Lahdelma, Tamás

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Localized labor flow networks in knowledge-intensive industries

Tamás Lahdelma

Department of Built Environment, School of Engineering, Aalto University, Aalto, Finland

Correspondence
Tamás Lahdelma, Department of Built Environment, School of Engineering, Aalto University, FI-00076 Aalto, Finland.
Email: tamas.lahdelma@aalto.fi

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Abstract

This study examines the relationship between agglomeration and labor market matching by investigating the small-scale sociospatial determinants of a network created by the within-region mobility of employees across organizations. The local labor flow network is constructed on the basis of an establishment-level matched employer–employee database covering selected knowledge-intensive industries in the Helsinki–Uusimaa Region in Finland during the period 2001–2015. The results from the analysis of various tie formation processes reveal that the formation of a link by interorganizational employee mobility within an integrated labor market area is more likely between organizations geographically closer to each other, all else being equal. The findings highlight the importance of local density for the job search process.

KEYWORDS

agglomeration, interorganizational network, job search, labor markets, location, matching, proximity

1 | INTRODUCTION

Economic activities, particularly when intensive in the use of knowledge as an input, tend to be geographically highly concentrated. Literature on regional and urban economics identifies three sources of agglomeration economies as reasons for the observed spatial clustering: sharing, learning, and matching effects (Duranton & Puga, 2004). A key issue in the discussion of the microfoundations based on matching is how agglomeration affects the quantity of matches between firms and workers. However, previous empirical studies comparing labor turnover across regions provide ambiguous evidence on the relationship between agglomeration and the number of job matches. While some studies find the employment or population density of a region to induce mobility (Anderson & Thulin, 2013; Finney & Kohlhase, 2008), others suggest that the rate at which workers change occupation or industry is, on average, lower in more dense urban areas (Bleakly & Lin, 2012; Wheeler, 2008). The present study contributes to the literature on the link between agglomeration and labor market dynamics by examining the microlevel sociospatial determinants of employee mobility within the knowledge-intensive business sector of the Helsinki–Uusimaa Region in Finland.

A substantial body of evidence suggests that hiring employees from competing firms, business partners, or other firms can be an important method of accessing knowledge-sharing networks (Almeida & Kogut, 1999; Breschi & Lissoni, 2009; Rao & Drazin, 2002; Song et al., 2003). Ties to previous coworkers have also been found to serve as a channel for knowledge exchange between organizations (Agrawal et al., 2006; Corredoira & Rosenkopf, 2010; Somaya et al., 2008). In line with these arguments, labor mobility is shown to be an important factor explaining firms' productivity (Csáfordi et al., 2020; Eriksson & Lindgren, 2009; Maliranta et al., 2009; Stoyanov & Zubanov, 2014) and competitiveness (Herstad et al., 2019), as well as regional growth (Boschma et al., 2014; Lengyel & Eriksson, 2017). In addition, there is evidence that job mobility is a significant determinant of workers' earnings growth over the life cycle (e.g., Keith & McWilliams, 1999; Topel & Ward, 1992; Wheeler, 2006).

The importance of job switching for local economies raises questions about the mechanisms underlying labor turnover and their spatial dimensions. An established empirical regularity is that worker flows are largely confined within regions, which can be attributed to social and economic constraints associated with long-distance mobility between regions, such as sunk costs for relocation and aversion to the risk of unemployment (e.g., Eriksson et al., 2008; Yankow, 2003). For example, Anderson and Thulin (2013) estimate that about 80% of all interfirm job changes are intraregional. However, sectors, industries, and occupations tend to cluster also within regions and cities (Larsson, 2017; Rosenthal & Strange, 2020). This means that the costs of job search may vary within a labor market area, to which less attention has been paid in the research literature. The current study aims to fill that research gap by considering the regional dimension of labor mobility from the viewpoint of the significance of small-scale spatial locations for job switching probability.

The tendency of employment to cluster within areas also complicates the analysis of the local dimension of job switching patterns, as it leads to that there are several spatially correlated processes affecting the probability of mobility between organizations. Therefore, it is a matter of interest for urban and regional analysis and planning to examine whether the proximate location of firms to each other induces labor turnover when other factors influencing interfirm worker mobility and the nonrandom spatial sorting of organizations are considered. This question is investigated in the empirical section of this study using network data in which organizations are nodes and ties are created by the movement of employees across organizations within the integrated labor market area of the Helsinki–Uusimaa Region. The local network of organizations is constructed based on a longitudinal establishment-level matched employer–employee database covering selected knowledge-intensive industries. The data thus enable the detailed analysis of the sociospatial determinants of employee mobility from a novel microlevel perspective combining network analysis and statistical methods.

1.1 | Literature review

The question regarding the spatial dimension of labor mobility is strongly related to previous research on how regional characteristics, such as the size and employment or population density of agglomerations are associated with variations in labor turnover rates. This literature provides ambiguous evidence on the relationship between the internal geography and labor market dynamics of regions. Using data on the labor market activity of young urban men in the United States, Finney and Kohlhase (2008) find that even though labor turnover is higher in larger urban areas, population density increases turnover only among the more densely populated regions. On the basis of a data set for Sweden, Anderson and Thulin (2013) observe that the employment density of a region induces interfirm job switching, especially for more highly educated employees.

In contrast, Bleakly and Lin (2012) find the rate at which workers change occupation or industry is, on average, lower in more densely populated US cities. However, they observed a positive relationship between density and occupational or industrial switching among younger workers. The authors suggest that workers search for a good sector match early in their career, which is easier in more urbanized areas with a larger number of choices. Wheeler (2008) also observes that industry changes occur more often in large local markets within a sample of first job changes, but this relationship becomes negative once a worker has held several jobs.

One potential reason explaining why the aforementioned literature has produced mixed results on the regional variation of labor turnover can be the different ways in which the studies deal with endogeneity concerns present both at the individual level and at the local economy level. Self-selection issues occur at the worker level because location is a choice variable and can thus be related to individual factors that cannot be controlled for or may be determined by decisions associated with local labor market characteristics. While Finney and Kohlhase (2008) and Wheeler (2008) account for this issue by estimating separately the job mobility of those who move out of their region and those who do not, Bleakly and Lin (2012) adjust for sorting across regions by using state-of-birth population density as an instrumental variable for density of the current residence. Anderson and Thulin (2013) address selectivity concerns arising from worker heterogeneity by controlling for observable employee and firm characteristics.

At the local level, endogeneity issues can arise, for instance, from omitted regional variables that determine both local outcomes and local characteristics (Combes & Gobillon, 2015). Local economy size and density may be correlated with other regional factors, which can lead to that density and size measures capture also correlated location-specific effects that are not accounted for in the specification. The above-mentioned studies on how labor turnover varies with the size or density of regions aim to control for heterogeneity at the local level by using different combinations of observed regional control variables. However, if regional unobserved heterogeneity is not addressed, the local economy size and density indicators used can measure different effects in different research settings.

From the perspective of the present study, a central issue with respect to the comparisons of labor turnover across regions is that as the studies are based on data aggregated at the regional or metropolitan level, they do not consider the interactions between firms and the labor markets of their locations within agglomerations. Several microlevel empirical studies, however, suggest that small-scale spatial locations are important for economic activities. In their study on advertising agencies in Manhattan, Arzaghi and Henderson (2008) reveal that agglomeration benefits decay sharply as early as after a few blocks. Analyzing data for the United States, Rosenthal and Strange (2008) demonstrate that human capital externalities measured as the effect of proximity to highly educated workers on productivity and wages are considerable within 8 km, after which they attenuate quickly. Regarding labor flows, Larsson (2017) identifies stronger clustering tendencies within Sweden's metropolitan areas in occupations involving nonroutine activities than in routine occupations. Using Swedish data, Bagley (2019) also demonstrates that centrally located spinoffs within a cluster of firms from the same industry have more efficient knowledge networks than firms located away from the geographic core of the cluster.

The tendency of economic activities to concentrate strongly within regions and cities and the importance of this type of clustering for communication exchanges means that the costs associated with job search and screening procedures can vary in different parts of a labor market area. Denser city-regions may have advantages in labor matching, as they offer many potential employment matches within commuting time distance, thus making it possible to change jobs without changing residence. Another relevant aspect of labor market matching through which urban density can have an influence on mobility rates is the significance of social networks in the mediation of information about job openings and potential candidates for both recruiters and job seekers (Fernandez et al., 2000; Granovetter, 1995; Ioannides & Loury, 2004). The importance of personal networks as sources of job information means that a job search is not only an economically rational process but it is also constrained and defined by social relations. A general view is that approximately half of all vacancies are filled by those who know someone from the firm offering the job (Durlauf, 2004).

The analysis presented in this paper focuses specifically on the small-scale sociospatial dimensions of the processes conditioning worker mobility, which has received less attention in research on the links between networks, information exchanges, and labor market outcomes. In general, physical closeness is often considered as a factor fostering interaction and cooperation. Closely located firms have more face-to-face contacts and thus are seen to be able to build trust more easily, which in turn is considered to lead to more personal relationships between firms (Boschma, 2005). The growth of distance between actors weakens these positive effects and makes communication more difficult. This may be particularly true in well-networked high-end service sectors in which informal interaction plays a key role (see Arzaghi & Henderson, 2008). On the other hand, it has been argued that due to advanced information and communication technologies, networks through which knowledge sharing takes place are no longer necessarily geographically limited (Rallet & Torre, 1999).

