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Structural and Cyclical Unemployment: What Can Be Derived from the Matching Function?*

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Abstract

We explain movements in the U-V (unemployment and vacancy) space – that is, the relationship between stocks of unemployment and job vacancies, known as the Beveridge curve – in the Czech Republic during 1995–2004. While the Beveridge curve is described by labor-market stocks, we explain shifts in the Beveridge curve using gross labor-market flows by estimating the matching function. We interpret parameter changes of the matching function during the business cycle, distinguishing cyclical and structural changes to the unemployment rate. We find that the labor-market flows are good coincidence predictors of business-cycle turning points. We show that the Czech economy suffers hysteresis (path dependency) on the labor market, which is common in many other developed market economies in the European Union.

1. Introduction

The Czech economy has witnessed remarkable changes in the aggregate activity since the 1990s. Following the buoyant economic growth in the middle of the decade, a slack in the aggregate activity was observed between 1997 and 1999 (*Table 1.1*). The recession of 1997–1999 was characterized by huge changes in the labor market flows and by a consequent rapid rise in unemployment. In particular, the rate of inflows into unemployment almost doubled between 1995 and 2000, while outflows from unemployment steadily decreased throughout the period. The consequent surge in the rate of unemployment was accompanied by the deceleration in the growth of labour productivity and real wages. After the recession faded out, economic growth rebounded in 1999, while a further slowdown in the activity was observed in 2001 and 2002.

Figure 1.1 provides a closer look at the labor market data and the business cycle. The periods of economic expansions are defined here as areas between consecutive turning points in the cyclical component of the gross domestic product in constant prices. The economy experienced increases in the rate of unemployment and,

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TABLE 1.1 Key Macroeconomic Indicators

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
GDP (%, y-o-y, real terms)										
Czech Republic		4.2	-0.7	-1.1	1.2	3.9	2.6	1.5	3.7	4.0
EU 15	2.4	1.6	2.5	2.9	2.9	3.6	1.7	1.0	0.8	2.3
Germany	1.7	0.8	1.4	2.0	2.0	2.9	0.8	0.2	-0.1	1.6
Registered unemployment rate (%, average)	3.1	3.2	4.4	6.1	8.6	9.0	8.5	9.2	9.9	10.2
Long-term unemployment rate (%, average)*				1.5	2.3	3.3	3.3	3.5	3.9	4.2
Inflow rate into unemployment (%)	0.6	0.6	0.8	1.1	1.3	1.2	1.1	1.2	1.2	1.2
Outflow rate from unemployment (%)	19.7	17.7	15.5	13.7	11.6	12.4	12.2	10.9	10.2	10.5
Vacancy rate (%)	1.9	2.0	1.6	1.1	0.7	1.0	1.2	1.0	0.9	1.0
Participation rate (%)**	86.1	85.9	86.0	85.3	85.2	84.9	85.0	85.0	84.9	85.3
Aggregate labor productivity (%, y-o-y)		2.9	0.0	0.8	4.0	4.6	2.2	0.8	4.4	4.2
Average monthly nominal wages in monitored organizations (%, y-o-y)	18.6	18.3	9.9	9.2	8.4	6.4	8.7	7.3	6.6	6.6
Average monthly real wages in monitored organizations (%, y-o-y)	8.7	8.7	1.3	-1.4	6.2	2.4	3.8	5.4	6.5	3.7

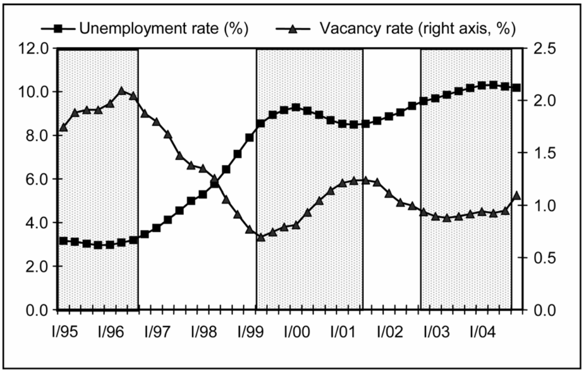
Note: Data for the Czech Republic if not specified otherwise.
* May to December average in 1998, ** aged 30–59 years

Source: Eurostat; Czech Statistical Office; Ministry of Labor and Social Affairs; own calculations

at the same time, drops in the vacancy rate during the recessions of 1997–1999 and 2001–2002. Changes in the unemployment and vacancy rates were less pronounced in the latter recession than between 1997 and 1999. On the other hand, periods of economic expansion are associated with rising vacancies and falling unemployment. A notable exception to this kind of distinction between the phases of the business cycle is observed between mid-1999 and mid-2000 and again in late 2003 when both the rates of unemployment and vacancy increased. This suggests rising frictions on the labor market, implying growth in the structural component of the unemployment rate in these periods. In other periods there seem to be mainly cyclical changes in unemployment.

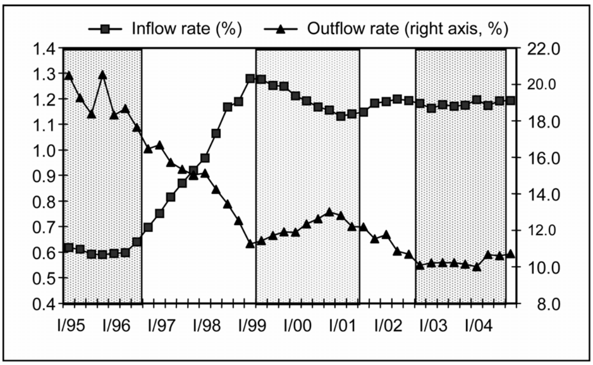
While the vacancy rate may be a good indicator of turning points of the business cycle, the unemployment rate follows the cycle with a certain lag (Figure 1.1). While the turning points of the cycle coincide with points of inflection in the rate of unemployment, the association with changes in the unemployment flows should be even closer. This is supported by *Figure 1.2* showing that the inflow rate into unemployment and the outflow rate from unemployment closely coincide with turning points of the business cycle. In particular, the economic recoveries in 1999 and in 2003 were signaled by reversing trends in unemployment flows. Furthermore, the economic slowdowns in 1997 and in 2001 may have been predicted by changing trends in the unemployment flows. For institutions practicing countercyclical policies, the unemployment flows may be used as coincidence indicators of turning

FIGURE 1.1 Unemployment, Vacancies and the Business Cycle



Note: Seasonally adjusted registry data on unemployment and vacancies. Shaded areas denote periods of expansion as observed between the turning points in the cyclical component of the gross domestic product in constant prices. The cyclical component is derived using the Band-Pass filter.

FIGURE 1.2 Unemployment Flows and the Business Cycle

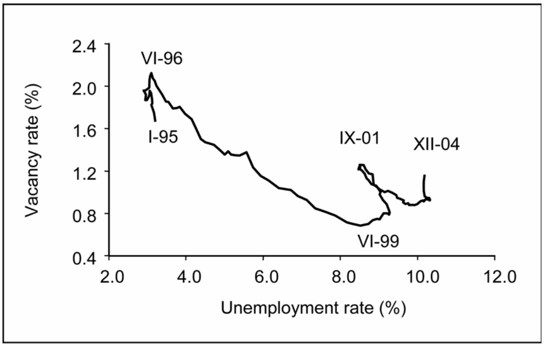


Note: Seasonally adjusted registry data on unemployment flows. Shaded areas denote periods of expansion as observed between the turning points in the cyclical component of the gross domestic product in constant prices. The cyclical component is derived using the Band-Pass filter.

points of the business cycle. This is because figures on productivity measures appear with a 3- to 9-month delay, while the information on unemployment flows is available within a few days after the end of each month.

