Working Paper 99-3
Statistics and Econometrics Series 1
January 1999

Departamento de Estadística y Econometría
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax 34 - 91- 624.9849

NON-UNIFORMITY OF JOB-MATCHING IN A TRANSITION ECONOMY - A NONPARAMETRIC ANALYSIS FOR THE CZECH REPUBLIC

Stefan Profit and Stefan Sperlich*

Abstract

In this study, we explore the properties and development of the matching technology in the Czech Republic during the transition to a market economy. Nonparametric additive modelling allows us assess flexible functional forms, which comprise for instance CES and translog specifications. This enable us to evaluate the matching process locally for each combination of unemployment vacancies rather than being restricted to global coefficients. Special interest is devoted to analysis and economic determinants of regional variation in the returns to scale of the marching function. We find non-linearities in the partial adjustment process of unemployment outflows, and a negative coefficient on vacancies in some years. Moreover, we find locally increasing returns to scale in job-marching. Returns to scale are found to be negatively correlated to the share in employment in services and to outmigration, positively correlated to the employment share in industry, the unemployment rate and various measures of active labor market policies.

Key Words

Job-matching; returns to scale; nonparametric analysis; separability; marginal integration; Czech Republic.

*Profit,Humboldt-Universität zu Berlin, Germany e-mail: profit@wiwi.hu-berlin.de; Sperlich, Department of Statistics and Econometrics, Universidad Carlos III de Madrid, Spain, e-mail: stefan@est-econ.uc3m.es. *JEL Classification:* C14, C52, J64. This research was financially supported by the Deutsche Forschungsgemeinschaft, Sonderforschungsbereich 373 "Quantification und Simulation Ökonomischer Prozesse" at Humboldt-Universität Berlin. We thanks Knut Bartels, Michael Burda, Antje Mertens and Olaf Bunke for helpful discussion and comments.

1 Introduction

The emergence of open unemployment in central and eastern European economies during the transformation process has created the need to establish modern institutions which provide a framework for worker and job flows on these newly created marketplaces. The question, whether job and worker reallocation in transition economies have evolved to exhibit a similar pattern known from western European labor markets, has been subject to extensive research in recent years. Empirical investigations of the aggregate matching function have frequently been used in this context, (see Burda (1994), Boeri and Burda (1996), Burda and Profit (1996), Münch, Svenjar and Terrell (1995) for studies on Czech labor markets).

Most previous studies have failed to account sufficiently for the heterogeneity of matching technologies: differences may not only appear in regional and district fixed effects but also in marginal effects of the matching factors. In addition, it is plausible that labor market reforms in transition economies have not evolved uniformly since the outset of the transformation period, and returns to scale may vary geographically and over time. Considering this heterogeneity in the matching technology is important, since a misspecified model renders misleading empirical results. Such flexibility enables us to evaluate the local properties of the job-matching. For example, finding locally increasing returns to scale for certain regions and periods, even with constant and decreasing returns to scale on aggregate, may induce multiple equilibria.[1]

The main contribution of this study is to present a mainly data adaptive analysis of the matching function with a minimum of restrictions on the empirical model.[2] Recently developed marginal integration techniques (going back to Tjøstheim and Auestad (1994)) allow for nonparametric analysis, which avoids so far necessary restrictive assumptions of parametric modelling. The motivation here is not to prove in a statistical sense that the linearized economic model is misspecified. We simply do not need the linear specification for our analysis nor is it necessary to maintain the linear model from an economic theory point of view.

Section 2 provides a brief survey of recent theoretical and empirical studies on job-matching. Section 3 introduces the nonparametric methods we will apply. In Section 4 we discuss potential problems with the data and present estimation results a parametric benchmark model. Section 5 summarizes the nonparametric results and estimates of returns to scale for the Czech matching function. Section 6 concludes.

[1] See Weder(1997) for a similar argument concerning the effects of increasing returns to scale in production in some sectors for the economy as a whole.

[2] The only assumptions are continuity of marginal effects and absence of higher order interaction.

2 Theory and Evidence on Job-Matching in Transition Economies

An analytical tool frequently applied to describe the process of unemployed workers' transition to jobs is the matching function. It models job-matches over an incremental time interval as a function of the number of total unemployed and vacancies in a well-defined labor market, $F = G(U, V)$, where F is the number of matches between unemployed job-seekers and firms, U is the stock of unemployed, V the stock of vacancies and G the matching function. Assuming that the job-search behavior of workers and firms can be described by a random sampling process, the matching function G can be shown to exhibit positive derivatives in both arguments (see Hall (1977) and Pissarides (1990)). Empirical studies have usually applied a Cobb-Douglas specification in which factor elasticities describe the marginal linear effects of unemployment and vacancies on unemployment exits, and a constant which measures the efficiency of the matching process. Since the matching technology plays a crucial role in determining the equilibrium rate of unemployment, various attempts have been made to parameterize this measure.

Another prominent feature of the matching function generally imposed in theoretical models is the constant returns to scale property (see Mortensen and Pissarides (1994) and Pissarides (1990)). Recently, many studies have challenged the validity of assumptions concerning the functional form and returns to scale in job-matching, in particular when it is applied to transition economies. A first group of studies is concerned with the functional form of the matching function, more precisely with the heterogeneity of the unemployment and vacancy pool, and their separability with respect to job-matching. If different types of inputs are not separable, marginal rates of substitution among unemployed and vacancies of separated groups are not independent of the level of inputs in another group (Denny and Fuss (1977) for an analogue application of these concepts to production functions). Boeri (1994) splits the pool of unemployed into long and short spells, and fits a CES function. Boeri (1999), Burgess (1993) and Profit (1997) consider (directly or indirectly) the role of on-the-job search. Storer (1994) introduces a test of concavity of the matching function as a possibility to differentiate a job-search from a simple queuing framework where the short side of the market always serves as the rationing factor. Another set of studies tries to fit more flexible translog functions of the matching technology (Warren (1995) and Münch, Svenjar and Terrell (1998)). This approach has been extensively used to estimate production functions (see Berndt and Christensen (1973) and Christensen, Jorgensen and Lau (1973)), and allows for interactions among production factors. Finally, Coles and Smith (1994) and Gregg and Petrongolo (1997) present models which drop the assumption of random sampling and re-specify the matching function such that the stock of vacancies is matched with the flow of newly unemployed and the unemployment stock with vacancy inflows.

A second group of studies is concerned with biases of matching parameters due to (dis-)aggregation. Courtney (1992) estimates matching functions on a sectoral level. Burda and Profit (1996) and Burgess and Profit (1998) show that generalizing the matching function to a multi-regional setting, and allowing for spatial spillovers, yield complex functional forms which possibly exhibit non-constant returns to scale. Burdett, Coles, and van Ours (1994) argue that standard estimates of matching parameters underestimate the underlying coefficients as a result of temporal aggregation. Finally, another set of studies underlines the importance of considering the time-series properties of unemployment-to-job transitions by estimating dynamic versions of the matching function (Baker, Hogan and Ragan (1996), Profit (1997) and Münch, Svenjar and Terrell (1998)).

Most empirical studies on the matching function have found constant or mildly increasing returns to scale (Blanchard and Diamond, 1989). Investigation in this property is important since increasing returns to matching have been identified as a necessary (though not sufficient) condition for multiple equilibria in unemployment rates (Diamond (1982) and Pissarides (1986)). Profit (1997) has suggested that increasing returns may have been responsible for the appearance of equilibria of high and low unemployment rates across labor market districts in the Czech Republic during the transformation process. Münch, Svenjar and Terrell (1998) argue that increasing returns to job-matching may be responsible for the superior performance of Czech labor markets compared to those in other central and eastern European countries.

While most studies treat the matching technology as a black-box, this paper aims at exploring non-uniformities through nonparametric estimation and testing. Our specification covers all commonly used models for the estimation of production or matching functions (see Fuss, McFadden and Mundlak (1978)). Furthermore, this approach allows us to analyze returns to scale for each combination of matching factors, and to study regional and temporal regularities of unemployment outflows in Czech labor markets. In particular, regional variations of returns to scale in the matching function of the Czech Republic are related to a set of structural economic characteristics and policy measures.

3 Nonparametric Estimation and Testing in Additive Models

In this section we give a brief introduction to the nonparametric methods for regression estimation and testing we use in this paper. These methods were developed, shown to be consistent, empirically studied and discussed in Severance-Lossin and Sperlich (1997), Sperlich, Tjøstheim and Yang (1998) and Sperlich, Linton and

Härdle (1997).

3.1 Nonparametric Regression Estimation

We consider an additive regression model with arbitrary but smooth functions f_α and allow for interaction terms $f_{\alpha\beta}$. The underlying model is

$$Y = m(X) + \sigma(X)\varepsilon \quad , \tag{1}$$

$$m(x) = c + \sum_{\alpha=1}^{d} f_\alpha(x_\alpha) + \sum_{1\le\alpha<\beta\le d} f_{\alpha\beta}(x_\alpha, x_\beta) \ , \tag{2}$$

where $X = (X_1, \dots, X_d)$ is a vector of explanatory variables, ε is independent of X with $E(\varepsilon) = 0$ and $Var(\varepsilon) = 1$ and Y is the response vector. [3]

Stone (1985) has proved that in these models f_α ($f_{\alpha\beta}$) can be estimated with the one (two) dimensional rate. Thus, such a model does not suffer from the curse of dimensionality, typical for nonparametric methods in higher dimensions. Traditionally, additive models have been estimated by using backfitting (Hastie and Tibshirani (1990)), but recently the method of marginal integration (Linton and Nielsen (1995), Newey (1994), Tjøstheim and Auestad (1994)) has attracted a fair amount of attention. In this paper we also focus on the latter approach since for this kind of estimator, theory for derivative estimation (Severance-Lossin and Sperlich (1997)), estimation of interaction terms and testing their significance (Sperlich, Tjøstheim and Yang (1998)) has already been developed. These tools are extremely useful for an economic analysis of production or matching functions.

In expression (2), $\{f_\alpha(\cdot)\}_{\alpha=1}^{d}$ and $\{f_{\alpha\beta}(\cdot)\}_{1\le\alpha<\beta\le d}$ are real-valued unknown functions. They are only uniquely identified when we fix them in the vertical direction and adjust the constant c accordingly. So for each α we set these functions to be centered, i.e.

$$Ef_\alpha(X_\alpha) = \int f_\alpha(x_\alpha)\varphi_\alpha(x_\alpha)dx_\alpha = 0, \tag{3}$$

and for all $1 \le \alpha < \beta \le d$,

$$\int f_{\alpha\beta}(x_\alpha, x_\beta)\varphi_\alpha(x_\alpha)dx_\alpha = \int f_{\alpha\beta}(x_\alpha, x_\beta)\varphi_\beta(x_\beta)dx_\beta = 0. \tag{4}$$

Here, $\{\varphi_\alpha(\cdot)\}_{\alpha=1}^{d}$ are marginal densities of the X_α's (assumed to exist). This is no restriction since any model equivalent to (2) can be transformed accordingly (see Appendix).

Let $X_{\underline{\alpha}}$ be the $(d-1)$-dimensional random variable obtained by removing X_α from $X = (X_1, \dots, X_d)$, and let $X_{\underline{\alpha\beta}}$ be defined analogously. With some abuse of notation

[3] For small samples it could be happen that such a model is not uniquely identified, i.e. the observed data could span a subspace only. This should be checked by an investigation of the sample distribution before starting with the intended estimation.

we write $X = (X_\alpha, X_\beta, X_{\underline{\alpha\beta}})$, respectively $X = (X_\alpha, X_{\underline{\alpha}})$. We denote the (marginal) density of $X_{\underline{\alpha\beta}}$ and of X by $\varphi_{\underline{\alpha\beta}}(x_{\underline{\alpha\beta}})$ and $\varphi(x)$.

The marginal effects of x_α, x_β and (x_α, x_β) can be defined by integration as

$$F_\alpha(x_\alpha) = \int m(x_\alpha, x_{\underline{\alpha}})\varphi_{\underline{\alpha}}(x_{\underline{\alpha}})dx_{\underline{\alpha}}, \tag{5}$$

for every $1 \leq \alpha \leq d$ and

$$F_{\alpha\beta}(x_\alpha, x_\beta) = \int m(x_\alpha, x_\beta, x_{\underline{\alpha\beta}})\varphi_{\underline{\alpha\beta}}(x_{\underline{\alpha\beta}})dx_{\underline{\alpha\beta}}, \tag{6}$$

for every pair $1 \leq \alpha < \beta \leq d$. Notice that F_α corresponds up to a constant to f_α and $F_{\alpha\beta} - F_\alpha - F_\beta$ to $f_{\alpha\beta}$.The exact identification of the model can be found in the Appendix.

It is obvious then to estimate the marginal influences by

$$\widehat{F}_\alpha(x_\alpha) = \frac{1}{n}\sum_{l=1}^{n} \widehat{m}(x_\alpha, X_{l\underline{\alpha}}) \quad , \quad \widehat{F}_{\alpha\beta}(x_\alpha, x_\beta) = \frac{1}{n}\sum_{l=1}^{n} \widehat{m}(x_\alpha, x_\beta, X_{l\underline{\alpha\beta}}), \tag{7}$$

where $X_{l\underline{\alpha\beta}}$ ($X_{l\underline{\alpha}}$) is the l^{th} observation of X with X_α and X_β (X_α) removed. To estimate these expressions we use kernel smoother. Imagine the X-variables to be equally scaled so that we can choose the same bandwidth h for the directions represented by α, β and g for $\underline{\alpha\beta}$. Further, let K and L be kernel functions and define $K_h(\cdot) = \frac{1}{h}K(\cdot/h)$ and $L_g(\cdot) = \frac{1}{g}L(\cdot/g)$. The same letters K, L are used to denote kernel functions of varying dimensions. It will be clear from the context what the dimensions are in each particular case.

