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Job matching in connected regional and occupational labour markets

Alexandra Fedorets[a], Franziska Lottmann[b] and Michael Stops[c]

ABSTRACT

Job mobility equilibrates disparities in local labour markets and influences the job-matching efficiency. We specify a matching function with regional, occupational and combined regional–occupational spillovers of unemployed and vacancies. To construct these spillovers, we use information on regional proximities and occupational similarities. Based on novel German data on new hires, the unemployed and vacancies, we find significant positive effects of all spillover terms, with the exception of the negative and significant spillovers of the unemployed in other occupations. The reverse spillover effects could be used for designing macro-oriented policies aiming to improve job matching.

KEYWORDS

matching function; job mobility; local labour markets

JEL C21, C23, J44, J64

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INTRODUCTION

Policies regarding economic development and job creation are aimed at local labour markets to achieve better targeted and, therefore, more efficient interventions. Indeed, Manning and Petrongolo (2017) show that labour market processes take place at local levels. In the literature, local labour markets are usually defined by geographical units (Topel, 1986) and their connectivity is defined by regional mobility (Burda & Profit, 1996; Fahr & Sunde, 2006b), with patterns varying by education and economic sector (Boschma, Eriksson, & Lindgren, 2014; Hensen, de Vries, & Corvers, 2009; Machin, Pelkonen, & Salvanes, 2008). Nevertheless, locality of labour markets goes beyond geography and can be also defined by occupational affiliations (Stops, 2014). Such local occupational labour markets are connected by occupational mobility. Moreover, the interdependence of labour markets along the regional and occupational dimension exists simultaneously. Thus, a study by Reichelt and Abraham (2017) documents that every fourth occupational change also involves regional mobility. In the present paper, we empirically estimate how the number of vacancies and unemployed in a local labour market relate to the emergence of new employment, that is, matching efficiency. To do this, we define the borders between local labour markets being simultaneously given by regional units *and* occupational titles, which is a novelty of the existing literature.[1] At the same time, we allow for connectivity between these local labour markets based on information about regional proximities and occupational similarities. This allows us to differentiate between the *direct* effect of unemployed and vacancies on matching efficiency within the regional–occupational labour market and the *indirect* or *spillover* effect[2] of unemployed and vacancies in connected regions and occupations. In particular, we differentiate between spillover effects from other regions and same occupations, from same regions and other occupations, and combined spillovers from other regions and other occupations. Besides the quantification of the magnitude of spillovers, we can assess whether their inclusion substantially affects the magnitude of the direct effects. This study contributes to the literature on job matching that relates the number of flows into employment to the number of vacancies and job searchers (Diamond, 1982; Petrongolo & Pissarides, 2001; Pissarides, 1979; Rogerson, Shimer, & Wright, 2005; Yashiv, 2007). The literature argues that

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estimation of the matching efficiency at the level of local labour markets better mirrors the actual matching process (Dauth, Hujer, & Wolf, 2016; Manning & Petrongolo, 2017) by utilizing information on the local factors driving the hiring process. Ignoring the existing variation between local labour markets may lead to biased estimates of matching efficiency (Coles & Smith, 1996). Until now, disaggregated estimation of matching elasticities has mainly focused on regional labour markets and their connectivity established by geographical proximities or other comparable proximity measures (Burda & Profit, 1996; Fahr & Sunde, 2006a; Haller & Heuermann, 2016; Lottmann, 2012). At the same time, Fahr and Sunde (2004) and Stops and Mazzoni (2010) document that matching efficiencies are heterogeneous across occupational labour markets. Stops (2014) is the only existing study addressing matching spillovers between *occupational labour markets*. Analogously with the spatial order of regional labour markets, Stops uses an 'occupational topology' that describes groups of occupational labour markets that are assumed to be substitutes given similarities in their job contents, formal requirements and qualifications. This definition follows Matthes, Burkert, and Biersack (2008) and is in line with Gathmann and Schönberg (2010), who state that workers can transfer their human capital across occupational labour markets, particularly between occupations with similar content. We employ a highly disaggregated data set based on administrative data for Germany. The data contain information on the number of new hires, unemployed and vacancies for local labour markets defined as intersections of occupational orders[3] and NUTS-3 regions. The data cover the period from 2000 to 2011 on a monthly basis. We then construct regional spillover terms based on measures of geographical proximity between regions. Next, we construct occupational spillover terms by using the assignment of occupations with similar task contents and job requirements to occupational segments (Matthes et al., 2008). Finally, we compute combined spillover terms using the information for both regional and occupational proximities. We then specify a matching function including the conventional direct effects and additional spillover terms that consist of occupational spillovers, regional spillovers and combined regional–occupational spillovers. This specification is novel to the literature. We motivate our matching function with a 'bulletin board' job search model that complements the model of Burda and Profit (1996) for regional spillovers with occupational spillovers and regional–occupational spillovers. Specifically, the model describes job search in local labour markets that are connected because job searchers apply for vacancies in different labour markets. Their search intensity depends on the expected returns given search costs that, in turn, depend on the distance between the local labour markets. Therefore, the number of resulting matches in each local labour market does not just depend on the number of job searchers and vacancies in the observed labour market, but also on the number of job searchers and vacancies in other connected local labour markets. We show that the resulting spillover effects on the job finding probability and, hence, on the number of matches could be either negative or positive. Thus, according to the model, the direction of the effects remain an empirical question. The fixed-effects estimation of this matching function reveals significant effects of all spillovers. Specifically, we find positive regional spillover effects of both unemployed and vacancies in other regions and a positive spillover effect of vacancies in similar occupations. In contrast, we find a negative occupational spillover effect of unemployed in similar occupations. Lastly, we find relatively small, but positive, combined regional and occupational spillover effects. Differentiating between West and East Germany, the observed pattern of spillover effects holds in both areas and we find that East Germany tends to higher matching elasticities than West Germany. The results are corroborated by robustness tests that are based on alternative weighting matrices for regional or occupational proximity and on a more restrictive data sample. The results imply that different dimensions of labour markets locality may help to balance out negative spillovers. For instance, the negative effect of the unemployed from other occupations is offset by positive spillovers along the regional dimensions. This means that if, for example, an occupational local labour market faces a negative shock, policy-makers might use regional-level instruments to level out the potential negative consequences.

The paper is structured as follows. The next section motivates disaggregated matching functions and the existence of regional–occupational spillovers. The following section presents the data, while the section after that contains estimation results. The paper then presents the robustness checks. The final section concludes.

EMPIRICAL MATCHING FUNCTION WITH REGIONAL AND OCCUPATIONAL SPILLOVER TERMS

In the following, we discuss theoretical motivation for regional, occupational and combined regional–occupational spillovers and incorporate them in the empirical matching function.

