Job Matching on Connected Occupational and Regional Labor Markets

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Abstract

The efficiency of job matching on local labor markets is susceptible to the spillovers caused both by regional and occupational mobility. In the present paper, we use novel administrative German data on the number of matches, unemployed and vacancies in the local labor markets that vary by both region and occupational titles. We compare the fixed-effects estimation of the matching function on disaggregated labor markets taking account of the connectedness both among regions and occupations. For doing this, we apply standard geographical topology for proximity between regions and an "occupational topology" that describes similarities between occupations in terms of qualification requirements and tasks. The estimation shows that negligence of spillover effect leads to biased estimation of the efficiency of job matching in the local labor markets. Moreover, we conclude that existing regional spillovers help to mitigate negative effects of competition for vacancies among the unemployed in similar occupations.

JEL-Classification: C21, C23, J44, J64.

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1 Introduction

Job mobility is, beside wage flexibility, one of the crucial mechanisms to equilibrate disparities on local labor markets, regarding both regional and occupational markets. In the present paper, we analyze the simultaneous spillovers in the matching function that arise due to the existing labor mobility across neighboring regions and similar occupations. Both regional and occupational mobility has drawn an increasing attention in the recent literature on job matching. However, due to the lack of appropriate data, empirical studies fail to analyze both types of job mobility simultaneously.

The theoretical grounds as well as empirical evidence on the process of matching between job seekers and vacancies are well documented (Rogerson et al., 2005; Yashiv, 2007). Nevertheless, Petrongolo and Pissarides (2001) refer to the matching function being a black box, since the multiple factors that can well affect the hiring process are not observable at the aggregate level. Coles and Smith (1996) argue that the estimation of matching efficiency at an aggregated level is substantially biased, because the matching process is taking place on local labor markets. The notion of local labor market in the empirical research is mainly related to geographical labor markets. For instance, the studies of Burda and Profit (1996), Fahr and Sunde (2006), Lottmann (2012) document sizable influence of the unemployed and vacancies in the neighboring regions on matching elasticities.

However, the local nature of labor markets goes beyond geography. For instance, Machin et al. (2008) and Hensen et al. (2009) report that educational levels significantly affect patterns of regional mobility. However, the evidence on the matching process across occupational groups is scarce. Fahr and Sunde (2004) and Stops and Mazzoni (2010) document that matching efficiency is highly heterogeneous within different occupations. The main caveat of their notion of occupational labor markets is that they disregard possible mobility across occupational groups which might bias their results. The borders between occupational groups can be defined by similarities in job contents, formal requirements and qualification. However, the evidence of Gathmann and Schoenberg (2010) convincingly shows that human capital can be transfered across these occupational borders, especially between occupations with similar content. To our best knowledge, Stops (2014) is the first study to document the existence of spillovers on occupational labor markets that can be defined by similar requirements to tasks and qualification of employees.

In the present study, we combine the theoretical models utilized by Burda and Profit (1996) for regional spillovers and Stops (2014) for occupational spillovers to motivate the simultaneous existence of regional and occupational spillovers in the disaggregated matching functions. Then, we use novel administrative data for Germany that define local labor markets to exist both at the level of regions and occupations. Thus, the data contain information of the number of new hires, unemployed and vacancies for each of 131.454 local labor markets (defined by intersections of 327 occupational groups and 402 regions), covering the time period from 2000 to 2011 on a monthly basis. Using these detailed data we contribute to the literature by showing how susceptible labor markets are to be affected by each other. For regional labor markets, we use measures on geographical proximity of regions to estimate how the unemployed and the stock of vacancies in the neighboring regions can affect efficiency of job matching. For occupational labor markets, we classify occupations with similar task contents and job requirements into occupational segments based on previous work by Matthes et al. (2008).

The estimation of empirical matching function with fixed effects and spillover reveals that both occupational and regional spillovers significantly affect the matching technology. Negligence of the spillover effects leads to biased estimates of the direct effect of the unemployed and vacancies on the number of matches within a local labor market. The results show that vacancies in the similar occupations as well as the unemployed and vacancies in neighboring regions exhibit a positive spillover effect of the matching elasticity. This finding corresponds to the direct effect of the unemployed and vacancies on the match probability, as described by our theoretical model. In contrast, the stock of unemployed in similar occupations negatively relates to the matching elasticity, meaning that there is a competition effect hampering matching efficiency which can be also described by the theoretical framework. However, the size of the coefficients corresponding to occupational spillovers is substantially lower that the size of the coefficient of regional spillovers. This implies that regional labor markets are easier to penetrate than occupational market. Furthermore, it means that regional mobility and its positive spillovers on the matching efficiency help to overcome possible negative spillovers in the occupational labor markets.

