

Stops, Michael

**Conference Paper**

## Job Matching on non-separated Occupational Labour Markets

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2011: Die Ordnung der Weltwirtschaft: Lektionen aus der Krise - Session: Empirical Labour Markets and Social Security, No. B11-V2

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Stops, Michael (2011) : Job Matching on non-separated Occupational Labour Markets, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2011: Die Ordnung der Weltwirtschaft: Lektionen aus der Krise - Session: Empirical Labour Markets and Social Security, No. B11-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft

This Version is available at:

<https://hdl.handle.net/10419/49161>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# Job Matching on non separated Occupational Labour Markets\*

Michael Stops (IAB Nuremberg)

31st July 2011

## Abstract

This paper refers to analyses of matching processes on occupational labour markets. Up to now, all studies in this field are based on the crucial assumption of separate occupational labour markets. I outline some theoretical considerations that occupational markets are probably not completely separated. By using information about similarities of occupational groups I constructed an "occupational topology" and tested my hypothesis of non separated occupational labour markets with OLS, Fixed Effects and Pooled Mean-Group models including cross-sectional dependency lags for regressors. The results show considerable dependencies between similar occupational groups in the matching process. Particularly, all in all the results indicate occupational specific set-up and set-down processes in similar occupational groups. This has important implications for estimating the matching efficiencies of unemployed and vacancies, because the matching process is not only determined by the unemployed and vacancies in the same occupational group but also by those in other occupational groups. Furthermore there are indications that the returns to scale derived from the results of the pooled mean-group model that considers cross-sectional dependency are constant.

**JEL classification:** C21, C23, J44, J64

**Keywords:** Unemployment; Vacancies; Matching Model; Panel data; Occupational Labour Markets.

## Contact:

Michael Stops  
Institut für Arbeitsmarkt- und Berufsforschung/Institute for Employment  
Research  
Weddigenstraße 20-22  
90478 Nürnberg  
GERMANY  
Tel.: 0049 (0) 911 179 4591  
Email: Michael.Stops@iab.de

---

\*Preliminary and not completed version - please do not circulate or cite without permission by the author.

# 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.<sup>1</sup>

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. Therefore, 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, 2004b; 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). Those 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, 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 OLS, Fixed Effects and Pooled Mean-Group Models including cross-sectional dependency lags for regressors. Therefore, the estimators consider interaction between cross-sectional units. 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 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

---

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

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 function  $f(U, V)$  is often specified by a Cobb-Douglas form:

$$M = AU^{\beta_U}V^{\beta_V}, \quad (1)$$

whereas  $A$  describes the "augmented" matching productivity. The variables  $\beta_U$  and  $\beta_V$  stand each for the matching elasticities of the unemployed and the vacancies respectively. From a theoretical viewpoint their values are positive and should be not higher than 1. Furthermore constant returns to scale are assumed, this implies  $\beta_U + \beta_V = 1$  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 construction jobs and in the health occupations, because of the different job requirements, apprenticeships and so on (for empirical evidence compare Fahr and Sunde, 2004b; Stops and Mazzoni, 2010). For Germany in particular occupations are adequate units for analyses of the matching processes, more than regions or economic sectors (compare also Fahr and Sunde, 2004b): Occupations comprise specific qualification requirements, tasks, and other characteristics. Furthermore individuals in Germany afford occupational specific knowledge during their careers. Usually firms with vacant jobs are looking for workers in certain occupations and job searchers are looking for jobs in certain occupations. Another point is the availability of well defined occupational data.

Nevertheless, the occupational markets are probably not strictly separated and the matching process on a certain occupational labour market is influenced by other occupational labour markets. One argument for this is that unemployed and employed persons could change their vocation during their employment biography (Fitzenberger and Spitz, 2004; Seibert, 2007; Kambourov and Manovskii, 2009; Schmillen and Möller, 2010). It is reasonable and can be shown that there are no flows between any kind of occupation, but there are flows between certain occupations. Another argument for interdependencies between different occupational labour markets is that the creation of new employment in a certain occupation could lead to the creation of new employment in other occupations, therefore occupational specific set-up or set-down processes respectively could be observed. The number of new matches in a certain occupation could be determined in a way by the number of unemployed and vacancies in other certain "similar" occupations.

The matching function would be modified in the following way:

$$M_i = A_i U_i^{\beta_U} V_i^{\beta_V} g(U_{J \Rightarrow i | J \neq i}) h(V_{J \Rightarrow i | J \neq i}), \quad (2)$$

whereas  $M_i$ ,  $A_i$ ,  $U_i$ , and  $V_i$  stand each for the matches, "augmented" matching productivity, unemployed, and vacancies in an occupational group  $i$ . The terms  $g(U_{i \Rightarrow j})$  and  $h(V_{i \Rightarrow j})$  denote each a functional relationship between the new hires in occupational group  $i$  and the sum of all unemployed persons as well as the sum of vacancies respectively in all occupational groups  $J$  that are similar with the observed occupational group  $i$ .

### 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 from 1988 (Kldb88<sup>2</sup>). Data for unemployed and vacancies stem from operative data of the Statistics of the German Federal Employment Agency. 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 employment from unemployment, employment or non-employment<sup>3</sup>.

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<sup>4</sup> (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 81 occupational groups to the 40 occupational sections (see table 4 in the appendix):

$$M_{i,t} = \frac{E_{o|i \in o,t}}{e_{o|i \in o,t}} \cdot m_{i,t}, \quad (3)$$

whereas variables have following definitions:

- $M_{i,t}$  is the interpolated number of new hires by the occupational groups  $i = 1, \dots, 81$  and the measuring time  $t$ ,
- $m_{i,t}$  is the number of new hires  $m$  from the SIAB 1975-2008 by occupational groups  $i = 1, \dots, 81$  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  $o = 1, \dots, 40$  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  $o = 1, \dots, 40$  at September 30th of each year  $t$ .

I have solely taken data for Western Germany, because data for Eastern Germany are only available since 1992. Therefore I have to accept a constraint: Western German job seekers who took up employment in Eastern Germany and Eastern German unemployed 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.

<sup>2</sup>Klassifizierung der Berufe 1988, compare table 3 in appendix.

<sup>3</sup>That means that a person was neither employed nor registered as unemployed.

<sup>4</sup>I used the number of employed who are subject to social insurance contributions.

