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**TWIN PEAKS IN REGIONAL UNEMPLOYMENT AND RETURNS TO
SCALE IN JOB-MATCHING IN THE CZECH REPUBLIC**

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Abstract

The regional distribution of unemployment rates in the Czech Republic during the transition period is shown to be characterized by twin peaks, i.e. a high and a low unemployment equilibrium. The emergence of strong regional disparities at the beginning of the 1990s can, at least partially, be explained by regionally different degrees of competition between the emerging private sector and state-owned enterprises for skilled labor and the role of on-the-job transitions on the parameters of the matching function. This study presents a formalization of these effects and estimates empirical matching functions for a panel of labor market districts of the Czech Republic between January 1992 and July 1994. When time-series properties of unemployment to job exits are taken into account and dynamic panel estimators are applied, the Czech matching function is shown to exhibit increasing returns to scale, being consistent with multiple unemployment equilibria.

JEL Classification: E24, J64

Keywords: regional labor markets, matching functions, returns to scale, multiple unemployment equilibria, on-the-job search, job-competition, Czech Republic

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1. Introduction

Despite a remarkable progress in restructuring the economy and developing the private sector, unemployment in the Czech Republic has remained at surprisingly low levels compared to most other Central and Eastern European transition economies. Moreover the unemployment rate shows none of the persistence known from western European labor markets. Nevertheless, low aggregate unemployment rates hide the fact that the regional dispersion increased sharply during the transition period (see OECD, 1995 and 1996). This study proposes increasing returns to job-matching caused by regionally disproportionate endogenous adjustments of search intensities of employed job-seekers as one possible explanation for increased labor market disparities in a country with a high degree of labor reallocation and low level of overall unemployment.

The aggregate matching function describes the process of workers and firms contacting each other and eventually forming employment relationships, and as such, captures informational deficiencies concerning the quality of a potential match, time-consuming and costly search, sorting and screening processes of workers and firms, as well as various forms of mismatch in labor markets due to qualification, sectoral and regional discrepancies. Moreover the institutional environment and legal regulations such as the administration and efficiency of labor offices in mediating vacant jobs with job-seekers, or the generosity of unemployment benefits may have an influence on search behavior, and impose or alleviate frictions on the outcome of job search activities.

In analogy to an aggregate production function the *trade friction approach* may be considered a *black box* implicitly taking into account individual search behavior on both sides of the market as well as interacting processes resulting from the aggregation over individuals, space and time. The specification of the matching function commonly adopted in the literature relates labor market stock variables, unemployment, possibly adding those who seek *on-the-job*, and the number of posted vacancies, as *matching factors* to the number of hires during a certain time interval, where the latter is often proxied by unemployment outflows in empirical work.

Hall (1977) derived a basic version of the matching function where the instantaneous number of hires is an increasing function of the number of job-seekers and vacancies, and

exhibits constant returns to scale (CRTS): i.e. doubling both, the number of unemployed and posted vacancies, doubles the number of hires. With CRTS the vacancy/unemployment ratio is a sufficient statistic to determine the transition rate from unemployment to employment. Theoretical reasoning for CRTS has found support from empirical analyses, as the assumption of constant returns in matching is consistent with constant unemployment rates along a steady-state growth path in theories of equilibrium unemployment (Pissarides, 1990). This is in line with empirical evidence of non-trending unemployment rates in the US and UK (Blanchard and Diamond, 1989, and Coles and Smith, 1994a).

On the other hand, theoretical studies have established the plausibility of increasing returns (IRTS) in matching due to various trading externalities resulting from endogenous adjustments of search activities of labor market participants. For instance, if individual search decisions do not consider spillover effects to search decisions of other agents, the outcome of the search process may possibly not be socially efficient (Diamond, 1982). Relaxing the assumption of random search and assuming that workers and firms are able to discriminate between currently arrived job seekers and vacancies, and those who have been in the market already produces similar effects (Coles, 1994 and Coles and Smith, 1994b).

Another possible source for IRTS in job-matching particularly relevant in transition economies is the ability of employers of private enterprises to discriminate between job offers to unemployed and employed job seekers, together with endogenous adjustments of search intensities of employed job seekers. Burgess (1993a,b) and Pissarides (1994) explore the role of on-the-job search for the matching process. In particular, Burgess (1993b) shows, that endogenous job competition between employed and unemployed job seekers has important consequences for returns to scale in matching and the interpretation of matching function parameters as a hole.

IRTS imply an increased matching efficiency in markets where job-reallocation and turnover is high, limiting their impact on the equilibrium unemployment rate (Courtney, 1992). Moreover, Pissarides (1986b) identifies IRTS in matching as a necessary condition for the existence of multiple, Pareto rankable labor market equilibria. Hence, modeling and estimation methods of matching functions have important implications for resulting unemployment dynamics in a macroeconomic framework. This is particularly true for regional labor

market dynamics where the existence of multiple equilibria may give scope to permanent effects of regional or active labor market policies.

The scope of this paper is to show how endogenous adjustments in search intensities of employed job seekers with respect to local labor market conditions may be responsible for increasing returns to matching, when potential employers are allowed to discriminate between employed and unemployed job seekers. This effect is particularly relevant for labor markets in Central and Eastern European transition economies, where emerging private enterprises compete with state enterprises for skilled labor. The empirical part of the paper explores regional labor market dynamics in the Czech Republic over the transformation period and presents estimates of matching functions from a monthly panel of unemployment, vacancies and unemployment-to-job transitions for 76 labor market districts between January 1992 and July 1994 taking into account the dynamic properties of unemployment-to-job transitions. The results show that, in contrast to previous evidence, the emerging pattern of regional unemployment in the Czech Republic is consistent with increasing returns to job-matching.

The subsequent section illustrates regional dynamics of unemployment and vacancy rates in the Czech Republic over the transformation process applying nonparametric smoothing techniques. Section 3 provides a short survey of externalities involved in the matching process and introduces a stylized model of job competition establishing the plausibility of increasing returns to job-matching in a transition economy with a high degree of labor reallocation. In section 4, I highlight econometric problems involved in estimating dynamic specifications of the matching function with panel data and apply GMM techniques to reduce the bias in estimates of matching elasticities. Moreover, I discuss the robustness of matching function estimates across various specifications, particularly with respect to the validity of instruments, and test for CRTS. Section 5 is a tentative analysis of the effects described in the model of section 3, and section 6 concludes.

2. Regional Unemployment-Vacancy Dynamics in the Czech Republic

Before analyzing the properties of the matching function in the Czech Republic, "the outcome" of the job-matching process, the prevailing regional dispersion of unemployment and unfilled vacancies are explored directly.

The phenomenon of low overall registered unemployment combined with a strong increase of regional disparities in the Czech Republic over the transformation period is widely documented and discussed in the literature (see Boeri, 1994, Munich, Svenjar, and Terrell, 1995). In Figure 2.1, I apply nonparametric smoothing techniques to estimate the dispersion of relative deviations of districts' unemployment rates from the national mean of 76 labor market districts of the Czech Republic for each month between December 1990 and June 1994.¹ A value of one on the x-axis indicates a local unemployment rate twice as high as the national mean. The figure reveals that while a large fraction of district unemployment rates is concentrated around a single peak until 1991, the cross-sectional distribution becomes much flatter and skewed to the right in subsequent years. The vacancy rate shows very different aggregate dynamics during that period: starting at very low levels at the outset of the transformation process, it peaked at above 1.5% of the labor force at mid-year 1992. However, the pattern of increasing regional disparities does not carry over to the demand side of the labor market. As displayed in Figure 2.2, there is no obvious trend in the regional cross-section distribution of vacancy rates despite some seasonal variation. Descriptive statistics in Table 2.1 support the finding of diverging regional unemployment rates. Additionally, coefficients of variation reveal a converging trend in unfilled vacancies.

The evolution of relative deviations of unemployment rates suggest that some districts were hit harder by the transformation process. Regions like Northern Moravia or parts of Northern Bohemia experienced comparably strong increases in unemployment as a result of reallocation of resources and labor shedding in industries which were given priority in the centrally planned economy. The stability of regional unemployment diffusion after 1991 im-

¹ Due to data limitations unemployment and vacancy rates are calculated on the basis of labor force figures from yearend 1992. The data used in this study are registered unemployment, vacancies, and unemployment-to-jobs exits collected from all labor market districts in the Czech Republic, and provided by the Czech Ministry of Labor and Social Affairs. I am grateful to Miroslav Pribyl for providing the data. All nonparametric estimations were done using XploRe. See Härdle (1990).

plies a limited role of labor mobility in overcoming such regional disequilibria, probably due to shortages in rental housing, and increasing cost of public transport. The convergence trend in the regional distribution of vacancies may be due to a proportionate emergence in small business dynamics or capital mobility even to depressed regions.² However, only considering the dynamics of regional distributions over time neglects important movements within the distribution. Identifying the relative position of a district's unemployment and vacancy rate within the regional distribution over several points in time is crucial to the understanding of the forces driving the transition process to a market economy. Such intra-distribution dynamics may evolve as the result of *mobility* or *churning* of districts within the distributions, possibly due to properties of the job-matching technology.³

Table 2.1 Evolution of Distributions over the Transition Period

	Unemployment Rate Deviations					
	Min	1. Quartile	Median	3. Quartile	Max	C.V.
6:1991	-0.84	-0.25	-0.04	0.22	1.00	0.38
6:1992	-0.86	-0.31	-0.02	0.46	1.49	0.49
6:1993	-0.90	-0.35	-0.04	0.55	1.39	0.53
6:1994	-0.92	-0.39	-0.03	0.53	1.46	0.54

	Vacancy Rate Deviations					
	Min	1. Quartile	Median	3. Quartile	Max	C.V.
6:1991	-0.86	-0.60	-0.29	0.06	1.40	0.63
6:1992	-0.79	-0.44	-0.18	0.10	1.08	0.52
6:1993	-0.84	-0.45	-0.18	0.21	1.03	0.52
6:1994	-0.70	-0.34	-0.06	0.23	1.23	0.40

I follow Quah's (1996) methodology in exploring transition patterns between cross-sectional densities through different points in time. Quah interprets such bivariate distributions as continuous versions of a Markov transition probability matrix. Suppose that, in a discrete setting, k classes of unemployment (or vacancy) rate deviations are given, $K = 1, \dots, K$, and transition probabilities for districts moving between or within these classes during the

² See Burda and Profit (1997).

³ Recently López-Bazo, Del-Barrio, Suriñach, and Artís (1996) and Bianchi and Zoega (1997) analyze intradistributional dynamics on regional labor markets for different countries.

time interval t and $t+n$ can be calculated. If $K \rightarrow \infty$, and each class becomes infinitesimally small, one obtains a continuous transition function from one labor market state in period t to any labor market state in $t+n$.

The intuition behind this methodology is demonstrated in the top panel of Figure 2.3, which shows intra-distribution transitions for regional unemployment rate deviations between June 1993 and June 1994 in the Czech Republic. The bottom panel in Figure 2.3 shows the corresponding contour plot. Two of the three axes show relative unemployment rates compared to the national mean in two points in time. The plot shows the bivariate density of relative unemployment rates between these two periods. Considering a district with a specific relative deviation from the national unemployment rate $\Delta u_t = \eta_t$ and cutting through the distribution parallel to the $t+n$ axis gives the marginal density $g(\Delta u_{t+n} | \Delta u_t = \eta_t)$, which can be interpreted as a measure of the conditional probability of a transition to another position in the regional unemployment distribution.