To compute the pre-estimator $\widehat{m}(x_\alpha, X_{l\underline{\alpha}})$ we make use of a specific kind of multidimensional local polynomial kernel estimation; see Ruppert and Wand (1994) for the general case. When we speak of a local quadratic estimator at point x_α, we consider the problem of minimizing

$$\sum_{i=1}^{n}\{Y_i - a_0 - a_1(X_{i\alpha} - x_\alpha) - a_2(X_{i\alpha} - x_\alpha)^2\}^2 K_h(X_{i\alpha} - x_\alpha)L_g(X_{i\underline{\alpha}} - X_{l\underline{\alpha}}) \ , \tag{8}$$

for each l fixed. This results in

$$\widehat{m}(x_\alpha, X_{l\underline{\alpha}}) = e_1(Z_\alpha^T W_{l,\alpha} Z_\alpha)^{-1} Z_\alpha^T W_{l,\alpha} Y$$

in which $Y = (Y_1, \ldots, Y_n)^T$, $e_1 = (1, 0, 0)$,

$$W_{l,\alpha} = \mathrm{diag}\left\{\frac{1}{n}K_h(X_{i\alpha} - x_\alpha)L_g(X_{i\underline{\alpha}} - X_{l\underline{\alpha}})\right\}_{i=1}^{n},$$

$$\text{and } \ Z_\alpha = \begin{pmatrix} 1 & X_{1\alpha} - x_\alpha & (X_{1\alpha} - x_\alpha)^2 \\ \vdots & \vdots & \vdots \\ 1 & X_{n\alpha} - x_\alpha & (X_{n\alpha} - x_\alpha)^2 \end{pmatrix}.$$

Notice that this is a local quadratic estimator in the direction α and a local constant one for the other directions. By centering $\widehat{F}_\alpha$ we obtain the estimator $\hat{f}_\alpha$. If we set $a_2 = 0$ in (8) before minimizing the expression, we obtain a local linear estimator. To estimate the first derivative of f_α we can simply take

$$\widehat{f'_\alpha} = \widehat{F'_\alpha}(x_\alpha) = \frac{1}{n}\sum_{l=1}^{n} e_2(Z_\alpha^T W_{l,\alpha} Z_\alpha)^{-1} Z_\alpha^T W_{l,\alpha} Y,$$

with $e_2 = (0, 1, 0)$.

Similarly, we obtain the pre-estimator for interactions from (7):

$$\widehat{m}(x_\alpha, x_\beta, X_{l\underline{\alpha\beta}}) = e_1(Z_{\alpha\beta}^T W_{l,\alpha\beta} Z_{\alpha\beta})^{-1} Z_{\alpha\beta}^T W_{l,\alpha\beta} Y$$

in which, for the local linear case, $e_1 = (1, 0, 0)$,

$$W_{l,\alpha\beta} = \operatorname{diag}\left\{\frac{1}{n} K_h(X_{i\alpha} - x_\alpha, X_{i\beta} - x_\beta) L_g(X_{i\underline{\alpha\beta}} - X_{l\underline{\alpha\beta}})\right\}_{i=1}^{n},$$

$$\text{and} \quad Z_{\alpha\beta} = \begin{pmatrix} 1 & X_{1\alpha} - x_\alpha & X_{1\beta} - x_\beta \\ \vdots & \vdots & \vdots \\ 1 & X_{n\alpha} - x_\alpha & X_{n\beta} - x_\beta \end{pmatrix}.$$

These estimators are consistent if the underlying model is of the form (2). They converge with the one, respectively two dimensional rate. Even if the model has not this kind of additive structure, the estimates still give the marginal influences of the input variables. But certainly then the sum of these functions is no longer a good estimator for the regression function m. Explicit theorems and proofs can be found in Severance-Lossin and Sperlich (1997) and Sperlich, Tjøstheim and Yang (1998).

In small samples these estimators can have a non-negligible bias, especially in areas where data are sparse (in the multidimensional space). There the estimates often have to oversmooth. But taking a local linear smoother we can at least estimate linear functions and thus the linear influence or direction unbiased. The same holds for estimating derivatives if we take local quadratic kernel smoothers. For a further discussion of the behavior of these nonparametric methods in additive models and of small sample properties, see Sperlich, Linton and Härdle (1997).

3.2 Testing for Interaction using Nonparametric Methods

Proceeding from model (2), we present a significance test for the interaction terms $f_{\alpha\beta}$. First, define the auxiliary function

$$\tilde{f}_{\alpha\beta}(x_\alpha, x_\beta) := F_{\alpha\beta}(x_\alpha, x_\beta) - F_\alpha(x_\alpha) - F_\beta(x_\beta) + \int m(x)\varphi(x)dx = f_{\alpha\beta}(x_\alpha, x_\beta) + c_{\alpha\beta}$$

which fulfills $\widetilde{f}_{\alpha\beta}(x_\alpha, x_\beta) \equiv 0 \iff f_{\alpha\beta}(x_\alpha, x_\beta) \equiv 0$, compare (12). Thus for testing the presence of the interaction term $f_{\alpha\beta}(x_\alpha, x_\beta)$ we check whether

$$\int \widehat{\widetilde{f}}^2_{\alpha\beta}(x_\alpha, x_\beta)\varphi_{\alpha\beta}(x_\alpha, x_\beta)dx_\alpha dx_\beta \neq 0$$

where[4]

$$\widehat{\widetilde{f}}_{\alpha\beta}(x_\alpha, x_\beta) = \widehat{F}_{\alpha\beta}(x_\alpha, x_\beta) - \widehat{F}_\alpha(x_\alpha) - \widehat{F}_\beta(x_\beta) + \frac{1}{n}\sum_{j=1}^{n} Y_j. \tag{9}$$

The test statistic we apply is $R = \frac{1}{n}\sum_{i=1}^{n} \widehat{\widetilde{f}}^2_{\alpha\beta}(X_{i\alpha}, X_{i\beta})$.

In Sperlich, Tjøstheim and Yang (1998) this test statistic and its asymptotic distribution is derived. However, for small and moderate sample sizes, typically found in economic applications, one has to be careful when using the asymptotic distribution in practice. The nonparametric test statistic has been known to possess a low degree of accuracy in its asymptotic distribution. In our case we have the additional problem of having unknown expressions in the bias and variance of the test statistic.

One possible alternative, which avoids these shortcomings, is to use the bootstrap or the wild bootstrap, the latter being first introduced by Wu (1986) and Liu (1988). The basic idea is to resample from residuals estimated under the null hypothesis by drawing each bootstrap residual from a two-point distribution which has mean zero, variance equal to the square of the residual and third moment equal to the cube of the residual for all $i = 1, 2, \ldots, n$. Thus, through the use of one single observation one attempts to reconstruct the distribution for each residual separately up to the third moment without additional assumptions on ε or $\sigma(\cdot)$. Drawing n^* bootstrap replications we obtain n^* different test statistics R^* with the same distribution as R under the hypothesis. So we finally can determine a p-value for R.

4 Data and Parametric Analysis

We begin with estimating a parametric benchmark model. Unemployment and vacancy stocks, unemployment inflows and outflows constitute registry data provided by the Czech Ministry of Social and Labor Affairs. The data suffer from the known deficiencies of underreporting of vacancies and exits from the registry due to exhausted benefit eligibility. Moreover, the distribution of the intensity of underreporting is likely to be uneven across districts. On the other hand, the data provide a unique opportunity of mirroring regional labor market processes during transition at a high time frequency.

We regress log unemployment-to-job exits in some labor market district i over period t on log unemployment and vacancies in this district at the beginning of the month.

[4] It follows from the strong law of large numbers that $\frac{1}{n}\sum_{j=1}^{n} Y_j \xrightarrow{a.s.} \int m(x)\varphi(x)dx$.

Accounting for the bias arising from differences in size of districts (Münch, Svenjar and Terrell (1998)), we divide all variables by the size of the labor force at the beginning of the month.[5]

As in Boeri (1994), we account for a diminishing job finding probability of unemployed at longer spells by allowing different matching efficiencies for long-term and newly unemployed. The number of short-term unemployed in period t is approximated with unemployment inflows in period $t-1$, $I_{i,t-1}$. Moreover, we correct the unemployment stock at the end of period $t-1$ with unemployment inflows of the preceding period, hence $U^*_{i,t-1} \equiv U_{i,t-1} - I_{i,t-1}$.

Burda and Lubyova (1995) and Burda and Profit (1996) have demonstrated that residuals of the static Czech matching function show strong serial correlation. This can be explained by a time lag between matching and hiring of workers with firms, and induces a complex partial adjustment pattern to the matching function. We account for these effects by including a lagged dependent variable into the estimation, which removes the serial correlation in residuals (tests are not reported). Finally, we capture the heterogeneity among districts by estimating individual constants for each district, and aggregate time trends by introducing period fixed effects. The parametric benchmark model is then described by the following regression:

$$(10) \quad \ln F_{i,t} = \nu_i + \delta_t + \gamma \ln F_{i,t-1} + \alpha_U \ln U^*_{i,t-1} + \alpha_I \ln I_{i,t-1} + \alpha_V \ln V_{i,t-1} + \epsilon_{i,t},$$

where $\ln F_{i,t}$ are log unemployment to job exits in district i during month t, and $\ln V_{i,t-1}$ is the log number of vacancies at the beginning of the period. ν_i and δ_t are district time and district fixed effects. Moreover, we assume at this point, that $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma^2)$ and $\text{Cov}(\epsilon_{i,t}, \epsilon_{j,s}) = 0 \quad \forall i, j, s, t$ with $i \neq j$ or $s \neq t$ applies.

In such a linear model, allowing for fixed effects is equivalent to applying to each variable the within transformation, which transforms $x_{i,t}$ to $\tilde{x}_{i,t} = x_{i,t} - \overline{x}_{i,\cdot} - \overline{x}_{\cdot,t} + \overline{\overline{x}}_{\cdot,\cdot}$, where $\overline{x}_{i,\cdot}$ and $\overline{x}_{\cdot,t}$ are the respective means over districts and time, $\overline{\overline{x}}_{\cdot,\cdot}$ is the overall mean, and $x_{i,t} \in \{\ln F_{i,t}, \ln F_{i,t-1}, \ln U^*_{i,t-1}, \ln V_{i,t-1}, \ln I_{i,t-1}\}$. This wipes out district and time fixed effects ν_i and δ_t in the regression model. For the ease of notation we keep the name of the variables as above.

Our findings resemble those found in previous studies for the Czech matching function: the coefficient on (long-term) unemployment is positive and highly significant, the coefficient on vacancies is, except for 1992, positive but very small and insignificant in most years. Moreover, we find a positive and significant coefficient of lagged unemployment inflows, which is however smaller than the coefficient on unemployment stocks. This result is at odds with the findings of Boeri (1994) who found a

[5] The size correction is empirically unimportant for the parametric regression .Burdett et al. (1994) and Gregg and Petrongolo (1997) discuss the time aggregation bias arising from using discrete–time data to estimate a continuous–time process. Since we use monthly data, we assume that the time aggregation bias is not too large in our estimates.

higher matching efficiency of newly unemployed. One possible explanation could be that unemployment inflows of the previous period are an inadequate measure for the short-term unemployed. If newly unemployed find new jobs within the same month, as likely in overheated local labor markets such as Prague, previous month's inflows overestimate short-term unemployment in these districts.

Comparing regression over time reveals the instability of matching coefficients. This already implies that structural changes during the transformation process obviously had a strong impact on unemployment-to-job exits, and alter the districts' fixed effects over time. Münch, Svenjar and Terrell (1998) have rejected stability of matching coefficients over the years in a similar specification. Therefore, we estimate the matching function nonparametrically on a year-by-year basis.

LSDV Estimates (dependent variable: ln $F_{i,t}$)

	ln $F_{i,t-1}$	ln $U^*_{i,t-1}$	ln $I_{i,t-1}$	ln $V_{i,t-1}$	RTS	adj Rsq
1992	0.171*	0.527*	0.193 *	-0.009	0.882	0.228
	(0.030)	(0.050)	(0.035)	(0.034)	(3.67)	
1993	0.118*	0.525*	0.224*	0.049	0.916	0.134
	(0.031)	(0.056)	(0.036)	(0.033)	(1.02)	
1994	0.136*	0.783*	0.137*	0.088*	1.144*	0.274
	(0.030)	(0.053)	(0.033)	(0.030)	(5.23)	
1995	0.225*	0.499*	0.122*	0.068	0.914	0.129
	(0.033)	(0.065)	(0.037)	(0.040)	(1.02)	
1996 (Sept.)	0.127*	0.805*	0.149*	0.015	1.096	0.105
	(0.035)	(0.096)	(0.038)	(0.047)	(0.56)	

Table 1: Standard errors are given in parentheses. We had 684 observations in 1996 and 912 in all other years. An F-test for returns to scale is given in parentheses below the returns to scale estimate, asterisks indicate rejection of Null hypotheses at 5% significance.

Recently, increasing returns to scale in job-matching in the Czech Republic were held responsible for the emergence of regional disparities (Profit (1997)) and the superior performance of Czech labor markets compared to other CEECs (Münch, Svenjar, and Terrell (1998)). In particular, both studies showed that accounting for the fixed-effects bias in least squares dummy variable regressions (LSDV) may produce matching coefficients which indicate increasing returns to scale (see also (Nickell (1981)). Table 1 shows, however, that even a simple LSDV regression indicates increasing returns to scale (RTS) in 1994, whereas constant returns to scale cannot be rejected for all other years. Since the nonparametric methods applied in the subsequent section do not yet allow for instrumental variable techniques, we disregard the effect of the Nickell-bias for the rest of this study, and consider returns to scale estimates as lower bounds.

5 Nonparametric Analysis

This section presents a more explorative analysis of the job-matching process on local labor markets in the Czech Republic. To allow for more flexible functional forms we first have to specify the kind of extensions of the linear fixed effects model

$$Y_{it} = \nu_i + \delta_t + X_{it}^T \beta + \epsilon_{i,t},$$

where we gather explanatory variables from (10) in vector X. The probably most general nonparametric model would be the model

$$Y_{it} = \alpha_i + \gamma_t + F(X_{it} + \mu_i + w_t) + \epsilon_{i,t}. \tag{11}$$

Such an extension, but with $\mu_i = w_t = 0$ as e.g. suggested in Porter (1995), would hardly comply with the case of spatial and temporal heterogeneity. We are looking for estimators which fulfill the following conditions: 1. Identifiability of the model, respectively the unknown parameters and functions, 2. nonparametric estimation of F and its partial derivatives having only one observation per district i and time t, and 3. equivalence to the parametric model (10), respectively the mean value corrected analogon.