Table 1: Descriptive statistics

		Average 1982-2007 (in numbers)	Share (in per cent)
<b>Labour market stocks</b>			
<b>Labour force</b>	$E + U$	25 436 839	100.00%
Employed	$E$	23 172 935	91.10%
Unemployed	$U$	2 263 904	8.90%
Vacancies	$V$	277 831	1.09%
<b>Flows in employment</b>	$M$	5 595 605	

Note: Own calculation of averaged stocks by years, source: data centre of the statistic department of the Federal Employment Agency, SIAB 1975-2008.

## 4 Empirical strategy and results

### 4.1 An occupational "topology"

The empirical strategy of this work is based upon the idea that cross-sectional units interact with others; therefore the interaction effect means that the average behaviour in a group influences the behaviour of the individuals that comprise the group (Manski, 1993; Elhorst, 2010). In this study I examine if new hires are influenced by exogenous regressors in other particular occupational groups. The number of unemployed of "similar" occupational groups should have a positive impact on the matches in a certain occupational group. The impact of vacancies is not clear: Both directions 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 (occupational specific set-up/set-down processes). 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 (occupational specific substitution processes). 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  $N \times N$  occupational weight-contiguity-matrix  $\mathbf{W}$  that refers to the similarities of occupational groups according to Matthes et al. (2008), compare table 5 in appendix. The basic idea of Matthes et al. (2008) was to aggregate somewhat "similar" or "homogeneous" respectively occupational groups according to the *KldB 88* to occupational segments (*Berufssegmente*). According to this, occupational groups on the 3-digits level are similar if they are alternatives for each other for recruitment decisions from the firms' perspective or for job search decisions from the employees' perspective. These information are available from the Federal Employment Agency and its Central Occupational File (*Zentrale Berufedatei*, Bundesagentur für Arbeit, Federal Employment Agency). To identify the similarities between certain occupational groups the Federal Employment Service analysed specific skills, licences, certificates, and knowledge needed as well as typical tasks and techniques for every occupational group (Matthes et al., 2008).

I transformed the results for occupational groups on the 3-digit level to occupational groups on the 2-digit level. Results are summarized in table 5 in the appen-

dix. On the base of this information I constructed a symmetric 81x81 first-order contiguity weight matrix consisting of ones reflecting similarity of occupational groups. The diagonal elements are set to zero by assumption, since an occupational group can not be similar to itself.

Thereby one restriction has to be beard in mind: some of the 2-digit groups are not assigned to only one occupational segment, because they contain some 3-digit groups belonging to one segment and some belonging to another segment<sup>5</sup>. However, these occupational groups could be handled as occupations that are similar with more than one segment (e.g. segment A and segment B), because they consist of some tasks or qualifications that are only found in segment A and some other that are only found in segment B. Therefore, segment A and segment B are not necessarily similar.

## 4.2 Estimation approach and results

For examining the influences by exogenous regressors in other occupational groups I use a modified Cobb-Douglas matching function with "spatial" lags for regressors as concretion for the functional terms  $g(U_{i=j})$  and  $h(V_{i=j})$ :

$$M_i = A_i U_i^{\beta_U} V_i^{\beta_V} U_{J=i}^{\gamma_U} V_{J=i}^{\gamma_V}, \quad (4)$$

Therefore, beside the well known matching elasticities  $\beta_V$  and  $\beta_U$  two further matching elasticities  $\gamma_V$  and  $\gamma_U$  have to be considered representing the effects due to dependencies of the occupational labour markets. In the first step I apply a pooled ordinary least square estimation (Pooled OLS). This model is used as reference for previous studies like this of Fahr and Sunde (2004a) or Stops and Mazzoni (2010) respectively. This estimator underlies two crucial assumptions: (i) equality of the parameters of the matching function in all occupational groups and (ii) stationarity of the used time series. In the second step I relax the assumption of equality of the intercept by applying a fixed effects estimator (FE). Finally I relax assumption (ii) by applying a Pooled-Mean-Group Model, as it was introduced by Pesaran et al. (1999, S. 623).

## 4.3 Pooled OLS and Fixed Effects estimators

The regression equation for the Pooled OLS and FE model based on the logarithm of both sides of equation (4) is

$$\log M = A_i + \beta^U \log U + \beta^V \log V + \gamma^U \log U + \gamma^V \log V + \omega t + \zeta \text{GDP}_{\text{cyc}} + E. \quad (5)$$

In line with the literature (LeSage and Pace, 2009, pp. 178)  $\beta_V$  and  $\beta_U$  can be interpreted as direct effects and  $\gamma_V$  and  $\gamma_U$  as indirect effects on the number of matches. Beside a comparison of the impacts of vacancies and unemployed on the matching process for labour market theory it is from certain interest to analyse the returns to scale in terms of the sum of the matching elasticities. LeSage and Pace (2009, pp. 34) show for the simple case of models with cross-sectional dependence regressors I apply in this paper ("SLX" models) that the (average) total elasticities is just the sum of the (direct) elasticity  $\beta$  and the indirect elasticity  $\gamma$ . Therefore, to analyse the returns to scale of the estimated

<sup>5</sup>To give an example compare table 5 and occupational group 63 "technical specialist": This group is assigned to "Miner/chemical occupations", "Glass, ceramic, paper production" as well as "Constructing".

matching functions I provide an Wald test with the Null that the same of all direct and indirect elasticities equals 1<sup>6</sup>.

For the Pooled OLS version of the model the "augmented productivity variable"  $A_i$  is equal and for the FE version it is individual for each occupational group. Furthermore the model contains a trend coefficient  $\omega$  and could be interpreted as an indicator for the development of the matching productivity during the observation period. The model is complemented by the cyclical component of the logarithm of the German real Gross Domestic Product  $GDP_{cyc}$  that is calculated with the Hodrick-Prescott-Filter (Hodrick and Prescott, 1997). The reasons for this are the following: for interpretation the empirical findings about the matching elasticities and consequently the returns to scale one has to bear in mind that the observable stocks of vacancies and unemployed are just proxies for all job searchers and vacancies on the labour market. This could lead to biased estimates (Broersma and Ours, 1999; Anderson and Burgess, 2000; Fahr and Sunde, 2005; Sunde, 2007). Probably this explains why most empirical studies do not provide evidence for constant returns of scale. Therefore, Anderson and Burgess (2000) proposed to interpret the empirical matching elasticities as these from a "reduced" model. Though, the number of all vacancies could be found if the shares of the observable vacancies<sup>7</sup> on all vacancies are known. These shares are reported from time to time (compare Heckmann et al., 2009) but for the observation period the shares are not known. Nevertheless Franz (2006) reports an partially counter-cyclical characteristics of these shares. This relationship can be used and in line with this, the coefficient of the  $GDP_{cyc}$  is expected to be positive<sup>8</sup>.