If unconditional distributions were perfectly stable over time, the contour plot of the bivariate distribution would degenerate to the main diagonal as illustrated in Figure 2.4. This is the case of *full distributional persistence* of regional unemployment rates over time. With complete convergence among districts, the ridge of the two-dimensional distribution should form parallel to the t -axis, whereas in the case of divergence, the ridge is a horizontal line. Finally, different modes along the main diagonal indicate the existence of *convergence clubs* or multiple equilibria among regional unemployment or vacancy rates.

Figures 2.5 and 2.6 present the results of a nonparametric kernel estimator for the bivariate densities of regional unemployment and vacancy rate deviations at the beginning of the transformation process (June 1991) and three years later (June 1994). The densities were estimated using a quartic kernel. Analytically correct bandwidths were estimated using Silverman's rule of thumb (see Silverman, 1986). In practice, these bandwidths rendered density estimates which were considerably oversmoothed; hence, the results reported below were estimated with bandwidths of 0.35.⁴ In Figure 2.5, the main peak of the bivariate distribution lies on the main diagonal slightly below the national unemployment rate. The ridge of the bivariate distribution is clearly flatter than the 45°-line indicating a diverging trend in the regional distribution of unemployment consistent with the evidence from inter-distributional

unemployment dynamics in Figure 2.1. In addition, I find a *twin-peaked* distribution with a second persistent mode which gathers districts showing an unemployment rate more than 50% above the national rate. Figure 2.1 demonstrated that regional unemployment disparities mainly emerged at the outset of the transformation. Figure 2.3 shows one-year transitions between June 1993 and June 1994 and supports this impression. The bivariate distribution of relative unemployment rates is fairly stable along the main diagonal between 1993 and 1994. Both panels clearly support the bimodality (*twin peaks*) and "distributional persistence" of the two unemployment equilibria during the respective period.⁵ The evidence on the dynamic evolution of vacancy rates in Figure 2.6 shows that the bivariate distribution is single peaked with a converging pattern (i.e. a vertical ridge).

Appendix A shows a classification of districts according to their intra-distributional dynamics in expanding, reallocating, and contracting districts. The first group of local labor markets is characterized by decreasing unemployment and increasing vacancy rates between mid-year 1991 and 1994 relative to the overall mean. Reallocating districts have increasing unemployment and vacancy rates, and contracting districts experienced increasing unemployment and decreasing vacancy rates. The residual subset of local labor market is characterized by decreasing unemployment and vacancy rates. One interpretation for this phenomenon could be a high relevance of out-commuting or migration in these districts. The map at the bottom panel Appendix A shows that expanding districts are mainly clustering at the Austrian border whereas most contracting districts gather along the east German border.

Such dynamic "sorting" processes towards district steady-states of high and low unemployment across regions can have a variety of explanations, such as the heterogeneity of districts with respect to industrial structure, or limited mobility of the labor force. A stylized model of job competition and endogenous job search intensity in Section 3 will demonstrate that increasing returns to scale in job-matching may also be a candidate to explain labor market disparities in the Czech Republic.

⁴ Contour line levels are given at the bottom of the figures.

⁵ Bianchi (1995) developed a nonparametric test for multimodality based on critical bandwidths but only for univariate distributions.

3. A Stylized Model of Job Competition and Endogenous Search Intensity of Employed Job Seekers

Trading externalities in job-matching can either originate in the mechanical component of the matching process, in feedback effects working through search intensities, or in endogenous effects in the matching technology (relating to institutional characteristics of the labor market and the availability of informational services).⁶

The most prominent trading externality discussed in the literature relates to a simple increase in scale, i.e. of the number of participants on either side of the market (unemployed or vacancies), which raises the density of searching workers and firms, and facilitates matching for all participating agents, since trading in thicker markets involves lower transaction costs. Diamond (1982, 1984) and Diamond and Fudenberg (1989) explain such "thin-market" externalities from interactions between production and exchange activities. Howitt and McAfee (1987) apply this externality arising from pure market size, or better market density, directly to labor market processes. In their approach, the external effect arises from endogenous adjustments of search intensities of workers responding to changes in recruiting effort of firms, and vice versa. When firms intensify recruitment activities, search becomes less costly for job-seekers, and motivates unemployed workers to increase their optimal search effort.⁷ Since workers and firms do not internalize these external effects, individually chosen levels of search and recruiting activity will not correspond to the social optimum.

A second important externality arises from a congestion effect. Increasing the number of searching agents of the same type reduces the probability of finding an acceptable match. This is a static version of the "common property externality" described by Mortensen (1982). In contrast to the thin-market externality, it induces labor market participants to search too little. A third "external" effect which has an impact on returns-to-scale in job-matching relates to all factors which affect the efficiency of the matching process directly. Examples are en-

⁶ See Blanchard and Diamond (1992) and Courtney (1992) for a decomposition of the matching function.

⁷ Burda and Profit (1997) show that this effect is not unambiguously positive: a higher recruitment activity of firms increases the unconditional job finding probability in a labor market, which raises the attractiveness of job search. But at the same time, given net returns, less job search is necessary to obtain the same benefit. In their model, the sign of the overall effect depends on the relative size of expected returns to the costs of job search: for sufficiently small search costs, search intensity of workers may fall with rising recruitment activity of firms, and vice versa.

ogenous increases in the effectiveness of labor market intermediation and information services⁸, the provision of active employment policies (Boeri and Burda, 1996), the degree of specialization in thick labor markets (Hall, 1989), or the intensity of reallocation (Blanchard and Diamond, 1992). All these effects may be relevant in job-matching and interact with each other.⁹

The stylized model presented here describes endogenous effects in search intensities of labor market participants, namely those who search on-the-job, and their impact on the parameters of empirical matching functions. It generalizes Burgess' (1993a,b) model which describes interactions in search intensities of unemployed and employed workers, where the likelihood of finding a job depends on a job offer probability which is given to both groups of labor market participants as well as on the shape of wage offer distributions. I accommodate the model to account for characteristics of a labor market in transition. Intensive transition and reallocation processes together with limited labor mobility in Central and Eastern European economies have caused tightness in booming local labor markets and excess labor supply in others. Such regional labor market mismatch has led to significant wage differentials between state and privately owned enterprises (see Flanagan, 1995). In contrast to Burgess (1993b), it is assumed that employed and unemployed job seekers, despite sampling from the same wage offer distribution, obtain offers from partially disjoint ranges of the wage distribution. The reasoning behind this assumption is that potential employers, in particular those from the emerging private sector, discriminate between types of job seekers and offer a wage premium to attract skilled workers from the state enterprises. In addition, I assume that the size of wage premium depends on labor market conditions in local labor markets. In contrast to Boeri (1995), it is assumed that job finding probabilities are equal among employed and unemployed, and independent of unemployment duration.

⁸ Courtney (1992) argues that labor market intermediaries incur fixed cost before starting their services, which prevents the formation of efficient intermediation services in thin markets. In addition, expected profits of intermediation will be higher in thick markets.

⁹ The role of wage determination in the matching process has been ignored so far. Hosios (1990) notes that in contrast to microeconomic search models, matching as well as the choice of search intensities precedes wage bargaining. But when agents choose their optimal search intensities, they trade-off expected benefits against the costs of job search or hiring activities. Thus, the characteristics of the wage bargaining process with respect to surplus sharing play an important role for the efficiency of matching. Pissarides (1986a) shows that there is no feasible wage which will internalize "thin-market" or "common-property" externalities in a bilateral-search environment, since the wage which is required to bring search intensities of either side of the market to its socially optimal level lies above, or respectively below, the level which is sufficient for either type of trading partner to participate in the search process.

Flek (1996) emphasizes the large share of job-to-job transitions in total labor reallocation and argues that the existence of a wage premium offered by expanding private enterprises is the result of the educational composition of the unemployment pool together with continued labor hoarding of state-owned or privatized state enterprises. Flanagan (1995) presents evidence from the Czech Survey of Economic Expectations and Attitudes, showing that in November 1994, the state sector comprises 40%, the private sector 28% and privatized state enterprises 32% of total employment. Moreover, earnings of full-time employees in the private sector are roughly 25% above those paid in the state sector. After controlling for human capital variables (education, experience and sex) the wage differential even rises to 46%.¹⁰ Večerník (1995) shows evidence based on the same data suggesting that the earnings gap is mainly due to self-employed workers whose earnings were almost 60% above average earnings. However, earnings of workers in other private enterprises are still more than 15% above those in the state sector.

Burgess' (1993a,b) model of endogenous job search has two main implications: it raises the number of matches (which can be interpreted as an increase in labor demand), but induces more job search on part of the employed, which crowds out unemployed job seekers, rendering an elasticity of the job finding probability with respect to changes in the number of total matches of smaller than one. Second, given the validity of this job competition model, the parameters estimated from a standard matching function cannot be interpreted in a usual way, but rather as the outcome of a reduced-form relationship. However, in the partial equilibrium of the model, the first argument crucially depends on the assumption that the process of vacancy creation is exogenous: crowding-out effects of job-to-job on unemployment transitions hinges on the assumption that vacancies left by successful employed job seekers are destroyed.¹¹

Although the model presented here remains in a partial equilibrium setting, I relax the exogeneity assumption for vacancy creation by stating that the range of the wage offer distri-

¹⁰ Flanagan (1995) does not control for selectivity bias. OECD (1995) reports smaller or even negative wage differentials between private and state-owned enterprises, which may be due to a composition bias from three sources: (1) whereas private enterprises are mainly created in services, state-owned enterprises consist mostly of industry paying relatively higher wages. (2) since official wage statistics only consider workers of firms above 25 employees they do not cover most emerging private enterprises which are mainly of very small size, and (3) small firms were exempted from wage controls agreed in the Tripartite Commission at the beginning of the transition process.

¹¹ Modeling the supply decision of firms with respect to vacancy creation along the lines of Pissarides (1990) is beyond the scope of this study.

bution, employed and unemployed job seekers sample from, differs for both types. Moreover, I assume that the size of the range, where only employed job seekers are offered jobs, depends on local labor market conditions. The wage offer distribution is assumed to be identically shaped for both types of job seekers except different truncation values, i.e. different maximum available wages offers.¹² The expected benefit from job search is given by

$$(3.1) \quad B(w_i, \bar{w}_i) = \mu \sigma_i \int_{w_i}^{\bar{w}_i} [V(\omega) - V(w_i)] dF(\omega), \quad i = e, u,$$

where $\mu (= M/S)$ is the "base" job offer probability, which is equal to the ratio of job-matches to total job seekers, and σ_i is the search intensity of employed (e) or unemployed (u) job seekers. $V(\omega)$ is the value function of the state characterized by a pay-off ω with $V'(\omega) > 0$ and $V''(\omega) < 0$ ¹³, and $F(\omega)$ is the cumulative wage offer distribution, which is assumed to be exogenously given. The range of the distribution is bounded from below by w_i which is equal to the unemployment income b or current income w if employed. Upper bounds, i.e. maximum available wage offers \bar{w}_i are assumed to differ for type i workers: potential (private) employers are assumed to offer positive wage premia to attract employed job seekers. These assumptions generate segments of the wage offer distribution which are characterized by different degrees of job competition, depending on the value of w . Figure 3.1 shows that wages in segment II will only be offered to employed job seekers, whereas segment I is the relevant region where Burgess' job competition model applies. In this part of the wage offer distribution job search activity of employed workers crowds out unemployed job seekers.

¹² An alternative strategy would be to assume equal shapes of offer distributions for both types with a positive shift parameter for those searching on-the-job.

¹³ This formulation implicitly assumes a non-sequential search strategy of job-seekers.

