equation (1) as a logit

[61] We divided the population of applicants into 16 groups defined by quartiles of composite score and demand for gymnasiums in a district and compared the average probability of admission for applicants living near and far from a university.

model clustering data by class.[62] Table 6 reports the estimation results.[63] Reported are marginal effects.

The local university dummy variable is not significant for either type of secondary school graduate,[64] indicating the decision about application is influenced neither by the direct costs of study nor by heterogenous information affecting the application decision. This conclusion assumes that the lower cost of study and heterogenous information act in the same direction, i.e. both lower the probability of applying for graduates living far from a university. Both the system of financial support for university students (e.g. dormitories) and the information availability seem to be sufficient to equalize the differences in the probability of applying caused by the presence/absence of a local university.

Furthermore, Table 6 suggests that in addition to individual skills gender and individual socio-economic background (parental education, computer ownership) are also significant determinants of the application decision. For example, the average female graduate from a specialized secondary school faces a 10% lower probability of applying to a university than the average male. This is a consequence of gender segregation on the level of secondary school field specialization. For example, only 4% (128 out of 3131) of graduates from secondary schools specializing in health care are male. The study programs of such secondary schools are not intended to prepare students for university study. Therefore, graduates from such schools usually do not go on to a tertiary level of education (only one-third of them apply).

The estimated impact of regional (district) characteristics suggests links between the local economic and living conditions and the graduates' behavior regarding application to university. Higher unemployment leads to a higher probability of applying, which is in line with the lower opportunity costs of university study in districts exhibiting high

[62] Moulton (1990) argues that individuals from the same socio-economic background (secondary school, class) could share the same unobservable characteristics. The disturbances of such groups of individuals are then correlated, and we take the possibility of clustering into account.

[63] Logistic regression diagnostics: We find that the model is correctly specified (specification error test—*linktest* in Stata), and it fits the data well in the case of specialized secondary schools (Hosmer and Lemeshow's test—*lfit* in Stata). The model's performance is worse for gymnasiums. Finally, we do not detect any multicollinearity problems (command *collin* in Stata).

[64] The result is robust to changes in the travel time threshold that defines the local university dummy.

unemployment. The effect is stronger for graduates from specialized secondary schools. Our interpretation is that they have specific skills and thus are more sensitive to unemployment changes. Similarly, higher regional economic growth lowers the incentives to go on with study. Again, higher growth increases opportunity costs, and graduates (especially from specialized schools) tend to enter the labor market immediately after graduation from secondary school.

Moreover, Table 6 shows that the propensity to apply is positively affected by the local share of the tertiary-educated population. Each percentage point of the share of tertiary-educated population in a district[65] accounts for at least a 0.31 percentage point higher probability of applying for gymnasium graduates (1.14 percentage points for graduates from specialized secondary schools). This result suggests that the source of heterogenous information we attempt to detect by the local university dummy is not the distance to a university but rather the local environment created by the highly educated population.[66]

Finally, Table 7 reports the marginal effects of dummy variables for subjects taken for the maturita exam (gymnasiums) and the field of school (specialized secondary schools) on application decision. Subjects taken for the maturita exam and the fields of secondary school determine the choice of the prospective field, which subsequently determines the costs and benefits of the schooling decision. Therefore, almost all the dummies are significant.[67] Regarding gymnasiums, the highest marginal effect is estimated for mathematics. This fact should be taken into account in the current discussion on mathematics as a compulsory part of the maturita exam.

Derivations presented in Appendices A and B yield that the structural parameters are, in absolute value, lower than the reduced form model estimates (a similar conclusion holds for marginal effects). Basically, this is a consequence of the fact that the prospective applicant considers whether to apply under a certain probability of being

[65] The standard deviation of the percentage share of the tertiary-educated population in a district is 2.1.
[66] The correlation coefficient between local university dummy variable and the share of tertiary-educated population in a district is 0.45.
[67] For each field of specialized secondary school, approximately half of the applicants apply to the corresponding program at a university (e.g. 57% applicants from secondary schools that specialized in light manufacturing apply to technical programs.).

admitted to a particular university department. Thus, the magnitudes of the effect of a particular determinant are lower (in absolute value) than estimated. So, for example, a 10% decrease in the probability of applying for the average female from a specialized secondary school is the upper bound of the real effect.

In Appendix B, we also derive that the standard error of the estimated coefficient of the local university dummy variable is lower in the reduced form model than when we are able to estimate a structural model. The local university dummy variable is, therefore, insignificant also in the structural model.

In the second part of the econometric analysis, we present the estimation results of the admission regression equation (2). Here, the unit of observation is an application. We estimate equation (2) as a logit model clustering data by individuals.[68] The model of admission derived in Appendix C suggests several specifications of the regression equation (2). The estimated marginal effects of the considered specifications are reported in Table 8 for gymnasiums and in Table 9 for specialized secondary schools. The marginal effects that are robust to specification are highlighted. The robustness is understood in the sense that the estimated marginal effects do not change signs or significance under various specifications of the regression equation. In the following, we discuss only the robust estimates that are shown in Table 10.

The coefficient on the dummy variable indicating the applicant's residence within commuting distance to a university that provides the program to which an applicant is applying, f_j, is positive and significant. For specialized secondary schools, the dummy variable for the presence of a local university d_j is not significant. This implies that living near an arbitrary university need not necessarily help in the admission process. Rather living near a university that provides the applicant's preferred program increases the admission probability to that program even if the applicant applies to that program at a different university. Information that brings an advantage to the admission process is, therefore, "program specific". For example, face-to-face contacts with older students who passed the admission process successfully, easier access to preparatory

[68] Post-estimation diagnostics suggest model specification problems for applications from specialized secondary schools.

courses organized by local universities or extra information provided by secondary school teachers or counselors who are experienced with the programs provided by local universities can be beneficial for local graduates.

Universities which do not experience high excess demand[69] usually admit the vast majority of applicants, and thus, one cannot expect that some applicants have an advantage on the grounds of access to information. On the other hand, in the case of highly over-subscribed university programs,[70] additional information can provide an advantage to an applicant. To test the dependence of the impact of heterogenous information on relative excess demand for a university, a dummy variable indicating the presence of the desired program at a local university, f_j, with the probability of admission to that program is interacted. The interaction term is significant for gymnasium graduates. So, living near a university with the preferred program increases the probability of being admitted for the average applicant from a gymnasium by 9.9%. Moreover, the lower the probability is of admission to the university program (i.e. higher excess demand for the program) to which an average applicant applies, higher is the advantage premium provided by a local university.

Other estimated marginal effects suggest the importance of individual characteristics (parental education, composite score) for the probability of being admitted. For the selected marginal effects of individual, class, and regional characteristics, see Table 10.

Heterogenous information that underlies relative success in the admission process is not distributed through the official study program at secondary schools. Gymnasiums provide general education not specialized in any particular fields of study. This need not be the case for the specialized secondary schools (transportation, health, teaching, engineering, etc.). Specialized secondary schools are, however, very evenly distributed across the Czech Republic, and there are more than five schools in 70% of the districts. Thus, the geographical distribution of specialized secondary schools does not drive the

[69] 10 out of 42 programs admitted more than 70% of applicants from secondary schools in 1998.
[70] 4 out of 42 programs admitted less than 10% of applicants from secondary schools in 1998.

differences in admission probabilities according to residence type for graduates from specialized secondary schools. [71]

In our econometric analysis, we find that the heterogenous information due to the presence/absence of a local university does not influence the application decision but does influence the admission decision. The information spread in a university neighborhood is relevant for the applicant's performance in admission. This kind of information does not contribute to a graduate's decision about application, however. Results suggest that it is a different kind of information that positively affects the secondary school graduate. Graduates living in an environment that is characterized by a high share of a tertiary-educated population tend to apply more. So, information that is disseminated by a highly educated environment constitutes the heterogeneity in information for secondary school graduates with regard to their application decision.

6. Conclusion remarks

We analyze the demand for tertiary education in the Czech Republic. We develop a structural model of the post-secondary decision process of a secondary school graduate and a model of admission to a university. The reduced form models are estimated employing data from 1998. The estimation results of both application and admission equations suggest a significant role of the environment around a secondary school graduate in the process of entering tertiary-level education. In the first stage, applying, those living in conditions that are characterized by high local shares of a tertiary-educated population exhibit a higher probability of applying to a university. Living near

[71] We distinguish 25 different study fields of specialized secondary schools. Almost 50% of schools are of business specialization, followed by engineering and electronic specializations with shares of 10% and 8%, respectively. Focusing on specialized secondary schools with very narrow specialization, we look at whether these schools are established close to a university with the same specialization and whether graduates of such secondary schools apply for these faculties. We find that highly specialized secondary schools are not usually established near a university with the same program specialization. For example, veterinary medicine at the tertiary level can be studied only in Brno; however, there are six secondary schools (212 students/60% apply) of veterinary specialization, none of them located in Brno. Only 36% of graduates apply to Brno. Some graduates (25% of applications) apply to a similar program like biology or agriculture. Next, there are four schools with a specialization in silicate chemistry (Tábor, Karlovy Vary, Jablonec nad Nisou, and Česká Lípa). Almost 90% of all graduates who choose to apply (40% apply), decide for tertiary education with a specialization in silicate chemistry. The universities with this program are located in Prague (65% of applications) and Pardubice (35% of applications). None of the secondary schools specializing in silicate chemistry are located near Prague or Pardubice.

a university does not influence the potential applicant's decision about applying—neither because of lower study costs nor because of more information available regarding university study. In the second stage, admission, we observe that for certain program specializations, there is a higher probability of being admitted for applicants with a local university that provides programs with the same program specialization. The effect is stronger in the case of highly over-subscribed programs.

The policy question that follows our findings is how to ensure equal conditions regarding the process of entering tertiary education by secondary school graduates in the Czech Republic. Equal conditions usually mean that all secondary school graduates can apply for university study; so, there are no constraints based, for example, on sex, race, or application fee that would prevent a particular group of potential university students from entering the tertiary level of education. However, our analysis uncovered some factors that underlie differences between secondary school graduates with respect to their chance of applying and being admitted. These factors relate to individual characteristics, socio-economic background, regional economic and social characteristics, and the characteristics of the secondary school.

The question arising here is what factors should be considered as those reflecting some inequality. So, for example, different probabilities of applying and being admitted for students with different levels of ability to study should not be viewed as a problem of unequal access to tertiary education. On the other hand, some factors have nothing to do with the individual ability to study but still influence the admission procedure. For example, we found that female students from specialized secondary schools have a remarkably lower (by 10%) probability of applying, which is caused by gender segregation by fields of secondary schools. We should therefore examine why some fields in secondary school prepare students for university study less than others.

In this paper, we focused on the effect of the presence of a local university on a secondary school graduate's prospects regarding university study. We found that a local university can constitute an advantage in the admission process for those living near the local university. To equalize the chance of admission, policy makers should consider expanding the system of universities. Moreover, we found that the advantage concerns the university programs that are offered by the local university. The expansion of universities should be, therefore, accompanied by the expansion of university programs. Alternatively, equal chances of entering tertiary education could be achieved also by the improvement of the information spread since we detected that it is the information emitted by a local university that provides the advantage. We suggested that such information can be spread, for example, by face–to–face contacts with university students. In this paper, we do not examine the nature of such information in detail. So, future research is needed to elaborate on the essence of such information and to answer the question whether information availability is an adequate alternative for the expansion of a system of institutions providing tertiary education.

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Appendix A: Structural and reduced form models of the decision on applying for a university study

A.1 Structural model of applying

In this section, we introduce the model of the application decision. The model combines standard models of a schooling decision based on human capital theory and the expected utility theory.

A secondary school graduate makes a decision whether to apply to a university or not by comparing the expected utility of those two actions. We denote the individual's expected utility of applying as U^a and the expected utility of non-applying as U^{na}. The secondary school graduate chooses to apply if $U^a > U^{na}$.

The unit a graduate can apply to is a university program, in the following text this is denoted simply as program. Suppose there are $F > 0$ programs. Further, an applicant spends one whole day participating in an admission procedure for a particular university (usually a written/oral test), and thus it is not possible to participate in another admission test if they are organized on the same day. All admission procedures (tests) are undertaken in a few days $T > 0$ during the year. Furthermore, an applicant to university program j bears the admission costs $AC_j > 0$ (admission fees, courses for preparing the student for admission tests, travel costs concerning the admission procedure, etc.). Each student has a certain amount of money $M > 0$ that can be used for financing her admission process.

If a graduate applies to just one program, then the expected utility from applying to that program equals $U^a = p_1(B_1 - C_1) + \sigma(M - AC_1)$, where p_1 is the probability of being admitted to the program conditional on application, B_1 and C_1 denote the present values of benefits and costs, respectively, of being admitted to the program. Finally, the coefficient σ represents how much dis-utility is related to admission costs with respect to the utility given by the expected benefits and costs.

Similarly, if an individual applies to two programs, the expected utility is given by:

$$U^a = p_1(1-p_2)(B_1-C_1) + p_2(1-p_1)(B_2-C_2) + p_1p_2 \max_{j\in\{1,2\}}\{B_j - C_j\} + \sigma(M - AC_1 - AC_2).$$

We basically divide the situation of the individual applying to two programs into three mutually exclusive events. An applicant is admitted either to the first program only (with probability $p_1(1-p_2)$), or to the second program only (with probability $p_2(1-p_1)$), or to both programs (with probability $p_1 p_2$).[72] However, we assume that an individual can enroll in only one program. Therefore, if she is admitted to both programs, the preferred program is the one with the higher present value of the expected benefits net of costs.

In general, a secondary school graduate chooses to apply to such programs to maximize his expected utility taking into account time and budget constraints. So, an applicant decides whether to apply to a program j ($t_j = 1$) or not ($t_j = 0$). The optimization problem takes the following form:

$$U^a = \max_{\{t_1,\dots,t_F\}} \left\{ \sum_{k=1}^{F} \left[\sum_{A\in C(N,k)} \left(\left(\prod_{j\in A} t_j p_j \right) \left(\prod_{j\in \mathrm{N}\setminus A} (1-t_j p_j) \right) \right) \max_{j\in A}\{B_j - C_j\} \right] + \sigma\left(M - \sum_{j=1}^{F} t_j AC_j \right) \right\} \text{(A1)}^{73}$$

$$\sum_{j=1}^{F} t_j \le T \qquad \text{(A2)}$$

$$\sum_{j=1}^{F} t_j AC_j \le M \qquad \text{(A3)}$$

$$t_j \in \{0,1\},\ j = 1,\dots,F. \qquad \text{(A4)}$$

The maximized function is a generalization of the case for one or two programs discussed above. The time constraint (A2) captures the fact that the admission process

[72] The form of compounded probabilities implicitly involves a reasonable assumption that the probability of being admitted to the first program does not affect the probability of being admitted to the second program. The two events are statistically independent.

[73] $\mathrm{N} \equiv \{1,\dots,F\}$, $C(N,k)$ is a set of combinations of size *k* from the set N.

takes place in a few days during the year, and it is possible to take part in one admission process a day only.[74] The budget constraint (A3) captures the limitations given by admission costs and the individual's disposable income.

The present values of benefits and costs related to university program j are denoted by B_j and C_j, respectively. The variable p_j denotes the graduate's subjective estimate of the probability of being admitted to program j conditional on application.[75] An individual can infer the probability in various ways, such as from admission probabilities in previous years (published every year) and from her performance at secondary school in comparison with her schoolmates.

The model (A1)-(A4) captures several phenomena observed in reality. Data in Table 11 suggest a high negative correlation (almost -0.9) between the average number of applications of an applicant and the average probability of admission (conditional on application) to programs to which an applicant applies.[76] In the model framework, if the individual's probability of being admitted to a program is close to one, he/she will not apply for another program since the marginal utility from sending another application could be lower than the dis-utility related to admission costs (i.e. the probability of being admitted to the additional program and not to being admitted to already considered programs could be so low that admission cost multiplied by σ could exceed the *expected* net benefits). So, if the graduate's estimate of the probability of admission is low, he/she sends an additional application. This yields a negative relationship between the average number of applications and the probability of being admitted.

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[74] Here we ignore the possibility that the admission tests of an individual's desired programs may take place on the same day.

[75] We assume that the probability of being admitted to program j conditional on application (p_j) is a primitive of the problem. If we assume that the primitive is a probability of being admitted to a program along with not being admitted at another university program conditional on application ($\tilde{p}_j$), then the maximized function would take the simple form:

$$\sum_{j=1}^{F} t_j \tilde{p}_j (B_j - C_j) + \sigma\left(M - \sum_{i=1}^{F} t_i AC_i \right).$$

[76] In Table 11, we divide the applicants according to secondary school type (gymnasium and specialized secondary school), residence type (with/without a local university), and the location of the university to which they apply (local only/non-local only/both). This yields eight sub-groups for the comparison of the number of applications and the probability of admission.

So far, we have discussed the expected utility of applying, U^a. In the case of the expected utility of non-applying, U^{na} , an individual compares the expected benefits and the costs of not applying. Non-appliers can enter the labor market or stay out of the labor market. We put these possibilities together into one outside option. The expected utility of non-applying is related to regional labor market prospects and individual and secondary school characteristics.

A.2 The reduced form model of applying

The optimization problem of a prospective university applicant (A1)-(A4) implies that the individual's expected utility of applying equals

$$U^a = \sum_{k=1}^{F}\left[\sum_{A\in C(N,k)}\left(\left(\prod_{j\in A} t_j p_j\right)\left(\prod_{j\in \mathrm{N}\setminus A}(1-t_j p_j)\right)\right)\max_{j\in A}\{B_j - C_j\}\right]+\sigma\left(M-\sum_{j=1}^{F} t_j AC_j\right)$$

(A5)

for some non-zero t_j's $j\in\{1,...,F\}$.

We denote the individual's present value of benefits from being admitted to a program *j* net of the present value of costs as u_j, i.e.

$$u_j = B_j - C_j. \qquad \text{(A6)}$$

The literature suggests many factors that influence the present value of costs and benefits related to participation in university study. A detailed discussion of the variables used can be found in Sá et al. (2004), Long (2004), Whitehead et al. (2006), and Brooks (2002).

Besides individual characteristics, also university characteristics significantly influence the benefits and costs of study at a university (Long 2004). According to the human capital approach, benefits reflect the present value of extra earnings that an individual earns from additional year(s) of schooling. We use dummy variables for the university programs an applicant applies to FS_k $k\in\{1,..,S\}$ as a proxy for future extra earnings.

Regarding the costs of study that are driven by the university, distance to the university is a principle determinant. Since there is no tuition paid at universities in the Czech Republic, moving (travel) costs are the substantial determinant of study costs. Those who live far from a university have to bear them. Those who live near a university have the low-cost option of university study. We therefore use a dummy variable indicating the presence of a local university d as a proxy for study costs. The distance dummy is of primary interest since it reveals several phenomena present in the process of entering a university. In addition to the effect of study costs, it captures also the effect of heterogenous information on the prospective applicant's behavior.

Finally, Sá et al. (2004) note that the benefits and costs of university study are related to expected employability and expected earnings in the region of parental household (spatial heterogeneity). Therefore, we also include regional characteristics R into our analysis. Furthermore, Sá et al. (2004) point out that localized social interaction among secondary school students plays an important role. Therefore, we add secondary school (class) characteristics C into the analysis.

Taking into account the above mentioned literature on the determinants of post-secondary schooling decisions, we model the present value u_j by a linear predictor containing the following set of variables:

$$u_j = \alpha I + \beta C + \sum_{k=1}^{K} \eta_k FS_k + \delta d + \varphi R , \qquad \text{(A7)}$$

where vector I includes individual characteristics, vector C includes secondary school (class) characteristics, $FS_k \quad k \in \{1,..,K\}$ are dummy variables for the university program to which an applicant applies, and d is a dummy variable for a local university. Vector R includes regional characteristics.

Combining (A5)-(A7), we obtain the general formula for the expected present value of applying to tertiary-level education:

$$U^a = \sum_{k=1}^{F}\left[\sum_{A\in C(N,k)}\left(\left(\prod_{j\in A} t_j p_j\right)\left(\prod_{j\in \mathrm{N}\setminus A}(1-t_j p_j)\right)\right)\max_{j\in A}\{\alpha I+\beta C+\sum_{k=1}^{K}\eta_k FS_{k_j} +\delta d+\varphi R\}\right]+\sigma\left(M-\sum_{j=1}^{F} t_j AC_j\right) \tag{A8}$$

for some non-zero t_j's $j\in\{1,...,F\}$. For instance, if an applicant maximizes his/her utility by applying to just one program (with the program indexed by 1), the formula takes the following form:

$$U^a = p_1\left(\alpha I+\beta C+\delta d+\varphi R\right)+p_1\eta_1 FS_1+\sigma\left(M-AC_1\right). \tag{A9}$$

If an applicant sends two applications (programs 1 and 2), the formula takes the form:

$$\begin{aligned} U^a &= (p_1+p_2-p_1p_2)\left(\alpha I+\beta C+\delta d+\varphi R\right)+p_1(1-p_2)\eta_1 FS_1+p_2(1-p_1)\eta_2 FS_2+\\ &+p_1p_2\max_{j\in\{1,2\}}\left\{\eta_j FS_j\right\}+\sigma\left(M-AC_1-AC_2\right). \end{aligned} \tag{A10}$$

If an applicant applies to two programs, the formula takes the form:

$$U^a = (p_1+p_2-p_1p_2)\left(\alpha I+\beta C+\delta d+\varphi R\right)+(p_1+p_2-p_1p_2)\eta_1 FS_1+\sigma\left(M-AC_1-AC_2\right). \tag{A11}$$

In general, the first part of the formula containing vectors I, C, d, R does not change (up to the multiplier representing the probability of being admitted). The difference between formulas consists of the part that contains program dummies and the sums of admission costs.

If we omit admission costs (admission costs are low with respect to disposable income and very similar across universities), the expected utility of applying takes the following form:

$$U^a = \hat{p}_{(i)}\left(\alpha I+\beta C+\delta d+\varphi R\right)+\sum_{k=1}^{K}\gamma_{k,(i)}\eta_k FS_k^* +\sigma M\ , \tag{A12}$$

where $\hat{p}_{(i)}$ is the individual's subjective probability of being admitted at least to one program, and $\gamma_{k,(i)}$ are multinomial of probabilities.

In formula (A12), we have to deal with two econometric issues. First, the variables denoted by an asterisk are not observable for graduates who choose not to apply. Therefore, we proxy the program dummies by dummies for subjects that students take for the maturita exam in gymnasium or by dummies for the field of their specialized secondary schools, denoted by $SD_s, s \in \{1,...,S\}$.[77]

The second econometric issue concerns the problem of parameter heterogeneity. Coefficients denoted by the subscript (i) differ across individuals. Moreover, the coefficients $\hat{p}_{(i)}$ and $\gamma_{(i)}$ are unobservable, and they are, in general, correlated with the variables they are multiplied with. On the other hand, all the coefficients are numbers between zero and one. In Appendix B, we derive the relationship between the maximum likelihood estimates of a logit model when we take the individual coefficients $\hat{p}_{(i)}$ and $\gamma_{(i)}$ into account and when we don't. We use the results derived in the Appendix in the discussion on the relationship between structural parameters and the reduced form parameters in the section describing the estimation results.

The reduced form of the model for the utility of applying is

$$U_{red}^{a} = \alpha^{*} I + \beta^{*} C + \delta^{*} d + \varphi^{*} R + \sum_{s=1}^{S} \mu_s SD_s + \sigma M + \varepsilon^{a} \ , \qquad \text{(A13)}$$

where the disturbance term captures, for example, the different preferences of individuals.

[77] In the main text, we discussed how the subjects taken for the maturita exam (fields of specialized secondary school) determine the program specialization at a university.