Table 2 presents in the columns (1) to (4) results for the pooled OLS and fixed effects model, for each one version with cross-sectional lags of exogeneous regressors and one without<sup>9</sup>.

---

<sup>6</sup> $H_0: \beta^U + \beta^V + \gamma^U + \gamma^V = 1$  vs.  $H_a: \beta^U + \beta^V + \gamma^U + \gamma^V \neq 1$

<sup>7</sup>These are the vacancies that are registered by the Federal Employment Service. Employers are not obligated to register vacancies.

<sup>8</sup>Compare detailed considerations in the appendix A.2

<sup>9</sup>Further results are presented in appendix A.3.1 and A.3.2.



dep. variable	(1) log $M$	(2) log $M$	(3) log $M$	(4) log $M$	(5) $\Delta \log M$	(6) $\Delta \log M$
	Pooled OLS i	Pooled OLS ii	FE i	FE ii	PMG i	PMG ii
$\beta^U$	0.481*** (0.025)	0.458*** (0.022)	0.137* (0.076)	0.189*** (0.071)	0.373*** (0.046)	0.493*** (0.038)
$\beta^V$	0.353*** (0.020)	0.377*** (0.017)	0.179*** (0.056)	0.236*** (0.041)	0.182*** (0.027)	0.255*** (0.019)
$\gamma^U$	-0.108*** (0.025)		0.191** (0.077)		0.250*** (0.062)	
$\gamma^V$	0.105*** (0.030)		0.148** (0.068)		0.166*** (0.036)	
<i>Trend</i>	-0.014*** (0.002)	-0.012*** (0.002)	-0.012*** (0.003)	-0.008** (0.003)	-0.036*** (0.002)	-0.032*** (0.002)
$GDP_{cyc}$	1.151 (1.247)	2.932** (1.198)	2.487*** (0.450)	2.248*** (0.807)	11.491*** (1.329)	9.757*** (1.139)
$\phi$					-0.253*** (0.020)	-0.263*** (0.023)
Constant	3.777*** (0.146)	3.528*** (0.126)	5.086*** (0.751)	6.987*** (0.760)	0.554*** (0.036)	1.096*** (0.087)
Observations	2,106	2,106	2,106	2,106	1,944	1,944
II	-1756	-1770	-251.2	-311.1	1877	1865
AIC	3526	3549	514.3	630.2	-3727	-3708
BIC	3566	3578	548.2	652.8	-3655	-3647
Wald test (Prob > F)	0.000	0.000	0.000	0.000	0.632	0.000
H(0): constant returns to scale						
Wald test (Prob > $\chi^2$ )	0.000		0.005		0.000	
H(0): $\gamma^U$ and $\gamma^V$ are simultaneously zero						

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Notes: (1) Pooled OLS and FE model: Robust standard errors in parentheses

(2) FE and PMG model: Constant = average of fixed effects

(3) PMG model: Short-run coefficients are not reported here; further results can be found in table 8 in the appendix A.3.3

Table 2: Results of the Pooled OLS estimations for log  $M$  as the dependend variable

Robust standard errors were calculated following Huber and White. Information criteria are reported, Akaike's information criteria (Akaike, 1974, AIC,) as well as Bayesian Information Criterion (Schwarz, 1978, BIC,). Therefore the models with the cross-sectional lags of the exogenous regressors should be preferred, because their information criteria are smaller than the ones of the variants without cross-sectional dependence.

The matching elasticities of the unemployed and vacancies respectively are significantly positive and robust in all model variations, nevertheless they are quite small in the FE models. The positive coefficient of the cyclical component of the real GDP and the negative parameter of the trend are - except for the pooled OLS version - robust.

The parameters for the impact of the regressors from other occupational groups  $\gamma^U$  and  $\gamma^V$  are both significant positive and robust for the FE models, but not for the pooled OLS version where  $\gamma^U$  is significant negative. A Wald test with the Null that both coefficients are simultaneously zero has to be rejected. The results of the FE estimations indicate a positive relationship between the new hires of an occupational group and the vacancies and unemployed in similar 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 – similar – occupational groups. Nevertheless the Wald test for constant returns to scale has to be rejected for all variant of the Pooled OLS and Fixed Effects model.

#### 4.4 Stationarity and Pooled Mean Group Model

The characteristics of the used panel variables are quite important for applying the right estimator. Blanchard and Diamond (1989, S. 55 ff.) used Augmented-Dickey-Fuller-Tests for the Null of Instationarity that could be rejected. Nevertheless they could not show cointegration between the observed data. Entorf (1998, S. 79 f.) confirmed, that unit roots are quite seldom in panel time series like new hires, vacancies and unemployment. Therefore it shall be evident, that the estimated parameters are significant unequal 0 for a  $t$ -statistics from a certain value. Fahr and Sunde (2004a, S. 426) used a stationarity test by Hadri (2000) with the Null of stationarity and showed that the Null could not be rejected for their data. Stops and Mazzone (2010) used the same test for similar data with more observation points in time and showed that the Null has to be rejected. I applied the same test for the data that is analysed in that paper. The results indicate, that the assumption of stationarity should not be kept. The Null of stationarity has to be rejected for all the time series of new hires, vacancies and unemployed. The Null could not be rejected for the first-order difference series in case of homoscedastic standard errors<sup>10</sup>. This allows the assumption of first-order integrated time series I(1). Furthermore from a theoretical point of view there is longtime linear relationship between the logarithm of the new hires and the unemployed and vacancies and it is conclusive to assume that these variables are co-integrated.

The Pooled Mean-Group model convinced by Pesaran et al. (1999) offers a good link to these data characteristics (Baltagi, 2002, S. 245). The base of the Pooled Mean-Group estimator is an autoregressive distributive lag ( $l, q_1, q_2, \dots, q_k$ ) model (ARDL model) with  $q = q_1 = q_2 = \dots = q_k$ . This model is reparameterized in a error correction form. Here I use a reparameterized ARDL(1,1,1) model:

$$\Delta \log M_{i,t} = \phi_i [\log M_{i,t-1} - (\beta^U \log U_{i,t} + \beta^V \log V_{i,t})] + \delta_i^U \Delta \log U_{i,t} + \delta_i^V \Delta \log V_{i,t} + A_i + \epsilon_{i,t} \quad (6)$$

In addition to the pooled OLS and FE estimators the following variables are now implemented:

- $\Delta \log M_{i,t}$  are each the first-order backward differences of the logarithm of the flow in employment,
- $\Delta \log U_{i,t}$  and  $\Delta \log V_{i,t}$  are the first-order backward differences of the logarithm of unemployed  $U_{i,t}$  and vacancies  $V_{i,t}$  and
- $\delta_i^U$  and  $\delta_i^V$  are the regression coefficients of these differences.

