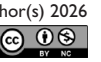
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Social network benefits for cluster firms: A co-worker mobility approach

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Abstract

Regional clusters facilitate social interaction and learning across firms. Here, we assess how social networks of firms influence their competitiveness in relation to cluster- and firm-characteristics. Using survey and administrative data, we simulate co-worker networks that, following the mobility of employees, generate links across companies. Analyzing Sweden's ICT firms over 20 years, we find that inter-firm co-worker ties, even across companies not directly linked by mobility, predict firm performance. We document that small firms benefit more from inter-regional links and from having access to diverse networks, while local links assist firms to accumulate local knowledge in growing regional clusters.

Keywords

co-worker networks, labor mobility, link prediction, administrative data, network simulation, firm growth, regional clusters

Introduction

Regional clusters are known to enhance firms' competitiveness by facilitating inter-firm learning and knowledge exchange (Duranton and Puga, 2004; Marshall, 1920). Since communication depends on social relationships more than mere proximity, many studies emphasize how social networks within

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clusters shape inter-firm learning (Owen-Smith and Powell, 2004; Saxenian, 1991). In particular, labor mobility has been identified as a central mechanism linking firms through the transfer of embodied knowledge and by generating lasting social connections (Almeida and Kogut, 1999; Boschma et al., 2009; Breschi and Lissoni, 2009; Maliranta et al., 2009; Song et al., 2003). Such relationships sustain information flows that enhance innovation, regional growth, and firm performance (Agrawal et al., 2006; Casper, 2007; Kemeny et al., 2016).

Despite this rich literature, the firm-level effects of co-worker networks remain poorly understood. Two challenges stand out. First, while previous studies often focus on inventors or managers (Kemeny et al., 2016; Tóth and Lengyel, 2021), networks that facilitate learning may also involve other employees whose ties persist beyond job mobility. Yet, identifying which co-worker relations matter after mobility is not straightforward. Second, since such ties originate from mobility events, distinguishing the independent contribution of co-worker connections from the direct effects of hiring remains difficult. Recent advances propose that probabilistic co-worker networks can be simulated by modeling tie formation based on employee similarity and shared experience (Lengyel and Eriksson, 2017). However, existing work has focused on aggregate regional outcomes, leaving open the question of which types of firms benefit from which kinds of networks (Glückler et al., 2023).

This paper addresses that gap by examining how inter-firm co-worker networks influence firm performance within Sweden's ICT industry. Using a mixed data approach, we first map information-sharing networks among employees in a regional ICT cluster through surveys and LinkedIn data. These insights inform a link prediction model that we apply to administrative data to simulate national co-worker networks spanning all ICT firms in Sweden over a 20-year period. The resulting dynamic networks capture both direct links (those created by actual labor mobility) and indirect links (ties between firms whose employees share prior workplaces but have not exchanged workers themselves).

We then test how these firm-level co-worker network structures relate to firm performance, measured by average wages, using fixed-effect panel regressions. Our findings show that not only direct, mobility-induced connections but also indirect co-worker ties positively affect firm performance. Furthermore, small firms gain relatively more from diverse and non-local networks, while local ties matter most in expanding clusters where local knowledge accumulation is strong. The findings remain robust across firms categorized by age, plant structure, across changing network simulation parameters and randomization, and testing in a variety of regression specifications. These results suggest that co-worker networks form a distinct, often overlooked, channel of inter-firm learning in clusters – one that extends beyond direct mobility and is shaped by both the structure and geography of social connections.

Literature and hypotheses

Research on regional clusters has long emphasized that the spatial concentration of related firms enhances competitiveness through localized learning and knowledge spillovers (Boschma, 2005; Delgado et al., 2010; Marshall, 1920; Maskell and Malmberg, 1999; Porter, 1990). Clusters facilitate interaction among firms, institutions, and individuals, allowing them to share tacit knowledge that is difficult to codify or transfer across distance. However, proximity alone does not automatically generate learning (Bathelt et al., 2004; Breschi and Lissoni, 2001). Instead, inter-firm learning depends on social and cognitive proximity among actors who can understand, interpret, and apply each other's knowledge (Boschma, 2005; Dahl and Pedersen, 2004; Giuliani, 2007; Glückler, 2007; Juhász and Lengyel, 2018).

The concept of "local buzz" captures how repeated face-to-face interactions and shared norms foster trust and informal exchange of information in clusters (Bathelt et al., 2004; Storper and Venables, 2004). Yet, this literature increasingly recognizes that local buzz is complemented

by networks of pipelines connecting firms and individuals beyond the region. These external ties introduce novel knowledge that fuels innovation (Morrison, 2008; Owen-Smith and Powell, 2004). Consequently, cluster learning should be viewed as an interplay between spatial proximity and social connectivity: co-location enables interaction, but social networks determine which relationships generate learning benefits (Glückler et al., 2023).