The papers proceeds with a description of the model of non-sequential search in section 2. In Section 3 we discuss the motivation for disaggregated matching functions and the existence of spillovers between regions and occupations. Section 4 contains the description of the data. In section 5 we present our empirical results, that are further tested for their robustness in section 6. Section 7 concludes.

2 Model of Non-sequential Search

The "bulleting board" model proposed by Hall (1979) and Pissarides (1979) describes non-sequential job search. In the following, we combine the version by Burda and Profit (1996) that incorporates the influence of the unemployed and vacancies from neighboring local labor markets and the version by Stops (2014) that considers mobility between different occupational markets. Thus, the model becomes available to explain the possible direct and indirect effects of the number of unemployed and vacancies in neighboring regions or similar occupations.

2.1 Optimal Search Intensity

Consider an economy that is divided into L regions, where it is possible to be employed in one of I occupations. The regions and occupations are respectively indexed by $l = 1, \ldots, L$ and $i = 1, \ldots, I$. Within each region l and occupation i there are u_{il} identical unemployed workers and v_{il} identical firms. Each firm searches for one workers to employ. In the center of each region there is an employment office that gathers information on all vacancies in all occupations $v_l, \ l = 1, \ldots, L$. The unemployed workers apply for jobs in their occupation i or in another occupation $j \neq i$, the application can be sent either to the employment office in their residence region l or to another region $m \neq l$. Moreover, the workers decide about their search intensity N_{ijlm}, which can be measured by the number of applications sent for each occupation to each regional employment center.

Each application is a random draw and is associated with search costs $c + aD_{lm} + bD_{ij}$, where c, a and b are positive constants. D_{lm} is the distance between the employment offices in the regions l and m. D_{ij} is the content dissimilarity between the current occupation of the unemployed and the occupation he or she applies to. Thus, the costs of the search linearly depend both on the net cost of applying to a different regions, as well as costs of gathering information to apply to another occupation. The search costs are minimum ($= c$) if an application is made within the current region of residence and the initial occupation, i.e. $D_{lm} = 0$ and $D_{ij} = 0$.

Following a successful search, the worker is employed in a region m in occupation j and receives a wage w. The interest rate in the economy is r, so that the real wage is equal to w/r.

Given the initial geographical location of the worker l and his initial occupation i, he or she decides on the number of interviews in each district m and occupation j. The worker knows about the probability of getting a job in region m and occupation j – f_{ijlm}. The decision on the optimal number of interviews is yielded from maximization of net total expected benefit from the search:

$$\underbrace{\left[1-(1-f_{ijlm})^{N_{ijlm}}\right]\frac{w}{r}}_{\text{total expected benefit}} - \underbrace{N_{ijlm}(c+aD_{lm}+bD_{ij})}_{\text{costs}} \xrightarrow[N_{ijlm}]{} \max \tag{1}$$

The first term in equation 1 refers to the total expected benefit of a job match between a worker in region l and occupation i and a vacancy in region m and occupation j. For simplicity, we assume that unemployment does not bring any income.

Solving for the optimal search intensity N^*_{ijlm} yields:

$$N^*_{ijlm} = \begin{cases} f^{-1}_{ijlm} \cdot \ln\left[\frac{f_{ijlm}\frac{w}{r}}{c+aD_{lm}+bD_{ij}}\right] & \text{if } \frac{f_{ijlm}\frac{w}{r}}{c+aD_{lm}+bD_{ij}} \geq 1, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Thus, the optimal search intensity is a positive function of the ration of expected gains and the search costs $f_{ijlm}\frac{w}{r}\Big/(c+aD_{lm}+bD_{ij})$. Further derivation can show that the optimal search is increasing in wages, decreasing in interest rate and decreasing in fixed application costs:

$$\frac{\partial N^*_{ijlm}}{\partial w} > 0; \quad \frac{\partial N^*_{ijlm}}{\partial r} < 0; \quad \frac{\partial N^*_{ijlm}}{\partial c} < 0. \tag{3}$$

Moreover, the optimal search intensity is increasing in attractiveness of expected returns from the search:

$$\frac{\partial N^*_{ijlm}}{\partial\left[f_{ijlm}\frac{w}{r}\Big/(c+aD_{lm}+bD_{ij})\right]} > 0. \tag{4}$$

The optimal search intensity N^*_{ijlm} also depends on the introduced distance parameters. Firstly, it depends on f_{ijlm}, the probability for a worker in occupation i and region l to find a job in occupation j and region m. Taking partial derivative with respect to f_{ijlm} yields:

$$\frac{\partial N^*_{ijlm}}{\partial f_{ijlm}} = f^{-2}_{ijlm}\left(1-\ln\left[\frac{f_{ijlm}\frac{w}{r}}{c+aD_{lm}+bD_{ij}}\right]\right). \tag{5}$$