The following mechanism is modelled: the dependent variable  $\log M_{i,t-1}$  and the regressors  $\log U_{i,t}$  as well as  $\log V_{i,t}$  are not in an equilibrium and therefore the steady state is not reached (this would only be the case by chance). Therefore there is an adjustment process for  $\log M_{i,t}$ ; the error-correction term  $\phi_i$  on the right side of the equation denotes the error-correcting speed of adjustment term

<sup>10</sup>This is also true in the case of heteroscedasticity of the residuals with an exception for the unemployed at a significance level of 10 per cent. Please compare the results in table 9 in appendix.

in the square brackets. There is no long time relationship between the dependent and independent variables if  $\phi_i$  equals Null. A significant negative parameter indicates that the variables tend to a long-run steady-state (Blackburne III and Frank, 2007, S. 199).

The pooled mean-group estimator includes fixed effects and short-run dynamics of the variables for each occupational group  $i$  and restrict the long-run coefficients as equal for all occupational groups  $i$ . The PMG model in equation (6) is non-linear in its parameters  $\phi_i$  and  $(\beta^U, \beta^V)$ . Therefore a Maximum-Likelihood estimator is applied (Pesaran et al., 1999, S. 465). The concentrated likelihood has the form <sup>11</sup>:

$$l_T(\boldsymbol{\theta}', \boldsymbol{\phi}', \boldsymbol{\sigma}') = -\frac{T}{2} \sum_{i=1}^N \ln(2\pi\sigma_i^2) - \frac{1}{2} \sum_{i=1}^N N \frac{1}{\sigma_i^2} [\Delta \log \mathbf{M}_{h,i} - \phi_i \boldsymbol{\xi}_i(\boldsymbol{\theta})]' \mathbf{H}_i [\Delta \log \mathbf{M}_{h,i} - \phi_i \boldsymbol{\xi}_i(\boldsymbol{\theta})]. \quad (7)$$

The symbols mean

$$\begin{aligned} \boldsymbol{\xi}_i(\boldsymbol{\theta}) &= \log \mathbf{M}_{h,i,-1} - (\log U_i, \log V_i)(\beta^U, \beta^V)', \\ \mathbf{H}_i &= \mathbf{I}_T - \mathbf{L}_i(\mathbf{L}_i' \mathbf{L}_i) \mathbf{L}_i \text{ with a identity matrix } \mathbf{I}_T, \text{ whereas} \\ \mathbf{L}_i &= (\log \mathbf{M}_{h,i,-1}, \dots, \log \mathbf{M}_{h,i,-p+1}, \Delta \log U_i, \Delta \log V_i, \boldsymbol{\ell}) \\ \boldsymbol{\phi} &= (\phi_1, \phi_2, \dots, \phi_N)' \\ \boldsymbol{\sigma} &= (\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2)' \end{aligned} \quad (8)$$

The residuals  $\boldsymbol{\xi}_i(\boldsymbol{\theta}) = \log \mathbf{M}_{h,i,-1} - (\log U_i, \log V_i)(\beta^U, \beta^V)'$  are included in the logarithm of the density function of the normal distribution.

Table 2 presents the results for the long-run coefficients and the averaged error-correction term of two variations of the model, one version with and one version without cross-sectional lags of the exogenous regressors. Also for these two model the Wald test that  $\gamma^U$  and  $\gamma^V$  are simultaneously equal zero has to be rejected and considering the information criteria the model with the cross-sectionals lags of regressors should be preferred. A table 8 with all results and more model versions can be found in the appendix A.3.3. A lagged first-order difference of the the new hires  $\zeta_1^{\Delta M-1}$  is included as well as variations with the trend  $\omega$ , the cyclical component of the real GDP  $GDP_{cyk}$  and the cross sectional regressors as long-run parameters in the error-correction term.

The upper part of the tables include the long-run elasticities for the vacancies and unemployed as well as the exogenous regressors, the cyclical component of the real GDP and the trend. The lower part contains the averaged error-correction term  $\phi$ , the averages of the estimated short-run parameters for each occupational group and the average fixed effect  $A$  (Pesaran et al., 1999, S. 626).

The long-run coefficients  $\beta^U, \beta^V, \gamma^U, \gamma^V$  and  $GDP_{cyk}$  are positive and the trend  $T$  is negative and significantly different from zero. These results are robust for all model variations. The impact of the unemployed is larger than of the vacancies, that is also true for the 95%-confidence intervals of  $\beta^V$  and  $\beta^U$ . That is in line with other studies for Germany (Stops and Mazzoni, 2010; Fahr and Sunde, 2004a; Burda and Wyplosz, 1994). The short-run parameters are mostly significantly different from zero. For all modell variations there is a significant positive relationship between changes in the number of new hires and changes in the number of vacancies and a significant negative relationship between changes in the number of new hires and changes in the number of unemployed.

<sup>11</sup>The equation is noted in vectors and matrices (bold letters). Data for different observation points in time are staggered in the columns of the matrices or vectors resp., therefore the index  $t$  becomes expendable.

Particularly the latter results could explain deviations from the steady state. The error-correction term  $\phi$  is significant negative for all variations of the model. This is a indication for the existence of movements against the deviations from the long-run equilibrium.

## 5 Conclusions

This paper refers to analyses of matching processes on occupational labour markets. Up to now, all studies in this field are based on the crucial assumption of separate occupational labour markets. I outlined some theoretical considerations that occupational markets are not separated. By using information about similarities of occupational groups I constructed an "occupational topology" and finally I tested my hypothesis of non separated occupational labour markets with pooled OLS, fixed effects and pooled mean-group models that include cross-sectional dependency lags for regressors.

The results show that there are considerable dependencies between "similar" occupational groups in the matching process. One result is the positive relationship between the new hires of an occupational group and the vacancies and unemployed in other "neighbouring" occupational groups. The (preliminary) results indicate occupational specific set-up and set-down processes respectively in 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. Furthermore there are indications that the returns to scale, derived from the results of the pooled mean-group model considering cross-sectional dependency are constant.

