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Job matching across occupational labour markets

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Contents

Abstract

This paper refers to an analysis of matching processes in occupational labour markets in terms of classes of jobs that share extensive commonalities in their required qualifications and tasks. To date, all studies in this field have been based on the assumption of separate occupational labour markets. This assumption suggests that job search and matching processes only transpire within distinct occupational labour markets and that no occupational changes occur. I present theoretical and empirical arguments that undermine the validity of this assumption. Moreover, I construct an "occupational" topology based on information about the ways in which occupational groups may be seen as alternatives in searches for jobs or workers respectively. I then use pooled ordinary least squares, fixed effects, and pooled mean-group models that consider cross-sectional dependency lags for regressors to test the hypothesis that job search and matching occur across occupational labour markets. In particular, I find significant and positive matching elasticities with respect to the averaged numbers of unemployed workers and vacancies in similar occupational groups; these results clearly support my hypothesis. Furthermore, there are indications that returns to scale that are derived from the results of the pooled mean-group model are constant. The findings of this study strongly suggest the use of an augmented matching function that considers job and worker searches across occupational labour markets.

Zusammenfassung

Dieses Papier befasst sich mit der Analyse von makroökonomischen Matchingfunktionen auf beruflichen Teilarbeitsmärkten. Allen bisher hierzu vorliegenden Papieren lag die Annahme zugrunde, dass berufliche Teilarbeitsmärkte abgeschottet voneinander sind und somit berufliche Mobilität nicht vorliegt. Ich präsentiere einige theoretische und empirische Belege gegen diese Annahme. Auf der Grundlage von Informationen darüber, welche Berufsgruppen bezogen auf die Arbeitssuche bzw. die Rekrutierung von Arbeitskräften Alternativen darstellen, konstruiere ich eine "Berufstopologie". Mit deren Hilfe teste ich die Hypothese der Durchlässigkeit der beruflichen Teilarbeitsmärkte. Dabei verwende ich Pooled OLS-, Fixed-Effects- und Pooled-Mean-Group-Schätzer und modelliere die Durchlässigkeit als Abhängigkeiten der jeweiligen Neueinstellungen in einer Berufsgruppe vom durchschnittlichen Bestand der Arbeitslosen und Vakanzen in ähnlichen Berufsgruppen. Es ergeben sich signifikant positive Matchingelastizitäten von Arbeitslosen und Vakanzen in ähnlichen Berufsgruppen und damit wird die beschriebene Hypothese auch empirisch gestützt. Des Weiteren bieten die Ergebnisse Indizien dafür, dass die Skalenerträge, die sich aus dem Pooled-Mean-Group-Modell ergeben, konstant sind. Alles in allem zeigen die Ergebnisse deutlich, dass bei der Modellierung und Schätzung von Matchingfunktionen berücksichtigt werden sollte, dass die Prozess der jeweils individuellen Job- bzw. Bewerbersuche häufig nicht nur auf einem sondern über mehrere berufliche Teilarbeitsmärkte ablaufen.

JEL classification: C21, C23, J44, J64

Keywords: Unemployment; Vacancies; Matching Model; Panel Data; Occupational Labour Markets

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1 Introduction

The determinants of matching labour demand and labour supply to create new jobs are of continual interest for both labour market researchers and politicians. In part, because it is difficult to observe the individual search processes that underlie this type of matching on the micro level, studies in this field typically refer to the analytical results obtained using macroeconomic matching functions that model the empirical dependency of the number of new hires on the number of job-seekers and vacancies in a particular context of interest; for an overview, compare the surveys of Petrongolo/Pissarides (2001), Rogerson/Shimer/Wright (2005), and Yashiv (2007). These studies help to elucidate the efficiency of matching processes both in aggregated and partial labour markets. Therefore, some studies have examined particular sectors (Broersma/Ours, 1999), regions (Anderson/Burgess, 2000; Kangasharju/Pehkonen/Pekkala, 2005), or occupational groups, which are classes of jobs that share extensive commonalities in their qualification requirements and tasks (Entorf, Mai 1994; Fahr/Sunde, 2004; Mora, John James/Santacruz, Jose Alfonso, 2007; Stops/Mazzoni, 2010). The central assumption of most studies in this field is that partial labour markets are completely separated from each other; in other words, there are no flows of job-seekers from one partial labour market to another partial labour market, and no correlations exist between different labour markets with respect to newly created jobs or numbers of job vacancies. This central assumption is not presumed by studies of regional labour markets (e.g., Burda/Profit, 1996; Fahr/Sunde, 2006; Dauth/Hujer, Reinhard/Wolf, 2010; Lottmann, 2012)that consider the penetrability of partial labour markets. However, to date, no study of occupational labour markets has considered the dependencies between these partial labour markets. In investigations by Entorf (Mai 1994); Fahr/Sunde (2004); Mora, John James/Santacruz, Jose Alfonso (2007); Stops/Mazzoni (2010), the number of new jobs in a certain occupational group is explained by the number of unemployed workers and vacancies in the occupational group of interest.

In this paper, I use both empirical and theoretical arguments to demonstrate that the assumption of separate occupational labour markets is not appropriate. I test my hypotheses using pooled ordinary least squares (pooled OLS), fixed effects and pooled mean-group models that include cross-sectional dependency lags for regressors. Therefore, the estimators consider the interactions between cross-sectional units. To achieve this purpose, I construct an empirically based "occupational topology" that respects the considerations of Gathmann/Schönberg (2010) and Matthes/Burkert/Biersack (2008). I also discuss a new potential source for biased estimations of matching elasticities, namely, the omission of job searchers and vacancies in other occupations from consideration.

In the following section, I describe the motivation and theoretical framework of my estimation approach for the matching function. In section 3, I present the data used in this study, and the empirical estimates are subsequently provided in section 4. Section 5 summarises the main results of the investigation and discusses several questions that may be answered in future research.

2 Motivation and theoretical framework

The standard model of the matching function assumes the existence of a homogeneous pool of unemployed workers and a homogeneous pool of vacancies. The search activities of both sides of the market sides can be described as a matching technology. The processes underlying this matching procedure are not explicitly modelled;[1] instead, the matching process can be regarded as a black box (Petrongolo/Pissarides, 2001). The variables U, V and M can be used to represent the number of unemployed workers, vacancies and new hires (matches), respectively. The matching function $f(U,V)$ is often specified using a Cobb-Douglas functional form:

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

where A describes the "augmented" matching productivity (e.g., Fahr/Sunde, 2004). The coefficients β_U and β_V represent the matching elasticities of the unemployed workers and the vacancies, respectively. In accordance with standard matching theory, both elasticities are positive. Furthermore, the theoretical model assumes constant returns to scale, which implies that $\beta_U + \beta_V = 1$ with $\beta_U, \beta_V > 0$.

In the following, the assumption of homogeneous pools of vacancies and unemployed workers will be relaxed: It is reasonable to assume that occupation-specific differences exist with respect to the matching processes due to differences in job requirements, apprenticeships and other factors (for empirical evidence, see Fahr/Sunde, 2004; Stops/Mazzoni, 2010). In Germany in particular, occupations are more suitable units than regions or economic sectors for analyses of matching processes (compare with Fahr/Sunde, 2004): Occupations include specific qualification requirements, tasks, and other characteristics. Furthermore, individuals in Germany acquire occupation-specific knowledge during the course of their careers. Typically, firms with vacancies attempt to hire workers with certain qualifications, whereas job searchers seek jobs in certain occupations. The aforementioned studies (Fahr/Sunde, 2004; Stops/Mazzoni, 2010) assume that the number of new jobs in an occupational group does not depend on the number of unemployed workers and vacancies in other occupational groups. Fahr/Sunde (2004) propose the existence of partial occupational labour markets that are aggregates of specific occupational groups. These labour markets should be separated from each other; no flows of workers between different occupational labour markets should occur, and no correlations should exist between different labour markets with respect to newly created jobs or numbers of job vacancies, but this may be the case within these markets. Both Fahr/Sunde (2004) and Stops/Mazzoni (2010) use the variation over the occupational groups that are assigned to each occupational labour market to estimate matching elasticities for these markets. However, these researchers do not explicitly engage in either empirical or theoretical considerations of the flows or correlations between occupational groups. Therefore, these researchers assume that partial labour markets are completely separate in terms of occupational groups.

This assumption is quite strong because occupational labour markets could certainly interact with each other with respect to the matching process. One argument for the existence

[1] Examples of these processes include job and worker search decisions, job searches, and negotiations about wages.

of these interactions is that both unemployed and employed persons change their occupations during their employment biographies (Fitzenberger/Spitz, 2004; Seibert, 2007; Kambourov/Manovskii, 2009; Schmillen/Möller, 2010; Gathmann/Schönberg, 2010). An observation of the flows of individuals into employment between 1982 and 2007 reveals that the shares of these flows that involve occupational changes can be rather high for various industries. In particular, these shares range from 16 per cent (the occupational changes of former foresters and huntsmen) to 75 per cent (the occupational changes of polymer processors; for more detailed information, see section A.3 of the appendix).