From the equation 5 follows that the optimal search intensity N^*_{ijlm} is decreasing in the probability to find a job in another region f_{ijlm} if the expected benefits are much higher than the costs of search:

$$\frac{\partial N^*_{ijlm}}{\partial f_{ijlm}} < 0 \quad \text{if} \quad \left[\frac{f_{ijlm}\frac{w}{r}}{c + aD_{lm} + bD_{ij}}\right] > 1. \tag{6}$$

In case that the search takes place, i.e. $N^*_{ijlm} > 0$, one can compute the maximum distance that an unemployed in occupation i and region l will cover to find a job in occupation j and region m:

$$f^{-1}_{ijlm} \cdot \ln\left[\frac{f_{ijlm}\frac{w}{r}}{c + aD_{lm} + bD_{ij}}\right] > 0 \tag{7}$$

$$\frac{w}{r} f_{ijlm} > c + D_{lm} + bD_{ij} \tag{8}$$

$$(D_{lm} + bD_{ij})^* = \text{int}\left[\frac{w}{r}\sup f_{ijlm} - c\right] \tag{9}$$

Thus, for a given regional distance $D_{lm} = \bar{D}_{lm}$ or occupational dissimilarity $D_{ij} = \bar{D}_{ij}$, the optimal distances can be computed:

$$D^*_{ij} = \frac{1}{b}\text{int}\left[\frac{w}{r}\sup f_{ijlm} - c - a\bar{D}_{lm}\right] \qquad \text{and} \qquad D^*_{lm} = \frac{1}{a}\text{int}\left[\frac{w}{r}\sup f_{ijlm} - c - b\bar{D}_{ij}\right] \tag{10}$$

Thus, equation 10 implies that a given non-zero distance between regions reduces the optimal dissimilarity between occupations, and vice versa.

2.2 The Unconditional Job Finding Probability

With the optimal intensity of search N^*_{ijlm}, the unconditional job finding probability for a local labor market in region l and occupation i can be defined. In the "bulletin board" type of models, the vacancy is filled if it is chosen by at least one worker. The total number of vacancies in occupation i posted at the bulletin board of the agency in region l is equal to the sum of vacancies in this occupation in all regions:

$$V_{il} = \sum_{i=1}^{I}\sum_{l=1}^{L} v_{il}. \tag{11}$$

Thus, the different degrees of competition of local labor markets results in possible spillovers. After all unemployed made their optimal number of application in each occupation and region ($U_{il} \equiv \sum_{il} = \sum_{i=1}^{I}\sum_{l=1}^{L} u_{il}$), the probability of a particular vacancy not being chosen is equal to:

$$\prod_{i=1}^{I}\prod_{l=1}^{L}\left[\prod_{k=1}^{N^*_{ijlm}}\left[1 - (V_{il} - k + 1)^{-1}\right]\right]^{u_{il}} \approx \prod_{i=1}^{I}\prod_{l=1}^{L}\left[\prod_{k=1}^{N^*_{ijlm}} e\right]^{-\frac{u_{il}}{V_{il}}} = \exp\left(-\frac{U_{il}}{V_{il}}\right). \tag{12}$$

Consequently, the unconditional job finding rate for each interview that is held in occupation i and region l, is defined as the number of vacancies per job seeker weighted by their job finding probabilities:

$$f_{ijlm} = \frac{V_{il}}{U_{il}}\left[1 - \exp\left(-\frac{U_{il}}{V_{il}}\right)\right]. \tag{13}$$

2.3 Exits to Employment

Based on the previous calculations, the number of exits into employment in occupation i and region l by unemployed in occupation j and region m can be derived:

$$x_{il}(\mathbf{u},\mathbf{v}) = u_{il}F_{il} = u_{il}\left[1 - \prod_{i=1}^{I}\prod_{l=1}^{L}(1-f_{ijlm})^{N^*_{ijlm}}\right], \tag{14}$$

where $\mathbf{u}$ and $\mathbf{v}$ are stocks of unemployed and vacancies in all regions and all occupations. F_{il} is the probability that an unemployed individual in occupation i and region l receives at least one job offer.

As mentioned above, this function of matches involves unemployed and vacancies in all occupations and all regions, giving rise to the possible regional and occupational spillovers:

$$\frac{\partial x_{il}}{\partial u_{jm}} = u_{il}\cdot\frac{\partial F_{il}}{\partial u_{jl}} + u_{il}\cdot\frac{\partial F_{il}}{\partial u_{im}}. \tag{15}$$

$$\frac{\partial x_{il}}{\partial v_{jm}} = v_{il}\cdot\frac{\partial F_{il}}{\partial v_{jl}} + v_{il}\cdot\frac{\partial F_{il}}{\partial v_{im}}. \tag{16}$$

Thus, exit into employment in occupation i and region l is influenced both by the stock of unemployed and occupations in other occupations $i \neq j$ and other regions $l \neq m$. It can be further shown that the sign of $\frac{\partial F_{il}}{\partial u_{jm}}$ depends on the sign of $\frac{\partial f_{ijlm}}{\partial u_{jm}}$, which determines the direct positive effect of the unemployed on the number of matches. At the same time, there an indirect effect through N^*_{ijlm}, which can be shown to be negative under particular conditions. Thus, the model predicts that the spillovers over regions and occupations are existent, but the direction of their influence can be ambiguous.

