Job Matching on non separated Occupational Labour Markets*

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17th November 2010

JEL classification: C23, J44, J64
Keywords: Unemployment; Vacancies; Matching Model; Panel data; Occupational Labour Markets.

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*Preliminary version - please do not cite without permission by the author. Paper is submitted for the 3rd Ph.D. Workshop "Perspectives on (Un-) employment" in Nuremberg, November 18-19, 2010

1 Introduction

Modern labour market policy exhibits an increasing interest in determinants for matching labour demand and labour supply to create new jobs. But it is difficult to observe the processes behind on the micro level. Nevertheless it is possible to observe the number of (job-seeking) unemployed, vacancies, and new hires. Therefore the relationship between the number of new hires on the one hand and the number of job-seekers and vacancies on the other hand can be modelled without considering every individual meeting of both market sides.[1]

Numerous studies deal with the empirical estimation of macroeconomic matching functions, compare the surveys of Petrongolo and Pissarides (2001), Rogerson et al. (2005) or Yashiv (2006). The estimation results shed light on the efficiency of matching processes on the labour market. This is important for aggregated labour market and partial labour markets as well. So matching functions have been estimated for particular sectors (Broersma and Ours, 1999), regions(Anderson and Burgess, 2000; Kangasharju, Aki et al., 2005), different skill levels or occupational groups (Entorf, Mai 1994; Fahr and Sunde, 2004; Mora, John James and Santacruz, Jose Alfonso, 2007; Stops and Mazzoni, 2010). The central assumption of most studies is that partial labour markets are completely separated from each other, what means that there are no flows of job-seekers from one partial labour market to another partial labour market and no correlations between the newly created jobs or the number of job vacancies. Exemptions are studies for regional labour markets (e.g. Dauth et al., 2010). These consider the penetrability of the partial markets. Currently there is no study for occupational labour markets that consider dependencies between these partial labour markets. However, several studies deal with employees' change of occupations (Fitzenberger and Spitz, 2004; Seibert, 19.1.2007; Kambourov and Manovskii, 2009; Schmillen and Möller, 2010).

Therefore, in this paper I show that the assumption of separate occupational labour markets is theoretical and empirical not appropriate. I outline theoretical reasons why occupational markets are not separated. I test my hypotheses with *Spatial Error Models*, *Spatial Autoregressive Models* (SEMP, SARP; Elhorst, 2003) and a special case of the *Spatial Durbin Model* (restricted SDMP Beer and Riedl, 2010) that include "spatial" lags for regressors. The estimators consider interaction between cross-sectional units and unobserved heterogeneity. For that purpose I construct an empirical based "occupational topology".

In the following section I describe the theoretical framework of my estimation approach for the matching function. In section 3 I present the data and the empirical estimates follow in section 4. Section 5 summarizes the main results and discusses several questions for future research.

2 Theoretical framework

The starting point of the matching process are the decisions of firms to create a new job or to fill a vacancy (job creation decision) and the decision of (unemployed) persons

[1] There is a considerable body of literature, compare e.g. the early papers of Pissarides (1979, 1985); Diamond (1982a,b); Mortensen (1982).

about their intensity to search for a new job (job search decision)(Pissarides, 2000, p. xi). Firms spend time, financial, and personal resources for job advertisements, screening, training, and vocational adjustments. Job seekers spend resources for job search and application procedures. Unemployed and firms are randomly matched and start to bargain about the wage.
The basic model assumes homogeneous unemployed and homogeneous jobs and the activities of both market sides can be described as matching technology. The processes behind are not explicitly modelled, so the matching process can be compared with a black box (Petrongolo and Pissarides, 2001). The variables U, V and M stand each for the number of unemployed, vacancies and new hires. The matching functon $f(U, V)$ is often specified by a Cobb-Douglas form:

$$M = AU^{\beta_U}V^{\beta_V}, \tag{1}$$

whereas A describes the "augmented" matching productivity. Constant returns of scale imply $\beta_U + \beta_V = 1$ with $\beta_U, \beta_V > 0$.
Now I relax the assumption of homogeneous vacancies and unemployed and separated partial labour markets. I distinguish between occupational groups and it is plausible that there could be differences for example between matching processes in the construction sector and in the health sector, because of the different job requirements, apprenticeships and so on (for empirical evidence compare with Fahr and Sunde, 2004; Stops and Mazzoni, 2010). Nevertheless the occupational markets are probably not separated because an unemployed person could change its vocation during its employment biography. Another important point is that a high demand for certain jobs could lead to a reduced demand in other because of structural changes. And finally it is possible that the creation of new employment in a certain occupation, for example physicians, could lead to the creation of new employment in other, e.g. receptionists, nurses or other staff. So the number of new matches in a certain occupation could be determined in a way by the number of new matches, unemployed, and vacancies in other occupations.

3 Data

I use a panel data set with 81 occupational groups and 26 (yearly) measuring times for the years 1982 to 2007. The groups result from the German occupational classification Scheme (Kldb88[2]), compare table 5 in appendix). Data for unemployed and vacancies stem from operative data of the Federal Employment Agency (Bundesagentur für Arbeit, 1985-2004, and Data Warehouse). They are disaggregated and available for the reference date September 30th of each year. I used the IAB Sample of Integrated Labour Market Biographies 1975-2008 (SIAB 1975-2008) for the calculation of new hires from October 1st of a year to September 30th of the following year. The SIAB 1975-2008 contains information about each individual's history of employment subject to social insurance contributions, since 1999 minor employment, and periods of receiving unemployment benefits (Dorner et al., 2010).
The number of new hires in the occupational groups is equal to the sum of flows to