The non-applying options consist of entering the labor market or staying out of the labor market. We assume that the econometric model of the expected utility of not applying $\left(U^{na}\right)$ takes the following form:

$$U^{na}_{red} = \tilde{\alpha} I + \tilde{\beta} C + \tilde{\varphi} R + \sum_{s=1}^{S} \tilde{\mu}_s SD_s + \varepsilon^{na} \,. \tag{A14}$$

If the disturbances $\varepsilon^{a}, \varepsilon^{na}$ have an extreme value distribution of type I, then the difference of disturbances yields a logistic distribution. So, the probability of applying is modeled as:

$$\begin{aligned}
&\Pr(Applying) = \Pr(U^{a} > U^{na}) = \Pr(U^{a} - U^{na} > 0) = \\
&= \Pr\left(\varepsilon^{na} - \varepsilon^{a} < \alpha^{*} I + \beta^{*} C + \delta^{*} d + \varphi^{*} R + \sum_{s=1}^{S} \mu_s SD_s + \sigma M - \tilde{\alpha} I - \tilde{\beta} C - \tilde{\varphi} R \right) = \qquad \text{(A13)} \\
&= \Lambda\left(I(\alpha^{*} - \tilde{\alpha}) + C(\beta^{*} - \tilde{\beta}) + R(\varphi^{*} - \tilde{\varphi}) + \delta^{*} d + \varphi^{*} R + \sum_{s=1}^{S} \mu_s SD_s + \sigma M \right),
\end{aligned}$$

where Λ is a logistic distribution function.

Appendix B: MLE estimates based on two dependent samples

In this section, we derive the relationship between the maximum likelihood estimates of the coefficients of the logit model in the case of a systematic change of the size of the explanatory variables.

Let us assume a logit model:

$$P(y = 1) = \Lambda(\alpha + \beta_1 x_1 + ... + \beta_k x_k) . \qquad \text{(B1)}$$

Let there be two random samples:

$$S_1 = \left\{ \left[y_i, x_{1i}, ..., x_{ki} \right], i \in 1,...,n \right\} \text{ and } S_2 = \left\{ \left[y_i, p_{1i}x_{1i}, ..., p_{ki}x_{ki} \right], i \in 1,...,n \right\},$$

where $p_{li} \in (0,1), l \in 1,...,k, i \in 1,...n$. Our goal is to derive the relationship between the maximum likelihood estimates of coefficients (or marginal effects) of the logit model (B1) employing samples S_1 and S_2 . The aim of this exercise is to find out the relative sizes of the MLE coefficients (and consequently marginal effects) and their standard errors. More precisely, we want to derive the change in the size of a coefficient caused by the systematic change in the size of an explanatory variable (both the variable that corresponds to the coefficient and the one which doesn't).

The case of one explanatory variable is depicted by the following figure. We consider a logit model estimated by MLE using two samples S_1 and S_2 . The movement of xs' towards the origin causes the movement of the logit curve in the direction depicted by the arrows. The coefficient in the linear term underlying the new logit curve increases.

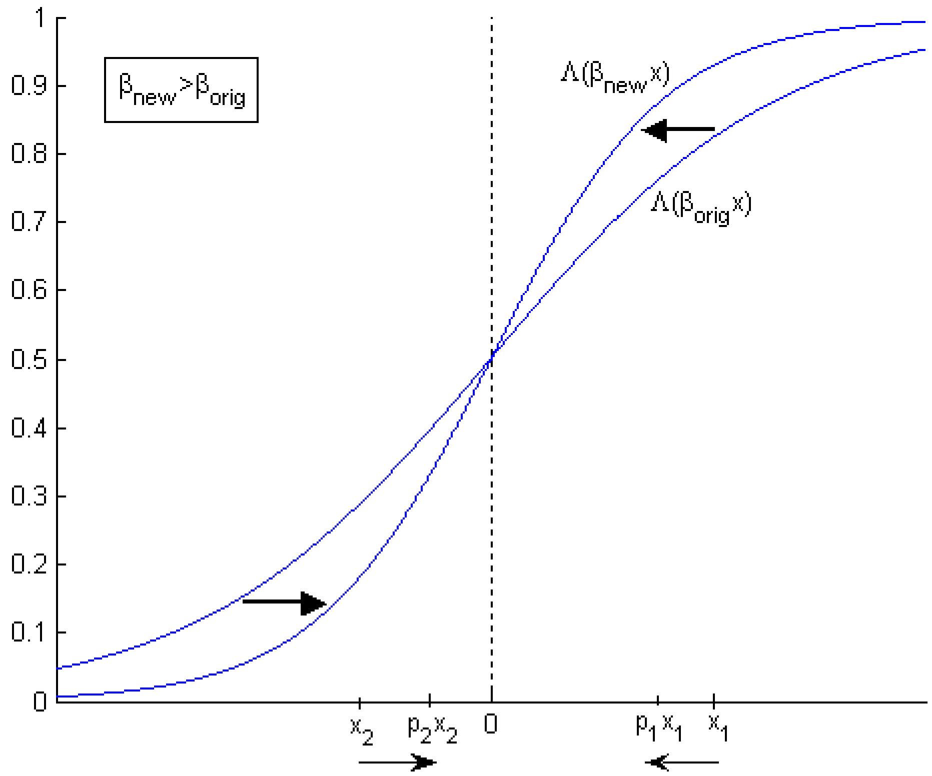


Figure: Estimation of a logit model with two samples.

For a multi-dimensional case, we derive the relationship using the maximum likelihood conditions of the logit model resulting from the first order conditions of the likelihood maximization problem (see e.g. Green 2003):

$$\sum_{i=1}^{n}(y_i - \Lambda_i) = 0$$

$$F_1(\beta; x_1,\ldots,x_k, y) \equiv \sum_{i=1}^{n}(y_i - \Lambda_i)x_{1i} = 0$$

$$\ldots$$

$$F_k(\beta; x_1,\ldots,x_k, y) \equiv \sum_{i=1}^{n}(y_i - \Lambda_i)x_{ki} = 0,$$

where $\Lambda_i \equiv \Lambda(\alpha + \beta_1 x_{1i} + \ldots + \beta_k x_{ki})$ is a logistic distribution function. The implicit function theorem gives

$$\frac{\partial \beta_l}{\partial x_l} = -\frac{\frac{\partial F_l}{\partial x_l}}{\frac{\partial F_l}{\partial \beta_l}} \quad \text{and} \quad \frac{\partial \beta_l}{\partial x_m} = -\frac{\frac{\partial F_l}{\partial x_m}}{\frac{\partial F_l}{\partial \beta_l}}. \qquad \text{(B2)}$$

The following calculations are mainly for illustrative purposes; we do not intend to provide an exact mathematical derivation. Therefore, we suppress the discrete property of the original conditions, and we take standard partial derivatives.[78]

Some rearrangements of the terms in the fractions (B2) yield:

$$\frac{\partial F_l}{\partial \beta_l} = \sum_{i=1}^{n} - \Lambda_i x_{li}^2 < 0 \qquad \text{(B3)}$$

$$\frac{\partial F_l}{\partial x_l} = \sum_{i=1}^{n} (y_i - \Lambda_i) - \sum_{i=1}^{n} x_{li}\lambda_i\beta_l = -\beta_l \sum_{i=1}^{n} x_{li}\lambda_i \qquad \text{(B4)}$$

$$\frac{\partial F_l}{\partial x_m} = -\beta_m \sum_{i=1}^{n} x_{li}\lambda_i\ , \qquad \text{(B5)}$$

where λ_i is a logistic density function.

So, the signs of the derivatives in (B2) are solely driven by the signs of the terms (B4) and (B5). The direction of the change of the coefficient caused by the systematic change in the explanatory variables ($\partial \beta_l / \partial x_{l(m)}$) is, therefore, determined by the signs of the original coefficients ($\beta_{l(m)}$) and explanatory variables. If all explanatory variables are positive and the original coefficient is positive, then derivatives in (B4) and (B5) are negative and derivatives in (B2) are also negative. So, if a new sample arises from the original one by a systematic lowering of the values of explanatory variables (the explanatory variable does not change), then the new coefficient is larger than the original coefficient. A similar conclusion holds for marginal effects since the marginal effect for the logit model can be expressed as a coefficient multiplied by a non-negative number (the probability density function evaluated in means of variables).

[78] On the other hand, we still use sums and not integrals.

In addition to the change in marginal effects, we also derive the change in standard errors. Basically, we focus on the change of the diagonal terms of the Hessian matrix since these terms determine the standard errors of MLE estimates. The diagonal terms of the Hessian matrix of the logit model (B1) take the following form:

$$[H]_{ll} = -\sum_{i=1}^{n} \Lambda_i \left(1-\Lambda_i\right) x_{il}^2 \ , \ l \in \{1,..,k\} .$$

Then,

$$\begin{aligned}\left[\frac{\partial H}{\partial x_{\bullet l}}\right]_{ll} &= -\sum_{i=1}^{n}\left(\lambda_i(1-\Lambda_i)x_{il}^2 - \Lambda_i\lambda_i x_{il}^2 + 2\lambda_i x_{il}\right) = \\ &= -\sum_{i=1}^{n}\left(\lambda_i x_{il}^2 - 2\Lambda_i\lambda_i x_{il}^2 + 2\lambda_i x_{il}\right) = -\sum_{i=1}^{n}\lambda_i x_{il}\left(x_{il} - 2\Lambda_i x_{il} + 2\right),\end{aligned}$$

where we use the fact that in the logistic distribution function $\lambda_i = \Lambda_i\left(1-\Lambda_i\right)$. Since $\Lambda_i \in (0,1)$, we can conclude that

$$\text{if } x_{il} \in [0,1] \text{ then } \left[\frac{\partial H}{\partial x_{\bullet l}}\right]_{ll} < 0 .$$

So, if the explanatory variable decreases (the new explanatory variable still satisfies $x_{il} \in [0,1]$), the corresponding diagonal term of the Hessian matrix increases. Since the asymptotic variance-covariance matrix of the MLE is the inverse of the Hessian matrix, the standard error decreases. So, if the estimation employing sample S_2 yields an insignificant variable (with a range between 0 and 1), then this variable is also insignificant in the estimation employing the original sample S_1.

Appendix C: Model of admission to a university

Applying to a university is a decision made by a secondary school graduate. The admission of those who applied is entirely the decision of a university. Universities base their decision solely on the results of admission tests. There are *no other criteria* for admission other than test scores. Therefore, the model of admission (conditional on application) is a model of admission test scores.

The result of the admission test depends mainly on individual capabilities. Moreover, some additional information may be provided by the applicant's secondary school or by her schoolmates, and therefore, secondary school characteristics may play a role as well. The performance in the admission test should not depend on regional economic characteristics; other regional characteristics that characterize the environment of an applicant can influence her performance at the admission test, however.

Finally, university characteristics should be taken into account. First, admission tests are different, and also, the test score threshold necessary for admission differs across university programs. Second, there are differences in demand for a university. An applicant applying to an over-subscribed program has a lower probability of admission than an otherwise similar applicant applying to a program that is not over-subscribed. Third, we encounter the self-selection problem, i.e. students with different abilities for university study apply to different programs. An applicant applying to a university whose pool of applicants has an overall higher ability faces a lower probability of admission than an otherwise similar applicant applying to a university whose pool of applicants has an overall lower ability. University characteristics employed in the model should control for these three differences among universities.

An econometric model of admission

The unit of observation is an application opposed to the model of applying, where the unit is a secondary school graduate. An individual's admission test score S^* is an unobservable (latent) variable. An individual is admitted to a program *j* if

$$S^* \geq T_j \,,$$

where T_j is a test score threshold necessary for admission to a particular program *j*. We model the latent variable S^* in the following way:

$$S^* = \beta_0 + \alpha I + \beta C + \delta d + \varphi R + \varepsilon \,,$$

where I denotes the set of individual characteristics, vector C includes the set of secondary school (class) characteristics, *d* stands for the dummy variable indicating the presence of a local university in the applicant's place of residence, and vector R contains regional characteristics. An individual is admitted to a program *j* if

$$S^* - T_j = \beta_0 + \alpha I + \beta C + \delta d + \varphi R - T_j + \varepsilon \geq 0 \,, \qquad \text{(C1)}$$

where the outcome (admitted or not) is given as

$$Admitted = 1\,[S^* - T_j \geq 0] \,.$$

If we assume logistic distribution for the disturbance, then the individual's probability of being admitted to program *j* (conditional on application) is given as

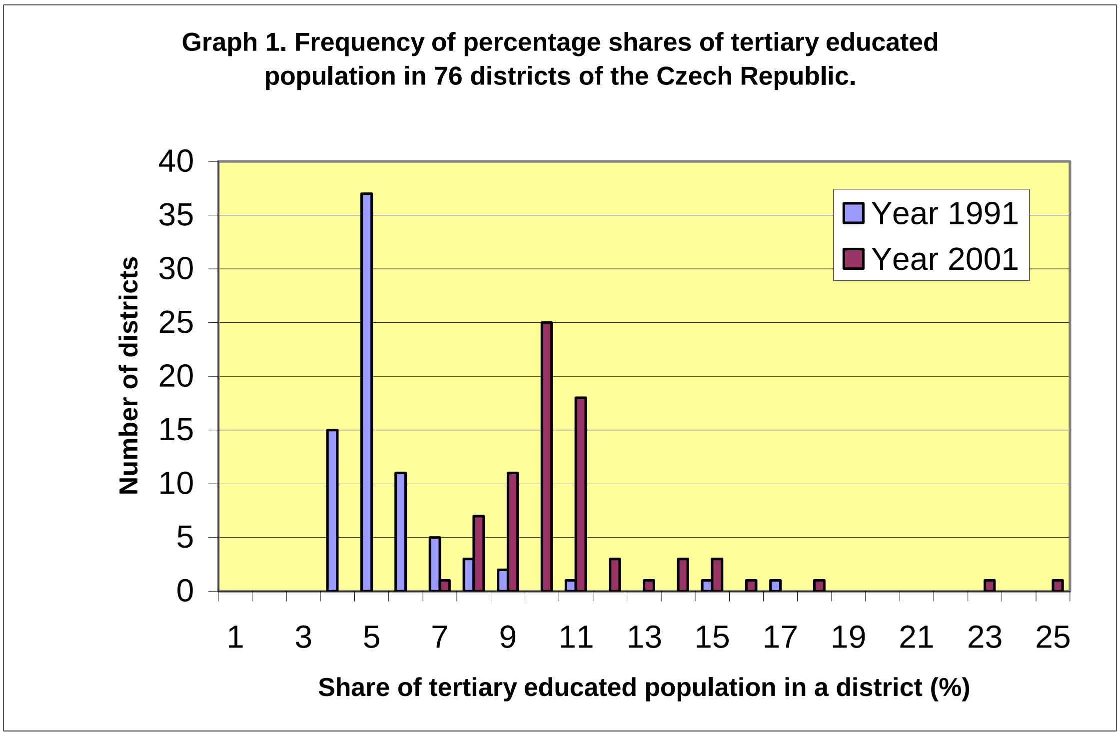
$$P(admitted = 1 \,|\, I, C, d, R, F_j) = \Lambda\left(\beta_0 + \alpha I + \beta C + \delta d + \varphi R + \tau F_j\right), \qquad \text{(C2)}$$

where F_j is a vector of university characteristics that serves as a proxy for the admission test score threshold T_j.

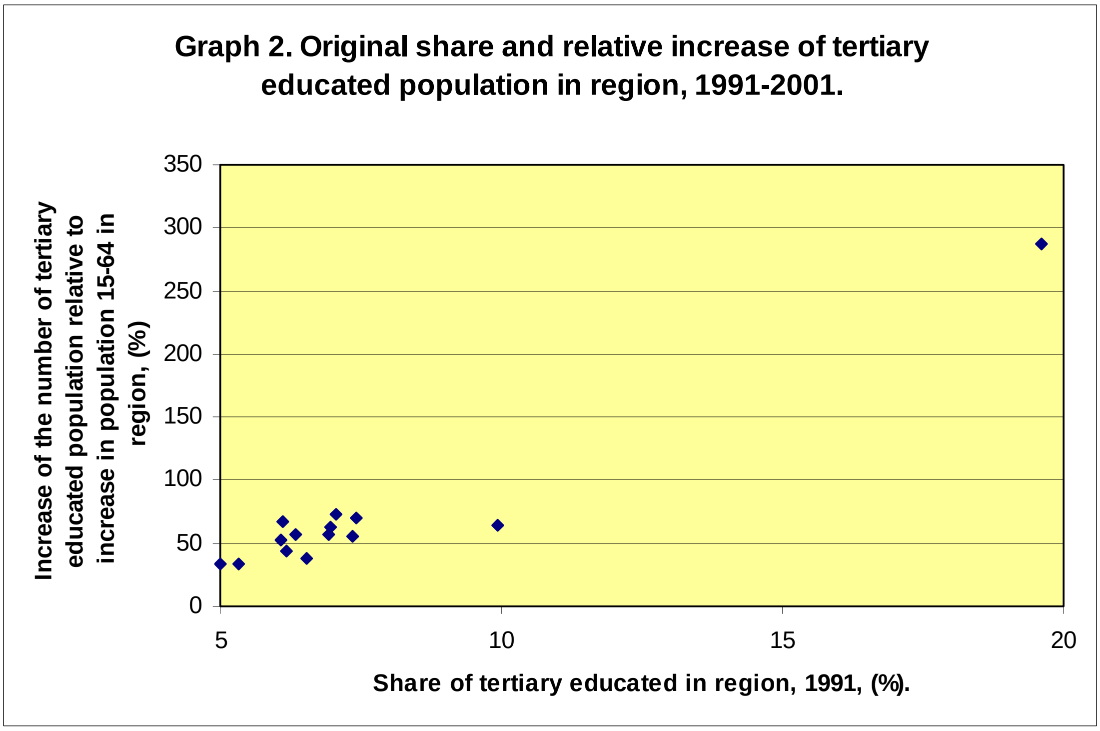
What are appropriate university characteristics F_j linked to the threshold T_j? Dummy variables for university (university program, program specialization) are used to control for differences in admission tests across universities. Furthermore, to control for the average quality of applicants at program *j* and excess demand for program *j,* we employ a composite score rank of a marginal applicant who is admitted. More precisely, we sort applicants into program *j* by their composite score. Using the information on the probability of being admitted, we find the lowest composite score that ensures an individual of being admitted if admission test scores duplicate the order of the applicants' composite score achievements.[79]

[79] The use of composite score rank makes sense if we employ dummy variables for university programs. For faculties, we already control for the average quality of applicants and excess demand by employing university dummies.

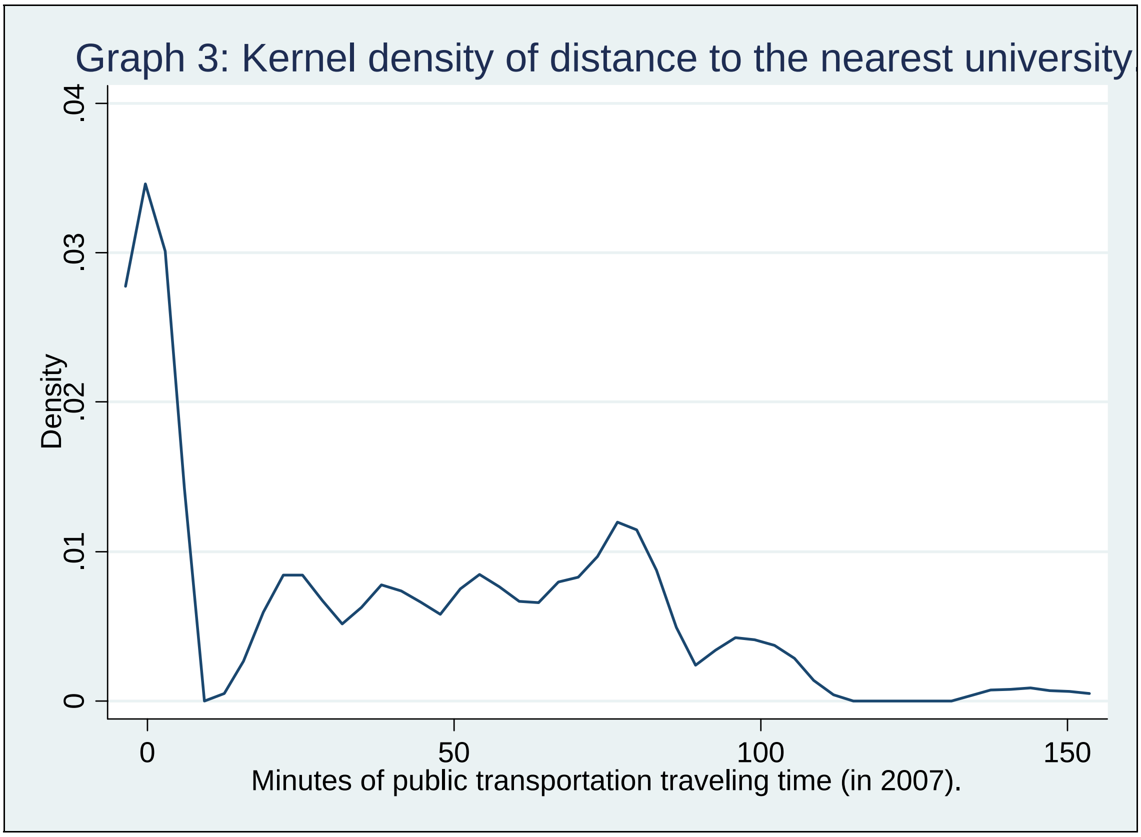
Appendix D: Graphs and Tables



Source: Census 1991, 2001.
Note: Districts correspond to NUTS4-level.

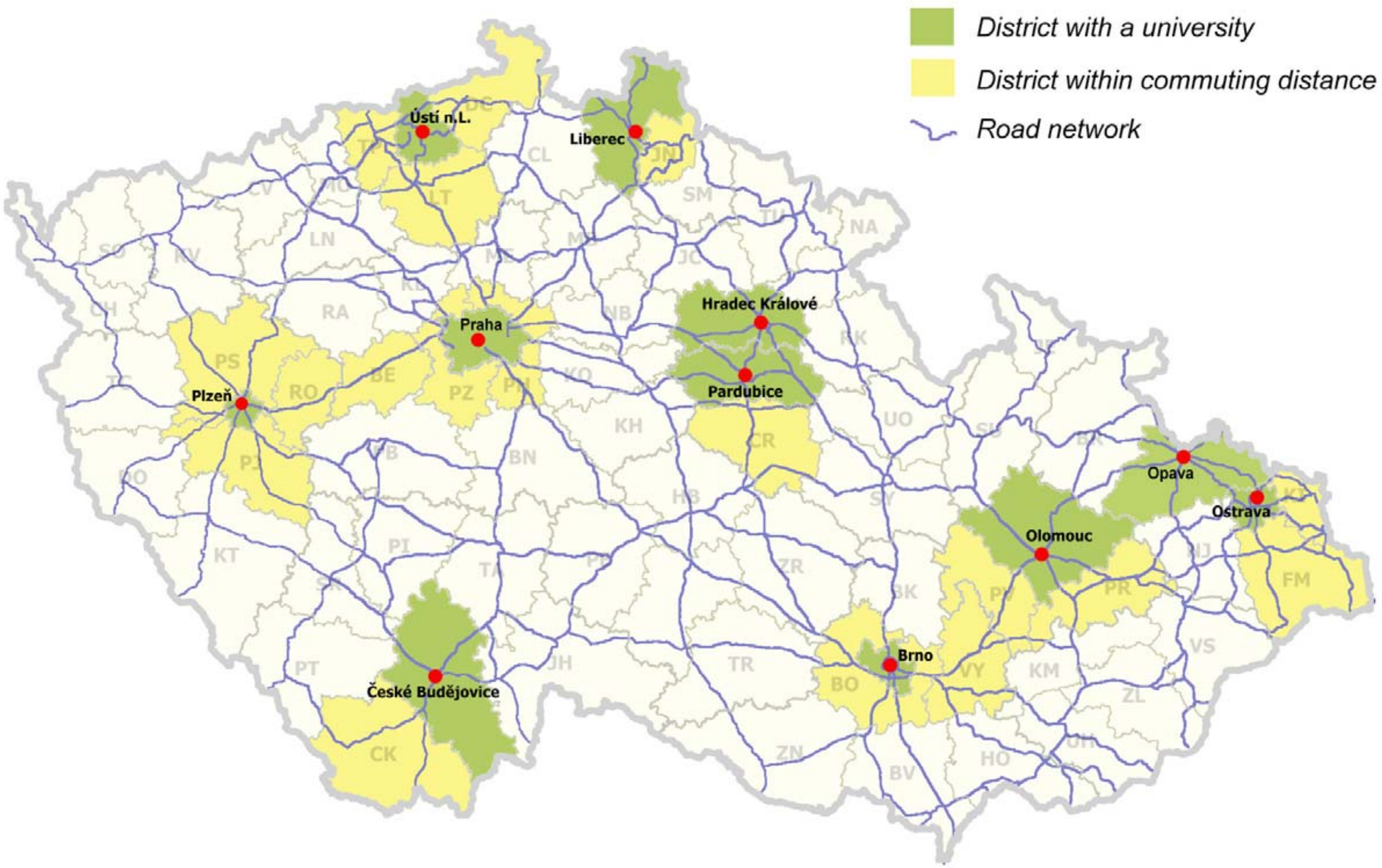


Source: Author's calculations based on Census 1991 and 2001.
Note: Region corresponds to NUTS3-level.