# A Appendix

## A.1 Further information tables

Table 3: Occupational groups according to the German occupational classification scheme (*KldB 88*)

Code (KldB 88)	Occupational group
1	farmer, fisher
3	agricultural administrator
4	helper in the agricultural sector, agricultural workers, stockbreeding professions
5	gardener, florist
6	forester and huntsman
7	miner and related professions
8	exhauster of mineral resources
(9	mineral rehasher, mineral burner )*
10	stone processor
11	producer of building materials
12	ceramicist, glazier
13	glazier, glass processor, glass refiner
14	chemical worker
15	polymer processor
16	paper producer
17	printer
18	woodworker, wood processor
19	metal worker
20	moulder, caster, semi-metal cleaner
21	metal press workers, metal formers
22	turner, cutter, drilller, metal polisher
23	metal burnisher, galvanizer, enameler
24	welder, solderer, riveter, metal gluter
25	steel smith, copper smith
26	plumber, plant locksmith
27	locksmith, fitter
28	mechanic
29	toolmaker
30	metal precision-workers, orthodontists, opticians
31	electricians
32	assemblers and metal related professions
33	spinner, ropemaker
34	weaver, other textile producer
35	tailor, sewer
36	textile dyer
37	leather and fur manufacturers, shoemaker
39	baker, confectioner
40	butcher, fishworkmansi and related

continued on the next page

<b>Code</b>	<b>Occupational group</b>
<b>(KIdB 88)</b>	
41	cooks, convenience food preparatory
42	brewer, manufacturer for tobacco products
43	milk/fat processor, nutriments producer
44	bricklayer, concrete builder
45	carpenter, roofer, spiderman
46	road/track constructors, demolisher, culture structurer
47	helper in the construction sector
48	plasterer, tiler, glazier, screed layer
49	interior designer, furniture supplier
50	joiner, modeler, cartwright
51	painter, varnisher and related professions
52	goods tester, consignment professions
53	unskilled worker
54	machinist and related professions
60	engineer, architect
61	chemist, physicist
62	technician
63	technical specialist
68	merchandise manager
69	banking professional, insurance merchant
70	merchant/ specialist in conveyance, tourism, other services
71	conductor, driver, motorist
72	navigator, ship engineer, water/air traffic professions
73	mail distributor
74	storekeeper, worker in storage and transport
75	manager, consultant, accountant
76	member of parliament, association manager
77	accounting clerk, cashier, data processing expert
78	clerk, typist, secretary
79	plant security, guard, gate keeper, servant
80	other security related professions, health caring professions
81	law related professions
82	publicist, translator, librarian
83	artist and related professions
84	physician, dentist, apothecaries
85	nurse, helper in nursing, receptionist and related
86	social worker, care taker
87	professor, teacher
88	scientist
89	helper for cure of souls and cult
90	beauty culture
91	guest assistant, steward, barkeeper
92	domestic economy, housekeeping
93	cleaning industry related professions

\*Note: Occupational group 9 contains some missing values for vacancies. That's why it has to be dropped out for the estimations.

Table 4: Assignment of the occupational groups to the occupational section of the employment statistics of the Federal Employment Agency

Occupational groups		Occupational section	
in data		in employment statistics	
$i = 1, \dots, 82$		$o = 1, \dots, 40$	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
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

Table 5: Assignment of the occupational groups to the occupational segments (Matthes et al., 2008)

Occupational segment		Occupational group	
Code	Name	Code	Name
101	"Green" occupations	1	farmer, fisher
		3	agricultural administrator
		4	helper in the agricultural sector, agricultural workers, stockbreeding professions
		5	gardener, florist
		6	forester and huntsman
		42	brewer, manufacturer for tobacco products
201	Miner/chemical occupations	7	miner and related professions
		8	exhauster of mineral resources
		9	mineral rehasher, mineral burner )*
		14	chemical worker
		15	polymer processor
		46	road/track constructors, demolisher, culture structurer
		54	machinist and related professions
		60	engineer, architect
		62	technician
63	technical specialist		
202	Glass, ceramic, paper production	11	producer of building materials
		12	ceramicist, glazier
		13	glazier, glass processor, glass refiner
		16	paper producer
		17	printer
		51	painter, varnisher and related professions
		63	technical specialist
83	artist and related professions		
203	Textile, leather production	33	spinner, ropemaker
		34	weaver, other textile producer
		35	tailor, sewer
		36	textile dyer
		37	leather and fur manufacturers, shoemaker
		54	machinist and related professions
		62	technician
93	cleaning industry related professions		
204	Metal producer	19	metal worker
		20	moulder, caster, semi-metal cleaner
		21	metal press workers, metal formers
		22	turner, cutter, driller, metal polisher
		23	metal burnisher, galvanizer, enameler
		24	welder, solderer, riveter, metal gluter
		25	steel smith, copper smith
		26	plumber, plant locksmith
		27	locksmith, fitter
		28	mechanic
		29	toolmaker

continued on the next page



Occupational segment		Occupational group	
Code	Name	Code	Name
		30	metal precision-workers, orthodontists, opticians
		32	assemblers and metal related professions
		50	joiner, modeler, cartwright
		60	engineer, architect
		62	technician
		68	merchandise manager
205	Electricians	31	electricians
		32	assemblers and metal related professions
		60	engineer, architect
		62	technician
		77	accounting clerk, cashier, data processing expert
206	Wood occupations	18	woodworker, wood processor
		30	metal precision-workers, orthodontists, opticians
		48	plasterer, tiler, glazier, screed layer
		50	joiner, modeler, cartwright
		51	painter, varnisher and related professions
207	Constructing	11	producer of building materials
		44	bricklayer, concrete builder
		45	carpenter, roofer, spiderman
		46	road/track constructors, demolisher, culture structurur
		47	helper in the construction sector
		48	plasterer, tiler, glazier, screed layer
		49	interior designer, furniture supplier
		51	painter, varnisher and related professions
		54	machinist and related professions
		60	engineer, architect
		62	technician
		63	technical specialist
		71	conductor, driver, motorist
		83	artist and related professions
301	Hotel/restaurant occupations	39	baker, confectioner
		40	butcher, fishworkmansip and related
		41	cooks, convenience food preparatory
		43	milk/fat processor, nutriments producer
		70	merchant/ specialist in conveyance, tourism, other services
		80	other security related professions, health caring professions
		91	guest assistant, steward, barkeeper
		92	domestic economy, housekeeping
		93	cleaning industry related professions
302	Storage/ transport occupations	52	goods tester, consignment professions
		70	merchant/ specialist in conveyance, tourism, other services
		71	conductor, driver, motorist
		72	navigator, ship engineer, water/air traffic professions
		73	mail distributor
		74	storekeeper, worker in storage and transport
303	Merchandise occupations	68	merchandise manager