This study combines the network-analytic approach with statistical methods to investigate matched employer–employee data, which provides an opportunity to gain insight into the link between agglomeration and labor market dynamics from a novel microlevel perspective. Network analysis is based on relational data describing not only the characteristics of a single actor but also the features of the relationships between pairs of actors. This can be essential for the study of employee mobility, as a job move takes place, by definition, between two organizations, which in turn may belong to a larger organizational network. Therefore, network data with information on the location of organizations and socioeconomic information on these organizations allow for a detailed analysis of the mechanisms underlying interfirm mobility, particularly how geographic proximity is related to within-region job switching probability while considering local heterogeneity as well as the nonrandom sorting of organizations on observable and unobservable characteristics associated with their position in the labor flow network.

1.2 | Empirical strategy

This study examines an interorganizational network in which links are generated by the mobility of employees from one organization to another in the knowledge-intensive sector[1] of the Helsinki–Uusimaa Region in Finland. The empirical analysis focuses strictly on job switches taking place within this integrated labor market area consisting of 26 municipalities. The database is constructed by combining individual-level employment data with information on the entire organizational population of the region from administrative business registers as well as with a range of demographic and socioeconomic information on the individuals employed within the organizations. The empirical analysis focuses on all private work establishments of the selected industries, subject to data availability (see Appendix A for the list of included Nomenclature des Activités Économiques dans la Communauté Européenne [NACE] industries). Data sets were merged by unique ID numbers assigned to all individuals, establishments, and firms of the registers. The database is a panel spanning from 2001 to 2015. All used registers are maintained by Statistics Finland and are generally of high quality.

In the study setting, each observation describes a pair of organizations, and the dichotomous outcome variable takes a value of 1 if an employee switches from organization i to organization j between time $t-1$ and t, and 0 if a link was not formed. An organization is defined as a firm's work establishment with a unique geographic location. To test the relationship between different tie formation processes and labor mobility, the parameters of the logistic regression models are estimated as follows:

[1]The number of establishments operating in the included industries accounted for about 29% of the total number of establishments in the region in 2015. Data from Regional statistics on entrepreneurial activity (Official Statistics of Finland [OSF], 2021b).

$$\ln\left(\frac{p_{ijt}}{1-p_{ijt}}\right) = \alpha + \beta N_{ijt-1} + \gamma H_{ijt-1} + \psi I_{ijt-s} + \eta X_{ijt-1},$$

where p_{ijt} is the probability that a link from organization i to organization j exists at time t. N_{ijt-1} is the variable measuring the geographical distance between organizations i and j at time $t-1$. H_{ijt-1} is a set of variables describing the organizational characteristics of i and j at time $t-1$. I_{ijt-s} is a set of network-related variables measured at $t-1$, $t-2$, and $t-3$ ($s = 1, 2, 3$). X_{ijt-1} is a set of dummy variables indicating the location and industry of organizations i and j as well as dummies for a year. Finally, α, β, γ, ψ, and η are the parameters to be estimated. The variables of the models are listed in Table 1. Regressions

TABLE 1 Variables used in the regression models

Main variables	
Link from workplace i to workplace j	Dichotomous variable with the value 1 if an employee switched from organization i to organization j between time $t-1$ and t, and 0 if not. Dependent variable in the models
Distance between workplaces i and j (ln)	Natural logarithm of the distance in kilometers between the employer in year $t-1$ and year t
Industry	Dummies for the industries of organizations i and j at the two-digit NACE industry level
Organizational characteristics	
Workplace employee size of i and j (ln)	Establishment size of the employer in year $t-1$ in terms of the natural logarithm of the number of employees
Difference on average age of employees in workplaces i and j	Absolute difference on average age of employees in i and j in year $t-1$
Difference in gender composition in workplaces i and j	Absolute difference in percentage of women in i and j in year $t-1$
Difference in educational composition in workplaces i and j	Absolute difference on average years of schooling in i and j in year $t-1$
Average wage in workplace j	Average wage in j (1000 EUR) in year $t-1$
Workplaces i and j are part of the same multiorganizational firm	Dummy denoting if i and j are part of the same multiorganizational firm (1) or not (0)
Difference in capital/employee (ln) in firm i and j	Absolute difference of the natural logarithm of capital relative to the total labor force of the firms i and j
Network-related	
Sociometric distance between workplaces i and j	Nine dummies denoting whether the geodesic distance between i and j was 1, 2, or 3 in year $t-1$, year $t-2$, and year $t-3$, path lengths greater than three or infinite acting as a reference category
In-degree of workplace j	The number of individuals who moved to organization j from organizations other than i between year $t-1$ and year t
Location	
Postal code area of i and j	Dummies for the postal code area of the organization
Labor market area category of the mobility event	Dummies indicating switches between or within the Capital Region and the rest of the region

Abbreviation: NACE, Nomenclature des Activités Économiques dans la Communauté Européenne.

are estimated in the Generalized Estimating Equations (GEEs) framework using the logistic population-averaged estimator with robust errors to account for the lack of independence within-organizational pairs due to the panel structure of the data. To address potential remaining heterogeneity after controlling for observable organizational characteristics, the model is also estimated using the logistic fixed-effects estimator at the organizational pair level to eliminate possible bias due to sorting among organizations along unobservable dimensions, which could in turn have implications for tie creation. In addition, a linear probability model of tie formation is estimated with separate fixed effects for both establishments forming the organizational pair.

The nature of the assembled database with relational data generates specific problems that need to be considered in an empirical setting. First, observations of network data are, by definition, nonindependent, while conventional inferential formulas are based on the assumption of independence of observations. In a network approach, an individual or organization is, in contrast, positioned among the network of social or economic relationships, and the analysis focuses specifically on the interdependencies between actors (see Abbott, 1997). Second, the rarity of job switching events and the size of the data pose some challenges for the empirical strategy, as the vast number of potential dyads makes the analysis of the database at the whole-network level computationally infeasible, while drawing a random sample of the dyads of a sparse network would not fully utilize the available information.

Hence, a so-called matched case–control approach (see Collet & Hedström, 2013; Sorenson & Stuart, 2008) is applied using the potential dyads that make up the network. The sample used for the estimation of the models described above is created so that all dyads directly linked to one another (with a value of 1 on the outcome variable) are included, forming the "cases" of the matched case–control design. Then, a control group is defined for these cases from five randomly selected organizational pairs with a value of 0 on the outcome variable. Controls are matched with the cases so that the dyads of the control group have the same industrial combination at the two-digit NACE industry level. This approach implies that all realized dyads are included and controls are selected randomly, and thus there is no risk of biased estimates due to the sampling strategy.[2] In total, 59,318 unique cases and 296,590 controls are included in the analysis.[3]

The explanatory variable of main interest is the geographic distance between job switchers' previous and current employer, measured by calculating the number of kilometers between the two establishments. Practically, this measure is defined by assigning the latitude and longitude to the employment-weighted center of each postal code area in which the establishments are located and by calculating the direct distance between the two points.[4] In the models, geographic distance is logged to account for the fact that the probability with which employees move from one workplace to another does not change linearly over geographic space.

The study region and its postal code areas are illustrated in Figure 1. With a population of 1.7 million,[5] the Helsinki–Uusimaa Region is the country's most populous area and the most important economic region in the country. The region's share of Finland's population is 31%, while it accounts for about 40% of the national gross

[2]Matched case–control data are often analyzed by matched methods (i.e., retaining the group matching of selected controls for each case), such as the conditional logistic estimator. However, this is not necessary as it has been shown that unconditional and conditional methods yield similar findings for loose-matching data when the matching between cases and controls is not unique, and one case can be matched to other controls in the data (Kuo et al., 2018; Pearce, 2016). This is also the case for this study, because an organizational pair can be matched to any other pair with the same industry combination. The unconditional approach allows, however, the use of estimators that are more compatible with the specific features of the data.

[3]In addition to serial correlation due to the longitudinal nature of the data, the statistical independence assumption can be violated in the setting by that even though the case–control design substantially reduces the number of times the same establishment enters the data, the analyzed data matrix has still organizational pairs that share a common establishment. There are also repeated occurrences when more than one employee leaves or enters the same workplace during the panel. To address these issues, clustering at the establishment level was experimented with in the GEEs framework as a robustness check. Doing so does not affect the significance levels of the coefficients of the variables of interest.

[4]The postal code of an establishment's address was the most exact location information provided by Statistics Finland at the time of the research. Employment-weighted coordinates were calculated based on data obtained from the Register of Enterprises and Establishments maintained by Statistics Finland. When both previous and current employers are located in the same postal code area, the distance between them is calculated as the mean distance of the establishments to the center of the respective postal code area, weighted by the area's number of employees in knowledge-intensive industries.

[5]Data from Population structure (OSF, 2021c).