[2] *Klassifizierung der Berufe 1988*

employment from unemployment, employment or non-employment[3].
I calculated the number of new hires in the national economy by using the relationship between the new hires to the employment level of SIAB 1975 - 2008 multiplied with the employment levels taken from the employment statistics of the Federal Employment Agency[4] (ratio estimator, see Cochran, 1977, pp. 150 f.). The level of employment and the number of new hires are highly positive correlated, that is why the ratio estimator is more exact than a simple extrapolation. I had to consider that there are only 40 occupational sections in the employment statistics of the Federal Employment Agency. Nevertheless I used the information: I assigned the 82 occupational groups to the 40 occupational sections (see table 6 in the appendix):

$$M_{i,t} = \frac{E_{o|i\in o,t}}{e_{o|i\in o,t}} \cdot m_{i,t}, \tag{2}$$

whereas variables have following definitions:

- $M_{i,t}$ is the interpolated number of new hires by the occupational groups $i = 1, ..., 82$ and the measuring time t,
- $m_{i,t}$ is the number of new hires m from the SIAB 1975-2008 by occupational groups $i = 1, ..., 82$ and years t,
- $e_{o|i\in o,t}$ is the number of employed person from the SIAB 1975-2008 by the occupational groups $i \in o$ assigned to the occupational sectors $o = 1, ..., 40$ at September 30th of each year t and
- $E_{o|i\in o,t}$ is the level of employment at September 30th of each year t in the occupational groups $i \in o$ assigned to the occupational sectors $o = 1, ..., 40$ at September 30th of each year t.

I have solely taken data for Western Germany, because data for Eastern Germany have been available only since 1992. Therefore I have to accept a constraint: Western German job seekers who took up employment in Eastern Germany and Eastern German workers who took up employment in Western Germany were not considered. Stocks of Western German unemployed and registered vacancies as explanatory variables shall explain the flows in employment in Western Germany as dependent variable. This has to be beard in mind for interpreting the results.
Table 1 shows some descriptive statistics for the aggregated stocks and flows from the data.

[3]That means that a person was neither employed nor registered as unemployed.
[4]I used the number of employed who are subject to social insurance contributions.

Table 1: Descriptive statistics

		Average 1982-2007 (in persons)	Share (in per cent)
Labour market stocks			
Labour force	$E + U$	23 665 024	100.00%
Employed	E	23 172 935	91.10%
Unemployed	U	2 263 904	8.90%
Vacancies	V	277 831	1.09%
Flows in employment	M	4 593 855	

Note: Own calculation of averaged stocks by years, source: data centre of the statistic department of the Federal Employment Agency, SIAB 1975-2007.

4 Empirical strategy and results

4.1 An occupational "topology"

The basic idea that cross-sectional units interact with others has recently received considerable attention, as evidenced in the development of theoretical frameworks to explain social phenomena. The interaction effect means that the average behaviour in some group influences the behaviour of the individuals that comprise the group (Manski, 1993). In this study I examine the following cases:

- New hires are influenced by the number of new hires in other particular occupational groups. Both directions of the impact could be conceived. On the one hand more hirings in certain occupational groups could induce more hirings in other "nearest neighbouring" occupational groups and vice versa. On the other hand because of substitution processes it is possible that the more hiring could be observed in an occupational group the less are observed in certain others.

- The number of new hires is influenced by not observable factors in other particular occupational groups. That is indicated by "spatial" dependence of the disturbances. Because of the character of this influence it is not possible to give a hypothesis.

- New hires are influenced by exogenous regressors in other particular occupational groups. The number of unemployed of "nearest neighbouring" occupational groups should have a positive impact on the matches in a certain occupational group. For similar reasons as well as for the influences of hirings in the nearest neighbouring occupational groups the direction of the impact of the vancancies is not clear.

Analogous to a regional topology that regularly depends on the distance of the regions I need an "occupational group topology" to estimate the dependencies. I constructed a NxN "spatial" weight matrix $\mathbf{W}$ that refers to the employees' changes between different occupational groups. For this purpose I observed all flows of employees in

one occupational group to the same or to other from 1982 to 2007. Then I calculated each of the percentages of the flows from one occupational group to all other occupational groups. These percentages could be understood as transition rates and - in terms of spatial econometrics - as "distances" between the occupational groups. The results show that there are considerable transitions from one occupational group to other occupational groups and furthermore some variation in the yearly transition rates as it is shown by minimum and maximum values of the transition rates for the years 1982 to 2007 (table 5 in the appendix).
Therefore, the averaged transition rates are utilized to construct a asymmetric $81x81$ "spatial" or "nearest neighbour" weight matrix respectively. The diagonal elements are set to zero by assumption, since no occupational group can be viewed as its own neighbour. This matrix is standardized for the SEMP and the SARP approaches, so that the resulting matrix $\mathbf{W}$ has row-sums of unity in that cases. Standardization is not necessary for the restricted SDMP approach.

4.2 Results

For examining the dependencies of new hires in a certain group from new hires in other occupational groups I use the *Spatial Autoregressive Panel Data Model* (Elhorst, 2003)):

$$\log \mathbf{M} = \rho \mathbf{W} \log \mathbf{M} + \alpha_{\mathbf{it}} \iota_{\mathbf{NT}} + \beta^{\mathbf{U}} \log \mathbf{U} + \beta^{\mathbf{V}} \log \mathbf{V} + \epsilon \tag{3}$$