continued on the next page

Occupational segment		Occupational group	
Code	Name	Code	Name
		70	merchant/ specialist in conveyance, tourism, other services
		77	accounting clerk, cashier, data processing expert
		85	nurse, helper in nursing, receptionist and related
		90	beauty culture
304	White collar worker	70	merchant/ specialist in conveyance, tourism, other services
		73	mail distributor
		75	manager, consultant, accountant.
		76	member of parliament, association manager
		77	accounting clerk, cashier, data processing expert
		78	clerk, typist, secretary
		81	law related professions
		86	social worker, care taker
		88	scientist
305	Security occupations	60	engineer, architect
		62	technician
		79	plant security, guard, gate keeper, servant
		80	other security related professions, health caring professions
306	Social/care occupations	86	social worker, care taker
		89	helper for cure of souls and cult
307	Medical occupations	85	nurse, helper in nursing, receptionist and related
308	Physicians	84	physician, dentist, apothecaries
309	Teaching professions	87	professor, teacher
310	Artists/Athlets	10	stone processor
		83	artist and related professions
		87	professor, teacher
311	Natural scientists	60	engineer, architect
		61	chemist, physicist
		84	physician, dentist, apothecaries
		88	scientist
312	Humanists	82	publicist, translator, librarian
		88	scientist
999	Unskilled worker	53	unskilled worker

## A.2 Real GDP and the shares of registered vacancies on all vacancies

<sup>12</sup> Only vacancies  $V$  could be observed that are registered by the Federal Employment Service. To estimate the matching function it would be better know all vacancies  $V_{ALL}$ .  $R_{BA}$  denotes the share of the registered vacancies  $V$  on all vacancies  $V_{ALL}$ :

$$V = R_{BA} \cdot V_{ALL} \quad (9)$$

Employers register their vacancies, when they expect, that searching via the Federal Employment Service would be successful. In times of booms the number of the registered job searchers decreases. That is noticed by the firms. Therefore it could be assumed that firms have more negative expectations to find staff by the services of the Employment Agencies in these times. In line with (vgl. Franz, 2006, S. 107 f.)  $R_{BA}$  decreases in phases of economic recoveries - it is anticyclical. Therefore, the (logarithm of)  $R_{BA}$  correlates negative with the cyclical component of the real Gross Domestic Product ( $GDP_{cyc}$ ). The latter one could be interpreted as the deviation of the GDP from its long-run trend. Therefore it is an indicator for the economic situation at a certain point of time and consequently the rate  $R_{BA}$  could be seen in functional relationship with  $GDP_{cyc}$ :

$$R_{BA} = f(GDP_{cyc}). \quad (10)$$

That means

$$V = f(GDP_{cyc}) \cdot V_{ALL} \quad (11)$$

and after some simple rearrangements

$$V_{ALL} = \frac{V}{f(GDP_{cyc})}. \quad (12)$$

The matching function

$$M = AV_{ALL}^{\beta^V} U^{\beta^U} \quad (13)$$

after finding the logarithm is

$$\log M = \log A + \beta^V \log V_{ALL} + \beta^U \log U. \quad (14)$$

Using equation (12) leads to

$$\log M = \log A + \beta^V [\log V - \log f(GDP_{cyc})] + \beta^U \log U \quad (15)$$

and the assumption  $\log f(GDP_{cyc}) \cong (-\beta^{gdp} GDP_{cyc})$  leads to

$$\log M = \log A + \beta^V \log V + \beta^{gdp} GDP_{cyc} + \beta^U \log U \quad (16)$$

with  $\beta^{GDP} = (-\beta^V) \cdot (-\beta^{gdp})$ .

Finally the assumptions  $\beta^V > 0$  and  $\beta^{gdp} > 0$  lead to  $\beta^{gdp} > 0$ .

---

<sup>12</sup>compare also Stops and Mazzoni (2010)

### A.3 Further empirical results

#### A.3.1 Pooled OLS Model

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled OLS 1	Pooled OLS 2	Pooled OLS 3	Pooled OLS 4	Pooled OLS 5	Pooled OLS 6
$\beta^U$	0.481*** (0.025)	0.460*** (0.022)	0.456*** (0.022)	0.458*** (0.022)	0.479*** (0.024)	0.490*** (0.025)
$\beta^V$	0.353*** (0.020)	0.373*** (0.017)	0.378*** (0.018)	0.377*** (0.017)	0.354*** (0.020)	0.345*** (0.020)
$\gamma^U$	-0.108*** (0.025)	-0.025*** (0.008)			-0.114*** (0.024)	-0.060*** (0.025)
$\gamma^V$	0.105*** (0.030)		-0.014 (0.011)		0.112*** (0.029)	0.042 (0.030)
<i>Trend</i>	-0.014*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.014*** (0.002)	
$GDP_{eye}$	1.151 (1.247)	2.777** (1.197)	3.077*** (1.191)	2.932** (1.198)		0.630 (1.259)
Constant	3.777*** (0.146)	3.761*** (0.146)	3.629*** (0.152)	3.528*** (0.126)	3.790*** (0.144)	3.568*** (0.142)
Observations	2,106	2,106	2,106	2,106	2,106	2,106
ll	-1756	-1765	-1769	-1770	-1757	-1786
AIC	3526	3541	3549	3549	3525	3584
BIC	3566	3575	3583	3578	3559	3618
Wald test (Prob > F)	0.000	0.000	0.000	0.000	0.000	0.000
H(0): constant returns to scale						

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 6: Results of the Pooled OLS estimations for log  $M$  as the dependent variable