Source: Author's calculations based on Maturant (1998) and Uchazec (1998).

Graph 4: Districts with universities and districts within commuting distance to the nearest university, the Czech Republic, 1998.



Source: Author’s calculations based on www.tranis.cz.

Table 1. The coefficient of the variation of the tertiary-educated population share in a region.

	Bulgaria	Czech R.	Hungary	Ukraine	Sweden	Greece
w/ capital city	0.35	0.33	0.34	0.3	0.15	0.25
w/out capital city	0.19	0.13	0.16	0.19	0.13	0.1

Source: Jurajda and Terrell (2008), SSO, GSO.

Notes: Numbers for Bulgaria, the Czech Republic, Ukraine, and Hungary come from 2001. Numbers for Sweden and Greece come from 2005. Regions are defined by NUTS3 classification.

Table 2. The descriptive characteristics of gymnasium (G) and specialized secondary school (S) graduates and applicants.

	G		S	
Residence type:	local university	no local university	local university	no local university
Secondary school graduates	n=10208	n=8617	n=18894	n=18393
share of applicants	0.92	0.90	0.53	0.47
Individual characteristics				
share of women	0.58	0.61	0.60	0.63
computer at home	0.60	0.47	0.46	0.37
born before 1980	0.52	0.49	0.59	0.58
composite score	64.7	63.9	49.4	48.8
Shares of parental highest education:				
basic & vocational	0.09	0.16	0.25	0.36
secondary	0.34	0.43	0.49	0.48
tertiary	0.57	0.40	0.26	0.16
Class characteristics				
class size (number of students)	28.38	28.16	26.08	26.81
Regional characteristics				
unemployment rate (%)	6.58	7.87	6.88	8.01
GDP growth (1997=100)	99.28	97.22	98.97	97.27
Applicants	n=9425	n=7784	n=9892	n=8599
share of those admitted	0.66	0.64	0.41	0.36
Individual characteristics				
share of women	0.57	0.60	0.51	0.54
computer at home	0.61	0.48	0.54	0.46
born before 1980	0.51	0.48	0.56	0.54
composite score	65.33	64.67	52.60	52.56
Shares of parental highest education:				
basic & vocational	0.08	0.15	0.19	0.26
secondary	0.33	0.43	0.49	0.52
tertiary	0.58	0.42	0.32	0.22
Class characteristics				
class size (number of students)	28.48	28.25	26.50	27.37
private school	0.10	0.02	0.21	0.18
Regional characteristics				
unemployment rate (%)	6.54	7.87	6.84	7.99
GDP growth (1997=100)	99.31	97.20	98.98	97.13

Source: Author’s calculations based on Maturant (1998), Uchazec (1998), and data provided by the CSO.

Notes: G denotes gymnasium graduates and S specialized secondary schools graduates.

The composite score is the average test score computed from four tests taken from Czech and one foreign language, mathematics and study aptitude.

Table 3. The share of applicants from gymnasiums (G) and specialized secondary schools (S) applying to one program specialization only.

	G		S	
Residence type:	Local university	Non-local university	Local university	Non-local university
Applying to:				
local university only	0.21		0.52	
non-local university/ies only	0.28	0.20	0.63	0.53
both	0.13		0.30	
total	0.19	0.20	0.48	0.53

Source: Author's calculations based on Maturant (1998), Uchazec (1998), and data provided by the CSO.

Table 4a. The difference between the average share of applicants without a local university and the share of applicants without a local university in selected programs by type of secondary school.

G				All applicants		Applicants to non-local universities only	
University program	Number of universities	Number of districts	Prob. of admission	**Difference I**	Number of applicants	**Difference II**	Number of applicants
Technical Chemistry	5	2	0.51	**0.08**	1142	**-0.03**	727
Architecture	4	3	0.18	**-0.07**	419	**-0.08**	201
Veterinary Medicine	2	1	0.25	**0.02**	421	**-0.06**	243
Medicine	11	7	0.29	**-0.03**	1925	**-0.03**	930
Philosophy, Theology	11	6	0.27	**-0.13**	1084	**-0.02**	410
Social Sciences	6	5	0.13	**-0.10**	951	**-0.02**	395
Education	10	5	0.12	**0.11**	685	**0.03**	431
Theory and History of Art	5	4	0.12	**-0.11**	398	**-0.02**	160

S				All applicants		Applicants to non-local universities only	
University program	Number of universities	Number of districts	Prob. of admission	**Difference I**	Number of applicants	**Difference II**	Number of applicants
Engineering	6	6	0.59	**-0.08**	2215	**-0.02**	1042
Construction	5	4	0.51	**-0.07**	1230	**-0.14**	687
Transportation	4	2	0.31	**-0.11**	555	**-0.04**	244
Agriculture	8	3	0.3	**0.04**	2822	**0.04**	1621
Education	10	5	0.12	**0.11**	702	**0.05**	435

Source: Author's calculations based on Maturant (1998) and Uchazec (1998).

Notes: The share of applicants from gymnasiums (specialized secondary schools) without a local university is 0.45 (0.46).

The share of applicants applying to non-local universities only is 0.86 for applicants from gymnasiums and 0.83 for applicants from specialized secondary schools.

G denotes gymnasiums, S denotes specialized secondary schools.

Table 4b. The cognitive and non-cognitive skills of applicants from gymnasiums (G) and specialized secondary schools (S) in selected university programs.

	Cognitive skills - composite score				Non-cognitive skills		**Difference I**
Residence type:	Local university			Non-local university	Local university	Non-local university	(taken from Table 4a)
Applying to:	Local university only	Non-local university only	Both				
G							
University program							
Technical Chemistry	66.66	68.49	66.55	66.29	0.012	0.019	**0.08**
Architecture	68.44	69.20	69.07	66.45	0.014	0.021	**-0.07**
Veterinary Medicine	63.19	63.57	64.10	64.40	0.009	0.016	**0.02**
Medicine	66.78	67.11	66.58	67.16	0.012	0.020	**-0.03**
Philosophy, Theology	67.53	68.69	66.39	65.52	0.018	0.021	**-0.13**
Social Sciences	68.18	68.84	66.41	65.71	0.014	0.017	**-0.10**
Education	58.88	60.65	62.15	60.07	0.010	0.018	**0.11**
Theory and History of Art	64.87	64.76	64.52	62.90	0.020	0.014	**-0.11**
S							
Engineering	51.63	50.37	51.28	49.97	0.014	0.022	**-0.08**
Construction	51.78	49.56	50.14	47.90	0.019	0.023	**-0.07**
Transportation	52.11	50.78	53.48	52.49	0.018	0.020	**-0.11**
Agriculture	55.32	49.68	55.19	54.31	0.019	0.021	**0.04**
Education	45.62	45.29	47.04	47.50	0.016	0.020	**0.11**

Source: Author's calculations based on Maturant (1998) and Uchazec (1998).

Non-cognitive skills are measured using the relative excess demand for a gymnasium in a district.

Table 5. University applicants from gymnasiums (G) and specialized secondary schools (S): Descriptive statistics.

	G				**S**			
Residence type:	Local university			No local university	Local university			No local university
Applying to:	Only local university	Only non-local university/ies	Both		Only local university	Only non-local university/ies	Both	
	n=3636	n=1427	n=4362	n=7784	n=5318	n=1966	n=2608	n=8599
Composite score	65.11	65.82	65.35	64.67	52.37	50.82	54.41	52.56
Average number of applications sent	2.82	3.60	4.53	4.09	1.85	2.30	3.44	2.63
Average probability of being admitted conditional on application	26.99	26.54	22.54	24.66	29.63	29.64	24.25	25.33
Share of admitted to at least one program	0.62	0.65	0.69	0.64	0.38	0.40	0.47	0.36
Average number of faculties an applicant is admitted to	0.99	1.14	1.24	1.16	0.47	0.52	0.68	0.50

Source: Author's calculations based on Maturant (1998) and Uchazec (1998).

Notes: G denotes gymnasium graduates, and S denotes specialized secondary schools graduates.

Table 6. The application equation: Estimated marginal effects.
(G - gymnasiums, S - specialized secondary schools)

	G	S
Local university dummy		
Living within commuting distance to a university	0.000	0.003
	(0.03)	(0.19)
Individual characteristics		
Female	-0.009**	-0.101***
	(2.18)	(11.67)
Highest level of parental education: secondary	0.022***	0.109***
	(5.70)	(14.33)
Highest level of parental education: tertiary	0.046***	0.210***
	(10.02)	(21.66)
Computer at home	0.010***	0.096***
	(2.71)	(14.17)
Born before 1980	-0.015***	-0.081***
	(4.68)	(11.57)
Composite score rank	0.001***	0.006***
	(14.60)	(36.16)
Estimated marginal effects for subjects taken at the maturita exam (gymnasiums) and field of secondary school (for specialized secondary schools) are presented in Table 7.		
Class (school) characteristics		
Class size	0.001**	0.005***
	(2.37)	(4.14)
Class average composite score rank	0.000**	0.002***
	(1.96)	(5.07)
Private secondary school	-0.007	0.025*
	(0.83)	(1.65)
Regional (district) characteristics		
District unemployment rate	0.002***	0.007***
	(2.67)	(3.51)
Regional GDP growth	-0.001*	-0.013***
	(1.77)	(6.26)
Share of the tertiary-educated population in a district	0.314***	1.135***
	(3.37)	(4.79)
Relative excess demand for gymnasiums in a district	0.187**	0.590**
	(2.14)	(2.57)
Constant	0.019	0.528**
	(0.23)	(2.57)
Observations	15809	31637

Absolute value of z statistics in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: The dependent variable is a dummy that equals 1 if the graduate applies to at least one university and 0 otherwise.

The reference individual is male, born in 1980, parents finished basic or vocational education, no computer at home, attends state secondary school, and resides outside of commuting distance to a university.

The field reference category is business for specialized secondary school graduates.

Table 7. The application equation: Estimated marginal effects for subjects taken for the maturita exam and the subject of secondary school.

Gymnasiums		Specialized secondary schools	
Subject taken for the maturita exam		Specialization	
Foreign language	-0.012	Agriculture	0.090***
	(0.59)		(4.43)
Mathematics	0.053***	Manufacturing	0.120***
	(9.74)		(8.38)
Biology	0.021***	Light manufacturing	0.121***
	(3.75)		(5.88)
Physics	0.019**	Health care	0.062***
	(2.39)		(3.10)
Chemistry	0.052***	Social sciences	0.263***
	(6.89)		(9.70)
History	0.030***	Art	0.230***
	(6.48)		(5.71)
Geography	-0.003		
	(0.74)		
Social sciences	0.004		
	(0.98)		

Absolute value of z statistics in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. The admission equation for gymnasiums: Estimated marginal effects.

	1	2	3	4	5	6	7
Local university dummy							
Living within commuting distance to a university	-0.004	-0.018**	-0.015	-0.057***	-0.028	-0.006	-0.050***
	(0.42)	(1.98)	(1.57)	(3.32)	(1.60)	(0.32)	(2.82)
Interaction with probability of admission	-	-	-	0.141***	0.034	-0.013	0.051
				(3.68)	(0.85)	(0.33)	(1.32)
Presence of preferred program at local university	0.067***	0.077***	0.061***	0.111***	0.105***	0.094***	0.099***
	(7.47)	(8.40)	(6.57)	(6.20)	(5.83)	(5.16)	(5.43)
Interaction with probability of admission	-	-	-	-0.108***	-0.137***	-0.091**	-0.098**
				(2.58)	(3.24)	(2.16)	(2.35)
Individual characteristics							
Female	-0.031***	-0.028***	-0.018**	-0.043***	-0.029***	-0.014*	-0.016**
	(4.49)	(3.83)	(2.44)	(6.23)	(4.06)	(1.93)	(2.14)
Highest level of parental education: secondary	0.017	0.026**	0.026**	0.015	0.024**	0.030***	0.029**
	(1.48)	(2.18)	(2.22)	(1.31)	(2.00)	(2.58)	(2.46)
Highest level of parental education: tertiary	0.080***	0.088***	0.092***	0.076***	0.089***	0.092***	0.089***
	(7.07)	(7.49)	(7.69)	(6.74)	(7.50)	(7.84)	(7.56)
Computer at home	0.007	0.006	0.003	0.012*	0.010	0.001	0.004
	(1.10)	(0.81)	(0.43)	(1.80)	(1.39)	(0.19)	(0.50)
Born before 1980	0.007	0.008	0.008	0.005	0.007	0.007	0.006
	(1.06)	(1.21)	(1.25)	(0.79)	(0.99)	(0.99)	(0.87)
Composite score rank	0.008***	0.009***	0.009***	0.008***	0.010***	0.009***	0.009***
	(30.33)	(30.98)	(30.99)	(30.18)	(31.52)	(30.82)	(31.24)
Subjects at maturita (dummies)	-	-	-	-	-	Included	Included
Class (school) characteristics							
Class size	0.003***	0.002**	0.002**	0.002**	0.002	0.001	0.000
	(2.64)	(2.21)	(2.00)	(2.42)	(1.49)	(1.44)	(0.09)
Class average composite score rank	0.004***	0.004***	0.005***	0.004***	0.005***	0.004***	0.003***
	(9.74)	(9.87)	(10.64)	(9.93)	(10.69)	(10.24)	(5.37)
Private secondary school	-0.053***	-0.047***	-0.049***	-0.055***	-0.054***	-0.069***	-0.044**
	(3.19)	(2.67)	(2.76)	(3.29)	(3.07)	(3.94)	(2.41)
% of admitted (gymnasium)	-	-	-	-	-	-	0.294***
							(9.00)
Regional (district) characteristics							
Share of the tertiary educated population in a district	-0.599***	-0.372***	-0.299**	-0.687***	-0.188	-0.282**	-0.161
	(5.25)	(2.98)	(2.37)	(6.04)	(1.61)	(2.40)	(1.36)
Relative excess demand for gym.	-0.011	0.028	0.028	0.050	0.068	-0.043	-0.322**
	(0.08)	(0.18)	(0.18)	(0.34)	(0.44)	(0.28)	(2.05)
University characteristics							
Program specialization dummies	Included	-	-	Included	Included	Included	Included
University dummies	-	Included	-	-	-	-	-
University program dummies	-	-	Included	-	-	-	-
Marginal rank of admittance to program	-	-	-	-	-0.015***	-0.015***	-0.015***
					(30.07)	(27.62)	(30.28)
Constant	-1.556***	-1.277***	-1.323***	-1.290***	-0.143**	-0.213***	-0.213***
	(33.16)	(28.35)	(29.23)	(31.01)	(2.50)	(2.83)	(3.08)
Observations	43073	42897	42771	42833	42833	43073	43073

Absolute value of z statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

The reference individual is male, born in 1980, parents finished basic or vocational education, no computer at home, attends state secondary school and resides outside of commuting distance to a university.

Pseudo R2 of reported specifications between 0.21-0.27. Mis-specification problems detected for some specifications.

Notes: Included – indicates group of dummies used in estimations but not reported here because of number of dummies.

Table 9. The admission equation for specialized secondary schools: Estimated marginal effects.

	1	2	3	4	5	6	7
Local university dummy							
Living within commuting distance to a university	0.009	-0.003	-0.007	0.016	0.014	0.015	-0.004
	(1.15)	(0.43)	(0.89)	(1.31)	(1.09)	(1.22)	(0.33)
Interaction with probability of admission	-	-	-	-0.017	-0.051*	-0.057*	-0.062**
				(0.59)	(1.71)	(1.90)	(2.05)
Presence of preferred program at local university	0.041***	0.048***	0.049***	0.039***	0.040***	0.045***	0.062***
	(4.91)	(5.97)	(5.86)	(2.97)	(3.15)	(3.53)	(4.87)
Interaction with probability of admission	-	-	-	0.007	0.016	0.008	-0.045
				(0.25)	(0.54)	(0.26)	(1.48)
Individual characteristics							
Female	-0.040***	-0.029***	-0.019***	-0.046***	-0.025***	-0.024***	-0.017***
	(6.24)	(4.44)	(2.84)	(7.14)	(3.86)	(3.58)	(2.62)
Highest level of parental education: secondary	0.017**	0.016**	0.017**	0.016**	0.019**	0.019**	0.018**
	(2.23)	(2.16)	(2.31)	(2.14)	(2.43)	(2.45)	(2.41)
Highest level of parental education: tertiary	0.045***	0.047***	0.048***	0.044***	0.049***	0.048***	0.046***
	(5.48)	(5.74)	(5.70)	(5.31)	(5.80)	(5.70)	(5.61)
Computer at home	0.001	0.006	0.004	0.003	0.004	0.004	0.005
	(0.18)	(0.97)	(0.72)	(0.54)	(0.68)	(0.69)	(0.83)
Born before 1980	0.003	-0.003	-0.001	0.001	0.001	0.002	-0.003
	(0.49)	(0.52)	(0.26)	(0.15)	(0.20)	(0.30)	(0.48)
Composite score rank	0.003***	0.004***	0.004***	0.003***	0.004***	0.004***	0.004***
	(20.78)	(22.25)	(22.51)	(20.28)	(22.46)	(22.89)	(23.59)
Field of secondary school (dummies)	-	-	-	-	-	Included	Included
Class (school) characteristics							
Class size	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001	-0.001
	(1.17)	(1.27)	(0.54)	(1.30)	(1.26)	(0.74)	(1.21)
Class average composite score rank	-0.000	0.001***	0.001***	0.000	0.001***	0.001***	-0.000
	(0.13)	(3.76)	(4.10)	(0.06)	(3.22)	(4.54)	(1.35)
Private secondary school	-0.101***	-0.083***	-0.080***	-0.104***	-0.085***	-0.074***	-0.046***
	(11.38)	(9.53)	(8.76)	(11.70)	(9.45)	(7.24)	(4.55)
% of admitted (gymnasium)	-	-	-	-	-	-	0.416***
							(16.43)
Regional (district) characteristics							
Share of the tertiary educated population in a district	-0.536***	-0.165	-0.165	-0.579***	-0.308***	-0.332***	-0.274***
	(5.53)	(1.63)	(1.56)	(5.97)	(3.18)	(3.46)	(2.80)
Relative excess demand for gymnasiums in a district	-0.135	-0.149	-0.205	-0.127	-0.115	-0.091	-0.204
	(0.94)	(1.05)	(1.38)	(0.88)	(0.78)	(0.62)	(1.43)
University characteristics							
Program specialization dummies	Included	-	-	Included	Included	Included	Included
University dummies	-	Included	-	-	-	-	-
University program dummies	-	-	Included	-	-	-	-
Marginal rank of admittance to program	-	-	-	-	-0.009***	-0.008***	-0.008***
					(28.26)	(27.40)	(26.52)
Constant	-0.671***	-0.501***	-0.550***	-0.250***	0.275***	-0.040	-0.051
	(11.69)	(19.11)	(19.93)	(9.06)	(8.55)	(0.64)	(0.83)
Observations	31060	31048	30259	30850	30850	31060	31060

Absolute value of z statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Reference individual is male, born in 1980, parents finished basic or vocational education, no computer at home, attends state secondary school and resides outside of commuting distance to a university.

Pseudo R2 of reported specifications between 0.25-0.30. Misspecification problems detected for some specifications.

Notes: Included – indicates group of dummies used in estimations but not reported here because of number of dummies.

Table 10. The admission equation: Selected marginal effects.
(G - gymnasiums, S - specialized secondary schools)

	G	S
Local university dummy		
Presence of study field at a local university	0.099***	0.062***
	(5.43)	(4.87)
Interaction with the probability of admission field	-0.098**	-0.045
	(2.35)	(1.48)
Individual characteristics		
Female	-0.016**	-0.017***
	(2.14)	(2.62)
Highest level of parental education: secondary	0.029**	0.018**
	(2.46)	(2.41)
Highest level of parental education: tertiary	0.089***	0.046***
	(7.56)	(5.61)
Computer at home	0.004	0.005
	(0.50)	(0.83)
Born before 1980	0.006	-0.003
	(0.87)	(0.48)
Composite score rank	0.009***	0.004***
	(31.24)	(23.59)
Class (school) characteristics		
Private secondary school	-0.044**	-0.046***
	(2.41)	(4.55)
Regional (district) characteristics		
Share of the tertiary educated population in a district	-0.161	-0.274***
	(1.36)	(2.80)
Relative excess demand for gym.	-0.322**	-0.204
	(2.05)	(1.43)
Faculty characteristics		
Marginal rank of admittance to a program	-0.015***	-0.008***
	(30.28)	(26.52)
Constant	-0.213***	-0.051
	(3.08)	(0.83)
Observations	43073	31060

Absolute value of z statistics in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

The reference individual is male, born in 1980, parents finished basic or vocational education, no computer at home, attends state secondary school, resides outside of commuting distance to a university.

Table 11. University applicants from gymnasiums (G) and specialized secondary schools (S): Descriptive statistics.

	G				S			
Residence type:	Local university			No local university	Local university			No local university
Applying to:	Only local university	Only non-local university(ies)	Both		Only local university	Only non-local university(ies)	Both	
	n=3636	n=1427	n=4362	n=7784	n=5318	n=1966	n=2608	n=8599
Composite score	65.11	65.82	65.35	64.67	52.37	50.82	54.41	52.56
Average number of applications sent	2.82	3.60	4.53	4.09	1.85	2.30	3.44	2.63
Average probability of being admitted conditional on application	26.99	26.54	22.54	24.66	29.63	29.64	24.25	25.33
Share of admitted to at least one university program	0.62	0.65	0.69	0.64	0.38	0.40	0.47	0.36
Average number of programs an applicant is admitted to	0.99	1.14	1.24	1.16	0.47	0.52	0.68	0.50

Source: Author's calculations based on Maturant (1998) and Uchazec (1998).