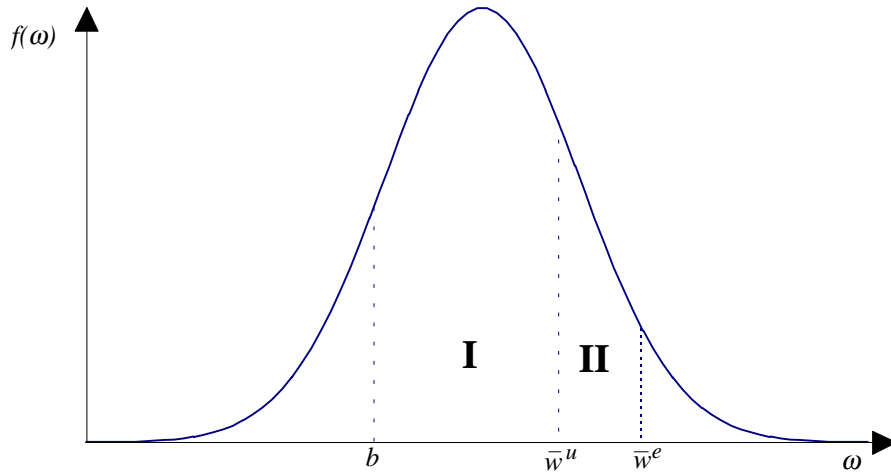


Figure 3.1: Segments of the wage offer distribution

Whereas unemployed job seekers are (for simplicity) assumed to search independent of labor market conditions, I assume that the upper bound for wage offers to employed job seekers is a function of labor market slackness, $t = v/u$, where $v = V/L$ and $u = U/L$, with V as the number of vacancies, U as the number of unemployed and L as labor force. The highest wage offer to employed job seekers is given by $\bar{w}_e = \bar{w}_u + \delta(t)$, with $\delta(0) \geq 0$ and $\delta'(t) > 0$, $\delta''(t) < 0$. The higher the ratio of posted vacancies to unemployed in a labor market, the higher the average wage premium potential employers are prepared to offer employed job seekers for job-to-job transitions.¹⁴

Employed and unemployed workers choose their optimal search intensities σ_i to maximize their net present value from job search, trading-off higher search costs against a higher probability of receiving an expected wage offer, which differs for employed and unemployed workers. Similar to Burgess (1993b), I model the offer arrival rate of a type i workers as $\theta_i = \mu\sigma_i$ and search cost as $c_i = c(\sigma_i)$, with $c_i' > 0$, $c_i'' > 0$ (see Pissarides, 1990, and Mortensen, 1986). Equating marginal benefits to marginal costs it follows that

¹⁴ Van Ours (1995) analyzes the degree job competition of employed and unemployed job seekers with respect to the choice and intensity of use of different recruitment channels. A similar argument applies here: it is assumed that within a certain range of the wage offer distributions only employed job seekers are offered jobs, which may coincide with specific recruitment channels not accessible to unemployed.

$$(3.2a) \quad c'(\sigma_e^*(\mu, w, t)) = \mu \int_w^{\bar{w}_u + \delta(t)} [V(\omega) - V(w)] dF(\omega) \quad \text{for } c'(\sigma_e(\mu, w, t)) > 0$$

and

$$(3.2b) \quad c'(\sigma_u^*(\mu, b)) = \mu \int_b^{\bar{w}_u} [V(\omega) - V(b)] dF(\omega) \quad \text{for } c'(\sigma_u^*(\mu, b)) > 0.$$

In equilibrium, optimal search intensities σ_e^* and σ_u^* depend on the base offer probability and the reservation wage for the respective job seeker type. Moreover the search intensity of the employed depends on the degree of labor market slackness.

The total number of contacts s in a labor market relative to the labor force is given by the pools of employed and unemployed job seekers weighted by their average search intensities,

$$(3.3) \quad s = u\sigma_u^*(\mu, b) + (1-u)\bar{\sigma}_e^*, \quad \bar{\sigma}_e^* = \int_b^{w_0} \sigma_e^*(\mu, \omega, t) dF(\omega),$$

where w_0 is defined by $\sigma_e^*(w_0) = 0$. From (3.3), the fact that $\mu = m/s$, and assuming a standard Cobb-Douglas specification with constant returns to scale for $m = \pi s^{1-\alpha} v^\alpha$, a reduced-form matching function is obtained, which considers the relevant interactions, as

$$(3.4) \quad \mu = m(s, v)/s(m, u, v) = \pi \left(\frac{v}{s} \right)^\alpha.$$

Comparative statics are carried out by using the implicit function theorem to derive expressions for the matching parameters of interest. First consider elasticity of the base job offer probability with respect to the unemployment rate

$$(3.5) \quad \eta_{\mu u} = - \frac{\alpha \left\{ \frac{u}{s} \sigma_u^* - \left[\frac{u}{s} - \frac{1-u}{s} \eta_{\bar{\sigma}_e^* u} \right] \bar{\sigma}_e^* \right\}}{1 + \alpha \left[\frac{u}{s} \sigma_u^* \eta_{\sigma_u^* u} + \frac{1-u}{s} \eta_{\bar{\sigma}_e^* \mu} \bar{\sigma}_e^* \right]} \begin{matrix} > \\ = \\ < \end{matrix} 0,$$

where η_{xy} is the elasticity of x with respect to changes in y . Without the possibility of potential employers to discriminate between employed and unemployed job seekers, $\eta_{\bar{\sigma}_e^* u} = 0$ as in Burgess (1993b), and since $\sigma_u^* > \bar{\sigma}_e^*$ (Mortensen, 1986), it follows that $\eta_{\mu u} < 0$. An increase in the unemployment rate decreases the base offer rate: the number of contacts between job

seekers and potential employers increases by more than the number of matches, given the number of vacancies. In empirical matching functions, regressing the log number of hires on log levels of unemployment and vacancies, this effect produces a coefficient on unemployment of less than unity. By allowing for the possibility of discrimination of job offers between employed and unemployed job seekers, and endogenizing search intensities of employed job seekers with respect to labor market conditions, the sign of $\eta_{\mu u}$ becomes ambiguous: for a high proportion of job search among the employed and a high elasticity of employed job search intensities with respect to local labor market conditions, $\eta_{\mu u}$ may even become positive, implying the possibility of IRTS in the matching function parameters. This formalizes the effect described in Baker et al. (1996). Moreover, note that endogenous effects on the search intensity of employed job seekers increase with a lower of the unemployment rate. To reveal the forces driving $\eta_{\sigma_e^* u}$, assume for simplicity that the search costs are given by $c_i = 0.5\sigma_i^2$, $i = e, u$, and that workers consider the base offer probability μ as given, hence

$$(3.6) \quad \begin{aligned} \left. \frac{\partial \sigma_e^*(\mu, k, t)}{\partial u} \right|_{\mu=\bar{\mu}} &= -\mu [V(\bar{w}_u + \delta(t)) - V(k)] V(\bar{w}_u + \delta(t)) \frac{\eta_{v_t}}{u} \\ &= -\mu \frac{\Delta V(k) V}{u} \eta_{v_t} \end{aligned}$$

and

$$(3.7) \quad \begin{aligned} \eta_{\sigma_e^* u} &= \frac{u}{\sigma_e^*} \int_b^{w_0} \frac{\partial \sigma_e^*(\mu, k, t)}{\partial u} dF(k) \\ &= -\frac{\mu V}{\sigma_e^*} \eta_{v_t} \int_b^{w_0} \Delta V(k) dF(k) < 0 \end{aligned}$$

From (3.7) it is obvious that the elasticity of the average search intensity of employed workers with respect to the unemployment rate is unambiguously negative, and depends on the elasticity of an individual's value function with respect to labor market slackness and the average expected net benefit of on the job-search, $\int_b^{w_0} \Delta V(k) dF(k)$. Plugging this result into (3.5) reveals, that a higher maximum wage premium offered to those searching on-the-job increases the elasticity of the base offer probability with respect the unemployment rate. This is one possible source of increasing returns to matching.

Similarly, a change in vacancy rates at a given unemployment rate changes the base offer probability according to

$$(3.8) \quad \eta_{\mu v} = \frac{\alpha \left[1 - \frac{1-u}{s} \eta_{\bar{\sigma}_e^* v} \bar{\sigma}_e^* \right]}{1 + \alpha \left[\frac{u}{s} \sigma_u^* \eta_{\sigma_u^* \mu} + \frac{1-u}{s} \eta_{\bar{\sigma}_e^* \mu} \bar{\sigma}_e^* \right]} \begin{matrix} > \\ \equiv \\ < \end{matrix} 0,$$

where

$$(3.9) \quad \left. \frac{\partial \sigma_e^*(\mu, k, t)}{\partial v} \right|_{\mu=\bar{\mu}} = \mu \frac{\Delta V(k)V}{v} \eta_{Vt},$$

and hence

$$(3.10) \quad \eta_{\bar{\sigma}_e^* v} = \frac{\mu V}{\sigma_e^*} \eta_{Vt} \int_b^{w_0} \Delta V(k) dF(k) > 0.$$

Equation (3.10) shows that a higher maximum wage premium has a dampening effect on the elasticity of base offer probability with respect to vacancies. In contrast to Burgess' (1993b) findings, an increase in vacancy rates may even decrease the probability of obtaining a job offer, if wage premia are sufficiently high to induce a strong positive effect on average search intensities of employed job seekers.

Section 4 estimates matching functions from a panel of Czech labor market districts over the transition period taking into account the time-series properties of unemployment-to-job exits, and testing for returns to scale in job-matching. Unfortunately, direct information on private to state-owned enterprise wage premia is unavailable. Therefore, I use the information attained from the analysis of Czech labor market dynamics in section 2 to approximate the impact of the intensity of structural change and on-the-job search in local labor markets in section 5.

4. Consistent Estimation of Regional Czech Matching Functions with Panel Data

Modeling endogenous adjustments in search intensities in the previous section has demonstrated that the assumption of CRTS in job-matching is not necessarily justified when the behavior of employed job seekers is taken into account. However, the majority of empirical studies have not rejected the hypothesis of constant returns to scale in job-matching. Table 4.1

provides a selection of recent returns to scale estimates from matching functions for various countries, time periods and data sets. Some studies have however challenged this view and argue that standard estimation procedures and specifications may render biased estimates of underlying elasticities of matches with respect to unemployment and vacancy changes. A first argument relates to the notion of heterogeneity of pools of job-seekers and job offers. Coles (1994) and Coles and Smith (1994b) drop the assumption of pure random search. They argue that, if no successful match is formed, agents only sample through currently arrived job offers or job candidates in subsequent periods. Hence, a correctly specified matching function implies a reduced form where hirings are a function of not only stocks of job-seekers and firms but also of inflows of new job-seekers and vacancies. Other studies question the relevance of the Cobb-Douglas technology of empirical matching functions and analyze the effects of functional misspecification on returns to scale estimates.¹⁵ Aggregation over space, sectors, or time possibly also biases matching function parameters downwards. Anderson and Burgess (1995) use a regional panel of US labor market data at MSE level and find slightly increasing returns to scale. Burda and Profit (1997) demonstrate that a matching function in local labor markets, which considers the importance of spatial spillovers through job-seekers and recruitment activities of firms from other regions, does not necessarily exhibit CRTS. Burdett, Coles, and van Ours (1994) argue that standard estimates of matching parameters may underestimate the underlying coefficients as a result of temporal aggregation.