From a theoretical point of view, the incorporation of flows between occupational labour markets causes analyses of the matching process to become considerably more complex: job searchers must decide on their search strategy with respect to their optimal number of job interviews in several different occupational labour markets.

In the following discussions, I refer to a theoretical matching model that provides deeper insights into the implications for the matching elasticities for unemployed workers and vacancies that derive from the fact that job and worker searches occur not only within occupational labour markets but also across these markets. Although the structure of this model is based on a paper by Burda/Profit (1996), the interpretation of the model has been widely modified. All of the formal considerations for this model can be found in the Appendix A.1. According to the model, an individual's optimal search intensity for a job search depends negatively on the probability of obtaining a job after completing a job application, negatively on the costs of the job search, and positively on the returns for a successful job search in terms of wages. The negative relationship between optimal job search intensity and the probability of obtaining a job after application could be explained by the assumption that the search costs will be linear and should be small relative to the expected revenues from the job search.[2]

In an analysis of regional labour markets, Burda/Profit (1996) complement fixed search costs with a variable element that depends positively on the regional distance between the region in which a job searcher is situated and the region in which this individual is searching for jobs. With respect to permeability, occupational labour markets may be quite similar to regional labour markets. In particular, workers and vacancies are typically related to particular occupational groups. Nevertheless, workers and firms often do not limit their search to a single occupational labour market. With respect to regional labour markets, various metrics, such as geographic distances or commuting flows, should represent the strength of the interdependencies (and causal relationships) between economic activities

[2] This finding contradicts the standard assumption of the discouraged worker hypothesis (Pissarides, 2000). According to this hypothesis, workers increase their job search intensity if the probability of obtaining a job increases but give up their job searches if the expected revenues of this search are relatively low. This hypothesis is derived from a model that assumes that search costs exponentially increase with job search intensity. Under the conditions, of this model, the optimal job search intensity positively depends on the job finding probability. The framework of this model is rather controversial; in particular, Shimer (2005) reveals that this model "[...] cannot generate business-cycle-frequency fluctuations in unemployment and job vacancies in response to shocks of a plausible magnitude[...]". One reason for this deficiency in the model could be that workers do not behave in accordance with the model's predictions. In a recession, the expected revenues of job searches may become quite low because of the decreased wages and smaller number of vacancies (which decrease the probability of finding a job); nonetheless, it could be reasonable for workers to increase their efforts to find a job under these difficult economic conditions. By contrast, in an economic upswing, workers may decrease their job search intensity because they know that a high search intensity is not required to obtain a job.

in different regions. In many instances, the topology of the regions of interest provides a good notion of the relationships that must be analysed: In occupational labour markets, the topology becomes more complex because there are no physical restrictions on the number of borders and neighbours of particular occupational groups. Thus, metrics are required that represent the similarity of occupational groups with respect to their property as alternatives for both job searchers and firms that seek workers.

In the following analyses, I differentiate only between the case of two or more occupations that are similar and thus constitute plausible alternatives in the job search and matching process and the opposite case of dissimilar occupations. Therefore, in the model, I assume that the variable portion of search costs could be zero if a job searcher is searching in his former occupational labour market, positive but moderate in situations involving a job search in similar occupational markets, or prohibitively high if the job search occurs in dissimilar occupational labour markets. In the case of job searches in dissimilar occupational labour markets, the optimal search intensity should be very low or even zero.

This approach directly implies that the number of matches in a certain occupation is determined not only by the number of unemployed workers and vacancies in the occupation itself but also by the number of unemployed workers and vacancies in similar alternative occupations. Therefore, the empirical matching function should be augmented accordingly. One can differentiate between the observed occupational market and similar occupational markets with respect to vacancies and unemployed workers. Thus, the following general modified matching function may be obtained:

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

where M_i, A_i, U_i, and V_i represent the matches, "augmented" matching productivity, unemployed workers, and vacancies in an occupational group i respectively. The term $g(U_{i \rightleftharpoons j})$ denotes the functional relationship between the new hires in occupational group i and the sum of all unemployed persons in all occupational groups J that are similar to the observed occupational group i; similarly, $h(V_{i \rightleftharpoons j})$ denotes the functional relationship between these new hires and the sum of the vacancies in occupational groups J.[3]

Based on a quasi-reduced form of the matching model,[4] the sign of these matching elasticities is determined by two mechanisms. The number of matches in a certain occupation decreases due to an increase in the number of unemployed workers in similar occupations due to decreases in the probability that a worker will receive a job offer in the occupation of interest. Simultaneously, this decreased probability of receiving a job offer causes a higher optimal job search intensity, assuming that the expected gain from a job search is significantly higher than the search (and travel) costs and that these costs are small in total and linearly increase with the number of job applications; this increase in search intensity tends to produce a higher number of job matches. Increasing the stock of vacancies, cet. par., would cause more matches due to a higher job finding rate but would also produce indirect negative effects due to the tendency towards lower optimal search intensities. Finally, the matching elasticities of the unemployed and vacancies in similar occupations could both

[3] In the empirical subsection 4.2, I propose a concrete specification of these functional terms.

[4] The matches directly depend only on the number of unemployed and the job finding rate. The latter depends also on the number of vacancies.

have positive signs if the (optimal) job search elasticity of the job finding rate is negative and lies in a certain range less than zero[5] .

3 Data

I construct a panel data set that is similar in its structure but larger in its time dimension than the data set that was used by Stops/Mazzoni (2010); Fahr/Sunde (2004). This data set consists of 81 occupational groups as cross-section units over the course of 26 time periods (1982 to 2007). The units are obtained from the German occupational classification scheme from 1988 (Kldb88[6]). Information about the unemployed and (registered) vacancies is provided by rich operative data from the Statistics of the German Federal Employment Agency. These data are only available at the required level of disaggregation for the reference date of September 30th of each year. To calculate new hires for each sampled year, I used the data from the IAB Sample of the Integrated Labour Market Biographies 1975-2008 (SIAB 1975-2008) from October 1st of each year to September 30th of the following year. The SIAB 1975-2008 is a representative 2% sample of an individual's history of unemployment and employment that is subject to social insurance contributions (Dorner et al., 2010). The number of new hires in the occupational groups is equal to the sum of flows to employment in each occupational group for each examined period (which ranges from October 1st of a year to September 30th of the following year). I calculated the number of new hires in the national economy using a ratio estimator that was suggested by Cochran (1977: pp. 150) and applied by Stops/Mazzoni (2010). In particular, the number of new hires is divided by the employment levels from the SIAB 1975 - 2008 data, and the resulting quotient is then multiplied by the employment levels[7] from the employment statistics of the Federal Employment Agency. This ratio estimator is more accurate than a simple extrapolation because the level of employment and the number of new hires are highly positively correlated. Because there are only 40 occupational sections in the employment statistics of the Federal Employment Agency, I assign the 81 occupational groups of this study to the 40 occupational sections (see table 5 in the appendix).

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

where the variables have following definitions:

- $M_{i,t}$ is the interpolated number of new hires by the occupational groups $i = 1, ..., 81$ for the time period t,
- $m_{i,t}$ is the number of new hires m from the SIAB 1975-2008 data by occupational groups $i = 1, ..., 81$ for the year t,
- $e_{o|i \in o,t}$ is the number of employed persons from the SIAB 1975-2008 data in the

[5] See section A.1 of the Appendix.

[6] *Klassifizierung der Berufe 1988*; see table 4 in the Appendix A.2.

[7] Employees who are subject to social insurance contributions are measured.

occupational group $i \in o$ that has been assigned to the occupational sectors $o = 1, ..., 40$ on September 30th of each year t, and

- $E_{o|i \in o,t}$ is the level of employment on September 30th of each year t in the occupational group $i \in o$ that has been assigned to the occupational sector $o = 1, ..., 40$ on September 30th of each year t.

The data set includes information about the German labour market since the early 1980s; however, data for Eastern Germany are only available since 1992. Thus, only the information for Western Germany can be used in this study, and neither Western German job seekers who obtained employment in Eastern Germany nor Eastern German unemployed workers were considered by this investigation. The numbers of Western German unemployed workers and registered vacancies are the explanatory variables used in this investigation to explain the dependent variable of the flows in employment in Western Germany. Another constraint of this study relates to the frequency of its time series. It has frequently been noted that information about the dynamic changes in the numbers of unemployed workers and vacancies is lost if yearly data are used; consequently, the estimation results could be biased (Petrongolo/Pissarides, 2001: for a broader discussion, see). However, I am forced to neglect this issue because data with greater frequencies are not available for the observed period.

Table 1 presents descriptive statistics for the aggregated stocks and flows from the data.

Table 1: Descriptive statistics

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

Note: The averaged stocks by year were calculated during the course of this study. Data sources: the data centre of the statistics department of the Federal Employment Agency and the SIAB 1975-2008.