3 Empirical Matching Function with Regional and Occupational Spillover Effects

This section introduces the general concept of matching on disaggregated labor market that can be defined either by geographical location or similarity of occupational content and requirements. After the formal introduction of regional and occupational spillovers to the matching technology, we will discuss the factors that both define the borders of local labor markets and give an empirical explanation to the possible existence of spillovers over these borders.

3.1 Spillovers in the Matching Function

On a homogeneous labor market, the matching technology between the pool of unemployed workers and existing vacancies, can be described by a matching function. Without an explicit definition of the matching process, the aggregated matching function captures the technology that brings the unemployed (denoted by U) and the vacancies (denoted by V) together and results in a job match (denoted by M):

$$M = M(U,V) = A\ U^{\beta_U}V^{\beta_V}, \tag{17}$$

where A describes the 'augmented', or factor-unrelated, matching productivity (Fahr and Sunde, 2004). The parameters β_U and β_V represent the matching elasticities of unemployed and vacancies. Under a standard assumption of constant returns to scale $\beta_U + \beta_V = 1$, with $\beta_U,\ \beta_V > 0$.

Within a regional local labor market $l = 1,\ \ldots,\ L$, the matching process is assumed to involve both the unemployed and the vacancies from the region l, and the unemployed and the vacancies from the neighboring region $m = 1,\ \ldots,\ M,\ m \neq l$. Formally, this assumption results in an extension of the matching function by the stock of the unemployed U_m and the number of vacancies V_m in the neighboring region m:

$$M_l = M(U_l, V_l, U_m, V_m) = A\ U_l^{\beta_U} V_l^{\beta_V} U_m^{\gamma_U} V_m^{\gamma_V}. \tag{18}$$

The matching technology on occupational markets can be similarly affected by the vacancies and the unemployed in the occupations with similar contents and requirements. Regarding the matches in an occupation $i = 1,\ \ldots,\ I$, we assume that the matching process can involve unemployed and vacancies from a similar occupation $j = 1,\ \ldots,\ J,\ j \neq i$. The occupation-specific matching function must be accordingly extended by the terms U_j and V_j:

$$M_i = M(U_i, V_i, U_j, V_j) = A\ U_i^{\alpha_U} V_i^{\alpha_V} U_j^{\mu_U} V_j^{\mu_V}. \tag{19}$$

Finally, the matching technology for occupation i in region l can be further adjusted to allow for spillovers from both occupations with similar contents j and neighboring regions m:

$$M_{il} = M(U_{il}, V_{il}, U_{im}, V_{im}, U_{jl}, V_{jl}, U_{jm}, V_{jm}) = A\ \underbrace{U_{il}^{\beta_U} V_{il}^{\beta_V}}_{\substack{\text{direct}\\ \text{effect}}}\ \underbrace{U_{im}^{\gamma_U} V_{im}^{\gamma_V}}_{\substack{\text{regional}\\ \text{spillover}}}\ \underbrace{U_{jl}^{\mu_U} V_{jl}^{\mu_V}}_{\substack{\text{occupational}\\ \text{spillover}}} \tag{20}$$

3.2 Connected Regional Labor Markets

Labor mobility between regions in order to overcome discrepancies in regional supply and demand is well documented by various empirical papers (Burda and Profit, 1996; Fahr and Sunde, 2006; Hensen et al., 2009; Lottmann, 2012). Regional mobility substantially varies even between European countries van Ours (1990). Though the overall mobility rates in Germany are moderate in international comparison, the yearly mobility rate between German districts (Kreise) has been risen from about five percent in the 1980s to about eight percent in mid nineties (Haas, 2000). The study by Arntz (2005) documents that the share of the unemployed who found a job in another district was at about nine percent during the same period of time.

The connectedness of regional labor markets is highly non-random (Fahr and Sunde, 2006). Lottmann (2012) does not only provide empirical tests for spatial dependency in the German labor market, but also shows that the spatial dependency has grown since 2000. Most studies of regional spillovers in the matching function employ geographical spatial structure given by geographical proximity between regions (Lottmann, 2012).[3]

[3]Possible alternatives would be to employ the measures of average time needed to cover the distance between regions or other types of transport connectedness between regions. However, these alternative might not fulfill the condition of the spatial structure being exogenous to the matching technology.