Essay 3: The Role of Inflation Persistence in the Inflation Process in the New EU Member States

(A joint work with Branislav Saxa and Kateřina Šmídková)

Abstract

The aim of this paper is to compare inflation persistence between the New Member States (NMS) that joined the European Union in the years 2004 and 2007 and selected euro area members. If the levels of inflation persistence between the two groups are different, NMS can encounter problems with fulfilling the Maastricht criterion on inflation and – after entering the euro area – with inflation divergence. We argue that the specific economic situation experienced by the NMS in the last 15 years asks for the careful selection of inflation persistence measures. Two measures are estimated. The first one is based on the simple univariate statistical model of inflation with a time-varying mean. The second one assumes inflation following fractionally integrated process and measures inflation persistence within an ARFIMA model. Statistical tests suggest that the model with a time-varying mean is preferable to ARFIMA models for almost all countries. Estimation results show that inflation persistence is not an issue for all of the NMS. On the one hand, Bulgaria, Cyprus, the Czech Republic, Malta, Romania, and Slovakia exhibit persistence levels similar to those in the selected euro area countries. On the other hand, Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia encounter a problem of high persistence stemming from both high intrinsic and expectations-based inflation persistence.

1. Introduction

In the last fifteen years, the average inflation rate in the New Member States (NMS) amounted to 20% in comparison to a much lower level of 2.5% in the euro area countries (EAC). This significant difference in inflation rates between the two groups of countries has been most often associated with real convergence and related factors such as the Balassa-Samuelson effect or with the repercussions of economic transformation such as price deregulations. One would expect that these factors would gradually move aside as the NMS reach the advanced stages of real convergence. However, there is another class of factors that may reflect the longer-term characteristics of national economies and thus contribute to prevailing inflation differences, even in the advanced stages of convergence. Specifically, inflation persistence and inflation expectations can have a considerable impact on inflation differences between the NMS and the EAC after the effects of economic transformation and real convergence fade away.

Inflation persistence differences between the NMS and EAC can result in problems with fulfilling the Maastricht criterion on inflation. Intuitively, high inflation persistence corresponds to the slow return of inflation to its long-run value after a shock occurs. Therefore, should a symmetric shock hit all EU members, the NMS, with high estimates of persistence, could struggle to meet the Maastricht inflation criterion. It would take them longer to combat the consequences of this symmetric shock and return inflation to its long-run value. Moreover, the limit for inflation is based on the inflation average of the best EU inflation performers. This inherently implies that in the case of a symmetric positive shock on inflation, the benchmark will be set by countries with a high speed of inflation adjustment, i.e. the lowest inflation persistence. In other words, in the case of large differences in national inflation persistence values across the EU, it would be very difficult to stay close to the Maastricht inflation benchmark for those NMS with relatively high inflation persistence. Analogously, similarities in inflation persistence would increase the likelihood of symmetric reactions to common shocks.

Regarding inflation persistence in the euro area context, it was shown that the inflation convergence reached prior to introducing the euro has not been sustained among the EAC since 1998, and inflation persistence has been pointed out to be one of the prominent reasons.[80] It has been asserted that the euro area economies adjust unevenly to symmetric shocks due to differences in inflation persistence. So, the risk of inflation divergence after the NMS enter the euro zone is another reason why it is necessary to examine inflation persistence in the NMS.

The current literature has not reached a consensus on whether inflation persistence in the NMS is higher than in the EAC or whether it is comparable. Studies dealing with the NMS are usually based on the disaggregated data on prices. Approaches drawing on inflation aggregates, however, have several advantages. First, an international comparison is easier than with disaggregated evidence. Second, it is the aggregate inflation that is relevant for conducting monetary policy. Third, the previous empirical work on the EAC focused on inflation aggregates, and it can serve as a useful benchmark study. The work with aggregated data involves certain disadvantages also. Specifically, results can suffer from an aggregation

[80] See Angeloni and Ehrmann (2004).

bias, i.e. inflation aggregates can exhibit higher persistence than any particular components included.

In this paper, we take the aggregate data approach and estimate two measures of inflation persistence based on two univariate models of inflation. The first model is a model with a time-varying mean that is estimated using Bayesian techniques. The estimated model results in the unobserved component model estimated by the Kalman filter. The model enables the identification of two types of inflation persistence: intrinsic and expectations-based inflation persistence. The second employed model, ARFIMA, assumes that inflation follows a fractionally integrated process. Both models are estimated using CPI quarterly inflation data covering approximately the last fifteen years.

The choice of models draws on the discussion in Franta, Saxa and Šmídková (2007)[81]. From Franta, Saxa and Šmídková (2007), it follows that standard statistical approaches to measuring inflation persistence, based on constant inflation means, can yield misleading conclusions about the role that persistence plays in forming inflation in the NMS. They have been primarily designed to assess the persistence in developed economies. As a result, they do not take fully into account the specific situation of the NMS (e.g. monetary policy regime switches, price deregulations, real convergence towards the euro area, and short time series etc.) and tend to overestimate inflation persistence in the NMS by assuming a constant mean. The univariate models with a time-varying mean and the ARFIMA models are preferable since they account for the specific traits of the inflation processes in the NMS. Finally, the structural measures are difficult to estimate due to the above-listed specific features of the NMS and consequent econometric problems in the New Keynesian Phillips Curve estimation.

Our analysis focuses on the NMS that had acceded into the EU by May 1st, 2004 and January 1st, 2007. Estimation results suggest that some NMS are close to the EAC in terms of inflation persistence and the relative importance of its components (e.g. Cyprus, Malta, the Czech Republic, and Bulgaria). Other NMS, however, exhibit remarkable differences relative to the euro area. We show that some NMS economies (e.g. Hungary, Latvia, and Lithuania) face a serious problem of accommodating inflation shocks. The problem stems from a high estimated level of intrinsic inflation persistence. Moreover, expectations-based inflation persistence is found to be higher in these countries in comparison with the EAC, which contributes to a long lasting difference between an inflation target pursued by a central bank and public inflation expectations.

In addition, the model with a time-varying mean demonstrates why inflation persistence measures, usually employed in the case of developed countries, produce biased results in the case of the NMS. We show that in general, the estimated perceived inflation target that plays the role of a time-varying mean does not exhibit breaks for the EAC. On the other hand, breaks in the mean are frequent and significant for the NMS. Inflation persistence measures, therefore, provide upward biased measures in the case of the NMS.

Finally, we also discuss whether inflation processes in the NMS are better represented as a stationary process with parameter instability (a time-varying mean) or as a fractionally integrated process. These processes both imply mean reversion and hence can look very similar. Despite looking similar, they can imply different inflation persistence levels. Although empirical results based on the ARFIMA model suggest that persistence in some NMS may be higher than indicated by models with a time varying mean, additional statistical

[81] In a pilot study, the NMS were represented by four countries (the Czech Republic, Hungary, Poland, and Slovakia).

tests imply that assuming a stationary process with breaks is a preferable assumption to using fractionally integrated models for almost all the considered countries.

The structure of the paper is as follows. Section 2 reviews the available literature on the topic with a special emphasis on the relevance of inflation persistence in the NMS. Section 3 describes stylized facts and the two adopted statistical approaches to measuring and estimating inflation persistence. Section 4 reports on and discusses the results of these alternative estimates. Section 5 concludes. Appendix 1 includes plots of inflation rates for all sample countries; Appendix 2 provides the complete results of the Bayesian estimation of the time-varying mean model. Appendix 3 presents the estimates of the perceived inflation targets.

2. Related literature

In this section, we briefly review key theoretical concepts that can be employed to model the inflation process and to measure inflation persistence. We focus on those concepts that are relevant for the NMS. Then we discuss the major empirical results related to the NMS. It is important to note that not all concepts look at inflation persistence from the same angle. Specifically, some measures separate the impact of persistence in nominal contracts on inflation from the impact of persistence in the real economy (intrinsic and extrinsic inflation persistence) and also from the impact of inflation expectations and monetary policy regime changes.

A possible distinction between models used for measuring inflation persistence can be drawn between statistical and structural approaches. Statistical measures of inflation persistence are usually based on a univariate representation of the inflation process. Marques (2004) provides a summary of such measures, e.g. measures based on the sum of autoregressive coefficients, the largest autoregressive root, half-life, and spectral density at frequency zero. Inflation persistence measures based on the structural models of inflation usually deal with some specification of the Phillips curve. Calvo (1983) introduces a model of nominal price rigidities, where only a fraction of firms can adjust their prices in a given period. The Calvo model leads to a forward looking reduced form specification, and the persistence in inflation originates from the persistence in inflation driving variables (e.g. an output gap, real marginal costs). This type of inflation persistence is denoted as extrinsic inflation persistence.

Since the models based on the Calvo structural approach have been, in terms of data fit, inferior to models that incorporate a lagged value of inflation, some attempts to extend the Calvo model for the backward looking behaviour of firms were made. Within the Calvo framework, Galí and Gertler (1999) assume that a fraction of backward looking firms set their prices according to prices in the previous period, adjusted for inflation. Christiano, Eichenbaum, and Evans (2005) incorporate a backward looking term by assuming the indexation of prices to the inflation in the previous period for firms not chosen to re-optimize in a given period. The resulting hybrid versions of the New Keynesian Phillips curve (NKPC) introduce a new type of inflation persistence that originates in the price setting process itself and thus is qualitatively different from the extrinsic inflation persistence. Inflation persistence that stems from the way wages and prices are set is called intrinsic inflation persistence.[82]

[82] The structural character of hybrid version of New Keynesian Phillips curve has been questioned on the grounds of micro-evidence. It turns out, for example, that individual prices remain unchanged for several periods contradicting Christiano et al. (2005) assumption on indexation of prices.

More recently, a question arises whether the intrinsic inflation persistence captured by the lagged values of inflation is spurious (see e.g. Sbordone, 2007). Within this debate, the attention of researchers turns to the role of the inflation trend for modeling the inflation process and for measuring inflation persistence. Regardless whether recent models take the form of NKPC or are purely statistical, the focus is on the process assumed for an inflation trend, interpreting the inflation trend changes, and on the implications for the persistence of inflation.

Marques (2004) considers several treatments for the inflation trend that is represented by a time-varying mean of inflation. For US and euro area inflation, he applies an HP filter and a moving average. Dossche and Everaert (2005) model the time-varying mean as an AR(2) process. Stock and Watson (2007) and Cogley, Primiceri, and Sargent (2008) assume the trend following a driftless random walk. In addition to Dossche and Everaert, they also impose a stochastic volatility in the inflation trend. Finally, Cogley and Sbordone (2006) derive NKPC by the log-linearization of the Calvo model specification around the time-varying trend. This procedure leads to a NKPC with time-varying coefficients.

The models with the time-varying inflation trend introduce another type of inflation persistence that stems from the changes in trend inflation. In general, papers mentioned in the previous paragraph find the trend inflation to be an important contributor to the overall inflation persistence. Moreover, some of the papers identify a significant influence of monetary policy on changes in the inflation trend.

Bilke (2005) and Dossche and Everaert (2005) discuss the role of monetary policy changes for the inflation mean – an unobserved component model of Dossche and Everaert includes the central bank's inflation target. The inflation mean follows a process dependent on the target. Mishkin (2007); Cecchetti, Hooper, Kasman, Schoenholtz, and Watson (2007); Sbordone (2007); Stock and Watson (1997); and Benati (2008) also discuss the significant influence of monetary policy on the decrease of overall inflation persistence in developed countries over the last two decades. Finally, note that not only monetary policy regime changes are examined as a source of change in the inflation trend. Gadzinski and Orlandi (2004) and Levin and Piger (2004), for example, focus on the influence of administrative price changes on the mean of inflation.

Two main contributions of the recent research on inflation persistence in developed countries are highly relevant for the NMS. First, to describe the inflation process and capture the inflation persistence fully, one has to allow for the variance in inflation trend (mean). Second, the changes in inflation trend relate to monetary policy regime switches and administrative price regulation. For the NMS, some additional factors need to be taken into account, e.g. the convergence and transition of an economy from one that is centrally planned to one that is market based.

Another stream of literature investigating inflation persistence employs a fractionally integrated process[83] to model inflation, e.g. Gadea and Mayoral (2006), and Kumar and Okimoto (2007). Motivation stems from the fact that the literature provides substantial evidence against inflation following both the I(0) and I(1) process. The common explanation is that this is the result of structural breaks in the time series. However, the other alternative is that the inflation series follow the fractionally integrated or the ARFIMA process. As Gadea

[83] Baillie, Chung, and Tieslau (1996) surveys the applications of fractionally integrated processes in economics and finance. Applications for inflation time series, although predominantly for forecasting purposes, can be found in Baillie et al. (1996), Doornik and Ooms (2004), and Gabriel and Martins (2004).

and Mayoral (2006) suggest, stationary processes with structural breaks and the fractionally integrated processes can be easily confused and thus subsequent testing between the two approaches is necessary.

As already mentioned in the introduction, so far most of the available research on inflation persistence in the NMS is based on a disaggregated level of data and on a limited sample of countries (the Czech Republic, Hungary, Poland and Slovakia). A disaggregated level data analysis is available for the Czech Republic in Babetskii, Coricelli and Horváth (2006), for Hungary in Ratfai (2006), for Poland in Konieczny and Skrzypacz (2005), and for Slovakia in Coricelli and Horváth (2006). They all work with one-country data sets and this makes any international comparisons rather difficult. As far as individual countries are concerned, the authors of the respective studies find that in the Czech Republic, inflation persistence is lower after the introduction of inflation targeting and that it is lower for non-durables and services. In the case of Hungary, the aggregation of disaggregated data from one sector is shown to provide additional information about inflation dynamics. However, due to a very limited data sample, specific conclusions about the level of inflation persistence are difficult to draw. The Polish study makes use of a large disaggregated data set. It finds out that data are consistent with the menu cost model and that economic agents are rather forward-looking.

The macro studies are even fewer than the ones based on disaggregated data. Two studies focus on a selected group from the NMS. They both work with statistical models of persistence. Darvas and Varga (2007) suggest using the time-varying-coefficient models and the Flexible Least Squares estimator in order to estimate inflation persistence in the Czech Republic, Hungary, Poland, and Slovakia. They argue similarly to the second study (Franta, Saxa and Šmídková [2007]) that models with time-varying coefficients are vital for the inflation persistence analysis in the NMS. The results of both studies are in accord. Inflation persistence in the NMS, at least the selected ones, is not very different from the one in the EAC. In addition, Franta, Saxa and Šmídková (2007) propose to look at the most likely causes of inflation persistence by using models that are capable of distinguishing between intrinsic and extrinsic persistence on one hand and persistence related to monetary policy and expectations on the other hand. This distinction might be useful to policy makers when they try to lower inflation persistence.

3. Stylized facts and models for estimating inflation persistence

In this section, we provide a data description and basic stylized facts on inflation in the NMS. We then discuss the two models we employ for the measurement of inflation persistence: the time-varying mean model and the ARFIMA model.

3.1 Description of data used in this study

We work with two groups of countries. The first group of NMS consists of the 12 countries that joined the EU in 2004 and 2007: Bulgaria, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia. The second group of selected EAC – the control group – consists of 4 countries: Belgium, Germany, Portugal, and Spain. For the sake of simplicity, we do not report the results for all EAC, but only for the selected four countries that represent interesting case studies from the point of view of the NMS. Specifically, Belgium is a developed, small open economy of a comparable size to most of the NMS. Germany is by many viewed as a country that anchors inflation in Europe. Portugal and Spain are small open converging economies that may face similar problems that are going to be encountered by the NMS in forthcoming years. We do not compare the NMS with the euro area as a whole because euro area inflation aggregates can suffer from aggregation bias.[84] Abbreviations of the countries used in the text, the number of observations available for the analysis, and the corresponding time spans are reported in Table 1.

TABLE 1: Country abbreviations and time spans.

Country	Abbreviation	Observations	Period
Bulgaria	BUL	68	1991Q2-2008Q1
Cyprus	CYP	72	1990Q2-2008Q1
the Czech Republic	CZE	60	1993Q2-2008Q1
Estonia	EST	64	1992Q2-2008Q1
Hungary	HUN	72	1990Q2-2008Q1
Latvia	LAT	68	1991Q2-2008Q1
Lithuania	LIT	63	1992Q3-2008Q1
Malta	MAL	72	1990Q2-2008Q1
Poland	POL	72	1990Q2-2008Q1
Romania	ROM	69	1991Q1-2008Q1
Slovakia	SVK	60	1993Q2-2008Q1
Slovenia	SLO	64	1992Q2-2008Q1
Belgium	BEL	72	1990Q2-2008Q1
Germany	GER	68	1991Q2-2008Q1
Spain	ESP	72	1990Q2-2008Q1
Portugal	POR	72	1990Q2-2008Q1

Regarding the inflation index that we use to measure persistence, we considered three possibilities: CPI inflation, inflation based on the GDP deflator and, core inflation defined as non-food, non-energy CPI inflation. Our preferred measure of inflation is CPI inflation because the CPI inflation rate is relevant for both domestic monetary policy in the NMS as well as for the Maastricht criteria. In addition, it was difficult to obtain data for all the NMS for the other indexes. The data for CPI inflation are taken from the International Financial Statistics prepared by the International Monetary Fund (IFS). We use a seasonally adjusted, annualized q-o-q rate of change of CPI computed as $400 * \ln\left(CPI_t / CPI_{t-1}\right)$.

3.2. Some stylized facts: Inflation in the NMS

In the last 15 years, inflation rates in the NMS have been notably higher than in the EAC. Table 2 provides the inflation rates for the period 1993Q2-2008Q1 and the sub-period 2001Q1-2008Q1. These are samples available for all analyzed countries, as documented by Table 1. Two observations are worth noting. First, the difference in inflation means between the NMS and the EAC has been decreasing over time. While the inflation rates do not change for the EAC if we restrict the sample to the sub-period 2001Q1-2008Q1, they decrease considerably for almost all NMS.

Second, the NMS are not a homogenous group. They started the EU accession process with very different inflation rates. In the last 15 years, two NMS (Bulgaria, Romania) had on average inflation above 20%; five NMS (Estonia, Hungary, Latvia, Lithuania, and Poland)

[84] For a discussion on the effect of aggregation on inflation persistence differentials in the euro area, see Fiess and Byrne (2007).

faced moderate inflation between 10-20%; three NMS (the Czech Republic, Slovakia, and Slovenia) achieved inflation relatively close to the EU average (5-10%); and two NMS (Cyprus and Malta) had their inflation rates fully converging to euro area inflation. Figures that depict inflation rates for all countries can be found in Appendix 1.

Table 2: Inflation means (%).

Period	BUL	CZE	EST	HUN
1993Q2-2008Q1	36	5	10	11
2001Q1-2008Q1	6	3	5	6
	LAT	LIT	POL	ROM
1993Q2-2008Q1	10	13	10	34
2001Q1-2008Q1	6	3	3	12
	SVK	SLO	MAL	CYP
1993Q2-2008Q1	7	8	3	3
2001Q1-2008Q1	5	5	2	3
	BEL	GER	ESP	POR
1993Q2-2008Q1	2	2	3	3
2001Q1-2008Q1	2	2	3	3

Source: Author's calculations based on IMF IFS database.

Inflation rates in the NMS were affected by various factors connected to economic transition, real convergence, EU accession, and various external shocks. Most typically, the transitional factors and EU accession affected inflation in the NMS in the first two-thirds of our data sample. For example, price deregulations and tax reforms, including harmonisation of the taxes and excise duties, were among the common shocks contributing to higher inflation in that period. A more detailed analysis can be found in EBRD (1999). These were all specific shocks that did not hit the EAC. More recently, common external shocks play a prominent role; those such as high energy and food prices hit both the NMS as well as the euro area, although one can claim that the NMS are more prone to them due to a higher openness. An analysis of more recent inflation factors can be found in ECB (2008). While we can expect these common external shocks to influence inflation in the NMS in the future, the re-occurrence of specific shocks is not very likely.

Despite the one-off character of these specific inflation factors affecting inflation in the NMS in the analyzed period, they have implications for the current estimates of inflation persistence. Their impact on inflation means was tremendous and is crucial to our working definition of inflation persistence. According to this definition, inflation persistence is high if inflation converges slowly to its long-term mean after a shock. In order to measure persistence properly, we need a good approximation of the long-term mean. We argue that a constant mean assumption would not fulfill this requirement because of the above-mentioned specific factors. A time-varying mean is a better approximation since it corresponds more to the idea of a medium-term mean converging to a long-term one[85], the former being much easier to estimate from the data than the latter.

Tables 3a and 3b illustrate well why it is so important to take into account specific attributes of inflation processes in the NMS when putting the definition of inflation persistence into practice. If we assume a model with a constant mean, then an inflation series that does not

[85] We find it useful to distinguish these two time horizons when discussing inflation persistence in the NMS since long-term and medium-term equilibria may differ in a period of convergence. For a discussion on the importance of time horizons when dealing with the concept of equilibrium, see Driver and Westaway (2005).

frequently oscillate around its statistical mean would be suspected of having a high persistence[86]. To find out which NMS would fit into this category, we compute the number of times that each national inflation series switched from above to below its mean and vice versa. We consider an inflation mean over the period 1993Q2-2008Q1 and its sub-period 2001Q1-2008Q1.

Table 3a: The number of crosses of inflation means.

Period	BUL	CZE	EST	HUN
1993Q2-2008Q1	4	14	4	3
2001Q1-2008Q1	13	6	12	6
	LAT	LIT	POL	ROM
1993Q2-2008Q1	2	1	3	7
2001Q1-2008Q1	3	5	4	1
	SVK	SLO	MAL	CYP
1993Q2-2008Q1	15	21	31	24
2001Q1-2008Q1	5	15	16	15
	BEL	GER	ESP	POR
1993Q2-2008Q1	24	10	18	18
2001Q1-2008Q1	17	6	14	12

Source: Author's calculations based on the IMF IFS database.

Table 3b: The crosses of inflation means (% of quarters).

Period	BUL	CZE	EST	HUN
1993Q2-2008Q1	7	23	7	5
2001Q1-2008Q1	45	21	41	21
	LAT	LIT	POL	ROM
1993Q2-2008Q1	3	2	5	12
2001Q1-2008Q1	10	17	14	3
	SVK	SLO	MAL	CYP
1993Q2-2008Q1	25	35	52	40
2001Q1-2008Q1	17	52	55	52
	BEL	GER	ESP	POR
1993Q2-2008Q1	40	17	30	30
2001Q1-2008Q1	59	21	48	41

Source: Author's calculations based on the IMF IFS database.

There are two observations that we would like to emphasize. First, the inflation series for the NMS that are the former transitional economies cross their means less frequently than in the inflation series for the control group, the EAC. On average, inflation crossed its mean 7 times since 1993 in the former transitional economies, 11 times in the NMS, and 18 times in the EAC control group. Second, this is only true for the whole sample (1993Q2-2008Q1). Once we restrict the sample by removing the first-half during which the inflation was most affected by the transition and real convergence factors and once we consider the second-half of the sample (2001Q1-2008Q1) characterized as the period of an advanced stage of convergence, the computed means for this restricted sample are more similar. In the restricted sample, inflation crossed its mean 7 times in the former transitional economies, 8 times in the NMS, and 12 times in the EAC control group. This similarity comes from the fact that in the

[86] Marques (2004) formally demonstrates the inverse relationship between inflation persistence and mean reversion in the case when we model the inflation process as an autoregressive process of order *k*.

restricted sample, inflation does not stay as often below the computed mean as it does in the case of the full sample, in which the mean is very high for the group of former transitional economies. We thus argue that transformation as well as convergence weakened the link between the persistence and the frequency of crossing the mean. This is why we propose to measure the inflation persistence in the NMS only by using models that allow for breaks in the inflation mean.