4 Empirical strategy and results

4.1 An occupational "topology"

The empirical approach of this work is based on the idea that cross-sectional units interact with others; this interaction effect implies that the average behaviour in a group influences the behaviours of the individuals that comprise this group (Manski, 1993; Elhorst, 2010). Analogously to a regional topology, which depends on the distances among the regions of interest, I derived an "occupational group topology" that relies on the similarities between occupational groups according to Matthes/Burkert/Biersack (2008); this table is provided in 6 in the appendix.

The fundamental concept of Matthes/Burkert/Biersack (2008) was to aggregate occupational groups that were somewhat "similar" or "homogeneous" according to the *KldB 88* into occupational segments (*Berufssegmente*) following the concept outlined in an earlier version of Gathmann/Schönberg (2010). In accordance with this approach, occupational groups on the 3-digit level[8] are similar if they are alternatives for each other for recruitment decisions by firms or for job search decisions by potential employees. This information is available from the Federal Employment Agency and its Central Occupational File (, Federal Employment Agency: *Zentrale Berufedatei*). To identify the similarities between certain occupational groups, the Federal Employment Service analysed not only the specific skills, licences, certificates, and knowledge but also the typical tasks and techniques involved in every occupational group (Matthes/Burkert/Biersack, 2008).

I transform the results for occupational groups on the 3-digit level to occupational groups on the 2-digit level; this transformation is possible due to the hierarchical structure of the occupational classification scheme. The results of this procedure are summarised in table 6 in the appendix. Based on this information, I constructed a symmetric 81 $\times$ 81 first-order contiguity weight matrix $\mathbf{W}$ in which the value of one reflects correlations between similar occupational groups. The diagonal elements are set to zero.

One restriction to this approach must be noted. Certain 2-digit groups are not assigned to only one occupational segment because they contain particular 3-digit groups that belong to one segment and other 3-digit groups that belong to another segment[9]. However, these occupational groups could be regarded as occupations that are similar to more than one segment (e.g., segment A and segment B) because they include certain tasks or qualifications that are only found in segment A and other tasks or qualifications that are only found in segment B. Therefore, segments A and B are not necessarily similar.

4.2 Estimation approach and results

To examine the influences of exogenous regressors in other occupational groups, I use a modified Cobb-Douglas matching function with "spatial" lags for regressors to obtain concrete forms for the functional terms $g(U_{i \rightleftharpoons j})$ and $h(V_{i \rightleftharpoons j})$:

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

Therefore, in addition to the well-known matching elasticities β_V and β_U, two further matching elasticities, γ_V and γ_U, must be considered because these latter elasticities represent the effects of the dependencies of the occupational labour markets. At this stage, I present

8 The German occupational classification scheme 88 (KldB 88) code is a hierarchical construction that incorporates the following levels (from lowest to highest): occupational classes, which have a 4-digit code; occupational orders, which have a 3-digit code; occupational groups, which have a 2-digit-code; and occupational ranges, which have a 1-digit code. This classification scheme implies that a certain occupational range includes certain occupational groups that each include certain occupational orders that each include certain occupational classes.

9 For example, consider occupational group 63 "technical specialist" in table 6. This group is assigned to "Miner/chemical occupations"; "Glass, ceramic, paper production"; and "Construction".

the model assuming the availability of perfect information about job searchers, vacancies, and new hires. Subsequently, to overcome several shortcomings of the available data, I complement the model with a recession and a time trend variable. In the first step of the model construction, I apply a pooled ordinary least squares (Pooled OLS) estimation. This model is used as a reference for previous studies, such as the works of Fahr/Sunde (2004) or Stops/Mazzoni (2010). This estimator is based on two further crucial assumptions: (i) the equality of the matching function parameters across all of the examined occupational groups and (ii) the stationarity of the used time series. In the second step of the estimation, I relax the assumption of the equality of the intercept by applying a fixed effects (FE) estimator. Finally, I relax assumption (ii) by applying a pooled mean-group model, an approach that was introduced by Pesaran/Shin/Smith (1999: S. 623).

4.3 Pooled OLS and fixed effects estimators

After taking the logarithm of both sides of equation (4), the Pooled OLS and FE models can be expressed in vector and matrix notation, respectively, using the following regression equation:

$$\log \mathbf{M} = \mathbf{A} + \beta_{\mathbf{U}} \log \mathbf{U} + \beta_{\mathbf{V}} \log \mathbf{V} + \mathbf{W} \log \mathbf{U} \gamma_{\mathbf{U}} + \mathbf{W} \log \mathbf{V} \gamma_{\mathbf{V}} + \omega \mathbf{t} + \zeta \mathbf{GDP_{cyc}} + \mathbf{E}. \quad (5)$$

In accordance with the literature (LeSage/Pace, 2009: pp. 178), β_V and β_U can be interpreted as direct effects on the number of matches, and γ_V and γ_U can be interpreted as indirect effects (of the average of unemployed workers in similar occupational groups) on the number of matches. With respect to the field of labour market theory, it is important to not only provide a comparison of the impacts of vacancies and unemployed workers on the matching process but also analyse the returns to scale in terms of the sum of the matching elasticities. LeSage/Pace (2009: pp. 34) demonstrate that for the simple case of models with cross-sectional dependence regressors ("SLX" models), such as the models presented in this paper, the (average) total elasticity is simply the sum of the (direct) elasticities, β_V and β_U, and the indirect elasticities, γ_V and γ_U. Therefore, to analyse the returns to scale of the estimated matching functions, I provide a Wald test with the null hypothesis that the sum of all direct and indirect elasticities is unity[10]. Among others, Berman (1997) sets forth the argument that (monthly) numbers of the unemployed and vacancies are reduced by every hiring, eventually producing a downward bias in the estimated elasticities. Several studies for different countries based on elasticity estimations without restrictions on the returns to scale empirically confirm this conjecture (see, e.g., Burda/Wyplosz, 1994; Fahr/Sunde, 2004; Stops/Mazzoni, 2010). In fact, in this paper, a further potential source for underestimated elasticities is addressed, namely, the omission of job searchers and vacancies in similar occupational groups.
In the Pooled OLS version of the model, the "augmented" productivity coefficient $\mathbf{A_i}$ is equal across all of the occupational groups; the value of this coefficient may vary in the FE version of the model. Furthermore, the model contains a trend coefficient ω and can

[10] H_0: $\beta_U + \beta_V + \gamma_U + \gamma_V = 1$ vs. H_a: $\beta_U + \beta_V + \gamma_U + \gamma_V \neq 1$

be interpreted as an indicator for the development of the matching productivity during the observation period.

Note that the observable numbers of vacancies and unemployed are proxies for all of the job searchers and vacancies on the labour market. The use of these proxies could produce biased estimates (Broersma/Ours, 1999; Anderson/Burgess, 2000; Fahr/Sunde, 2005; Sunde, 2007). Therefore, Anderson/Burgess (2000) propose interpreting the empirical matching elasticities as quantities that are obtained from a "reduced" model. However, the number of all vacancies could be found if the ratios of the observable vacancies[11] to all vacancies were known. These ratios are reported on occasion (Heckmann/Kettner/Rebien, 2009), but data for the entire observation period are not available. However, Franz (2006) reports that these ratios demonstrate partially counter-cyclical characteristics. This finding can be used to obtain the unbiased coefficient for the matching elasticity of the vacancies. Therefore, I complemented the model by incorporating the cyclical component of the logarithm of the German real gross domestic product GDP_{cyc} that is calculated using the Hodrick-Prescott filter (Hodrick/Prescott, 1997)[12]. In accordance with the work of Franz (2006), the coefficient of the GDP_{cyc} is expected to be positive.

In columns (1) to (4) of Table 2, I present the results for the pooled OLS and fixed effects models including one version of each model that includes the cross-sectional lags of exogeneous regressors and one version of each model that does not include these lags[13].

[11] These observable vacancies are those registered by the Federal Employment Service; employers are not obliged to register vacancies.

[12] Detailed considerations are provided in Appendix A.4.

[13] Further results are presented in Appendix A.6.1 and A.6.2.