Another possible source of misspecification in the analysis of matching functions, especially when estimated with regional panel data, arises from neglecting the time series properties of unemployment outflows. Estimation results for Czech labor markets will demonstrate that unemployment-to-job flows are highly correlated, even after controlling for unemployment and vacancy stocks at the beginning of the period. Matches between job-seekers and firms do not occur instantaneously. The process of screening potential workers and workplaces takes time, during which search activities for other *trading* partners may be suspended. And even when an employment contract is signed, the match may not become productive at

¹⁵ Warren (1996) generalizes the functional form to a more flexible trans-log specification and finds support of locally IRTS in US manufacturing during the 1970s. Using the same data set, Fox (1996) additionally emphasizes the necessity of modeling "technical progress" in matching. He finds that returns to scale estimates crucially depend on the functional form assumptions. Storer (1994) applies nonparametric spline techniques, and also stresses the importance of analyzing the functional form of the aggregate matching function, but does not explicitly analyze returns-to-scale.

the same instant. A more realistic description of labor markets is to assume that contracts fix a starting date for the employment relationship. During the time between signing the contract and starting work, an unemployed person will not be engaged in job search and a vacancy though possibly still posted will not accept further applications. This implies that the elasticities of hires with respect to unemployment and vacancies in a matching function will only gradually adjust to their long-term values. Another explanation for serial correlation in unemployment outflows is the dependence of search intensities on aggregate economic activity which shows strong serial correlation (Baker, et al., 1996). Empirical matching functions applied to regional panels, neglecting such dynamics may yield seriously biased estimates of the parameters of interest and have severe implications for predicted unemployment dynamics in regional labor markets.

Table 4.1 Comparison of the Returns-to-scale Estimates in Matching Functions

	Country, Period	Data	Estimation Method	RTS
Anderson and Burgess (1995)	US, 1978-1984	reg. panel	LSDV	IRTS
Blanchard and Diamond (1989)	US, 1968-1986	time series	OLS, NLS, IV	CRTS, (IRTS)
Boeri (1994)	CEECs, ~ 1991-1993	reg. panel	LSDV and random effects	DRTS, CRTS
Burda (1994)	East Ger., 1990-1992	reg. panel	LSDV	CRTS
	CR, 1990-1992	reg. panel		DRTS
Burda and Profit (1996)	CR, 1992-1994	reg. panel	LSDV	CRTS, DRTS
Coles and Smith (1994a)	UK, March 1987	cross-section	OLS	CRTS
Fox (1996)	US, 1969-1974	time series	OLS	CRTS, IRTS
Gorter and van Ours (1994)	NL, 1980-1993	reg. panel	NLS	CRTS
Storer (1994)	CAN, 1972-1978	reg. panel	spline regression	--
Warren (1996)	US, 1969-1974	time series	OLS, IV	IRTS

Increased availability of regional and international panel data sets has allowed the identification of cross-section effects to control for unobserved heterogeneity in the data. In contrast to typical microeconomic panel data, macroeconomic panels often have much larger time-series dimensions. Analyses of such data sets have been widely applied to the field of economic growth and convergence between countries and regions, but also to labor markets,

especially to the estimation of matching functions.¹⁶ However, the latter category of studies largely ignores the time-series properties of unemployment-to-jobs exits.

Consider the Cobb-Douglas specification of the matching function in levels in log-linear form, where lower-case letters are logarithms.

$$(4.1) \quad f_{it} = \alpha_0 + \gamma f_{it-1} + \alpha_1 u_{it-1} + \alpha_2 v_{it-1} + \eta_i + \mu_t + \varepsilon_{it}$$

f_{it} is the log number of outflows from unemployment to jobs in district i over period t , which is regressed on its lagged value f_{it-1} , on the stock of log registered unemployment and on log notified vacancies in district i at the beginning of period t . η_i is a time-invariant group-specific fixed effect and μ_t is a period fixed effect capturing seasonal effects and an aggregate time trend. Let N be the number of cross-sections and T the number of time-series observation in the panel. I assume for the error term ε_{it} to have the usual properties

$$E[\varepsilon_{it} | f_{it-1}, u_{it-1}, v_{it-1}] = 0,$$

$$V[\varepsilon_{it} | f_{it-1}, u_{it-1}, v_{it-1}] = \sigma_u^2 \text{ for all } i \text{ and } t,$$

$$Cov[\varepsilon_{it}, \varepsilon_{js} | f_{it-1}, u_{it-1}, v_{it-1}] = 0 \text{ for all } i \neq j \text{ or } t \neq s.$$

The model in section 3 has established the importance of endogeneity of the participation of the participation of the employed in the search process and its relevance for the size of α_1 and α_2 . Endogenous adjustments of search intensities of those searching on-the-job has been shown to increase the elasticity of job-matches with respect to unemployment on the one hand, and to dampen elasticity of job-matches with respect to vacancies on the other hand. The overall effect on returns to scale of the matching function depends on the strength of both effects. Table 4.2 presents regression results for all 76 local labor markets in the Czech Republic between January 1992 and July 1994.¹⁷ I estimate a *bare bones* matching function, which does not parametrize exogenous effects on the matching technology such as the impact

¹⁶ Mankiw, Romer, and Weil (1992), and more recently, Islam (1995) use panel data to estimate rates of convergence in growth between countries.

¹⁷ Appendix B shows regression updates for the period August 1994 to September 1996.

of active labor market policies, the role of local spillover effects in job-matching, or the heterogeneity of labor market districts due to structural composition.¹⁸

Regression 1 in Table 4.2 reports the benchmark results of model (4.1) from pooled OLS and confirms the theoretical prediction of significant positive elasticities of unemployment exits with respect to unemployment and vacancies. With a Wald test statistic of 1.784 the null hypothesis of constant returns to scale ($\alpha_1 + \alpha_2 = 1$) cannot be rejected at 5% significance. A Breusch-Godfrey test reveals clear evidence of first-order serial correlation in regression residuals. I include lagged unemployment exits to account for partial adjustment in job-matching in regression 3 of Table 4.2. Again the hypothesis of (long-run) constant returns to scale ($\alpha_1 + \alpha_2 + \gamma = 1$) cannot be rejected. A Breusch-Godfrey test statistic shows no further evidence of first-order serial correlation.¹⁹

Table 4.2 Regressions in Levels of the Czech Matching Function, # of observations: 2356, N=76, T=31 (1:1992 - 7:1994), Dependent Variable: Log Unemployment-to-Jobs Exits, $\ln f_{it}$

		$\ln f_{it-1}$	$\ln u_{it-1}$	$\ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>B-G(1)</i>
1	Pooled OLS	--	0.829 (87.9)	0.153 (15.7)	0.982	284.5	1.784	541.6*
2	LSDV, time and district fixed effects	--	0.774 (24.3)	0.134 (7.31)	0.908	111.7	5.642*	193.6*
3	Pooled OLS, dynamic	0.418 (25.4)	0.500 (32.4)	0.072 (7.77)	0.990	223.4	0.745	0.261
4	LSDV, time and district fixed effects, dynamic	0.276 (15.2)	0.623 (19.6)	0.099 (5.63)	0.998	101.2	0.002	2.754

Keys: Absolute t-values are given in parentheses. Intercept is not reported. Asterisks indicate rejection of the Null hypothesis at 5% significance. Under the Null hypothesis of (long-run) constant returns to scale the Wald statistic is distributed $\chi^2(1)$. The Breusch-Godfrey statistic under the Null of no first-order serial correlation in residuals is also $\chi^2(1)$.

These estimates neglect the possibility of heterogeneity of districts and seasonality in unemployment exits. In regressions 2 and 4 of Table 4.2, a fixed effects model (LSDV) for time and

¹⁸ See Burda and Profit (1997), Burda and Lubyova (1995), Boeri and Burda (1996), and Boeri and Scarpetta (1995).

¹⁹ Burda and Lubyova (1995) and Burda and Profit (1997) show that this partial adjustment process may be of higher order. However, they also show that about 60% of the adjustment occurs within the first month. Hence, I restrict the analysis to a first-order process.

districts accounts for these effects. Compared to the dynamic OLS regression, the partial adjustment parameter drops sharply whereas short-term coefficients on unemployment and vacancies increase slightly. While the Wald statistic even indicates decreasing returns to scale for the static fixed effects model, constant returns to scale cannot be rejected in the dynamic model, regression 4. The inclusion of a lagged dependent variable removes first-order serial correlation in residuals.

Doel and Kiviet (1994) demonstrate that estimates obtained from OLS or from a "least-square with dummy variables" approach (LSDV) are severely biased and inconsistent when partial adjustment dynamics are neglected. Nickell (1981) shows that even when lagged dependent variables are included, fixed effects models yield inconsistent and biased estimates, and derives an expression for the bias. This expression is shown to disappear as $T \rightarrow \infty$. Whereas studies of economic growth are mostly concerned with the coefficient of the lagged dependent variable, the "convergence parameter", long-run coefficients of explanatory variables, unemployment and vacancies, are of interest in the context of job-matching. Nickell (1981) demonstrates how in dynamic fixed effects models estimated with OLS the inconsistency and the bias carries over to coefficients on exogenous variables. This inconsistency may have severe consequences for returns to scale estimates and the implied dynamics of equilibrium unemployment.

Judson and Owen (1996) present Monte Carlo evidence that even in the presence of relatively long time-series the bias in autoregressive fixed effects models estimated with OLS (or LSDV) may still be important. They find that even with T in the range of 30 observations the bias still accounts for 30% of the true values of γ , whereas the bias in the estimates of α_i is found to be relatively small. Even though Judson and Owen (1996) find the LSDV estimator to perform well with large T , they advise alternative techniques which produce consistent estimates for partial adjustment model using panel data sets.

Anderson and Hsiao (1982) have proposed an estimator which removes individual fixed effects by differencing (4.1),

$$\begin{aligned}
 f_{it} - f_{it-1} &= \gamma(f_{it-1} - f_{it-2}) + (\mathbf{x}_{it-1} - \mathbf{x}_{it-2})\alpha + (\varepsilon_{it} - \varepsilon_{it-1}) \\
 (4.2) \quad &\text{or} \\
 \Delta f_{it} &= \gamma \Delta f_{it-1} + \Delta \mathbf{x}_{it-1} \alpha_t + \Delta \varepsilon_{it},
 \end{aligned}$$

where $\mathbf{x}_{it-1} = (u_{it-1}, v_{it-1}, t)'$ and $\alpha_t = (\alpha_1, \alpha_2, \mu_t)'$. Since the disturbance $\Delta \varepsilon_{it}$ in (4.2) is correlated with Δf_{it-1} , Anderson and Hsiao (1982) recommend instrumenting the latter with Δf_{it-2} and estimate with 2SLS. Arrelano (1989) proposes f_{it-2} as an instrument, since it can be shown to render more efficient estimation results for some combinations of parameters. Arrelano and Bond (1991) suggest a more efficient estimator which exploits a larger set of moment conditions. This estimator is "most semi-asymptotically efficient" among available IV estimators, which use lagged values of the dependent variable as instruments (Sevestre and Trognon, 1992 ; Harris and Mátyás, 1996). The formal expressions for the Anderson-Hsiao (AHIV) and Arrelano-Bond (GMM(1)) estimator are given in Appendix B. In the presence of heteroscedasticity, Arrelano and Bond (1991) show that applying a 2-step procedure yields more efficient results: first, regression residuals are obtained from a consistent one-step GMM estimator. The regression residuals are then exploited to construct the optimal weighing matrix for the GMM(2) estimator (see Appendix B).

The Anderson-Hsiao estimator in regression 5 in Table 4.3 includes lagged difference in log exits from unemployment whereas regression 6 uses lagged log levels of unemployment exits as instruments. Regressions 7 to 8 apply variants of GMM estimators. To reduce the dimension of the instrument matrix for the GMM in the presence of a large time-series dimension, I restrict the number of instruments for the exogenous variables to lagged first differences as proposed by Sevestre and Trognon (1992), and the triangular expansion matrix to a maximum of two in unemployment exits.²⁰ In addition, the reported estimates of standard errors are robust against heteroscedasticity which is often present in cross-section data.