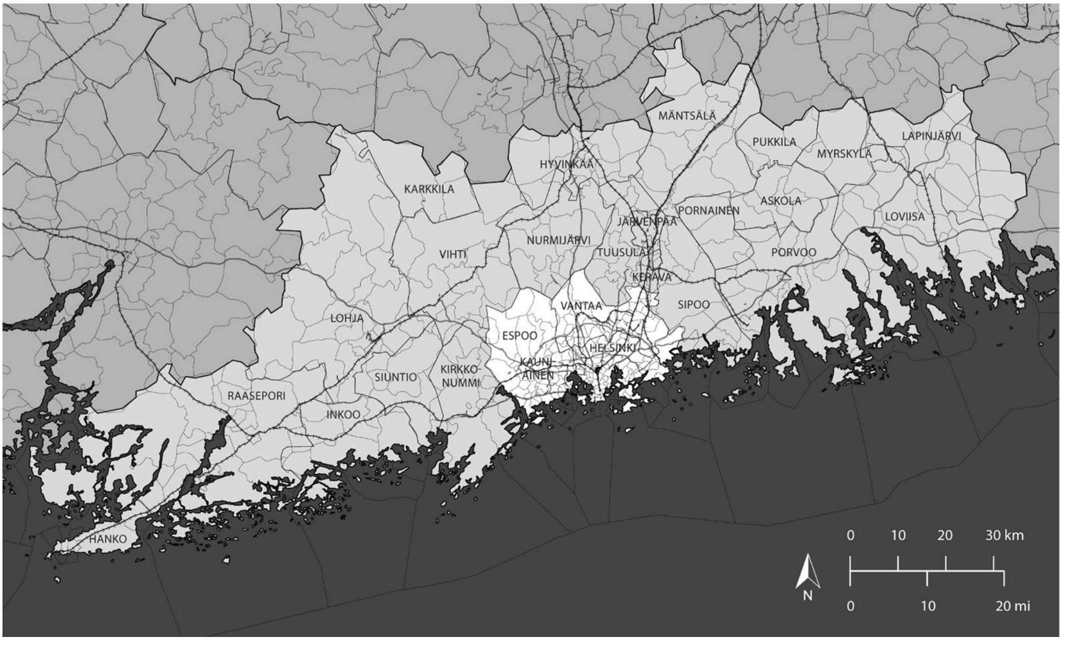

FIGURE 1 Postal code areas and municipalities of the Capital Region (in white) and the rest of the Uusimaa region (in light gray). *Note*: Geographic data from: Statistics Finland, the National Land Survey of Finland, and the Finnish Transport Infrastructure Agency.

domestic product.[6] Although the business structure of the whole region is service-oriented compared with the rest of the country, knowledge-intensive production is concentrated mainly in the major cities of Helsinki, Espoo, and Vantaa in the Capital Region. The municipalities surrounding the Capital Region are specialized in logistics and construction, while the areas on the fringe of the region are more industrial. However, a special characteristic that distinguishes the region from other urban areas of the country is that there are concentrations of knowledge-intensive business services also outside the center of the region, such as in Lohja on the west side of the region, in Porvoo on the east side of the region, and in the larger municipalities of Hyvinkää, Järvenpää, and Kerava along the main railway line north of the Capital Region.

When analyzing tie formation mechanisms, the nonrandom sorting of organizations on characteristics associated with their network position must be considered. It has been shown in the literature on organizational networks that connections tend to form at a much higher rate between actors who are similar in relation to some of their characteristics (McPherson et al., 2001). This homogeneity of networks implies that a link between organizations *i* and *j* is more likely to form if they are similar in terms of aggregate statistics summarizing employees' demographic characteristics. Homophilous tie formation mechanisms are accounted for by including variables measuring the similarity of organizational pairs regarding their gender, age, and educational composition.

In addition to demographic characteristics, proximity in organizational terms may also be important for network dynamics. It can be expected that a link from organization *i* to *j* is more likely to form if the two organizations belong to the same industry or multiorganizational firm or are similar in terms of the capital intensity of their production. This is because, in these cases, the type of work carried out in the organizations is more similar, thus facilitating the mobility of employees between them.

[6]Data from Regional account (OSF, 2021a).

Financial incentives are also likely to be important since job mobility decisions can be assumed to be influenced by prospective gains in wage earnings. The probability of a link being formed from organization *i* to organization *j* is therefore expected to be positively related to wages in *j*. The probability that an employee will move between two organizations also increases with their workplace size. This effect is controlled for by including an estimate of the establishment size in terms of the number of employees.

Dummy variables indicating the postal code areas of *i* and *j* are added to the models to control for location-specific effects, which is important in addressing endogeneity concerns at the local level. For instance, productive amenities such as transport infrastructures and universities affect potentially both local characteristics and outcomes. Labor market dynamics can vary regionally also due to the nonrandom spatial selection of firms with different productivity levels into higher- and lower-cost subregions (e.g., Puga, 2010). In addition, the tendency of knowledge-intensive industries to cluster within cities means that the industry structures and the number of potential employment matches can vary greatly among urban areas (Larsson, 2017). Such processes may also have a systematic effect on regional worker-firm match quality and thus on the incentives of employees to change jobs.

Regional dummies describing mobility events at the organizational pair level are also included in all models so that job changes can be analyzed within the type of wider labor market area in which they occurred. These dummies reflect whether the switch was within the Capital Region, from the Capital Region to the rest of the Uusimaa region, from the rest of the Uusimaa region to the Capital Region, or within the rest of the Uusimaa region. This classification has been applied because the Capital Region is clearly more integrated in terms of labor flows than other parts of the region. As can be seen in Table 2, which reports descriptive statistics for all variables included in the models, 84% of matches were within the Capital Region, 10% between the Capital Region and the rest of the region, and 5% within the rest of the region.

Furthermore, movements of employees across organizations create paths along which workers can follow each other, thus influencing job search and future mobility patterns (Fernandez et al., 2000; Granovetter, 1995; Ioannides & Loury, 2004). As a result, organizational pairs that are directly linked to one another at one point in time are more likely to form a link in the future. In addition to direct connections, short indirect links are also shown to matter for tie creation. In their study on interorganizational employee mobility, Collet and Hedström (2013) determined that movements of employees occur most frequently at sociometric distances of two and three, suggesting that even though the number of contacts expands considerably at greater distances, the circulation of relevant information becomes very limited. Other studies on information flows in networks have also shown that connections are rarely formed at path lengths of four or greater (Granovetter, 1995; Singh, 2005; Sorenson et al., 2006). Therefore, when estimating the probability of a tie being formed at a given point in time, it is important to consider that ties created by the mobility of employees across organizations are contingent on the links generated by the previous movements of other employees. Network paths are also likely to be spatially correlated due to the regional concentration of employment, and thus they need to be addressed in the analysis of the spatial dimensions of network dynamics.

To account for tie formation processes endogenous to the network (i.e., depending on existing network patterns), lagged sociometric distance variables calculated along the shortest path from *i* to *j* or from *j* to *i* at time points $t - 1$, $t - 2$, and $t - 3$ are introduced. The dummy variables indicate whether the establishments had a lagged sociometric distance of one, two, or three; path lengths greater than three or infinite[7] acting as a reference category. Another presumable network-related effect is that employees in organization *i* would be more interested in moving to organization *j* if they observed that individuals from other organizations moved to *j* (Collet & Hedström, 2013). This effect is controlled for by including a variable indicating the in-degree of organization *j* measured as the number of individuals who moved to organization *j* from organizations other than *i*.

[7]A path between two nodes is infinite, if the nodes are disconnected, that is, they do not belong to the same component and there is thus no path between them. Sociometric distance is treated as a dummy variable so that dyads which are not part of the same component at some point in time can be included in the analysis.

TABLE 2 Descriptive statistics for variables included in the models

Variable	Full sample Mean	Full sample SD	Cases Mean	Cases SD	Controls Mean	Controls SD	Mean difference Cohen's *d*
Distance between workplaces *i* and *j* [ln (km)]	2.074	1.281	1.515	1.322	2.185	1.243	0.533
Distance, capital → capital	1.581	1.042	1.260	1.162	1.656	0.997	0.385
Distance, capital → rest of the region	3.581	0.489	3.462	0.557	3.590	0.482	0.262
Distance, rest of the region → capital	3.562	0.490	3.500	0.541	3.568	0.485	0.137
Distance, rest of the region → rest of the region	3.107	1.346	1.729	1.505	3.493	1.001	1.560
Workplace employee size of *i* (ln)	2.836	1.588	3.908	1.780	2.622	1.455	−0.850
Workplace employee size of *j* (ln)	2.886	1.556	3.848	1.733	2.693	1.443	−0.772
Difference on average age of employees in workplaces *i* and *j*	7.101	5.640	5.494	4.605	7.422	5.771	0.345
Difference in gender composition in workplaces *i* and *j*	0.281	0.228	0.202	0.171	0.297	0.234	0.421
Difference in educational composition in workplaces *i* and *j*	1.934	1.562	1.288	1.138	2.063	1.603	0.505
Average wage in workplace *j* (1000 EUR)	3.479	2.491	3.765	4.820	3.422	1.668	−0.138
Workplaces *i* and *j* are part of the same multiorganizational firm	0.009	0.094	0.051	0.219	0.001	0.024	−0.543
Difference in capital/employee (ln) in firm *i* and *j*	1.362	1.254	1.218	1.176	1.391	1.267	0.137
Sociometric distance of one between workplaces *i* and *j* at $t-1$	0.029	0.168	0.160	0.366	0.003	0.052	−1.000
Sociometric distance of two between workplaces *i* and *j* at $t-1$	0.053	0.224	0.185	0.389	0.027	0.161	−0.733
Sociometric distance of three between workplaces *i* and *j* at $t-1$	0.097	0.295	0.159	0.366	0.084	0.277	−0.255
Sociometric distance of four or greater between workplaces *i* and *j* at $t-1$	0.821	0.383	0.496	0.500	0.887	0.317	1.103
Sociometric distance of one between workplaces *i* and *j* at $t-2$	0.020	0.141	0.111	0.314	0.002	0.047	−0.806
Sociometric distance of two between workplaces *i* and *j* at $t-2$	0.042	0.200	0.151	0.358	0.020	0.140	−0.674
Sociometric distance of three between workplaces *i* and *j* at $t-2$	0.075	0.263	0.137	0.344	0.062	0.242	−0.287
Sociometric distance of four or greater between workplaces *i* and *j* at $t-2$	0.863	0.344	0.601	0.490	0.916	0.278	0.974
Sociometric distance of one between workplaces *i* and *j* at $t-3$	0.016	0.126	0.087	0.282	0.002	0.044	−0.697
Sociometric distance of two between workplaces *i* and *j* at $t-3$	0.034	0.180	0.123	0.329	0.016	0.124	−0.613

(Continues)

TABLE 2 (Continued)

Variable	Full sample Mean	SD	Cases Mean	SD	Controls Mean	SD	Mean difference Cohen's *d*
Sociometric distance of three between workplaces *i* and *j* at *t* − 3	0.059	0.236	0.113	0.317	0.049	0.215	−0.274
Sociometric distance of four or greater between workplaces *i* and *j* at *t* − 3	0.891	0.312	0.677	0.468	0.934	0.249	0.867
In-degree of workplace *j*	8.180	33.514	22.100	61.956	5.396	23.101	−0.507
Capital → capital	0.743	0.437	0.843	0.364	0.723	0.447	−0.275
Capital → rest of the region	0.116	0.320	0.052	0.222	0.129	0.335	0.241
Rest of the region → capital	0.100	0.300	0.052	0.222	0.110	0.313	0.193
Rest of the region → rest of the region	0.041	0.198	0.053	0.225	0.038	0.192	−0.078
Number of observations	355,908		59,318		296,590		

Notes: Cohen's *d* indicates the standardized difference between the means of cases and controls. It is defined as the difference between the means divided by the standard deviation (SD) for the data. Effect sizes (in absolute values) can be classified as “small” ($d = 0.2$), “medium” ($d = 0.5$), and “large” ($d \geq 0.8$) (Cohen, 1988). The indicator shows that the groups differ the most in terms of establishment size and network proximity. For the other variables, the differences between the groups are mostly small or moderate.