Table 2: The Results for the Matching equation

	(1)	(2)	(3)	(4)	(5)	(6)
dep. variable	$\log M$	$\log M$	$\log M$	$\log M$	$\Delta \log M$	$\Delta \log M$
	Pooled OLS i	Pooled OLS ii	FE i	FE ii	PMG i	PMG ii
β_U	0.481***	0.458***	0.137*	0.189***	0.373***	0.493***
	(0.025)	(0.022)	(0.076)	(0.071)	(0.046)	(0.038)
β_V	0.353***	0.377***	0.179***	0.236***	0.182***	0.255***
	(0.020)	(0.017)	(0.056)	(0.041)	(0.027)	(0.019)
γ_U	-0.108***		0.191**		0.250***	
	(0.025)		(0.077)		(0.062)	
γ_V	0.105***		0.148**		0.166***	
	(0.030)		(0.068)		(0.036)	
Trend	-0.014***	-0.012***	-0.012***	-0.008**	-0.036***	-0.032***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
GDP_{cyc}	1.151	2.932**	2.487***	2.248***	11.491***	9.757***
	(1.247)	(1.198)	(0.450)	(0.807)	(1.329)	(1.139)
ϕ					-0.253***	-0.263***
					(0.020)	(0.023)
Constant	3.777***	3.528***	5.086***	6.987***	0.554***	1.096***
	(0.146)	(0.126)	(0.751)	(0.760)	(0.036)	(0.087)
Observations	2,106	2,106	2,106	2,106	1,944	1,944
ll	-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) H(0): constant returns to scale	0.000	0.000	0.000	0.000	0.632	0.000
Wald test (Prob > χ^2) H(0): γ_U and γ_V are simultaneously zero	0.000		0.005		0.000	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: (1) Pooled OLS and FE model: Robust standard errors in parentheses. Akaikes Information Criteria (AIC), Bayesian Information Criteria (BIC) on the base of the Likelihood (ll) derived by the estimation results.
(3) FE and PMG model: Constant = average of fixed effects
(4) PMG model: Short-run coefficients are not reported here; further results can be found in Table 3.
Akaikes Information Criteria (AIC), Bayesian Information Criteria (BIC) on the base of the Maximum Likelihood estimation (ll).

Robust standard errors are calculated in accordance with Huber and White. Information criteria are reported, including the Akaike information criterion (AIC, Akaike, 1974) and the Bayesian information criterion (BIC, Schwarz, 1978). According to the AIC and BIC, the models with the cross-sectional lags of the exogenous regressors should be preferred over the other examined models.

The matching elasticities of the unemployed workers and vacancies are significantly positive and robust in all variations of the model; however, these elasticities are rather small in the FE models. The positive coefficient of the cyclical component of the real GDP and the negative parameter of the trend are robust for all of the models except for the pooled OLS estimation.

The parameters for the impact of the regressors from other occupational groups, γ_U and γ_V, are both significant, positive, and robust for the FE models but not for the pooled OLS model; in this model, γ_U is significant and negative. The null of a Wald test that both coefficients are simultaneously zero must 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 workers in similar occupational groups. This finding has important implications for estimating the matching efficiencies of unemployed workers and vacancies. In particular, this result indicates that these efficiencies are determined not only by number of unemployed workers and vacancies in the same occupational group but also by number of unemployed workers and vacancies in similar occupational groups. Moreover, the null of the Wald test for constant returns to scale must be rejected for all of the variants of the Pooled OLS and Fixed Effect models.

4.4 Stationarity and the pooled mean-group model

The properties of the used panel variables are very important for ensuring that the correct estimator is applied. Blanchard/Diamond (1989: S. 55 ff.) report the results of augmented Dickey-Fuller tests that reject the null of non-stationarity. However, these researchers could not reveal the existence of cointegration in the observed data. Entorf (1998: pp. 79) confirmed that unit roots are quite seldom found in panel time series for certain metrics such as new hires, vacancies and unemployed workers. Fahr/Sunde (2004) use a stationarity test by Hadri (2000) with the null of stationarity and reveal that the null could not be rejected for their data. Stops/Mazzoni (2010) employ the same test for similar data with more observation timepoints and demonstrate that the null must be rejected.

I apply the same test for the data that are analysed in Stops/Mazzoni (2010). The results indicate that the assumption of stationarity should not be maintained. The null of stationarity must be rejected for all of the time series of new hires, vacancies and unemployed workers. By contrast, the null could not be rejected for the first-order difference series because of the possibility of homoscedastic standard errors[14]. Thus, the time series are likely integrated of order 1. Furthermore, from a theoretical perspective, there is a long-run linear relationship between the logarithm of new hires and both unemployed workers

[14] This conclusion is also true with respect to the heteroscedasticity of the residuals, with an exception for unemployed workers at a significance level of 10 per cent. Please compare the results in Table 10 in the Appendix.

and vacancies, and it can be conclusively assumed that these variables are co-integrated. Therefore, I apply the pooled mean-group model (PMG) conceived by Pesaran/Shin/Smith (1999), which models these data characteristics well(Baltagi, 2002: p. 245). The base of the pooled mean-group estimator is an autoregressive distributive lag (l, q_1, q_2, ..., q_k) model (ARDL model) with $q = q_1 = q_2 = ... = q_k$. This model is reparameterised in a error correction form. In this study, I use a reparameterised ARDL(1,1,1) model as follows:

$$\Delta \log M_{i,t} = \phi_i[\log M_{i,t-1} - (\beta^U \log U_{i,t} + \beta^V \log V_{i,t} + \mathbf{w_i}(\log \mathbf{U_t}, \log \mathbf{V_t})(\gamma_\mathbf{U}, \gamma_\mathbf{V})')] + ... \tag{6}$$

$$... + \delta_i^U \Delta \log U_{i,t} + \delta_i^V \Delta V_{i,t} + A_i + \epsilon_{i,t}$$

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

- $\mathbf{w_i}$ is the row vector of the ith row of the weight matrix bfW,
- $\Delta \log M_{i,t}$ are 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 persons and vacancies, and
- δ_i^U and δ_i^V are the regression coefficients of these differences.

There is an adjustment process for $\log M_{i,t}$; the error-correction term ϕ_i on the right-hand side of equation (6) denotes the speed of adjustment, whereas the term in the square brackets represents deviations from the long-run equilibrium. If ϕ_i is equal to the null, then there is no long-run equilibrium between the dependent and independent variables. A significant negative parameter indicates that the variables tend to a long-run steady state.

The pooled mean-group estimator includes the fixed effects and short-run dynamics of the variables for each occupational group i and requires the long-term coefficients to be equal across all of the occupational groups i. The PMG model in equation (6) is non-linear in its parameters ϕ_i and (β^U, β^V). Therefore, a maximum likelihood estimator is applied (Pesaran/Shin/Smith, 1999: S. 465, see Appendix A.5). 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 cross-sectional lags of the exogenous regressors and one version without. In addition, for these two models, the null hypothesis of a Wald test that states that γ_U and γ_V are simultaneously equal to zero must be rejected. Given the examined information criteria, the model with the cross-sectional lags of regressors should be preferred over the model without these lags. Table 3 contains all the model results. This table includes the lagged first-order difference of the new hires, $\varsigma_1^{\Delta M_{-1}}$; variations with the trend, ω; the cyclical component of the real gross domestic product GDP_{cyc}; and the cross sectional regressors as long-term parameters in the error-correction term.

The long-run elasticities for vacancies and unemployed workers, the exogenous regressors, the cyclical component of the real GDP, and the trend can be found in the upper part of Table 3. At the bottom of this table, the following quantities appear: the error-correction term ϕ, the averages of the estimated short-term parameters for each occupational group and the average fixed effect A (Pesaran/Shin/Smith, 1999: S. 626).

Table 3: The results of the PMG estimations that use $\Delta \log M$ as the dependent variable

	(1) PMG 1	(2) PMG 2	(3) PMG 3	(4) PMG 4	(5) PMG 5	(6) PMG 6
		Long-run coefficients				
β_U	0.373***	0.413***	0.469***	0.493***	0.346***	0.376***
	(0.046)	(0.046)	(0.038)	(0.038)	(0.031)	(0.054)
β_V	0.182***	0.246***	0.168***	0.255***	0.266***	-0.095**
	(0.027)	(0.021)	(0.025)	(0.019)	(0.016)	(0.038)
γ_U	0.250***	0.246***			0.004	0.301***
	(0.062)	(0.060)			(0.036)	(0.081)
γ_V	0.166***		0.162***		0.096***	0.072
	(0.036)		(0.033)		(0.022)	(0.049)
Trend	-0.036***	-0.034***	-0.033***	-0.032***	-0.026***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	
GDP_{cyc}	11.491***	12.389***	9.747***	9.757***		19.448***
	(1.329)	(1.391)	(1.119)	(1.139)		(2.287)
ϕ	-0.253***	-0.247***	-0.266***	-0.263***	-0.342***	-0.166***
	(0.020)	(0.020)	(0.023)	(0.023)	(0.035)	(0.014)
		Short-run coefficients				
$\varsigma_1^{\Delta M_{-1}}$	-0.104***	-0.099***	-0.094***	-0.088***	-0.031	-0.088***
	(0.021)	(0.022)	(0.022)	(0.023)	(0.025)	(0.023)
$\delta_0^{\Delta U}$	-0.161***	-0.175***	-0.160***	-0.180***	-0.206***	-0.046
	(0.029)	(0.029)	(0.030)	(0.030)	(0.033)	(0.029)
$\delta_{-1}^{\Delta U}$	-0.058***	-0.064***	-0.050**	-0.058**	-0.053**	0.014
	(0.022)	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)
$\delta_0^{\Delta V}$	0.051***	0.050***	0.051***	0.046***	0.025	0.126***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)	(0.016)
$\delta_{-1}^{\Delta V}$	0.045***	0.046***	0.046***	0.044***	0.041***	0.109***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.012)
Constant	0.554***	0.648***	1.008***	1.096***	1.583***	0.626***
	(0.036)	(0.043)	(0.076)	(0.087)	(0.159)	(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

The error-correction term ϕ is significant and negative for all variants of the model. This result indicates the existence of movements against deviations from the long-run equilibrium and therefore implies the existence of stable relationships between matches and both unemployed workers and vacancies.