$\log \mathbf{M}$ denotes an $NTx1$-vector containing the logarithm of the number of new hires for every occupational group ($i = 1, ..., N$) in every year ($t = 1, ..., T$) in the sample, ι is an $NTx1$ matrix of ones associated with the constant term resp. fixed effects term parameter vector $\alpha_{\mathbf{it}}$, $\log \mathbf{U}$, $\log \mathbf{V}$ denote each a $NTx1$ vector of the explanatory variables for the logarithm of number of unemployed and vacancies, with the associated parameters β^U and β^V. These parameters represent the impact of vacancies and unemployed on the matching process and in line with the theory they are expected to be significantly positive. This and the following models will be supplemented by a time trend and the cyclical component of the real gross domestic product (GDP_{cyc}) that is calculated by using the *Hodrick Prescott filter* (Hodrick and Prescott, 1997). The time trend serves as indicator for the averaged development of the matching productivity. The cyclical component of the real GDP is utilized as a control variable for the economic situation that influences the matching processes in a certain way. In earlier studies the estimated coefficient of the time trend was significantly negative and of the cyclical component of the real GDP positive (compare with Stops and Mazzoni, 2010). Finally, ϵ is a $NTx1$ vector of disturbance terms, where all ϵ_{it} are independently and identically distributed error terms for all it with zero mean and variance σ^2. Because of the non-linear relationship a maximum likelihood estimation approach is used.
The endogenous interaction effect $\mathbf{W} \log \mathbf{M}$ means the propensity of new hires to change in some way varies with the new hires of other occupational groups. As mentioned before $\mathbf{W}$ is an NxN matrix describing the "spatial" arrangement of the occupational groups in the sample.
In the following I present the results for 4 variations of the SARP approach. The variations are

- SAR-Pooled: pooled model corrected for spatial autocorrelation, including constant (α_{it} is constant for all occupational groups i and years t),
- SAR-Spatial FE: pooled model corrected for spatial autocorrelation, without constant ($\alpha_{it} = 0$ for all occupational groups i and years t),
- SAR-Time FE: spatial fixed effects and spatial autocorrelation (α_{it} is different for the occupational groups i and constant for all years t), and
- SAR-Spatial/Time FE: time period fixed effects and spatial autocorrelation (α_{it} is constant for all occupational groups i and different for the years t; in case of time period fixed effects the cyclical component of the real GDP BIP_{zyk} must left out: I only have information about the real GDP for the aggregated labour market, not for each occupational group.).

Table 2: Estimations for four variations of the SARP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$								
	SAR-Pooled		**SAR-Spatial FE**		**SAR-Time FE**		**SAR-Spatial/Time FE**	
Constant	-3.513	***	-		-		-	
	(-21.084)							
β^U	0.431	***	0.113	***	0.421	***	0.118	***
	(31.164)		(9.038)		(29.768)		(8.891)	
β^V	0.331	***	0.131	***	0.342	***	0.161	***
	(29.900)		(13.902)		(30.440)		(16.083)	
trend	-0.008	***	-0.001		-		-	
	(-5.425)		(-0.887)					
GDP_{cyc}	0.506		-0.412		-		-	
	(0.486)		(-0.838)					
ρ	0.747	***	0.864	***	0.788	***	0.904	***
	(48.930)		(75.601)		(89.407)		(80.943)	
$n = NT$	2106		2106		2106		2106	
R^2	0.867		0.973		0.874		0.974	
R^2_{adj}	0.867		0.971		0.872		0.972	
AIC	3112.392		-6.050		3416.120		24.755	
BIC	3146.308		480.069		3580.044		640.883	
σ^2	0.246		0.051		0.233		0.049	
ll	-1550.196		89.025		-1679.060		96.622	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 2 shows the results[5]. The upper part of the table contains the estimation results for the parameters, except the spatial, time or spatial and time period fixed effects[6]. The lower part of the table presents the number of observation $n = NT$, the (adjusted) coefficient of determination R^2 resp. R^2_{adj} with relatively high values for each model. For model selection information criteria like *Akaikes information criterion* or *Bayes Information Criterion* are the better indicators. In line with Akaike (1974) and Schwarz (1978) each of the spatial fixed effects estimators of both SARP and SEMP approaches should be preferred, because the information criteria have the lowest values. The quality criteria are complemented by the overall variance of each model σ^2 and the value of the maximized likelihood function *ll*.
For examining the spatial dependence in the disturbances I use the *Spatial Autoregressive Error Panel Data Model* (Elhorst, 2003)):

$$\log \mathbf{M} = \alpha_{\mathbf{it}} \iota_{\mathbf{NT}} + \beta^{\mathbf{U}} \log \mathbf{U} + \beta^{\mathbf{V}} \log \mathbf{V} + \mathbf{r} \quad (4)$$

$$\mathbf{r} = \lambda \mathbf{W} \mathbf{r} + \epsilon \quad (5)$$

The variable $\mathbf{r}$ means the autocorrelated residuals; autocorrelation is modelled in the second equation. The endogenous interaction effect $\lambda \mathbf{W} \mathbf{r}$ means the propensity of disturbances to change in some way varies with the disturbances of other occupational groups.
In the following I present the results for four variations of the SEMP approach. The variations are similar to these of the SARP model. I estimated a model with pooled data, spatial fixed effects, time period fixed effects plus spatial and time period fixed effects. Table 3 shows the results[7]. It is as structured as table 2.

[5]Section A.2.1 in the appendix contains further results.
[6]The author will provide these results upon request.
[7]Further results are shown in the appendix A.2.2.

Table 3: Estimations for four variations of the SEMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$								
	SEM-pooled		**SEM-Spatial FE**		**SEM-Time FE**		**SEM-Spatial/Time FE**	
Constant	3.957	***	-		-		-	
	(29.521)							
β^U	0.410	***	0.101	***	0.414	***	0.109	***
	(26.473)		(7.401)		(26.500)		(7.865)	
β^V	0.381	***	0.164	***	0.383	***	0.167	***
	(30.846)		(14.957)		(30.811)		(15.094)	
trend	-0.012	*	0.030	***	-		-	
	(-1.893)		(3.914)					
GDP_{cyc}	1.496		-0.775		-		-	
	(0.347)		(-0.152)					
λ	0.755	***	0.910	***	0.706	***	0.885	***
	(27.094)		(82.237)		(21.787)		(63.124)	
$n = NT$	2106		2106		2106		2106	
R^2	0.853		0.972		0.851		0.972	
R^2_{adj}	0.853		0.971		0.849		0.970	
AIC	3317.196		22.814		3377.593		94.605	
BIC	3345.459		503.280		3535.865		705.080	
σ^2	0.271		0.051		0.274		0.052	
ll	-1653.598		73.593		-1660.797		60.698	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

In all models the parameters are highly significant and quite robust, matching elasticities of the unemployed and vacancies respectively are positive. The parameter estimators for the cyclical component of the real GDP and the trend are not robust. Nevertheless the parameters for the interaction effect ρ of the SARP approach and λ of the SEMP approach are significantly positive what means there is a (positive) relationship between the new hires respectively the disturbances of "nearest neighbouring" occupational groups.