All *difference* estimators of the Czech matching function in Table 4.3 yield very similar results, in particular significantly higher elasticities of unemployment exits with respect to unemployment stocks compared to Table 4.2. Most importantly, the Wald test soundly rejects long-run constant returns to scale in all cases. The Sargan test for overidentifying restrictions reported in the right hand column of Table 4.3 cannot reject the hypothesis of instrument validity. However, in contrast to Nickell's (1981) findings the coefficient on lagged unemployment-to-job outflows is smaller compared to regression 4 in Table 4.2 when estimated with IV or GMM, indicating additional problems with this specification.

²⁰ Estimates with higher order lags in the instrument matrix produced similar results.

Table 4.3 Regressions in first Differences (IV and GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, **Instruments:** $\ln f_{it-2}$ (resp. $\Delta \ln f_{it-1}$), $\Delta \ln u_{it-1}$, $\Delta \ln v_{it-1}$

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
5	AHIV, time fixed effects, diff. instr.	0.097 (1.91)	1.904 (17.3)	0.048 (1.48)	2.049	163.4	52.3*	--
6	AHIV, first diffs, time fixed effects, lev. instr.	0.169 (1.68)	1.980 (13.7)	0.047 (1.40)	2.196	174.5	26.9*	--
7	GMM(1), time fixed effects, A-B instr. restr. to 2 lags ^{a)}	0.164 (2.81)	1.926 (14.8)	0.081 (2.16)	2.171	173.7	60.5*	69.5 (60)
8	GMM(2), time fixed effects, A-B instr. restr. to 2 lags	0.160 (15.8)	1.917 (67.3)	0.085 (9.02)	2.162	173.2	131.4*	69.7 (60)

Keys: See Table 4.2. The Sargan test for orthogonality of overidentifying restrictions is also distributed χ^2 with degrees of freedom equal to the number of overidentifying instruments given in parentheses. The number in parenthesis below the Sargan test statistic show degrees of freedom for the test. ^{a)} T-values calculated with White's heteroscedasticity robust standard errors. See Arrelano and Bond (1991).

Table 4.4 Regressions in first Differences (GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, **Instruments:** $\ln f_{it-2}$, $\Delta \ln u_{it-2}$, $\Delta \ln v_{it-1}$

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
9	GMM(1), time fixed effects, A-B instr. restr. to 2 lags ^{a)}	0.169 (4.06)	0.946 (3.49)	0.071 (1.91)	1.186	182.8	0.48	81.4* (60)
10	GMM(2), time fixed effects, A-B instr. restr. to 2 lags	0.161 (18.3)	0.997 (13.3)	0.089 (8.15)	1.247	180.7	9.6*	68.0 (60)

Keys: See Table 4.2 and 4.3.

The ability of estimators based on the specification of the matching function in differences in reducing the "Nickell" bias crucially hinges the availability of exogenous instruments for lagged unemployment-to-job flows and the assumption of an uncorrelated error term in the equation 4.1 (Sevestre and Trognon, 1992). However, the definition of flow variables implies that the change in unemployment over a certain time interval equals the number of inflows into unemployment, $u_{it} = u_{it-1} + i_{it} - f_{it} - g_{it}$, where g_{it} is the flow from unemployment out of the labor force. From $\Delta f_{it} = \Delta u_{it} - \Delta u_{it-1} + \Delta i_{it} - \Delta g_{it}$ it is likely that $corr(\Delta \varepsilon_{it} \Delta \ln u_{it-1}) \leq 0$, hence the residual in (4.2) is correlated with the instrument, which produces an upward bias in the coefficient on unemployment (see Burda, 1994). As an escape route, a twice lagged differ-

ence in unemployment is used as instrument in Table 4.4. As expected, regressions 9 and 10 show that the elasticity of unemployment outflows with respect to unemployment drops from 1.9 to about 1. At least for GMM(2), constant returns to matching are still rejected.

Table 4.5 Regressions in first Differences (GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, **Instruments:** $(\ln u_{it-3}, \ln v_{it-2})$, 1:1992 - 7:1994

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
11	GMM(1), time fixed effects, A-B instr., complete ^{a)}	0.281 (2.75)	1.229 (5.47)	0.099 (1.45)	1.609	201.3	7.28*	136.7* (119)
12	GMM(2), time fixed effects, A-B instr., complete	0.252 (13.6)	1.283 (19.3)	0.103 (4.94)	1.638	194.4	110.9*	73.2 (119)
13	GMM(1), time fixed effects, A-B instr., complete ^{a)}	0.323 (2.79)	0.647 (1.79)	0.156 (3.04)	1.126	222.3	0.18	72.8 (58)
14	GMM(2), time fixed effects, A-B instr., complete	0.300 (11.8)	0.757 (9.26)	0.159 (12.5)	1.216	214.4	9.33*	46.8 (58)

Keys: See Table 4.2 and 4.3.

Second, allowing for serially correlated error terms ε_{it} in equation (4.1) also invalidates $\ln f_{it-1}$ as a feasible instrument. Hence, I only use triangular expansion matrices for the levels of twice lagged unemployment and lagged vacancy stocks in regressions 11 and 12 of Table 4.5. Again the coefficient on unemployment is lower compared to Table 4.4, but still greater than one. CRTS are rejected at 5% significance. Taking together the implications of residual correlation and the stock-flow identity, even further lagged unemployment is invalid as an instrument for lagged outflows to employment. Hence, regressions 13 and 14 show GMM estimates only taking the triangular expansion matrix on lagged vacancies. The results show a short-term elasticity with respect to unemployment of less than one, but at least for the two-step GMM, long-run returns to scale are still rejected in favor of IRTS in job-matching. In addition, the coefficient on the lagged dependent variable is increased to a value of 0.3 which is higher compared to the OLS estimates in regression 4 in Table 4.2, as predicted by Nickell (1981).

The main finding that emerges from Table 4.5 and conflicts with most earlier studies is the robustness of (long-run) IRTS in the Czech matching function when consistent estimators are applied. The tables in Appendix C demonstrate that IRTS in job-matching also persist

between 8:1994 and 9:1996. Theoretical arguments analyzing matching externalities have identified IRTS as a necessary condition for multiple labor market equilibria. Hence, finding IRTS in job-matching on local labor markets in the Czech Republic is consistent with the double-peak property of the regional distribution of unemployment rates found in section 2.

5. Decomposition of Returns to Job-Matching

The stylized model section 3 provides theoretical underpinning to the importance of job-to-job movements for the matching process: it predicts a larger coefficient on unemployment and a smaller coefficient on vacancies for a higher fraction of employed to total job seekers. However, the effect of on-the-job-search is difficult to infer directly since data on employed job search is not readily available in the Czech Republic, especially not on a regional level, which is the perspective taken in this study. It is, however, possible to find variables which possibly provide information on the intensity of job-to-job transitions and its impact on job-matching. The model of section 3 assumes for simplicity that the wage premium offered by private enterprises is solely dependent on labor market slackness. Flek (1996) lists other potential determinants in the Czech Republic, such as the qualificational composition of the labor force, and small inflows into unemployment caused by labor hoarding of state owned or privatized firms.

A first possible approach to analyze the impact of employed job search on the matching process is related to the analysis of intradistributional dynamics of regional unemployment and vacancy rates in section 2. A simple cluster analysis which minimizes the average distance between two clusters classifies districts into three groups for relative unemployment rates and two clusters for relative vacancy rates, as shown in Figure 5.1. A dummy variable for each of the five clusters is interacted with log unemployment and vacancies, and interaction terms are included as explanatory variables to estimate the reduced-form matching.

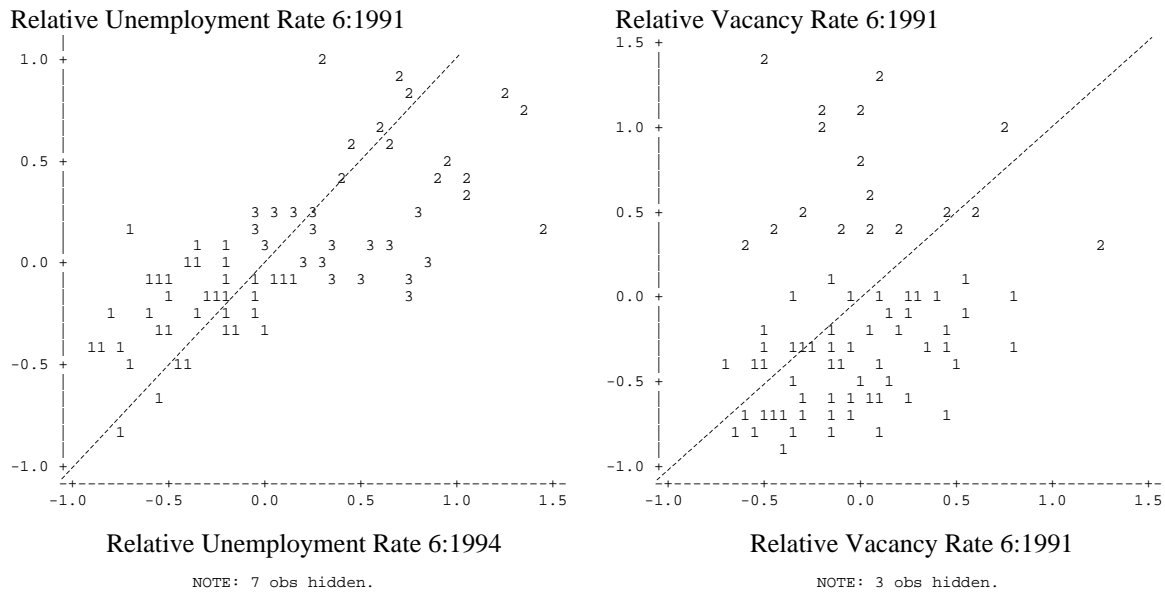


Figure 5.1 Clusters of Districts

Table 5.1 shows matching function estimates with separate coefficients for each interaction. The method is GMM(2) using lagged vacancies as instruments as in regression 14 in Table 4.5. The results show clear heterogeneity of matching coefficients depending on the relative position of a district within the regional distribution. The matching coefficients in the *high unemployment* cluster show the expected parameter constellations in the presence of strong employed job search: a coefficient on log unemployment larger than one and, in contrast to the standard matching theory, a negative coefficient on log vacancies. However, the stylized model in section two predicts a high coefficient on unemployment in regions with low unemployment rates. The large coefficient on unemployment may be explained by a strong qualifical mismatch in districts of cluster 2 which contains districts dominated by agriculture and heavy industry in Southern and Northern Moravia.

Another interesting observation is the insignificant elasticity of unemployment-to-job exits with respect to unemployment in districts of cluster 3 which contains districts that are moving between the high and low unemployment equilibrium. As Flek (1996) argues, the incentive to private firms to offer wage premia to motivate job-to-job transitions is less important in regions with lower degree of labor hoarding of state-owned and privatized enterprises. Following the model in section 3, a lower wage premium means less on-the-job search and a smaller coefficient on unemployment in the reduced-form matching function. Finally,

the large coefficient on unemployment in districts with higher relative vacancy rates at the outset of the transition process also supports the predictions of our stylized model in section 3.