Theoretical considerations on spillovers

The existence of spillovers over local labour markets can be explained by the theoretical framework of the bulletin board model (Hall, 1979; Pissarides, 1979). Burda and Profit (1996) provide a version of this model for regional labour markets, whereas Stops (2014) applies the same model structure and interprets it for occupational labour markets. This model can be also applied to combined regional–occupational labour markets by assuming that the unemployed search for vacancies either in their residence region l or in another region $m \neq l$, as well as in their occupation i or in another occupation $j \neq i$. In the following, we present the most important modifications of the base model that are necessary to motivate our empirical specification. For further details on the model notations, structure and derivation, see Appendix A in the supplemental data online. In the model, job searchers decide about their optimal number of applications to be sent to different labour markets (N^*_{ijlm}) by maximizing the difference of expected benefits from taking up a new job and the search costs:

$$\underbrace{[1-(1-f_{jm})^{N_{ijlm}}]\ \frac{w}{r}}_{\text{total expected benefit}} - \underbrace{N_{ijlm}(c + aD_{lm} + bD_{ij})}_{\text{costs}} \underset{N_{ijlm}}{\longrightarrow} \max, \quad (1)$$

where N_{ijlm} is the number of sent applications to all local labour markets, each leading to a job with wage w with the probability f_{jm}. The aggregate costs are given by the total number of applications times application costs that increase with the distance between regions l and m and dissimilarity between occupations i and j. The terms a, b and c are positive constants; D_{lm} and D_{ij} are regional and occupational distances; whereas r denotes the interest rate. Aggregating the individual search behaviour over all local labour markets allows for modelling the number of exits out of unemployment into employment in occupation i and region l:

$$x_{il}(\mathbf{u}, \mathbf{v}) = u_{il}F_{il} = u_{il}\left[1 - \prod_{j=1}^{J}\prod_{m=1}^{M}(1-f_{jm})^{N^*_{ijlm}}\right], \quad (2)$$

where $\mathbf{u}$ and $\mathbf{v}$ are the vectors of 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. This matching function involves the unemployed and vacancies in all occupations and all regions; therefore, regional, occupational, and combined regional–occupational spillover terms can be derived:

$$\frac{\partial x_{il}}{\partial u_{il}} = F_{il} + u_{il}\cdot\frac{\partial F_{il}}{\partial u_{il}}, \quad (3a)$$

$$\frac{\partial x_{il}}{\partial u_{jm}} = u_{il}\cdot\frac{\partial F_{il}}{\partial u_{jm}};\ i \neq j \vee m \neq l, \quad (3b)$$

$$\frac{\partial x_{il}}{\partial v_{jm}} = u_{il}\cdot\frac{\partial F_{il}}{\partial v_{jm}};\ \text{for all } j, m. \quad (3c)$$

According to equation (3a), the direct effect of an increase in the unemployed stock in a local labour market, il, on the exit of unemployed into employment in the same local labour market is positive, which is a common finding in the literature on job matching. Equations (3b) and (3c) show that exits into employment in occupation i and region l are also influenced both by the stock of unemployed and vacancies in other occupations $i \neq j$ or other regions $l \neq m$. It can be further shown that the sign of $\partial F_{il}/\partial u_{jm}$ depends on the sign of $\partial f_{jm}/\partial u_{jm}$, which determines the direct positive effect of the unemployed on the number of matches (cf. Burda & Profit, 1996; and Stops, 2014). At the same time, there is an indirect effect through N^*_{ijlm}, which can be shown to be negative under specific conditions. Thus, the model predicts that the number of matches in the local labour market is positively affected by the unemployed and vacancies in the same labour market, but can be either positively or negatively affected by the unemployed and vacancies from other local labour markets. The positive effect stems from the scope effect of having more applications in the labour market, whereas the negative effect stems from competition of applicants for vacancies. Which of the effects prevails is the matter of an empirical evaluation.

Spillovers in the empirical matching function

The number of matches in the labour market can be related to the pool of unemployed workers and vacancies by specifying 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, resulting in a job match (denoted by M):

$$M = M(U, V) = AU^{\beta_U}V^{\beta_V}, \quad (4)$$

where A describes the matching technology parameter. The parameters β_U and β_V represent the matching elasticities of unemployed and vacancies. Labour mobility between regions in order to overcome discrepancies in supply and demand is well documented in empirical studies (Burda & Profit, 1996; Fahr & Sunde, 2006b; Haller & Heuermann, 2016; Hensen et al., 2009; Lottmann, 2012). Regional mobility varies substantially, even between European countries (Ours, 1990). In Germany in the mid-1990s, every fifth job change involved regional mobility (Haas, 2000). For unemployment-to-job transitions, this rate is even higher (Arntz, 2005; Haas, 2000). The connectedness of regional labour markets is non-random (Fahr & Sunde, 2006a). Studies of regional spillovers in the matching function employ spatial dependence structures given by geographical proximity between regions (Haller & Heuermann, 2016; Lottmann, 2012); this approach is also often used for other applications in the spatial literature (see, for example, Hautsch & Klotz, 2003, on the dependence structure of innovation decisions). Moreover, Lottmann (2012) documents that spatial dependency between German regions has grown since 2000. Therefore, we assume that within a regional local labour market $l = 1, \ldots, L$, the matching process involves both the unemployed and the vacancies from region l, as well as a weighted average of unemployed and vacancies from other regions $m = 1, \ldots, M$, $m \neq l$. We assume that nearby regions are more related to each other in terms of job search and worker recruiting than more distant regions. Formally, this assumption results in larger weights for the unemployed and vacancies in nearby regions and smaller weights for the unemployed and vacancies in more distant regions. We extend our matching function by the weighted average stock of the unemployed $U_{\bar{M}}$ with its elasticity γ_{U_r} and the weighted average number of vacancies $V_{\bar{M}}$ with its elasticity γ_{V_r} (Burda & Profit, 1996):

$$M_l = M(U_l, V_l, U_{\bar{M}}, V_{\bar{M}}) = AU_l^{\beta_U}V_l^{\beta_V}U_{\bar{M}}^{\gamma_{U_r}}V_{\bar{M}}^{\gamma_{V_r}}. \quad (5)$$