3.3 The time-varying mean model

To examine the persistence of inflation, we have set up a simple statistical model that reflects the recent studies which deal with the modeling of the inflation process. The model is univariate and incorporates permanent (trend) and transitory components. Moreover, it enables the distinction of intrinsic and expectations-based inflation persistence. Intrinsic inflation persistence relates to nominal rigidities and to the way wages and prices are set. Expectations-based inflation persistence is driven by the differences between public perceptions about the inflation target and the central bank's true (explicit or implicit) inflation target.[87] Since the model is univariate, it cannot capture extrinsic inflation persistence. The measures of real activity in the NMS are, at least for the beginning of the considered period, of questionable quality, and thus, we do not attempt to incorporate the measures into the model for the purpose of extending if for measuring extrinsic inflation persistence.[88]

The model specification is close to the univariate version introduced in Dossche and Everaert (2005). Basically, the model specification consists of three equations.

$$\pi_{t+1}^{T} = \pi_{t}^{T} + \eta_{t} \qquad (1)$$

$$\pi_{t+1}^{P} = (1-\delta)\pi_{t}^{P} + \delta\pi_{t+1}^{T}, \qquad 0 < \delta < 1 \qquad (2)$$

$$\pi_{t} = \left(1 - \sum_{i=1}^{4}\varphi_{i}\right)\pi_{t}^{P} + \sum_{i=1}^{4}\varphi_{i}\pi_{t-i} + \varepsilon_{t}, \qquad \sum_{i=1}^{4}\varphi_{i} < 1 \qquad (3)$$

where π_t^T is the central bank's inflation target, π_t^P is the inflation target as perceived by the public, and disturbances η_t and ε_t are mutually independent, zero-mean, white noise processes.

In the first equation, the central bank's inflation target is modeled as a random walk and thus represents a permanent component of the modeled inflation process. It is a common practice nowadays to assume that inflation target changes have a permanent effect (see e.g. Leigh, 2005). The model assumes a random walk for the inflation target even if the central bank does not target inflation explicitly. On the other hand, if a country adopted inflation targeting (e.g. the Czech Republic in 1997/98), we do not impose the known targets into the model.

The second equation describes the relationship between the central bank's inflation target and the target as perceived by the public. The public forms its inflation expectations based on the current inflation target announced by a central bank and on the public's expectations in the previous period. The parameter δ represents the weight on the two sources. A similar specification of inflation expectations is assumed, e.g. in Bomfim and Rudebusch (2000).

[87] For details of the definitions see Angeloni, Aucremanne, Ehrmann, Gali, Levin, and Smets (2006).
[88] We realize that omitting extrinsic inflation persistence term in the model can affect our results. The influence of real activity terms on inflation is captured by the unobserved component of the model.

The parameter δ captures the expectations-based inflation persistence – a persistence that relates to the time how long a central bank's inflation target and the public's inflation expectations can differ after a shock occurs to the central bank's inflation target. In the framework of heterogenous agents, the parameter δ denotes the fraction of the forward-looking public. The parameter δ could also be interpreted as a parameter capturing the credibility of a central bank. Values close to 1 indicate that changes in the inflation target are immediately passed into public's inflation expectations.

The third equation imposes an autoregressive structure on the level of inflation. The time-varying mean is represented by the perceived inflation target. The sum of autoregressive coefficients captures the intrinsic inflation persistence.

The model, (1)-(3), was originally set up to measure inflation persistence net of monetary policy actions. However, in the case of the NMS, a component modeled as a random walk captures many other influences. Apart from the changes in monetary policy (e.g. monetary policy regime switch), other processes like administrative price changes, deregulations, and price convergence can be viewed as processes affected by shocks with permanent effects. The interpretation of our estimates, therefore, is broader than in the original model, and we recall this in the section describing the estimation results.

Putting one period lagged equation (2) into the equation (1) and the resulting equation back into equation (2) yields:

$$\pi_t = \left(1-\sum_{i=1}^{q}\varphi_i\right)\pi_t^P + \sum_{i=1}^{q}\varphi_i L^i \pi_t + \varepsilon_t \qquad \varepsilon_t \approx N(0,\sigma_\varepsilon^2) \tag{4}$$

$$\pi_{t+1}^P = (2-\delta)\pi_t^P + (\delta-1)\pi_{t-1}^P + \delta\eta_t \qquad \eta_t \approx N(0,\sigma_\eta^2). \tag{5}$$

Since the system (4)-(5) includes an unobservable component (π_t^P), we transform the system into a state space form and use the state space analysis methods. The state space form follows:

$$\begin{bmatrix}\pi_{t+1}^P\\ \pi_t^P\end{bmatrix} = \begin{bmatrix}2-\delta,\delta-1\\ 1,0\end{bmatrix}\begin{bmatrix}\pi_t^P\\ \pi_{t-1}^P\end{bmatrix} + \begin{bmatrix}\delta\\ 0\end{bmatrix}\eta_t \tag{6}$$

$$\pi_t = \left[\left(1-\sum_{i=1}^{4}\varphi_i\right),0\right]\begin{bmatrix}\pi_t^P\\ \pi_{t-1}^P\end{bmatrix} + \sum_{i=1}^{4}\varphi_i\pi_{t-i} + \varepsilon_t. \tag{7}$$

To estimate the unobservable series of the perceived inflation π_t^P, we use the exact initial Kalman filter (the case of unknown initial conditions) as described, for example, in Koopman and Durbin (2003). The Kalman filtering assumes known coefficients; therefore, we have to estimate them before we employ the filtering procedure on the system (6)-(7).

An estimation of the parameter vector $\theta = [\delta,\varphi_1,\varphi_2,\varphi_3,\varphi_4,\sigma_\varepsilon^2,\sigma_\eta^2]$ is carried out using Bayesian estimation techniques. The advantage of the Bayesian estimation consists in exploiting the maximum of available information. We do not build our estimates solely on the information in data (Y) as the maximum likelihood approach does. On the other hand, we do not rely on information from other sources only, as in the case of a model calibration. So, we combine the information involved in data on inflation with the information provided by other studies that deal with similar issues. We avoid the problem of unrealistic estimates sometimes obtained by the maximum likelihood estimation procedure. Moreover, we do not suffer from a low amount of related work for the NMS that would provide sufficiently reliable values for the parameters.

The basic idea behind the Bayesian estimation stems from Bayes theorem:

$$p(\theta \mid Y) = \frac{p(Y \mid \theta) p(\theta)}{p(Y)}. \tag{8}$$

This says that the posterior distribution of parameters, $p(\theta \mid Y)$, is proportional to the product of the likelihood of data given the parameter vector, $p(Y \mid \theta)$, and the prior distribution $p(\theta)$. The product, posterior kernel, is then normalized by the marginal data density computed as

$$p(Y) = \int_{\Theta} p(\theta, Y) d\theta = \int_{\Theta} p(\theta) \times p(Y \mid \theta) d\theta, \tag{9}$$

where the integrand is integrated over the whole parameter space Θ.

The likelihood function $p(Y \mid \theta)$ is estimated by using the Kalman filter, and the posterior kernel is simulated by using the Metropolis Hastings sampling algorithm. For a detailed explanation of the Bayesian estimation see, for example, An and Schorfheide (2006).

Following Dossche and Everaert (2005), we take over the priors $p(\theta)$ from several studies that use various estimation techniques and underlying models to estimate particular parameters. The prior for the sum of the autoregressive coefficients (intrinsic inflation persistence) is taken from Gadzinski and Orlandi (2004) and Levin and Piger (2004), i.e. from studies that take into account breaks in the inflation mean. These studies are, however, focused on developed countries. For the NMS, we, therefore, use prior distributions with higher standard deviations to reflect the higher uncertainty in the priors regarding the NMS. Similarly, we assume higher variances of shocks than Dossche and Everaert (2005) since the NMS have been facing structural changes and in general a more volatile economic environment. Original variances of shocks on the inflation target and inflation are taken from Kozicki and Tinsley (2003) and Smets and Wouters (2005).

Finally, the prior for the parameter δ is taken from the studies dealing with signal extraction (Erceg and Levin, 2003; and Kozicki and Tinsley, 2003) and sticky information (Mankiw and Reis, 2002). The distribution of priors, prior means, and the standard deviations are reported in Table 4.

Table 4: Priors.

Parameter	Distribution	Mean	Std. dev.
φ_1	Beta	0.2	0.3
φ_2	Beta	0.1	0.3
φ_3	Beta	0.05	0.3
φ_4	Beta	0.05	0.3
δ	Beta	0.15	0.2
σ_ε^2	Inverse Gamma	2	Inf
σ_η^2	Inverse Gamma	0.5	Inf

The estimation is carried out using the Matlab toolbox Dynare.[89] We simulate the posterior distribution using 5 blocks of Metropolis Hastings algorithm with 20 000 replications. The acceptance ratio is between 0.2 and 0.4.[90] The results of the Metropolis Hastings algorithm are assessed based on Brooks and Gelman (1998). Details are provided in the section dealing with the estimation results. Finally, note that the time series for inflation and the inflation target are used as data for the estimation. The inflation target is an HP filtered time series of inflation. The HP filtering parameter is equal to 1600 as this is typical for quarterly data.

3.4 ARFIMA models

As outlined earlier in this paper, not accounting for structural breaks in an inflation time series can lead to an upward bias in the inflation persistence estimates. However, as Gadea and Mayoral (2006) suggest, stationary processes with breaks and fractionally integrated processes can resemble each other, and it can be difficult to distinguish them. Therefore, we follow the approach of Gadea and Mayoral (2006) and model the inflation series of the NMS and EAC as a fractionally integrated process.

The time series π_t follows the ARFIMA(p,d,q) process if

$$\phi(L)(1-L)^d \pi_t = \theta(L)\varepsilon_t , \qquad (10)$$

where d is a fractional differencing parameter, $\phi(L) = 1-\phi_1 L - \phi_2 L^2 - ... - \phi_p L^p$ is an autoregressive polynomial, $\theta(L) = 1-\theta_1 L - \theta_2 L^2 - ... - \theta_q L^q$ represents a moving average polynomial, the roots of $\phi(L)$ and $\theta(L)$ lie outside the unit circle, and ε_t is white noise.

Baillie et al. (1996), Baum, Barkoulas, and Caglayan (1999) as well as Gadea and Mayoral (2006) argue that the ARFIMA model can be an appropriate representation of the stochastic behavior of inflation time series for many countries. The family of ARFIMA models allows a high degree of persistence without assuming a presence of a unit root. On the other hand, modeling the inflation process within the ARFIMA framework does not allow for distinguishing the types of inflation persistence identified by the time-varying mean models.

In the first step, we follow Gadea and Mayoral (2006) and estimate the fractional differencing parameter d using Geweke and Porter-Hudak's technique[91]. Parameter d indicates how long a shock affects the process. The value of d equal to zero describes a short memory process, and $|d| \in (0,0.5)$ implies a long memory process. If $d \in [0.5,1)$, shocks are transitory and the variance of the process is unbounded. The process, however, still exhibits a mean reversion. Finally, if $d \geq 1$, the effect of a shock is permanent.

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[89] For details on Dynare see http://www.cepremap.cnrs.fr/dynare/.
[90] Note that the acceptance ration between 0.2-0.4 is recommended in order for simulations to cover the parameter space reasonably.
[91] Geweke and Porter-Hudak's is a semi-parametric approach based on a spectral regression. It is implemented in STATA by Baum and Wiggins (1999).

Based on the estimated value of parameter d, we estimate the impulse response function of ARFIMA $(0,d,0)$[92]. To compare the persistence of shocks in the time series, we report the values of the impulse response function for the time horizons of 4 and 12 quarters after the realization of a shock.

In the next step, we test the hypothesis of a time series following a fractionally integrated process of order d versus a stationary process with breaks, proposed in Mayoral (2004). In order to reflect the convergence process observed in the inflation time series of the NMS, we allow for a break both in level and trend. The test statistics have the following form:

$$R(d) = T^{1-2d} \frac{\inf_{\omega \in \Omega}(\sum (\pi_t - \hat{\alpha}_1 - \hat{\delta}_1 DC_t - \hat{\beta}_1 t - \hat{\delta}_2 DT_t)^2)}{\sum (\Delta^d (\pi_t - \hat{\alpha}_0 - \hat{\beta}_0 t))^2}, \qquad (11)$$

where T is the number of periods, $\Omega = [0.15, 0.85]$ are trimming thresholds, $DC_t = 1$ if $t > \omega T$ and 0 otherwise, and $DT_t = (t - T_B)$ if $t > \omega T$ and 0 otherwise. α_0, α_1, β_0, β_1, δ_1 and δ_2 are coefficients from the appropriate regressions. Δ^d is the operator of differencing of order d. Critical values are computed according to Mayoral (2004). The null hypothesis assumes a fractionally integrated process while the alternative hypothesis assumes a stationary process with breaks.

4. Results

In this section, we provide the estimation results of inflation persistence measures introduced in the previous sections. First, we report the estimates of intrinsic and expectations-based inflation persistence based on the time-varying mean model. Second, we discuss the estimates obtained from the ARFIMA model.

4.1 Time-varying mean models

In this sub-section, we present the estimation results of the statistical model introduced in Section 3.3. The model allows for the inflation mean to change over time. Thus, it enables us to measure inflation persistence net of the effects of monetary policy, administrative price changes, price convergence, etc. We discuss the estimation results obtained by using Bayesian estimation techniques. Moreover, we touch upon the robustness of the results regarding the model specification. Finally, we also present graphically the estimates of the unobserved components of the model.

The complete results can be found in Appendix 2. Prior distributions and posterior means with 90% confidence intervals of all coefficients and countries are reported. Furthermore, in the appendix we also discuss the performance of the Metropolis-Hastings algorithm and the tools we employ to strengthen the reliability of the estimation results.

Here we confine ourselves to the measures of the intrinsic and expectations-based inflation persistence. The intrinsic inflation persistence is captured by the sum of autoregressive

[92] The impulse response function measures the effects of the realization of shock in y_t on subsequent values of time series. We used STATA implementation for ARFIMA written by Baum (2000).

coefficients at the lagged values of inflation, $\sum \varphi_i$, and expectations-based persistence by the coefficient δ. Table 5 suggests several general differences between and within groups of the countries.

The selected EAC exhibit a very low or even negative level of intrinsic inflation persistence. In the majority of cases, this type of persistence is not significantly different from zero.[93] For example, for Belgium all four coefficients at lagged values of the inflation rate are not significantly different from zero, and thus, the sum is not statistically significant either. For Portugal, intrinsic inflation persistence is found negative but only two coefficients φ_i are significantly different from zero, while the other two are positive or close to zero.

Table 5: Intrinsic and expectations-based inflation persistence.

Country	$\sum \varphi_i$	δ
BUL	0.24	0.23
CZE	0.10	0.31
EST	0.91	0.19
HUN	0.92	0.17
LAT	0.94	0.13
LIT	0.94	0.12
POL	0.99	0.13
ROM	0.43	0.29
SVK	0.29	0.25
SLO	0.94	0.13
MAL	-0.30	0.30
CYP	-0.44	0.25
BEL	0.08	0.33
GER	-0.28	0.40
ESP	0.07	0.33
POR	-0.49	0.45

Note: Complete results are reported in Appendix 2.

For the group of the NMS, the results are more diverse. The NMS can be divided into three sub-groups with respect to the extent of intrinsic inflation persistence. The first sub-group of countries (Bulgaria, the Czech Republic, Romania, and Slovakia) attains similar or slightly higher levels of intrinsic inflation persistence than the selected EAC. The inflation process in the second sub-group of countries (Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia) follows almost unit root process even though we impose non-stationarity in the process for the inflation mean. Finally, for Malta and Cyprus, we observe a level of intrinsic inflation persistence comparable to the group of EAC. All coefficients φ_i are not, for example, statistically different from zero for Cyprus.

[93] Note that DYNARE provides confidence intervals for single coefficients φ_i only, not for the whole sum. Since the intrinsic inflation persistence is captured by the sum of the coefficients, it is difficult to conclude anything about the statistical significance of the intrinsic inflation persistence estimated measure. On the other hand, the confidence intervals for single φ_i s provide some evidence. For the coefficient δ , we obtain a confidence interval directly.

Within the framework of our model, the negative estimates of intrinsic inflation persistence suggest that inflation after a shock converges to its long-run value oscillating around the value. In the case of a positive value, inflation decays without exhibiting this oscillating pattern.[94]

Regarding the expectations-based inflation persistence, the NMS and EAC also differ. The estimated values of the coefficient δ are lower for the NMS than for the selected EAC. The cross-country differences are often statistically significant (e.g. Latvia, Lithuania, and Slovenia vs. Germany and Portugal) – see 90% confidence intervals in Appendix 2. It is worth noting that the coefficient δ can be viewed as the measure of the public's tendency to be forward looking. Therefore, the countries with low δ can be viewed as having a high fraction of a backward-looking public. So, changes in the random walk component of the model are passed into public inflation expectations very slowly – a country exhibits high level of expectations-based inflation persistence.

There are also differences among the NMS themselves. Again, some of the differences are statistically significant (e.g. the Czech Republic vs. Latvia). The Czech Republic, Romania, Slovakia, Malta, and Cyprus exhibit estimates of the parameter δ close to values estimated for the selected EAC. On the other hand, some countries have δ close to zero, and hence, they face problems with anchoring inflation expectations (Latvia, Lithuania, Poland, and Slovenia).

In order to assess the effect of the model specification on the estimated values, we estimate two extensions of the benchmark model. First, we estimate the model from Dossche and Everaert (2005), i.e. the model where the inflation target is unobservable. We encounter a problem of identification of the coefficient δ. Intuitively speaking, coefficients at lagged values of inflation are identified since they appeared at the observable variables (lagged values of inflation). The time-varying mean, however, consists of two unobserved components (the central bank's inflation target and the perceived inflation target). Therefore, the parameter representing the relationship between the two unobserved components need not be identified. The posterior distribution of the parameter δ closely follows the prior distribution, which may indicate the lack of identification. Therefore, we view the results of the benchmark model as more reliable. We also impose an autocorrelation structure on the disturbance η_t; the results of main interest do not change significantly.[95]

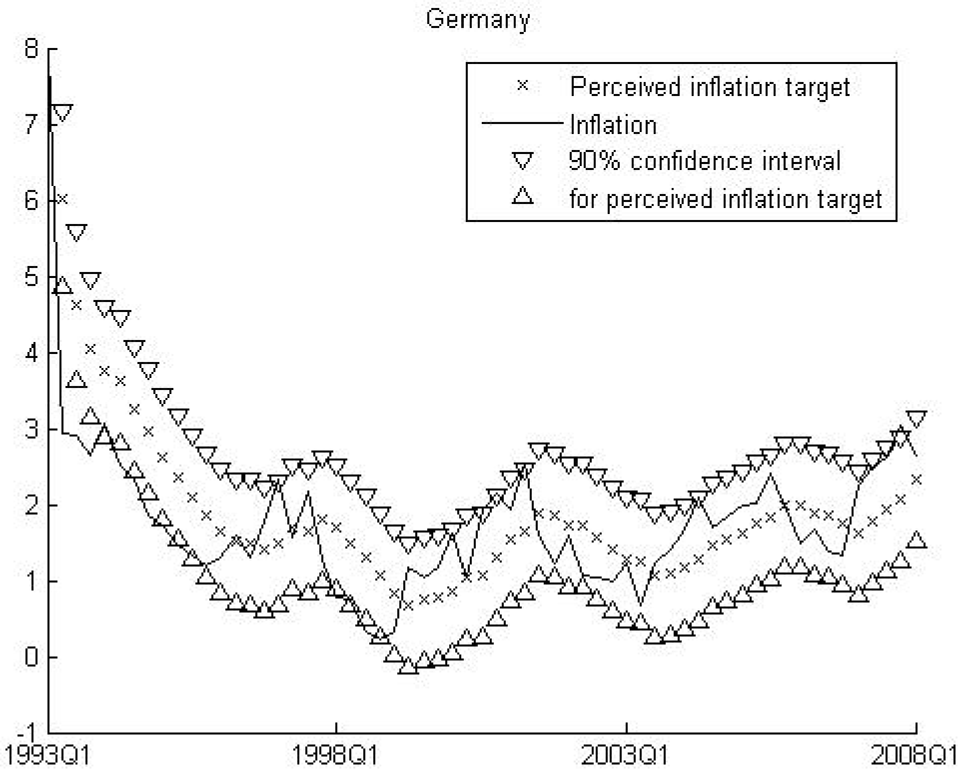
The model with estimated parameters can be re-formulated into a state space form (see system (6)-(7) in Section 3.3) and the method of the exact initial Kalman filter can be used to estimate the unobservable components of the system. One has to bear in mind that we do not know the exact parameter values and must work with estimates. So, the informational value of the filtering exercise is lowered because of the state space model parameter uncertainty. The purpose of the filtering, however, is to point out the various profiles of the unobserved component – the perceived inflation target – for various countries. For that purpose, our knowledge of the parameter estimates is sufficient.

[94] Note that since we use a statistical model of inflation, the negative values are not in conflict with any optimization problem on the micro level which would be the problem in the case of a negative sum of the coefficient in the structural measures based, for example, on some specification of the New Keynesian Phillips curve.
[95] We do not report the results here. They are, however, available upon request.

Figures 1-3 show the inflation rate and filtered perceived inflation target for several countries from our sample. We present countries that represent each sub-group discussed above. Germany represents the EAC with almost negligible intrinsic inflation persistence and a low level of expectations-based inflation persistence. Slovakia is a member of a sub-group of the NMS that exhibits moderate level of intrinsic inflation persistence and Hungary represents the high intrinsic inflation persistence countries with high a fraction of a backward-looking public. Note that the perceived inflation target serves as a time-varying mean of the inflation process and follows a non-stationary AR(2) process.

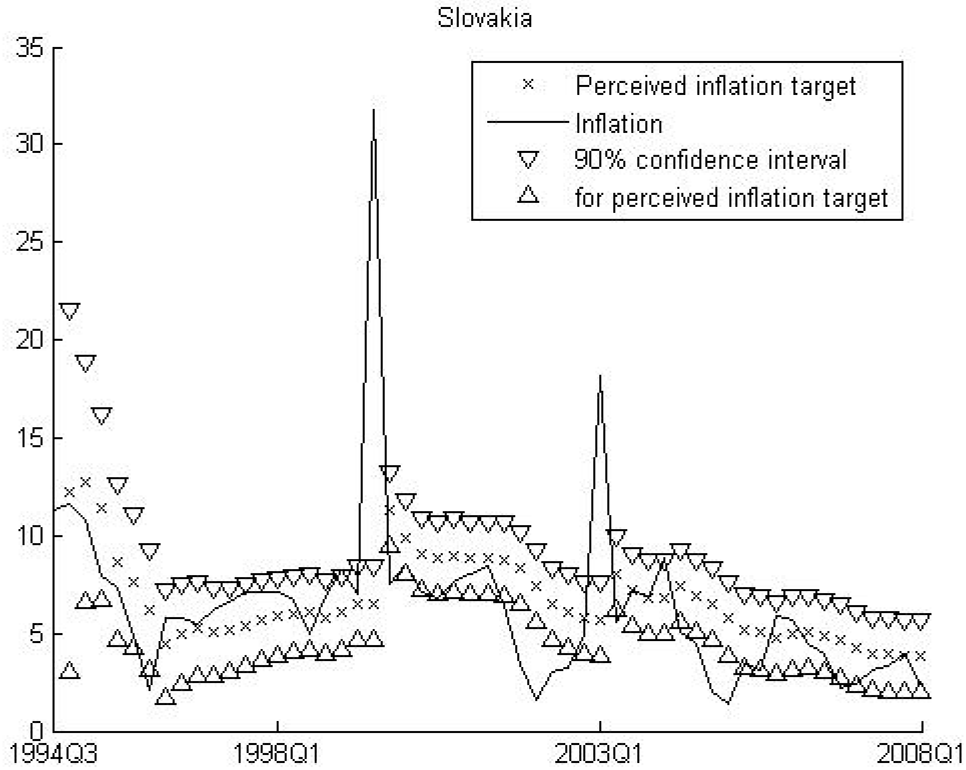
First note that we do not report the results of the filtering exercise for the whole period of available data. The method of the exact initial Kalman filter assumes infinite variances for initial values of unobserved components of the system. Confidence intervals for the perceived inflation target are, therefore, very large for the few first observations, and we focus on a sub-period with a reasonable width of confidence intervals for the unobserved variable.