### A.3.2 Fixed Effects Model

	(1)	(2)	(3)	(4)	(5)	(6)
	FE 1	FE 2	FE 3	FE 4	FE 5	FE 6
$\beta^U$	0.137* (0.076)	0.127* (0.073)	0.187*** (0.070)	0.189*** (0.071)	0.133* (0.076)	0.157* (0.083)
$\beta^V$	0.179*** (0.056)	0.233*** (0.041)	0.172*** (0.055)	0.236*** (0.041)	0.182*** (0.056)	0.171*** (0.054)
$\gamma^U$	0.191** (0.077)	0.235*** (0.077)			0.149** (0.074)	0.163** (0.081)
$\gamma^V$	0.148** (0.068)		0.172** (0.069)		0.169** (0.068)	0.055 (0.058)
<i>Trend</i>	-0.012*** (0.003)	-0.009*** (0.003)	-0.011*** (0.003)	-0.008** (0.003)	-0.012*** (0.003)	
$GDP_{cyc}$	2.487*** (0.450)	3.933*** (0.782)	0.936 (0.635)	2.248*** (0.807)		2.347*** (0.447)
Constant	5.086*** (0.751)	5.399*** (0.730)	6.277*** (0.814)	6.987*** (0.760)	5.342*** (0.760)	5.717*** (0.752)
Observations	2,106	2,106	2,106	2,106	2,106	2,106
Number of groups	81	81	81	81	81	81
ll	-251.2	-280.1	-271.5	-311.1	-258.3	-321.7
AIC	514.3	570.2	553.1	630.2	526.6	653.4
BIC	548.2	598.4	581.3	652.8	554.8	681.7
Wald test (Prob > F)	0.000	0.000	0.000	0.000	0.000	0.000
H(0): constant returns to scale						

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Constant = average of fixed effects

Table 7: Results of the Fixed Effects estimations for  $\log M$  as the dependent variable

### A.3.3 Pooled Mean-Group Model

	(1)	(2)	(3)	(4)	(5)	(6)
	PMG 1	PMG 2	PMG 3	PMG 4	PMG 5	PMG 6
Long-run coefficients						
$\beta^U$	0.373*** (0.046)	0.413*** (0.046)	0.469*** (0.038)	0.493*** (0.038)	0.346*** (0.031)	0.376*** (0.054)
$\beta^V$	0.182*** (0.027)	0.246*** (0.021)	0.168*** (0.025)	0.255*** (0.019)	0.266*** (0.016)	-0.095** (0.038)
$\gamma^U$	0.250*** (0.062)	0.246*** (0.060)			0.004 (0.036)	0.301*** (0.081)
$\gamma^V$	0.166*** (0.036)		0.162*** (0.033)		0.096*** (0.022)	0.072 (0.049)
<i>Trend</i>	-0.036*** (0.002)	-0.034*** (0.002)	-0.033*** (0.002)	-0.032*** (0.002)	-0.026*** (0.001)	
$GDP_{cyc}$	11.491*** (1.329)	12.389*** (1.391)	9.747*** (1.119)	9.757*** (1.139)		19.448*** (2.287)
$\phi$	-0.253*** (0.020)	-0.247*** (0.020)	-0.266*** (0.023)	-0.263*** (0.023)	-0.342*** (0.035)	-0.166*** (0.014)
Short-run coefficients						
$\zeta_1^{AM-1}$	-0.104*** (0.021)	-0.099*** (0.022)	-0.094*** (0.022)	-0.088*** (0.023)	-0.031 (0.025)	-0.088*** (0.023)
$\delta_0^{\Delta U}$	-0.161*** (0.029)	-0.175*** (0.029)	-0.160*** (0.030)	-0.180*** (0.030)	-0.206*** (0.033)	-0.046 (0.029)
$\delta_{-1}^{\Delta U}$	-0.058*** (0.022)	-0.064*** (0.023)	-0.050*** (0.022)	-0.058*** (0.023)	-0.053** (0.022)	0.014 (0.023)
$\delta_0^{\Delta V}$	0.051*** (0.014)	0.050*** (0.014)	0.051*** (0.014)	0.046*** (0.014)	0.025 (0.017)	0.126*** (0.016)
$\delta_{-1}^{\Delta V}$	0.045*** (0.014)	0.046*** (0.014)	0.046*** (0.014)	0.044*** (0.014)	0.041*** (0.016)	0.109*** (0.012)
Constant	0.554*** (0.036)	0.648*** (0.043)	1.008*** (0.076)	1.096*** (0.087)	1.583*** (0.159)	0.626*** (0.045)
Observations	1,944	1,944	1,944	1,944	1,944	1,944
Number of groups	81	81	81	81	81	81
ll	1877	1870	1872	1865	1829	1789
AIC	-3727	-3716	-3719	-3708	-3634	-3554
BIC	-3655	-3649	-3653	-3647	-3568	-3487
Wald test (Prob > F)	0.632	0.116	0.000	0.000	0.000	0.000
H(0): constant returns to scale						
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Constant = average of fixed effects						

Table 8: Results of the PMG estimations for  $\Delta \log M$  as the dependent variable

### A.3.4 Hadri's LM test

Table 9: Results of the LM test by Hadri (2000) for the levels and the first-order differences of the logarithm of time series

Variable	Characteristics of Residuals	Model I (without trend)		Modell II (with trend)	
		t-stat	P-value	t-stat	P-value
log $M$	Homoscedasticity	93.390	0.000	30.515	0.000
	Heteroscedasticity	66.107	0.000	34.453	0.000
log $U$	Homoscedasticity	46.723	0.000	44.480	0.000
	Heteroscedasticity	45.825	0.000	38.670	0.000
log $V$	Homoscedasticity	63.112	0.000	47.491	0.000
	Heteroscedasticity	52.905	0.000	42.465	0.000
$\Delta \log M$	Homoscedasticity	-4.507	1.000	-6.010	1.000
	Heteroscedasticity	-1.303	0.904	-3.182	0.999
$\Delta \log U$	Homoscedasticity	-0.919	0.821	-4.150	1.000
	Heteroscedasticity	7.357	0.000	3.490	0.000
$\Delta \log V$	Homoscedasticity	-2.200	0.986	-1.759	0.9607
	Heteroscedasticity	0.483	0.315	1.699	0.045