Apart from the geographical connectedness between regions, other definitions of local labour markets can be applied. For instance, Broersma and Van Ours (1999) document the heterogeneities in the matching technology in different industries. However, Fahr and Sunde (2004), Kambourov and Manovskii (2009) and Stops and Mazzoni (2010) observe the strongest influence on the patterns of the matching efficiency on occupational labour markets. The connectedness of occupational labour markets is observed based on the frequency of occupational switches (Fitzenberger & Spitz, 2004). Gathmann and Schönberg (2010) document that 10–19% of job changes involve an occupational switch and show that occupational mobility is more pronounced between occupations with similar content. Thus, we assume that, regarding matches in occupation $i = 1, \ldots, I$, the matching process involves weighted averages of unemployed and vacancies from similar occupations $j = 1, \ldots, J, j \neq i$. Therefore, we extend the matching function (4) by the proximity-weighted average stock of the unemployed $U_{\bar{J}}$ with elasticity γ_{U_o} and the proximity-weighted number of vacancies $V_{\bar{J}}$ with elasticity γ_{V_o} in other similar occupations (similar to Stops, 2014):

$$M_i = M(U_i, V_i, U_{\bar{J}}, V_{\bar{J}}) = AU_i^{\beta_U} V_i^{\beta_V} U_{\bar{J}}^{\gamma_{U_o}} V_{\bar{J}}^{\gamma_{V_o}}. \quad (6)$$

Job search evolves simultaneously along regional and occupational dimensions, which is reflected in the patterns of job mobility (Reichelt & Abraham, 2017). We conclude that the matching technology for occupation i in region l can be further adjusted by allowing spillovers from both occupations with similar contents j and other regions m:

$$\begin{aligned} M_{il} &= M(U_{il}, V_{il}, U_{i\bar{M}}, V_{i\bar{M}}, U_{\bar{J}l}, V_{\bar{J}l}, U_{\overline{JM}}, V_{\overline{JM}}) \\ &= A \underbrace{U_{il}^{\beta_U} V_{il}^{\beta_V}}_{\substack{\text{direct}\\ \text{effect}}} \underbrace{U_{i\bar{M}}^{\gamma_{U_r}} V_{i\bar{M}}^{\gamma_{V_r}}}_{\substack{\text{regional}\\ \text{spillover}}} \underbrace{U_{\bar{J}l}^{\gamma_{U_o}} V_{\bar{J}l}^{\gamma_{V_o}}}_{\substack{\text{occupational}\\ \text{spillover}}} \underbrace{U_{\overline{JM}}^{\gamma_{U_{ro}}} V_{\overline{JM}}^{\gamma_{V_{ro}}}}_{\substack{\text{combined}\\ \text{regional and}\\ \text{occupational}\\ \text{spillover}}} \end{aligned} \quad (7)$$

The latter equation is an approximation of what we understand as connected regional and occupational labour markets.

DATA

We use data from the Federal Employment Agency on outflows from unemployment into employment and stocks of unemployed and registered vacancies.[4] These data stem from a unique administrative panel data set for 327 occupational orders in 402 NUTS-3 regions, with 138 observation periods from January 2000 to June 2011. The occupational orders are coded according to the German occupational classification scheme (three digits, KldB 1988). We separately compute regional and occupational lags of unemployment and vacancy stocks. For the regional lags, we define the proximity of two regions to be the inverse distance between pairs of geographical centres measured in kilometres.[5] Based on this information, a 402 × 402 weights matrix is constructed. This matrix is row normalized and the diagonal elements are set to zero, which corresponds to the fact that a region cannot neighbour itself. The resulting weights matrix W^R is used to compute proximity-weighted averages of the stocks of unemployed and vacancies for each region in each single occupation:

$$\overline{\mathbf{U}}^{\mathbf{R}} \equiv (\mathbf{I}_{327} \otimes \mathbf{W}^{\mathbf{R}})\mathbf{U} \quad \text{and} \quad \overline{\mathbf{V}}^{\mathbf{R}} \equiv (\mathbf{I}_{327} \otimes \mathbf{W}^{\mathbf{R}})\mathbf{V}, \quad (8)$$

The vectors $\overline{\mathbf{U}}^{\mathbf{R}}$ and $\overline{\mathbf{V}}^{\mathbf{R}}$ of dimension 131,454 contain the proximity weighted average of unemployment stocks, $U_{i\bar{M}}$, and registered vacancies, $V_{i\bar{M}}$, in other regions; see also equation (7). $\mathbf{I}_{327}$ is an identity matrix of dimension 327 that corresponds to the number of occupational orders. $\mathbf{U}$ and $\mathbf{V}$ denote the vectors of dimension 131,454 containing all observations on the unemployed and registered vacancies, respectively. Analogous to the regional proximity, we use an occupational 'topology' that classifies occupations into groups by similarity of their content and qualification requirements. More specifically, we follow Matthes et al. (2008) and assign 327 occupational orders into 21 segments with similar job requirements. The approach is similar to the study by Gathmann and Schönberg (2010), which defines content proximity between occupations based on detailed survey information on tasks performed in the jobs.[6] The methodology of Matthes et al. (2008) relies on information from the Federal Employment Agency and its Central Occupational File,[7] which is an administrative database containing all professional education titles, job titles and task titles in Germany that are reviewed and verified by experts. Matthes et al. (2008) derive similarities between occupations from the database's information on specific skills, licenses, certificates, knowledge requirements, as well as tasks and techniques that are typical for each occupation. Stops (2014) applies such an occupational topology in a spatial analysis to investigate spillovers between two-digit occupational groups. The present study relies on an occupational topology based on more disaggregated three-digit occupational orders.[8] With information on occupational proximity at hand, we construct a 327 × 327 first-order contiguity weights matrix in which an entry of 1 denotes two occupational orders belonging to the same occupational segment. We row-normalize it and replace the diagonal elements with zeros. Hence, the resulting matrix W^O contains information on similarities between the occupational orders and it is used to compute occupational similarity-weighted averages of the stocks of unemployed and vacancies in each occupational order in each single region:

$$\overline{\mathbf{U}}^{\mathbf{O}} \equiv (\mathbf{W}^{\mathbf{O}} \otimes \mathbf{I}_{402})\mathbf{U} \quad \text{and} \quad \overline{\mathbf{V}}^{\mathbf{O}} \equiv (\mathbf{W}^{\mathbf{O}} \otimes \mathbf{I}_{402})\mathbf{V} \quad (9)$$

The vectors $\overline{\mathbf{U}}^{\mathbf{O}}$ and $\overline{\mathbf{V}}^{\mathbf{O}}$ of dimension 131,454 denote the occupational similarity-weighted sums of unemployment stocks and registered vacancies in other occupations; the single elements of these vectors are denoted as $U_{\bar{J}l}$ and $V_{\bar{J}l}$ in equation (9). $\mathbf{I}_{402}$ is an identity matrix of dimension 402 that corresponds to the number of regions. In the next step, we combine regional proximity and occupational similarity by augmenting the occupational weights matrix $\mathbf{W^O}$ with regional information. Technically, we compute the Kronecker product of $\mathbf{W^O}$ and $\mathbf{W^R}$:

$$\mathbf{W^{OR}} = \mathbf{W^O} \otimes \mathbf{W^R}. \tag{10}$$

After row-normalizing and replacing the diagonal elements with zeros, we obtain a $131,454 \times 131,454$ weights matrix $\mathrm{W^{OR}}$ that is used to weight the stock of unemployed $\boldsymbol{U}$ and vacancies $\boldsymbol{V}$ for all occupational orders and all regions depending on occupational similarity and regional proximity:

$$\overline{\mathbf{U}}^{\mathbf{OR}} \equiv \mathbf{W^{OR}U} \quad \text{and} \quad \overline{\mathbf{V}}^{\mathbf{OR}} \equiv \mathbf{W^{OR}V} \tag{11}$$