Figure 1: Inflation and the perceived inflation target: Germany



The figures demonstrate what the recent literature put forward as a problem in the inflation persistence measurement and what we thoroughly discussed for the NMS above. Structural breaks in the economy lead to breaks in the inflation mean and consequently to the bias in persistence measures built on models with a constant mean. While perceived inflation targets do not exhibit clear breaks for Germany, a few statistically significant breaks are observable for Slovakia, and the difference in the perceived inflation target over time attains almost 30 percentage points in Hungary.[96] So, standard measures are not appropriate for the NMS, and more flexible models of the inflation process should be employed to avoid such biased results.

Figure 2: Inflation and the perceived inflation target: Slovakia



In addition, the results of the Kalman filtering can capture the effect of introducing inflation targeting on the public's inflation expectations. Figure 4 shows the evolution of the public's inflation expectations (perceived inflation target) for the Czech Republic. The Czech Republic has been targeting inflation since 1998. According to our estimates, expectations reached the level of the announced target (3%) in 5 years and have been close to it since then. Recently, an upsurge can be observed as a consequence of higher energy and food prices and changes in indirect taxes.

[96] On the other hand, the confidence interval for the Hungarian perceived inflation target is very wide.

Figure 3: Inflation and the perceived inflation target: Hungary

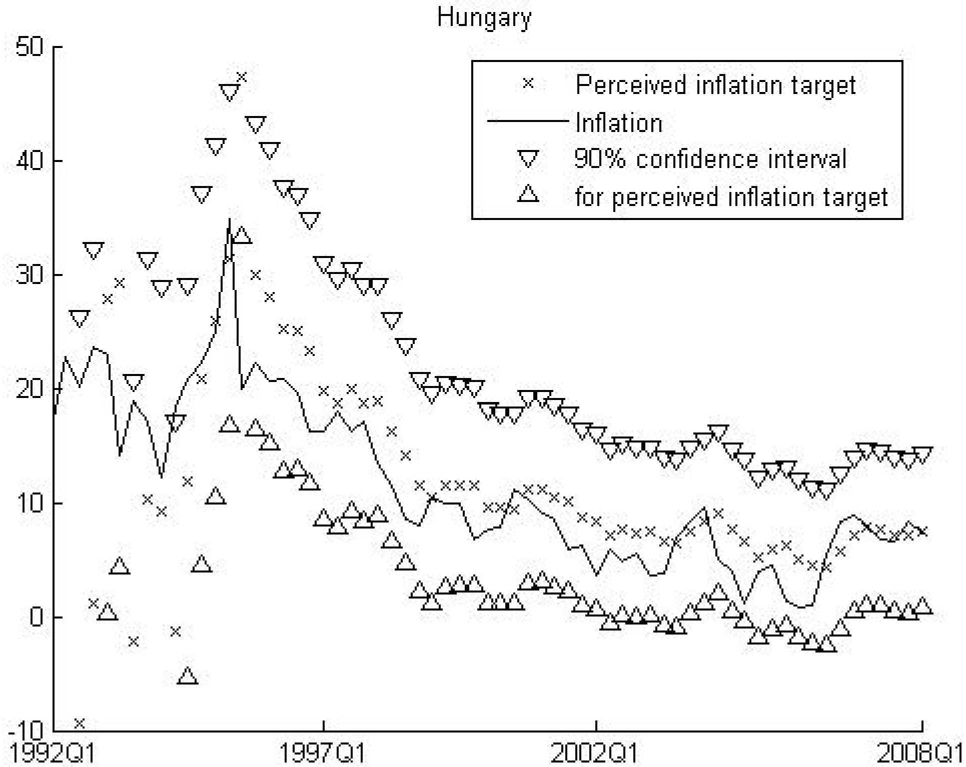
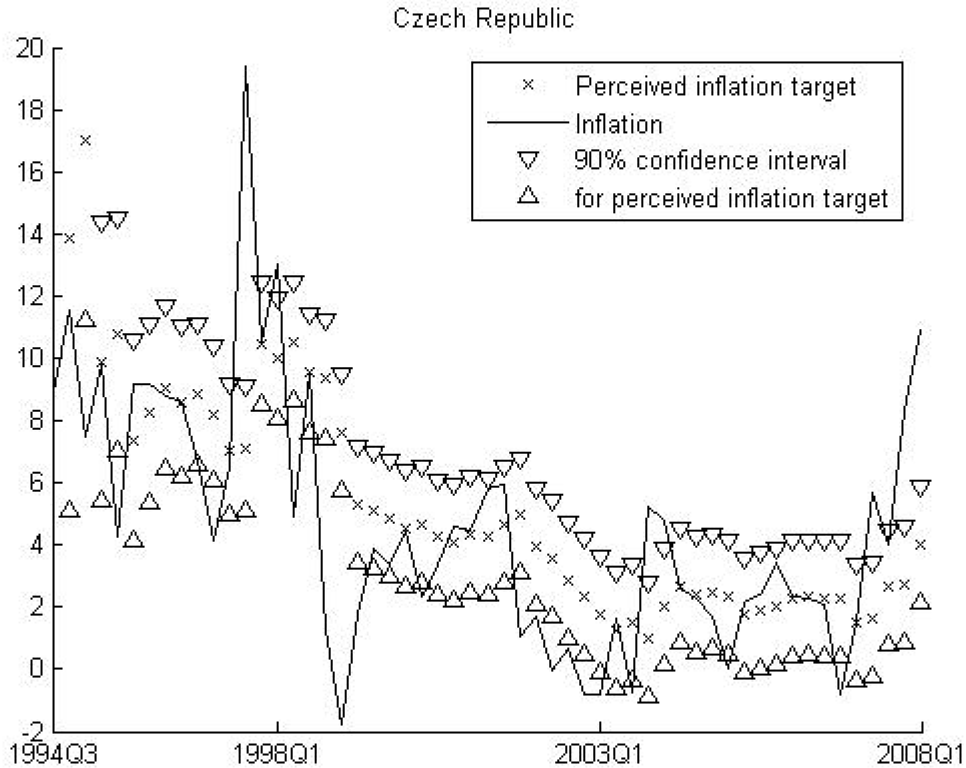


Figure 4: Inflation and the perceived inflation target: the Czech Republic



The figures for the rest of the NMS and EAC are presented in Appendix 3.

4.2. The ARFIMA model

In this section, we present estimation results based on the assumption that the inflation series follow a fractionally integrated process. The estimate of the parameter of fractional differencing *d* along with its standard error are reported in the second and the third column of Table 6. The last two columns of Table 6 show the values of the impulse response function for the time horizons of 4 and 12 quarters after the realization of a positive shock of the size equal to one.

The results demonstrate that based on the estimate of the fractional differencing parameter *d*, no general distinction can be made between the inflation persistence in the EAC and the NMS. Among EAC, Belgium and Portugal exhibit relatively low persistence, while Germany and Spain end up with fairly high persistence estimates. Among the NMS, Malta and Cyprus exhibit very low inflation persistence and Bulgaria, the Czech Republic, Romania and Slovakia can be considered as countries with moderate inflation persistence. On the other side, Estonia, Hungary, Latvia, Lithuania, Poland and Slovenia show high inflation persistence, if evaluated on the basis of a fractional differencing parameter.

Table 6: The estimation of the fractional differencing parameter *d* and the value of the impulse response function in selected time horizons.

Country	*d*	SE(*d*)	IPF(4)	IPF(12)
BUL	0.19	0.11	0.07	0.03
CZE	0.50	0.37	0.28	0.16
EST	0.99	0.19	0.98	0.97
HUN	1.71	0.63	2.94	6.41
LAT	1.34	0.12	1.80	2.61
LIT	0.62	0.08	0.41	0.27
POL	1.20	0.10	1.44	1.79
ROM	0.40	0.31	0.20	0.10
SVK	0.42	0.67	0.21	0.11
SLO	0.90	0.22	0.81	0.72
MAL	-0.03	0.41	0.01	0.00
CYP	0.07	0.35	0.02	0.01
BEL	0.43	0.37	0.22	0.12
GER	0.84	0.51	0.72	0.60
ESP	1.01	0.43	1.02	1.03
POR	0.11	0.59	0.03	0.01

Table 7: Test of fractional integration of the order *d* versus a stationary process with breaks.

	d							
Country	0.6		0.8		1		1.2	
BUL	**0.293**	***	0.051	*	0.009	***	0.001	***
CZE	**0.346**	**	0.062		0.011	***	0.002	***
EST	0.399		0.089		**0.018**	*	0.003	***
HUN	0.549		0.104		0.018		**0.003**	***
LAT	0.231	***	0.085		0.026		**0.006**	***
LIT	**0.946**		0.104		0.012	***	0.002	***

POL	0.431	0.088	0.016 **	**0.003** ***
ROM	**0.492**	0.109	0.022	0.004 ***
SVK	**0.337** **	0.056	0.009 ***	0.001 ***
SLO	0.285 ***	0.049 **	**0.008** ***	0.001 ***
MAL	**0.287** ***	0.047 **	0.007 ***	0.001 ***
CYP	**0.296** ***	0.049 **	0.008 ***	0.001 ***
BEL	**0.280** ***	0.046 **	0.007 ***	0.001 ***
GER	0.525	**0.106**	0.019	0.003 ***
ESP	0.313 ***	0.053 *	**0.009** ***	0.001 ***
POR	**0.342** **	0.060	0.010 ***	0.002 ***
1% critical values	0.335	0.043	0.015	0.008
5% critical values	0.364	0.050	0.017	0.009
10% critical values	0.381	0.054	0.018	0.009

Notes: Critical values are based on Mayoral (2004). ***, **, and * denote significance at the 1%, 5% and 10% levels. For each country, the cell in bold determines the column closest to the value of *d* estimated using Geweke and Porter-Hudak's technique and are reported in Table 6.

Table 7 summarizes the results of testing the null hypothesis of the fractionally integrated process against the alternative of a stationary process with breaks. For each country, the cell in bold determines the column closest to the estimated value of parameter *d* reported in Table 6. At the 10% level of significance, we can reject the null hypothesis of the fractionally integrated process for all countries except Lithuania, Romania and Germany. Modeling the inflation time series as a stationary process with breaks is thus preferable for most of the considered countries. In light of this result, we consider the analysis employing the time-varying mean presented in the previous part of the paper as our preferred.

Finally note that the alternative hypothesis to the test presented in Table 7 is that the inflation time series follows a stationary process with *just one* break. So, if the test suggests rejecting the null of a fractionally integrated process, it follows that the model with a time-varying mean (i.e. the model allowing for more breaks) is preferable. On the other hand, if the test doesn't find enough evidence against the null, it still doesn't imply that the model with *more than one* break is not preferable.

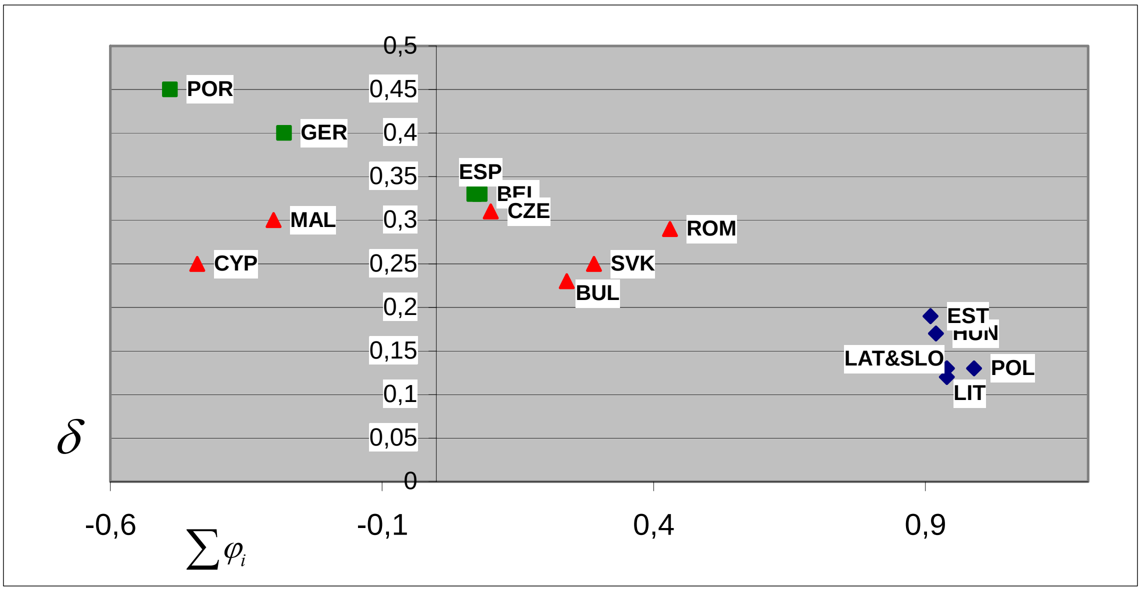
5. Inflation processes in the NMS: Empirical findings

The empirical findings show several interesting features of the inflation processes occuring in the NMS. First, the NMS – as a group – differ from the selected EAC in both intrinsic inflation persistence that captures the impact of persistence in nominal contracts on inflation as well as in expectations-based inflation persistence that relates to how well inflation expectations are anchored or, equivalently, how forward-looking the public is. Inflation persistence can be, therefore, one of the driving factors behind the inflation differences between the EAC and NMS.

Second, the NMS are not a homogenous group. The NMS do exhibit neither similar intrinsic inflation persistence nor similar levels of expectations-based inflation persistence.[97] We can identify two groups within the NMS with respect to the extent of intrinsic and expectations-based inflation persistence. In the first group, there are six NMS (Bulgaria, Cyprus, the Czech Republic, Malta, Romania, and Slovakia). These countries have similar or even nearly the same inflation persistence as the selected EAC. In the second group, there are six NMS (Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia) where local economies are not in general able to accommodate inflation shocks to the extent observed in the selected EAC and where the backward-looking character of expectation formation contributes to problems with anchoring inflation expectations.

Third, Figure 5 captures an interesting empirical regularity. There seems to be a negative correlation between estimated values of the sum of coefficients φ_i (intrinsic inflation persistence) and the coefficient δ (expectations-based inflation persistence). Countries that face high levels of intrinsic inflation persistence when fighting inflation face also problems when they try to anchor inflation expectations.

Figure 5: Intrinsic and expectations-based inflation persistence



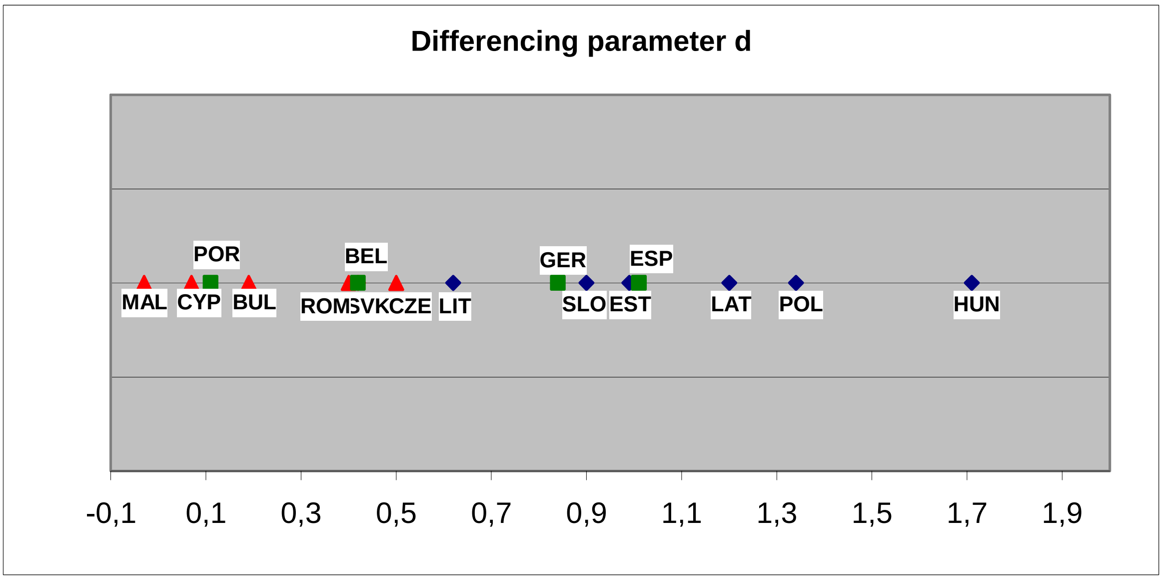
Note: The figure depicts three groups of countries: green squares denote the selected EAC (Belgium, Germany, Portugal, and Spain), the red triangles represent the NMS with similar features of inflation persistence to the EAC (Bulgaria, Cyprus, the Czech Republic, Malta, Romania, and Slovakia), and the blue diamonds denote the NMS with higher levels of inflation persistence and problems with anchoring inflation expectations (Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia).

Fourth, the ARFIMA model provides similar results regarding the propagation of shocks to inflation. The estimated values of the differencing parameter *d* are reported in Figure 6. The NMS are on the bottom line and the selected EAC on the upper line. Regarding the NMS, one can observe that the ordering of countries is in general similar to the ordering of the levels of

[97] We remind the reader that some conclusions cannot be stated in terms of statistical significance at a 90% level of significance. For details see the discussion in the section dealing with estimation results and the results presented in Appendix 2.

intrinsic inflation persistence provided by the time-varying mean model.[98] The selected EAC, however, do not follow the ordering suggested by the model with a time-varying mean. On the other hand, confidence intervals for the parameter *d* are, in the case of Germany and Spain, wide. Statistical tests comparing the two models are necessary. We demonstrated that the model with a time-varying mean is preferable for the vast majority of countries.

Figure 6: The estimated differencing parameter in the ARFIMA model



6. Conclusions

In this paper, we examine inflation persistence in the countries that joined the European Union in the years 2004 and 2007. We argue that reliable estimates of the inflation persistence are necessary for understanding the obstacles that the New Member States (NMS) can face when they decide to enter the euro area. More precisely, differing levels of inflation persistence between the NMS and countries constituting the euro area can bring about the difficulties of fulfilling the Maastricht criterion on inflation. Moreover, some recent studies point out that inflation persistence differences cause inflation divergence within a monetary union.

We assert that the specific economic situation of the NMS in the last 15 years demands careful consideration of an appropriate model fot the inflation process that is suitable for measuring inflation persistence. First, frequent breaks in the inflation time series caused, for example, by administrative price changes or by monetary policy regime switches discriminate from models using a constant mean of inflation. Second, data availability and quality reduce the possibility for a successful estimation of inflation persistence measures based on multivariate statistical and structural models.

The estimation results of the time-varying mean model suggest that the NMS can be in general divided into two groups. One group consists of Bulgaria, Cyprus, the Czech Republic,

[98] Note that ARFIMA cannot distinguish the types of inflation persistence that can be identified within the framework of time-varying mean models.

Malta, Romania, and Slovakia. The main traits of the inflation persistence in this group are very similar to the selected euro area countries (Belgium, Germany, Portugal, and Spain). The other group of the NMS (Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia) exhibits a very high level of intrinsic inflation persistence. Moreover, in the model, the public is found to be highly backward-looking for this group, which indicates problems with anchoring inflation expectations.

The members of the second group of the NMS could face a problem when they want to fulfill the Maastricht criterion on inflation since their economies experience difficulties in accommodating inflation shocks. The problem increases by the indicated problems with anchoring inflation expectations.

Since we focus on statistical models, one has to be careful with the interpretation of results. Still one can attempt to compare micro-evidence with estimation results. One possible way is to employ theories that relate inflation and the labour market. For example, recent firm-level data evidence suggests that countries with a high proportion of firms linking base wages to expected inflation are those countries identified by this paper as having a high portion of a forward-looking public (high δ).[99] A detailed interpretation of the results is, however, beyond the scope of the current paper that was primarily intended to compare inflation persistence between the NMS and the EAC.

The examination of inflation persistence in the NMS faces challenges that should be overcome by future research. Since the choice of models that underlie measures of inflation persistence is partly driven by data quality and availability, the natural direction of future research is to employ multivariate statistical or structural models. With longer time spans and data of higher quality, the original disadvantage of low quality data will be compensated by the possibility to exploit more information from other relevant time series (output gap, interest rates, exchange rates, etc.). Next, the research dealing with inflation persistence should closely follow a new achievement in modeling the inflation process. Better models of the inflation process lead to better measures of inflation persistence.

[99] Indeed, the proportion of firms linking base wage formally or informally to expected inflation (Table 7 in Druant, Fabiani. Kezdi, Lamo, Martins, and Sabbatini [2009]) is highly correlated with our estimated δ. For the set of countries consisting of CZE, EST, HUN, LIT, POL, SLO, ESP, and POR, the correlation coefficient is 0.93.