For examining the influences by exogenous regressors in other occupational groups I use a restricted *Spatial Durbin Model for panel data* (SDMP)[8]:

$$\log \mathbf{M} = \alpha_{\mathbf{it}} \iota_{\mathbf{NT}} + \beta^{\mathbf{U}} \log \mathbf{U} + \beta^{\mathbf{V}} \log \mathbf{V} + \mathbf{W}(\log \mathbf{U} \quad \log \mathbf{V}) \gamma + \epsilon \tag{6}$$

Parameters can be estimated by an OLS type regression that includes a spatial lag on the regressors U and V. Table 4 presents results for some variations of the restricted

[8] Actually the SDMP approach is $\log \mathbf{M} = \alpha_{\mathbf{it}} \iota_{\mathbf{NT}} + \rho \mathbf{W} \log \mathbf{M} + \beta^{\mathbf{U}} \log \mathbf{U} + \beta^{\mathbf{V}} \log \mathbf{V} + \mathbf{W}(\log \mathbf{U} \quad \log \mathbf{V}) \gamma + \epsilon$. Here the model is restricted by $\rho = 0$ (Beer and Riedl, 2010)

SDMP approach, namely pooled OLS, with fixed effects (FE), and random effects (RE) versions[9].

Table 4: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$								
	SDMP-OLS 1		**SDMP-FE 1**		**SDMP-FE 2**		**SDMP-RE 1**	
$Constant$	4.816	***	-		-		-	
	(43.179)							
β^U	0.283	***	0.160	***	0.165	***	0.160	***
	(16.578)		(10.132)		(10.524)		(10.141)	
β^V	0.379	***	0.210	***	0.210	***	0.210	***
	(32.216)		(17.508)		(17.511)		(17.521)	
$Trend$	-0.019	***	-0.016	***	-0.016	***	-0.016	***
	(-11.724)		(-16.933)		(-16.943)		(-16.922)	
GDP_{cyc}	1.478		2.163	***	1.769	***	2.147	***
	(1.300)		(3.317)		(2.810)		(3.294)	
γ^U	0.006		0.083	**	-		0.079	**
	(0.302)		(2.275)				(2.208)	
γ^V	0.056	**	0.157	***	0.153	***	0.156	***
	(1.984)		(8.563)		(8.367)		(8.542)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.852		0.303		0.301		0.303	
R^2_{adj}	0.852		0.301		0.299		0.301	
σ^2	0.274		0.082		0.082		0.082	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

The results for the fixed effects and random effects model are quite similar. The results of a *Haussman* test to compare the equivalent FE and RE models (FE1 and RE1, FE2 and RE 2, a.s.o.) show that for every model pair the Null of preferring the random effects model can not be rejected. Nevertheless the coefficients of determinants are quite low. That implicates that the models do not perfectly fit he data.
However, the matching elasticities of the unemployed and vacancies respectively are significantly positive and robust in all model variations. The positive coefficient of the cyclical component of the real GDP and the negative parameter of the trend are - except for the OLS version - robust. Also the parameters for the impact of the regressors from other occupational groups γ^U and γ^V are both significant and robust. That means there is a positive relationship between the new hires of an occupational

[9]Further results are presented in appendix A.2.3.

group and the vacancies and unemployed in the "nearest neighbouring" occupational groups. This has important implications for estimating the matching efficiencies of unemployed and vacancies - they are each not only determined by the unemployed and vacancies in the same occupational group but also by those in other occupational groups.

5 Interim Conclusions and outlook

This paper refers to analyses of matching processes on occupational labour markets. Up to now, all studies in this field are based on the cruel assumption of separate occupational labour markets. I outlined some theoretical considerations that occupational markets are probably not separated. By using the IAB Sample of Integrated Labour Market Biographies 1975-2008 (SIAB 1975-2008) I found empirical indices by observing employees' job changes between occupational groups and calculated transition rates. On that base I constructed an "occupational topology" and finally I tested my hypothesis of non separated occupational labour markets with *Spatial Error Models*, *Spatial Autoregressive Models* and a restricted case of the Spatial Durbin Model that includes "spatial" lags for regressors.

The results show that there are considerable dependencies between "neighbouring" occupational groups in the matching process. The propensity of new hires to change with new hires of "neighbouring" occupational groups is as positive as the propensity of disturbances changing with these in other occupational groups (SARP and SEMP approaches). Another important result is the positive relationship between the new hires of an occupational group and the vacancies and unemployed in other "neighbouring" occupational groups (SDMP approach). This has important implications for estimating the matching efficiencies of unemployed and vacancies - they are each not only determined by the unemployed and vacancies in the same occupational group but also by those in other occupational groups. Nevertheless, more efforts are necessary to identify the reasons why the latter model does not perfectly fit the data.

Furthermore, more research concerning explanations for the more or less volatile transition rates has to be conducted. Probably there are two explanations for flows from one occupational group to other occupational groups: a systematic one and a stochastic one. The identification of systematic explanations shall be one topic for further research.