Finally, the model is also estimated using a fixed-effects estimator at the establishment pair level to address potential remaining heterogeneity. In this specification, identification is based on changes over time in the explanatory variables within-organizational pairs that show variation in the outcome variable (pairs that have both one and zero on the dependent variable during the panel), thereby eliminating unobservable time-invariant factors associated with each pair that may have implications for tie formation. However, this leads that when there is not enough within-organizational pair variation in an explanatory variable, its effect cannot be identified even if it exists. For example, establishment pair fixed effects can be assumed to account for a large degree of variation in organizational pair characteristics that are relatively constant over time, such as organizational differences in terms of aggregate statistics summarizing employees' demographic attributes. In the case of the geographic distance variable, identification relies on changes in the spatial distance between *i* and *j* that occur in the data when at least one of the organizations relocates during the sample period.

The fact that fixed-effects estimates are based on a subset of the data also means that they can be driven by selective groups, which limits the generalizability of the estimation results. In the context of the present study, this problem is less pronounced when the model is estimated with separate fixed effects for both *i* and *j*, because the same organization enters the panel both as a case and a control more often than the same organizational pair. However, it is not possible to estimate such a specification with logistic regression due to the so-called incidental parameter problem in the case of nonlinear panel regression models with multiple high-dimensional fixed effects. Hence, an alternative linear probability model of tie formation is also estimated with fixed effects for both establishments forming the organizational pair.

A further limitation of fixed-effects estimation that should be considered is that even though it helps address bias due to time-constant unobserved heterogeneity, bias still could be present if the selection is on the basis of time-varying factors. This potential source of bias is reduced by including almost the same set of control variables in the fixed-effects estimations as in the specifications without establishment fixed effects. One of the differences between the sets of controls is that while industry dummies can be included in the models without fixed effects at the organizational pair level (thus accounting also for the interaction between the industries of *i* and *j*), this is not possible in the fixed-effects estimation, as an organization's change of industry is a relatively rare event and thus there are no observations in most industry pair groups in the subset of the data used by this model. This is the case for the postal code area dummies as well. However, establishment fixed effects account also for all time-constant location and sector effects (Combes & Gobillon, 2015).

2 | RESULTS

Each year, between 2100 and 3200 establishments were part of the network generated by the interfirm mobility of employees in the selected industries. Various statistics describing the structural properties of the network are presented in Table 3. As depicted in the table, labor market fluctuations influence the size of the network during the period considered. The bursting of the information and communication technology bubble in the early 2000s shrank the network at the beginning of the period, after which the network grew steadily during a strong macroeconomic growth period until the global financial crisis in 2008. The economic recovery after the recession and the network's growth slowed again in 2012.

From Table 3, it can be seen that the network generated by interfirm mobility is sparse and weakly connected. Each year, between 77% and 88% of organizations forming the network belonged to one giant component in which any two organizations are connected to one another by paths. However, clustering coefficients are significantly higher than could have been expected in a similar random network. Despite the low density of the network, on average, any randomly selected organization can reach any other organization in five steps.

The main results of the logistic regression models examining network tie formation are reported in Table 4, and the full regression results are presented in Table C1 in Appendix C. A correlation matrix is presented in Appendix B. The dependent variable in the logistic regression models indicates whether there was a direct link between workplaces i and j. The industrial sectors of the establishments at the two-digit NACE industry level are controlled for in all model specifications. Year dummies are also included in all specifications to eliminate bias due to any correlation between spatial location and job switching resulting from time-varying shocks. In addition, dummy variables describing the within-region geographical locations of the organizations are included to control for location-specific effects.

The results of the first estimation adjusting for industry, time, location, and observed organizational characteristics show that networks generated by job switches are highly localized. The odds ratio, that is, the exponentiated value of the logistic regression coefficient, for the variable measuring geographic distance between workplaces i and j is 0.64 ($\approx e^{-0.446}$) and is statistically highly significant. This means that a 1% increase in distance between the previous and the new employer is associated with a 0.36% decrease in the odds of forming a link between the organizations.

The first model also indicates that network dynamics are the outcome of several organizational processes. The parameter estimates of the size of organizations i and j are both positive, and the larger the differences in terms of gender composition, average age, and average years of schooling in the two organizations, the less likely a tie will be formed between them. Furthermore, the results suggest that proximity at the organizational level matters; if organizations are part of the same multiorganizational firm, it is more likely that a tie will be formed between them. The similarity in terms of capital intensity at the firm level also has a positive relationship with tie creation. The results suggest that financial incentives are also important, as the probability of a tie from i to j has a positive relationship with the pay level in j.

Model 2 includes controls for tie formation processes endogenous to the network by adding dummy variables for lagged sociometric distances between establishments that were directly linked at time t. The results indicate that short lagged sociometric distances are positively related to the probability of a link being formed. The positive coefficient of sociometric proximity decreases over time but remains highly significant until the sociometric distance of two at $t-3$. The variable measuring the number of individuals who moved to establishment j from

TABLE 3 Descriptive statistics of network structure evolution

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Number of organizations	2262	2072	2112	2292	2397	2749	2941	2672	2861	3166	3062	3122	3131	3069
Number of links	3439	2894	3258	4112	4556	5756	6078	4403	5305	6418	6024	5679	5367	5620
Number of organizations in the largest component	1799	1587	1690	1933	2058	2422	2555	2194	2348	2736	2666	2636	2596	2589
Clustering coefficient	0.052	0.051	0.058	0.068	0.070	0.074	0.066	0.059	0.063	0.068	0.065	0.059	0.048	0.056
Average shortest path	5.3	5.6	5.3	5.0	5.0	4.8	4.7	5.1	4.9	4.8	4.8	5.0	5.0	4.9

TABLE 4 Logit models of tie formation

Variable/model	(1)	(2)	(3)
Distance between workplaces *i* and *j* [ln (km)]	−0.446*** (0.0070)	−0.425*** (0.0073)	−0.443*** (0.1039)
Controls for organizational characteristics	Yes	Yes	Yes
Controls for network-related characteristics	No	Yes	Yes
Organizational pair fixed effects	No	No	Yes
Dummies for the industry combination of the *ij* pair	Yes	Yes	No
Dummies for the industries of *i* and *j*	N/A	N/A	Yes
Dummies for the postal code areas of *i* and *j*	Yes	Yes	No
Dummies for the labor market area of the *ij* pair	Yes	Yes	Yes
Dummies for year	Yes	Yes	Yes
Number of observations	355,450	355,450	4691

Notes: Regressions one and two are estimated using the logistic population-averaged estimator with cluster-robust errors at the organizational pair level. Regression three is estimated using the logistic fixed-effects estimator at the organizational pair level. Dummies for the industries of *i* and *j* are nested within the dummies for the industry combination of the *ij* pair and are thus non-applicable in regressions one and two.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

establishments other than *i* also has a highly significant positive association with tie formation, suggesting that employees tend to move to organizations that attract individuals from other organizations.

A comparison of the odds ratios of the proximity variables from Model 2 shows that geographical proximity is especially important compared with other types of proximities influencing the interorganizational network. As can be seen in Table 2, a typical variation as measured by a standard deviation is 1.28 in the geographical distance variable, 5.64 in the age difference variable, 1.56 in the educational difference variable, and 0.23 in the gender difference variable. This suggests that the tie formation odds ratio for a typical variation in geographic distance is approximately 0.58 (0.65^1.28), compared with 0.65 for a typical variation in the average level of education, 0.83 for a typical variation in age composition, and 0.75 for a typical variation in gender composition. Given the significance placed on employees' demographic characteristics as drivers of network formation (McPherson et al., 2001), the relationship between geographic proximity and tie creation appears to be substantively important.

To examine the relationship between geographic proximity and tie formation probability in different parts of the region, the adjusted marginal effects of the variable measuring geographic distance between workplaces *i* and *j* on tie formation probability in different regional labor market categories are estimated. According to the results, shorter distances increase the probability that a tie is created through employee mobility statistically significantly in all area categories. However, as shown in Figure 2, the comparison of the estimates indicates that geographical distance is of the greatest consequence for the formation of network ties when the movement of employees occurs within a subregion, that is, within the Capital Region or within the rest of the region. Even though the smaller marginal effect of geographic distance in the case of between-area switches implies that physical proximity is less significant relative to other determinants of labor mobility when the switch takes place between more remote parts of the region, geographic distance still is an important predictor of mobility events also in these labor market categories.