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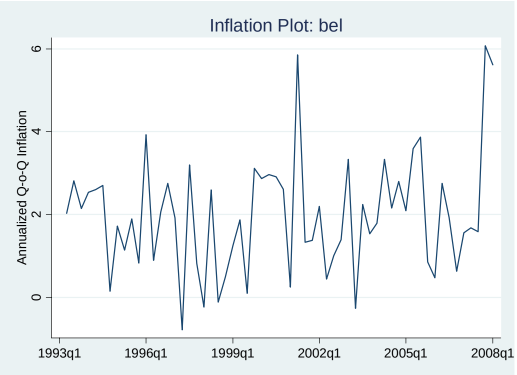
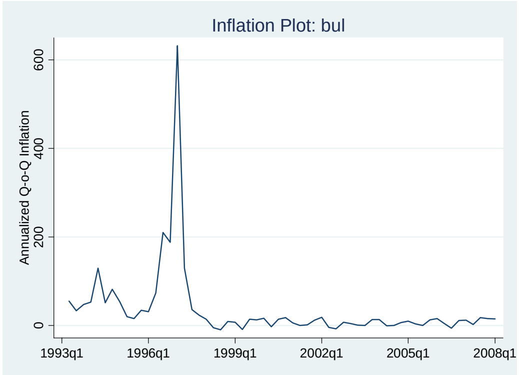
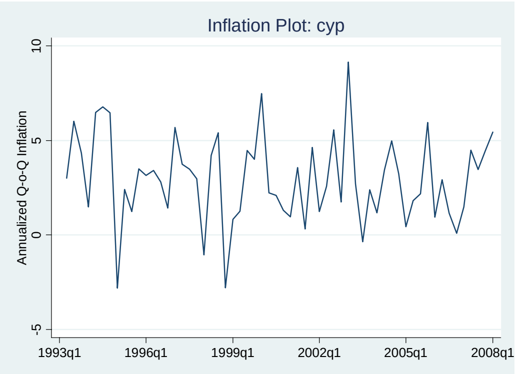
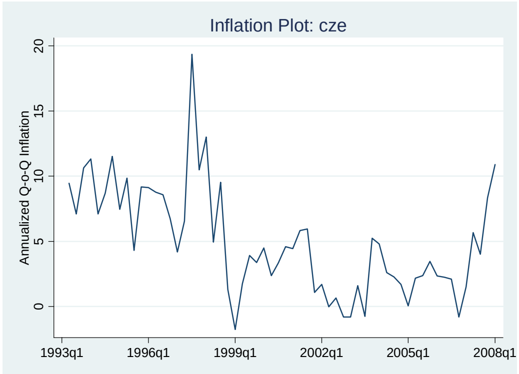
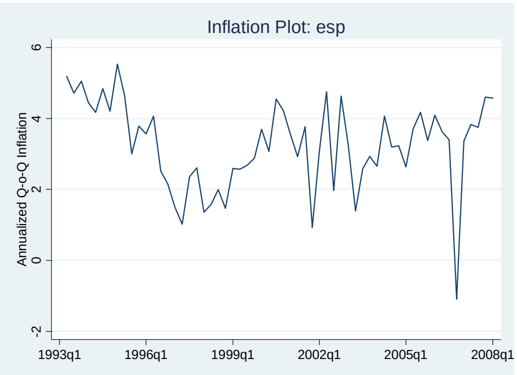
Appendix 1: Inflation plots

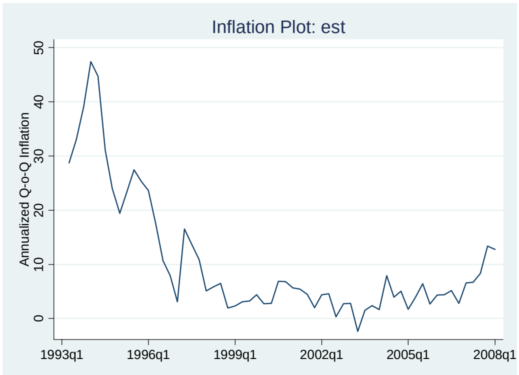


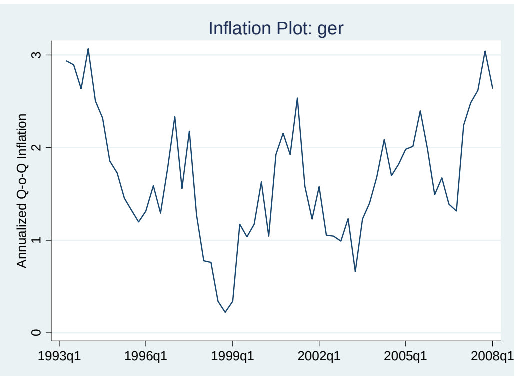


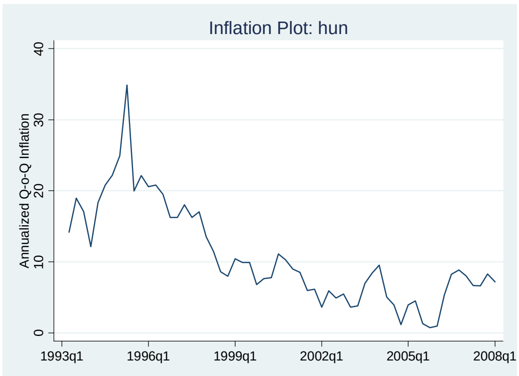


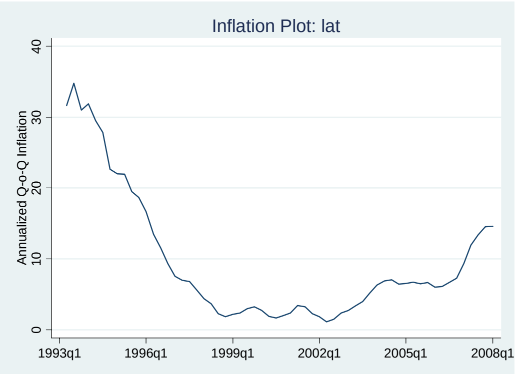








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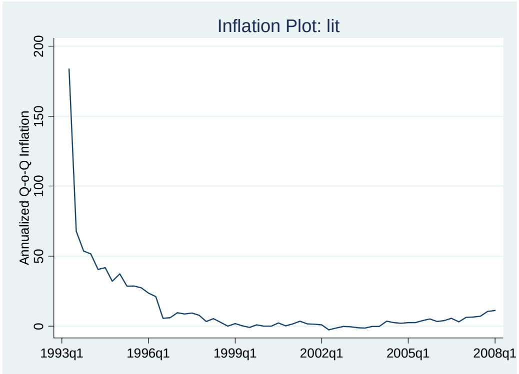
Annualized Q-o-Q Inflation
0 10 20 30 40
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1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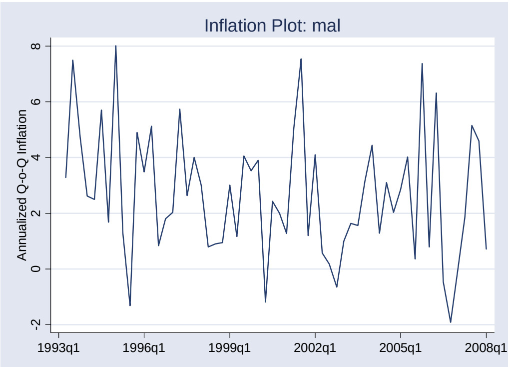
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1


Inflation Plot: mal
Annualized Q-o-Q Inflation
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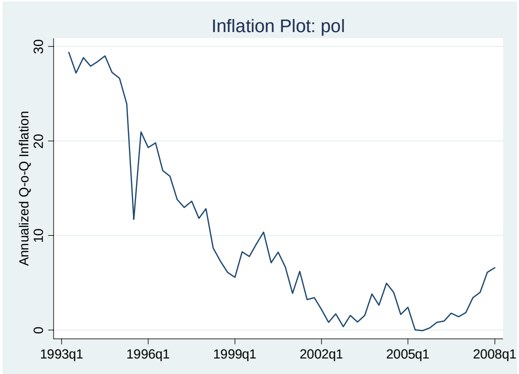
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1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Annualized Q-o-Q Inflation
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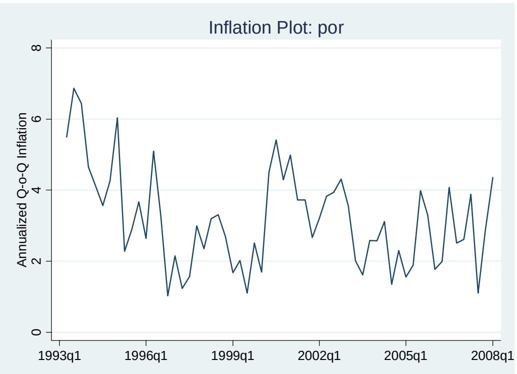
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1


Inflation Plot: por
Annualized Q-o-Q Inflation
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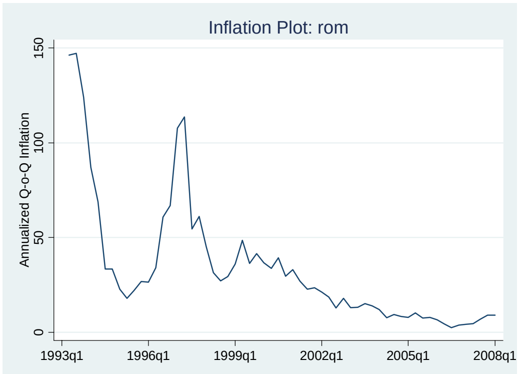
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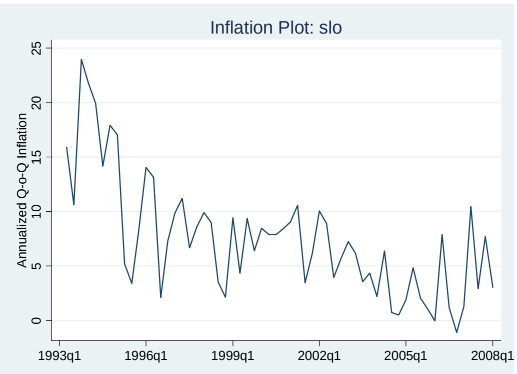
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1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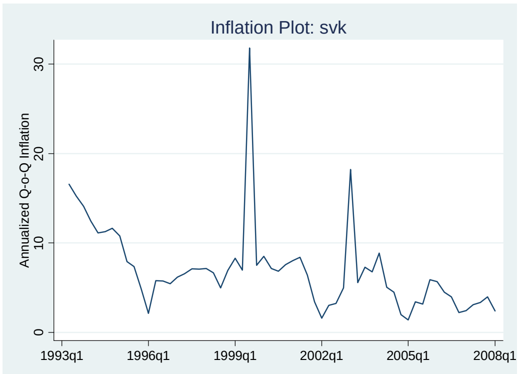
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Annualized Q-o-Q Inflation
0 10 20 30
1993q1 1996q1 1999q1 2002q1 2005q1 2008q1

Appendix 2: Complete estimation results of a time-varying mean model

In Section 4.1, we discuss measures of intrinsic and expectations-based inflation persistence estimated within the framework of the statistical model introduced in Section 3.3. Here, the complete estimation results are reported. The following tables report type, mean, and standard deviation of the prior distribution and the posterior mean with a 90% confidence interval. Results for four selected EAC and all NMS are reported.

Prior distributions are introduced in Table 4 and discussed in Section 3.3. The performance of the sampling procedure is based on the Monte Carlo Markov Chain (MCMC) diagnostics that examine whether the Metropolis-Hastings simulations lead to similar numbers within and between respective simulations. If this is not the case, more iterations of the sampling algorithm should be tested or prior beliefs about the distributions of coefficients should be re-considered.

For several countries involved in our analysis, we encountered problems indicated by the univariate MCMC diagnostics and, we switched to "more flexible" priors: a uniform distribution over a wider interval. The uniform priors for some coefficients were taken for Latvia, Romania, Malta, and Portugal. Priors that are different from those introduced in Table 4 are denoted by the shaded areas in the following tables. For some countries, we also increased the number of iterations up to 100 000, e.g. Hungary and Bulgaria. Finally, the bad convergence diagnostics for Latvia and Lithuania are resolved by dropping the first few observations for which the inflation rate attains levels over 100%.

The estimated measures of intrinsic inflation persistence (sum of coefficients φ_i) and expectations-based inflation persistence are discussed in Section 4.1. Regarding the other estimated parameters, two issues should be pointed out. First, estimated variances of the inflation shock (σ_ε^2) for the NMS are significantly higher than for the EAC. This result is a consequence of many shocks specific to the NMS related to the transition of their economies as discussed in Section 3. Second, the estimated variances of shocks to the inflation target (σ_η^2) are different both within and between the NMS and EAC. The changes in the inflation target are almost negligible for the EAC. In general, the NMS exhibit higher estimates of variance of the inflation target shock. Moreover, inflation target shocks in Bulgaria, Estonia, Latvia, Lithuania, Poland, and Romania are remarkably higher than for the rest of the group of the NMS.

Table A2.1: Estimation results of the time-varying mean model.

	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
BUL						
φ_1	0.2	0.32	0.12	0.51	beta	0.3
φ_2	0.1	0.15	-0.05	0.36	beta	0.3
φ_3	0.05	-0.10	-0.31	0.10	beta	0.3
φ_4	0.05	-0.13	-0.33	0.06	beta	0.3
$\sum \varphi_i$		0.24				
δ	0.15	0.23	0.07	0.40	beta	0.1
σ_ε	2	73.60	63.56	84.75	invg	Inf
σ_τ	0.5	2.47	2.14	2.83	invg	Inf
CZE						
φ_1	0.2	0.26	0.07	0.49	beta	0.3
φ_2	0.1	0.15	-0.05	0.36	beta	0.3
φ_3	0.05	-0.15	-0.37	0.04	beta	0.3
φ_4	0.05	-0.16	-0.39	0.02	beta	0.3
$\sum \varphi_i$		0.10				
δ	0.15	0.31	0.16	0.45	beta	0.1
σ_ε	2	2.86	2.40	3.27	invg	Inf
σ_τ	0.5	0.23	0.19	0.26	invg	Inf
HUN						
φ_1	0.2	0.66	0.50	0.82	beta	0.3
φ_2	0.1	0.18	-0.02	0.39	beta	0.3
φ_3	0.05	0.08	-0.14	0.31	beta	0.3
φ_4	0.05	0.00	-0.18	0.21	beta	0.3
$\sum \varphi_i$		0.92				
δ	0.15	0.17	0.00	0.29	beta	0.1
σ_ε	2	3.81	3.26	4.33	invg	Inf
σ_τ	0.5	0.41	0.35	0.47	invg	Inf

Table A2.2: Estimation results of the time-varying mean model.

	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
EST						
φ_1	0.2	0.81	0.69	0.93	beta	0.3
φ_2	0.1	0.11	-0.13	0.33	beta	0.3
φ_3	0.05	-0.14	-0.39	0.13	beta	0.3
φ_4	0.05	0.13	-0.08	0.35	beta	0.3
$\sum \varphi_i$		0.91				
δ	0.15	0.19	0.00	0.40	beta	0.1
σ_ε	2	4.33	3.66	5.00	invg	Inf
σ_τ	0.5	2.59	2.21	2.97	invg	Inf
LAT						
φ_1	0	0.91	0.88	1.00	unif	0.5774
φ_2	0	0.57	0.37	0.64	unif	0.5774
φ_3	0	-0.23	-0.31	-0.11	unif	0.5774
φ_4	0	-0.32	-0.40	-0.26	unif	0.5774
$\sum \varphi_i$		0.94				
δ	0.5	0.13	0.00	0.12	unif	0.2887
σ_ε	2	1.39	1.15	1.59	invg	Inf
σ_τ	0.5	2.33	2.01	2.69	invg	Inf
LIT						
φ_1	0.2	0.74	0.58	0.90	beta	0.3
φ_2	0.1	0.37	0.12	0.55	beta	0.3
φ_3	0.05	0.08	-0.21	0.27	beta	0.3
φ_4	0.05	-0.24	-0.36	0.20	beta	0.3
$\sum \varphi_i$		0.94				
δ	0.15	0.12	0.00	0.24	beta	0.1
σ_ε	2	3.31	2.77	3.88	invg	Inf
σ_τ	0.5	3.23	2.71	3.72	invg	Inf

Table A2.3: Estimation results of the time-varying mean model.

	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
POL						
φ_1	0.2	0.68	0.52	0.82	beta	0.3
φ_2	0.1	0.24	0.04	0.43	beta	0.3
φ_3	0.05	0.22	0.12	0.40	beta	0.3
φ_4	0.05	-0.15	-0.33	0.09	beta	0.3
$\sum \varphi_i$		0.99				
δ	0.15	0.13	0.00	0.26	beta	0.1
σ_ε	2	4.79	4.13	5.48	invg	Inf
σ_τ	0.5	1.18	1.02	1.34	invg	Inf
ROM						
φ_1	0.2	0.81	0.70	0.94	beta	0.3
φ_2	0.1	0.03	-0.21	0.27	beta	0.3
φ_3	0	0.13	-0.18	0.44	unif	0.5774
φ_4	0	-0.54	-0.75	-0.33	unif	0.5774
$\sum \varphi_i$		0.43				
δ	0.15	0.29	0.25	0.32	unif	0.1
σ_ε	2	14.45	12.23	16.60	invg	Inf
σ_τ	0.5	2.43	2.09	2.77	invg	Inf
SVK						
φ_1	0.2	0.24	0.04	0.46	beta	0.3
φ_2	0.1	0.17	-0.05	0.39	beta	0.3
φ_3	0.05	-0.02	-0.25	0.22	beta	0.3
φ_4	0.05	-0.10	-0.32	0.12	beta	0.3
$\sum \varphi_i$		0.29				
δ	0.15	0.25	0.06	0.46	beta	0.1
σ_ε	2	4.39	3.76	5.10	invg	Inf
σ_τ	0.5	0.25	0.21	0.28	invg	Inf

Table A2.4: Estimation results of the time-varying mean model.

	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
SLO						
φ_1	0.2	0.51	0.23	0.76	beta	0.3
φ_2	0.1	0.22	-0.10	0.52	beta	0.3
φ_3	0.05	0.27	-0.05	0.55	beta	0.3
φ_4	0.05	-0.06	-0.40	0.21	beta	0.3
$\sum \varphi_i$		0.94				
δ	0.15	0.13	0.00	0.28	beta	0.1
σ_ε	2	9.25	7.92	10.51	invg	Inf
σ_τ	0.5	1.00	0.86	1.13	invg	Inf
MAL						
φ_1	0	-0.05	-0.24	0.15	unif	0.5774
φ_2	0	0.10	-0.09	0.31	unif	0.5774
φ_3	0	-0.15	-0.37	0.03	unif	0.5774
φ_4	0	-0.24	-0.46	0.00	unif	0.5774
$\sum \varphi_i$		-0.34				
δ	0.15	0.30	0.11	0.43	beta	0.1
σ_ε	2	2.15	1.87	2.47	invg	Inf
σ_τ	0.5	0.06	0.06	0.07	invg	Inf
CYP						
φ_1	0.2	-0.08	-0.27	0.11	beta	0.3
φ_2	0.1	-0.16	-0.34	0.03	beta	0.3
φ_3	0.05	-0.06	-0.25	0.13	beta	0.3
φ_4	0.05	-0.14	-0.32	0.04	beta	0.3
$\sum \varphi_i$		-0.44				
δ	0.15	0.25	0.10	0.38	beta	0.1
σ_ε	2	2.45	2.11	2.79	invg	Inf
σ_τ	0.5	0.09	0.08	0.10	invg	Inf

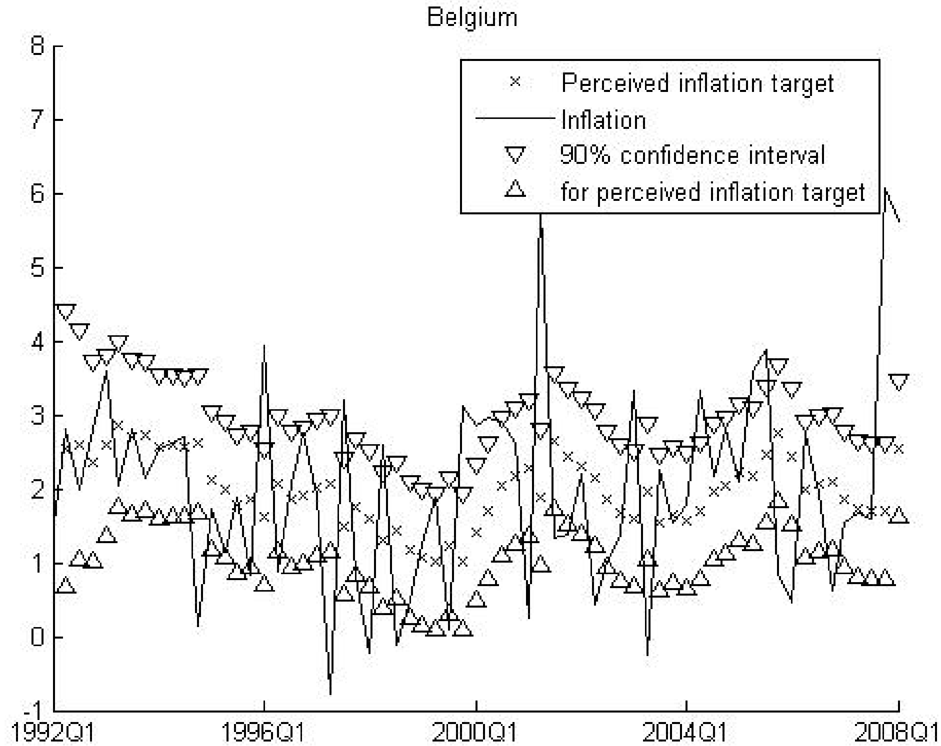
Table A2.5: Estimation results of the time-varying mean model.

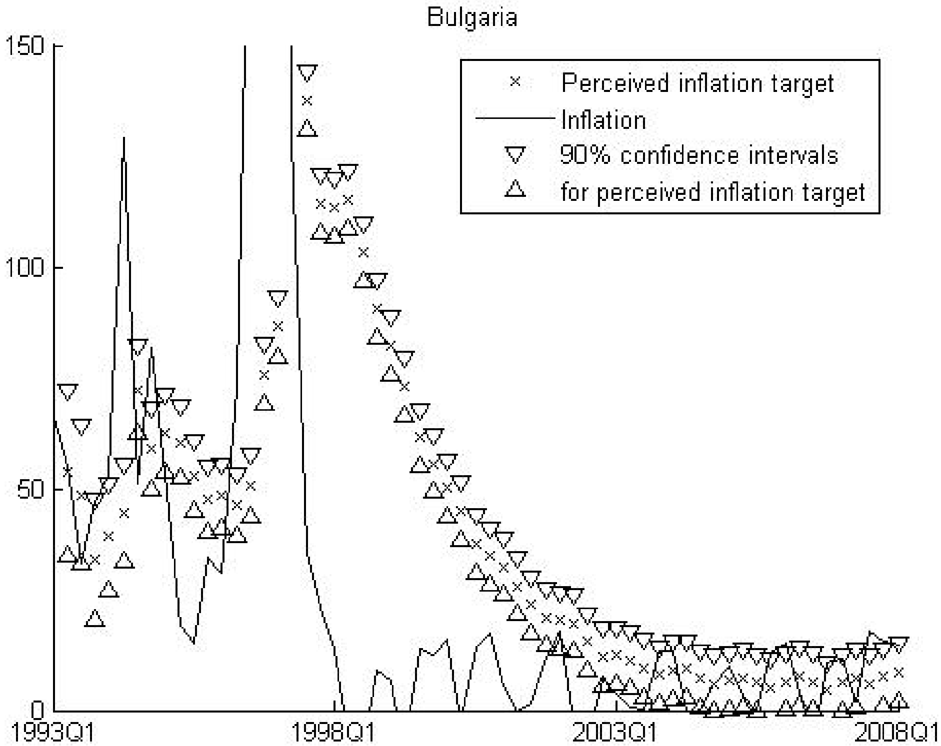
	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
BEL						
φ_1	0.2	-0.03	-0.22	0.17	beta	0.3
φ_2	0.1	0.00	-0.21	0.20	beta	0.3
φ_3	0.05	0.16	-0.05	0.35	beta	0.3
φ_4	0.05	-0.06	-0.24	0.15	beta	0.3
$\sum \varphi_i$		0.08				
δ	0.15	0.33	0.17	0.49	beta	0.1
σ_ε	2	1.32	1.13	1.48	invg	Inf
σ_τ	0.5	0.08	0.07	0.09	invg	Inf
GER						
φ_1	0.2	0.03	-0.17	0.24	beta	0.3
φ_2	0.1	-0.08	-0.30	0.14	beta	0.3
φ_3	0.05	-0.13	-0.35	0.08	beta	0.3
φ_4	0.05	-0.10	-0.30	0.10	beta	0.3
$\sum \varphi_i$		-0.28				
δ	0.15	0.40	0.26	0.55	beta	0.1
σ_ε	2	1.00	0.84	1.12	invg	Inf
σ_τ	0.5	0.12	0.11	0.14	invg	Inf
ESP						
φ_1	0.2	0.19	-0.01	0.38	beta	0.3
φ_2	0.1	0.04	-0.15	0.23	beta	0.3
φ_3	0.05	0.07	-0.14	0.25	beta	0.3
φ_4	0.05	-0.23	-0.41	-0.06	beta	0.3
$\sum \varphi_i$		0.07				
δ	0.15	0.33	0.16	0.48	beta	0.1
σ_ε	2	1.01	0.87	1.14	invg	Inf
σ_τ	0.5	0.10	0.08	0.11	invg	Inf

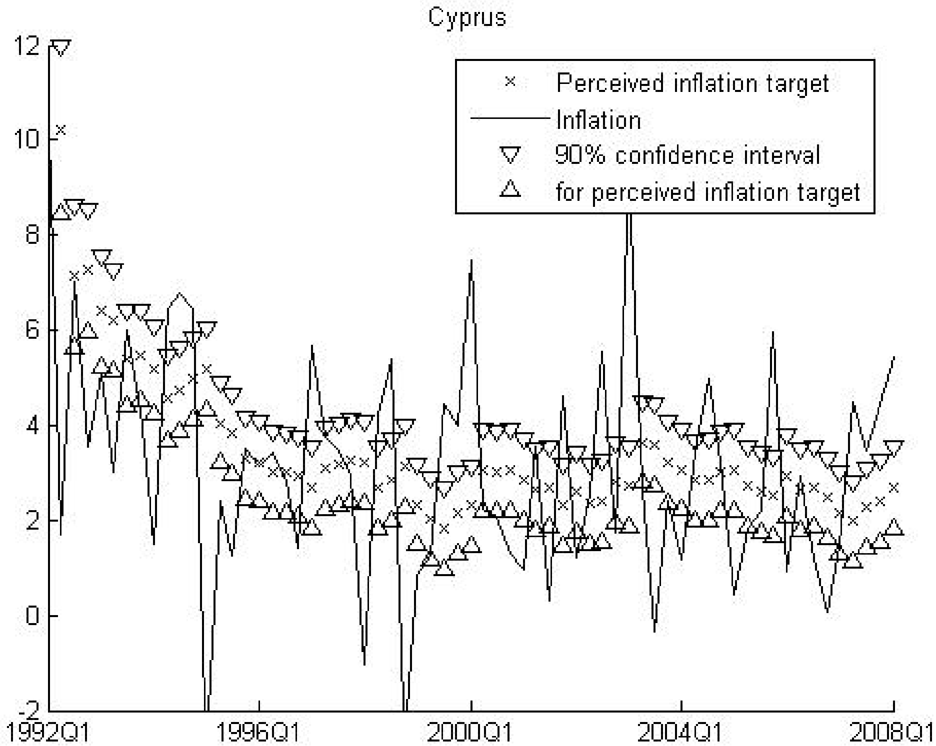
Table A2.6: Estimation results of the time-varying mean model.