Here, $\overline{\mathbf{U}}^{\mathbf{OR}}$ and $\overline{\mathbf{V}}^{\mathbf{OR}}$ contain regional proximity and occupational similarity weighted averages of unemployment stocks and registered vacancies from all local labour markets; these averages are denoted as $U_{\overline{JM}}$ and $V_{\overline{JM}}$ in equation (7). Finally, to obtain unbiased matching parameter estimates, we adjust the data set with observations for 327 occupational orders and 402 NUTS-3 regions, respectively, where vacancies, unemployed or flows into employment are zero. This leads to an unbalanced panel data structure with 2,394,250 observations for 55,422 regional–occupational labour markets. Table 1 shows descriptive statistics for all measures. For the average regional–occupational labour market, we observe 11.2 exits into employment, 156 unemployed and 14.8 vacancies. Furthermore, this labour market is exposed to the regional proximity-weighted averages of 122.4 unemployed and of 11.0 vacancies from other regions. From other similar occupations, we observe occupational proximity-weighted averages of 54.6 unemployed and of 5.1 vacancies. Finally, from other regions and other similar occupations, there are 36.4 unemployed and 3.6 vacancies. Given our definitions of the regional and occupational proximity matrices, the observed regional–occupational labour markets are more exposed to unemployed and vacancies from other regions than from other similar occupations.

ESTIMATION OF SPILLOVERS

Taking logarithms of the model described by equation (7) and adding a time index t for the month of observation yields the following specification:

$$\begin{aligned}
\log M_{il,t} = {} & \log A + \beta_U \log U_{il,t} + \beta_V \log V_{il,t} \\
& + \gamma_{U_r} \log U_{i\bar{M},t} + \gamma_{V_r} \log V_{i\bar{M},t} \\
& + \gamma_{U_o} \log U_{\bar{J}l,t} + \gamma_{V_o} \log V_{\bar{J}l,t} \\
& + \gamma_{U_{ro}} \log U_{\overline{JM},t} + \gamma_{V_{ro}} \log V_{\overline{JM},t} + \mu_{il} \\
& + \delta_t + \epsilon_{il,t},
\end{aligned} \tag{12}$$

where μ_{il} denotes the region-occupational fixed effects; δ_t denotes the time fixed effects; and $\epsilon_{il,t}$ denotes the error term. Table 2 presents the results of the estimation of equation (12) using ordinary least squares (OLS) and fixed effects (FE).[9] The results of the specifications (OLS), (FE1) and (FE2) rely on a basis specification of the matching function without spillovers. The OLS specification does not contain any of the fixed effects. The specification in column (FE1) is complemented with fixed effects of the regional–occupational labour markets and the specification in column (FE2) additionally contains time fixed effects. Specifications (FE3)–(FE5) are stepwise complemented with only regional spillovers, whereas specifications (FE6)–(FE8) are stepwise complemented with only occupational spillovers. Specifications (FE9)–(FE11) include only the combined regional–occupational spillovers. Finally, specification (FE12) contains the full set

Table 1. Descriptive statistics.

		Monthly averages, 2000–11 (per observed regional–occupational labour market)	
		Mean	Standard deviation
Exits into employment	M_{il}	11.2	(22.8)
Number of unemployed	U_{il}	156.0	(410.8)
Number of registered vacancies	V_{il}	14.8	(34.5)
Regional proximity weighted averages			
Number of unemployed in other regions	$U_{i\bar{M}}$	122.4	(161.9)
Number of registered vacancies in other regions	$V_{i\bar{M}}$	11.0	(11.2)
Occupational proximity weighted averages			
Number of unemployed in other similar occupations	$U_{\bar{J}l}$	54.6	(126.6)
Number of registered vacancies in other similar occupations	$V_{\bar{J}l}$	5.1	(11.2)
Occupational and regional proximity weighted averages			
Number of unemployed in other regions, and in other similar occupations	$U_{\overline{JM}}$	36.4	(24.4)
Number of registered vacancies in other regions, and in other similar occupations	$V_{\overline{JM}}$	3.6	(2.4)

Source: Authors' own calculation based on administrative data from the Federal Employment Agency.

Table 2. Ordinary least squares (OLS) and fixed-effects (FE) estimation of a matching function across occupational and regional labour markets.

Model	**(1) (OLS)**	**(2) (FE1)**	**(3) (FE2)**	**(4) (FE3)**	**(5) (FE4)**	**(6) (FE5)**	**(7) (FE6)**	**(8) (FE7)**	**(9) (FE8)**	**(10) (FE9)**	**(11) (FE10)**	**(12) (FE11)**	**(13) (FE12)**
β_U	0.573***	0.514***	0.623***	0.549***	0.624***	0.552***	0.639***	0.626***	0.641***	0.626***	0.625***	0.622***	0.566***
	(0.000)	(0.003)	(0.003)	(0.003)	(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***	0.040***	0.024***	0.025***	0.038***	0.036***	0.034***	0.039***	0.035***	0.035***	0.022***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
γ_{U_r}				0.144***		0.140***							0.130***
				(0.004)		(0.004)							(0.004)
γ_{V_r}					0.085***	0.082***							0.064***
					(0.002)	(0.002)							(0.002)
γ_{U_o}							−0.058***		−0.056***				−0.034***
							(0.003)		(0.003)				(0.003)
γ_{V_o}								0.024***	0.022***				0.014***
								(0.001)	(0.001)				(0.001)
$\gamma_{U_{ro}}$										−0.025***		0.021***	0.035***
										(0.004)		(0.004)	(0.005)
$\gamma_{V_{ro}}$											0.099***	0.103***	0.076***
											(0.002)	(0.002)	(0.003)
Constant	−0.784***	−0.428***	−0.970***	−1.265***	−1.112***	−1.392***	−0.843***	−0.996***	−0.872***	−0.895***	−1.072***	−1.137***	−1.464***
	(0.001)	(0.013)	(0.014)	(0.017)	(0.015)	(0.018)	(0.014)	(0.014)	(0.014)	(0.016)	(0.014)	(0.017)	(0.019)
Time FE			×	×	×	×	×	×	×	×	×	×	×
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	2,394,250	2,394,250	2,394,250
Number of id		55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422	55,422
R^2	0.657	0.791	0.817	0.818	0.818	0.818	0.817	0.817	0.817	0.817	0.818	0.818	0.819
Within R^2	–	0.206	0.304	0.307	0.306	0.309	0.305	0.304	0.305	0.304	0.307	0.307	0.312
Breusch and Pagan Lagrangian multiplier test for random effects variance: (H_0:$Var(u_i) = 0$)													
χ^2	–	1.6e+07	1.9e+07	1.9e+07	1.8e+07	1.8e+07	1.8e+07	1.7e+07	1.7e+07	1.8e+07	1.7e+07	1.8e+07	1.7e+07
$p > \chi^2$		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(*Continued*)

Table 2. Continued.