When comparing the magnitudes of the estimates for different regional categories, the fact that the areas of the classification differ significantly in terms of geographical scope must be considered; therefore, the average distances moved by employees as well as potential distances between establishments vary substantially depending on the type of labor market area of the organizational pairs. The average switching distance is 6 km within the

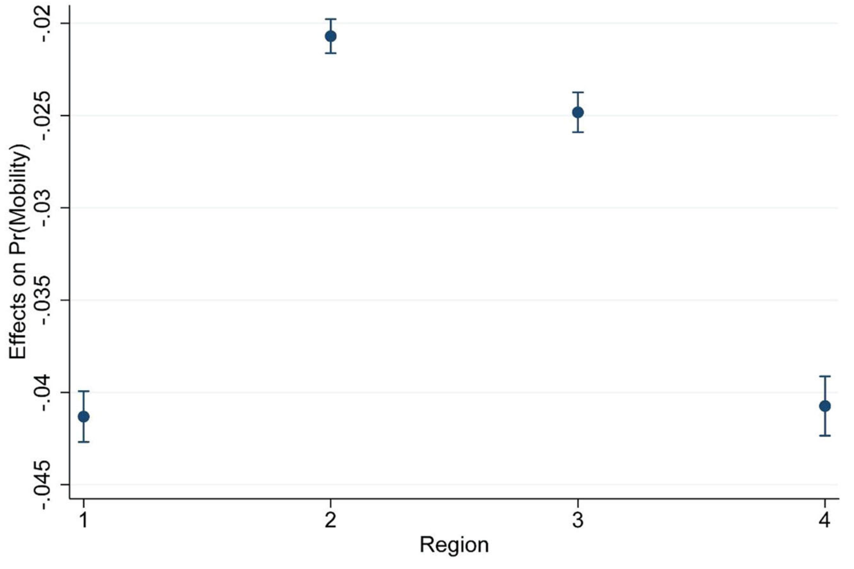

FIGURE 2 Average marginal effects of geographic distance with 95% confidence intervals in different labor market area categories. *Note*: Region 1, capital → capital; region 2, capital → rest of the region; region 3, rest of the region → capital; region 4, rest of the region → rest of the region.

Capital Region, 15 km within the rest of the region, 36 km from the Capital Region to the rest of the region, and 37 km from the rest of the region to the Capital Region. The finding that geographic distance is equally important for job switching in the rest of the region, where establishments are located on average more remotely from each than within the more urbanized Capital Region can be explained by the fact that in a densely built area, mobility events also occur between establishments located further from each other, while in geographically more expansive areas the possible distances become quite long, but economic activities are still often concentrated around the largest urban center in the area.

In Model 3 in Table 4, organizational pair fixed effects are included to address the potential remaining unobserved heterogeneity. In this specification, the source of identification of the relationship between geographic distance and job switching is the changes over time in the spatial distance between *i* and *j* that occur in the data when at least one of the organizations relocates during the sample period. That is, the identification is based on variation over time in distance within-organizational pairs, thereby eliminating unobservable time-invariant factors associated with each organizational pair that may otherwise bias the estimates. However, this also means that fixed-effects estimates can be driven by selective groups, which limits the generalizability of the estimation results.

Because in a fixed-effects model identification is solely based on within-organizational changes, the estimation only utilizes observations that enter the panel multiple times and have variation in the dependent variable. In practice, this means that the analysis is likely to be restricted to more established organizations within the sample.[8] The subset of organizational pairs with both values on the outcome variable has 4691 observations. In the fixed-effects specification, time-varying heterogeneity is accounted for by the same control variables as in the previous estimations even though in the case of most covariates, there is not enough within-organizational pair variation during the panel period so that their effects could be identified. The variables measuring lagged sociometric distances can be expected to capture to a large extent the same endogenous mechanisms as the organizational pair

[8]For example, the average number of employees in organization *j* is 185 for the subset of observations with variation in the dependent variable, while it is 72 for the rest of the sample.

fixed effects, but they are also included in the fixed-effects model to account for possible time-varying changes in patterns internal to the network.

As displayed in Table 4, the results from the fixed-effects estimation show a highly similar relationship between geographic distance and employee mobility than from the previous specifications. The estimated coefficient for the spatial distance variable is −0.44 from the fixed-effects regression, while it is −0.43 from the most comprehensive model without organizational pair fixed effects.

Because a fixed-effects logistic estimation does not allow one to take into account the dependence that occurs with multiple observations per organizational pair and correlated residuals (see Wooldridge, 2010), the model is also estimated in a linear probability framework with clustered standard errors as a robustness test.[9] In addition, the linear framework allows the model to be estimated with separate fixed effects for organizations *i* and *j*, which is a less restrictive approach with respect to the data used to obtain the parameter estimates than the organizational pair fixed-effects model, as the same establishment enters the panel more often than the same pair of establishments. Such a specification cannot be estimated with logistic regression because the incidental parameter problem has not been resolved for nonlinear panel regression models with multiple high-dimensional fixed effects. The results of the linear probability models are summarized in Table 5, and the full regression results are presented in Table C2 in Appendix C.

When comparing the results across different models, it must be acknowledged that differences between modeling techniques affect sample composition and coefficient interpretations. For example, unlike the logit specification, a linear probability model with fixed-effects estimates the average marginal effect of a covariate as a linear combination of group data regardless of whether they show variation in the outcome variable, thus shrinking the estimated coefficients when the share of homogeneous outcome groups (which all also have slope coefficients of zero by construction) is significant (Beck, 2020).[10]

As presented in Table 5, the estimated coefficient for the spatial distance variable is −0.046 from the most comprehensive linear probability model without fixed effects, while the average marginal effect from the corresponding logistic specification is −0.037. Again, the coefficient from the linear specification with separate fixed effects for *i* and *j* is −0.022, which is smaller in absolute terms than the average marginal effects from the logistic models or from the linear models without fixed effects. However, when using only within-establishment variation for the estimation, the coefficient of the geographical distance variable is still substantial and statistically highly significant, and also according to this specification it is especially important for tie formation compared with other types of proximities influencing the interorganizational network.[11] Therefore, even though the meaningful comparison of the estimates from different models is difficult, the main results from the linear probability estimations can be considered to be consistent across different specifications and with those from the logistic regression models.

[9]Despite the concern of unbounded predicted values (predicting probabilities below 0 or above 1) with linear probability models, these models can provide unbiased and consistent estimates of average effects (Wooldridge, 2010). In addition to allowing serial correlation between errors within-organizational pairs in a fixed-effects specification to be taken into account, a linear framework facilitates also experimenting with clustering errors at more aggregate levels, such as the firm level or postal code area level to check for possible spatial dependencies; the findings remain after these tests.

[10]This effect can be expected to be reasonably large in the context of the present study due to limited mobility on the labor market. To assess the magnitude of this effect, estimates should be also calculated using only the heterogeneous establishment group data. However, the dyadic structure of the data set leads to that it cannot be restricted to establishment groups with a mix of zeros and ones on the outcome variable in an unambiguous way when estimating the model with separate fixed effects for organizations *i* and *j*, because the establishments that make up an organizational pair may belong to different groups on their own. When using fixed effects at the organizational pair level, results from linear and logit estimations have been made more comparable by estimating the linear model on the subset of data used by the logistic form.

[11]The comparison of the estimates based on the typical amount of variation observed within fixed-effect units suggests that a within-establishment one standard deviation increase in geographic distance is associated with a 0.017 decrease in tie formation probability, compared with a change of 0.012 for a within-establishment standard deviation in the average level of education, a change of 0.008 for a typical within-establishment variation in gender composition, and a change of 0.004 for a typical within- establishment variation in age composition.

TABLE 5 Linear probability models of tie formation

Variable/model	(1)	(2)	(3)	(4)
Distance between workplaces *i* and *j* [ln (km)]	−0.060*** (0.0010)	−0.046*** (0.0009)	−0.022*** (0.0013)	−0.118*** (0.0264)
Controls for organizational characteristics	Yes	Yes	Yes	Yes
Controls for network-related characteristics	No	Yes	Yes	Yes
Fixed effects for *i* and *j*	No	No	Yes	No
Organizational pair fixed effects	No	No	No	Yes
Dummies for the industry combination of the *ij* pair	Yes	Yes	No	No
Dummies for the industries of *i* and *j*	N/A	N/A	Yes	Yes
Dummies for the postal code areas of *i* and *j*	Yes	Yes	No	No
Dummies for the labor market area of the *ij* pair	Yes	Yes	Yes	Yes
Dummies for year	Yes	Yes	Yes	Yes
Number of observations	355,908	355,908	354,417	4691
R^2	0.264	0.340	0.086	0.174

Notes: Regressions one and two are estimated using the ordinary least squares estimator with clustered standard errors at the organizational pair level. Regression three is estimated using separate fixed effects for organizations *i* and *j* with standard errors clustered at the level of both organizations. Regression four is estimated using the fixed-effects estimator at the organizational pair level with standard errors clustered at the same level. Dummies for the industries of *i* and *j* are nested within the dummies for the industry combination of the *ij* pair and are thus non-applicable in regressions one and two.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

3 | CONCLUSIONS

The literature on regional and urban economics identifies matching effects as one of the main sources of agglomeration economies (Combes & Gobillon, 2015; Duranton & Puga, 2004). A key issue in the discussion of the microfoundations based on matching is how agglomeration affects the quantity of matches between firms and workers. However, previous empirical studies have produced ambiguous results on how labor turnover varies with the density or size of urban regions. While some studies find labor mobility to increase with the employment or population density of a region (Anderson & Thulin, 2013; Finney & Kohlhase, 2008), others suggest the rate at which workers change occupation or industry to be lower in more dense urban areas (Bleakly & Lin, 2012; Wheeler, 2008). The differences between previous results can be attributable to the different ways in which the studies address selection issues present both at the worker level and at the local economy level.