Since F is flexible and thus shiftable in all directions, we only have to account for fixed effects induced by the variables itself. Therefore, reasonable estimates which fulfill the mentioned conditions are

$$\begin{aligned} \hat{\alpha}_i &= \bar{y}_{i\cdot} + c_1, \quad \hat{\mu}_i = \bar{x}_{i\cdot} + c_3 \\ \hat{\gamma}_i &= \bar{y}_{\cdot t} + c_2, \quad \hat{w}_i = \bar{x}_{\cdot t} + c_4 \end{aligned}$$

where c_1, c_2, c_3 and c_4 are appropriate constants for each element of the explanatory vector. The functional F will be estimated with a kernel smoother decomposed as described in Section 3, equation (2). Notice that this estimation procedure has several additional, partly practical advantages. E.g. the implicit transformation of the arguments of $F(\cdot)$ facilitates a lot the else rather crucial bandwidth choice. Furthermore estimating (11) and (1) is equivalent in the nonparametric world. Therefore and for a direct comparison with the parametric linear model we keep the same notation as in Section 4.

For the interpretation of the nonparametric estimates and comparisons to their parametric counterparts, we show density estimates in Figures 1a to 1e of each transformed exogenous variable and for each year between 1992 and 1996. Note that the 1996 sample only contains observations for January to September. Even with a fairly small bandwidth ($h = 0.05$) all densities appear well behaved and look close to normal. Due to the within transformation, all densities are centered to a value of zero.

Figures 2 to 11 show estimates of additive components, which represent the marginal effects $f_\alpha(x_\alpha)$ in equation (2) where the respective x_α are lagged unemployment-to-job exits, $\ln F_{i,t}$, long- and short-term unemployment and vacancies within each year. Separately estimated derivatives are given in the panel below each marginal effect. The additive components are obtained using a local linear estimator with bandwidths $h = 0.3$ for the direction of interest and $g = 0.6$ for the nuisance directions from 1992 to 1995, and $(h, g) = (0.4, 0.8)$ in 1996, which yield reasonable smoothness.[6] The derivatives are obtained by applying a local quadratic polynomial estimator. There, the bandwidths were set to $(h, g) = (0.5, 0.9)$ between 1992 to 1995, and to $(h, g) = (0.75, 1.2)$ in 1996 respectively.

The two upper-left panels show marginal contribution and derivatives for $\ln F_{i,t-1}$, the upper-right panels plot $\ln U^*_{i,t-1}$, the lower-left panels $\ln V_{i,t-1}$, and the lower-right panels $\ln I_{i,t-1}$. Note that the range of additive components on the vertical axis indicate the strength of the effects. The solid lines in each diagram show the parametric estimate, which are centered at the origin. In addition, derivative plots contain 90% significance intervals from the parametric model as dashed lines. The confidence intervals are constructed using the asymptotics of the parametric estimation.

Interactions among exogenous variables allow for more complex functional forms of the matching function. Economically, estimated interactions provide a basis for testing the separability of matching factors. This concerns first the degree of heterogeneity of the unemployment stock, i.e. the separability between short- and long-term unemployed, and second the separability between newly unemployed and vacancies. If long-term ($\ln U^*_{i,t-1}$) and short-term unemployed ($\ln I_{i,t-1}$) were not separable, aggregating them into a single variable would render a misspecified model, and neglecting interactions would bias the additive components and derivative estimates. Münch, Svenjar and Terrell (1998) consider the special case of multiplicative interactions and reject strong separability among $\ln U^*_{i,t-1}$ and $\ln I_{i,t-1}$ in the Czech Republic except in 1995. Beside the problem of aggregation of $\ln U^*_{i,t-1}$ and $\ln I_{i,t-1}$, significant interaction can provide evidence for non-random job search as inflows of unemployed may only match with the current pool of vacancies, and vice versa (see Coles and Smith (1994), and Gregg and Petrongolo (1997)). Nonparameric interactions among the matching factors are displayed as three-dimensional surfaces following additive components and their derivative plots for each year in Figures 2 to 11. Bandwidths for the estimation of interactions were set according to the estima-

[6]Since we have less observations for 1996, and given a similar support of the densities, larger bandwidths are chosen accordingly. For a detailed discussion of the optimal choice of bandwidths when the integration estimator is applied, see Hengartner (1996) and Sperlich, Linton, Härdle (1997).

tion of the additive components. For the derivation of the bootstrap test statistics R^* for significance of interactions, larger bandwidths have been chosen (see Härdle and Marron (1991)).

The following subsections summarize the results for marginal contributions of each matching factor and the lagged dependent variable, their derivatives and interaction effects.

5.1 Additive Components and Derivative Estimates

The overall impression is that marginal contributions for $\ln U^*_{i,t-1}$ and $\ln I_{i,t-1}$ display the theoretically expected shape and are fairly similar to the parametric coefficients. For the other additive components the nonparametric estimates reveal clear non-linearities which are partly contradictive to economic theory. For 1992 and 1996 regressions the additive components for vacancies seem to be negatively sloped over considerable ranges of the underlying distribution. Moreover, the slopes of several marginal contributions are non-uniform for certain ranges of the respective exogenous variable.

The marginal contribution of the lagged dependent variable $\ln F_{i,t-1}$ appears to be S-shaped or even kinked in some years. For an intermediate range of lagged district outflow rates, the additive component is positively sloped, but somewhat steeper than suggested by the parametric model. This implies a slower adjustment process of unemployment outflows as a response to changes in matching factors. The marginal effect of $\ln F_{i,t-1}$ is the strongest in 1992, which lends support to the hypothesis, that labor market adjustments were much slower in early stages of the transition. However, the partial adjustment process is non-uniform over the whole range of $\ln F_{i,t-1}$. Especially, for districts where the fraction of vacancies to labor force is small, the slope becomes negative, which means that the short-term effect of a change in matching factors overshoots the long-run effects. The higher inertia of unemployment outflows in 1992 is probably due to a malfunctioning job-matching process at the outset of the transition process or to discouragement effects in the job search behavior caused by the generosity of unemployment benefits at that time.

The additive components for $\ln U^*_{i,t-1}$ and $\ln I_{i,t-1}$ both closely resemble the linear estimators from Table 1. However, both marginal contributions show slight S-shapes becoming flatter towards the tails of the distribution of long- and short-term unemployment rates. Moreover, analyzing the location of single observations in multidimensional space spanned by the explanatory variables reveals that these short-run reactions of unemployment exits cannot generally be explained by counter movements in the partial adjustment process. The size of the range of the vertical axis for (long-term) unemployed indicates the importance of these effects.

A comparison of the regression functions for each year between 1992 and 1996 confirms the non-uniformity of job-matching over time already gained from the inspection of Table 1. This is particularly true for vacancies, of which the marginal effect is positive between 1993 and 1995 as expected from matching theory, but negative in 1992 and 1996 at least for certain ranges of the distribution. The non-linearities explain the insignificance of α_V in the parametric regression. The kinked form of the marginal distribution of vacancies in districts with weak job creation during 1992 is only a short-term effect, which is at least for some districts mitigated through the overshooting behavior of unemployment-to-job transitions in this range. Note however that the overall range of the marginal contribution of vacancies on the vertical axis is small compared to the other variables in all years. Derivative estimates lie outside 90% confidence bands in important ranges of the underlying distributions for several matching factors, underlining the superiority of nonparametric estimation in fitting the data for this application.

5.2 Interactions

Together with the single additive components, we have also estimated the contribution of interactions between each pair of explanatory variables (except the autoregressive variable). Plots for all three interactions follow the figures of marginal effects and derivatives for each year. Although interaction surfaces form distinctive shapes, their significance can be formally tested as described in Section 3. These tests indicate that except for 1992, all interactions were far from being significant, i.e. they have p-values of about 45% or more. Only for 1992, strong separability between $\ln U^*_{t-1}$ and $\ln I_{t-1}$ is rejected with a p-value of less than 1%. This is in line with our findings for marginal contributions, which have shown that during 1992 Czech labor markets have behaved quite differently, compared subsequent years as well as compared to theoretical considerations.

5.3 Returns to Scale

Given the insignificance of interaction effects, local returns to scale can be determined directly through summing up the derivatives of all exogenous variables for each observation in the four-dimensional space. [7]

[7] We estimate returns to scale at each observation as

$$RTS = \sum_{\alpha=1}^{d} \frac{\partial m(\mathrm{x})}{\partial x_j} = \sum_{j=1}^{d} \frac{\partial f_j(x_j)}{\partial x_j} + \sum_{j=1}^{d} \frac{\sum_{\beta \neq j} \partial f_{j\beta}(x_j, x_\beta)}{\partial x_j},$$

see Fuss, McFadden and Mundlak (1978). Hence, returns to scale are given by the sum of derivatives on marginal effects and the sum of the partial derivatives of all interactions. The second term in the equation was dropped whenever interactions were insignificant.

Figure 12 shows density estimates of local returns to scale in job-matching for each year. The figures demonstrate that the distribution of local returns to scale is skewed to the left with a single mode clearly above one. For 1992, 43% of all observations exhibit increasing returns to scale. Neglecting the interaction term it is only 37%. In 1993, this fraction increases to 55% in 1993, and 82% in 1994 and 1996 (in 1995 it drops to 41%). In 1995 and 1996, the variance of the distribution of local returns to scale increases compared to previous years. Hence, the nonparametric estimates confirm the findings of slightly increasing returns to job-matching on Czech labor markets as in Profit (1997). Moreover, we find some seasonal variation in returns to scale estimates with higher values during spring and summer (not reported).

The regional pattern of average returns to scale between 1993 and 1995 is shown in Figure 13, where shaded districts indicate increasing returns to scale. Surprisingly, we find a concentration of increasing returns to scale in labor market districts close to the Slovak border, where unemployment rates are above average, and decreasing returns at the German and Austrian border. A possible explanation of the first finding may be that weak vacancy creation constrains job-matching there, since firms search less. Another possible explanation is related to job search behavior of the employed (see Profit (1997)). If employed job seekers adapt their search intensities very elastically to local labor market conditions, job-competition between employed and unemployed job seekers may cease quickly as unemployment rises, resulting in higher returns to scale in the estimation of our reduced–form matching functions.[8] Higher returns to scale at the German and Austrian border may possibly be due to people being in the unemployment register but working illegally abroad.

Table 2 contains simple correlations between average local returns to scale estimates between 1993-1995 to several of economic characteristics of Czech labor market districts. The analysis with respect to employment shares shows that RTS are positively related to the share of industrial but negatively to the share in service sector employment. Moreover, the analysis confirms the impression from Figure 13, that returns to scale are positively correlated to the district unemployment rate. We do not find any significant correlation with real wages, the density of population or the change in industrial production. Only the correlation between RTS and migration rates (in 1994) are weakly significant, supporting the evidence in Burda and Profit (1996). They show that internal mobility induces regional spillovers in the matching function and influences returns to scale.

Finally, Table 2 shows clear evidence, that active labor market policies (ALMP) have a strong impact on the matching technology in the Czech Republic. Higher ALMP expenditures, higher participation in the Publicly Useful Jobs (PUJ), Socially Purposeful Jobs (SPJ), and Training for Youth and School Leavers program (all measured as % of the district labor force) are associated with significantly higher

[8] In the empirical specification job search of employees can not considered since it is not observable.

Correlation with Structural Variables

Variable	Mean	StDev	Correlation with RTS 1993-1995
Employment Share in Agriculture, 1994	0.092	0.050	0.001
Employment Share in Industry, 1994	0.365	0.065	0.258**
Employment Share in Services, 1994	0.200	0.041	−0.254**
Real Wage, in CZK, 1994	4381	318.4	−0.005
Unemployment Rate, June 1993	0.029	0.015	0.229**
Population Density, persons per km^2 1994	210.9	392.8	−0.122
Change in Industrial Production, 1994	−3.39	9.03	0.083
Inmigration as % of Total Pop., 1994	1.046	0.267	−0.177
Outmigration as % of Total Pop., 1994	0.957	0.222	−0.217*
Expenditures on ALMP as % of Labor Force, 1993	156.7	102.8	0.248**
Participants in Publicly Useful Jobs Program (PUJ) as % of Labor Force, 1993	0.103	0.130	0.258**
Participants in Socially Purposeful Jobs (SPJ) as % of Labor Force, 1993	1.757	1.412	0.282**
Participants in Training Programs for Youth and School Leavers as % of Labor Force, 1993	0.425	0.413	0.199*
DLO Staff involved in ALMP, counseling & mediation as % of Labor Force, 1993	0.054	0.013	0.238**
DLO staff involved in Administration as % of Labor Force, 1993	0.039	0.011	0.053

Table 2: One asterisk indicates rejection of Null hypotheses of zero correlation at 10% significance, two at 5%. The SPJ program consists of wage subsidies to employers hiring unemployed workers and assistance to new entrepreneurs. The PUJ is a public employment program which provides temporary jobs to the most difficult-to-employ. See Ham et al.(1995). See text for further explanations.

RTS. Moreover, the analysis shows, that while the provision of District Labor Offices (DLO) with administrative staff has no significant effect on RTS in job-matching, we find a strong and highly significant positive correlation with DLO staff involved in ALMP, job-counseling and mediating employment. This inforces the evidence in Boeri and Burda (1996)

6 Conclusions

The use of nonparametric estimation and testing has enabled us to detect non-uniformities in the job-matching process in the Czech Republic during the transition period. In particular, we find a negatively sloped or hump-shaped marginal contribution of vacancies in some years, which helps to explain why the coefficient on vacancies is small and insignificant in the parametric model. Our analysis has shown that the Czech matching function exhibits mildly increasing returns to scale for important parts of the multidimensional distribution of matching factors. This is an important finding, since "local" returns to scale may be responsible for the emergence of multiple equilibria in unemployment rates. The fact that Czech labor market districts with above average unemployment rates have increasing returns to job-matching is consistent with multiple equilibria with these districts being trapped in a *bad* equilibrium. Another important finding is the positive correlation of active labor market policies (program participation, staffing of district labor offices and ALMP expenditures) and the matching technology in the Czech Republic.

Further research could entail a finer disaggregation of matching factors – for instance with respect to the educational composition of the unemployment pool or vacant positions – to gain more insights into the separability issue or the inclusion of regional spillover effects. Moreover, analyzing the matching process across national borders may help to explain the finding of higher returns to scale in labor market districts neighboring Austria and Germany.

Appendix

We give first a possible transformation for an arbitrary model equivalent to (2) to normalize it in the sense of conditions (3) and (4). Afterwards it is shown that only using the idea of marginal integration, such a model can be identified and estimated uniquely.