A popular way to illustrate changes in the economy using the labor market data employs the notion of the Beveridge curve describing the relationship between the unemployment rate and the rate of vacancy (*Figure 1.3*). While periods of increasing aggregate demand are characterized by increasing vacancies and decreasing unemployment, the opposite is true for recessions. On the other hand, outward shifts in the U-V space, i.e. simultaneous increases in the rates of unemployment and vacancy, are due to increased frictions or rising mismatch in the labor market. While an increase in the number of simultaneously existing unmatched unemployed and vacancies can be due to frictions, the same outcome can also be due to higher labor market turnover. Comparing the Czech Beveridge curve to the key macroeconomic

FIGURE 1.3 The Czech Beveridge Curve



Note: Seasonally adjusted monthly data.
Source: Ministry of Labor and Social Affairs.

indicators in Table 1.1, we observe that the significant growth of the economy in 1995 and 1996 seems to be accompanied by a simultaneous rise in frictions. This is indicated by an outward shift in the Beveridge curve (Figure 1.3). During 1996, the economy was hit by a recession that lasted until 1999, followed by a further rise in frictions. The consequent recovery observed since 1999 was interrupted in the middle of 2001 by a slight decline in the aggregate demand. In the aftermath of the curtailed economic growth in 2001–2002, a further deterioration in the functioning of the labor market has been observed since 2003.

A number of authors contributed to explaining effects shifting the Beveridge curve (see, for example, (Jackman et al., 1990), or a recent survey by Petrongolo and Pissarides (2001)). While the Beveridge curve is mapped by stock variables, the underlying changes are driven by flow variables: inflow into and outflow from unemployment. The key relationship linking outflows from unemployment with stocks of unemployment and posted vacancies is the matching function. The matching function is a tool of analysis similar to the widely used concept of the production function. Understanding regularities in flow variables is important to identifying the origins of shifts of the Beveridge curve. These shifts are associated with parameter changes in the matching function. In other words, estimates of the matching function may help to distinguish cyclical and structural changes in the unemployment rate.

This paper is aimed at interpreting recent developments in the Czech economy based on shifts of and movements along the Beveridge curve and as reflected in parameter changes in the matching function. In particular, we distinguish cyclical and structural changes in the rate of unemployment. For this purpose, we use monthly registry data on unemployment and vacancy stocks and gross flows. To our knowledge, this is the first study attempting to explain parameter changes in the matching function during the business cycle and using the Czech data on vacancy flows.[1] From the policy perspective, the registry data do not suffer from the drawbacks of commonly used aggregate economic indicators, particularly productivity measures. Registry data are comprehensive[2] published a few days after collection, and are not subject to revisions. Given that the data are of high frequency, we are able to construct coincidence indicators of economic growth. However, it should be borne in mind that vacancy flow data, reported by labor offices for only the last few years, suffer from a particular type of measurement error. Especially for this reason, the results of the paper should be interpreted with caution.

The paper is organized as follows: the next section describes the evolution of the Czech Beveridge curve using theoretical concepts of the Beveridge curve and the matching function. Section 3 outlines the estimation strategy, while the next two sections deal with the data and results. The last section concludes the paper.

2. Stylized Facts

In the long-term perspective, many European countries have experienced a simultaneous rise in unemployment and vacancies since the early 1970s. This has induced further research on the origins of this phenomenon. The stylized negative empirical relationship between unemployment and vacancies is known as the Beveridge curve (Blanchard, Diamond, 1989), (Pissarides, 2000). The underlying relationship explaining shifts in the Beveridge curve is the matching function that relates outflows from unemployment to stocks of vacancies and unemployment. The matching function allows describing frictions on the labor market with a limited complexity in the same way as the production function is a tool to describe complex productive processes. In this section, relying primarily on Berman (1997), Jackman et. al (1990), and Petrongolo and Pissarides (2001), we discuss how specific economic shocks affect the Beveridge curve and employ this framework to explain developments in the Czech economy. We consider specific forms of the matching function and examine parameter changes in the matching function during the business cycle.

2.1 Beveridge Curve

Each point on the Beveridge curve in the unemployment-vacancy space illustrated in Figure 1.3 is represented by an intersection of a downward sloping unemployment vacancy (*UV*) curve and an upward sloping vacancy-supply (*V*S) curve (*Figure 2.1*). Given that in the steady state the flow into unemployment is equal to the outflow from unemployment, the *UV* curve may be characterized by a steady state stock-flow unemployment identity as

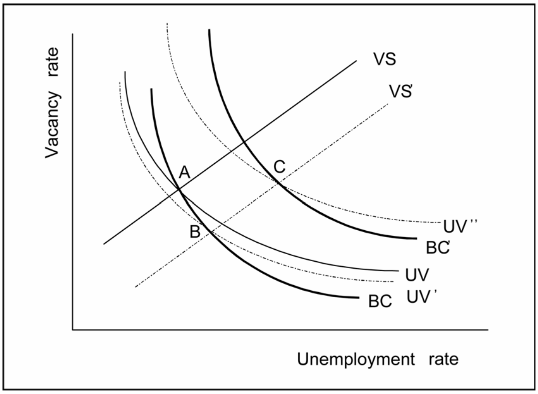
$$u \equiv \frac{s}{s+o} \tag{2.1}$$

while the *VS* curve, following Berman (1997), is described by

[1] Previous studies by Münich et al. (1995, 1999), Münich (2001), Burda and Profit (1996), and Jurajda and Münich (1999) focused primarily on the issue of transition dominating standard business cycle features. Petrongolo and Pissarides (2001) survey existing estimates of the matching function. Estimates of matching function during 1990s for Central European countries were published by Burda (1993), Boeri (1994), Münich, Svejnar and Terrell (1995, 1999), Lubyova and van Ours (1994), Boeri and Scarpetta (1995), Burda and Lubyova (1995), Boeri and Burda (1995), Burda and Profit (1996), and Profit (1997). Other studies on the efficiency of matching include, for example, Lindeboom, van Ours and Renes (1994) and Gregg and Petrongolo (2005).

[2] Statistical offices present GDP and other productivity indicators as estimates – approximate indicators.

FIGURE 2.1 Beveridge Curve



$$\frac{1-\lambda}{\gamma} = v\left[\frac{1}{u} + \frac{r+s}{s(1-u)}\right] \tag{2.2}$$

In (2.1), u is the unemployment rate and o and s are rates of outflows from and inflows into unemployment. The matching function enters (2.1) in parametric form:

$$o = p(\theta)\left[1 - G(\alpha_R)\right] \tag{2.3}$$

where $p(.)$ is the rate at which the unemployed meet posted vacancies with $\theta = v/u$ measuring the labor market tightness. It is assumed that a match between an unemployed worker and a vacant job is formed only if the marginal product from the match exceeds the reservation marginal product α_R. The stochastic nature of the matching function is represented in the second term of (2.3) by a non-degenerate distribution function $G(.)$. Its argument is:

$$\alpha_R = z + \gamma_0 \theta \tag{2.4}$$

where z is the income while unemployed and γ_0 are search costs incurred by firms. In (2.2), r is the interest rate, λ and γ are replacement ratios between the income of the unemployed and the expected wage and between the search costs and the expected wage.

The UV curve described in (2.1) defines a steady state rate of unemployment.[3] Provided that the inflow rate in (2.1) is constant, any change in the unemployment rate is due to changes in the outflow rate. A change in the outflow rate resulting from changes in the labor market tightness corresponds to movements along a particular UV locus. On the other hand, changes in parameters of $p(.)$ or any variation in the reservation product α_R lead to shifts in the whole UV curve.

[3] The inflow rate into unemployment and the matching function are key determinants of the unemployment equilibrium in (2.1). The matching function is contained in the denominator through (2.3). It should be noted that (2.1) is an implicit form defining the steady state unemployment rate. For this reason and because the labor market rarely reaches the steady state, parameters of the matching function cannot be estimated using (2.1). We describe models of the matching function in Section 2.2 and our estimation strategy in Section 3.