The long-term coefficients β^U, β^V, γ_U, γ_V and GDP_{cyk} are positive, and the trend T is negative and significantly different from zero. These results are robust for all estimated model variations. The impact of the unemployed workers on matches is larger than the impact of the vacancies on matches even after accounting for the 95%-confidence intervals of β^V and β^U. This finding is in accordance with other studies for Germany (Stops/Mazzoni, 2010; Fahr/Sunde, 2004; Burda/Wyplosz, 1994). Most of the short-term parameters are significantly different from zero. For all of the examined model 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 workers.

5 Conclusions

This paper analyses matching processes in occupational labour markets in terms of classes of jobs that share commonalities with respect to their required qualifications and tasks. All previous studies in this field have been based on the assumption that job search and matching processes occur separately for every occupational labour market. However, this assumption is not reasonable, even from a theoretical perspective. From the perspectives of both potential workers and hiring firms, optimal search intensities on each occupational labour market are weighted against the expected gains and costs from the search, the latter of whom could be the (additional) financial burden of the training that is required for a change from one occupation to another. Therefore, workers who are prepared to work in a certain occupation may decide to search for a job in other occupations if the resulting search costs are not overly high relative to the expected gains; similarly, firms with vacancies in a certain occupation may decide to search for workers belonging to other occupations that could be regarded as viable alternatives. This reasoning implies that the processes of job search and matching take place not only within each occupational labour market but also across certain occupational labour markets. I support this prediction by observation of occupational changes in German microdata.

I argue that these findings have crucial implications for the estimation of the macroeconomic matching function because the explanation of matches (in terms of new hires) in a certain occupation requires the consideration of not only vacancies and unemployed workers in the occupation of interest but also vacancies and unemployed workers in certain other relevant occupations. I use information about similarities of occupational groups with respect to their capacities to be alternatives in the processes of worker and job searches to construct an "occupational topology". Based on this topology, it is possible to calculate the average of vacancy and unemployed worker stocks in similar occupations for each single occupation. Finally, I estimate an augmented matching function using pooled ordinary least squares, fixed effects and pooled mean-group models that include cross-sectional dependency lags for regressors in terms of vacancies and unemployed workers in similar occupational groups.

The results of this study indicate that there are considerable dependencies between similar occupational groups in the matching process. I reveal the existence of significant and positive matching elasticities of vacancies and the unemployed in similar occupational groups. This finding has important implications for estimating the matching elasticities of unemployed workers and vacancies; these elasticities are determined not only by the unemployed workers and vacancies in the occupational group of interest but also by the unemployed workers and vacancies in other occupational groups. Furthermore, the results reveal that the returns to scale that are implied by the results of the pooled mean-group model, which considers cross-sectional dependency, are constant. In summary, the findings of this study strongly suggest that to obtain unbiased elasticity estimates, an augmented matching function that considers job and worker searches across different occupational labour markets should be employed.

A Appendix

A.1 Theoretical model

A.1.1 Job search and matching on non-separated occupational labour markets

The following paragraphs are based on the work of Burda/Profit (1996), which provide a spatial extension of the "bulletin board" matching process model that was conceived by Hall (1979) and Pissarides (1979). Although I use the structure of this model, its interpretation is modified to apply to the context of the current study.

Assume an economy with J occupational labour markets, which are denoted by $j = 1, ..., J$. There are U_j identical unemployed job searchers in each occupational labour market and V_j identical firms, each of which is searching for one worker in occupation j. All of the prospective workers reach decisions about their search intensity in two separate dimensions. Assuming that these workers choose to engage in a search for employment, they can decide to search in more than one occupational group, and they fix the number of jobs that they apply for in each occupation. In accordance with Burda/Profit (1996), I assume that the return on an effective search in terms of the wage w is equal over all potential occupations. An application or a job interview costs $c + a_u D_{ij}$ and can be regarded as a random draw. The terms c and a_u are constants, and D_{ij} is a measure for the dissimilarity of the occupations i and j[15]. Thus, D_{ij} refers to the capacity of occupations to be alternatives to each other in the search and matching process. The term $a_u D_{ij}$ denotes additional costs for job searches in other occupational groups. These costs result from the financial burden of the additional training that would be required to change from one occupation to another. Generally, these costs will be greater for occupations that are less similar to each other.

The job searchers decide on their search intensities for each occupation, which can be denoted by their optimal number of job interviews N^*_{ij} in occupation j. To keep the model simple, workers' search costs are assumed to be relatively small. This assumption implies that income effects from searches for jobs in other similar occupations can be ignored. Therefore, optimal search intensities can be analysed within each occupation j. The probability of obtaining a job after an interview within occupation j is provided by p_j for each occupation $j = 1, ..., J$. The job searcher is assumed to maximise the (net) utility of the job search, which is equal to the difference between the revenue from the job search and the costs of this search:

$$\max_{N_{ij}} \{[1 - (1 - p_j)^{N_{ij}}]\frac{w}{r} - N_{ij}(c + a_u D_{ij})\}. \tag{7}$$

In the above equation, $\{[1 - (1 - p_j)^{N_{ij}}]w/r\}$ denotes the expected revenue to a job searcher who is currently in occupation i from realising N_{ij} interviews in occupation j, given p_j, the probability of obtaining a job, and the assumption that a worker cannot hold more than one job at any given time. I also assume that the expected income of unemployment

[15] Because every pair of occupations is separated by a certain distance D_{ij}, the model allows for the implementation of a continuous distance measure or a contiguity measure as well, as I use it in section 2.

is zero. It can be shown that the first-order condition of the optimisation problem in (7) can be expressed as follows:

$$-(1-p_j)^{N_{ij}}\ln(1-p_j)\frac{w}{r}-(c+a_uD_{ij})=0. \tag{8}$$

with the following solution:

$$N_{ij}^{*}=\frac{1}{\ln(1-p_j)}\ln\left(-\frac{c+a_uD_{ij}}{\frac{w}{r}\ln(1-p_j)}\right). \tag{9}$$

For small p_j, I obtain the following approximation:

$$N_{ij}^{*}=\begin{cases}\frac{1}{p_j}\ln(\frac{(w/r)p_j}{c+a_uD_{ij}}) & \text{for } \frac{w}{r}p_j\geq(c+a_uD_{ij}),\\ 0 & \text{for } \frac{w}{r}p_j<(c+a_uD_{ij}).\end{cases} \tag{10}$$

Therefore, optimal job search intensity depends positively on the ratio of the gains to the costs of a particular job search. A higher wage w has positive effects on job search intensity, whereas higher search costs and higher interest rates have negative effects on this intensity. The effects of a change in p_j, the probability of obtaining a job, are not clear; a higher probability leads to higher expected revenues of the job search, but this increased probability also implies that less intensive job searching will be required to obtain a given level of expected benefits. The differentiation of the upper case on the right-hand side of equation (10) leads to the following expression:

$$\frac{\partial N_{ij}^{*}}{\partial p_j}=\frac{1}{p_j^2}(1-\ln\frac{(w/r)p_j}{c+a_uD_{ij}}) \tag{11}$$

Equation (11) implies that a higher p_j has negative effects on the optimal search intensity if the expected gain from a job search is significantly larger than the search costs ($(w/r)p_j >> c+a_uD_{ij}$). Given the assumption of low search costs, an increase of p_j will, cet. par., reduce the search intensity. Furthermore, the optimal choice of search intensity determines the range of the job search. Because the job search intensity must be positive, a maximum measure of similarity of occupational groups is present; this result can be derived from equation (10):

$$D_i^{*}=\frac{1}{a_u}(\frac{w}{r}p^{max}-c)\text{ with }p^{max}\equiv\sup p_j. \tag{12}$$

An increasing maximum of the job-finding probabilities over p_j leads to a higher optimal range D_i. Furthermore, this range decreases with increasing dissimilarity costs a_u and increasing search costs c.