H(0): Stationarity

## References

- Akaike, Hirotugu (1974): A New Look at the Statistical Model Identification. *IEEE Transactions on Automatic Control*, 19(6):716–723.
- Anderson, Patricia M. and Simon M. Burgess (2000): Empirical Matching Functions: Estimation and Interpretation Using State-Level Data. *Review of Economics and Statistics*, 82(1):93–102.
- Baltagi, Badi H. (2002): *Econometrics*. Springer, Berlin, 3rd edn.
- Blackburne III, Edward F. and Mark W. Frank (2007): Estimation of nonstationary heterogeneous panels. *The Stata Journal*, 7(2):197–208.
- Blanchard, Olivier J. and Peter Diamond (1989): The Beveridge Curve. *Brookings Papers on Economic Activity*, (1):1–76.
- Broersma, Lourens and Jan C. Ours (1999): Job searchers, job matches and the elasticity of matching. *Labour Economics*, 6(1):77–93.
- Bundesagentur für Arbeit (Federal Employment Agency) (2010): Zentrale Berufedatei (Central occupational file). <http://berufenet.arbeitsagentur.de>.
- Burda, Michael Christopher and Charles A. Wyplosz (1994): Gross worker and job flows in Europe. *European Economic Review*, 38(6):1287–1315.
- Cochran, William G. (1977): *Sampling Techniques*. Wiley series in probability and mathematical statistics. Wiley, New York, 3rd edn.
- Dauth, Wolfgang; Hujer, Reinhard; and Katja Wolf (2010): Macroeconometric Evaluation of Active Labour Market Policies in Austria. *IZA Discussion Paper*, (5217).
- Diamond, Peter A. (1982a): Aggregate Demand Management in Search Equilibrium. *The Journal of Political Economy*, 90(5):881–894.
- Diamond, Peter A. (1982b): Wage Determination and Efficiency in Search Equilibrium. *The Review of Economic Studies*, 49(2):217–227.
- Dorner, Matthias; Jörg Heining; Peter Jacobebbinghaus; and Stefan Seth (2010): Sample of Integrated Labour Market Biographies (SIAB) 1975-2008. *FDZ-Datenreport*, (1).
- Elhorst, Jean Paul (2010): Applied spatial econometrics: Raising the bar. *Spatial economic analysis*, 5(1):9–28.
- Entorf, Horst (1998): *Mismatch Explanations of European Unemployment: A Critical Evaluation*. European and Transatlantic Studies. Springer.
- Entorf, Horst (Mai 1994): *Trending time series and spurious mismatch*. Beiträge zur angewandten Wirtschaftsforschung. Inst. für Volkswirtschaftslehre und Statistik, Mannheim.
- Fahr, René and Uwe Sunde (2004a): Datensatz (STATA) für Beitrag von Fahr & Sunde 2004 "Occupational job creation: patterns and implications": Beitrag ersch. in *Oxford Economic Papers* (56) 2004. 407-435.
- Fahr, René and Uwe Sunde (2004b): Occupational job creation: patterns and implications. *Oxford Economic Papers*, 56:407–435.
- Fahr, René and Uwe Sunde (2005): Job and vacancy competition in empirical matching functions. *Labour Economics*, 12(6):773–780.



- Fitzenberger, Bernd and Alexandra Spitz (2004): Die Anatomie des Berufswechsels: Eine empirische Bestandsaufnahme auf Basis der BIBB/IAB-Daten 1998/1999. *ZEW-Discussion Paper*, (04-05).
- Franz, Wolfgang (2006): *Arbeitsmarktökonomik*. Springer-Lehrbuch. Springer, Berlin, 6th edn.
- Hadri, Kadour (2000): Testing for stationarity in heterogenous panel data. *Econometrics Journal*, (3):148–161.
- Heckmann, Markus; Anja Kettner; and Martina Rebien (2009): Einbruch in der Industrie - soziale Berufe legen zu: Offene Stellen im IV. Quartal 2008. *IAB-Kurzbericht*, (11):1–8.
- Hodrick, Robert J. and Edward C. Prescott (1997): Postwar US business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.
- Kambourov, Gueorgui and Iourii Manovskii (02 2009): Occupational Specificity Of Human Capital. *International Economic Review*, 50(1):63–115.
- Kangasharju, Aki; Pehkonen, Jaakko; and Pekkala, Sari (2005): Returns to Scale in a Matching Model: Evidence from Disaggregated Panel Data. *Applied Economics*, 37(1):p115 – 118.
- LeSage, James P. and Robert Kelley Pace (2009): *Introduction to spatial econometrics*, vol. 196 of *Statistics*. CRC Press, Boca Raton.
- Manski, Charles F. (1993): Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3):531–542.
- Matthes, Britta; Carola Burkert; and Wolfgang Biersack (2008): Berufssegmente: Eine empirisch fundierte Neuabgrenzung vergleichbarer beruflicher Einheiten. *IAB-Discussion Paper*, <http://doku.iab.de/discussionpapers/2008/dp3508.pdf>, (35/2010).
- Mora, John James and Santacruz, Jose Alfonso (2007): Emparejamiento entre desempleados y vacantes para Cali: Un analisis con datos de panel. (Unemployment and Vacancies in a Matching Model for Cali: A Panel Data Analysis. With English summary.). *Estudios Gerenciales*, 23(105):p85 – 91.
- Mortensen, Dale T. (1982): Property Rights and Efficiency in Mating, Racing, and Related Games. *The American Economic Review*, 72(5):968–979.
- Pesaran, M. Hashem; Yongcheol Shin; and Ron P. Smith (1999): Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association*, 94(446):621–634.
- Petrongolo, B. and C. Pissarides (2001): Looking into the black box: a survey of the matching function. *Journal of Economic Literature*, XXXIX:S. 390–431.
- Pissarides, C. A. (1979): Job matchings with state employment agencies and random search. *The Economic Journal*, 89 (1979):818–833.
- Pissarides, Christopher A. (1985): Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages. *The American Economic Review*, 75(4):676–690.
- Pissarides, Christopher A. (2000): *Equilibrium unemployment theory*. MIT Press, Cambridge, Mass., 2nd edn.
- Rogerson, Richard; Robert Shimer; and Randall Wright (2005): Search-

- Theoretic Model of the Labor Market: A Survey. *Journal of Economic Literature*, XLIII:959–988.
- Schmillen, Achim and Joachim Möller (2010): Determinants of lifetime unemployment : a micro data analysis with censored quantile regressions. *IAB Discussion Paper*; <http://doku.iab.de/discussionpapers/2010/dp0310.pdf>, (3/2010).
- Schwarz, Gideon (1978): Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464.
- Seibert, Holger (2007): Wenn der Schuster nicht bei seinem Leisten bleibt ... *IAB-Kurzbericht*, (1).
- Stops, Michael and Thomas Mazzoni (2010): Job Matching on Occupational Labour Markets. *Journal of Economics and Statistics (Jahrbuecher fuer Nationaloekonomie und Statistik)*, 230(3):287–312.
- Sunde, Uwe (2007): Empirical Matching Functions: Searchers, Vacancies, and (Un-)biased Elasticities. *Economica*, 74(295):537–560.
- Yashiv, Aran (2006): Search and Matching in Macroeconomics. *CEPR Discussion Papers*, (5459):1–70.