While the *UV* curve describes the steady state rate of unemployment, the *VS* curve reflects the profit maximizing behavior of firms and employees in a given bargaining setting. A firm creates additional vacancy if its marginal product exceeds the wage rate plus the search costs, $\alpha > w + \gamma_0$. A higher level of unemployment reduces wages through weaker bargaining power of workers. The lower wage reduces the marginal cost of labor, resulting in additional vacancies posted by firms. These relationships lead to an upward sloping *VS* curve, representing a locus of the steady state vacancy rate.

What induces shifts in the *VS* curve? Consider a decrease in labor demand caused, for example, by a hike in interest rates. Higher interest rates reduce the labor demand, leading to fewer vacancies posted by firms (see equation (2.2)). This is illustrated in Figure 2.1 as a downward shift of the *V*S curve into the *VS'* curve. However, this is not the only change in the *U-V* space stemming from the decreased labor demand. The weaker labor market tightness decreases the reservation product (2.4) through lower search costs for workers, γ_0, and through less choosy job seekers represented by lower θ in (2.4). These effects entail more outflows in (2.3), depleting both stocks of vacancies and unemployment and shifting the *UV* curve inwards.[4] While primary movements associated with changes in the aggregate demand are explained by shifts in the *VS* curve, there are secondary effects shifting the *UV* curve. The resulting path between points *A* and *B* draws the Beveridge curve displayed in Figure 2.1. Other factors shifting the *VS* curve downward include, for example, an increase in effective taxation of labor or greater wage pressure resulting from increased bargaining power of workers.

Contrary to aggregate activity shocks shifting the *VS* curve, structural shocks associated with changes in the efficiency of matching shift the *UV* curve. In particular, structural shocks drive outward shifts of the *UV* curve as depicted by the movement from *B* to *C* in Figure 2.1. It follows from (2.3) and (2.4) that this type of shocks may be caused by a higher non-labor income (unemployment and welfare benefits), higher search costs or by factors such as structural changes in the demand or the geographical or occupational mismatch. All these effects affect the probability *p*(.) in (2.3) with which the jobless encounter unfilled vacancies and the reservation product defined in (2.4).[5] Furthermore, the *UV* curve shifts outwards as a result of an exogenous increase in the unemployment inflow rate, increased choosiness of the unemployed or firms, or due to hysteresis effects. Hysteresis effects emanate from negative duration dependence when the skills and the job search effort of the jobless decrease with the duration of their unemployment. The hysteresis, following an adverse demand shock, translates into an irreversible outward shift of the *UV* curve, as the skills and search effort of the jobless are upgraded only partially during a consequent labor demand surge.[6] It follows from Figure 1.1 that, so far, significant hysteresis effects have followed the periods of lower aggregate demand. In

[4] This negative effect of labor market tightness on the matching process is consistent with the efficiency wage theory.

[5] The higher non-employment income also leads to higher wages through the increased bargaining power of workers, shifting the *VS* curve downward. While this leads to higher unemployment, the total effect of more generous welfare benefits on vacancies is ambiguous.

[6] Jackman et al. (1990) shows that hysteresis effects are a common feature of many European labor markets.

particular, the deterioration in the efficiency of matching is observed in 1999–2000 and in 2003–2004, driving the long-term rate of unemployment irreversibly to higher levels (Table 1.1)[7]

2.2 Matching Function

Differentiation between particular types of shocks and associated cyclical and structural changes in the unemployment rate depends on the nature of changes in the matching function. The most general model has the form

$$M = m(U, V) \tag{2.5}$$

where the number of matches M is explained by stocks of unemployment U and vacancies V. The matching takes place in an infinitesimal time period by assumption. The most widely used form of the matching function is the Cobb-Douglas log-linear specification

$$M = AU^{\beta_1}V^{\beta_2} \tag{2.6}$$

or its logarithmic version

$$\log M = \log A + \beta_1 \log U + \beta_2 \log V \tag{2.7}$$

In (2.5) it is assumed that all unemployed and all vacancies are homogenous. Since job seekers may differ in their characteristics and preferences, a common extension to (2.5) introduces worker heterogeneity in terms of the reservation wage. In particular, the matching function becomes

$$M = (1 - G(w_R))\, m(U, V) \tag{2.8}$$

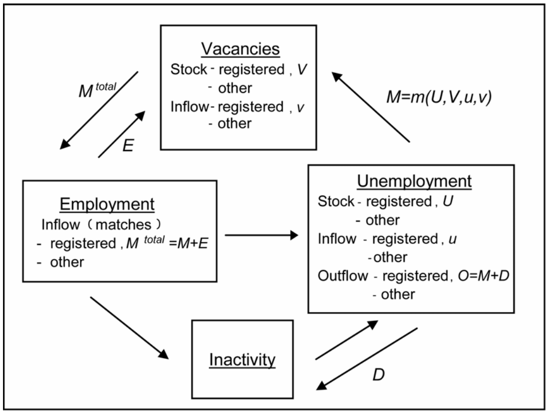
where $G(.)$ is a non-degenerate distribution function of the reservation wage w_R. Once an unemployed person meets a vacant job, the match is formed only if the wage exceeds the reservation wage. The reservation wage depends on the opportunity costs (e.g. the welfare scheme) and the demographic and local structures such as the share of youths in the population (given that youths search with different intensity than adults) or costs of residential moving. Comparing (2.8) to the Cobb-Douglas specification (2.6), we may infer that the effect of the reservation wage on matching is contained in the additive term in (2.7). Furthermore, the functional form (2.8) allows incorporating aggregate variables that influence the job search of individuals.

In (2.8) the heterogeneity of job seekers is incorporated by reservation wages. As an alternative, we may suppose that in terms of the matching probability, the characteristics of the newly unemployed differ from those among the stock of unemployed (or new vacancies from the stock of vacancies). A common extension to the matching model thus introduces flow variables. Following the notation of (2.7), we may write

$$\log M = \log A + \beta_1 \log U + \beta_2 \log V + \gamma_1 \log u + \gamma_2 \log v \tag{2.9}$$

[7] Such changes to the structural component of the unemployment rate are consistent with estimates of the time-varying NAIRU. In particular, Hurník and Navrátil (2005) provide some evidence that the Czech NAIRU shifted from about 6.0 % to about 7.5 % during 1997–1999. Although their estimates are based on the Labor Force Survey data, they coincide with shifts in the Beveridge curve displayed in Figure 1.3.

FIGURE 2.2 Stocks and Flows in the Labor Market



where u and v are unemployment and vacancy inflows realized during a time period. Another reasoning for introducing flow variables into the matching function assumes that inflows match only with stocks, while stocks match with inflows as all the stock of vacancies is known to the stock of the unemployed from previous periods (Coles, Smith, 1998). The stock-flow matching rules out the possibility that the unemployed job seekers may change their reservation wage during the spell of unemployment, while, on the other hand, firms may change the wage attached to their vacancies depending to how successful they are in their recruitment search.

Existing empirical studies rely on simplified versions of the matching function such as (2.9) or (2.7) due to data limitations. These simplifications are necessary to keep the estimation tractable but introduce potential biases. While we face similar empirical obstacles, we find expressions for possible biases and take these biases into account when interpreting our empirical findings. In order to describe these biases, we refer to *Figure 2.2* showing labor market stocks and flows. Total matches which represent the inflow into employment are formed by vacancies registered at the labor offices and by unregistered vacancies. The matches are formed by the unemployed, registered and unregistered, and by on-the-job seekers. The inactive population may match with vacancies only through unemployment as everyone seeking a job is considered a job seeker.