In the next step of the analysis, the unconditional job finding probabilities in any occupation can be derived from the optimal number of interviews in occupation j in which job searchers from occupation $i \in 1,...,J$ have participated. I assume that there is no information exchange between job searchers. Therefore, it is reasonable that certain vacancies could attract many applicants, whereas other vacancies do not attach strong applicant interest. Furthermore, I assume that all vacancies in all occupations $V_j = V$ are known by all job searchers (in other words, a "bulletin board" of potential jobs exists). Consequently, the decision of job searchers in a certain occupation to search in other occupations depends on the competitive contexts among all of the job searchers in that occupation. By defining $U_j \equiv \sum_i N_{ij}{}^* u_i$ as the sum of applications by unemployed workers, I approximately derive the probability that a vacancy will not be considered as follows:

$$\prod_{i=1}^{J}[\prod_{k=1}^{N_{ij}^*}(1-\frac{1}{V_j-k+1})]^{u_i} \approx \prod_{i=1}^{J}[\prod_{k=1}^{N_{ij}^*} e]^{-\frac{u_i}{V_j}} = \exp{(-\frac{U_j}{V_j})} \tag{13}$$

The job finding probability, p_j, can now be derived. This probability will be equal to the ratio of the number of vacancies considered ($V_j - V_j \exp(-\frac{U_j}{V_j})$) to U_j, the number of applications that were submitted by unemployed workers:

$$p_j = \frac{V_j}{U_j}[1-\exp(-\frac{U_j}{V_j})] \tag{14}$$

Finally, in accordance with Burda/Profit (1996), a matching function that returns the number of flows from unemployment to employment in an occupation i can be formulated:

$$M_i(\mathbf{U},\mathbf{V}) = \mathbf{U_i P_i} = \mathbf{U_i}[\mathbf{1} - \prod_{\mathbf{j=1}}^{\mathbf{J}}(\mathbf{1}-\mathbf{p_j})^{\mathbf{N_{ij}^*}}] \tag{15}$$

In the equation above, $\mathbf{U}$ and $\mathbf{V}$ denote the vectors of the number of unemployed workers and vacancies in each occupation, P_i represents the probability that a job searcher in occupation i will receive at least one job offer. This probability is equal to 1 minus the probability of receiving no job offer from all occupations.

The matching function above relates exits from unemployment to employment in a certain occupation to the labour market situation in every occupation. From an empirical perspective, a problem arises, namely, the optimal search intensity cannot be observed. To address this issue, according to Burda/Profit (1996), this matching function could be addressed in a quasi-reduced form that regards vacancies and wages as given quantities. This approach renders it possible to study the effects of the changes in the number of unemployed workers and vacancies on the number of matches:

$$\frac{\partial M_i}{\partial U_i} = P_i + U_i\frac{\partial P_i}{\partial U_i}, \tag{16}$$

$$\frac{\partial M_i}{\partial U_j} = U_i\frac{\partial P_i}{\partial u_j}\text{ , } j \neq i,, \tag{17}$$

$$\frac{\partial M_i}{\partial V_j} = U_i\frac{\partial P_i}{\partial v_j}\text{ , for all } j = 1,...,J. \tag{18}$$

The first term in equation (16) is positive, implying that an increase in the number of unemployed workers in occupation i leads to more matches M_i given a particular (constant) probability P_i. The sign of the second term could be either negative or positive. This term represents the external effect of additional unemployed workers on the job-finding probabilities of workers who are already unemployed in occupation i.

Burda/Profit (1996) showed that, in theory, for the second terms in equations (17) and (18), both positive and negative external effects are plausible:

$$\frac{\partial P_i}{\partial u_\tau} = \sum_{j=1}^{J} \{ [\frac{N_{ij}^*}{1-p_j} - \frac{\partial N_{ij}^*}{\partial p_j} \ln(1-p_j)] \frac{\partial p_j}{\partial u_\tau} \prod_{k=1}^{J} (1-p_k)^{N_{ik}^*} \} \tag{19}$$

Analogously to (19), the first derivative of the job-finding probability P_i with respect to the vacancies v_τ is expressed as follows:

$$\frac{\partial P_i}{\partial v_\tau} = \sum_{j=1}^{J} \{ [\frac{N_{ij}^*}{1-p_j} - \frac{\partial N_{ij}^*}{\partial p_j} \ln(1-p_j)] \frac{\partial p_j}{\partial v_\tau} \prod_{k=1}^{J} (1-p_k)^{N_{ik}^*} \} \tag{20}$$

The effect on the job-finding probability P_i induced by an increase either in unemployment or in the vacancies in occupation τ results from the weighted average of the effects on the (unconditional) job finding probabilities in all occupations $\partial p_j / \partial u_\tau$. Therefore, these results represent the net effect of variation in p_j for $j = 1, ..., J$. A change in p_j directly affects the job-finding probability for unemployed workers in occupation i given a search intensity of $[N_{ij}^*/(1-p_j)]\partial p_j/\partial u_\tau$ in a situation involving the variation of u_τ and a search intensity of $[N_{ij}^*/(1-p_j)]\partial p_j/\partial v_\tau$ in a situation involving the variation of v_τ. This change indirectly affects the optimal search intensity in all occupations and the employment prospects of the unemployed workers in occupation i, $(\partial N_{ij}^*/\partial p_j)\ln(1-p_j)(\partial p_j/\partial u_\tau)$. Therefore, the sign of $\partial P_i/\partial u_\tau$ in a situation involving a cet. par. change of u_τ depends on the spillover effects, $\partial p_j/\partial u_\tau$, which provide feedback to P_i by affecting search intensity. The same argument holds for $\partial P_i/\partial v_\tau$ in a situation involving a cet. par. change of v_τ and the spillover effects of $\partial p_j/\partial v_\tau$.
This model structure allows for the conditions for positive (or negative) external effects of job searches across different occupations to be defined. The starting point of this model is the total differential of the job-finding probability in equation (14) for occupation j.

A.1.2 The matching elasticities of unemployed workers

To obtain a prediction for the matching elasticities of unemployed workers, only the unemployment in occupation τ should be allowed to vary:

$$dp_j = \kappa_j N_{\tau j}^* du_\tau + \kappa_j \sum_{k=1}^{J} (u_k \frac{\partial N_{kj}^*}{\partial p_k}) dp_k \tag{21}$$

with

$$\kappa_j \equiv \frac{1}{U_j}[\exp(-\frac{U_j}{V_j}) - p_j] \tag{22}$$

In the above equation, as discussed by Burda/Profit (1996), κ_j is assumed to be smaller than zero[16]. The change in the unconditional finding rate dp_j of occupation j reacts to du_τ via two channels. First, for $\kappa_j < 0$, there is a negative direct effect due to the dilution of job-finding prospects. The second indirect effect of a change in u_τ results from the shift in the search intensity of the unemployed who are searching in occupation j; this shift is caused

[16] Given equation (14) for p_j, this assumption holds true for $\frac{U_j}{V_j} > 0.806$, which should represent the real situation in the most occupational labour markets.

by the implications of the change in u_τ on their job-finding probabilities p_k ($\partial N^*_{kj}/\partial p_k$, for $k = 1, ..., J$, including $k = j$). In accordance with equation (10), it must be concluded that the optimal search intensity N^*_{kj} for occupation j of an unemployed worker in occupation k depends only on the job-finding probability in occupation j and does not depend on this probability in occupation k, which implies that $\partial N^*_{kj}/\partial p_k = 0$ except for $k = j$[17].
Therefore, equation 21 can be simplified to the following form:

$$dp_j = \kappa_j N^*_{\tau j} du_\tau + \kappa_j u_j \frac{\partial N^*_{jj}}{\partial p_j} dp_j \tag{23}$$

After several simple transformations, I obtain the following expression:

$$\frac{dp_j}{du_\tau} = \frac{\kappa_j N^*_{\tau j}}{1 - \kappa_j u_j (\partial N^*_{jj}/\partial p_j)} \tag{24}$$

The sign of $\partial p_j/\partial u_\tau$ depends on the sign and the absolute value of $\kappa_j u_j(\partial N^*_{jj}/\partial p_j)$. The standard situation in job matching theory is $\partial N^*_{jj}/\partial p_j = 0$. This situation would lead to a negative external effect[18]. According to equation (19), the condition of $\partial P_i/\partial u_\tau > 0$, which represents a positive external effect, results in the following range for the elasticity $\eta_{N_{ij},p_j} \equiv (\partial N^*_{ij}/\partial p_j)/(N^*_{ij}/p_j)$:

$$-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < \frac{p_j}{\kappa_j N^*_{ij} u_j} \tag{25}$$

A.1.3 The matching elasticities of vacancies

In contrast to the previous subsection, the number of vacancies in occupation τ should be allowed to vary, cet. par.; in this situation, the total differential of equation (14) is as follows:

$$dp_j = -\frac{U_j}{V_j}\kappa_j dv_\tau + \kappa_j \sum_{k=1}^{J} (u_k \frac{\partial N^*_{kj}}{\partial p_k}) dp_k \tag{26}$$

Again, κ_j is assumed to be smaller than zero. Analogously to the previous finding, I find once again that a change in the number of vacancies in occupation τ has effects on the job-finding probability via two channels; these effects are different and merit further consideration. In particular, an increase in the vacancy stock produces a direct and positive effect on job-finding probabilities because of the change in the supply of vacancies. The second indirect effect can be ascribed to changes in the optimal search strategy. As discussed above, equation (10) implies that $\partial N^*_{kj}/\partial p_k = 0$ except for $k = j$; therefore, equation (26) may be simplified as follows:

$$dp_j = -\frac{U_j}{V_j}\kappa_j dv_\tau + \kappa_j u_j \frac{\partial N^*_{jj}}{\partial p_j} dp_j \tag{27}$$

[17] This holds only under the strong assumption of small costs and no substitution effects between occupational labour markets, which would be important in the case of budget constraints and income effects. However, a theoretical treatment of this case is left for further research.