Table 5.1 Decomposition of Empirical Matching Functions, 1:1992 - 7:1994, Regressions in first Differences (GMM(2)), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, **Instruments:** $\ln v_{it-2}$

<i>Explanatory variable</i>	(15)	(16)	(17)
$\Delta \ln f_{it-1}$	0.327 (7.3)	0.285 (10.0)	0.158 (4.5)
$\Delta \ln u_{it-1}$	--	0.486 (1.7)	-0.125 (0.3)
- cluster 1: low unempl. rates	0.742 (3.4)	--	--
- cluster 2: high unempl. rates	1.849 (3.9)	--	--
- cluster 3: intermediate unempl. rates	-0.449 (0.9)	--	--
- cluster 1: low vacancy rates	0.773 (3.0)	--	--
- cluster 2: high vacancy rates	1.368 (3.0)	--	--
- priv. enterprises/total employment (1994)	--	0.675 (0.5) [0.630]	--
- empl. in services/total employment (1994)	--	--	0.602 (0.6) [0.037]
$\Delta \ln v_{it-1}$	--	-0.563 (2.1)	1.390 (6.4)
- cluster 1: low unempl. rates	0.427 (4.6)	--	--
- cluster 2: high unempl. rates	-0.635 (6.3)	--	--
- cluster 3: intermediate unempl. rates	0.290 (2.8)	--	--
- cluster 1: low vacancy rates	-0.127 (1.1)	--	--
- cluster 2: high vacancy rates	0.208 (1.4)	--	--
- priv. enterprises/total employment (1994)	--	3.480 (2.7) [0.180]	--
- empl. in services/total employment (1994)	--	--	-4.443 (5.3) [0.192]
<i>SEE</i>	222.2	215.0	204.5
<i>Sargan</i>	46.3 (50)	45.0 (57)	51.6 (57)

Keys: See Table 4.2 and 4.3. Equations (16) and (17) contain the vector of log vacancies multiplied with the share of private enterprises to total employment, and the share of employment in service industries in 1994, respectively. Square brackets contain the total coefficient on unemployment or vacancies evaluated at the mean of the interaction variable, the mean value of the ratio of private enterprises to total employment is 0.2136 across districts, the mean share of employment in service industries is 0.2697.

A second approach to measure the effects of endogenous on-the-job search on job-matching is to interact the ratio of private enterprises and the ratio of employment in the serv-

ice sector to total employment at yearend 1994 with log unemployment and vacancies, and to augment the matching function with these terms.²¹ The results are shown in regression 16 and 17 in Table 5.1. The value in square brackets gives the short-run elasticity of unemployment-to-job exits with respect to unemployment and vacancy changes evaluated at mean ratio of private enterprises (21.4%) and service sector employment (27%) to total employment. Surprisingly, for the coefficient on unemployment, both interactions are insignificant. But for the elasticity of unemployment outflows with respect to vacancies, different levels of private enterprises or service sector employment to total employment have a strong and opposed impact: a larger relative number of private enterprises increases the coefficient on vacancies, whereas a larger share of employment in services reduces the coefficient. While the latter is consistent with a strong negative effect of endogenous on-the-job search on unemployment outflows, the former may possibly be explained by the large share of self-employed in the total number of private enterprises in the Czech Republic.

6. Conclusion

Emergence of strong regional disparities in regional unemployment in the Czech Republic since the outset of the transformation at the beginning of the 1990s can, at least partially, be explained by endogenous processes from local labor markets in this country. In particular, the competition between the emerging private sector and state-owned enterprises for skilled labor, which gives rise to large job-to-job movements and wage premia offered to sectoral movers, is an important phenomenon of labor markets in a transition economy. Together with low level of (registered) unemployment in the Czech Republic, such endogenous adjustments in search intensities of employed job seekers have been shown to have external effects on the matching technology implying increasing returns in the reduced-form matching function.

This observation is consistent with the analysis of intra-distributional dynamics of regional unemployment rates between 1991 and 1994, which shows the pattern of a twin-peaked distribution, with a low- and a high unemployment rate equilibrium, and some labor market districts churning between these equilibria. In contrast, the intra-distributional dynamics for

²¹ The ratios of private enterprises and sectoral employment to total employment are provided by the Czech Statistical Office. Service sector employment includes retail, tourism, hotel and restaurants, transport and communication, banking and insurance, and services provided by enterprises.

vacancy rates show a clear trend of convergence across Czech districts over the same period of time.

A properly specified and consistently estimated matching function which accounts for autocorrelation in unemployment-to-job exits, the presence of heteroscedasticity, and the validity of instruments reveals elasticities of outflows to jobs with respect to unemployment and vacancies which imply increasing returns to matching. Earlier studies, which neglect the time-series properties of unemployment outflows, have failed to find this effect. Finding direct evidence on the empirical relevance of job-to-job transition in the Czech Republic is difficult due to the lack of data. However, taking into account the specific position of districts within the regional distribution of unemployment and vacancy rates yields a strong heterogeneity of matching parameters, which may result from disproportionate participation of employed workers in the job search process. Strong regional differences in the matching technology also imply a limited role to the regional mobility of the unemployed, possibly due to housing restrictions or limited transport facilities, giving scope to regional policies encouraging job-related mobility.

Regional heterogeneity in the matching technology is only one possible explanation for regional unemployment disparities in transition economies. High demand for inexpensive labor from across national borders and implied cross-border commuting, the predominance of single industries within particular local labor markets, or budget constrained active labor market policies are other possible candidates to explain regional labor market dynamics. Conditioning regional unemployment rates on these regional characteristics of districts may partially remove evidence on multiple equilibria, and also increasing returns to matching. On the other hand, the convergence in vacancy rates suggests increased capital mobility even towards depressed regions, which probably disqualifies structural problems as the predominant explanation for diverging unemployment dynamics in the Czech Republic.

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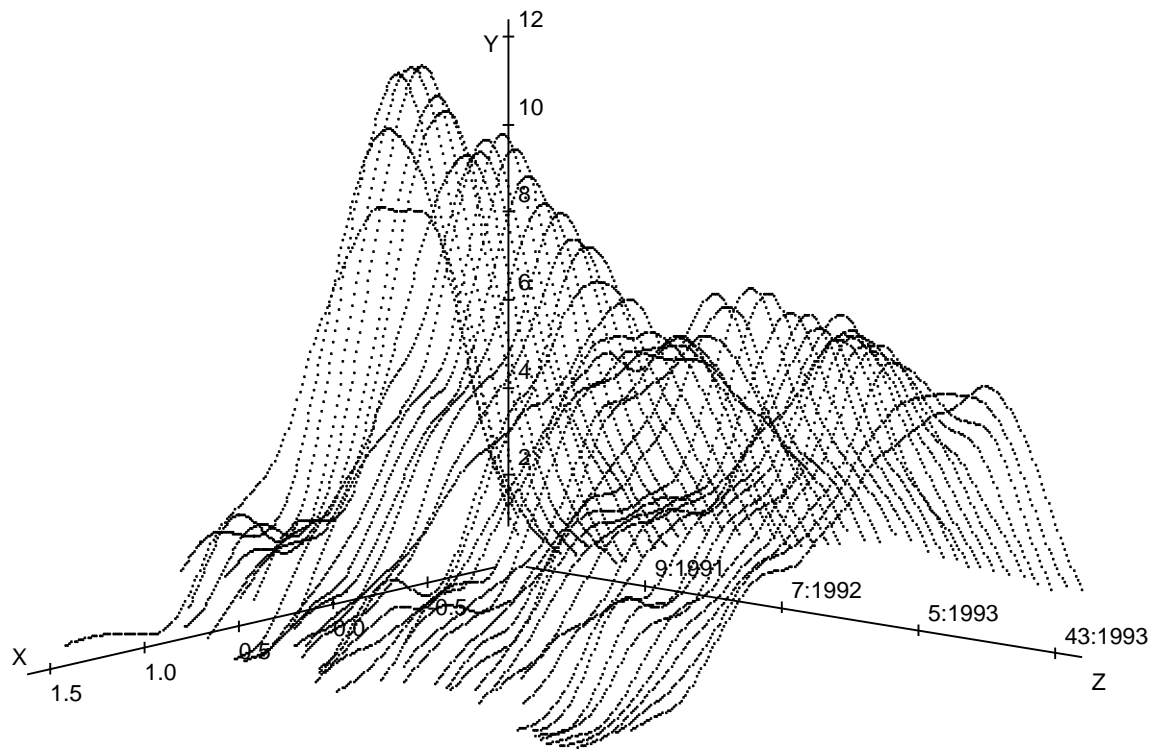
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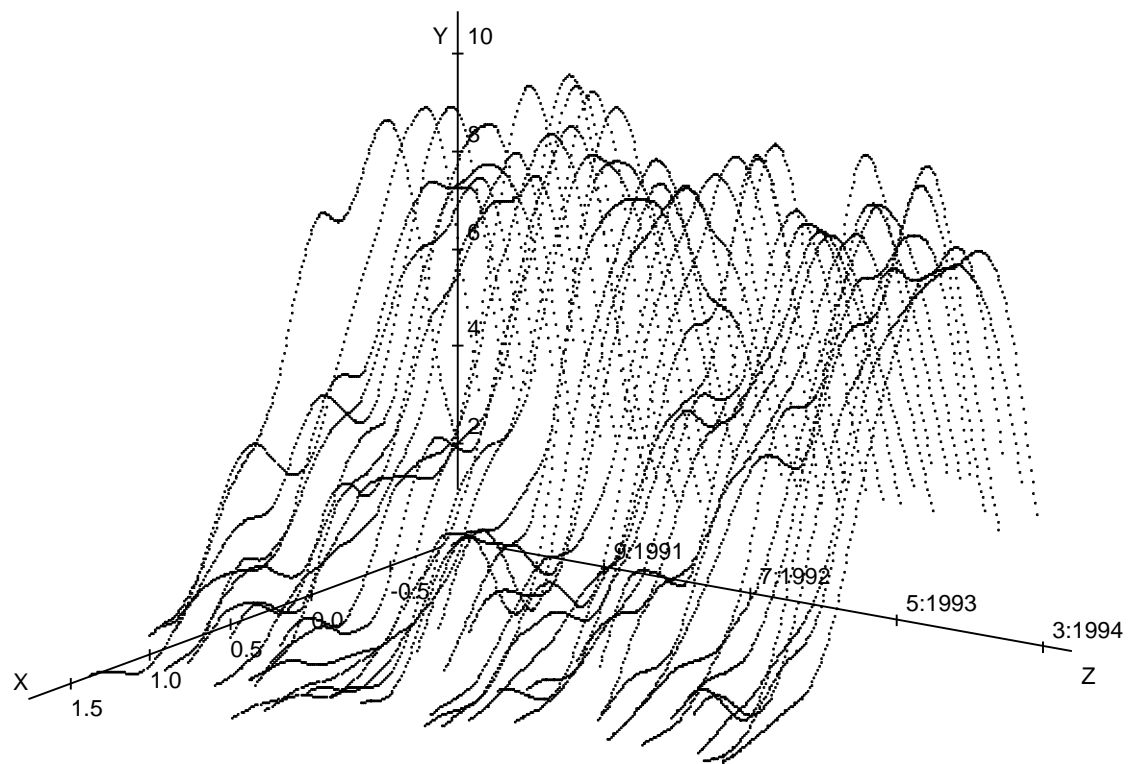
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Figure 2.1 Dispersion of unemployment rates in the Czech Republic, 12:1990-6:1994



X: Regional deviation from national unemployment rate
Y: Frequency
Z: 12:1990 - 6:1994, Bandwidth $h = 0.35$

Figure 2.2 Dispersion of vacancy rates in the Czech Republic, 12:1990-6:1994



X: Regional deviation from national vacancy rate
Y: Frequency
Z: 12:1990 - 6:1994, Bandwidth $h = 0.35$

Figure 2.4 Convergence, divergence and persistence of the cross-district distributions