3.3 Connected Occupational Labor Markets

Apart from the geographical connectedness between regions, several other definitions of local labor markets can be applied. For instance, Broersma and van Ours (1999) document the heterogeneities in the matching technology in different industries. However, the strongest influence on the patterns of job mobility is observed on occupational labor markets, as Kambourov and Manovskii (2008), Stops (2014) and Fahr and Sunde (2001) show. The penetrability of the borders between occupational labor markets varies between countries. For instance, the German labor market rely on strong occupational institutions such as the system of dual vocational training and formal occupational requirements, so that job postings and job searches take place within occupational groups.

At the same time, occupational labor markets are not connected by the flows of occupational switchers Fitzenberger and Spitz (2004). Analogously to the spatial dependence between regions, it can be shown that occupational mobility also follows a particular pattern that is related to content similarity between occupations. For instance, Gathmann and Schoenberg (2010) develop a measure of similarity of occupational content to show that most changes occur between occupational groups that are similar with respect to their occupational contents.

4 Data

Our analysis is based on an unique administrative panel data set for 327 occupational orders in 402 NUTS3 regions with 138 observation periods from January 2000 to June 2011. The occupational orders are coded according to the German occupational classification scheme (3 digits, Kldb88[4]). All the data stem from the Federal Employment Agency.
We use data about outflows of unemployment into employment and stocks of unemployed and registered vacancies. We separately compute regional and occupational lags of unemployment and vacancy stocks.
For the regional lags we define proximity of two regions to be represented by the distance in kilometers from their geographic centers. This approach is most frequently used in the spatial literature (Hautsch and Klotz, 2003; Lottmann, 2012). Based on the usual procedure, the resulting 402×402 matrix is row-normalized and the diagonal elements are set equal 0, which corresponds to the fact that a region cannot be neighbored to itself. The resulting weight matrix W^R is used to weight the stock of unemployed and vacancies in the neighboring regions:

$$U^R_{lm} \equiv w^r_l U = \sum_1^{402}(w^r_{lm} U_m) \quad \text{and} \quad V^R_{lm} \equiv w^r_l V = \sum_1^{402}(w_{lm} V_m). \tag{21}$$

Analogously to the regional proximity, we introduce occupational "topology" that classifies occupations into groups that are similar by their content and qualification requirements. More specifically, we employ the methodology of Matthes et al. (2008) to construct "occupational topology" that classifies 327 occupational groups into 21 segments with similar job requirements. A similar "topology" for two-digit occupations was derived by Stops (2014) to investigate the spillovers between occupations. The methodology of Matthes et al. (2008) relies on the information by the Federal Employment Agency and its Central Occupational

[4] *Klassifizierung der Berufe 1988.*

File that contains groups of occupations that can be regarded as alternatives in recruitment decisions by firms and job search via employment offices. The identified similarities between occupations are derived from the similarities between the specific skills, licenses, certificates, knowledge requirements as well as tasks and techniques that are typical for this occupation. A related approach to define similarities between occupations was used by Gathmann and Schoenberg (2010), who employ detailed survey information on tasks to compute content proximity between occupations. However, for our purpose, the approach by Matthes et al. (2008) is preferable since it is less technical and more embracive.

Based on the information on occupational proximity, we construct a 327×327 first-order contiguity weight matrix W^O, in which an entry of 1 denotes two occupations that belong to one occupational segment. We convert this matrix to contain "dissimilarities" instead of "proximities" between occupations, row-normalize it and replace the diagonal elements by zeros. The resulting matrix is used to weight the stock of unemployed U_{ij} and vacancies V_{ij} in each occupational group:

$$U_{ij}^O \equiv w_i^o U = \sum_1^{327} (w_{ij}^o U_j) \quad \text{and} \quad V_{ij}^O \equiv w_i^o V = \sum_1^{327} (w_{ij} V_j) \tag{22}$$

Finally, to get unbiased matching parameter estimations, we adjust the data set by observations for occupations and NUTS3 regions, respectively, where vacancies, unemployed or flows into employment are zero. This leads to an unbalanced panel data structure with 2,394,250 observations. Table 1 shows some descriptive statistics for all measures.

5 Estimation of Spillovers Using Fixed-Effects Model

Taking logarithms of the model described by the equation 20 yields the following specification for econometric estimation using panel data:

$$\log M_{il,t} = \log A + \beta_U \log U_{il,t} + \beta_V \log V_{il,t} + \gamma_U \log U_{im,t} + \gamma_V \log V_{im,t} + \mu_U \log U_{jl,t} + \mu_V \log V_{jl,t} + \epsilon_{il,t}, \tag{23}$$

where the error term is modeled to contain fixed effects for regions, occupations and time: $\epsilon_{il,t} = \epsilon_l^R + \epsilon_i^O + \epsilon_t^T + e_{il,t}$. Introduction of time fixed effects makes it redundant to additionally control for time trend or regional GDP, which are frequently used in analogous empirical specification used in literature.