Model	(1) (OLS)	(2) (FE1)	(3) (FE2)	(4) (FE3)	(5) (FE4)	(6) (FE5)	(7) (FE6)	(8) (FE7)	(9) (FE8)	(10) (FE9)	(11) (FE10)	(12) (FE11)	(13) (FE12)
Test of over-identifying restrictions: (H_0:$E(X_{it}*u_i) = 0$)													
Sargan–Hansen statistic (χ^2)	–	1819.050	5873.860	6618.973	6682.443	7615.865	5913.119	8049.508	6715.472	6428.440	8450.554	8165.205	9830.278
$p > \chi^2$		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Occupational and regional (id) cluster robust standard errors are shown in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
All FE specifications include regional–occupational fixed effects.
The Breusch and Pagan Lagrangian multiplier test for random effects variance is based on a comparison of the pooled OLS specification and the random effects specification (Breusch & Pagan, 1980). The specifications correspond to the fixed effects specifications in each column. The test of over-identifying restrictions is based on a comparison of the FE specification in each column with the corresponding random effects specification with robust standard errors (Arellano, 1993).

of regional spillovers, occupational spillovers, plus the combined regional–occupational spillovers. We calculate robust standard errors clustered within the regional–occupational labour markets. We additionally provide the number of observations and the number of observed regional–occupational labour markets (denoted as ids) as well as two measures of explained variance. For the OLS and FE models, we report a comparable R^2 that accounts for fixed effects in the fixed-effects models. Moreover, we report the within R^2 to obtain a notion of the proportion of the explained variance by the explanatory variables from the within equations. At the bottom of Table 2 we report the results of specification tests that allow us to compare pooled OLS, random-effects and fixed-effects specifications. First, we conduct the Breusch and Pagan Lagrangian multiplier test to explore whether the variance of the random effects is zero (Breusch & Pagan, 1980). The test results suggest that the random-effects model should be preferred to the pooled OLS. Second, we report results of an implicit test of the necessity of fixed effects, as suggested by Arellano (1993). In doing so, we estimate a random effects model with clustered robust standard errors and test for orthogonality of explanatory variables and random effects. The test results show that orthogonality has to be rejected and, therefore, the fixed-effects model should be preferred to the random-effects model.[10]