[18] I obtain the same result if $\partial N^*_{jj}/\partial p_j > 0$. A positive external effect is induced by $\partial N^*_{jj}/\partial p_j > \frac{1}{\kappa_j u_j}$, given $\kappa_j, \partial N^*_{jj}/\partial p_j < 0$.

allowing me to obtain the following equation:

$$\frac{dp_j}{dv_\tau} = \frac{-\frac{U_j}{V_j}\kappa_j}{1 - \kappa_j u_j(\partial N^*_{jj}/\partial p_j)}. \tag{28}$$

In either the standard case ($\partial N^*_{jj}/\partial p_j = 0$) or the situation in which $\partial N^*_{jj}/\partial p_j < \frac{1}{\kappa_j u_j}$, given $\kappa_j < 0$, I would obtain a positive external effect. Using equation (20), I can derive the condition for $\partial P_i/\partial v_\tau > 0$, which results in the following range for the elasticity η_{N_{ij},p_j}:

$$-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < 0 \tag{29}$$

A.1.4 Conclusions for the matching elasticities

The absolute values of η_{N_{ij},p_j} will vary with the similarity of the occupations i and j. In particular, workers will not seek interviews in occupations that are not similar to their original occupation; therefore, the condition above will not hold for all combinations of occupations j and i. In the model mechanisms conceived by Burda/Profit (1996), it can be demonstrated that both positive and negative external effects are conceivable. Within a certain range of η_{N_{ij},p_j}, the external effects of vacancies and unemployed can both be positive.[19]

[19] $-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < \frac{p_j}{\kappa_j N^*_{ij} u_j}$

A.2 Additional informational tables

Table 4: 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, 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
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

continued on the next page

Code (KldB 88)	Occupational group
40	butcher, fishworkmansip and related
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 distributer
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

continued on the next page

Code (KldB 88)	Occupational group
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 5: 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
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

continued on the next page

Occupational groups in data i=1,... , 82		Occupational section in employment statistics o=1 ,... ,40	Name of the occupational section
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 6: Assignment of the occupational groups to the occupational segments (Matthes/Burkert/Biersack, 2008)

Occupational segment Code	Occupational segment Name	Occupational group Code	Occupational group 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

continued on the next page

Occupational segment		Occupational group	
Code	**Name**	**Code**	**Name**
		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
		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	Construction	11	producer of building materials
		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
		51	painter, varnisher and related professions
		54	machinist and related professions

continued on the next page

Occupational segment		Occupational group	
Code	Name	Code	Name
		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 distributer
		74	storekeeper, worker in storage and transport
303	Merchandise occupations	68	merchandise manager
		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 distributer
		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

continued on the next page

Occupational segment		Occupational group	
Code	**Name**	**Code**	**Name**
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.3 Observing occupational changes in administrative data

I use the SIAB data set[20] to count the flows of either unemployment or employment in one occupational group to employment in other occupational groups. To obtain this count, certain restrictions must be employed. (1) The first observed employment sequence of every individual is not considered because no information about the (unobserved) employment status and any related occupation of the individual is available prior to the first observation. Therefore, I disregard these initial employment sequences in this study. (2) Cases of flows from unemployment to employment are treated as flows in employment with an occupational change if the occupation of the employment sequence before the unemployment period differs from the occupation in the employment sequence after unemployment. These flows are treated as flows in employment without an occupational change if the occupation for the employment sequence prior to the unemployment period is the same as the occupation for the employment that occurred after the unemployment period. If there was no employment sequence prior to the unemployment period, then the flow from unemployment to subsequent employment is not considered by this study. The results of this study demonstrate that the averaged percentages of all flows in employment with occupational changes ranged from 16 per cent (forester and huntsman) to 75 per cent (polymer processor; see table 7).

Table 7: Percentages of flows in employment with occupational changes on all flows

Code	Percentages of flows in employment with change of occupation (1982-2007)**		
	average	min.	max.
01 farmer, fisher	0.48	0.36	0.67
03 agricultural administrator	0.60	0.36	0.83
04 helper in the agricultural sector, agricultural workers, stockbreeding professions	0.56	0.46	0.66
05 gardener, florist	0.38	0.31	0.47
06 forester and huntsman	0.16	0.10	0.41
07 miner and related professions	0.21	0.07	0.50
08 exhauster of mineral resources	0.34	0.26	0.54
09 mineral rehasher, mineral burner)*	0.56	0.33	1.00
10 stone processor	0.30	0.20	0.45
11 producer of building materials	0.40	0.24	0.59
12 ceramicist, glazier	0.68	0.41	0.79
13 glazier, glass processor, glass refiner	0.68	0.17	0.89
14 chemical worker	0.66	0.30	0.83
15 polymer processor	0.75	0.37	0.86
16 paper producer	0.73	0.56	0.84
17 printer	0.49	0.36	0.60
18 woodworker, wood processor	0.57	0.40	0.77

continued on the next page

[20] See section 3 for further details.

Code	Percentages of flows in employment with change of occupation (1982-2007)**		
	average	min.	max.
19 metal worker	0.63	0.36	0.87
20 moulder, caster, semi-metal cleaner	0.71	0.49	0.84
21 metal press workers, metal formers	0.72	0.53	0.85
22 turner, cutter, driller, metal polisher	0.54	0.39	0.66
23 metal burnisher, galvanizer, enameler	0.71	0.54	0.89
24 welder, solderer, riveter, metal gluter	0.54	0.41	0.65
25 steel smith, copper smith	0.69	0.54	0.91
26 plumber, plant locksmith	0.36	0.28	0.45
27 locksmith, fitter	0.47	0.37	0.57
28 mechanic	0.42	0.34	0.53
29 toolmaker	0.49	0.34	0.64
30 metal precision-workers, orthodontists, opticians	0.27	0.16	0.41
31 electricians	0.30	0.23	0.39
32 assemblers and metal related professions	0.74	0.60	0.82
33 spinner, ropemaker	0.63	0.25	0.85
34 weaver, other textile producer	0.55	0.21	0.78
35 tailor, sewer	0.40	0.28	0.58
36 textile dyer	0.64	0.39	0.81
37 leather and fur manufacturers, shoemaker	0.48	0.33	0.63
39 baker, confectioner	0.36	0.26	0.49
40 butcher, fishworkmansip and related	0.39	0.27	0.52
41 cooks, convenience food preparatory	0.45	0.39	0.53
42 brewer, manufacturer for tobacco products	0.65	0.45	0.75
43 milk/fat processor, nutriments producer	0.65	0.45	0.78
44 bricklayer, concrete builder	0.26	0.18	0.36
45 carpenter, roofer, spiderman	0.34	0.24	0.45
46 road/track constructors, demolisher, culture structurer	0.42	0.28	0.55
47 helper in the construction sector	0.60	0.48	0.68
48 plasterer, tiler, glazier, screed layer	0.41	0.27	0.55
49 interior designer, furniture supplier	0.56	0.38	0.68
50 joiner, modeler, cartwright	0.36	0.26	0.43
51 painter, varnisher and related professions	0.27	0.20	0.39
52 goods tester, consignment professions	0.74	0.63	0.80
53 unskilled worker	0.72	0.60	0.86
54 machinist and related professions	0.42	0.28	0.63
60 engineer, architect	0.41	0.37	0.46
61 chemist, physicist	0.52	0.36	0.64
62 technician	0.47	0.39	0.56
63 technical specialist	0.39	0.28	0.51
68 merchandise manager	0.41	0.35	0.50
69 banking professional, insurance merchant	0.32	0.21	0.42

continued on the next page

Code	Percentages of flows in employment with change of occupation (1982-2007)**		
	average	min.	max.
70 merchant/ specialist in conveyance, tourism, other services	0.55	0.46	0.65
71 conductor, driver, motorist	0.38	0.27	0.46
72 navigator, ship engineer, water/air traffic professions	0.25	0.14	0.42
73 mail distributer	0.61	0.40	0.75
74 storekeeper, worker in storage and transport	0.68	0.60	0.73
75 manager, consultant, accountant.	0.52	0.47	0.56
76 member of parliament, association manager	0.69	0.57	0.77
77 accounting clerk, cashier, data processing expert	0.54	0.45	0.61
78 clerk, typist, secretary	0.38	0.32	0.45
79 plant security, guard, gate keeper, servant	0.65	0.55	0.76
80 other security related professions, health caring professions	0.44	0.26	0.64
81 law related professions	0.63	0.52	0.81
82 publicist, translator, librarian	0.51	0.43	0.60
83 artist and related professions	0.34	0.20	0.46
84 physician, dentist, apothecaries	0.23	0.11	0.41
85 nurse, helper in nursing, receptionist and related	0.27	0.23	0.35
86 social worker, care taker	0.35	0.29	0.42
87 professor, teacher	0.53	0.36	0.62
88 scientist	0.65	0.52	0.73
89 helper for cure of souls and cult	0.66	0.47	0.83
90 beauty culture	0.20	0.14	0.30
91 guest assistant, steward, barkeeper	0.46	0.38	0.62
92 domestic economy, housekeeping	0.61	0.56	0.72
93 cleaning industry related professions	0.54	0.43	0.64
Total	0.50	0.07	1.00