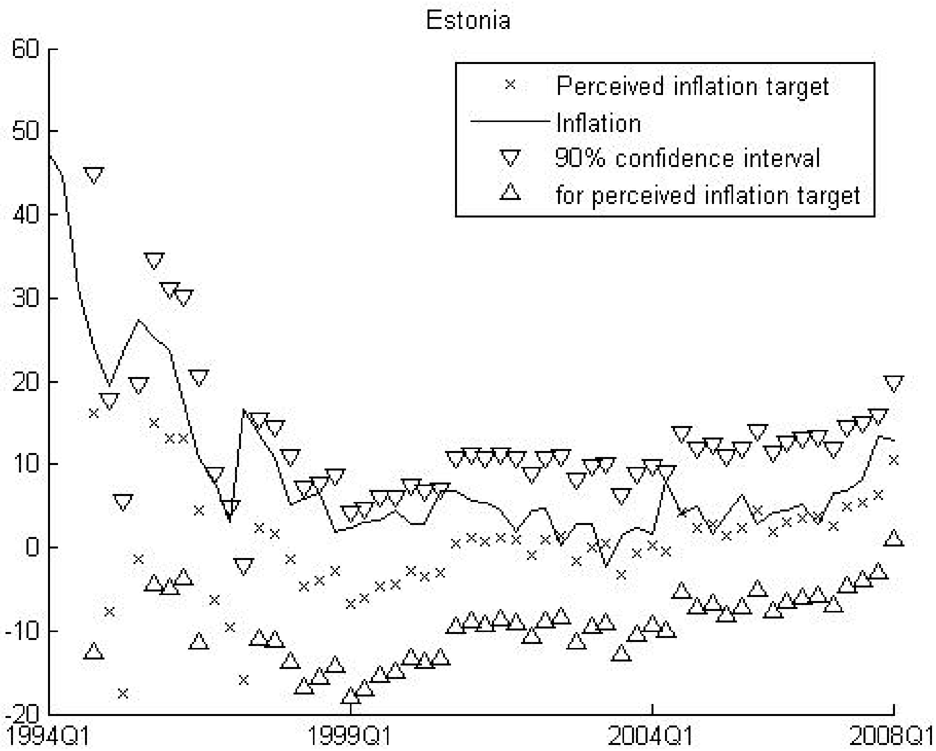
POR	Prior mean	Posterior mean	90% confidence interval		Prior distribution: type	std dev
φ_1	0	0.36	0.11	0.59	unif	0.5774
φ_2	0	-0.37	-0.62	-0.14	unif	0.5774
φ_3	0	-0.05	-0.28	0.19	unif	0.5774
φ_4	0	-0.48	-0.68	-0.27	unif	0.5774
$\sum \varphi_i$		-0.54				
δ	0.15	0.44	0.32	0.55	beta	0.1
σ_ε	2	1.39	1.20	1.60	invg	Inf
σ_τ	0.5	0.23	0.19	0.26	invg	Inf

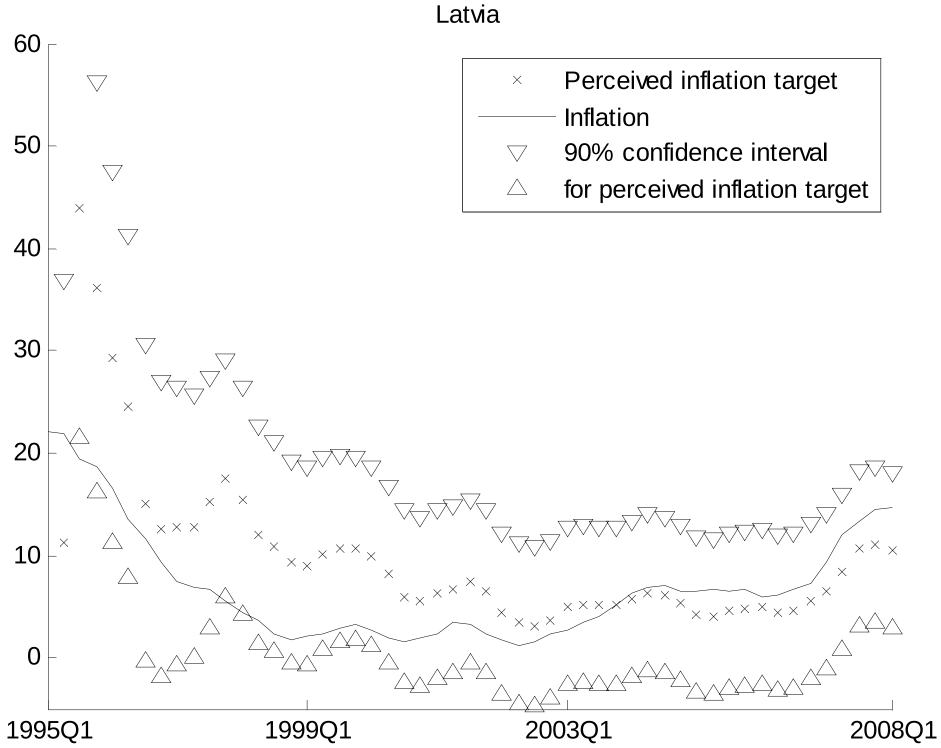
Appendix 3: Perceived inflation targets

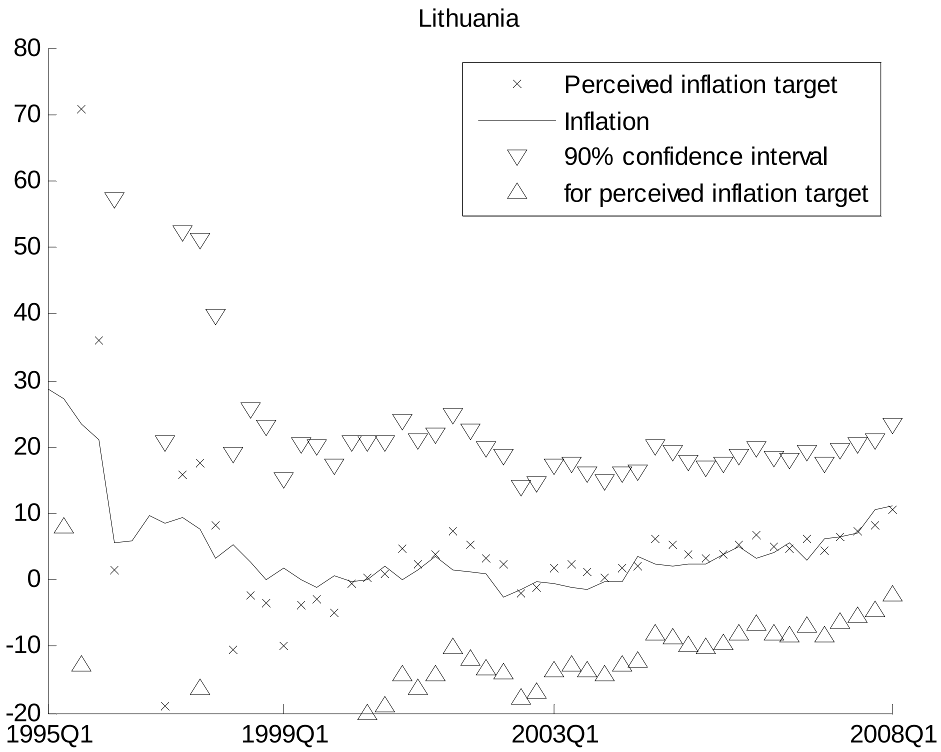


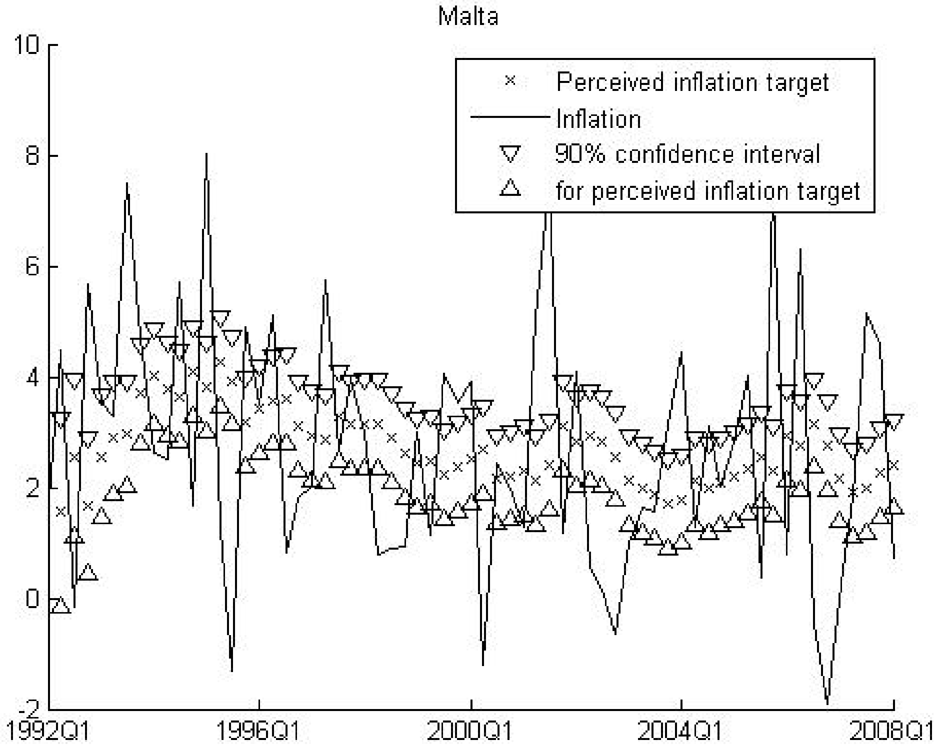


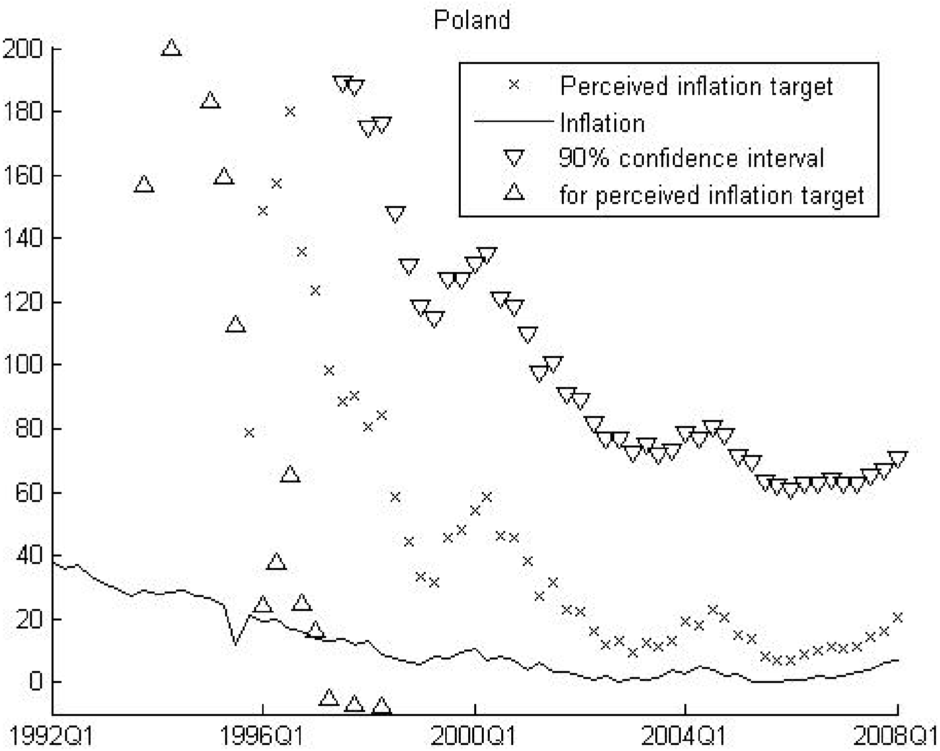

Cyprus
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
12
10
8
6
4
2
0
-2
1992Q1
1996Q1
2000Q1
2004Q1
2008Q1

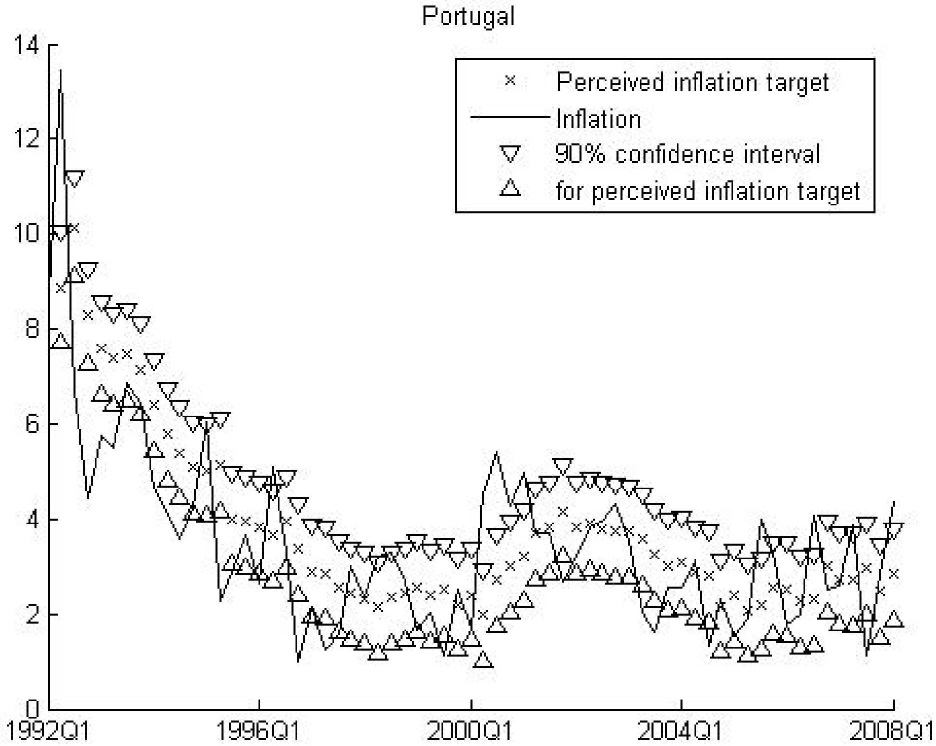

Estonia
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
60
50
40
30
20
10
0
-10
-20
1994Q1
1999Q1
2004Q1
2008Q1

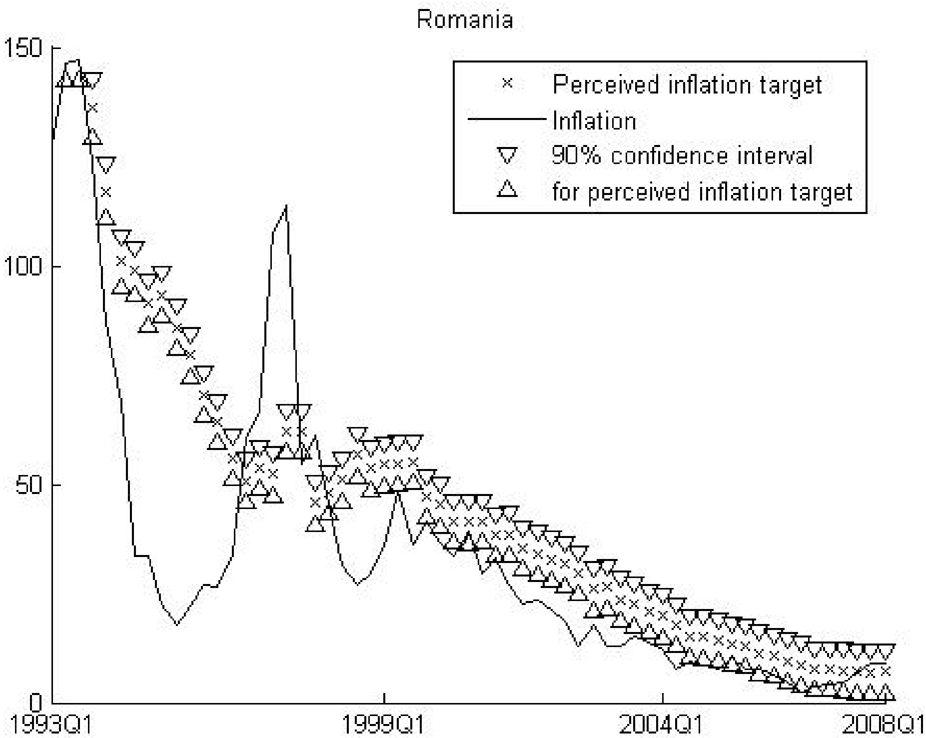

Latvia
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
60
50
40
30
20
10
0
1995Q1
1999Q1
2003Q1
2008Q1

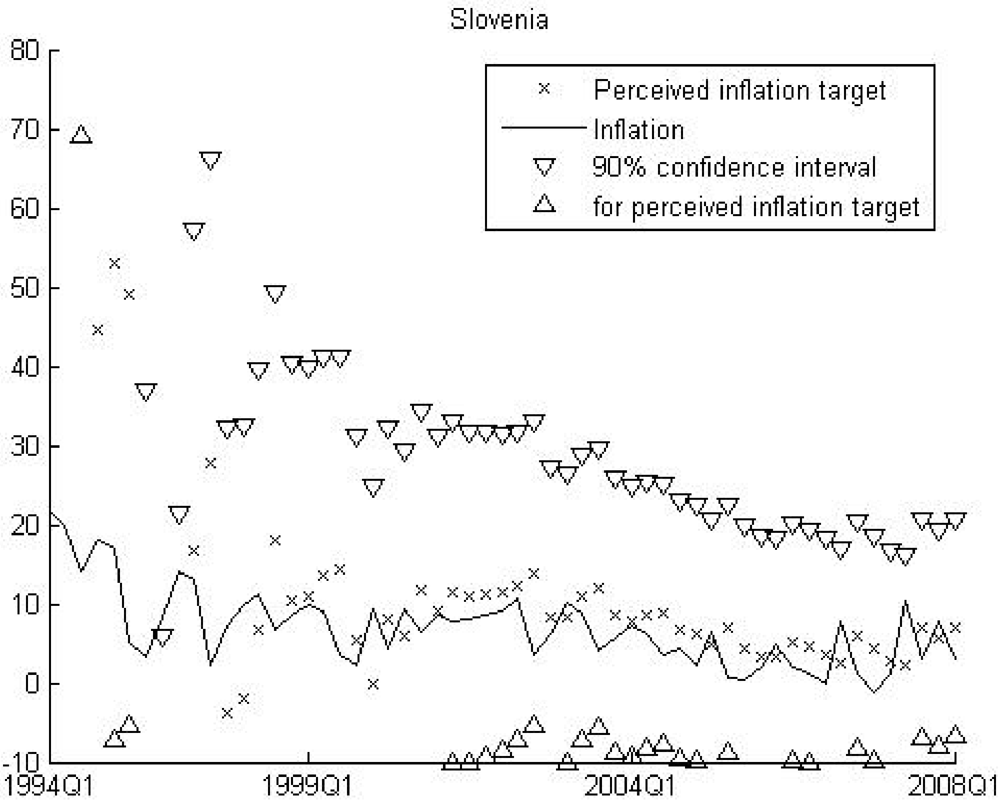

Lithuania
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
80
70
60
50
40
30
20
10
0
-10
-20
1995Q1
1999Q1
2003Q1
2008Q1

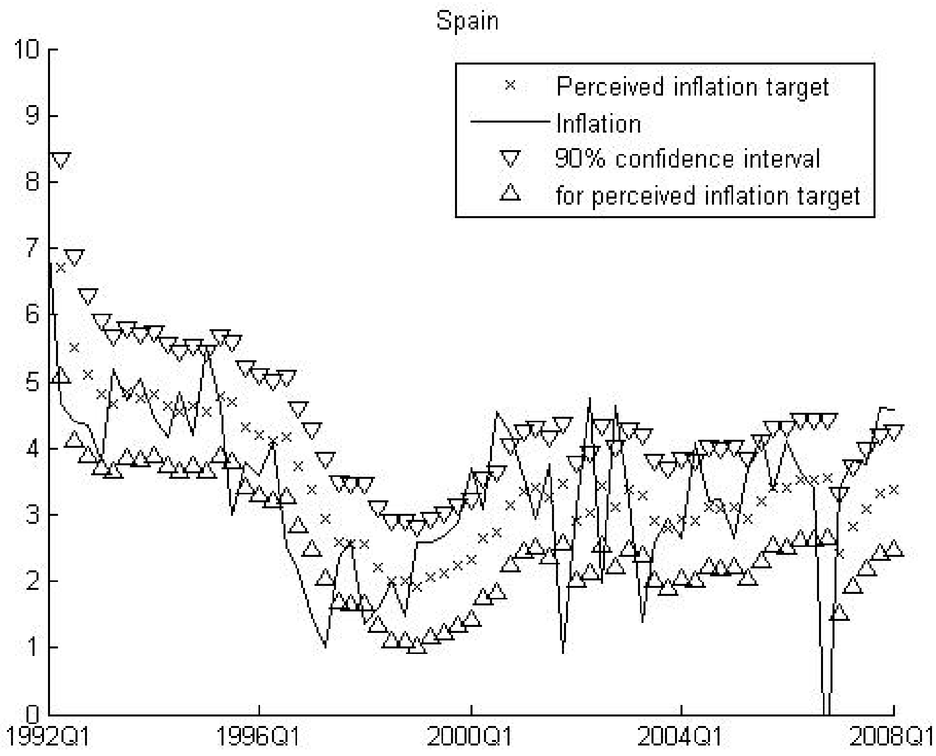

Malta
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
10
8
6
4
2
0
-2
1992Q1
1996Q1
2000Q1
2004Q1
2008Q1


Poland
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
200
180
160
140
120
100
80
60
40
20
0
1992Q1
1996Q1
2000Q1
2004Q1
2008Q1


Portugal
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
14
12
10
8
6
4
2
0
1992Q1
1996Q1
2000Q1
2004Q1
2008Q1


Romania
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
150
100
50
0
1993Q1
1999Q1
2004Q1
2008Q1


Slovenia
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
80
70
60
50
40
30
20
10
0
-10
1994Q1
1999Q1
2004Q1
2008Q1


Spain
Perceived inflation target
Inflation
90% confidence interval
for perceived inflation target
10
9
8
7
6
5
4
3
2
1
0
1992Q1
1996Q1
2000Q1
2004Q1
2008Q1