A Appendix

A.1 Further information tables

Table 5: Occupational groups according to the German occupational classification scheme (*KldB 88*) and transition rates

Code (KldB 88)	Occupational group	Transition rates 1982-2007 into other groups** average	minimum	maximum
1	farmer, fisher	0.62	0.54	0.75
3	agricultural administrator	0.59	0.39	0.80
4	helper in the agricultural sector, agricultural workers, stockbreeding professions	0.71	0.59	0.81
5	gardener, florist	0.53	0.47	0.60
6	forester and huntsman	0.57	0.21	0.74
7	miner and related professions	0.42	0.19	0.68
8	exhauster of mineral resources	0.67	0.31	0.85
(9	mineral rehasher, mineral burner)*	0.66	0.41	1.00
10	stone processor	0.60	0.39	0.71
11	producer of building materials	0.77	0.55	0.89
12	ceramicist, glazier	0.75	0.53	0.86
13	glazier, glass processor, glass refiner	0.73	0.36	0.92
14	chemical worker	0.68	0.36	0.85
15	polymer processor	0.78	0.51	0.88
16	paper producer	0.77	0.61	0.86
17	printer	0.53	0.39	0.66
18	woodworker, wood processor	0.77	0.62	0.88
19	metal worker	0.65	0.39	0.88
20	moulder, caster, semi-metal cleaner	0.74	0.55	0.84
21	metal press workers, metal formers	0.76	0.57	0.87
22	turner, cutter, driller, metal polisher	0.57	0.45	0.69
23	metal burnisher, galvanizer, enameler	0.75	0.59	0.85
24	welder, solderer, riveter, metal gluter	0.58	0.45	0.69
25	steel smith, copper smith	0.78	0.60	0.93
26	plumber, plant locksmith	0.49	0.43	0.56
27	locksmith, fitter	0.55	0.48	0.62
28	mechanic	0.57	0.49	0.65
29	toolmaker	0.60	0.51	0.67
30	metal precision-workers, orthodontists, opticians	0.37	0.24	0.52
31	electricians	0.42	0.35	0.48
32	assemblers and metal related professions	0.77	0.68	0.83
33	spinner, ropemaker	0.75	0.51	0.91

continued on the next page

Code (KldB 88)	Occupational group	Transition rates 1982-2007 into other groups**		
		average	minimum	maximum
34	weaver, other textile producer	0.67	0.49	0.79
35	tailor, sewer	0.59	0.36	0.74
36	textile dyer	0.72	0.52	0.85
37	leather and fur manufacturers, shoemaker	0.65	0.48	0.78
39	baker, confectioner	0.53	0.43	0.61
40	butcher, fishworkmansip and related	0.51	0.38	0.58
41	cooks, convenience food preparatory	0.51	0.44	0.58
42	brewer, manufacturer for tobacco products	0.74	0.60	0.83
43	milk/fat processor, nutriments producer	0.77	0.50	0.91
44	bricklayer, concrete builder	0.45	0.32	0.56
45	carpenter, roofer, spiderman	0.49	0.38	0.58
46	road/track constructors, demolisher, culture structurer	0.62	0.47	0.74
47	helper in the construction sector	0.75	0.68	0.81
48	plasterer, tiler, glazier, screed layer	0.55	0.45	0.64
49	interior designer, furniture supplier	0.65	0.53	0.72
50	joiner, modeler, cartwright	0.51	0.40	0.56
51	painter, varnisher and related professions	0.42	0.31	0.49
52	goods tester, consignment professions	0.79	0.68	0.85
53	unskilled worker	0.72	0.59	0.89
54	machinist and related professions	0.54	0.41	0.71
60	engineer, architect	0.32	0.28	0.36
61	chemist, physicist	0.49	0.29	0.61
62	technician	0.45	0.39	0.51
63	technical specialist	0.48	0.41	0.57
68	merchandise manager	0.45	0.38	0.51
69	banking professional, insurance merchant	0.32	0.26	0.37
70	merchant/ specialist in conveyance, tourism, other services	0.56	0.50	0.63
71	conductor, driver, motorist	0.38	0.28	0.45
72	navigator, ship engineer, water/air traffic professions	0.29	0.16	0.54
73	mail distributer	0.66	0.42	0.85
74	storekeeper, worker in storage and transport	0.69	0.62	0.74
75	manager, consultant, accountant.	0.47	0.40	0.50
76	member of parliament, association manager	0.64	0.52	0.72
77	accounting clerk, cashier, data processing expert	0.49	0.43	0.56
78	clerk, typist, secretary	0.36	0.31	0.41
79	plant security, guard, gate keeper, servant	0.63	0.53	0.77
80	other security related professions, health caring professions	0.45	0.28	0.62
81	law related professions	0.50	0.40	0.76
82	publicist, translator, librarian	0.46	0.37	0.55
83	artist and related professions	0.35	0.22	0.47
84	physician, dentist, apothecaries	0.12	0.09	0.35

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Code (KldB 88)	Occupational group	Transition rates 1982-2007 into other groups** average	minimum	maximum
85	nurse, helper in nursing, receptionist and related	0.29	0.22	0.37
86	social worker, care taker	0.35	0.28	0.43
87	professor, teacher	0.46	0.33	0.53
88	scientist	0.63	0.49	0.70
89	helper for cure of souls and cult	0.61	0.43	0.83
90	beauty culture	0.37	0.25	0.44
91	guest assistant, steward, barkeeper	0.52	0.42	0.65
92	domestic economy, housekeeping	0.68	0.59	0.74
93	cleaning industry related professions	0.54	0.45	0.63

Notes:

*Occupational group 9 contains some missing values for vacancies. Thats why it has to be dropped out for the estimations.