As most other studies, we have available total outflows from registered unemployment.[8] This is an imperfect measure of total matches for several reasons, as illustrated in Figure 2.2. First, unemployment outflows contain outflows into inactivity representing discouraged job seekers. Secondly, some proportion of total matches is formed by job-to-job flows. Thirdly, registered unemployment outflows underreport total outflows from unemployment as some job seekers are not registered with labor offices. Finally, some matches are formed with vacancies which are not registered at labor offices. The effect of underreported unemployed job seekers and vacancies may be removed by using first differences transformation if unregistered

[8] With total outflows in (2.7) or (2.9), the matching function enters the UV curve in (2.1), allowing interpretation of shifts in the Beveridge curve using parameter changes of the matching function.

job seekers match only with unregistered vacancies. Estimates of the matching function comprising the registered unemployed and registered vacancies may therefore be little affected if their unregistered counterparts are omitted in the estimation.[9]

In (2.6), (2.8) and (2.9) we assume that total matches are formed by the registered unemployed and by registered vacancies. In what follows we inspect possible effects of omitting the employed job seekers and discouraged unemployed, proceeding from Petrongolo and Pissarides (2001). We describe these effects using the stock specification (2.6) and the stock-flow model (2.9).

We have assumed that vacancies are searched for only by the unemployed job seekers. If employed workers are also involved in search and job-to-job matches, their impact on the matching function depends on specific conditions. If the employed match with vacancies other than those posted at the labor offices, the matching function of the unemployed is unaffected. This is the case of segmented job market places. Otherwise, if unemployed job seekers form a proportional number of all matches, $U/(E + U)$, the instant rate M of matching of the unemployed job seekers is

$$M = \frac{U}{E+U} A(U+E)^{\beta_1} V^{\beta_2} \tag{2.10}$$

On-the-job seekers compete with the unemployed for available vacancies, which is represented in the third term. Assume that the number of employed job seekers E is procyclical so that

$$E = \lambda \left(\frac{V}{U} \right)^{\alpha} \tag{2.11}$$

where λ and α are positive numbers. Differentiating (2.10) with (2.11) with respect to U and V provides an insight into how coefficients of the matching function are affected and how they change over the business cycle when E of the form (2.11) is omitted. In particular,

$$\frac{\partial M}{\partial U}\frac{U}{M} = \beta_1 + \frac{E}{E+U}(1+\alpha)(1-\beta_1) \tag{2.12}$$

and

$$\frac{\partial M}{\partial V}\frac{V}{M} = \beta_2 - \frac{E}{E+U}\,\alpha\,(1-\beta_1) \tag{2.13}$$

We may see that if $\beta_1 < 1$, the estimated coefficient of unemployment is biased upward when effects of on-the-job search are omitted, while the bias is procyclical because $E/(E + U)$ is procyclical. On the other hand, the coefficient of vacancies is biased downward and is countercyclical if $\beta_1 < 1$. The impact of on--the-job search on coefficient estimates diminishes when β_1 is close to unity. In addition, the size of the bias of the unemployment stock coefficient is greater than the bias of the vacancy stock coefficient (and exhibits a more pronounced cyclical pattern) as $1 + \alpha > \alpha$.

[9] Labor offices as a market place serve as a specific segment of the market. Registered job seekers and registered vacancies are those that expect non-zero probability of match. The unemployed also register to be eligible for various types of benefits.

In addition to the effect of employed job seekers on matching of the unemployed, some matches may be formed by the inflows of job seekers from inactivity. This is rather a result of inadequate measuring as anyone entering employment is a job seeker for at least some time. Using high-frequency data, the number of direct moves from inactivity into employment may be neglected.

The second caveat related to data limitations concerns the possible presence of discouraged unemployed job seekers, i.e. the flow from unemployment into inactivity.[10] Neglecting on-the-job search for a while, total outflows from unemployment, O, comprise labor market matches and outflows of discouraged job seekers D:

$$O = M + D \tag{2.14}$$

Suppose that the number of discouraged job seekers is countercyclical so that

$$D = U^{\gamma} V^{-\delta} \tag{2.15}$$

where γ and δ are positive numbers. If the spell of unemployment has an additional influence on D with respect to the effect of the business cycle, then $\gamma > \delta$. Neglecting the presence of discouraged job seekers leads to biases which can be expressed. Differentiating (2.14) with (2.6) and (2.15) yields

$$\frac{\partial O}{\partial U}\frac{U}{O} = \beta_1 - \frac{D}{O}\left(\beta_1 - \gamma\right) \tag{2.16}$$

and

$$\frac{\partial O}{\partial V}\frac{V}{O} = \beta_2 - \left(\beta_2 + \delta\right)\frac{D}{O} \tag{2.17}$$

If $\gamma < \beta_1$,[11] the effect of unemployment on matches is underestimated and procyclical, while the effect of vacancies on matches is also underestimated and procyclical.

We have investigated how estimates of the stock model (2.6) may be biased when on-the-job search or discouraged job seekers are omitted and how these biases change during the business cycle. In the stock-flow specification (2.9), we may assume that discouraged job seekers recruit among the existing stock of unemployed and not among the unemployment inflow. This may be the case given that unemployment outflows into out of the labor force are associated with a certain unsuccessful job search history. Therefore, omitting discouraged job seekers affects coefficients of stocks of unemployment and vacancies as shown in (2.16) and (2.17), while coefficients on flows in (2.9) are not affected.

In order to describe the effect of omitting on-the-job search in the stock--flow specification (2.9), we assume that the employed job seekers compete with

[10] In the empirical part of the paper, we estimate the matching function using total outflows instead of outflows to jobs in order to explain shifts in the Beveridge curve using parameter changes of the matching function. The link between the Beveridge curve and the matching function is given by equations (2.1) and (2.3).

[11] This may be a plausible assumption meaning that unemployment has a greater effect on the number of matches than on the number of discouraged job seekers.

the newly unemployed and not with the stock of the unemployed. This may be a plausible assumption as the newly unemployed probably do not differ much from the employed job seekers in terms of the reservation wages. Following the notation of (2.10), the proportion of matches formed by the newly unemployed is $u/(E+u)$, while on-the-job seekers compete with the newly unemployed so that we may write

$$M = \frac{u}{E+u} AU^{\beta_1} V^{\beta_2} \left(u+E\right)^{\gamma_1} v^{\gamma_2} \tag{2.18}$$

Differentiating (2.18) with (2.11), we have

$$\frac{\partial M}{\partial U}\frac{U}{M} = \beta_1 + \frac{\alpha E}{E+U}\left(1-\gamma_1\right) \tag{2.19}$$

$$\frac{\partial M}{\partial V}\frac{V}{M} = \beta_2 - \frac{\alpha E}{E+U}\left(1-\gamma_1\right) \tag{2.20}$$

$$\frac{\partial M}{\partial u}\frac{u}{M} = \gamma_1 + \frac{E}{E+U}\left(1-\gamma_1\right) \tag{2.21}$$

$$\frac{\partial M}{\partial v}\frac{v}{M} = \gamma_2 \tag{2.22}$$

Assuming that $\gamma_1 < 1$, the unemployment stock coefficient as well as the unemployment inflow coefficient are biased upward in this case and are procyclical. If $\alpha < 1$, the size of the bias and the cyclical pattern are more pronounced in the unemployment flow coefficient than in the unemployment stock. On the other hand, the vacancy stock coefficient is biased downward and is countercyclical, while the vacancy flow coefficient is unbiased and exhibits no cyclical pattern. These inferences are the same as those drawn for the stock specification (2.6) and represented in (2.12) and (2.13).[12]

In addition to the effects described by equations (2.10) to (2.22), we may consider the possibility that the reservation wage of job seekers as well as firms changes during the business cycle. In particular, unemployed job seekers receive higher wage offers during an economic expansion for a given number of vacancies. Firms offer higher wages as it is more difficult for them to attract job seekers when the marginal product of labor is higher and firms compete for available labor. During expansion, to fill a vacancy with the same probability, a firm has to search for workers more intensively. As a result, the unemployed receive more job offers per unit of time for a given number of vacancies. During the expansion when stocks of job seekers are depleted, the counseling at labor offices becomes more efficient. One may also argue that during an economic boom, job seekers may be more successful in finding jobs that are not posted at labor offices. All these effects may increase the procyclical pattern of the effect of the stock of unemployed on matches. On the other hand, the increased labor market tightness during an expansion may

[12] The analysis of biases is too complicated in the presence of significant correlations between individual explanatory variables in (2.7) or (2.9).