The matching elasticities of the unemployed and vacancies (β_U and β_V) are positive and significant throughout all specifications. 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 & Wyplosz, 1994; Fahr & Sunde, 2004; Stops, 2014, 2016; Stops & Mazzoni, 2010). These matching elasticities remain qualitatively unchanged when introducing regional, occupational and time fixed effects (specifications FE1 and FE2). Specifications (FE3)–(FE5) include spillovers of the unemployed and vacancies from other regions. The coefficient of the regional spillover term of the unemployed is positive, significant and smaller in magnitude than the corresponding direct effect ($|\beta_U| >> |\gamma_{U_r}|$). Thus, an increase in the number of unemployed in the observed occupation and the observed region leads to a larger number of matches than the same increase of the average number of unemployed in the observed occupation in other regions. The coefficient of the regional spillover term of the vacancies is also positive and significant, but larger than the corresponding direct effect ($|\beta_V| << |\gamma_{V_r}|$). Therefore, an increase in the number of vacancies in the observed occupation in the observed region leads to a smaller number of matches than the same increase of the average number of vacancies in the same occupation in other regions. Though our underlying theoretical model does not define whether this spillover effect should be less or more pronounced than the direct effect, it allows for such an outcome. According to the model, the results imply that the unemployed adjust their search intensity to changes in the number of vacancies in the observed regional labour market to a lower extent compared with the same change of the weighted averaged sum of vacancies in the neighboured markets. Inclusion of both regional spillover terms of the unemployed and vacancies in other regions (specification FE5) does not alter the magnitude of the corresponding coefficients in the specifications that include only one of the spillover terms (FE3 and FE4). Specifications (FE6)–(FE8) include spillovers of the unemployed and vacancies from similar occupations. The coefficients of both occupational spillover terms are substantially lower than the corresponding direct effects ($|\beta_U| >> |\gamma_{U_o}|$ and $|\beta_V| >> |\gamma_{V_o}|$). The spillover effect of the unemployed in similar occupations is negative and significant, whereas the spillover effect of vacancies in similar occupations is positive and significant. The magnitudes of spillover coefficients in specification (FE6) with both occupational spillover terms of vacancies and unemployed remain virtually unchanged compared with specifications (FE7) and (FE8), which include only one of the spillovers. Specifications (FE9)–(FE11) include the combined regional–occupational spillovers of the unemployed and vacancies in similar occupations in regions. The combined regional and occupational spillover effect of the unemployed in similar occupations from other regions is relatively small, negative and significant when it is separately included (FE9). The combined regional–occupational spillover effect of the vacancies in similar occupations from other regions is positive and significant. In specification (FE11), with both effects, the sign of the spillover effect of the unemployed changes compared to specification (FE9).[11] Similar to specifications (FE3)–(FE5), the indirect effect of the unemployed in similar occupations from other regions on matching elasticity is substantially smaller than the direct effect ($|\beta_U| >> |\gamma_{U_{ro}}|$), while the indirect effect of the vacancies is notably higher than the direct effect ($|\beta_V| << |\gamma_{V_{ro}}|$). These results, again, show that a spillover effect can exceed the direct effect, which can be explained by the different extents to which unemployed adjust their search intensity to changes of the number of vacancies in the observed labour market compared with same change of the proximity-weighted-averaged sum of vacancies in other regional–occupational labour markets. In specification (FE12), we include regional spillovers, occupational spillovers, plus the combined regional–occupational spillovers. The relative size of the direct effect of the unemployed and vacancies as well as the different spillover effects is robust compared with the previous specifications. However, the size of the direct effect of the unemployed and vacancies (β_U and β_V) is affected by the introduction of the spillover terms. Comparing β_U and β_V in (FE2) and (FE12) shows that neglecting spillover effects leads to an overestimation of the direct effects of the matching elasticity with respect to unemployed and vacancies. More specifically, comparison of (FE2) and (FE5) shows that negligence of regional spillovers results in overestimation of the matching elasticities, with respect to both unemployed and vacancies. Comparison of (FE2) and (FE8) 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. Thus, the spillover effects are positive and significant with one exception: the estimate results of specifications (FE6), (FE8) and (FE12) document that an increase of the number of unemployed from other similar occupations leads to a lower number of matches in the observed market. Our theoretical model provides an explanation for this result. The model describes that an increase of unemployed in other labour markets can have two reverse effects on the hires in the observed local labour market. First, such an increase has a direct positive effect on the number of job matches. Second, the increased number of unemployed can also have an indirect negative effect on the job finding probability and, thus, a negative indirect effect on the number of matches (see equation (7) in Appendix A in the supplemental data online). From our model, we conclude that, in the case of regional spillovers, the negative effect is smaller than the positive effect. In case of occupational spillovers, the negative effect is larger than the positive effect. The reason for the different signs of the regional spillover and the occupational spillover may lie in the different efforts needed to overcome the regional and the occupational distances. Whereas workers in same occupations from other regions 'only' have to pay transport costs to overcome regional distances to work, workers in other occupations in the same region have to pay for information on, or training in, other occupations as a part of the search process. In addition to that, the investment decision related to human capital investment which is needed for occupational mobility has to be done under uncertainty. Moreover, given the existing travel infrastructure, costs for interregional applications can be covered virtually immediately, whereas meeting requirements for interoccupational applications may take more time. In light of our model, the implication is that more applicants from other regions with the same occupation as in the observed market can be hired immediately and this leads to a higher number of matches per observation period and explains the positive regional spillover coefficient. In contrast, more unemployed from other occupations in the observed region cannot be immediately hired due to efforts for collecting information or training; nevertheless, these unemployed are in the market and increase competition and coordination efforts of firms. This is reflected in a smaller number of matches per observation period and, thus, explains the negative occupational spillover coefficient. Under specific assumptions, our results allow for a comparison of the magnitudes of regional and occupational spillovers. For the comparison, we must consider that regional proximities are based on physical distances and occupational proximities are given by task similarity assessment by experts, i.e., they are different in their nature. Owing to the row normalization of both matrices and based on the assumption that the utilized weighting matrices represent the regional and occupational cross-sectional dependence structures, the magnitudes of the coefficients can be compared. The finding that the coefficients of regional spillovers are substantially larger than the coefficients of occupational spillovers (FE12) might mirror the fact that regional mobility is related, on average, to lower costs than occupational mobility and is observed more frequently. At the same time, the comparison of the within R^2 in specifications (FE2) and (FE5), as well as (FE2) and (FE8), shows that inclusion of regional spillovers contributes to a higher increase of the explained variance than the inclusion of occupational spillovers. Comparing to (FE2), the highest explanatory power has the specification (FE12), indicating that both spillover types and their interactions are relevant. To test whether the choice of the weight matrices influences our main results, we discuss estimates based on alternative weight matrices in the robustness section. To get a notion about regional differences of these effects, we modify specification (FE12) by including coefficients of our main variables and the monthly time dummies that interact with a dummy that marks whether observed regions belong to East or West Germany. The results are reported in Table 3. To explore whether the magnitudes of these coefficients differ, we conduct Wald tests based on F-statistics and present the results in the right column of Table 3. As expected, the magnitudes of the coefficients of (FE12) in the previous Table 2 lie between the respective magnitudes of the coefficients for East and West Germany. The coefficients for East and West Germany differ significantly at the 1% level with two exceptions: there are no significant differences for the regional lag of the unemployed and the occupational lag of the vacancies. Regarding the other coefficients, we find that the magnitudes for the direct effects of unemployed and vacancies, as well as the regional and occupational lags of unemployed and vacancies have larger matching elasticities in East Germany than in West Germany. These results suggest that an increase of vacancies and unemployed in the observed region and occupation, but also in other regions and other similar occupations lead, *ceteris paribus*, to more matches in the observed region and occupation in East Germany than in West Germany. The regional lag of vacancies in West Germany has a larger coefficient than in East Germany, suggesting that more vacancies in other regions lead to more matches in West Germany than in East Germany.

Table 3. Fixed-effects (FE) estimation of a matching function across occupational and regional labour markets, full specification including interaction terms with a binary indicator for East and West Germany.

Model specification	**(FE13)**		**Wald test**
Coefficient that interacts with the dummy for *region*	**East Germany**	**West Germany**	**$F(1, 55{,}422)$ $p > F$**
region # β_U	0.664***	0.542***	294.00
	(0.006)	(0.003)	0.0000
region # β_V	0.027***	0.019***	15.17
	(0.002)	(0.001)	0.0001
region # γ_{U_r}	0.135***	0.120***	2.46
	(0.008)	(0.004)	0.1171
region # γ_{V_r}	0.054***	0.067***	7.03
	(0.004)	(0.002)	0.0080
region # γ_{U_o}	−0.044***	−0.022***	7.52
	(0.007)	(0.004)	0.0061
region # γ_{V_o}	0.014***	0.012***	0.60
	(0.002)	(0.001)	0.4381
region # $\gamma_{U_{ro}}$	0.127***	0.015***	70.12
	(0.012)	(0.006)	0.0000
region # $\gamma_{V_{ro}}$	0.092***	0.069***	14.43
	(0.005)	(0.003)	0.0001
region # Time fixed effects	×	×	
Constant	−1.249***		
	(0.017)		
Observations	2,394,250		
Number of id	55,422		
R^2	0.821		
Within R^2	0.319		

Notes: Occupational and regional (id) cluster robust standard errors are shown in parentheses.
Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
In the regional classification, East Germany comprises Berlin.
All specifications include regional–occupational fixed effects (FE).
The F-test compares the coefficients that interact with the dummy variable for East and West Germany with the null that the magnitudes are equal.

According to our model, this implies that workers in West Germany increase their search intensity by observing more vacancies in other regions and this has also a positive effect on the numbers of matches in the observed region and occupation. Additionally, the negative effect of unemployed in similar occupations in the observed region on the number of matches in the observed occupation in the same region in West Germany is smaller than in East Germany. This suggests that the number of matches in West Germany is less susceptible to the competition from the unemployed in other similar occupations than is the case in East Germany. To sum up, we find a pattern of larger matching elasticities in East Germany than in West Germany with some minor exceptions. A further investigation of the behavioural aspects behind this pattern deserves further exploration but this is beyond the scope of this paper.