Table 2 presents the results of the estimation of equation 23 using OLS and fixed effects estimator. In the specifications 2 and 3 we gradually introduce the fixed effects. Specifications 4-6 introduce occupational spillovers, whereas specifications 7-9 contain only regional spillovers. Finally, specification 10 contains both occupational and regional spillovers and the full set of fixed effects. We calculate the standard errors using White's heteroskedasticity-consistent estimator.

The matching elasticities of the unemployed and vacancies are significantly positive throughput all specifications. We find a clear evidence of diminishing returns to scale of the matching technology, in line with the findings of Stops (2014) that uses a comparable empirical setting. The returns to scale of the matching functions constitutes one of the empirical topics that are debated in literature. However, the variation in the estimates for returns to scale is found to be substantially influenced by the level of aggregation (Nordmeier, 2014) as well as the exact definition of the involved variables (Broersma and van Ours, 1999).

The estimated elasticity of matches with respect to the unemployed is higher than the matching elasticity with respect to vacancies, which is in line with the existing estimates for Germany (Burda and Wyplosz, 1994; Fahr and Sunde, 2004; Stops and Mazzoni, 2010; Stops, 2014). These matching elasticities remain qualitatively unchanged when introducing regional, occupational and time fixed effects (specifications FE1 and FE2).

The estimates of occupational spillovers are displayed in specifications FE3-FE5. The indirect effects of the unemployed and vacancies from similar occupations are both substantially lower than the direct effects ($|\beta_U| >> |\gamma_{U_O}|$ and $|\beta_V| >> |\gamma_{V_O}|$). The spillover effect of the unemployed in the similar occupational group is negative, whereas the spillover effect of vacancies is positive. Using the results of the model from section 2, the unemployed affect the number of matches negatively through the indirect competition effect, whereas the effect of vacancies is direct. The size of spillover coefficients in the simultaneous estimation (FE5) remains almost unchanged in comparison to the specifications where spillover effect are introduced separately (FE3, FE4). This evidence points to the seeming independence of spillover effects of unemployed and vacancies from each other.

The estimates of regional spillovers can be found in specifications FE6-FE8. As in the case of occupational spillovers, the indirect effect of the unemployed and vacancies from neighboring regions on matching elasticity is substantially smaller than the direct effect ($|\beta_U| << |\gamma_{U_R}|$ and $|\beta_V| << |\gamma_{V_R}|$). The matching elasticity with respect to both unemployed and vacancies from the neighboring regions is significantly positive. Thus, both regional spillovers are associated with a higher elasticity of the matching technology. Introduction of both the unemployed and vacancies in the neighboring regions to the regression (FE8) does not change the size of the respective coefficients in the specifications with single spillover effects (FE6 and FE7), which speaks for their mutual independence.

In our last specification (FE9), we introduce both occupational and regional spillover effect through the unemployed and vacancies simultaneously. The main predictions of the estimation remain the same. The size of the direct effect of the unemployed and vacancies on matching elasticity is larger than the size of the respective spillover effects. However, the size of the direct effect of the unemployed and vacancies (β_U and β_V) is affected by the introduction of spillovers. Thus, comparing β_U and β_V in FE2 and FE9 shows that neglecting spillover effects leads to an overestimation of the direct effects of the matching elasticity with respect to the unemployed and vacancies. More specifically, comparison of FE2 and FE6 reveals that negligence of occupational spillovers underestimates the matching elasticity with respect to the unemployed and slightly overestimates the matching elasticity with respect to vacancies. Comparison of FE2 and FE8 shows that negligence of regional spillovers results in overestimation of the matching elasticities both with respect to the unemployed and vacancies. Thus, only the stock of unemployed from similar occupations intensifies competition among job seekers, thus, leading to a lower efficiency of the matching technology. This corresponds to the indirect effect of the stock of unemployed on the job finding probability through the intensity of job search, described by our theoretical framework in section 2. All other spillovers (vacancies in similar occupations, the unemployed and vacancies in neighboring regions) work in favor of higher efficiency of the matching technology.

Additionally, the estimates in table 2 reveal that the coefficients for regional spillovers sizably exceed the coefficients for occupational spillovers. Though we cannot directly compare the coefficient estimates, the results suggest that the positive regional spillovers alleviates the negative effect of the unemployed in similar occupations on the matching elasticity.