TABLE 2.1 Biases and Cyclical Patterns of Matching Function Coefficients

	Omitting *E*	Omitting *D*	Reservation wage variations
U	↑if $\beta_1 < 1$ or $\gamma_1 < 1$	↓if $\gamma<\beta_1$	+
V	↓if $\beta_1 < 1$ or $\gamma_1 < 1$	↓	–
u	↑if $\gamma_1 < 1$	unbiased, no pattern	+
v	unbiased, no pattern	unbiased, no pattern	–

Note: ↑ upward, ↓ downward bias; + procyclical, – countercyclical pattern

attract discouraged job seekers that start competing for the same vacancies, resulting in a countercyclical effect of the unemployment stock on matches.

Higher wage offers are also directed to newly unemployed so that we may assume to observe a procyclical dependence of the effect of unemployment flows on matches, while other effects described in the preceding paragraph may also be applied here. Following the same line of reasoning, the effect of the vacancy stock as well as the vacancy inflow on matches may be countercyclical as long as the reservation wage of job seekers rises in booms and declines in recessions.

Table 2.1 summarizes the results of this subsection. Coefficient estimates of the unemployment stock and the unemployment inflow may both exhibit a procyclical pattern primarily due to presumed changes in the reservation wage during the business cycle. The same reasoning leads to a countercyclical behavior of the vacancy stock and the vacancy inflow. Additional inferences have been drawn as for how coefficient estimates are biased and what their cyclical pattern is when on-the-job search and discouraged workers are omitted in the estimation of (2.7) or (2.9). In particular, the omission of on-the-job search leads to an upward bias in the coefficient of the unemployment stock and the unemployment flow and to a downward bias in the coefficient of the vacancy stock, while the coefficient of the vacancy flow is unbiased. The unemployment stock and flow are procyclical, while the vacancy stock coefficient exhibits a countercyclical pattern. Regarding the effect of omitting discouraged workers in the estimation, the unemployment stock and the vacancy stock are biased downward and are countercyclical under plausible assumptions. The flow coefficients are unaffected when discouraged job seekers are omitted.

The analysis presented in this subsection suggests that the outflow into inactivity biases estimates if the share of this outflow on the total outflow changes over time. Natural causes of these changes can be business cycle effects such as the discouraged and the added-worker effects. In particular, one expects that during a recession, an increasing number of unemployed are discouraged from the job search and they no longer register as unemployed. The added-worker effect works in the opposite direction. While inactive people are not job seekers and thus do not fulfil the standard definition of unemployed,[13] in the Czech Republic most of them stay registered at labor offices. This is because labor offices have very limited tools to screen the willingness of the unemployed to work, and because counseling officers are reluctant to be consistent. Finally, there are strong incentives for the inactive

[13] According to the International Labor Organization (ILO) definition, a person is considered as unemployed if he has no paid job, is an active job searcher, and is able to accept a job offer.

unemployed to pretend they are searching for a job, because registration guarantees their eligibility for various types of rather generous social security benefits. This practice at the labor offices overstates the actual number of unemployed by the standard ILO definition. While this practice is not fiscally efficient, it is advantageous for our analysis since it guarantees that discouraged workers are captured by the unemployment variable. Therefore, discouraged workers do not contribute to the total outflow from unemployment, at least not systematically. Discouragement of the unemployed, resulting in their decreasing search intensity, decreases the efficiency and intensity of matching. This is the effect we are interested in which is represented by shifts in the intercept parameter.[14] Being familiar with actual practices at labor offices, we are convinced that biases due to outflows to inactivity do not complicate the interpretation of parameter changes in the estimated matching function.

While the coefficients in (2.9) capture the marginal effects of the job search and the search for workers, the additive constant term aggregates all other effects that are not captured by marginal effects. The additive term thus indicates changes in the structural component of unemployment or, in other words, in the mismatch. On the other hand, the coefficient estimates in (2.9) reflect the effects of the business cycle.[15] Given that the unemployment inflow rate is constant, changes in the additive term of the matching function may be associated with shifts in the Beveridge curve. On the contrary, changing unemployment inflows may also explain movements in the Beveridge curve, while they may not affect our interpretation of parameter changes of the matching function.

3. Estimation Strategy

The matching function of the form (2.9) describes continuous matching and is defined for a continuous time framework. An estimable version of a matching function relies on its discrete-time approximation. Time aggregation has several problems associated with it. For a particular time period, stocks are averages during the period while flows are sums over the period. During the time period, stocks of unemployment and vacancies are depleted by matches made during that period, inroducing a correlation between the stocks and the error term. As a remedy to this problem, lagged stocks are often used as explanatory variables. The lagged stocks are however imperfect measures of current stocks, resulting in biased estimates. This kind of measurement error in explanatory variables may be removed by first differences given that the error has an additive form and is time persistent. Furthermore, the dependent variable is also measured with errors due to time aggregation. In particular, the number of matches in a given time period includes matches from the initial stocks as well as from the inflow over the time period. In order to tackle this problem,

[14] The statistical evidence on inactivity based on the Labor Force Survey is in line with our arguments. The participation rates shown in Table 1.1 do not indicate any clear relationship between the business cycle and the aggregate participation during the business cycle under study. Furthermore, no clear cyclical pattern is observed in the ratio of the number of discouraged persons to the population in the same age group.

[15] The additive term probably captures some of the effect of omitting discouraged job seekers. In particular, a decrease in total outflows may indicate an increasing mismatch, which implies that the ratio of inactivity to employment outflows increases. When discouraged job seekers are omitted and total outflows are used in the estimation, the estimated decrease in the additive term underestimates the deterioration in matching.

the explanatory variables of the matching function should include some proportion of unemployment and vacancy inflows. The inflows are already included in (2.9).

The problems introduced by the discrete-time approximation may be to a great extent mitigated by using high-frequency data. Using high frequency data reduces the role of direct moves from out of the labor force into employment as described in the preceding section. In particular, everyone transiting into employment becomes a job seeker for at least some time. The occurrence of transitions from out of the labor force into employment may therefore be viewed as a consequence of the discrete-time approximation.

The matching function (2.9) is defined for a closed labor market. It is assumed that the job seekers encounter all vacancies in the labor market. This is unlikely in the economy-wide labor market, but may be the case in regions that may be viewed as closed labor markets. Suppose that we estimate the matching function using the region-level data. If there are interactions between the regions in terms of matching, doubling the size of the labor market leads to more than two times more matches, implying higher returns to scale as compared to the region-level matching.[16] It is therefore advisable to use such a geographical level of aggregation for which the mutual interactions in matching may be neglected.[17]

The matching function (2.9) defines matches, while the steady-state unemployment rate (2.1) contains outflows from unemployment. On that account, given data limits, we have to assume that all outflows from unemployment result in job placements through registered vacancies and that there is no on-the-job search.[18] An estimable version of the log-linear matching function (2.9) may be written as

$$\log o_{it} = \beta_1 \log U_{i,t-1} + \beta_2 \log V_{i,t-1} + \gamma_1 \log u_{it} + \gamma_2 \log v_{it} + \alpha_i + \varepsilon_{it} \tag{3.1}$$

where o_{it} is the number of persons leaving unemployment in region i during the time period t, $U_{i,t-1}$ and $V_{i,t-1}$ are stocks of unemployed persons and vacancies at the end of period t–1 (beginning of period t), u_{it} is the number of persons entering the pool of unemployed (inflows into unemployment during t), v_{it} is the number of new vacancies (vacancy inflows), and α_i are region-specific fixed effects.[19]

[16] Consider for example two urns representing local labor markets each containing two balls. In each urn, one match may be formed. After pooling the two urns, six matches may be formed if mutual interactions are allowed while only two matches may appear if there are no interactions between the two urns.