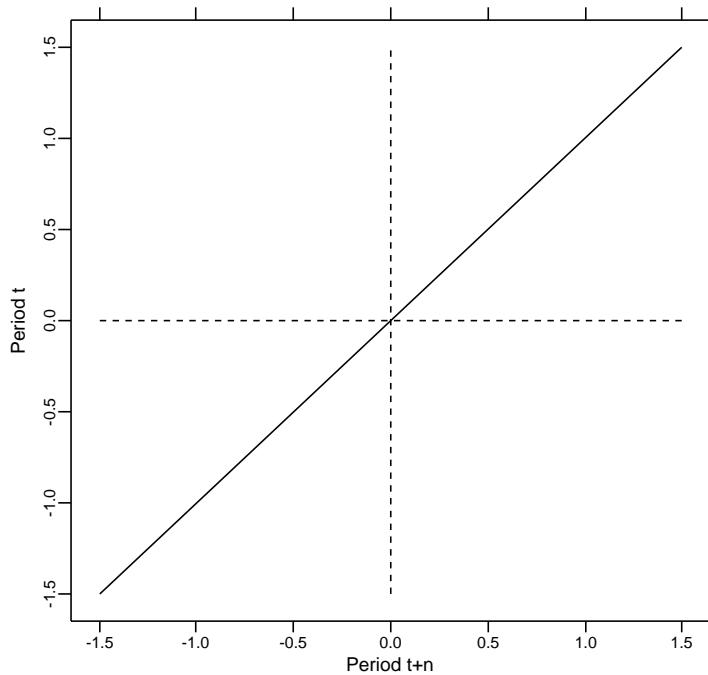


Figure 2.5 Three-year transitions in the cross-district distribution of relative unemployment rate deviations, June 1991 - June 1994

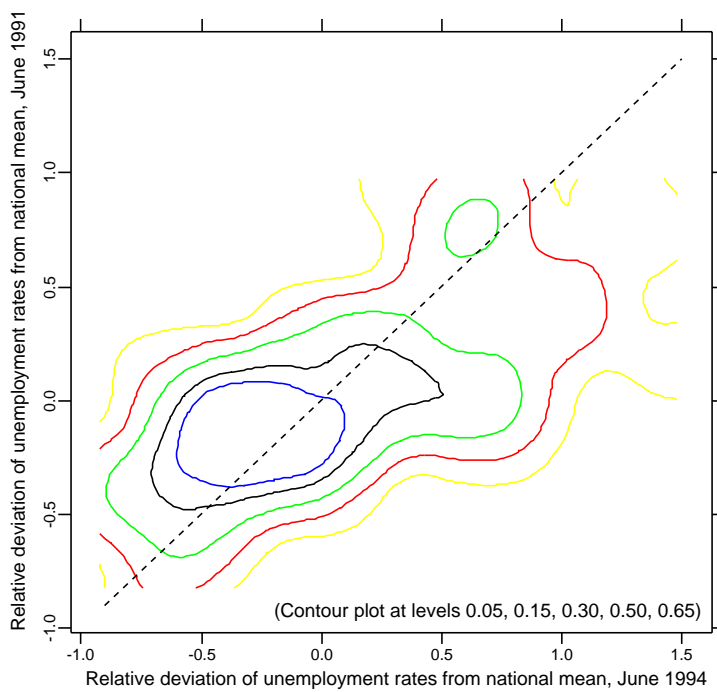


Figure 2.3 One-year transitions in the cross-district distribution of relative unemployment rate deviations, June 1993 - June 1994

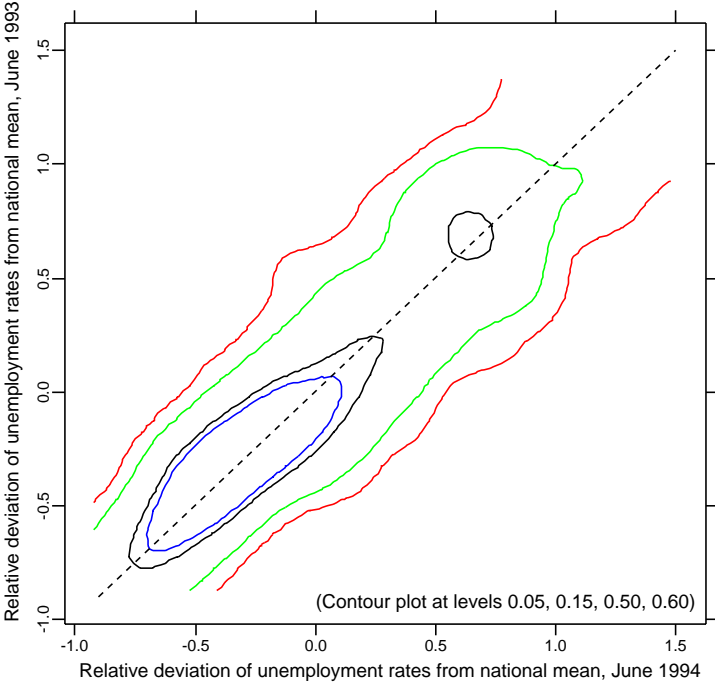
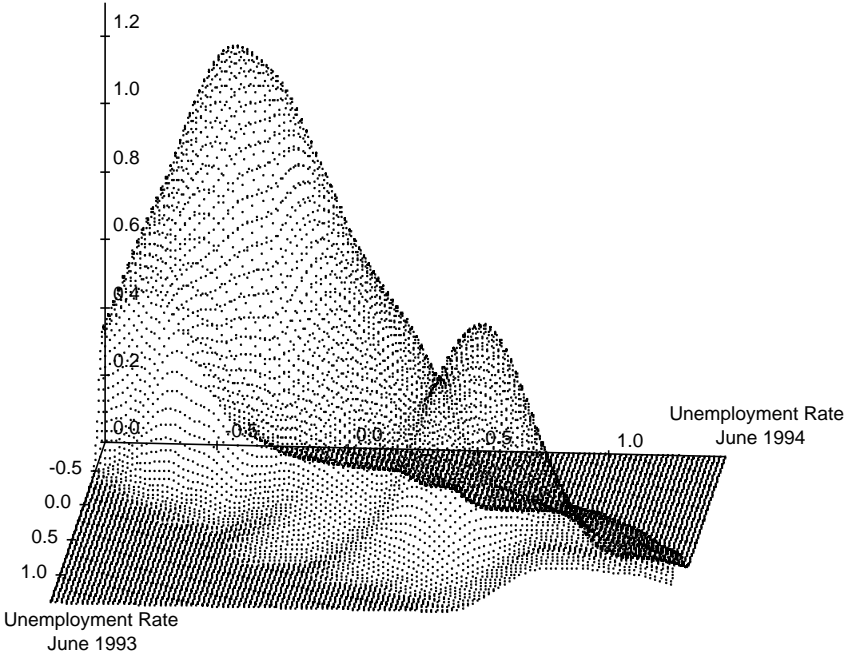
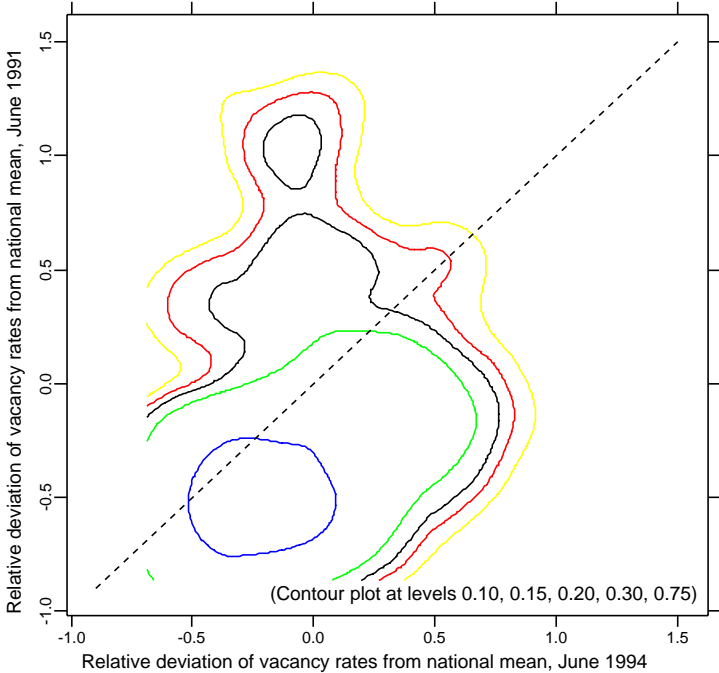
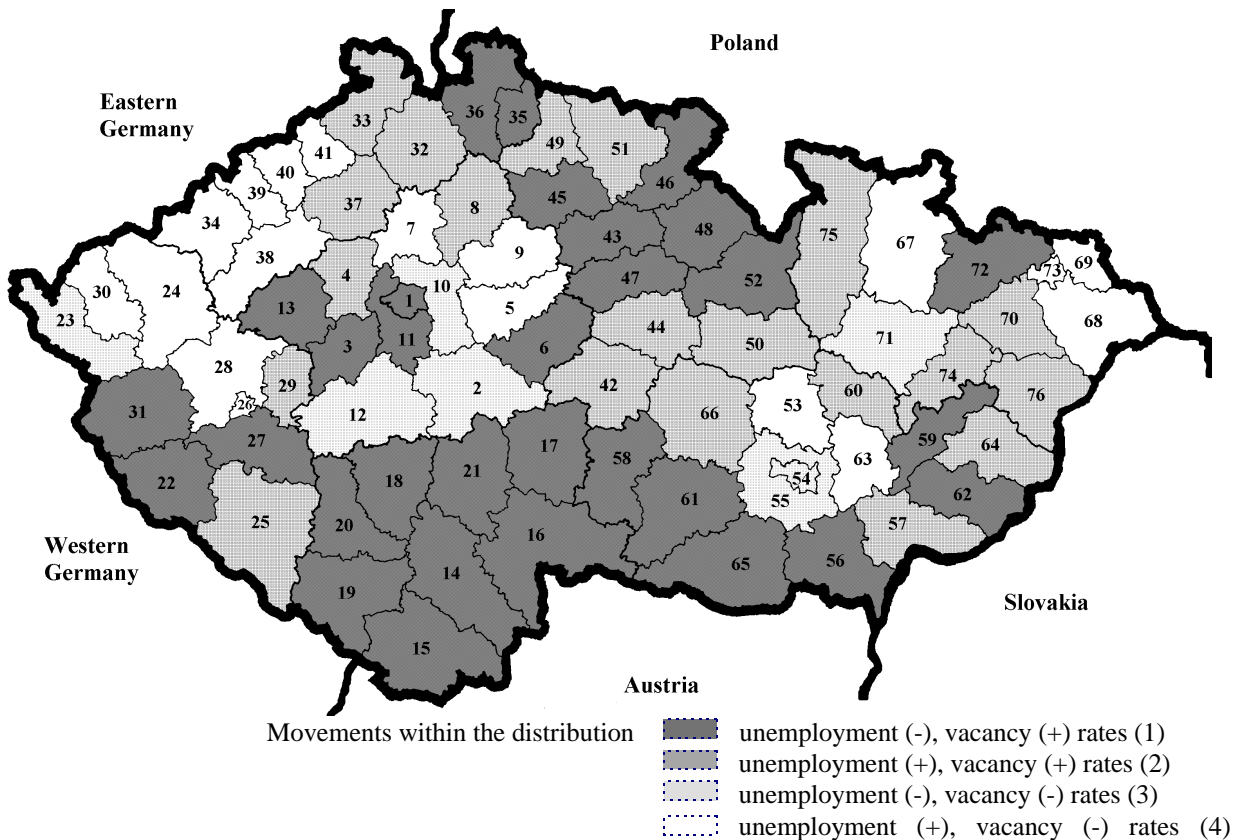
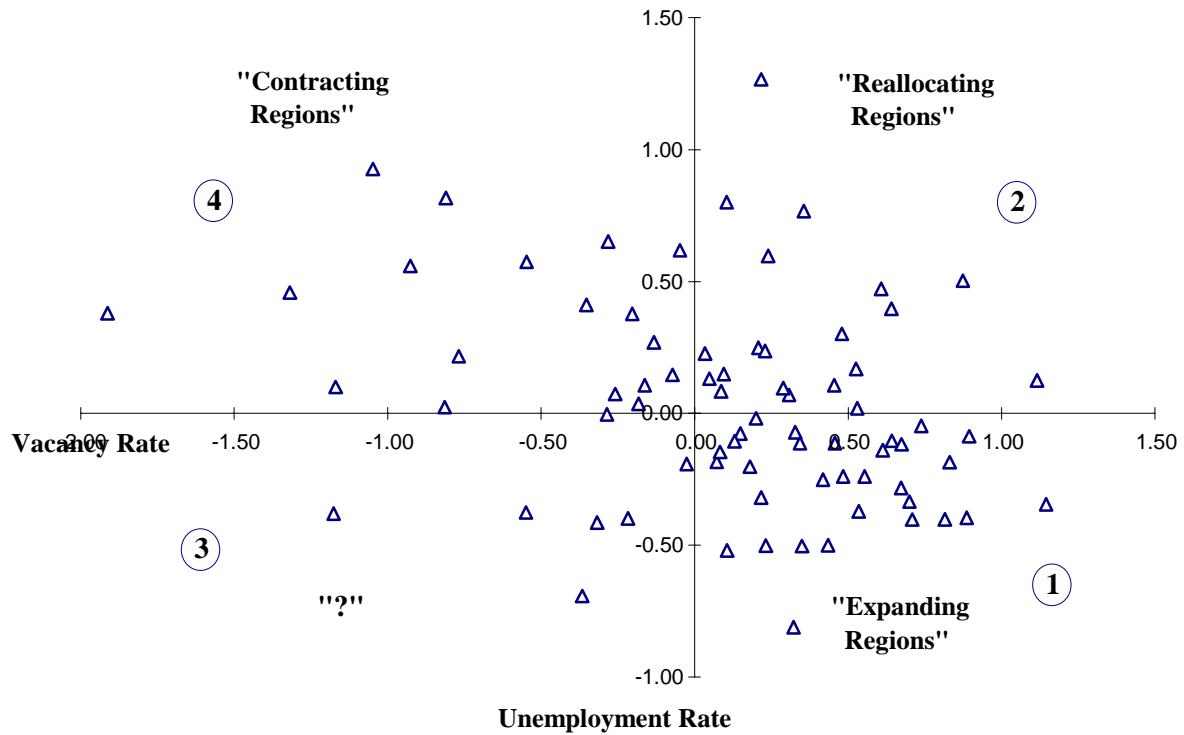