Given a function $m(\cdot)$ of the form given in (2) not necessarily satisfying (3) and (4), the following steps could be taken to :

1. Replace all $\{f_{\alpha\beta}(x_\alpha, x_\beta)\}_{1\leq\alpha<\beta\leq d}$ by $\{f_{\alpha\beta}(x_\alpha, x_\beta) - \int f_{\alpha\beta}(x_\alpha, u)\varphi_\beta(u)du$
$$- \int f_{\alpha\beta}(u, x_\beta)\varphi_\alpha(u)du + \int f_{\alpha\beta}(u, v)\varphi_\alpha(u)\varphi_\beta(v)dudv\}_{1\leq\alpha<\beta\leq d}.$$
2. Replace all $\{f_\beta(x_\beta)\}_{\beta=1}^d$ by $\{f_\beta(x_\beta) - \int f_\beta(u)\varphi_\beta(u)du\}_{\beta=1}^d$
3. and adjust the constant term c accordingly so as to keep $m(\cdot)$ the same function and we end up with an equivalent model fulfilling (3) and (4).

Now we turn to the identification. Remember the definition of marginal integration by (5), respectively (6). Denote by D_α the subset of $\{1, 2, ..., d\}$ with α removed for every $1 \leq \alpha \leq d$. Moreover, let

$$D_{\alpha\alpha} = \{(\gamma, \delta) \mid 1 \leq \gamma < \delta \leq d, \gamma \in D_\alpha, \delta \in D_\alpha\}$$

while

$$D_{\alpha\beta} = \{(\gamma, \delta) \mid 1 \leq \gamma < \delta \leq d, \gamma \in D_\alpha \cap D_\beta, \delta \in D_\alpha \cap D_\beta\}$$

and

$$c_{\alpha\beta} = \int f_{\alpha\beta}(u, v)\varphi_{\alpha\beta}(u, v)dudv \tag{12}$$

for every pair $1 \leq \alpha < \beta \leq d$. Then (3) and (4) entail the following equations:

$$F_\alpha(x_\alpha) = f_\alpha(x_\alpha) + c + \sum_{(\gamma,\delta)\in D_{\alpha\alpha}} c_{\delta\gamma} \tag{13}$$

$$F_{\alpha\beta}(x_\alpha, x_\beta) = f_{\alpha\beta}(x_\alpha, x_\beta) + f_\alpha(x_\alpha) + f_\beta(x_\beta) + c + \sum_{(\gamma,\delta)\in D_{\alpha\beta}} c_{\delta\gamma} \ , \tag{14}$$

which imply:

$$f_{\alpha\beta}(x_\alpha, x_\beta) + c_{\alpha\beta} = F_{\alpha\beta}(x_\alpha, x_\beta) - F_\alpha(x_\alpha) - F_\beta(x_\beta) + \int m(x)\varphi(x)dx$$

$$f_{\alpha\beta}(x_\alpha, x_\beta) = F_{\alpha\beta}(x_\alpha, x_\beta) - F_\alpha(x_\alpha) - \int \{F_{\alpha\beta}(u, x_\beta) - F_\alpha(u)\} \varphi_\alpha(u)du$$

and finally

$$c_{\alpha\beta} = \int \{F_{\alpha\beta}(u, x_\beta) - F_\alpha(u)\} \varphi_\alpha(u)du - F_\beta(x_\beta) + \int m(x)\varphi(x)dx \ .$$

So indeed we can identify and consequently estimate all parameters and functions of the underlying model (1),(2).

References

Baker, S., S. Hogan, and C. Ragan (1996) "Is There Compelling Evidence against Increasing Returns to Matching in the Labour Market?," *Canadian Journal of Economics* 29: 976-993.

Berndt, E.R. and L.R. Christensen (1973). "The Internal Structure of Functional Relationships: Separability, Substitution, and Aggregation," *Review of Economic Studies* 40: 403-410.

Blanchard, O.J., and P.A. Diamond (1989). "The Beveridge Curve," Brookings Papers of Economic Activitiy, 26(1): 1-76.

Boeri, T. (1994). "Labour Market Flows and the Persistence of Unemployment in Central and Eastern Europe." In: OECD (ed.), *Unemployment in Transition Countries: Transient or Persistent?*, Paris.

Boeri, T. (1999). "Enforcement of Employment Security Regulation, On-the-Job Search and Unemployment Duration," European Economic Review 43: 65-89.

Boeri, T., and M.C. Burda (1996). "Active Labour Market Policies, Job Matching and the Czech Miracle," *European Economic Review* 40: 805-817.

Burda, M.C. (1994). "Modeling Exits from Unemployment in Eastern Germany: A Matching Function Approach." In: H. König and V. Steiner (eds.), *Arbeitsmarktdynamik und Unternehmensentwicklung in Osteuropa*, Baden-Baden: Nomos.

Burda, M.C., and S. Profit (1996). "Matching Across Space: Evidence on Mobility in the Czech Republic," *Labour Economics*, 3: 255-278.

Burdett, K., M. Coles, and J. van Ours (1994). "Temporal Aggregation Bias in Stock–Flow Models," *CEPR Discussion Paper* No. 967.

Burgess, S. (1993a) "A Model of Competition between Unemployed and Employed Job Searchers," *Economic Journal* 103: 1190-1204.

Burgess, S. and S. Profit (1998) "Externalities in the Matching of Workers and Firms in Britain," *mimeo.*

Christensen, L.R., D.W. Jorgensen, and L.J. Lau (1973). "Transcendental Logarithmic Production Frontiers," *Review of Economics and Statistics* 55: 28-45.

Coles, M.G., and E. Smith (1998). "Market Places and Matching," *International Economic Review* 39: 239-255.

Courtney, H.G. (1992). "Returns to Scale in Aggregate and Regional Job-Matching Functions," *mimeo*, Washington University, November.

Denny, M., and M. Fuss (1977). "The Use of Approximation Analysis to Test for Separability and the Existence of Consistent Aggregates," *American Economic Review* 67: 404-418.

Diamond, P. (1982). "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy* 90: 881-893.

Fuss, M., D. McFadden, and Y. Mundlak (1978). "A Survey of Functional Forms in the Economic Analysis of Production." In: M. Fuss and D. McFadden (eds.), *Production Economics: A Dual Approach to Theory and Applications*, Vol. 1, North-Holland.

Gregg, P. and B. Petrongolo (1997). "Random or Non-Random Matching? Implications for the UV Curve as a Measure of Matching Effectiveness," *Centre for Economic Performance* No. 348 (June).

Hall, R.E. (1977). "An Aspect of the Economic Role of Unemployment." In: G. Harcourt (ed.), *Microeconomic Foundations of Macroeconomics*, London: MacMillan Press.

Ham, J.,J. Svenjar, and K. Terrell (1995). "Czech Republic and Slovakia," in: S. Commander and F. Coricelli (eds.). *Unemployment, Restructuring, and the Labor Market in Eastern Europe and Russia.* Economic Development Institute of the World Bank, Washington.

Hastie, T.J. and R.J. Tibshirani (1990). *Generalized Additive Models.* London: Chapman and Hall.

Härdle, W. and J.S. Marron (1991). "Bootstrap Simultaneous Error Bars for Nonparametric Regression," *Ann. Statist.* 19: 778-796.

Hengartner, N. (1996). "Rate Optimal Estimation of Additive Regression via the Integration Method in the Presence of Many Covariates", *Working Paper,* Yale

Linton, O.B. and J.P. Nielsen (1995). "A Kernel Method of Estimating Structured Nonparametric Regression based on Marginal Integration," *Biometrika* 82: 93-101.

Liu, R. (1988). "Bootstrap Procedures under Some Non i.i.d. Models," *Ann. Statist.* 16: 1696-1708.

Mortensen, D.T., and C.A. Pissarides (1994). "Job Creation and Job Destruction in the Theory of Unemployment", *Review of Economic Studies* 61: 397-415.

Münich, D., J. Svenjar and K. Terrell (1995). "Regional and Skill Mismatch in the Czech and Slovak Republics." In: OECD (ed.), *The Regional Dimension of Unemployment in Transition Countries*, Paris.

Münich, D., J. Svenjar and K. Terrell (1998). "The Worker-Firm Matching in Transition Economies: (Why) Are The Czechs More Successful than Others?" *Paper presented at a workshop on Labor Markets in Transition at the William Davidson Institute at the University of Michigan Business School*, October.

Newey, W.K. (1994). "Kernel Estimation of Partial Means," *Econometric Theory* 10: 233-253.

Nickell, S. (1981). Biases in Models with Fixed Effects, *Econometrica*, 49: 1417-1426.

Pissarides, C.A. (1986). "Search Intensity, Job Advertising and Efficiency," *Journal of Labor Economics* 2: 128-143.

Pissarides, C.A. (1990). *Equilibrium Unemployment Theory*, Oxford: Basil Blackwell.

Porter, J. (1995). "Essays in Semiparametric Econometrics," *PhD Thesis,* MIT.

Profit, S. (1997). "Twin Peaks in Regional Unemployment and Returns to Scale in Job-Matching in the Czech Republic," *Discussion Paper 63 of the SFB 373, Humboldt Universität zu Berlin, Germany.*

Ruppert, D. and M.P. Wand (1994). "Multivariate Locally Weighted Least Squares Regression," *Ann. Statist.* 22: 1346-1370.

Severance-Lossin, E. and S. Sperlich (1997). "Estimation of Derivatives for Additive Separable Models," *Discussion Paper 30 of the SFB 373, Humboldt-Universität zu Berlin, Germany.*

Sperlich, S., Linton, O. and W. Härdle (1997). "A Simulation Comparison between Integration and Backfitting Methods of Estimating Separable Nonparametric Regression Models," *Discussion Paper 66 of the SFB 373, Humboldt-Universität zu Berlin, Germany.*

Sperlich, S., Tjøstheim, D. and L. Yang (1998). "Nonparametric Estimation and Testing of Interaction in Additive Models," *Discussion Paper of the SFB 373, Humboldt-Universität zu Berlin, Germany.*

Stone, C.J. (1985). "Additive Regression and other Nonparametric Models," *Ann. Statist.* 13: 689-705.

Storer, P. (1994). "Unemployment Dynamics and Labour Market Tightness: An Empirical Evaluation of Matching Function Models," *Journal of Applied Econometrics* 9: 389-419.

Tjøstheim, D. and B.H. Auestad (1994). "Nonparametric Identification of Nonlinear Time Series: Projections," *J. Amer. Statist. Assoc.* 89: 1398-1409.

Warren, R.S. (1996). "Returns to Scale in a Matching Model of the Labor Market," *Economics Letters* 50: 135-142.

Weder, M. (1997). "Fickle Consumers, Durable Goods and the Business Cycle," *Journal of Economic Theory* (forthcoming).

Wu, C.F.J. (1986). "Jackknife, Bootstrap and other Resampling Methods in Regression Analysis," (with discussion) *Ann. Statist.* 14: 1261-1350.

Figures

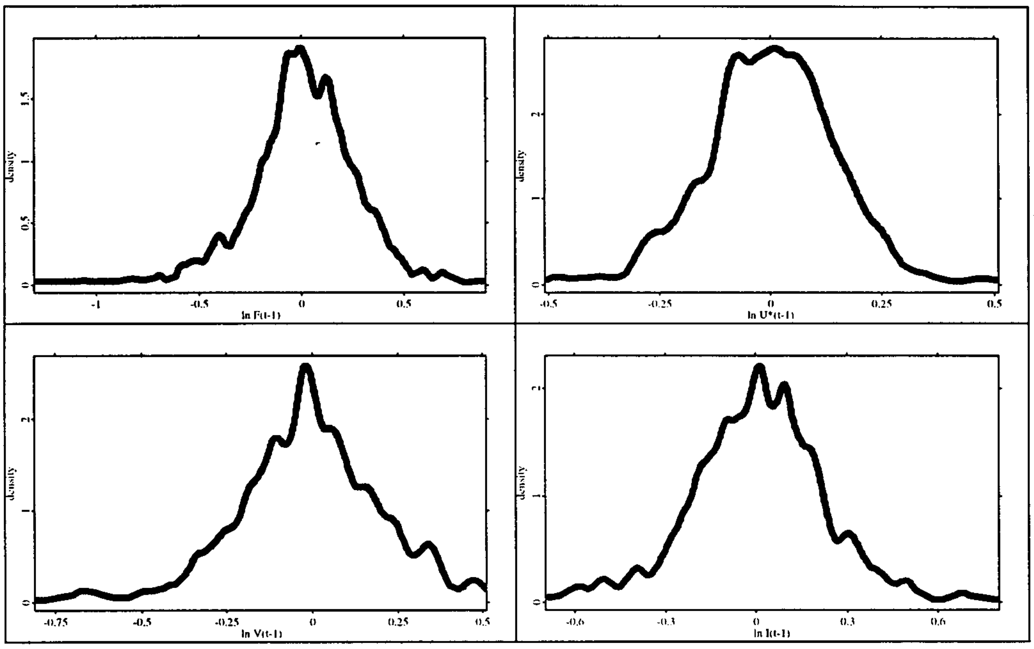


Figure 1a: *Density estimates for 1992, upper left:* $\ln F_{i,t-1}$*, upper right:* $\ln U^{*}_{i,t-1}$*, lower left:* $\ln V_{i,t-1}$*, lower right:* $\ln I_{i,t-1}$

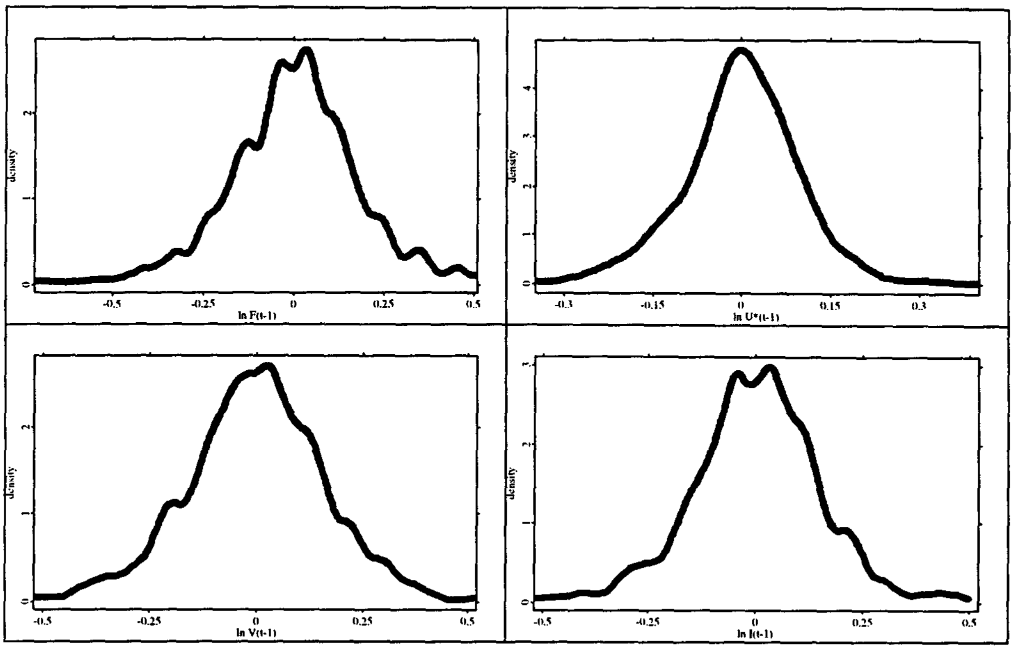


Figure 1b: *Density estimates for 1993, upper left:* $\ln F_{i,t-1}$, *upper right:* $\ln U^*_{i,t-1}$, *lower left:* $\ln V_{i,t-1}$, *lower right:* $\ln I_{i,t-1}$