ROBUSTNESS OF THE SPILLOVER ESTIMATES

Regional proximity based on travel times

The main results are based on regional proximity weights that are derived from distances between the geographical centres of German NUTS-3 regions. This approach is common to studies on regional spillovers (Haller & Heuermann, 2016; Hautsch & Klotz, 2003; Lottmann, 2012). Studies in geographic information science argue that average travel times between regions are a more important factor for regional connectedness (Kemp, 2008). However, from the econometric perspective, these alternatives might not fulfil the assumption that the spatial structure is exogenous to the matching technology. In addition to this, Haller and Heuermann (2016) empirically show that, compared with the mentioned alternatives and based on a similar German data set, regional distances turn out to be the best approximation for regional dependence structures. Nevertheless, we use regional proximity weights based on car travel times to test the robustness of the results. Our information on car travel times stems from OpenStreetMap (from 1 January 2014) and were computed with a routine described by Huber and Rust (2016).[12] Owing to the normalizing procedure, we obtain a good alternative proxy for a matrix that contains information on the relative accessibility of regions, even though these data relate to a more recent observation period than the data in our analysis. We compute the multiplicative inverse of each travel distance, row normalized the resulting matrix, set the diagonal elements to zero and combined it with the occupation proximity weights matrix from our main analysis. We then re-estimate our main specification (FE12). The results are reported in column (1) of Table 4. Compared with the main results of specification (FE12) in Table 2, the coefficients have very similar magnitudes and virtually the same standard errors. Thus, we conclude that our main results are robust to the choice of the regional proximity matrix.

Task-based occupational topologies

Our main results rely on the occupational topology that is based on the Central Occupational File provided by the Federal Employment Agency. Information in this database is generated and updated by experts with the objective to describe the most common and most important features of each known occupation in Germany. An alternative way to construct such an occupational topology is to use survey information on job tasks and calculate content similarities between occupations, directly following Gathmann and Schönberg (2010). We use the 2006 wave of the German Employment Survey (also known as Qualification and Career Survey), which allows us to construct a binary variable of individual involvement in 12 different tasks.[13] Based on this information, we compute a 12-dimensional tasks vector τ_k^i, $k \in \{1, \ldots, 12\}$ for each occupational order i defined at the three-digit level of the occupational classification code (KldB 1988). The survey facilitates computing such vectors for 275 occupational orders. We then use these vectors to construct a matrix of occupational dissimilarities based on the angular separation measure. This measure stems from the literature on proximity of production technologies and is also used to quantify task-based job similarities, for instance by Gathmann and Schönberg (2010). In particular, dissimilarity between two different occupations i and j is measured as:

$$\begin{aligned} Dis^A_{i\leftrightarrow j} &= 1 - AngSep_{i\leftrightarrow j} \\ &= \frac{\sum_{k=1}^{12} \tau_k^i \cdot \tau_k^j}{\left[\left(\sum_{k=1}^{12} (\tau_k^i)^2\right)\left(\sum_{k=1}^{12} (\tau_k^j)^2\right)\right]^{1/2}}. \end{aligned} \tag{13}$$

The distance measure varies between 0 and 1, taking higher values for less similar occupations. In order to use this matrix as the alternative weight matrix for occupational spillovers, we conduct inversion, row normalization and replacement of diagonal elements by zeros. Using these occupational proximity weights, we re-estimate the specification (FE12) from our main results (Table 2). The results are presented in column (2) of Table 4. The results are very similar to our main results. Virtually all coefficients of the main and the alternative analyses have same signs and very comparable magnitudes. The exception are the coefficients γ_{U_o} and γ_{V_o} with remarkably higher magnitudes. These differences lie in the fact that the alternative weighting matrix features continuous dissimilarity measures instead of binary similarity indexes, thus additionally accounting for the impact of the number of unemployed in occupations that were previously regarded as dissimilar. Overall, we conclude that our main results are generally robust to the choice of occupational proximity weights.

Exclusion of labour markets with a low number of observations

Another concern regarding our data could be its unbalanced panel data structure. In our main analysis, we consider all regional–occupational labour markets with non-zero information on unemployment outflows, the number of unemployed and the number of vacancies for at least

Table 4. Robustness checks: different weight matrices and sample restriction.

Specification	**(1) (FE12)**	**(2) (FE12)**	**(3) (FE12)**
Regional proximity weights based on:	Car travel times	Distances (from the main analysis)	Distances (from the main analysis)
Occupational proximity weights based on:	Matthes et al. (2008) (from the main analysis)	Gathmann and Schönberg (2010)	Matthes et al. (2008) (from the main analysis)
Sample restriction	$T \geq 1$ (from the main analysis)	$T \geq 1$ (from the main analysis)	$T \geq 30$
β_U	0.568***	0.584***	0.611***
	(0.003)	(0.003)	(0.003)
β_V	0.022***	0.020***	0.022***
	(0.001)	(0.001)	(0.001)
γ_{U_r}	0.128***	0.121***	0.114***
	(0.004)	(0.004)	(0.004)
γ_{V_r}	0.065***	0.074***	0.072***
	(0.002)	(0.002)	(0.002)
γ_{U_o}	−0.035***	−0.110***	−0.050***
	(0.003)	(0.004)	(0.004)
γ_{V_o}	0.015***	0.032***	0.016***
	(0.001)	(0.002)	(0.001)
$\gamma_{U_{ro}}$	0.040***	0.030***	0.048***
	(0.005)	(0.011)	(0.006)
$\gamma_{V_{ro}}$	0.077***	0.074***	0.070***
	(0.003)	(0.007)	(0.003)
Constant	−1.480***	−1.272***	−1.616***
	(0.019)	(0.040)	(0.020)
Time fixed effects	×	×	×
Observations	2,394,250	2,390,671	2,133,345
Number of id	55,422	54,869	24,675
R^2	0.819	0.819	0.811
Within R^2	0.312	0.311	0.329
Breusch and Pagan Lagrangian multiplier test for random effects variance (H_0:$Var(u_i) = 0$)			
χ^2	1.7e+07	1.6e+07	1.5e+07
$p > \chi^2$	0.0000	0.0000	0.0000
Test of over-identifying restrictions: (H_0:$E(X_{it} * u_i) = 0$)			
Sargan–Hansen statistic (χ^2)	9906.062	9057.875	5443.290
$p > \chi^2$	0.0000	0.0000	0.0000

Notes: Occupational and regional (id) cluster robust standard errors are shown in parentheses.
Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
All specifications include regional–occupational fixed effects (FE).
The Breusch and Pagan Lagrangian multiplier test for random effects variance is based on a comparison of the pooled ordinary least squares (OLS) specification and the random effects specification (Breusch & Pagan, 1980). The specifications correspond to the FE specifications in each column. The test of over-identifying restrictions is based on a comparison of the FE specification in each column with the corresponding random effects specification with robust standard errors (Arellano, 1993).

one observation period. A low number of observational periods is harmless to the estimation of the direct and spillover effects, but can bias estimates of fixed effects (which are not in the focus of our analysis). Nevertheless, we perform a robustness check of our main specification (FE12) in Table 2 that is based on a data set with non-zero information on unemployment outflows, the number of unemployed, and the number of vacancies for at least 30 observation periods. Such data restrictions ensure considerable variation of the data across time, but reduces the number of regional–occupational labour markets for the analysis to 24,675. Our estimations results are reported in column (3) of Table 4. Differences to the full sample estimation can be explained, on the one hand, by the loss of information on more than the half of regional–occupational labour markets. On the other hand, the higher within R^2 suggests that the estimation results from the within regression explain a bigger part of the variation in the dependent variable than the results from our main analysis. These results corroborate our main findings because the coefficient signs remain the same, the coefficients' magnitudes are comparable and the standard errors are virtually the same.