[17] Burda and Profit (1996) extended the matching function by introducing regional spillovers. They presuppose that the effect of adjacent districts on local matching depends on the road distance between the district capital cities. They estimated the matching function with regional spillovers for 76 Czech districts and found that unemployment in neighboring districts has a statistically significant effect on local matching. Another approach was used by Petrongolo and Wasmer (1999). They introduced cross-sectional spillovers, allowing each worker to search in his own and other regions with different search intensities. They estimated the matching function for Britain and France and found that the search intensity is positive and significant in adjacent districts, although it is only about 10 percent of the level of the search intensity in the region of residence.

[18] What happens when omitting the role of discouraged workers and employed job seekers is described in the preceding section.

[19] We do not impose a restriction on constant returns to scale. While some authors impose a restriction on constant returns, the theory does not require it and there are numerous studies finding empirical evidence on non-constant returns as in (Burda, Wyplosz, 1994), (Blanchard, Diamond, 1990), (Waren, 1996), (Yashiv, 2000), and (Münich, Svejnar, Terrell, 1999).

In order to remove spurious scale effects associated with heterogeneous district size, we divide all variables by the district-specific labor force. The labor force is time-invariant by assumption.[20] As shown by Münich et al. (1999), spurious scale effects appear if the variance in the district size translates into variance of the explanatory and the explained variables in the regression. In such a case, the variance in the district size, albeit having no economic impact, biases estimated coefficients toward the value of one.[21]

Applying first differences to (3.1) removes region-specific fixed effects and spurious scale effects at the same time. In particular, denoting $\Delta\log o_{it} = \log o_{it} - \log o_{i,t-1}$, $\Delta\log U_{i,t-1} = \log U_{i,t-1} - \log U_{i,t-2}$, etc., we have

$$\Delta\log o_{it} = \beta_1 \Delta\log U_{i,t-1} + \beta_2 \Delta\log V_{i,t-1} + \gamma_1 \Delta\log u_{it} + \gamma_2 \Delta\log v_{it} + \Delta\varepsilon_{it} \tag{3.2}$$

In equation (3.2), $\Delta\log U_{i,t-1}$ and $\Delta\log V_{i,t-1}$ are correlated with the error term $\varepsilon_{i,t-1}$ through $o_{i,t-1}$ from (3.1) and the relation $U_{i,t-1} \equiv U_{i,t-2} + u_{i,t-1} - o_{i,t-1}$ (the same applies for $V_{i,t-1}$). Instrumental variables are therefore needed to prevent endogenity biases. Our choice might prefer instruments such as lagged inflows into unemployment and the inflow of vacancies from own and adjacent regions (Wooldridge, 2001).[22]

The estimation of (3.2) using ordinary least squares with appropriate instruments for $\Delta\log U_{i,t-1}$ and $\Delta\log V_{i,t-1}$ is a standard approach used in the literature. However, the estimation suffers from the autocorrelation of residuals. In particular, we may surmise that the internal composition of both unemployment and vacancy stocks changes little over time. If for example a bunch of hard-to-match workers arrive into unemployment in a given period, they are likely to affect outflows in the current as well as subsequent time periods. This duration dependence appears in the estimation as serially correlated residuals. Furthermore, the serial correlation is magnified by using high-frequency data. In order to obtain efficient and unbiased estimates, we may drop the first few lags among the instruments and retain only further lags as valid instruments.[23]

In order to examine changes in coefficients during the business cycle, we estimate (3.2) in moving windows, i.e. over a particular fixed time span that moves period by period. Within the estimation window, the regression imposes a restriction on constant coefficients over time. With coefficient estimates at hand, we may calculate the district-specific fixed effects. For average values of variables in the particular estimation period denoted with superscript j, the fixed effects in district i are computed as

$$\overline{\log \alpha_i^j} = \overline{\log o_{it}^j} - \beta_1^j \overline{\log U_{i,t-1}^j} - \beta_2^j \overline{\log V_{i,t-1}^j} - \gamma_1^j \overline{\log u_{it}^j} - \gamma_2^j \overline{\log v_{it}^j} \tag{3.3}$$

[20] The pace at which the labor force changes is much lower than the variability of the stock and flow variables.

[21] Spurious scale effects are also removed by applying differences to the log-linear specification.

[22] Monthly dummies are included in (3.1) and (3.2) to capture seasonal effects.

[23] As an alternative, we may estimate a dynamic model including lagged dependent variables on the right hand side. Such a remedy is not preferred because lagged dependent variables require a larger set of intruments.

where means are calculated over the period j. The district fixed effects may be aggregated into an economy-wide parameter

$$\log A^j = \sum_i w_i \overline{\log \alpha_i^j} \tag{3.4}$$

where weights w_i are district labor force shares such that $\Sigma w_i = 1$.[24]

It follows from (2.1) and (2.3) that changes in the unemployment rate are directly associated with parameter changes in the matching function when the inflow into unemployment is stable, as is our case. Changes in the parameter A thus capture movements in the UV curve illustrated in Figure 1.3. In particular, A in (3.4) traces secondary effects during changes in the aggregate demand and all improvements or any deterioration in the efficiency of matching. The parameter A captures the average rate of matching, while the coefficient estimates express the marginal rate of matching. For example, the coefficient on unemployment (vacancy) stock in (3.2) determines a percentage change in the outflow from unemployment as a result of a 1-percent change in the number of unemployed (vacancies). The same interpretation applies to coefficients on unemployment and vacancy inflows. The coefficient estimates contain the effects of the business cycle as well as the effects related to omitting on-the-job search and discouraged workers.

4. Data

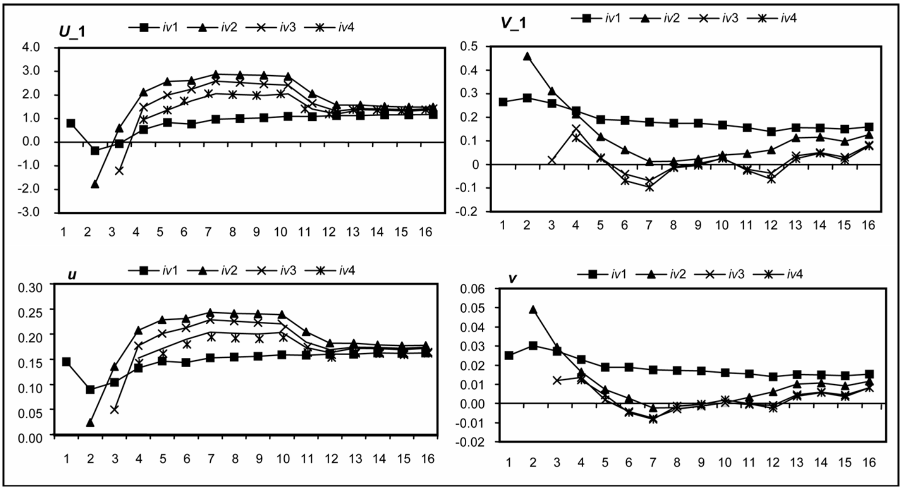
The district-level data on registry unemployment and vacancies come from the registers of 77 district labor offices in the Czech Republic and represent detailed and standardized monthly sources of information collected for the Ministry of Labor and Social Affairs. The data include end-of-month values of stock variables and period-cumulative values of gross flows of unemployment and vacancies. We exclude the districts of Prague, Prague-East and Prague-West from the data because their labor markets are too specific. This leaves us with data on 74 districts.[25]

The registry unemployment data are likely to underestimate the actual number of unemployed. Some people do not register with a labor office when they change jobs. Underreporting is more likely in urban areas, where other channels of job search are used. The underreporting is consequently likely to be uneven across districts. Assuming that the differences in the underreporting of unemployment across districts are time-invariant, this effect is removed by the differences used in this paper. In contrast to this problem, the registry unemployment might be over-reported since some people register with a labor office in order to be eligible for social security benefits. Again, we assume that this effect is to a great extent removed by first-specific differences. The vacancy data are also underreported as some vacancies may not be registered at the labor offices. All the data limitations are described in other sections of the paper.