**Source: SIAB 1975-2008.

Table 6: Assignment of the occupational groups to the occupational section of the employment statistics of the Federal Employment Agency

Occupational groups in data $i = 1, ..., 82$		Occupational section in employment statistics $o = 1, ..., 40$	Name of the occupational section
1, 3	-5	1	Plant cultivator/stockbreeding/fisher
6		2	Forester/huntsman
7	-9	3	Miner/exhauster of mineral resources
10	-11	4	Stone processor/producer of building materials
12	-13	5	Ceramicist/glazier
14	-15	6	Chemical worker/polymer processor
16		7	Paper producer
17		8	Printer
18		9	Woodworker/wood-processor
19	-24	10	Metal worker
25	-30	11	Locksmith/mechanic
31		12	Electrician
32		13	Assembler/metal-related professions
33	-36	14	Textile-related professions
37		15	Leather and fur manufacturer
39	-43	16	Nutrition-related professions
44	-47	17	Construction-related professions
48	-49	18	Interior designer/furniture supplier/upholsterer
50		19	Carpenter/modeller
51		20	Painter/varnisher/related professions
52		21	Goods tester/consignment professions
53		22	Unskilled worker

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Occupational group in data $i = 1, ..., 82$	**Occupational section in employment statistics** $o = 1, ..., 40$	**Name of occupational section**
54	23	Machinist/related professions
60 -61	24	Engineer/chemist/physicist/mathematician
62	25	Technician
63	26	Technical specialist
68	27	Merchandise manager
69 -70	28	Service merchants
71 -73	29	Transportation-related professions
74	30	Storekeeper/worker in storage and Transport
75 -78	31	Organization-/management-/office- related professions
79 -81	32	Security service-related professions
82	33	Publicist/translator/librarian
83	34	Artists and related professions
84 -85	35	Health care-related professions
86 -89	36	Social worker/pedagogue/science careers
90	37	Beauty culture
91	38	Guest assistant/steward/barkeeper
92	39	Domestic economy/housekeeping
93	40	Cleaning industry-related professions

A.2 Further empirical results

A.2.1 SARP

Table 7: Estimations for two further variations of the SARP model ("distance" based matrix, excl. GDP_{cyc})

Dependent variable: $\log \mathbf{M}$				
	SAR-Pooled		**SAR-Spatial FE**	
$Constant$	-3.555	***	-	
	(-21.710)			
β^U	0.429	***	0.115	***
	(31.994)		(9.678)	
β^V	0.332	***	0.129	***
	(30.929)		(14.170)	
$Trend$	-0.008	***	-0.001	
	(-5.381)		(-0.977)	
ρ	0.752	***	0.864	***
	(50.146)		(75.426)	
$n = NT$	2106		2106	
R^2	0.867		0.973	
R^2_{adj}	0.867		0.971	
AIC	3110.655		-7.345	
BIC	3138.917		473.122	
σ^2	0.246		0.051	
ll	-1550.327		88.672	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 8: Estimations for four variations of the SARP model ("distance" based matrix)

	Dependent variable: log $\mathbf{M}$							
	SAR-Pooled		**SAR-Spatial FE**		**SAR-Time FE**		**SAR-Spatial/Time FE**	
Constant	-4.017	***	-		-		-	
	(-27.522)							
β^U	0.443	***	0.113	***	0.421	***	0.118	***
	(32.401)		(9.095)		(29.768)		(8.891)	
β^V	0.316	***	0.128	***	0.342	***	0.161	***
	(29.004)		(14.172)		(30.440)		(16.083)	
GDP_{cyc}	-0.556		-0.475		-		-	
	(-0.540)		(-0.971)					
ρ	0.786	***	0.872	***	0.788	***	0.904	***
	(60.034)		(81.213)		(89.407)		(80.943)	
$n = NT$	2106		2106		2106		2106	
R^2	0.866		0.973		0.874		0.974	
R^2_{adj}	0.866		0.971		0.872		0.972	
AIC	3138.581		-7.752		3416.120		24.755	
BIC	3166.843		472.714		3580.044		640.883	
σ^2	0.248		0.051		0.233		0.049	
ll	-1564.290		88.876		-1679.060		96.622	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

Table 9: Estimations for four variations of the SARP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$				
	SAR-Pooled		**SAR-Spatial FE**	
Constant	-4.034	***	-	
	(-27.914)			
β^U	0.445	***	0.116	***
	(33.918)		(9.814)	
β^V	0.315	***	0.125	***
	(30.150)		(14.585)	
ρ	0.787	***	0.873	***
	(60.305)		(81.550)	
$n = NT$	2106		2106	
R^2	0.866		0.973	
R^2_{adj}	0.866		0.971	
AIC	3136.907		-8.823	
BIC	3159.517		465.991	
σ^2	0.248		0.051	
ll	-1564.453		88.411	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

A.2.2 SEMP

Table 10: Estimations for two further variations of the SEMP model ("distance" based matrix, excl. GDP_{cyc})

	Dependent variable: $\log \mathbf{M}$			
	SEM-Pooled		**SEM-Spatial FE**	
$Constant$	3.953	***	-	
	(29.608)			
β^U	0.410	***	0.102	***
	(26.494)		(7.406)	
β^V	0.381	***	0.164	***
	(30.916)		(14.961)	
$trend$	-0.011	*	0.029	***
	(-1.851)		(3.967)	
λ	0.759	***	0.909	***
	(27.623)		(81.260)	
$n = NT$	2106		2106	
R^2	0.853		0.972	
R^2_{adj}	0.853		0.971	
AIC	3315.321		20.855	
BIC	3337.931		495.669	
σ^2	0.271		0.051	
ll	-1653.661		73.572	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

Table 11: Estimations for four variations of the SEMP model ("distance" based matrix)