6 Testing the Occupational Spillovers for Robustness

As it was shown above, the usage of the contiguity weight matrix adopted from Matthes et al. (2008) delivers robust and significant estimates for occupational spillovers. However, analogously to the methodology in Stops (2014), we conducted an additional test to show that the estimated effect of occupational spillovers is non-random. For the testing we constructed 500 random “occupational topologies” that fulfill the following conditions:

- contains the same amount of occupational segments (implying same size of segments as in the empirical “topology”),
- are symmetric,
- contains zeros at its main diagonal,
- prevents occupations from the same empirical occupational segment to be in one random occupational segment.

Then, we repeated the fixed effect estimation of the spillover effects in the matching function using these random matrices. To isolate the pure "occupational specific effect" we additionally (beside the time fixed effects) control for contemporaneous shocks by including the yearly federal state specific cyclical component of the Gross Domestic Product. The results of the estimation are displayed in figure 1. The horizontal green lines in both charts of the figure correspond to the estimation result based on the empirical “occupational topology” based on the classification of occupations into segments by Matthes et al. (2008). The solid line corresponds to the point estimates, whereas the dashed lines correspond to the 95% confidence intervals. The point estimates and confidence intervals for the random matrices are substantially and significantly different from the estimates that are based on the empirical “occupational topology”. Though the size of the coefficients differ substantially, the coefficients from the estimations with random and empirical weight matrices exhibit same direction of influence on the matching technology. In particular, the sign of the coefficient of the randomly weighted unemployed is negative, whereas the sign of the coefficient of the randomly weighted vacancies is positive. Thus, we conclude that the estimation of occupational spillovers described in section 5 captures relationships due to tasks similarities within occupational segments that result in non-random occupational mobility which is considered by our analysis .

7 Conclusion

This paper investigates to what extent job matching on local labor markets is susceptible to the influence by regional and occupational labor mobility. Though connectedness of regional labor markets is widely explored in the literature on spatial dependencies (Burda and Profit, 1996; Fahr and Sunde, 2006; Lottmann, 2012), most studies on occupational markets neglect the possibility of labor mobility across occupations, with exception of Stops (2014). However, literature provides both evidence on labor mobility (Fitzenberger and Spitz, 2004) as well as the observation that the patterns of labor mobility are heterogeneous by job task similarity (Gathmann and Schoenberg, 2010). Thus, we employ a classification of occupations into occupational segments that was suggested by Matthes et al. (2008) and takes account of commonalities of different job titles among tasks and qualification requirements. The implication of integration of regional and occupational proximities is to allow for the possibility to conduct job search beyond the borders of one local labor market in one occupation.

Geographical and occupational topology matrices are used to calculate possible spillovers of the unemployed and vacancies from the neighboring regions and similar occupations. Empirical results reveal sizable dependencies both between occupational, and regional local labor markets. The estimates of the matching elasticities in local and occupational labor markets is overestimated, if regional and occupational spillovers are neglected. In particular, vacancies and unemployed in the neighboring regions as well as vacancies in similar occupations, are positively related to the matching efficiency in the local labor market. In contrast, the unemployed in the similar occupation intensify the competition in the local labor market and, consequently, negatively affect the efficiency of the local matching technology. However, this adverse effect is overbalanced to some extent by the positive influence of regional spillovers. In sum, the results suggest that local labor markets are susceptible to penetration, especially between neighboring regions and this should be considered in analyses and comparisons of the matching efficiencies in partial labor markets.

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Table 1: Descriptive statistics.

Measure	Monthly averages 2000-2011 (per region and occupational order)	
	Mean	Standard deviation
Employment inflows M_{il}	11.2	22.8
Unemployment stock U_{il}	156.0	410.8
Regional lags of unemployment stocks U_{im}	125.7	165.9
Occupational lags of unemployment stocks U_{jl}	54.6	126.6
Registered vacancies stock V_{il}	14.8	34.5
Regional lags of registered vacancies stocks V_{im}	10.5	10.7
Occupational lags of registered vacancies stocks V_{jl}	5.1	11.2

Source: Own calculation based on administrative data of the centre of the statistics department of the Federal Employment Agency 2000-2011.