[24] Variables on the right hand side of (3.3) are divided by district labor force to eliminate spurious scale effects.

[25] Inspection of the Labor Force Survey data reveals that 12.2 % of employed persons in our sample were commuting to other districts in the first quarter of 2001. Restricting the sample to 66 districts with the share of commuters being less than 25 % in each district, we repeated the estimation of the matching function, as described in the next section. Results are almost the same as in the case of the full sample of 74 districts. This justifies our choice of the geographical level for the estimation.

FIGURE 5.1 Choosing the Appropriate Set of Instruments



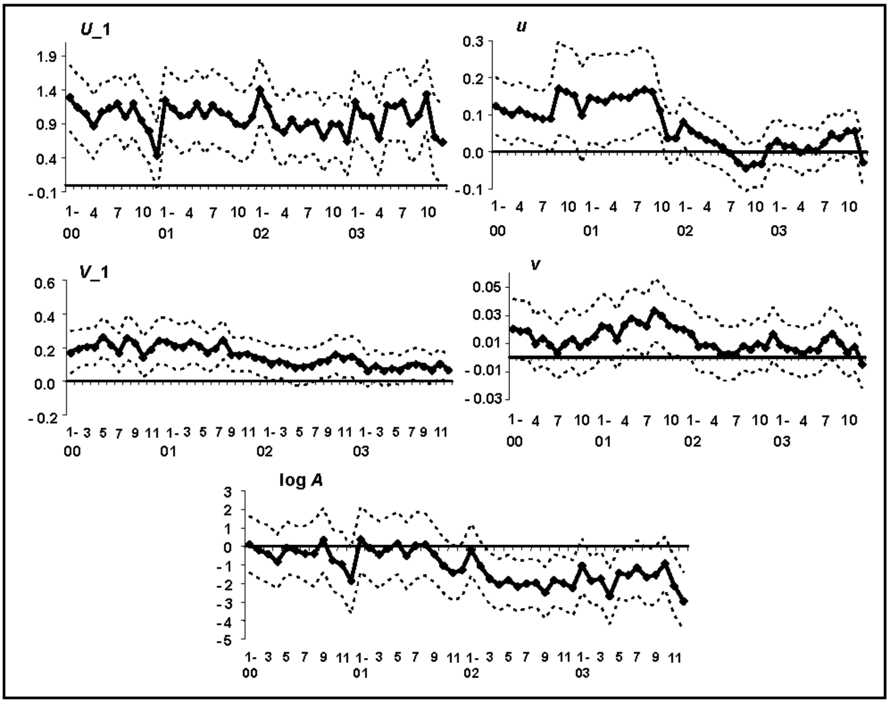
Note: Equation (3.2) is estimated over the period between January 2000 and January 2001. Instruments include lags of the unemployment inflow and lags of the vacancy inflow from own and neighboring districts. The set *iv*1 starts from the first lag, *iv*2 from the second, *iv*3 from the third and *iv*4 from the forth lag. The order number of the last lag used is on the horizontal axis, the size of the coefficient estimate is on the vertical axis.

5. Results

Parameter changes in the matching function have direct consequences allowing us to distinguish cyclical and structural changes in the unemployment rate given that the inflow rate into unemployment does not change (see (2.1) and (2.3)). Actually, the inflow rate into unemployment has been stable since 2000 (see Table 1.1). With respect to that and due to the data availability we estimate (3.2) for 74 districts in the period between January 2000 and December 2004. We estimate the matching function over a fixed time span covering 13 months that moves period by period, i.e. between January 2000 and January 2001, between February 2000 and February 2001, etc. We use the shortest possible estimation periods in order to be able to trace accurate positions of the economy during the business cycle. On the other hand, the need for a sufficient number of degrees of freedom in the estimation requires a longer panel. The choice of the length of time span is arbitrary and the results are robust to that choice.

In the first step we select an appropriate set of instruments. As instruments we use lagged inflows of unemployment and vacancies from own and adjacent districts. We find that the presence of the serial autocorrelation leads to sizeable changes in the coefficient estimates as the number of lags rises (*Figure 5.1*). In order to mitigate the effect of the autocorrelation on coefficient estimates, we use as many as 16 lags. We also drop the first few lags from the set of instruments since they are most likely infected by the autocorrelation. This is illustrated in Figure 5.1. Using up to 16 lags, the size of the coefficient estimates becomes similar for instruments lagged 1 to 16 and for lags 4 to 16. Therefore, we estimate (3.2) with instruments lagged 1 to 16 and with lags of the order 4 to 16 as an alternative.

FIGURE 5.2 Matching Function Estimates



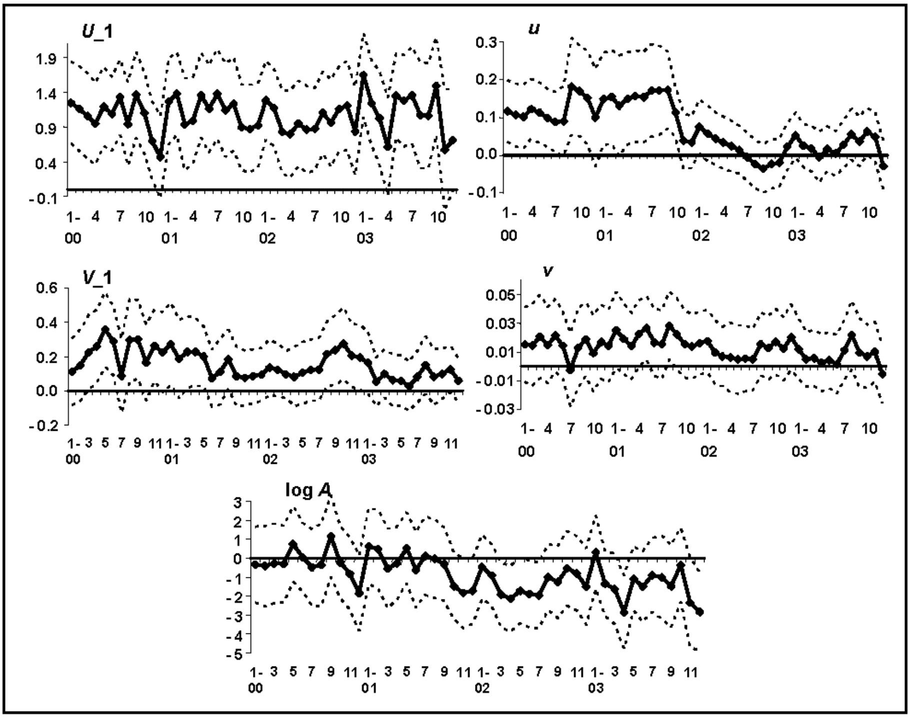
Note: Equation (3.2) is estimated in rolling windows spanned over 13 months starting at January 2000–January 2001 and ending at December 2003–December 2004. The horizontal axis refers to starting points of the estimation windows, while the size of coefficient estimates is on the vertical axis. The unemployment rate is instrumented using inflows of unemployment and vacancies from own and adjacent districts lagged 1 to 16. The 95 percent confidence intervals based on robust standard errors are shown.