	Dependent variable: $\log \mathbf{M}$							
	SEM-Pooled		**SEM-Spatial FE**		**SEM-Time FE**		**SEM-Spatial/Time FE**	
Constant	3.823	***	-		-		-	
	(36.399)							
β^U	0.410	***	0.106	***	0.414	***	0.109	***
	(26.493)		(7.680)		(26.500)		(7.865)	
β^V	0.380	***	0.169	***	0.383	***	0.167	***
	(30.789)		(15.411)		(30.811)		(15.094)	
GDP_{cyc}	-0.474		3.176		-		-	
	(-0.106)		(0.822)					
λ	0.771	***	0.882	***	0.706	***	0.885	***
	(29.307)		(61.379)		(21.787)		(63.124)	
$n = NT$	2106		2106		2106		2106	
R^2	0.853		0.972		0.851		0.972	
R^2_{adj}	0.853		0.971		0.849		0.970	
AIC	3318.254		34.232		3377.593		94.605	
BIC	3340.865		509.046		3535.865		705.080	
σ^2	0.271		0.052		0.274		0.052	
ll	-1655.127		66.884		-1660.797		60.698	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 12: Estimations for two further variations of the SEMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$				
	SEM-Pooled		**SEM-Spatial FE**	
Constant	3.824	***	-	
	(36.421)			
β^U	0.410	***	0.106	***
	(26.540)		(7.693)	
β^V	0.379	***	0.170	***
	(30.846)		(15.513)	
λ	0.772	***	0.886	***
	(29.456)		(63.720)	
$n = NT$	2106		2106	
R^2	0.853		0.972	
R^2_{adj}	0.853		0.971	
AIC	3316.251		32.801	
BIC	3333.208		501.962	
σ^2	0.270		0.052	
ll	-1655.125		66.600	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

A.2.3 SDMP

Table 13: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$								
	SDMP-FE 1		**SDMP-FE 2**		**SDMP-FE 3**		**SDMP-FE 4**	
$Constant$	-		-		-		-	
β^U	0.160	***	0.165	***	0.161	***	0.148	***
	(10.132)		(10.524)		(10.044)		(9.599)	
β^V	0.210	***	0.210	***	0.250	***	0.218	***
	(17.508)		(17.511)		(22.124)		(18.521)	
$Trend$	-0.016	***	-0.016	***	-0.014	***	-0.016	***
	(-16.933)		(-16.943)		(-15.403)		(-16.705)	
GDP_{cyc}	2.163	***	1.769	***	2.736	***	-	
	(3.317)		(2.810)		(4.147)			
γ^U	0.083	**	-		0.051		0.051	
	(2.275)				(1.388)		(1.442)	
γ^V	0.157	***	0.153	***	-		0.164	***
	(8.563)		(8.367)				(8.929)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.303		0.301		0.278		0.278	
R^2_{adj}	0.301		0.299		0.277		0.277	
σ^2	0.082		0.082		0.084		0.084	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

Table 14: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$								
	SDMP-FE 5		**SDMP-FE 6**		**SDMP-OLS 1**		**SDMP-OLS 2**	
$Constant$	-		-		4.816	***	4.814	***
					(43.179)		(43.251)	
β^U	0.152	***	0.146	***	0.283	***	0.284	***
	(10.127)		(9.295)		(16.578)		(16.983)	
β^V	0.217	***	0.262	***	0.379	***	0.378	***
	(18.468)		(23.972)		(32.216)		(32.890)	
$Trend$	-0.016	***	-0.014	***	-0.019	***	-0.020	***
	(-16.754)		(-15.038)		(-11.724)		(-12.210)	
GDP_{cyc}	-		-		1.478		1.393	
					(1.300)		(1.265)	
γ^U	-		0.009		0.006		-	
			(0.239)		(0.302)			
γ^V	0.160	***	-		0.056	**	0.065	*
	(8.813)				(1.984)		(20.059)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.298		0.272		0.852		0.852	
R^2_{adj}	0.297		0.271		0.852		0.852	
σ^2	0.082		0.085		0.274		0.274	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 15: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$								
	SDMP-OLS 3		**SDMP-OLS 4**		**SDMP-OLS 5**		**SDMP-OLS 6**	
$Constant$	4.815	***	4.835	***	4.835	***	4.842	***
	(43.137)		(43.699)		(43.917)		(43.731)	
β^U	0.278	***	0.278	***	0.278	***	0.270	***
	(16.452)		(16.635)		(17.223)		(16.474)	
β^V	0.384	***	0.381	***	0.382	***	0.389	***
	(33.356)		(32.952)		(34.187)		(34.828)	
$Trend$	-0.019	***	-0.019	***	-0.019	***	-0.018	***
	(-11.596)		(-11.652)		(-12.169)		(-11.439)	
GDP_{cyc}	2.052	*	-		-		-	
	(1.866)							
γ^U	0.048	***	-0.000		-		0.048	***
	(19.945)		(-0.019)				(20.087)	
γ^V	-		0.066	**	0.065	***	-	
			(2.394)		(20.257)			
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.852		0.852		0.852		0.852	
R^2_{adj}	0.852		0.852		0.852		0.851	
σ^2	0.274		0.274		0.274		0.274	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 16: Estimations for four further variations of the SDMP model ("distance" based models)

	Dependent variable: log $\mathbf{M}$							
	SDMP-RE 1		**SDMP-RE 2**		**SDMP-RE 3**		**SDMP-RE 4**	
$Constant$	-		-		-		-	
β^U	0.160	***	0.161	***	0.161	***	0.148	***
	(10.141)		(10.042)		(10.042)		(9.597)	
β^V	0.210	***	0.250	***	0.250	***	0.218	***
	(17.521)		(22.119)		(22.119)		(18.516)	
$Trend$	-0.016	***	-0.014	***	-0.014	***	-0.016	***
	(-16.922)		(-15.399)		(-15.399)		(-16.701)	
GDP_{cyc}	2.147	***	2.737	***	2.737	***	-	
	(3.294)		(4.147)		(4.147)			
γ^U	0.079	**	-		0.051		0.051	
	(2.208)				(1.395)		(1.441)	
γ^V	0.156	***	0.051		-		0.164	***
	(8.542)		(1.395)				(8.927)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.303		0.278		0.278		0.278	
R^2_{adj}	0.301		0.276		0.276		0.276	
σ^2	0.082		0.084		0.084		0.084	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 17: Estimations for two further variations of the restricted SDMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$				
	SDMP-RE 5		**SDMP-RE 6**	
$Constant$	-		-	
β^U	0.152	***	0.146	***
	(10.125)		(9.292)	
β^V	0.217	***	0.262	***
	(18.464)		(23.967)	
$Trend$	-0.016	***	-0.014	***
	(-16.750)		(-15.034)	
GDP_{cyc}	-		-	
γ^U	-		0.009	
			(0.243)	
γ^V	0.160	***	-	
	(8.811)			
ρ	-		-	
$n = NT$	2106		2106	
R^2	0.298		0.272	
R^2_{adj}	0.297		0.271	
σ^2	0.082		0.085	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