Figure 2.6 Three-year transitions in the cross-district distribution of relative vacancy rate deviations, June 1991 - June 1994



Appendix A.

Intra-distributional Dynamics in Unemployment and Vacancy Rates of Czech districts between 6:1991 and 6:1994



Appendix B.

Dynamic Panel Estimators

After stacking observations, I transform (4.2) to

$$(4.3) \quad \Delta f = [\Delta X : \iota_N \otimes D] \beta + \Delta \varepsilon$$

with

$$\Delta f = \begin{pmatrix} \Delta f_{12} \\ \vdots \\ \Delta f_{1T} \\ \vdots \\ \Delta f_{NT} \end{pmatrix}, \quad \Delta X = \begin{pmatrix} \Delta f_{11} & \Delta u_{11} & \Delta v_{11} \\ \vdots & \vdots & \vdots \\ \Delta f_{1T-1} & \Delta u_{1T-1} & \Delta v_{1T-1} \\ \vdots & \vdots & \vdots \\ \Delta f_{NT-1} & \Delta u_{NT-1} & \Delta v_{NT-1} \end{pmatrix}, \quad \Delta \varepsilon = \begin{pmatrix} \Delta \varepsilon_{12} \\ \vdots \\ \Delta \varepsilon_{1T} \\ \vdots \\ \Delta \varepsilon_{NT} \end{pmatrix},$$

and

$$D = \begin{pmatrix} 1 & 0 & & & 0 \\ -1 & 1 & & & \\ 0 & -1 & \ddots & & \\ & & \ddots & 1 & 0 \\ & & & -1 & 1 \\ 0 & & & 0 & -1 \end{pmatrix}, \quad \iota_N = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}, \quad \beta = \begin{pmatrix} \gamma \\ \alpha_1 \\ \alpha_2 \\ \mu_1 \\ \vdots \\ \mu_{T-1} \end{pmatrix}.$$

The $N(T-1) \times T-1$ matrix $\iota_N \otimes D$ captures time fixed effects. The instrument matrix Z equals $[\Delta X : \iota_N \otimes D]$ except for the first column which is replaced by Δf_{-2} , or f_{-2} respectively. The Anderson-Hsiao estimator is obtained from

$$(4.4) \quad \hat{\beta}_{AH} = (Z' [\Delta X : \iota_N \otimes D])^{-1} Z' \Delta f$$

and the covariance matrix is estimated as

$$(4.5) \quad \hat{V}(\hat{\beta}_{AH}) = \hat{\sigma}^2 \left\{ [\Delta X : \iota_N \otimes D]' Z (Z' Z)^{-1} Z' [\Delta X : \iota_N \otimes D] \right\}^{-1},$$

where $\hat{\sigma}^2 = 1/(NT - K)(\Delta \varepsilon' \Delta \varepsilon)$ and K is the number of columns of $[\Delta X : \iota_N \otimes D]$. Arellano and Bond (1991) suggested a more efficient estimator which exploits a larger set of moment conditions. This estimator is "most semi-asymptotically efficient" among available IV estimators,

which use lagged values of the dependent variable as instruments (Sevestre and Trognon, 1992 ; Harris and Mátyás, 1996). The estimator is given by

$$(4.6) \quad \hat{\beta}_{AB} = \left([\Delta X : \iota_N \otimes D]' \tilde{Z} \psi \tilde{Z}' [\Delta X : \iota_N \otimes D] \right)^{-1} [\Delta X : \iota_N \otimes D]' \tilde{Z} \psi \tilde{Z}' \Delta f,$$

and the covariance matrix of this estimator is obtained from

$$(4.7) \quad \hat{V}(\hat{\beta}_{AB}) = \hat{\sigma}^2 \left([\Delta X : \iota_N \otimes D]' \tilde{Z} \psi \tilde{Z}' [\Delta X : \iota_N \otimes D] \right)^{-1}.$$

The original proposal of Arellano and Bond (1991) is to construct the instrument matrix \tilde{Z}_i as a triangular expansion matrix for lagged dependent and exogenous variables with the s th block equal to $(f_{i0}, \dots, f_{is}, \Delta x_{i1}, \dots, \Delta x_{is+1})$ with $s = 0, \dots, T-2$, the row vector $\Delta x_{it-1} = (\Delta u_{it-1} \Delta v_{it-1} \Delta \mu_t)$ and $\tilde{Z} = (\tilde{Z}_1, \dots, \tilde{Z}_N)$. For the generalized instrumental variable (one-step) estimator the weight matrix ψ takes the form

$$(4.8) \quad \psi = \left(1/N \sum_{i=1}^N \tilde{Z}_i' \Sigma \tilde{Z}_i \right)^{-1} \quad \text{with } \Sigma = \begin{pmatrix} 2 & -1 & & & 0 \\ -1 & \ddots & \ddots & & \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & -1 \\ 0 & & & -1 & 2 \end{pmatrix}.$$

In the presence of heteroscedasticity a two-step general method of moments estimator is more efficient: first, regression residuals are obtained from a consistent one-step estimator, like (4.6). The weight matrix of GMM(2) is then defined as

$$(4.9) \quad \psi = \left(1/N \sum_{i=1}^N \tilde{Z}_i' \Delta \hat{\epsilon}_i \Delta \hat{\epsilon}_i' \tilde{Z}_i \right)^{-1} \quad \text{where } \Delta \hat{\epsilon}_i = (\Delta \hat{\epsilon}_{i2}, \dots, \Delta \hat{\epsilon}_{iT})$$

Appendix C.

Regression Result Updates: 8:1994 - 9:1996

Table 4.2b Regressions in Levels of the Czech Matching Function, # of observations: 1976, N = 76, T=26, Dependent Variable: Log Unemployment-to-Jobs Exits, $\ln f_{it}$

		$\ln f_{it-1}$	$\ln u_{it-1}$	$\ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>B-G(1)</i>
1	Pooled OLS	--	0.842 (84.5)	0.091 (6.7)	0.933	225.1	19.82*	429.2*
2	LSDV, time and district fixed effects	--	0.752 (19.3)	0.109 (4.71)	0.970	56.7	8.68*	98.5*
3	Pooled OLS, dynamic	0.434 (8.6)	0.483 (23.3)	0.051 (4.19)	0.968	176.3	5.64*	6.29*
4	LSDV, time and district fixed effects, dynamic	0.225 (10.9)	0.656 (16.9)	0.084 (3.74)	0.965	53.3	0.45	2.07

Table 4.3b Regressions in first Differences (IV and GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, Instruments: $\ln f_{it-2}$ (resp. $\Delta \ln f_{it-1}$), $\Delta \ln u_{it-1}$, $\Delta \ln v_{it-1}$

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
5	AHIV, time fixed effects, diff. instr.	0.083 (1.60)	2.022 (16.1)	-0.003 (0.08)	2.102	93.4	48.0*	--
6	AHIV, time fixed effects, diff. instr.	0.147 (1.06)	2.095 (10.8)	-0.007 (0.19)	2.235	93.4	15.8*	--
7	GMM(1), time fixed effects, A-B instr. restr. to 2 lags ^{a)}	0.090 (1.04)	1.896 (9.2)	-0.019 (0.57)	1.967	70.2	15.1*	91.7* (42)
8	GMM(2), time fixed effects, A-B instr. restr. to 2 lags	0.078 (3.08)	2.073 (24.2)	-0.025 (9.02)	2.126	69.5	124.9*	46.8 (42)

Table 4.4b Regressions in first Differences (GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, Instruments: $\ln f_{it-2}$, $\Delta \ln u_{it-2}$, $\Delta \ln v_{it-1}$

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
9	GMM(1), time fixed effects, A-B instr. restr. to 2 lags ^{a)}	0.174 (2.40)	0.983 (2.75)	-0.025 (0.82)	1.132	78.8	0.17	72.3* (42)
10	GMM(2), time fixed effects, A-B instr. restr. to 2 lags	0.117 (4.15)	1.219 (8.47)	-0.033 (1.75)	1.303	73.4	5.4*	45.9 (42)

Table 4.5b Regressions in first Differences (GMM), Dependent Variable: Log Unemployment-to-Jobs Exits, $\Delta \ln f_{it}$, Instruments: $(\ln u_{it-3}, \ln v_{it-2})$, 8:1994 - 9:1996

		$\Delta \ln f_{it-1}$	$\Delta \ln u_{it-1}$	$\Delta \ln v_{it-1}$	<i>RTS</i>	<i>SSE</i>	<i>Wald</i>	<i>Sargan</i>
11	GMM(1), time fixed effects, A-B instr., complete ^{a)}	0.172 (2.29)	1.319 (3.88)	0.035 (0.08)	1.526	77.1	2.73	139.4* (83)
12	GMM(2), time fixed effects, A-B instr., complete	0.149 (8.62)	1.351 (39.7)	0.066 (3.70)	1.566	75.4	367.6*	72.6 (83)
13	GMM(1), time fixed effects, A-B instr., complete ^{a)}	0.372 (3.02)	1.827 (3.99)	-0.008 (0.08)	2.191	93.0	5.68*	43.7 (40)
14	GMM(2), time fixed effects, A-B instr., complete	0.335 (11.8)	1.678 (9.59)	-0.038 (0.94)	1.975	89.7	28.4*	44.0 (40)