Figure 5.2 shows coefficient estimates of (3.2) estimated in moving windows from January 2000–January 2001 until December 2003–December 2004. In each panel, the horizontal axis shows the starting points of the estimation periods. The set of instruments consists of lags of the order 1 to 16 of inflows of unemployment and vacancies from own and adjacent districts. The last panel shows the aggregated fixed effects calculated using (3.3) and (3.4). *Figure 5.3* depicts the same results as Figure 5.2 but with the alternative set of instruments with lags of the order 4 to 16.

The coefficient estimates of the unemployment stocks are high and close to unity. The cyclical pattern in coefficients is less obvious although some procyclical behavior may be traced out in Figures 5.2 and 5.3. The vacancy stock estimates are much smaller between 0.1 and 0.3. Contrary to expectations, these estimates are not countercyclical. The size of the estimates of the unemployment inflow is between zero and 0.15, while it may exhibit a stronger cyclical pattern than the unemployment stock. On the other hand, estimates of the vacancy inflow are negligible and almost always insignificant.

In order to examine the effect of omitting discouraged job seekers on estimates, we estimated (3.2) for job placements as a dependent variable instead of all

FIGURE 5.3 Matching Function Estimates with the Alternative Set of Instruments



Note: Equation (3.2) is estimated in rolling windows spanned over 13 months starting at January 2000–January 2001 and ending at December 2003–December 2004. The horizontal axis refers to starting points of the estimation windows, while the size of coefficient estimates is on the vertical axis. The unemployment rate is instrumented using inflows of unemployment and vacancies from own and adjacent districts lagged 4 to 16. The 95 percent confidence intervals based on robust standard errors are shown.

outflows from unemployment. The results are very similar to those in Figures 5.2 and 5.3 as for how estimates change across estimation periods. While the size of coefficient estimates of flow variables does not differ significantly, the coefficients of both stocks of unemployment and vacancy are 20 % greater than in the case of total outflows reported in Figure 5.2. This supports our findings in (2.16) and (2.17), and presented in Table 2.1, that $\gamma < \beta_1$ in (2.16) and that the unemployment and vacancy stocks are biased downward due to omitting discouraged job seekers. However, this is not confirmed using an alternative set of instruments. These results therefore support our argument that the effect of omitting discouraged job seekers from the analysis is minor.

The coefficient estimates of the unemployment stock are much higher than estimates of the vacancy stock, implying that the former may be biased upward and the latter downward due to omitting on-the-job search. In accordance with our expectations, the unemployment stock exhibits some procyclical dependence, while the cyclical pattern may be more pronounced in the unemployment inflow.[26] This meets our expectations regarding possible effects of omitting on-the-job search in the estimation or effects related with changes of reservation wages during the business cycle. Especially the unemployment inflow coefficient may be used as an indicator of cyclically induced changes in matching. When interpreting the results, we should have in mind that the estimation windows cover as many as 13 months. While the unemployment inflow coefficient has been rising at least since the beginning of 2000, it started to fall in late 2001 after the recession effects in matching had prevailed. The coefficient started to rise again in 2003 probably due to the economic recovery in 2003–2004. Nevertheless, the coefficient has remained insignificant since 2002, so these results should be interpreted with caution.

Contrary to our expectations, the coefficient estimate of the vacancy stock is not countercyclical. Starting at about 0.3 in 2000 and 2001, it dropped to 0.1 throughout 2002 where it remains and is statistically insignificant. The size of the coefficient confirms our expectations that it may be biased downward as a result of omitting on-the-job search. On the other hand, the evolution of the vacancy stock coefficient may point to the deterioration of the role of registered vacancies in the matching process. Finally, the coefficient estimate of the vacancy inflow is small and insignificant. Its pattern is difficult to interpret. Vacancy coefficients perform very badly, indicating a worsening in the functioning of the Czech labor market during recent years.[27] On the other hand, they suggest possible data problems.[28]

The last panels in Figures 5.2 and 5.3 contain estimates of the parameter *A*. The parameter was almost constant in 2000 and 2001, but dropped in late 2001 and in 2002, indicating a rise in labor market mismatch during that period.[29] This corresponds to the outward shift in the Beveridge curve in Figure 1.3. While the Beveridge curve shifts due to changes in stock variables, primarily due to the long-term component of the unemployment rate, rising frictions as indicated in the parameter *A* concern flow variables. This implies that matching function parameters may signal changes in mismatch and in advance changes in stock variables as observed in the Beveridge curve.

6. Conclusions

In this paper we used the theoretical concepts of the Beveridge curve and the matching function to interpret cyclical and structural shocks in the economy using the empirical example of the Czech economy. While the Beveridge curve describes changes in the labor market using stock variables, the key relationship behind movements in the Beveridge curve is the matching function introducing flow variables into the analysis. The flows help us to explain shifts in the Beveridge curve and we showed that they can be used as predictors of business cycle turning points.

[26] Mutual correlations of the right hand side variables in (3.2) are low, indicating that the interpretation of the results and their biases is not complicated.

[27] We assume that the underreporting of vacancies does not change and that this effect is removed by first differencing. However, given that the underreporting may increase with the increasing mismatch, this introduced a negative bias into the vacancy coefficient estimates.

[28] On the other hand, learning by doing and the expanded use of cheap information technology and communication, labor offices should have improved the collection of data on vacancies over time.

[29] As we already pointed out in Section 2.2, with total outflows as the dependent variable, the estimated decrease in *A* probably underestimates the deterioration in matching. For example, a decrease in overall outflows indicates an increasing mismatch between demand and supply, which implies a decreasing employment-to-inactivity-outflow ratio. Outflows to jobs fall faster than overall outflows.

From in-time intervention policy perspectives, the advantage of the registry data in constructing coincidence indicators is that the data are comprehensive, published monthly with no delay and are not subject to revision.

We showed that movements in the *U-V* space coincide with macroeconomic changes in the economy and that the Czech economy already exhibits features common in developed market economies. Our estimates of the matching function provide a better understanding of movements in the *U-V* space. Changes in parameters of the matching function allow us to distinguish cyclical and structural changes on the labor market. We traced some cyclical pattern in the unemployment inflow coefficient. Contrary to coefficient estimates, the fixed effects in the matching function reflect mismatches. Increases or decreases in fixed effects indicate improvement or deterioration in the matching.[30] We showed that omitting the effects of on-the-job search and discouraged workers from the model could in principle lead to biases, but we presented at least indirect evidence that the scope of these effects is minor when discouraged workers are omitted. Provided that measurement errors have a minor impact on estimates, our results clearly indicate the deterioration in the functioning of the Czech labor market during the most recent years. Our findings support the view that outward shifts in the Beveridge curve are due to increasing mismatches.

This is probably the first study to examine the matching function over the business cycle and using the Czech vacancy flow data. Although the data and methodology we employ are far from what would be theoretically optimal and our estimates should be interpreted with caution, we provided new insights on how cyclical and structural components of the unemployment rate may be empirically separated. Such distinction is crucial when interpreting observed changes in the economy. The insight we presented here should be confronted with other, mostly macroeconomic approaches to the issue of structural and cyclical movements in the economy. From the perspective of policy tools available in a small open EU economy, the (dis)functioning of the labor market is becoming more important with the enlargement of the monetary union. This makes labor market measures more important indicators of actual and a predictor of future economic development. The framework we proposed and explored in this paper should provide more comprehensive information than is revealed by individual labor market series.

[30] Given that the unemployment inflow rate is constant, changes in the additive term of the matching function may be associated with shifts in the Beveridge curve. On the other hand, changing unemployment inflows may also explain movements of the Beveridge curve, while they may not affect our interpretation of parameter changes of the matching function.

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