Table 18: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: $\log \mathbf{M}$								
	SDMP-FE 1		**SDMP-FE 2**		**SDMP-FE 3**		**SDMP-FE 4**	
Constant	-		-		-		-	
β^U	0.178	***	0.184	***	0.178	***	0.170	***
	(10.615)		(11.022)		(10.535)		(10.426)	
β^V	0.155	***	0.156	***	0.185	***	0.161	***
	(12.609)		(12.609)		(16.753)		(13.427)	
GDP_{cyc}	1.409	**	0.979		1.839	***	-	
	(2.031)		(1.464)		(2.653)			
γ^U	0.090	**	-		0.068	*	0.069	*
	(2.318)				(1.757)		(1.841)	
γ^V	0.102	***	0.098	***	-		0.107	***
	(5.310)		(5.089)				(5.581)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.207		0.205		0.197		0.197	
R^2_{adj}	0.206		0.204		0.195		0.195	
σ^2	0.093		0.093		0.094		0.094	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 19: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$								
	SDMP-FE 5		**SDMP-FE 6**		**SDMP-OLS 1**		**SDMP-OLS 2**	
$Constant$	-		-		4.490	***	4.441	***
					(40.281)		(40.104)	
β^U	0.177	***	0.167	***	0.305	***	0.319	***
	(11.071)		(10.182)		(17.446)		(18.723)	
β^V	0.160	***	0.194	***	0.358	***	0.347	***
	(13.333)		(18.552)		(29.824)		(29.928)	
GDP_{cyc}	-		-		0.220		-0.865	
					(0.188)		(-0.770)	
γ^U	-		0.039		0.069	***	-	
			(1.048)		(3.307)			
γ^V	0.102	***	-		-0.029		0.064	*
	(5.371)				(-1.034)		(19.055)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.204		0.194		0.843		0.842	
R^2_{adj}	0.204		0.193		0.842		0.841	
σ^2	0.093		0.094		0.291		0.293	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 20: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$								
	SDMP-OLS 3		**SDMP-OLS 4**		**SDMP-OLS 5**		**SDMP-OLS 6**	
Constant	4.424	***	4.481	***	4.483	***	4.494	***
	(40.816)		(40.975)		(40.292)		(40.828)	
β^U	0.323	***	0.309	***	0.308	***	0.304	***
	(19.806)		(18.666)		(17.923)		(17.788)	
β^V	0.345	***	0.354	***	0.354	***	0.358	***
	(31.021)		(31.982)		(30.619)		(30.442)	
GDP_{cyc}	-		-		-0.131		-	
					(-0.117)			
γ^U	-		0.048	***	0.048	***	0.068	***
			(19.392)		(19.356)		(3.392)	
γ^V	0.063	***	-		-		-0.028	
	(19.073)						(-1.024)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.842		0.842		0.842		0.843	
R^2_{adj}	0.841		0.842		0.842		0.842	
σ^2	0.293		0.291		0.291		0.291	

t-statistics in parantheses.
* significant on 10 percent level.
** significant on 5 percent level.
*** significant on 1 percent level.

Table 21: Estimations for four further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$								
	SDMP-RE 1		**SDMP-RE 2**		**SDMP-RE 3**		**SDMP-RE 4**	
Constant	-		-		-		-	
β^U	0.178	***	0.182	***	0.182	***	0.199	***
	(10.615)		(10.786)		(10.786)		(12.272)	
β^V	0.155	***	0.189	***	0.189	***	0.188	***
	(12.610)		(17.125)		(17.125)		(15.805)	
GDP_{cyc}	1.406	**	1.916	***	1.916	***	-	
	(2.028)		(2.848)		(2.848)			
γ^U	0.090	**	-		0.087	***	0.032	**
	(2.312)				(5.324)		(2.266)	
γ^V	0.102	***	0.087	***	-		0.079	***
	(5.306)		(5.324)				(4.482)	
ρ	-		-		-		-	
$n = NT$	2106		2106		2106		2106	
R^2	0.207		0.224		0.224		0.224	
R^2_{adj}	0.205		0.222		0.222		0.222	
σ^2	0.093		0.095		0.095		0.095	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

Table 22: Estimations for two further variations of the SDMP model ("distance" based matrix)

Dependent variable: log $\mathbf{M}$				
	SDMP-RE 5		**SDMP-RE 6**	
$Constant$	-		-	
β^U	0.209	***	0.190	***
	(13.395)		(11.773)	
β^V	0.178	***	0.215	***
	(16.104)		(20.869)	
GDP_{cyc}	-		-	
γ^U	-		0.084	***
			(11.232)	
γ^V	0.112	***	-	
	(11.867)			
ρ	-		-	
$n = NT$	2106		2106	
R^2	0.342		0.339	
R^2_{adj}	0.342		0.338	
σ^2	0.099		0.100	

t-statistics in parantheses.

* significant on 10 percent level.

** significant on 5 percent level.

*** significant on 1 percent level.

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