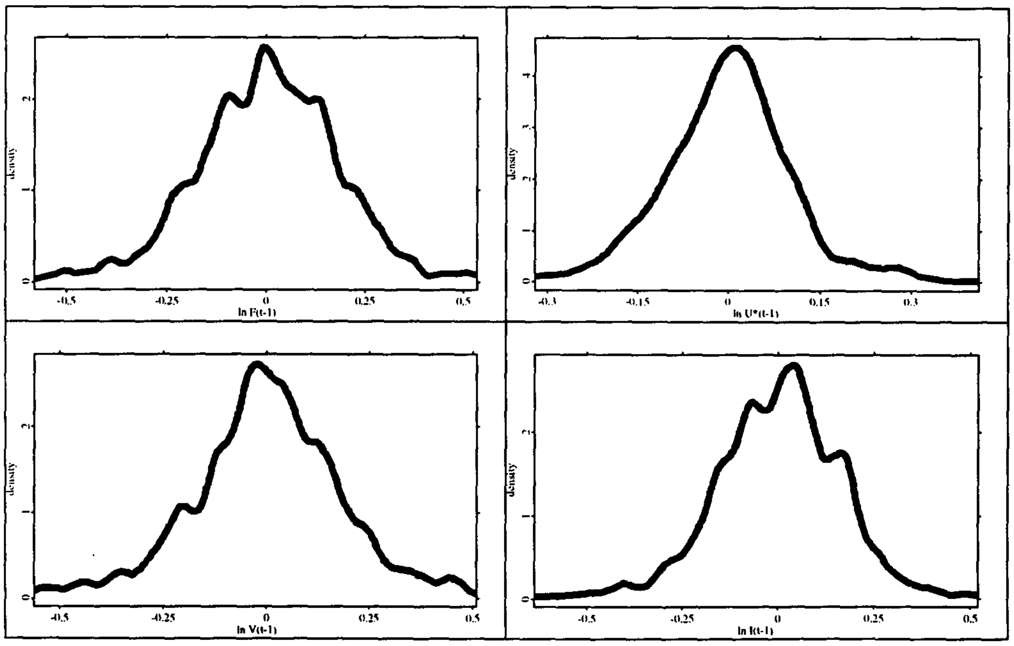


Figure 1c: *Density estimates for 1994, upper left:* $\ln F_{i,t-1}$, *upper right:* $\ln U^*_{i,t-1}$, *lower left:* $\ln V_{i,t-1}$, *lower right:* $\ln I_{i,t-1}$

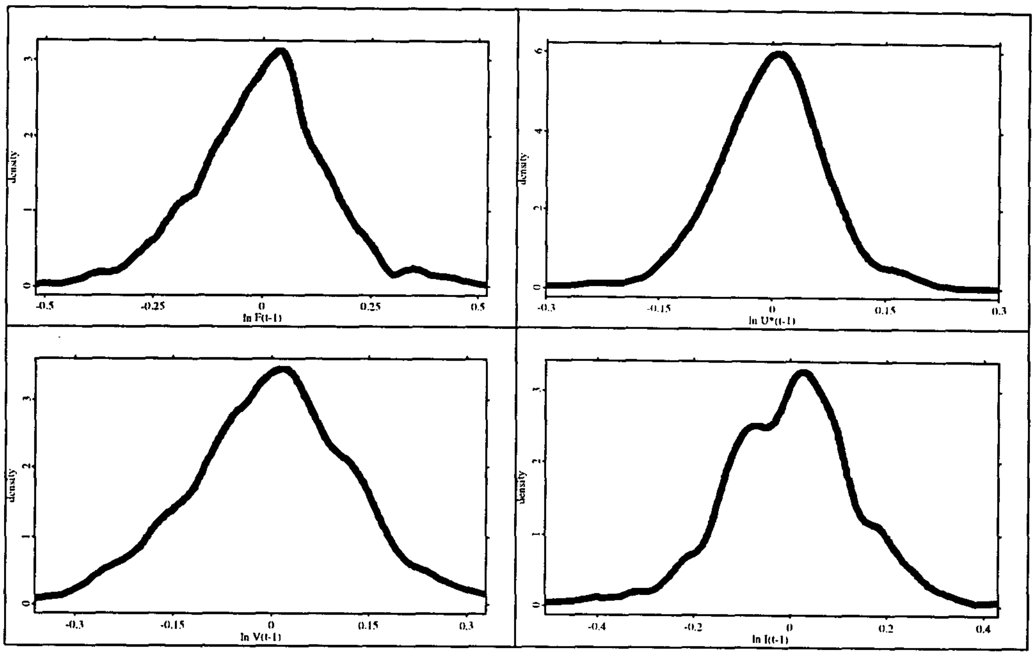


Figure 1d: *Density estimates for 1995, upper left:* $lnF_{i,t-1}$, *upper right:* $lnU^*_{i,t-1}$, *lower left:* $lnV_{i,t-1}$, *lower right:* $lnI_{i,t-1}$

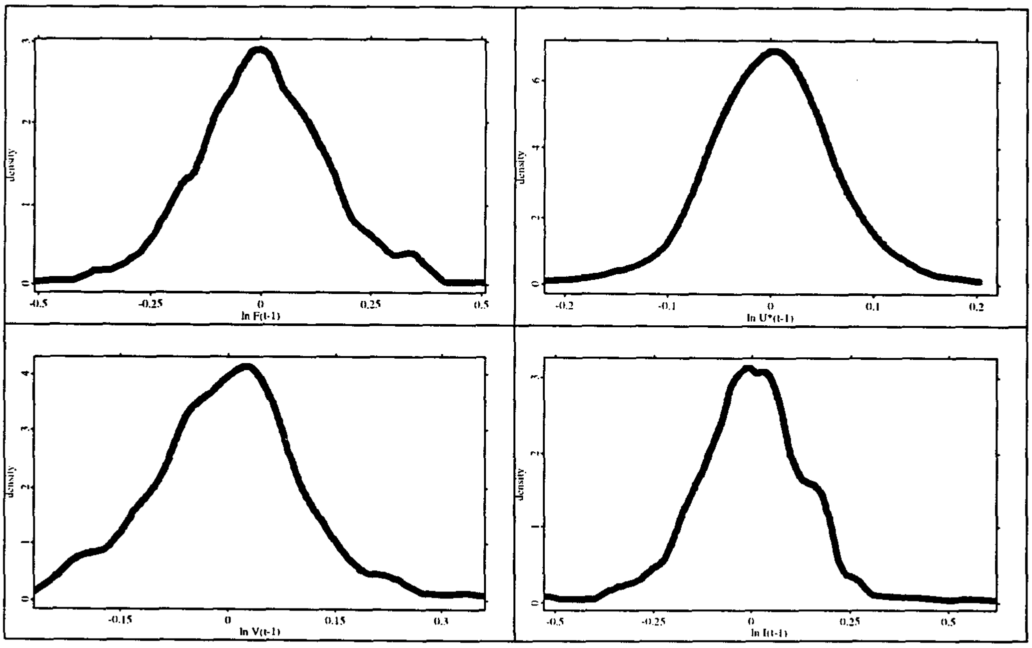


Figure 1e: *Density estimates for 1996, upper left:* $lnF_{i,t-1}$, *upper right:* $lnU^*_{i,t-1}$, *lower left:* $lnV_{i,t-1}$, *lower right:* $lnI_{i,t-1}$

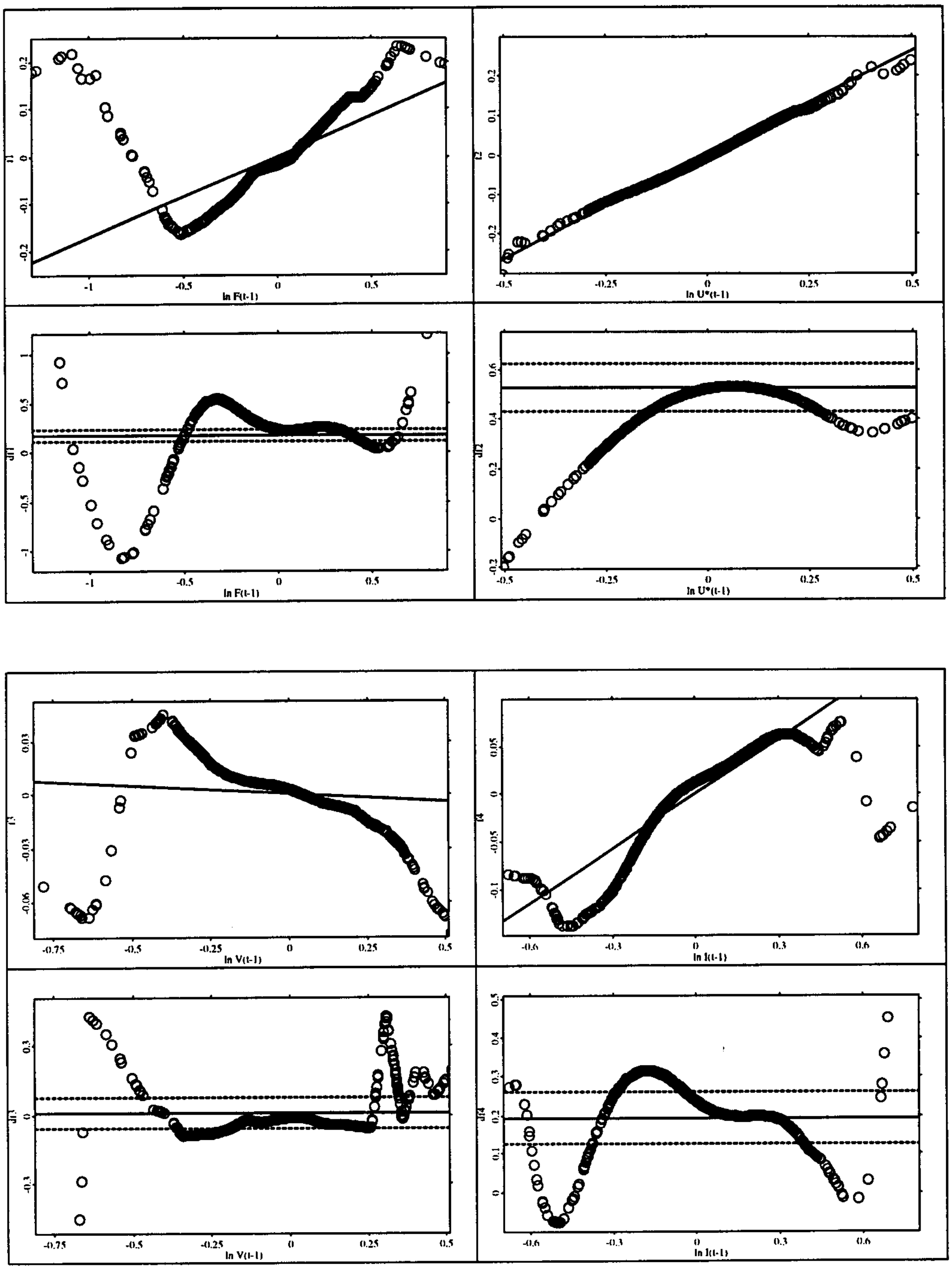


Figure 2: *Estimates of additive components and derivatives (each below the corresponding function) for 1992. Solid lines show parametric estimates, dashed lines in panels with derivative estimates show 90% confidence intervals. Upper left:* $lnF_{i,t-1}$, *upper right:* $lnU^{*}_{i,t-1}$, *lower left:* $lnV_{i,t-1}$, *lower right:* $lnI_{i,t-1}$.