CONCLUSIONS

In this paper, we estimate an empirical matching function with regional spillovers, occupational spillovers, as well as combined regional and occupational spillovers. Our analyses rely on a highly disaggregated data set that contains information on new matches, the unemployed and vacancies in local labour markets, defined as a combination of the regional and the occupational dimensions. To the best of our knowledge, we provide the first empirical evidence on the simultaneous influence of regional, occupational and combined regional–occupational spillovers on job matching. We compute regional and occupational spillovers by summing up stocks of unemployed and vacancies across all labour markets weighted by their regional and occupational proximity. In total, we define three types of spillovers: regional spillovers given by the vacancies and unemployed in other regions, occupational spillovers given by vacancies and unemployed in other similar occupations, and, lastly, combined regional and occupational spillovers given by vacancies and unemployed from other regions and other similar occupations. We incorporate these spillovers into the specification for an empirical matching function that relates inflows into employment in a local labour market to vacancies and unemployed in the same local labour market. Thus, in addition to the direct matching elasticities of unemployed and vacancies that are observed in the same local labour market like the inflows in employment, we estimate the influence of spillover effects. Our results reveal sizable and significant direct matching elasticities and spillover effects. Specifically, we find positive regional spillover effects of both unemployed and vacancies in other regions and positive occupational spillover effects of vacancies in other similar occupations. In contrast, we find a negative occupational spillover effect of unemployed in other similar occupations; this can be explained by the negative effect of the number of unemployed on their individual probability to find a job. We also find relative small positive combined occupational and regional spillover effects. In sum, the results suggest that local labour markets are susceptible to penetration, especially between nearby regions. The inclusion of regional and occupational spillovers also affects the magnitude of the direct matching elasticities. Our study explicitly explores a simultaneous effect of connectedness of local labour markets along two different dimensions. As our results suggest, the negative effect of an increased number of unemployed from similar occupations on the number of matches can be balanced out by the positive effect of an increased number of unemployed in nearby regions. Though our data do not contain information on worker flows between the labour markets, the latter result may be interpreted as an indication to the existing trade-off underlying the mobility decisions between regions and/or occupations, given the current job situation, family boundedness, and potential human capital losses of job seekers. The results also imply that policies that aim to boost the penetrability of labour markets do not necessarily lead to a higher matching efficiency. At the same time, a shock to a local labour market defined by, e.g., occupational dimension can be levelled out by policy measures aiming at regional labour markets. The presented evidence motivates future research on the multidimensional nature of labour mobility that may create competition in local labour markets, e.g., penetrability of the borders, regional disparities, and symmetry of the mutual affectedness of local labour markets.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. We define occupations as groups of jobs that share extensive commonalities in terms of skill requirements and tasks.
2. Henceforth, we will use the terms 'indirect effects' and 'spillover effects' interchangeably as synonyms as they are used in the literature (LeSage & Pace, 2009; Vega & Elhorst, 2015).
3. Occupational orders are defined by the three-digit code of the German occupational classifications scheme 1988 ('Klassifizierung der Berufe 1988' – KldB 1988).
4. Administrative data on unemployed and vacancies represent the matching process at the Federal Employment Agency. Although the results can be interpreted as the

outcome of a 'reduced' model, their generalization must be used with caution due to potential biasedness (Anderson & Burgess, 2000).

5. An alternative choice of weighting matrix is discussed in the subsection 'Regional proximity based on travel times'.

6. The subsection 'Task-based occupational topologies' provides a robustness check of the results based on an alternative weights matrix.

7. BERUFENET (https://berufenet.arbeitsagentur.de).

8. For the assignment of the occupational orders to the occupational segments, see in Appendix B in the supplemental data online. For more details on methodological aspects, see Stops (2014). We also conducted a placebo test to explore the empirical relevance of the derived weights (for further details, see in Appendix C in the supplemental data online).

9. Some of the related studies consider empirical specifications involving spatial lags of the dependent variable or the error term to exploit empirically matching efficiency in local labour markets (cf., for example, Haller & Heuermann, 2016; and Lottmann, 2012). We abstain from using such a specification due to their sensitivity to the real data-generating process (DGP), which makes identification of the 'true' model impossible (Gibbons & Overman, 2012). This implies that the real DGP should be reflected and assumptions on the real DGP should be well founded by theory (Vega & Elhorst, 2015). The present paper proposes such a suitable theoretical model that allows for deriving and estimating a matching function with spillover effects using the explanatory variables. The model does not describe a matching process that involves new hires in a local labour market that (at least partly) depend on (simultaneously generated) hires in other local labour markets. Furthermore, according to our theoretic model, our regression model includes all relevant variables and, therefore, is unlikely to suffer from an omitted variable bias of spatially dependent unobservables that potentially could, beside others, result in spatially dependent error terms.

10. A conventional Hausman test is not feasible because our model includes clustered robust standard errors.

11. We interpret the negative sign of the coefficient in (FE9) as an omitted variable bias. From an econometric perspective, such a change in the sign of a coefficient after including further variables points to collinearity of the included variables. Generally, the number of vacancies follows the business cycle, whereas the number of unemployed follows an acyclical pattern. Thus, both measures are negatively correlated (cf. the Beveridge curve literature, e.g., Elsby, Michaels, & Ratner, 2015). According to our theoretical model, we prefer a specification that includes both spillover terms for vacancies and unemployed.

12. We are grateful to Peter Haller for sharing data and code.

13. (1) Teaching, training others; (2) Consulting, advising, informing others; (3) Measuring, testing, quality control; (4) Operating, monitoring machines/processes; (5) Repairing, constructing; (6) Selling, buying; (7) Organizing, planning, coordinating; (8) Advertising, marketing, public relations; (9) Collecting and analyzing data, documenting; (10) Research, engineering; (11) Installing, constructing, manufacturing; and (12) Serving others, accommodating, cooking.

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