This study contributes to the research on local labor market matching by examining the small-scale sociospatial determinants of a network created by the within-region mobility of employees across organizations in the knowledge-intensive business sector of the Helsinki–Uusimaa Region. The application of a microlevel perspective combining network-analytic and statistical methods to study employer–employee data allows for a detailed analysis of the spatial dimensions of job switching while considering local heterogeneity as well as the nonrandom sorting of organizations and their workers on characteristics related to their position in the labor flow network.

Employment in sectors, industries, and occupations, especially when intensive in the use of knowledge as an input, tend to cluster strongly even within regions and cities (Larsson, 2017; Rosenthal & Strange, 2020). This means that the costs associated with job search processes may vary within a labor market area, to which less attention has been paid in the literature on job matching. However, the clustered nature of employment also leads to that there are several spatially correlated processes making organizations interact, which complicates the question of whether proximity in itself induces interfirm labor mobility. The results of this study on the mechanisms underlying intraregional job switching indicate that, all else being equal, mobility events are more likely between establishments geographically closer to each other, which suggests the importance of local density for the job search process. This finding is robust for all the examined area categories of the region and across different model specifications. In addition, the results show that spatial proximity seems to be a particularly significant determinant of tie formation compared with other types of organizational proximities considered important in the research literature on organizational relations, implying that the relationship between geographic proximity and labor mobility is also substantively significant.

The robustness of the result indicating a positive relationship between local clustering and interorganizational mobility contrasts with previous findings suggesting that density increases turnover only among the more densely populated regions (Finney & Kohlhase, 2008) or that the relationship between density and mobility is on average negative (Bleakly & Lin, 2012; Wheeler, 2008). The authors who find job turnover rates to be lower in denser urban areas suggest this to be due to that employees engage in greater experimentation early in their working lives, which is easier in more urbanized areas with a larger number of choices. Because the increased number of potential employers produces more efficient job matches during the initial search phase, employees in larger urban areas have fewer incentives to change jobs later in their careers. On the other hand, it can be argued that to assess the link between agglomeration and labor mobility, this kind of local heterogeneity needs also to be addressed in the analysis, which is the approach applied in this study.

The results of the present study imply that spatial proximity between knowledge-intensive businesses can promote labor market matching processes in both dense urban environments as well as in areas, where the local market scale is smaller. The specificity of the study region must, however, be acknowledged when interpreting these findings. The Helsinki–Uusimaa Region is the most urbanized area in Finland with a well-developed infrastructure and is by far the strongest concentration of knowledge-intensive activities in the country. Proximate location can be particularly important in well-networked high-end service sectors in which informal interaction plays a key role (see Arzaghi & Henderson, 2008). Therefore, future research is needed on whether the results presented in this paper hold also for less urbanized concentrations specialized in other types of productions and for low-density areas located further away from larger agglomerations.

Another area of future research is whether the observed spatial dimension of job switching patterns extend to agglomerations in other countries. Central to the generalizability of the results can be the similarity of other regions compared with the Helsinki–Uusimaa Region in terms of industry composition, institutional environment, and urban structure. Presumably the most comparable regions in these terms are the large urban areas of other Nordic and Western European countries, where the educational and occupational structures of the labor force can also be assumed to be quite similar to that of the Helsinki–Uusimaa Region. The international generalizability of the results may also be enhanced by the fact that knowledge-intensive industries form an especially international part of national economies, and the requirements of these industries regarding their business environments can be expected to be quite homogeneous across larger urban areas of different countries.

The spatial characteristics of the network generated by interorganizational employee mobility found in this study imply that the physical proximity of businesses to each other can reduce the cost of changing jobs and facilitate search and screening procedures through local professional networks. The formation of ties by the movement of employees between organizations is important for the functioning of labor markets because worker mobility links networks, thus creating social cohesion among firms changing personnel. This process generates organizational ties, which can further enhance mobility. Increased job turnover is in turn essential for local economies, as labor mobility is shown to explain workers' earnings growth (Keith & McWilliams, 1999; Topel & Ward, 1992; Wheeler, 2006), firms' productivity (Csáfordi et al., 2020; Eriksson & Lindgren, 2009; Maliranta et al., 2009; Stoyanov & Zubanov, 2014) and competitiveness (Herstad et al., 2019), as well as regional growth (Boschma et al., 2014; Lengyel & Eriksson, 2017).

Empirical research has so far analyzed labor market matching from a spatial perspective at the regional or metropolitan level. However, the finding that geographic distance remains a substantively and statistically significant predictor of intraregional employee mobility after controlling for different tie formation processes implicates that location within an urban area may also be an important determinant of interactions between organizations and their local labor markets. This result is in line with previous studies demonstrating the significance of small-scale spatial locations for economic activities (Arzaghi & Henderson, 2008; Bagley, 2019; Rosenthal & Strange, 2008). Again, the evolution of the labor flow network is simultaneously explained by several other processes, such as the preference of individuals to work with similar others. Different mechanisms affecting mobility patterns can operate conjointly as well, meaning that the relevance of one form of proximity for the probability of a link being formed may depend on how similar organizations are in some other terms (Collet & Hedström, 2013). It would therefore be interesting to investigate how geographic proximity interacts with other tie formation mechanisms when influencing labor market outcomes.

A subject of future work is also to find alternative estimation methods that can be used to account for all unobserved heterogeneity potentially related to organizational characteristics and labor mobility. While location and establishment fixed effects help address bias due to time-constant heterogeneity, bias still could be present if the selection is on the basis of unobserved time-varying factors. For instance, changes in firm characteristics related to management or ownership could not be observed from the registers used in this study, although such changes may affect business relationships. However, the assumption that the sources of bias are limited to time-varying unobservables that potentially correlate with the main variable of interest as well as with the outcome variable is much weaker than the strong exogeneity assumption of standard models.

The question about the localized character of interfirm job switching can also have some implications for urban and regional planning. For instance, in the context of this study, the findings suggest that the promotion of existing business districts towards denser and more compact concentrations enabling the proximate location of businesses to each other is essential in terms of the operating conditions of knowledge-intensive production in the Helsinki–Uusimaa Region. Further intensification of concentrations can also mean the redevelopment of old structures so that the supply of office space and production facilities can adapt to changing demands of firms in attractive business areas both in dense urban centers and in smaller economic concentrations of the region. This question is directly related to the region's future growth prospects as the significance of knowledge in production processes increases.

Even though the potential to change jobs without change of residence is greater in large and dense regions, residence location can also affect labor market outcomes in different ways within urban concentrations. For example, there is evidence that social interactions among neighbors at the level of a city block can increase the propensity to work in the same location (Bayer et al., 2008). A subject of further research could therefore be how the distance between place of work and place of residence is associated with intraregional employee mobility, which could not be examined in the context of the present research. Additional extension regarding individual-specific effects would be to decompose the analysis by the stage of the individual's working career, for previous research has found heterogeneity in the relationship between density and employer transitions across different levels of experience in the labor market (Bleakly & Lin, 2012). Future research could also investigate how mixing residential and employment uses within urban concentrations is related to local job switching rates, as both uses can support neighborhood-level development activities by contributing to creating a critical mass of activity. Furthermore, the results obtained through the analysis of employer–employee data from a relational perspective raises the question of whether the found sociospatial features of labor flows influence the economic value of interfirm mobility for firms and workers.

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CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Statistics Finland. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://www.tilastokeskus.fi/tup/mikroaineistot/index_en.html with the permission of Statistics Finland.

ORCID

Tamás Lahdelma http://orcid.org/0000-0003-0001-0164

REFERENCES

Abbott, A. (1997). Of time and space: The contemporary relevance of the Chicago school. *Social Forces*, *75*(4), 1149–1182. https://doi.org/10.1093/sf/75.4.1149

Agrawal, A., Cockburn, I., & McHalle, J. (2006). Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, *6*(5), 571–591. https://doi.org/10.1093/jeg/lbl016

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917. https://doi.org/10.1287/mnsc.45.7.905

Anderson, M., & Thulin, P. (2013). Does spatial employment density spur inter-firm job-switching? *The Annals of Regional Science*, *51*(1), 245–272. https://doi.org/10.1007/s00168-012-0544-y

Arzaghi, M., & Henderson, J. V. (2008). Networking off Madison avenue. *The Review of Economic Studies*, *75*(4), 1011–1038. https://doi.org/10.1111/j.1467-937X.2008.00499.x

Bagley, M. J. O. (2019). Small worlds, inheritance networks and industrial clusters. *Industry and Innovation*, *26*(7), 741–768. https://doi.org/10.1080/13662716.2018.1539650

Bayer, P., Ross, S. L., & Topa, G. (2008). Place of work and place of residence: Informal hiring networks and labour market outcomes. *Journal of Political Economy*, *116*(6), 1150–1196. https://doi.org/10.1086/595975

Beck, N. (2020). Estimating grouped data models with a binary-dependent variable and fixed effects via a logit versus a linear probability model: The impact of dropped units. *Political Analysis*, *28*(1), 139–145. https://doi.org/10.1017/pan.2019.20

Bleakly, H., & Lin, J. (2012). Thick-market effects and churning in the labor market: Evidence from U.S. cities. *Journal of Urban Economics*, *72*(2), 87–103. https://doi.org/10.1016/j.jue.2012.04.003

Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Boschma, R. A., Eriksson, R. H., & Lindgren, U. (2014). Labour market externalities and regional growth in Sweden: The importance of labour mobility between skill-related industries. *Regional Studies*, *48*(10), 1669–1690. https://doi.org/10.1080/00343404.2013.867429

Breschi, S., & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography*, *9*(4), 439–468. https://doi.org/10.1093/jeg/lbp008