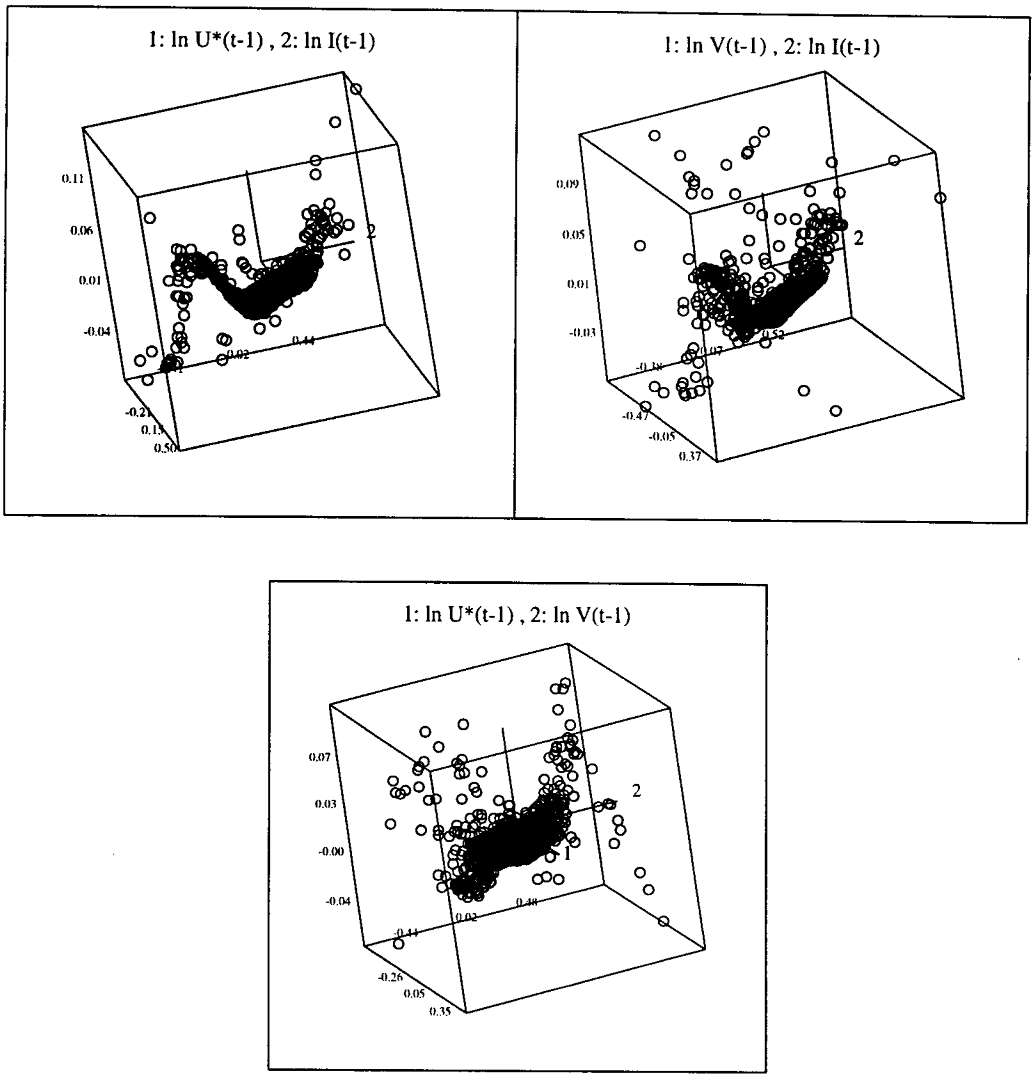


Figure 3: *Estimates of the interaction terms for 1992.*

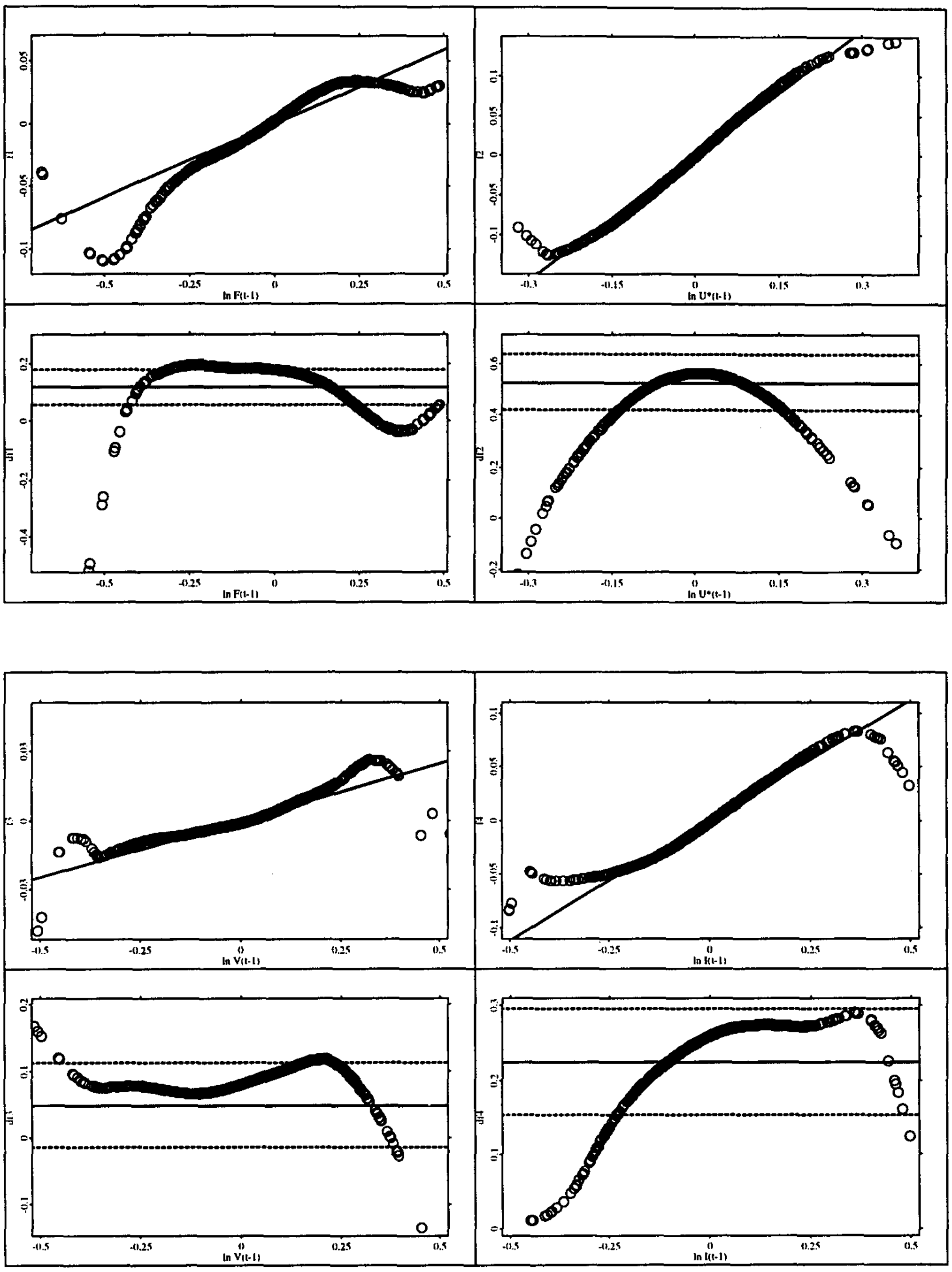


Figure 4: *Estimates of additive components and derivatives (each below the corresponding function) for 1993. Solid lines show parametric estimates, dashed lines in panels with derivative estimates show 90% confidence intervals. Upper left:* $\ln F_{i,t-1}$*, upper right:* $\ln U^*_{i,t-1}$*, lower left:* $\ln V_{i,t-1}$*, lower right:* $\ln I_{i,t-1}$.

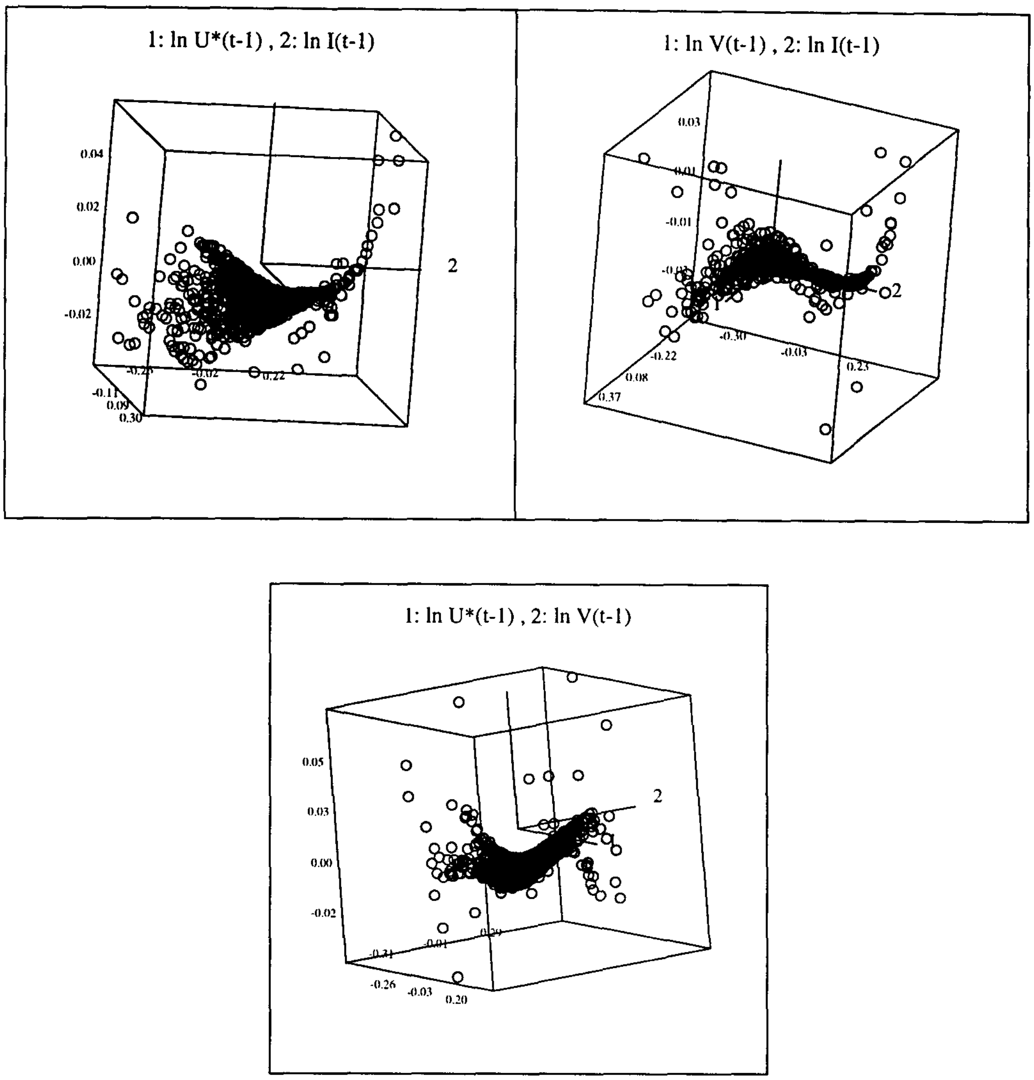


Figure 5: *Estimates of the interaction terms for 1993.*

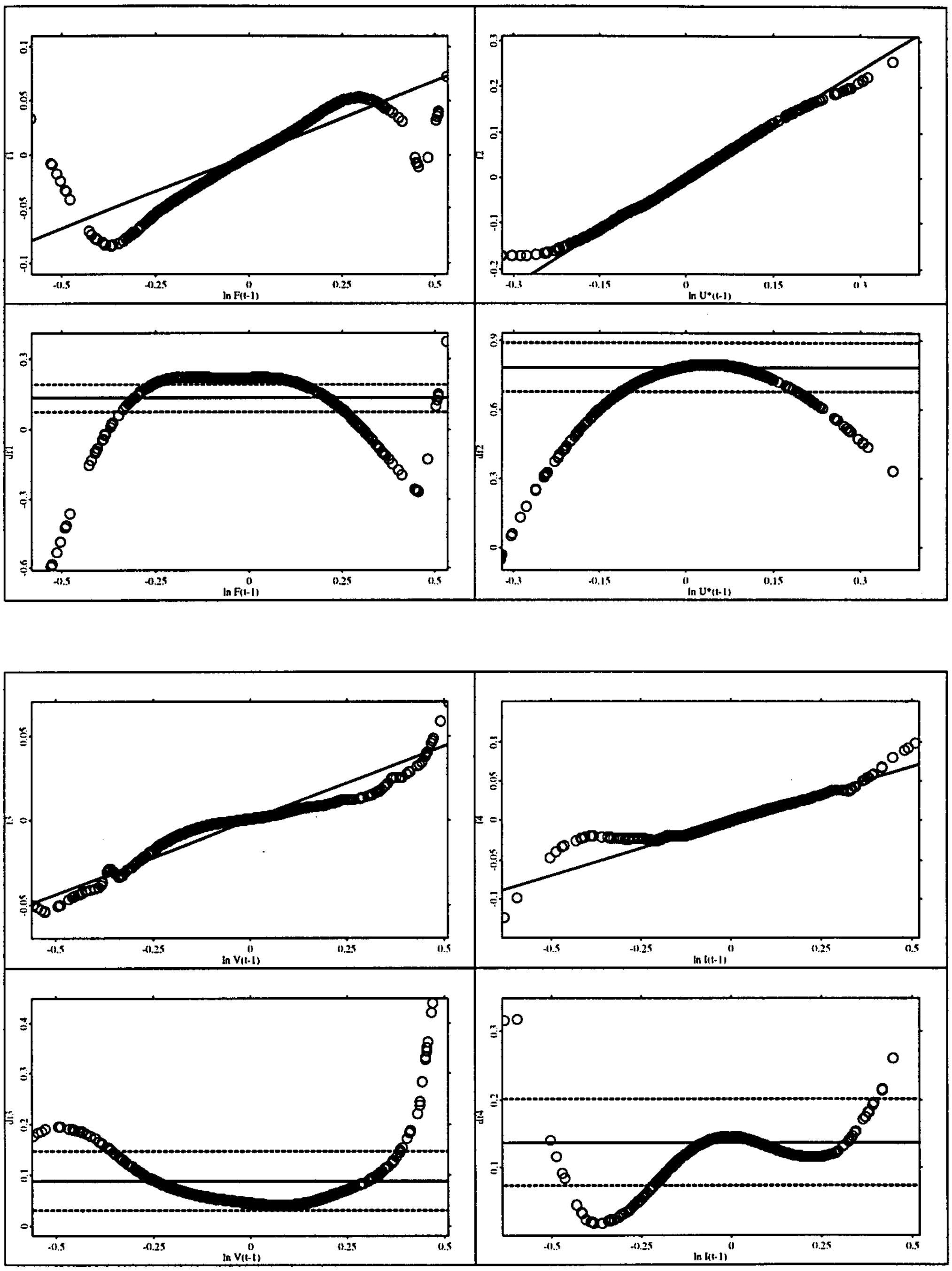


Figure 6: *Estimates of additive components and derivatives (each below the corresponding function) for 1994. Solid lines show parametric estimates, dashed lines in panels with derivative estimates show 90% confidence intervals. Upper left:* $lnF_{i,t-1}$, *upper right:* $lnU^*_{i,t-1}$, *lower left:* $lnV_{i,t-1}$, *lower right:* $lnI_{i,t-1}$.