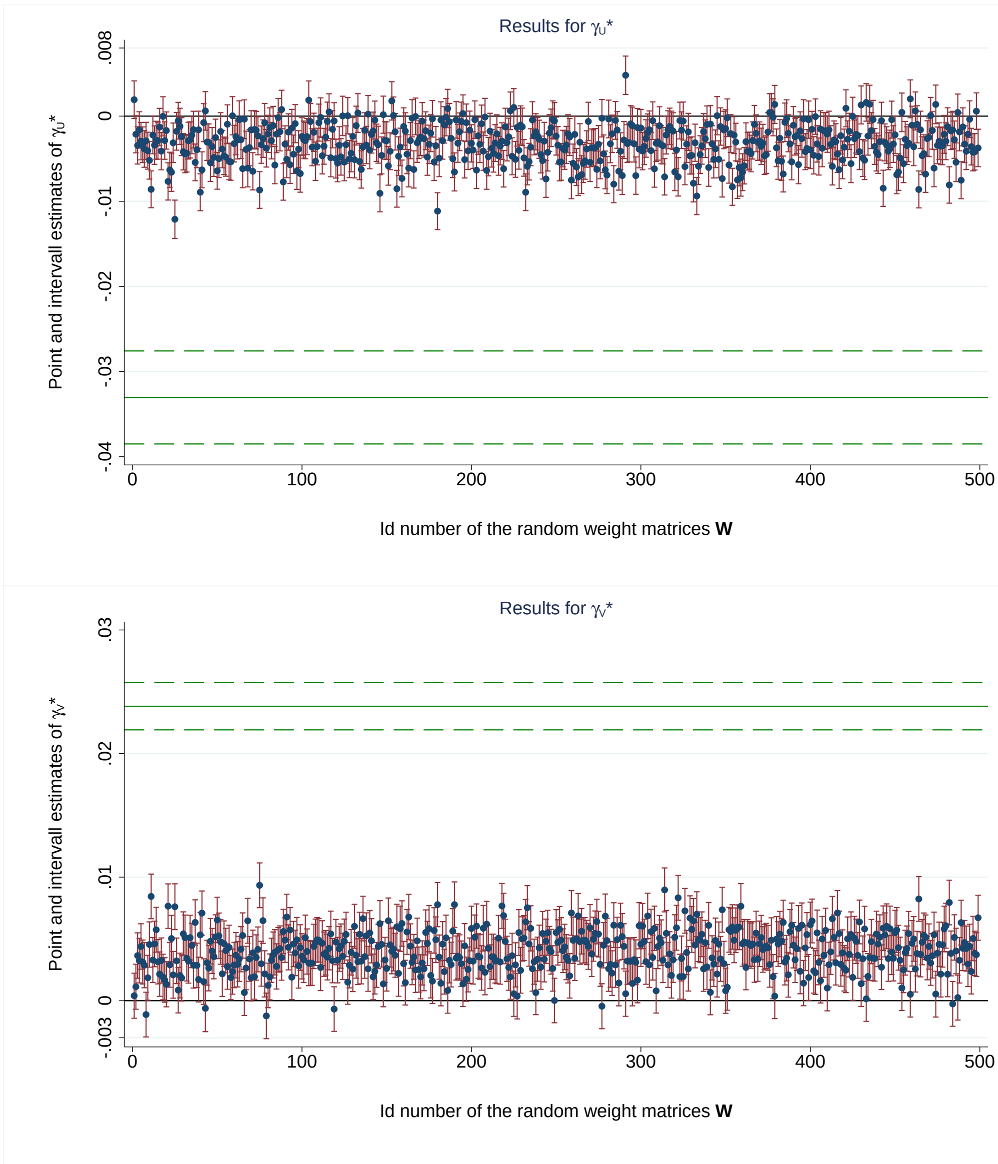

Figure 1: Test of 500 random "occupational topology" matrices in the estimation of the effect of occupational spillovers on matching efficiency.

Table 2: OLS and FE estimation of a matching function across occupational and regional labour markets.

VARIABLES	(1) OLS	(2) FE 1	(3) FE 2	(4) FE 3	(5) FE 4	(6) FE 5	(7) FE 6	(8) FE 7	(9) FE 8	(10) FE 9
β_U	0.573***	0.514***	0.623***	0.639***	0.626***	0.641***	0.564***	0.623***	0.566***	0.579***
	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
β_V	0.115***	0.060***	0.040***	0.038***	0.036***	0.034***	0.040***	0.028***	0.028***	0.024***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
γ_{U_o}				-0.058***		-0.056***				-0.034***
				(0.003)		(0.003)				(0.003)
γ_{V_o}					0.024***	0.022***				0.024***
					(0.001)	(0.001)				(0.001)
γ_{U_r}							0.128***		0.125***	0.123***
							(0.004)		(0.004)	(0.003)
γ_{V_r}								0.073***	0.071***	0.065***
								(0.002)	(0.002)	(0.002)
Constant	-0.784***	-0.428***	-0.970***	-0.843***	-0.996***	-0.872***	-1.261***	-1.086***	-1.367***	-1.302***
	(0.001)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)	(0.015)	(0.018)	(0.017)
Within / area and occupational fixed effects estimator		x	x	x	x	x	x	x	x	x
Time fixed effects			x	x	x	x	x	x	x	x
Observations	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.657	0.206	0.304	0.305	0.304	0.305	0.307	0.306	0.308	0.309
Number of id		55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1