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Routledge. https://doi.org/10.4324/9780203771587

Collet, F., & Hedström, P. (2013). Old friends and new acquaintances: Tie formation mechanisms in an interorganizational network generated by employee mobility. *Social Networks*, *35*(3), 288–299. https://doi.org/10.1016/j.socnet.2013.02.005

Combes, P.-P., & Gobillon, L. (2015). The empirics of agglomeration economies. In G. Duranton, & W. Strange (Eds.), *Handbook of regional and urban economics* (Vol. 5, pp. 247–348). Elsevier. https://doi.org/10.1016/b978-0-444-59517-1.00005-2

Corredoira, R. A., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal*, *31*(2), 159–181. https://doi.org/10.1002/smj.803

Csáfordi, Z., Lőrincz, L., Lengyel, B., & Kiss, K. M. (2020). Productivity spillovers through labor flows: Productivity gap, multinational experience and industry relatedness. *The Journal of Technology Transfer*, *45*(1), 86–121. https://doi.org/10.1007/s10961-018-9670-8

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson, & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2063–2117). Elsevier. https://doi.org/10.1016/s1574-0080(04)80005-1

Durlauf, S. N. (2004). Neighborhood effects. In J. V. Henderson, & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2173–2242). Elsevier. https://doi.org/10.1016/s1574-0080(04)80007-5

Eriksson, R. H., & Lindgren, U. (2009). Localized mobility clusters: Impacts of labour market externalities on firm performance. *Journal of Economic Geography*, *9*(1), 33–53. https://doi.org/10.1093/jeg/lbn025

Eriksson, R. H., Lindgren, U., & Malmberg, G. (2008). Agglomeration mobility: Effects of localisation, urbanisation, and scale on job changes. *Environment and Planning A*, *40*(10), 2419–2434. https://doi.org/10.1068/a39312

Fernandez, R., Castilla, E., & Moore, P. (2000). Social capital at work: Networks and employment at a phone center. *American Journal of Sociology*, *105*(5), 1288–1356. https://doi.org/10.1086/210432

Finney, M. M., & Kohlhase, J. E. (2008). The effect of urbanization on labor turnover. *Journal of Regional Science*, *48*(2), 311–328. https://doi.org/10.1111/j.1467-9787.2008.00553.x

Granovetter, M. (1995). *Getting a job: A study of contacts and careers*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226518404.001.0001

Herstad, S. J., Solheim, M. C., & Engen, M. (2019). Learning through urban labour pools: Collected worker experiences and innovation in services. *Environment and Planning A*, *51*(8), 1720–1740. https://doi.org/10.1177/0308518x19865550

Ioannides, Y. M., & Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature*, *42*(4), 1056–1093. https://doi.org/10.1257/0022051043004595

Keith, K., & McWilliams, A. (1999). The returns to mobility and job search by gender. *Industrial and Labor Relations Review*, *52*(3), 460–477. https://doi.org/10.1177/001979399905200306

Kuo, C.-L., Duan, Y., & Grady, J. (2018). Unconditional or conditional logistic regression model for age-matched case–control data? *Frontiers in Public Health*, *6*(57). https://doi.org/10.3389/fpubh.2018.00057

Larsson, J. P. (2017). Non-routine activities and the within-city geography of jobs. *Urban Studies*, *54*(8), 1808–1833. https://doi.org/10.1177/0042098016643266

Lengyel, B., & Eriksson, R. H. (2017). Co-worker networks, labour mobility and productivity growth in regions. *Journal of Economic Geography*, *17*(3), 635–660. https://doi.org/10.1093/jeg/lbw027

Maliranta, M., Mohnen, P., & Rouvinen, P. (2009). Is inter-firm labor mobility a channel of knowledge spillovers? evidence from a linked employer–employee panel. *Industrial and Corporate Change*, *18*(6), 1161–1191. https://doi.org/10.1093/icc/dtp031

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Official Statistics of Finland (OSF) (2021a). *Regional account [e-publication]*. Statistics Finland. ISSN: 1799-3393.

Official Statistics of Finland (OSF) (2021b). *Regional statistics on entrepreneurial activity [e-publication]*. Statistics Finland. ISSN: 2342-6268.

Official Statistics of Finland (OSF) (2021c). *Population structure [e-publication]*. Statistics Finland. ISSN: 1797-5395.

Pearce, N. (2016). Analysis of matched case–control studies. *BMJ*, *352*, i969. https://doi.org/10.1136/bmj.i969

Puga, D. (2010). The magnitude and causes of agglomeration economies. *Journal of Regional Science*, *50*(1), 203–219. https://doi.org/10.1111/j.1467-9787.2009.00657.x

Rallet, A., & Torre, A. (1999). Is geographical proximity necessary in the innovation networks in the era of global economy? *GeoJournal*, *49*(4), 373–380. https://doi.org/10.1023/a:1007140329027

Rao, H., & Drazin, R. (2002). Overcoming resource constraints on product innovation by recruiting talent from rivals: A study of the mutual fund industry, 1986–1994. *Academy of Management Journal*, *45*(3), 491–507. https://doi.org/10.5465/3069377

Rosenthal, S. S., & Strange, W. C. (2008). The attenuation of human capital spillovers. *Journal of Urban Economics*, *64*(2), 373–389. https://doi.org/10.1016/j.jue.2008.02.006

Rosenthal, S. S., & Strange, W. C. (2020). How close is close? The spatial reach of agglomeration economies. *Journal of Economic Perspectives*, *34*(3), 27–49. https://doi.org/10.1257/jep.34.3.27

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*(5), 756–770. https://doi.org/10.1287/mnsc.1040.0349

Somaya, D., Williamson, I. O., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal*, *51*(5), 936–953. https://doi.org/10.5465/amj.2008.34789660

Song, J., Almeida, P., & Wu, G. (2003). Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science*, *49*(4), 351–365. https://doi.org/10.1287/mnsc.49.4.351.14429

Sorenson, O., Rivkin, J. W., & Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, *35*(7), 994–1017. https://doi.org/10.1016/j.respol.2006.05.002

Sorenson, O., & Stuart, T. E. (2008). Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, *53*(2), 266–294. https://doi.org/10.2189/asqu.53.2.266

Stoyanov, A., & Zubanov, N. (2014). The distribution of the gains from spillovers through worker mobility between workers and firms. *European Economic Review*, *70*, 17–35. https://doi.org/10.1016/j.euroecorev.2014.03.011

Topel, R. H., & Ward, M. P. (1992). Job mobility and the careers of young men. *The Quarterly Journal of Economics*, *107*(2), 439–479. https://doi.org/10.2307/2118478

Wheeler, C. H. (2006). Cities and the growth of wages among young workers: Evidence from the NLSY. *Journal of Urban Economics*, *60*(2), 162–184. https://doi.org/10.1016/j.jue.2006.02.004

Wheeler, C. H. (2008). Local market scale and the pattern of job changes among young men. *Regional Science and Urban Economics*, *38*(2), 101–118. https://doi.org/10.1016/j.regsciurbeco.2008.01.011

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

Yankow, J. J. (2003). Migration, job change, and wage growth: A new perspective on the pecuniary return to geographic mobility. *Journal of Regional Science*, *43*(4), 483–516. https://doi.org/10.1111/1467-9787.00308

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APPENDIX A

See Table A1

TABLE A1 List of included industries according to the NACE Rev. 2 classification

582 Software publishing
62 Computer programming, consultancy, and related activities
63 Information service activities
72 Scientific research and development
69 Legal and accounting activities
70 Activities of head offices; management consultancy activities
71 Architectural and engineering activities; technical testing and analysis
73 Advertising and market research
74 Other professional, scientific, and technical activities
78 Employment activities
82 Office administrative, office support, and other business support activities
8532 Technical and vocational secondary education
854 Higher education
8559 Other education n.e.c.
856 Educational support activities
24 Manufacture of basic metals
25 Manufacture of fabricated metal products, except machinery, and equipment
26 Manufacture of computer, electronic, and optical products
27 Manufacture of electrical equipment
28 Manufacture of machinery and equipment n.e.c.
29 Manufacture of motor vehicles, trailers, and semitrailers
30 Manufacture of other transport equipment
33 Repair and installation of machinery and equipment
43292 Installation of lifts and escalators
20 Manufacture of chemicals and chemical products
21 Manufacture of basic pharmaceutical products and pharmaceutical preparation

Abbreviation: NACE, Nomenclature des Activités Économiques dans la Communauté Européenne.