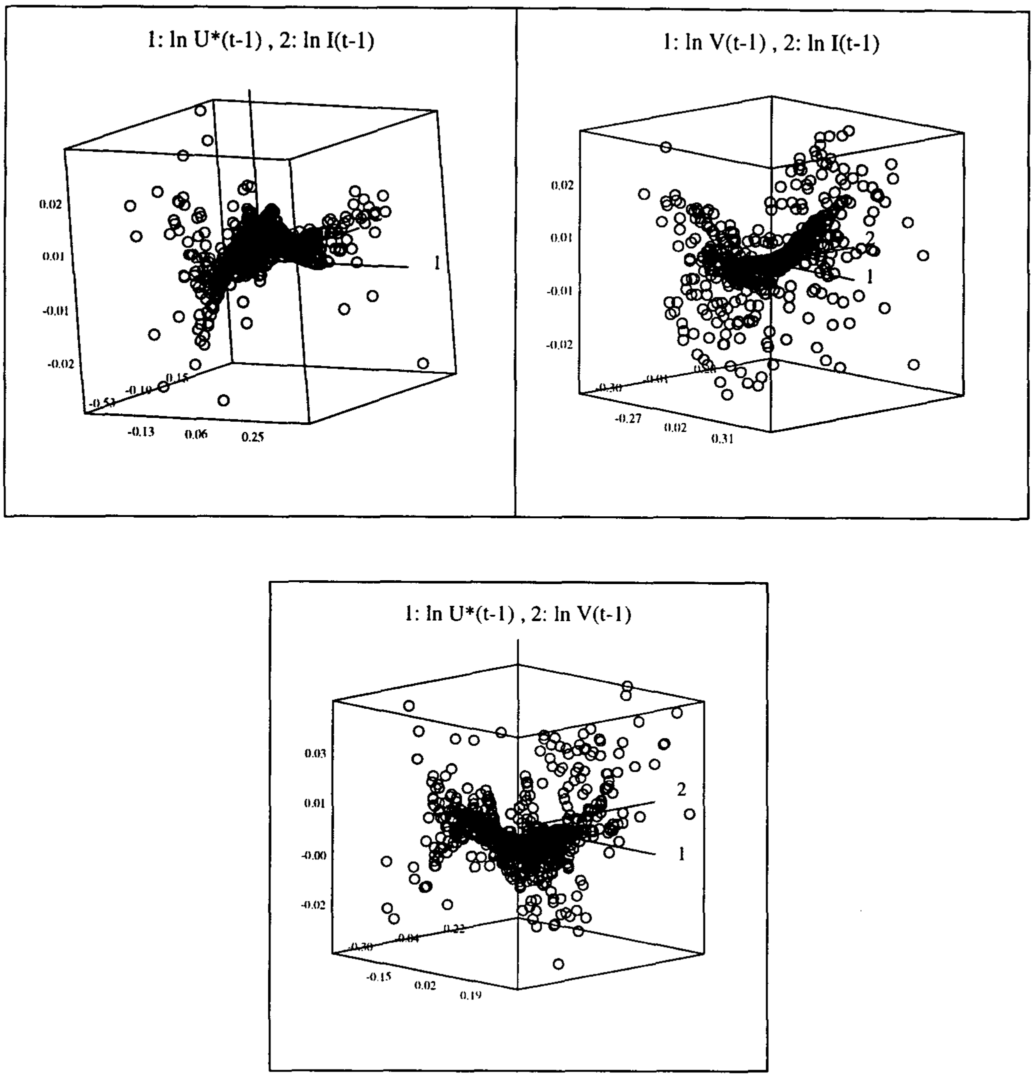
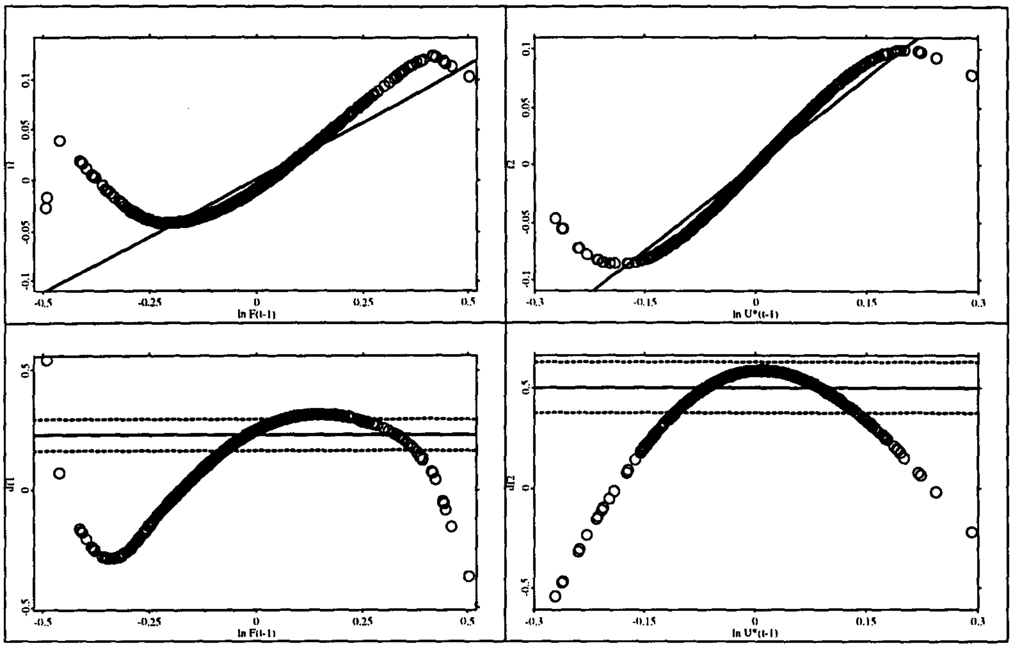


Figure 7: *Estimates of the interaction terms for 1994.*



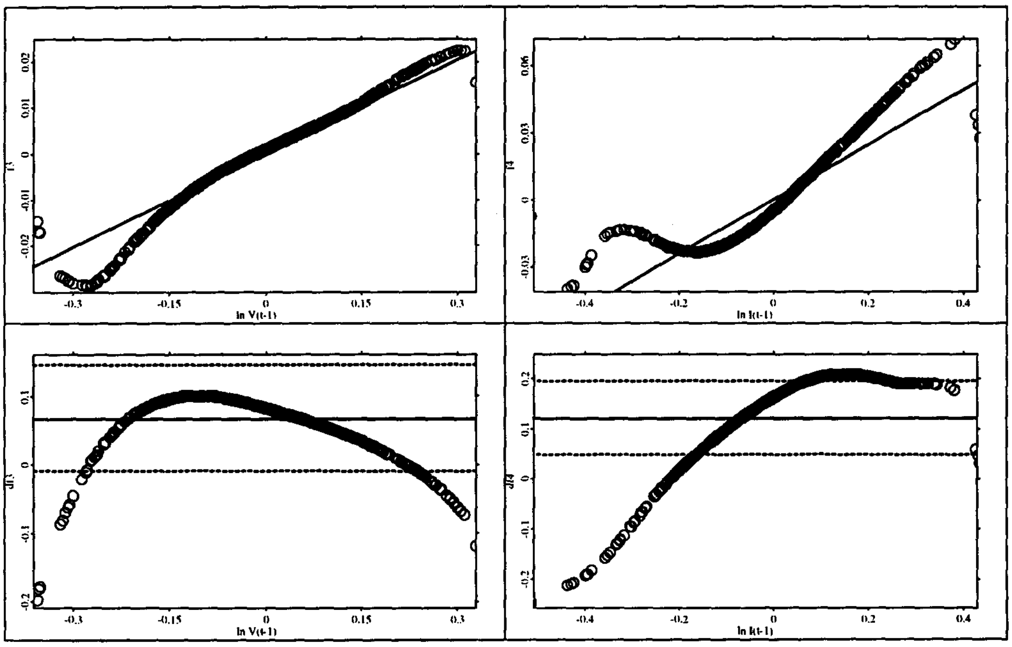


Figure 8: *Estimates of additive components and derivatives (each below the corresponding function) for 1995. Solid lines show parametric estimates, dashed lines in panels with derivative estimates show 90% confidence intervals. Upper left:* $lnF_{i,t-1}$, *upper right:* $lnU^*_{i,t-1}$, *lower left:* $lnV_{i,t-1}$, *lower right:* $lnI_{i,t-1}$.

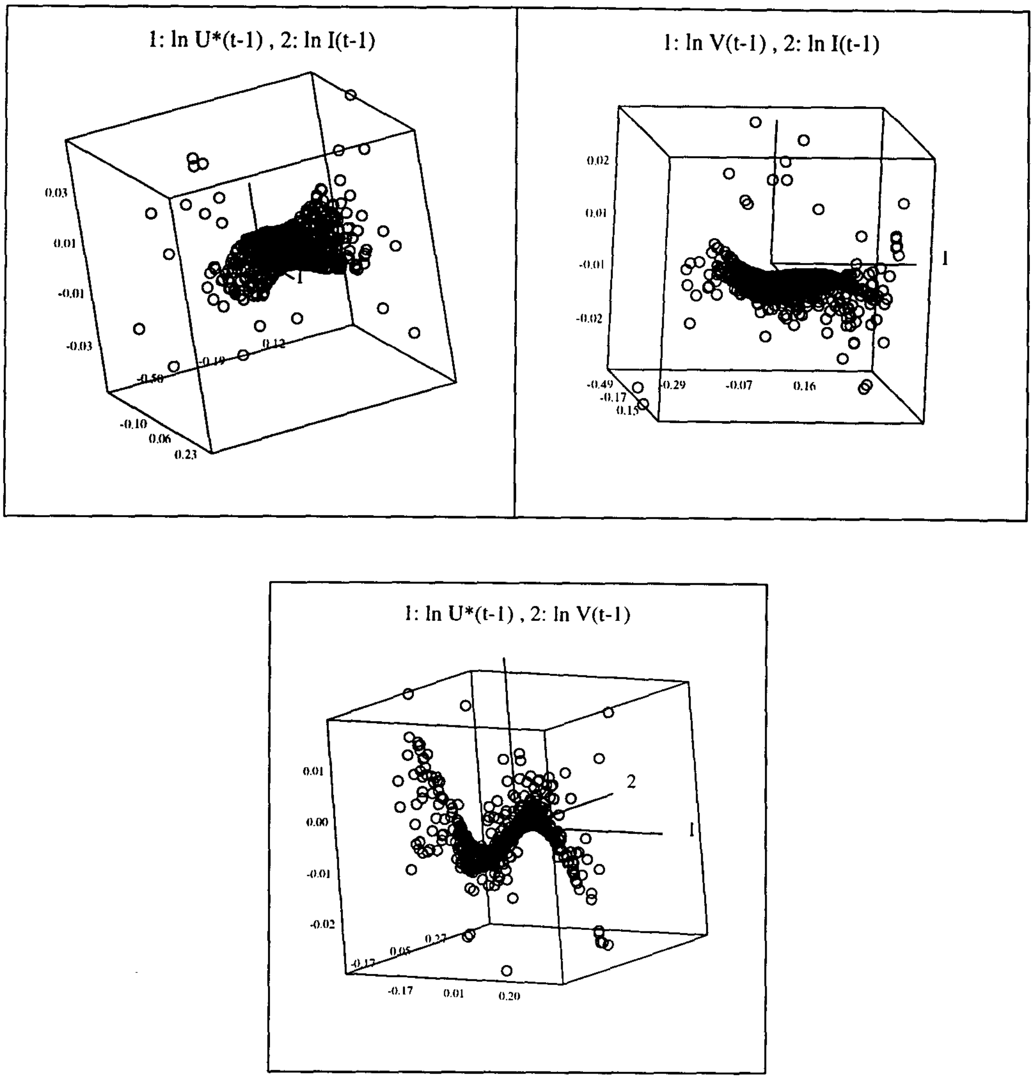


Figure 9: *Estimates of the interaction terms for 1995.*

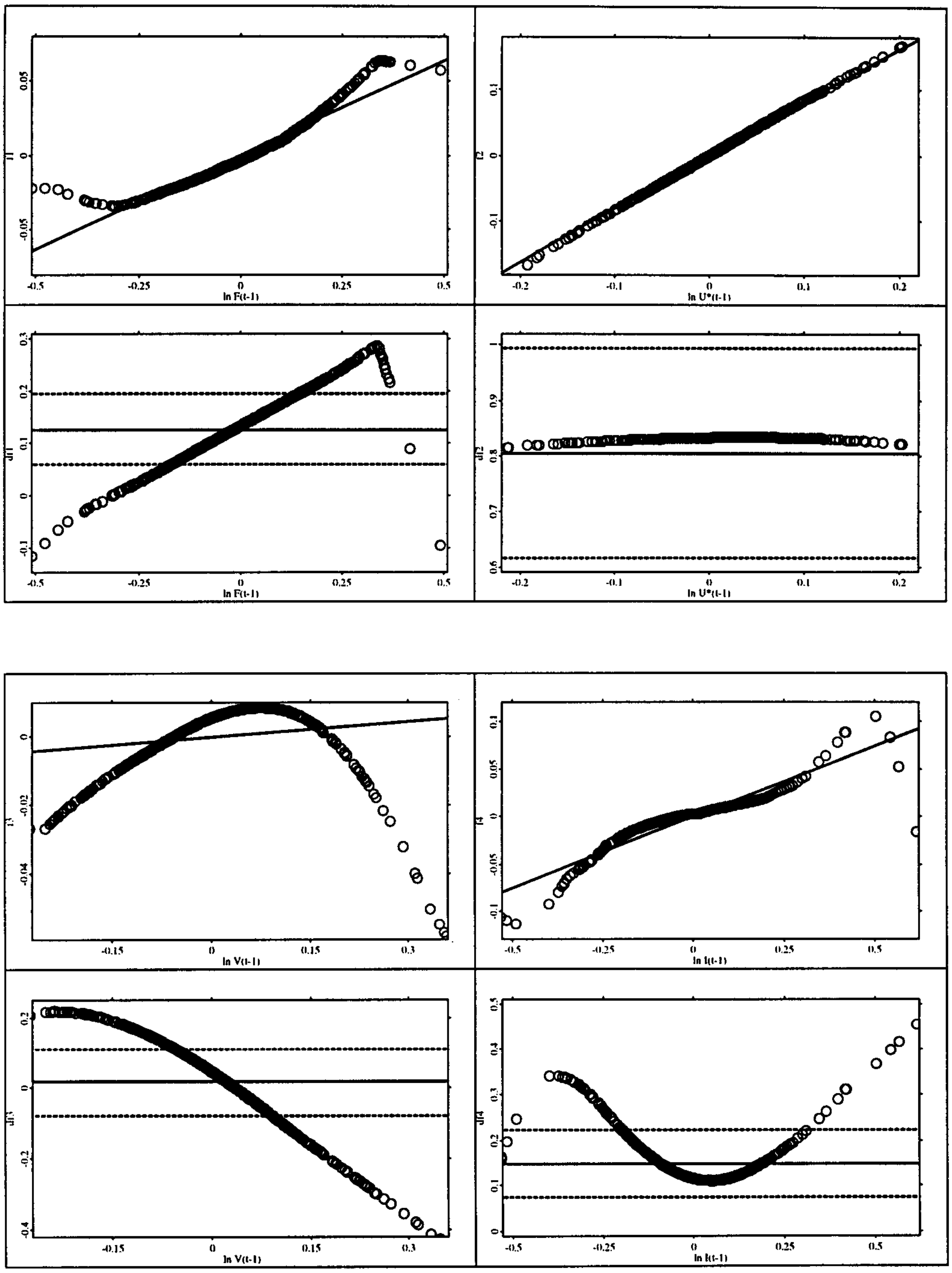


Figure 10: *Estimates of additive components and derivatives (each below the corresponding function) for 1996. Solid lines show parametric estimates, dashed lines in panels with derivative estimates show 90% confidence intervals. Upper left:* $lnF_{i,t-1}$*, upper right:* $lnU^{*}_{i,t-1}$*, lower left:* $lnV_{i,t-1}$*, lower right:* $lnI_{i,t-1}$.