Co-worker mobility as a channel of knowledge transfer

Labor mobility has been identified as one of the most powerful channels linking firms within regional clusters (Almeida and Kogut, 1999; Breschi and Lissoni, 2009; Eriksson and Lindgren, 2009). When employees move between firms, they not only transfer individual knowledge but also create bridges through which ideas, routines, and reputational information circulate. Thus, mobility facilitates both direct knowledge transfer – through the hiring of skilled workers – and indirect transfer, as former co-workers maintain professional relationships that continue to transmit information (Agrawal et al., 2006; Casper, 2007; Corredoira and Rosenkopf, 2010).

These interpersonal links can form a lasting "social infrastructure" for inter-firm learning (Boschma and Frenken, 2010). Even if direct labor flows are limited, firms may still be connected through overlapping employment histories among their staff, creating what can be conceptualized as co-worker networks (Glückler et al., 2023; Lengyel and Eriksson, 2017). Such networks capture the broader social context of mobility and extend its learning effects far beyond the immediate job move.

Despite these insights, quantifying the contribution of co-worker networks to firm performance remains difficult. Existing studies often focus narrowly on inventors or managers (Kemeny et al., 2016; Tóth and Lengyel, 2021), overlooking the larger employee population that also facilitates knowledge diffusion. Moreover, most analyses conflate the direct impact of hiring with the indirect effects of the social ties mobility generates. Recent methodological advances have begun to disentangle these mechanisms by simulating probabilistic co-worker networks based on shared employment histories (Eriksson and Lengyel, 2019). This approach allows researchers to infer which firms are likely to be socially connected through their workforce and to assess how these inferred networks contribute to firm outcomes.

Since inter-firm co-worker networks are generated by job mobility, it is nevertheless important to further disentangle the role of co-worker ties from the direct knowledge transfer via labor mobility. For example, Lengyel and Eriksson (2017) decomposed inter-firm co-worker ties into a segment in which the firms are linked through labor mobility, and to another one, in which firms have never been directly linked via labor mobility before.

Hypothesis 1: Co-worker networks between firms enhance firm performance, even if only indirectly linked by labor mobility.

Network access for small and new firms

Social network theory provides a key conceptual foundation for understanding how inter-firm connections shape performance. Two dimensions are particularly relevant: the strength and the structure of network ties. Strong, cohesive relationships promote trust, reciprocity, and the transfer of complex or tacit knowledge (Coleman, 1988; Uzzi, 1997). At the same time, diverse networks that bridge otherwise disconnected actors expose firms to non-redundant information and new opportunities (Burt, 1992, 2004; Granovetter, 1973). Balancing these forms of embeddedness – closure and openness – enables firms to exploit existing knowledge efficiently while exploring new ideas (Fleming et al, 2007; Ter Wal et al., 2016).

Within clusters, firms may benefit from both cohesive and open networks. Cohesive local ties foster reliability and coordination, while open networks spanning structural holes provide access to diverse knowledge and novel insights. These properties shape how co-worker connections translate into firm performance: firms with many co-worker links gain from broader access to expertise, whereas firms embedded in diverse networks benefit from cross-fertilization and innovation.

Yet, network advantages vary by firm type. For small firms, diversity is particularly valuable as it provides exposure to new ideas crucial for growth (Brüderl and Preisendörfer, 1998; McEvily and Zaheer, 1999). Research shows that while cohesive networks support early development (Hite and Hesterly, 2001), open, boundary-spanning networks better sustain long-term learning and innovation (Macpherson and Holt, 2007; Tortoriello and Krackhardt, 2010; Vissa and Chacar, 2009). Because smaller firms in clustered industries often have limited access to the full spectrum of local knowledge (Danley and Eriksson, 2022; Funk, 2014), diverse interpersonal linkages – such as those formed through co-worker mobility – are especially important for their performance and growth. Therefore, we hypothesize that:

Hypothesis 2: Diverse rather than cohesive co-worker networks enhance firm performance, but a diversity of links is mainly beneficial for firms that are small and new.

Geography of co-worker networks

The spatial dimension of networks adds another layer of complexity to how knowledge circulates within and beyond clusters. Local co-worker ties typically foster trust and enable the transfer of context-specific, tacit knowledge embedded in shared routines and cultural understanding (Bathelt et al., 2004; Storper and Venables, 2004). Conversely, distant ties connect firms to different institutional and technological environments, providing access to new ideas and complementary resources (Grillitsch and Nilsson, 2015; Trippl et al., 2018).