APPENDIX B

See Table B1

TABLE B1 Bivariate correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Distance between workplaces																			
2 Workplace employee size of *i*	−0.030																		
3 Workplace employee size of *j*	−0.010	0.167																	
4 Difference in age of employees	0.052	−0.127	−0.127																
5 Difference in gender composition	0.027	−0.147	−0.148	0.104															
6 Difference in years of schooling	0.083	−0.145	−0.136	0.117	0.116														
7 Average wage in workplace *j*	−0.050	0.020	0.096	−0.050	−0.056	0.036													
8 Part of the same firm	−0.027	0.051	0.063	−0.049	−0.046	−0.046	0.007												
9 Difference in capital/employee	0.053	0.024	0.029	0.111	0.057	0.163	0.083	−0.103											
10 Sociometric distance of one at $t-1$	−0.121	0.195	0.193	−0.083	−0.092	−0.103	0.017	0.237	−0.045										
11 Sociometric distance of two at $t-1$	−0.087	0.261	0.256	−0.075	−0.082	−0.106	0.016	0.030	−0.012	−0.041									

(Continues)

TABLE B1 (Continued)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
12 Sociometric distance of three at $t-1$	−0.047	0.208	0.209	−0.053	−0.056	−0.069	0.026	−0.020	0.021	−0.056	−0.077								
13 Sociometric distance of one at $t-2$	−0.109	0.177	0.176	−0.073	−0.079	−0.088	0.020	0.226	−0.038	0.427	0.121	−0.003							
14 Sociometric distance of two at $t-2$	−0.081	0.244	0.241	−0.072	−0.078	−0.095	0.028	0.026	−0.007	0.161	0.325	0.113	−0.030						
15 Sociometric distance of three at $t-2$	−0.044	0.202	0.205	−0.052	−0.056	−0.063	0.035	−0.017	0.018	0.015	0.144	0.238	−0.041	−0.059					
16 Sociometric distance of one at $t-3$	−0.099	0.161	0.166	−0.066	−0.072	−0.077	0.022	0.221	−0.032	0.380	0.110	−0.002	0.450	0.132	0.008				
17 Sociometric distance of two at $t-3$	−0.075	0.223	0.222	−0.067	−0.073	−0.085	0.037	0.024	−0.0003	0.150	0.274	0.101	0.152	0.331	0.138	−0.024			
18 Sociometric distance of three at $t-3$	−0.045	0.188	0.188	−0.054	−0.055	−0.060	0.041	−0.015	0.016	0.026	0.135	0.190	0.019	0.155	0.249	−0.032	−0.047		
19 In-degree of workplace j	−0.031	0.088	0.382	−0.042	−0.055	−0.047	0.071	0.052	0.049	0.121	0.151	0.062	0.113	0.141	0.062	0.105	0.128	0.061	

Note: $N = 355{,}908$.

APPENDIX C

See Tables C1 and C2

TABLE C1 Logit models of tie formation

Variable/model	(1)	(2)	(3)
Distance between workplaces *i* and *j* [ln (km)]	−0.446***	−0.425***	−0.443***
	(0.0070)	(0.0073)	(0.1039)
Workplace employee size of *i* (ln)	0.513***	0.397***	0.648***
	(0.0045)	(0.0050)	(0.0836)
Workplace employee size of *j* (ln)	0.495***	0.323***	0.226**
	(0.0049)	(0.0057)	(0.0863)
Absolute difference on average age of employees in workplaces *i* and *j*	−0.036***	−0.032***	0.016
	(0.0012)	(0.0012)	(0.0153)
Absolute difference in percentage of women in workplaces *i* and *j*	−1.332***	−1.251***	−0.668
	(0.0303)	(0.0308)	(0.3923)
Absolute difference on average years of schooling in workplaces *i* and *j*	−0.299***	−0.277***	0.021
	(0.0048)	(0.0049)	(0.0709)
Average wage in workplace *j* (1000 EUR)	0.029***	0.033***	−0.057
	(0.0046)	(0.0046)	(0.0629)
Workplaces *i* and *j* are part of the same multiorganizational firm	5.163***	4.777***	3.860**
	(0.1134)	(0.1200)	(1.328)
Absolute difference in capital/employee (ln) in firm *i* and *j*	−0.049***	−0.060***	−0.135
	(0.0053)	(0.0056)	(0.0722)
In-degree of workplace *j*		0.005***	0.002*
		(0.0002)	(0.001)
Sociometric distance of one between workplaces *i* and *j* at $t-1$		2.358***	−1.215***
		(0.0391)	(0.1209)
Sociometric distance of two between workplaces *i* and *j* at $t-1$		1.036***	0.242*
		(0.0227)	(0.107)
Sociometric distance of three between workplaces *i* and *j* at $t-1$		0.378***	0.221*
		(0.0171)	(0.109)
Sociometric distance of one between workplaces *i* and *j* at $t-2$		1.382***	−1.114***
		(0.0512)	(0.1283)
Sociometric distance of two between workplaces *i* and *j* at $t-2$		0.484***	0.333**
		(0.0259)	(0.1114)

(Continues)

TABLE C1 (Continued)

Variable/model	(1)	(2)	(3)
Sociometric distance of three between workplaces i and j at $t - 2$		0.122***	0.235*
		(0.0190)	(0.1086)
Sociometric distance of one between workplaces i and j at $t - 3$		0.968***	−1.410***
		(0.0590)	(0.1428)
Sociometric distance of two between workplaces i and j at $t - 3$		0.299***	0.113
		(0.0280)	(0.1149)
Sociometric distance of three between workplaces i and j at $t - 3$		−0.033**	0.283*
		(0.0206)	(0.1146)
Constant	−4.503***	−4.105***	
	(0.104)	(0.114)	
Organizational pair fixed effects	No	No	Yes
Dummies for the industry combination of the ij pair	Yes	Yes	No
Dummies for the industries of i and j	N/A	N/A	Yes
Dummies for the postal code areas of i and j	Yes	Yes	No
Dummies for the labor market area of the ij pair	Yes	Yes	Yes
Dummies for year	Yes	Yes	Yes
Number of observations	355,450	355,450	4691

Notes: Regressions one and two are estimated using the logistic population-averaged estimator with cluster-robust errors at the organizational pair level. Regression three is estimated using the logistic fixed-effects estimator at the organizational pair level. Dummies for the industries of i and j are nested within the dummies for the industry combination of the ij pair and are thus non-applicable in regressions one and two.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

TABLE C2 Linear probability models of tie formation

Variable/model	(1)	(2)	(3)	(4)
Distance between workplaces *i* and *j* [ln (km)]	−0.060***	−0.046***	−0.022***	−0.118***
	(0.0010)	(0.0009)	(0.0013)	(0.0264)
Workplace employee size of *i* (ln)	0.061***	0.035***	0.016***	0.182***
	(0.0005)	(0.0005)	(0.0012)	(0.0242)
Workplace employee size of *j* (ln)	0.061***	0.029***	−0.003	0.069*
	(0.0005)	(0.0005)	(0.0017)	(0.0274)
Absolute difference on average age of employees in workplaces *i* and *j*	−0.003***	−0.001***	−0.001***	0.003
	(0.0001)	(0.0001)	(0.0001)	(0.0050)
Absolute difference in percentage of women in workplaces *i* and *j*	−0.113***	−0.093***	−0.041***	−0.210
	(0.0024)	(0.0021)	(0.0027)	(0.1161)
Absolute difference on average years of schooling in workplaces *i* and *j*	−0.022***	−0.018***	−0.009***	−0.004
	(0.0004)	(0.0003)	(0.0005)	(0.0225)
Average wage in workplace *j* (1000 EUR)	0.002*	0.002*	0.0004*	−0.017
	(0.0008)	(0.0008)	(0.0002)	(0.0209)
Workplaces *i* and *j* are part of the same multiorganizational firm	0.614***	0.374***	0.257***	0.777**
	(0.0077)	(0.0100)	(0.0180)	(0.2881)
Absolute difference in capital/employee (ln) in firm *i* and *j*	−0.004***	−0.004***	−0.001	−0.042
	(0.0005)	(0.0004)	(0.0007)	(0.0227)
In-degree of workplace *j*		0.001***	0.0002*	0.001*
		(0.00002)	(0.00009)	(0.0003)
Sociometric distance of one between workplaces *i* and *j* at $t-1$		0.423***	0.186***	−0.323***
		(0.0045)	(0.0094)	(0.0352)
Sociometric distance of two between workplaces *i* and *j* at $t-1$		0.236***	0.089***	0.064
		(0.0039)	(0.0049)	(0.0342)
Sociometric distance of three between workplaces *i* and *j* at $t-1$		0.062***	0.020***	0.073*
		(0.0024)	(0.0026)	(0.0343)
Sociometric distance of one between workplaces *i* and *j* at $t-2$		0.200***	0.100***	−0.286***
		(0.0059)	(0.0089)	(0.0368)
Sociometric distance of two between workplaces *i* and *j* at $t-2$		0.121***	0.051***	0.081*
		(0.0043)	(0.0049)	(0.0332)
Sociometric distance of three between workplaces *i* and *j* at $t-2$		0.027***	0.013***	0.070*
		(0.0027)	(0.0028)	(0.0345)
Sociometric distance of one between workplaces *i* and *j* at $t-3$		0.104***	0.067***	−0.355***
		(0.0064)	(0.010)	(0.0368)

(Continues)

TABLE C2 (Continued)

Variable/model	(1)	(2)	(3)	(4)
Sociometric distance of two between workplaces *i* and *j* at *t* − 3		0.082***	0.041***	0.023
		(0.0045)	(0.0061)	(0.0355)
Sociometric distance of three between workplaces *i* and *j* at *t* − 3		0.006	0.008**	0.081*
		(0.0030)	(0.0026)	(0.0365)
Constant	−0.159***	−0.063***		−0.793
	(0.0101)	(0.0087)		(0.9361)
Fixed effects for *i* and *j*	No	No	Yes	No
Organizational pair fixed effects	No	No	No	Yes
Dummies for the industry combination of the *ij* pair	Yes	Yes	No	No
Dummies for the industries of *i* and *j*	N/A	N/A	Yes	Yes
Dummies for the postal code areas of *i* and *j*	Yes	Yes	No	No
Dummies for the labor market area of the *ij* pair	Yes	Yes	Yes	Yes
Dummies for year	Yes	Yes	Yes	Yes
Number of observations	355,908	355,908	354,417	4691
R^2	0.264	0.340	0.086	0.174

Notes: Regressions one and two are estimated using the ordinary least squares estimator with clustered standard errors at the organizational pair level. Regression three is estimated using separate fixed effects for organizations *i* and *j* with standard errors clustered at the level of both organizations. Regression four is estimated using the fixed-effects estimator at the organizational pair level with standard errors clustered at the same level. Dummies for the industries of *i* and *j* are nested within the dummies for the industry combination of the *ij* pair and are thus non-applicable in regressions one and two.

**p* < 0.05; ***p* < 0.01; ****p* < 0.001.