A.4 Real GDP and the proportion of all vacancies that are registered vacancies[21]

Only vacancies V can be observed that are registered by the Federal Employment Service. To estimate the matching function, it would be ideal to know of all vacancies V_{ALL}. R_{BA} denotes the proportion of all vacancies V_{ALL} that are composed of registered vacancies V:

$$V = R_{BA} \cdot V_{ALL} \tag{30}$$

Employers register their vacancies if they expect that searches for workers via the Federal Employment Service will be successful. During economic booms, the number of registered job searchers decreases. This phenomenon is noticed by firms; therefore, it could be assumed that firms have more negative expectations about their abilities to find staff through the Federal Employment Service during prosperous economic times. In accordance with

[21] In addition to the following subsection, please compare with Stops/Mazzoni (2010)

(vgl. Franz, 2006: S. 107 f.), R_{BA} decreases during economic recovery phases; in other words, this variable is anticyclical. Therefore, the (logarithm of) R_{BA} correlates negatively with the cyclical component of the real gross domestic product (GDP_{cyc}). This component could be interpreted as the deviation of the GDP from its long-term trend. Therefore, GDP_{cyc} is an indicator for the economic situation at a certain time; consequently, the rate R_{BA} could be regarded as a function of GDP_{cyc}:

$$R_{BA} = f(GDP_{cyc}). \tag{31}$$

Thus,

$$V = f(GDP_{cyc}) \cdot V_{ALL} \tag{32}$$

and after several simple rearrangements, I obtain

$$V_{ALL} = \frac{V}{f(GDP_{cyc})}. \tag{33}$$

The matching function is specified by the following expression:

$$M = AV_{ALL}^{\beta_V} U^{\beta_U} \tag{34}$$

Taking the logarithm of both sides yields

$$\log M = \log A + \beta_V \log V_{ALL} + \beta_U \log U. \tag{35}$$

The use of equation (33) allows this equation to be rewritten as follows:

$$\log M = \log A + \beta_V [\log V - \log f(GDP_{cyc})] + \beta_U \log U \tag{36}$$

The assumption $\log f(GDP_{cyc}) \cong (-\beta_{gdp} GDP_{cyc})$ permits the following simplification:

$$\log M = \log A + \beta_V \log V + \beta_{GDP} GDP_{cyc} + \beta_U \log U \tag{37}$$

where $\beta_{GDP} = (-\beta_V) \cdot (-\beta^{gdp})$.
Finally, the assumptions $\beta_V > 0$ and $\beta_{gdp} > 0$ imply that $\beta_{GDP} > 0$.

A.5 Concentrated maximum likelihood estimation

The concentrated likelihood that is used to estimate the model in equation (6) has the following form:[22]

$$l_T(\vartheta', \phi', \sigma') = -\frac{\mathbf{T}}{\mathbf{2}}\sum_{\mathbf{i=1}}^{\mathbf{N}}\mathbf{log(2}\pi\sigma_{\mathbf{i}}^{\mathbf{2}}) - \frac{\mathbf{1}}{\mathbf{2}}\sum_{\mathbf{i=1}}\mathbf{N}\frac{\mathbf{1}}{\sigma_{\mathbf{i}}^{\mathbf{2}}}[\mathbf{\Delta}\log\mathbf{M_{h,i}} - \phi_{\mathbf{i}}\xi_{\mathbf{i}}(\vartheta)]'\mathbf{H_i}[\mathbf{\Delta}\log\mathbf{M_{h,i}} - \phi_{\mathbf{i}}\xi_{\mathbf{i}}(\vartheta)], \tag{38}$$

where

$\xi_{\mathbf{i}}(\vartheta) = \log\mathbf{M_{h,i,-1}} - (\log\mathbf{U_i}, \log\mathbf{V_i})(\beta^{\mathbf{U}}, \beta^{\mathbf{V}})' - \mathbf{w_i}(\log\mathbf{U}, \log\mathbf{V})(\gamma_{\mathbf{U}}\mathbf{I_N}, \gamma_{\mathbf{V}}\mathbf{I_N})'$,
with ϑ as the vector of the coefficients
$\mathbf{H_i} = \mathbf{I_T} - \mathbf{L_i}(\mathbf{L_i'}\mathbf{L_i})\mathbf{L_i}$ for an identity matrix $\mathbf{I_T}$, whereas
$\mathbf{L_i} = (\log\mathbf{M_{h,i,-1}}, ..., \log\mathbf{M_{h,i,-p+1}}, \mathbf{\Delta}\log\mathbf{U_i}, \mathbf{\Delta}\log\mathbf{V_i}, \iota)$
$\phi = (\phi_{\mathbf{1}}, \phi_{\mathbf{2}}, ..., \phi_{\mathbf{N}})'$
$\sigma = (\sigma_{\mathbf{1}}^{\mathbf{2}}, \sigma_{\mathbf{2}}^{\mathbf{2}}, ...\sigma_{\mathbf{N}}^{\mathbf{2}})'$

The residuals $\xi_{\mathbf{i}}(\vartheta) = \log\mathbf{M_{h,i,-1}} - (\log\mathbf{U_i}, \log\mathbf{V_i})(\beta^{\mathbf{U}}, \beta^{\mathbf{V}})' - \mathbf{w_i}(\log\mathbf{U}, \log\mathbf{V})(\gamma_{\mathbf{U}}\mathbf{I_N}, \gamma_{\mathbf{V}}\mathbf{I_N})'$ are included in the logarithm of the density function of the normal distribution.

[22] The equation is expressed in terms of vectors and matrices (bold letters). Data for different observation times are staggered in the columns of the matrices or in the vectors; therefore, the index t becomes expendable.

A.6 Additional empirical results

A.6.1 The pooled OLS model

Table 8: The results of the Pooled OLS estimations with $\log M$ as the dependent variable

	(1) Pooled OLS 1	(2) Pooled OLS 2	(3) Pooled OLS 3	(4) Pooled OLS 4	(5) Pooled OLS 5	(6) Pooled OLS 6
β_U	0.481***	0.460***	0.456***	0.458***	0.479***	0.490***
	(0.025)	(0.022)	(0.022)	(0.022)	(0.024)	(0.025)
β_V	0.353***	0.373***	0.378***	0.377***	0.354***	0.345***
	(0.020)	(0.017)	(0.018)	(0.017)	(0.020)	(0.020)
γ_U	-0.108***	-0.025***			-0.114***	-0.060**
	(0.025)	(0.008)			(0.024)	(0.025)
γ_V	0.105***		-0.014		0.112***	0.042
	(0.030)		(0.011)		(0.029)	(0.030)
Trend	-0.014***	-0.012***	-0.012***	-0.012***	-0.014***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
GDP_{cyc}	1.151	2.777**	3.077***	2.932**		0.630
	(1.247)	(1.197)	(1.191)	(1.198)		(1.259)
Constant	3.777***	3.761***	3.629***	3.528***	3.790***	3.568***
	(0.146)	(0.146)	(0.152)	(0.126)	(0.144)	(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

A.6.2 The fixed effects model

Table 9: The results of the fixed effects estimations with $\log M$ as the dependent variable

	(1) FE 1	(2) FE 2	(3) FE 3	(4) FE 4	(5) FE 5	(6) FE 6
β_U	0.137*	0.127*	0.187***	0.189***	0.133*	0.157*
	(0.076)	(0.073)	(0.070)	(0.071)	(0.076)	(0.083)
β_V	0.179***	0.233***	0.172***	0.236***	0.182***	0.171***
	(0.056)	(0.041)	(0.055)	(0.041)	(0.056)	(0.054)
γ_U	0.191**	0.235***			0.149**	0.163**
	(0.077)	(0.077)			(0.074)	(0.081)
γ_V	0.148**		0.172**		0.169**	0.055
	(0.068)		(0.069)		(0.068)	(0.058)
Trend	-0.012***	-0.009***	-0.011***	-0.008**	-0.012***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
GDP_{cyc}	2.487***	3.933***	0.936	2.248***		2.347***
	(0.450)	(0.782)	(0.635)	(0.807)		(0.447)
Constant	5.086***	5.399***	6.277***	6.987***	5.342***	5.717***
	(0.751)	(0.730)	(0.814)	(0.760)	(0.760)	(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

A.6.3 Hadri's LM test

Table 10: Results of the LM test by Hadri (2000) for the levels and the first-order differences of the logarithm of time series

	Characteristics of	Model I (without trend)		Model II (with trend)	
Variable	Residuals	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

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