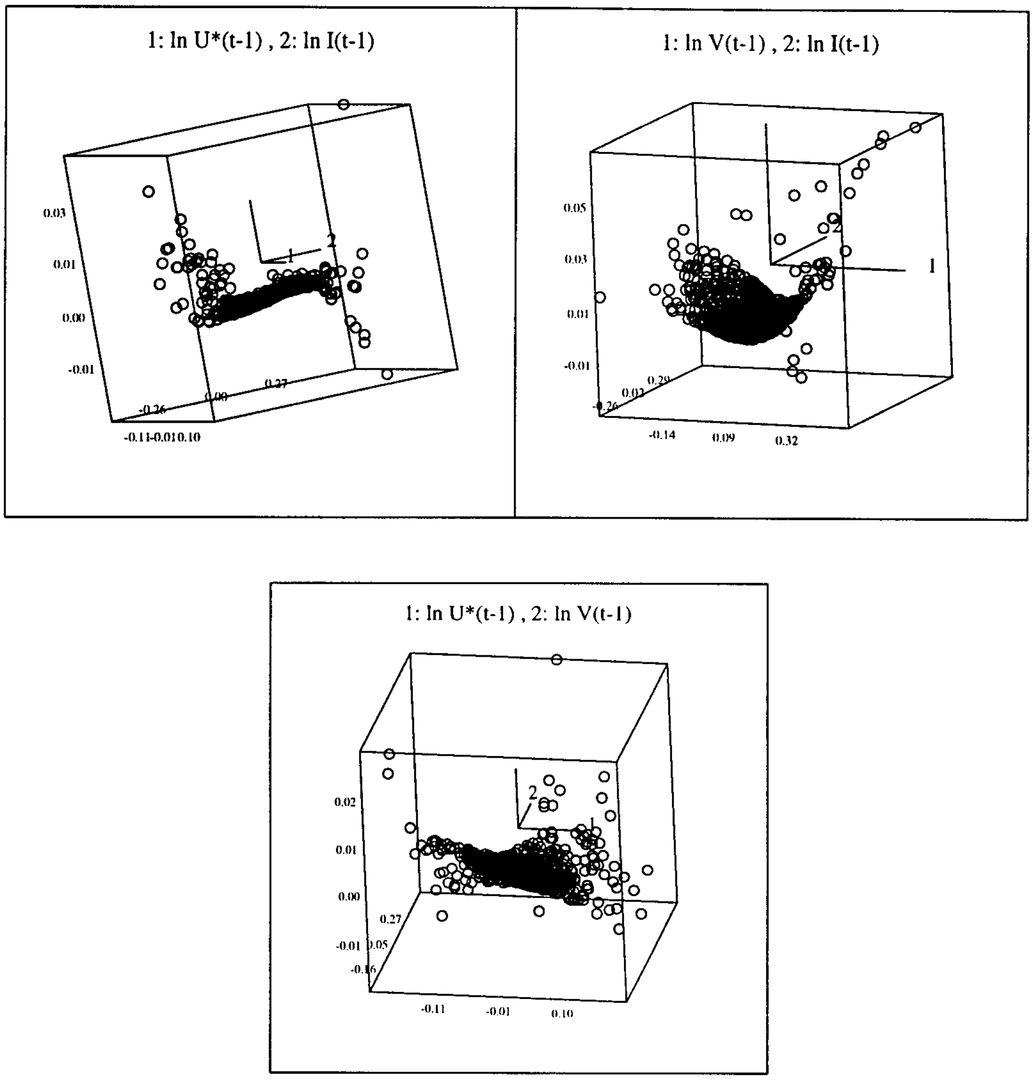


Figure 11: *Estimates of the interaction terms for 1996.*

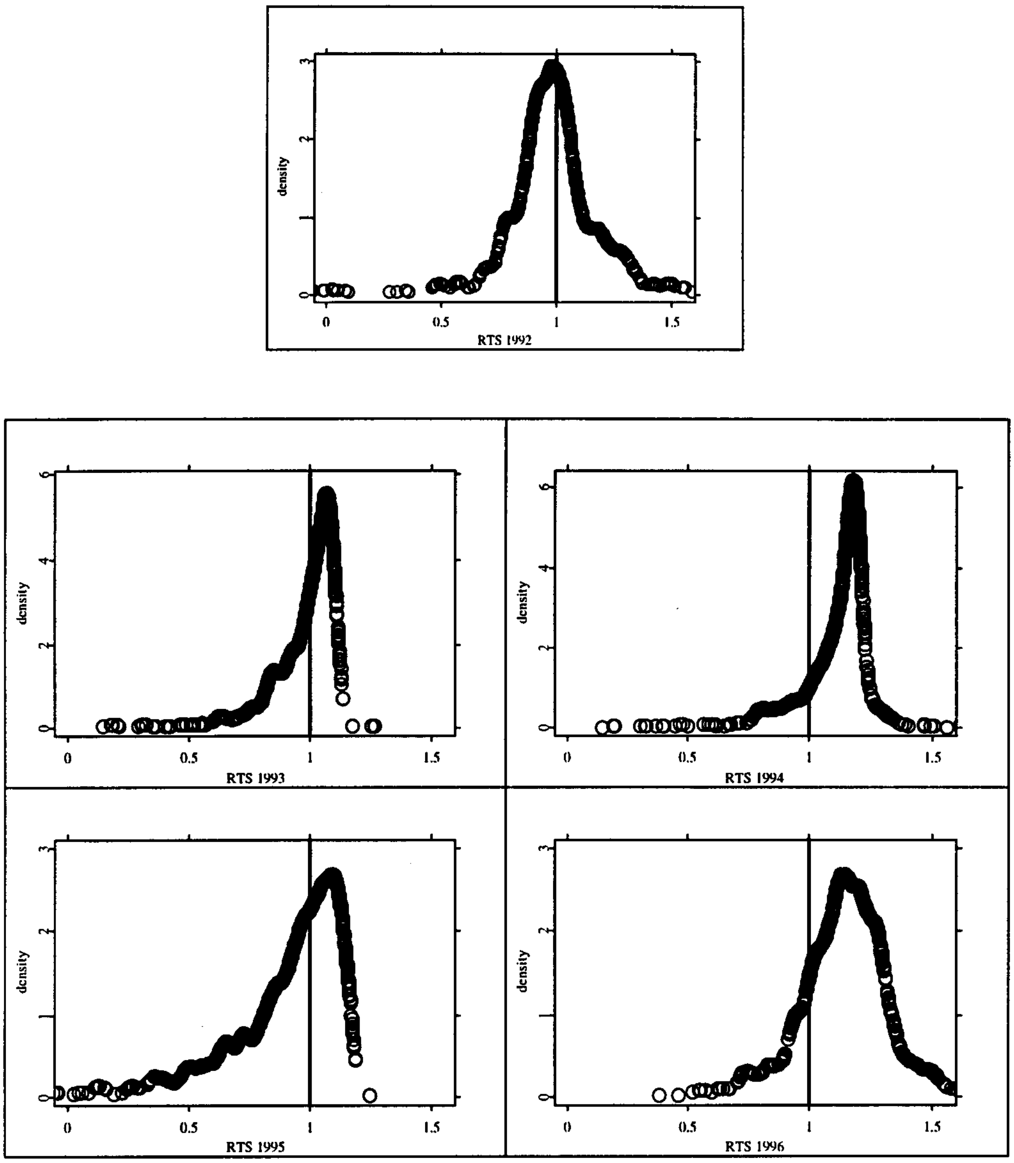


Figure 12: *Density estimates for the returns to scale in 1992 - 1996.*

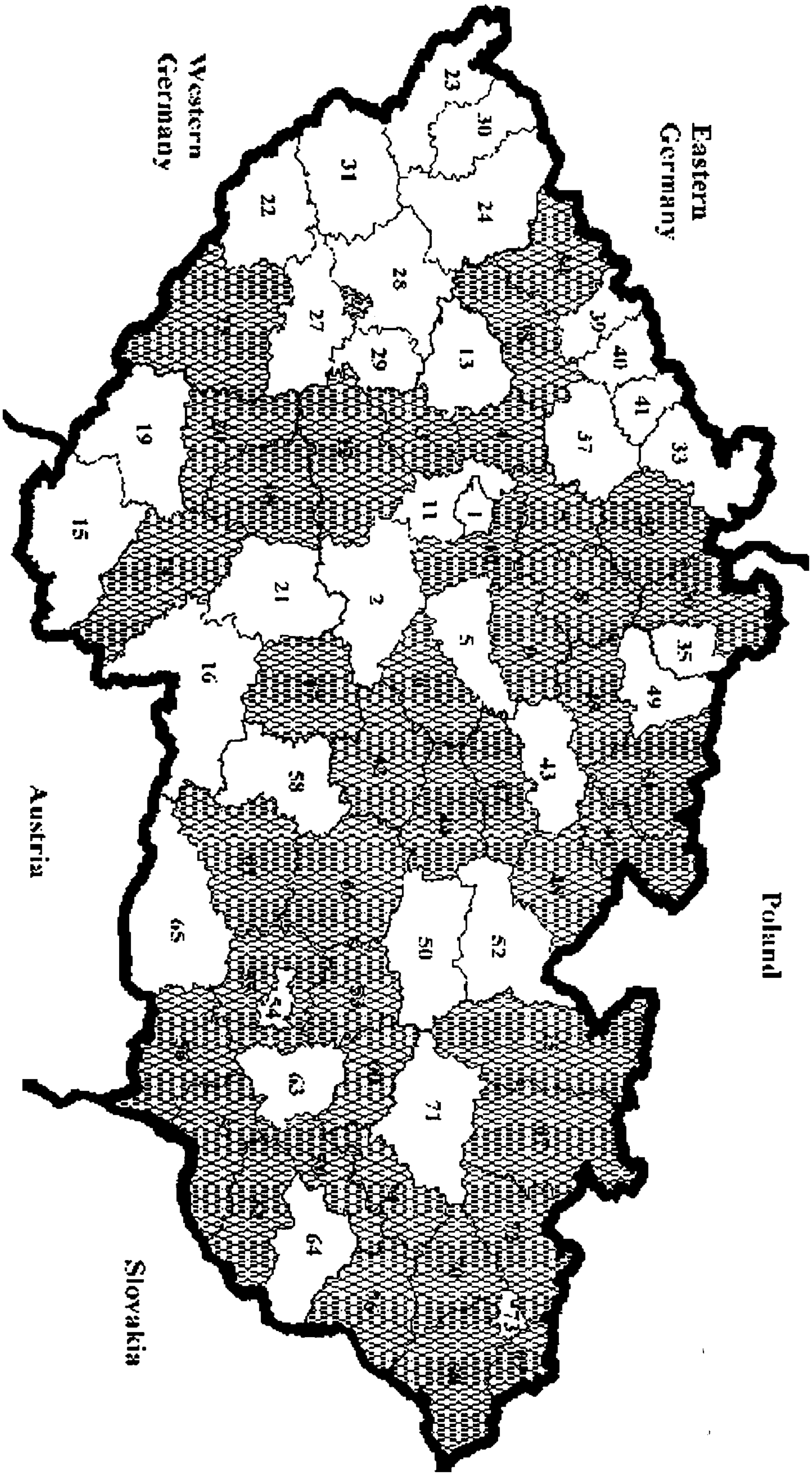


Figure 13: *Average returns to scale in the Czech Republic in 1993 - 1995, shaded districts indicate increasing returns on average.*

Czech Labor Market Districts

Central Bohemia:							
1	Praha	2	Benesov	3	Beroun	4	Kladno
5	Kolin	6	Kutna Hora	7	Melnik	8	Mlada Boleslav
9	Nymburk	10	Prague-vychod	11	Prague-zapat	12	Pribram
13	Rakovnik						
South Bohemia:							
14	C. Budejovice	15	C. Krumlov	16	Jindr. Hradec	17	Pelhrimov
18	Pisek	19	Prachatice	20	Strakonice	21	Tabor
West Bohemia:							
22	Domazlice	23	Cheb	24	Karlovy Vary	25	Klatovy
26	Plzen-mesto	27	Plzen-jih	28	Plzen-sever	29	Rokycany
30	Sokolov	31	Tachov 6				
North Bohemia:							
32	C. Lipa	33	Decin	34	Chomutov	35	Jablonec n/N
36	Liberec	37	Litomerice	38	Louny	39	Most
40	Teplice	41	Usti n/L				
East Bohemia:							
42	Hav. Brod	43	H. Kralove	44	Chrudim	45	Jicin
46	Nachod	47	Pardubice	48	Rychnov n/K	49	Semily
50	Svitavy	51	Trutnow	52	Usti n/O		
South Moravia:							
53	Blansko	54	Brno-mesto	55	Brno-venkov	56	Breclav
57	Hodonin	58	Jihlava	59	Kromeriz	60	Prostejov
61	Trebic	62	Uherske Hradiste	63	Vyskov	64	Zlin
65	Znojmo	66	Zdar n/S				
North Moravia:							
67	Bruntal	68	Frydek-Mistek	69	Karvina	70	Novy Jicin
71	Olomouc	72	Opava	73	Ostrava-mesto	74	Prerov
75	Sumperk	76	Vestin				