While inter-regional ties may be valuable for firms in peripheral or mature clusters, not all firms are equally able to benefit from them. Small and young firms typically possess fewer internal resources, narrower knowledge bases, and more limited local networks than large established firms (Hite and Hesterly, 2001; McEvily and Zaheer, 1999). Consequently, they rely more heavily on external sources of information and opportunities. Inter-regional co-worker networks can provide access to non-redundant knowledge, market information, and complementary capabilities that are not available locally. In contrast, larger firms often possess broader internal knowledge resources and are therefore less dependent on distant network connections. We therefore expect the benefits of inter-regional co-worker ties to be particularly pronounced among small and young firms.

Hypothesis 3: Inter-regional co-worker networks enhance firm performance and are particularly beneficial for small and new firms.

The balance between local and non-local connections depends on the developmental stage of a cluster. In rapidly expanding regions, where related industries and knowledge bases accumulate, dense local networks enhance the diffusion of specialized expertise (Eriksson and Lengyel, 2019; Menzel and Fornahl, 2010; Morrison et al., 2013). In contrast, in mature or peripheral clusters, where local learning opportunities are limited, distant co-worker links can substitute for missing local spillovers and help firms access external sources of innovation (Boschma and Iammarino, 2009; Grillitsch and Nilsson, 2015; Ter Wal and Boschma, 2011). Thus, we expect that:

Hypothesis 4: Local co-worker networks enhance access to local knowledge and particularly benefit firms in large industry clusters.

Data and methods

Unlike in seminal contributions that investigate mobility of inventors and their enduring connections (Breschi and Lissoni, 2009), it is not clear which co-worker relations should be considered after the mobility of employees. The problem is that co-worker relations are not as likely in large companies due to the internal division of labor, but an economic geography approach cannot omit these big firms, as it is frequently done in labor economics (Hensvik and Skans, 2016). In a recent framework, Lengyel and Eriksson (2017) have proposed that probabilistic co-worker networks can be generated by assuming that similar co-workers are more likely to establish connections in firms. This approach can generate meaningful co-worker ties following labor mobility (Eriksson and Lengyel, 2019). However, relational data collection on the co-worker tie level is an important missing element that can improve the generation of co-worker networks, if one focuses on firm-level outcomes. In the following, we go through the process that includes prediction of information networks from relational data, generating co-worker networks from matched employer-employee data and labor mobility events, and finally, a regression analysis that uses network variables on the firm level.

Data sources

Our analysis builds on two data sources, a survey and an administrative data collection. First, we exploit a survey that we ran among 214 employees of 16 ICT firms in the Swedish city of Umeå. This survey collected network data within companies asking respondents to pick from a list of those co-workers, from whom they obtained essential work-related information, have recently collaborated with, or socialized with. For that aim, we asked HR departments of participant companies to provide us with the list of their employees. The survey collected further individual data on education, gender, and age. At the end of the questionnaire, we asked respondents to friend the account of the research group on LinkedIn and asked their informed consent to use their LinkedIn profile data in the research. According to GDPR, this enabled us to collect supplementary information that respondents document on LinkedIn. This information made it possible to calculate the number of years that each pair of subjects worked at the same workplace.[1] By means of information on joint tenure and individual characteristics, parameters for predicting probabilities of co-worker links were obtained.

Next, the parameters gained from the sample were applied for network simulation on the administrative data. This source of administrative data comes from several Swedish registers. The database includes longitudinal records for every person in Sweden and contains information on employer, firm location, firm industrial classification, income, educational degree, field of education, date of birth, and gender, among others. The data covers the period 2001–2016 and enables us to replicate the network data format of the survey information. Our analysis uses data from firms in the following industries of the ICT sector (NACE Rev. 2 in parentheses): Manufacture of computers and peripheral equipment (26200); Computer consultancy activities (62020); Publishing of computer games (58210); Other software publishing (58290); Computer programming activities (62010); Computer consultancy activities (62020); Other information technology and computer service activities (62090); Computer facilities management activities (62030); Data processing, hosting and related activities (63110); Web portals (63120), Research and experimental development on biotechnology (72110), Other research and experimental development on natural sciences and engineering (72190). Over the period we have 60,566 unique firms in the sample ending with 18,084 firms and 134,910 workers in 2016.

Co-worker network generation

The inter-firm co-worker network was generated in three steps from the survey and administrative data sources as illustrated in Figure 1. First, using data from the survey (and LinkedIn), we estimated

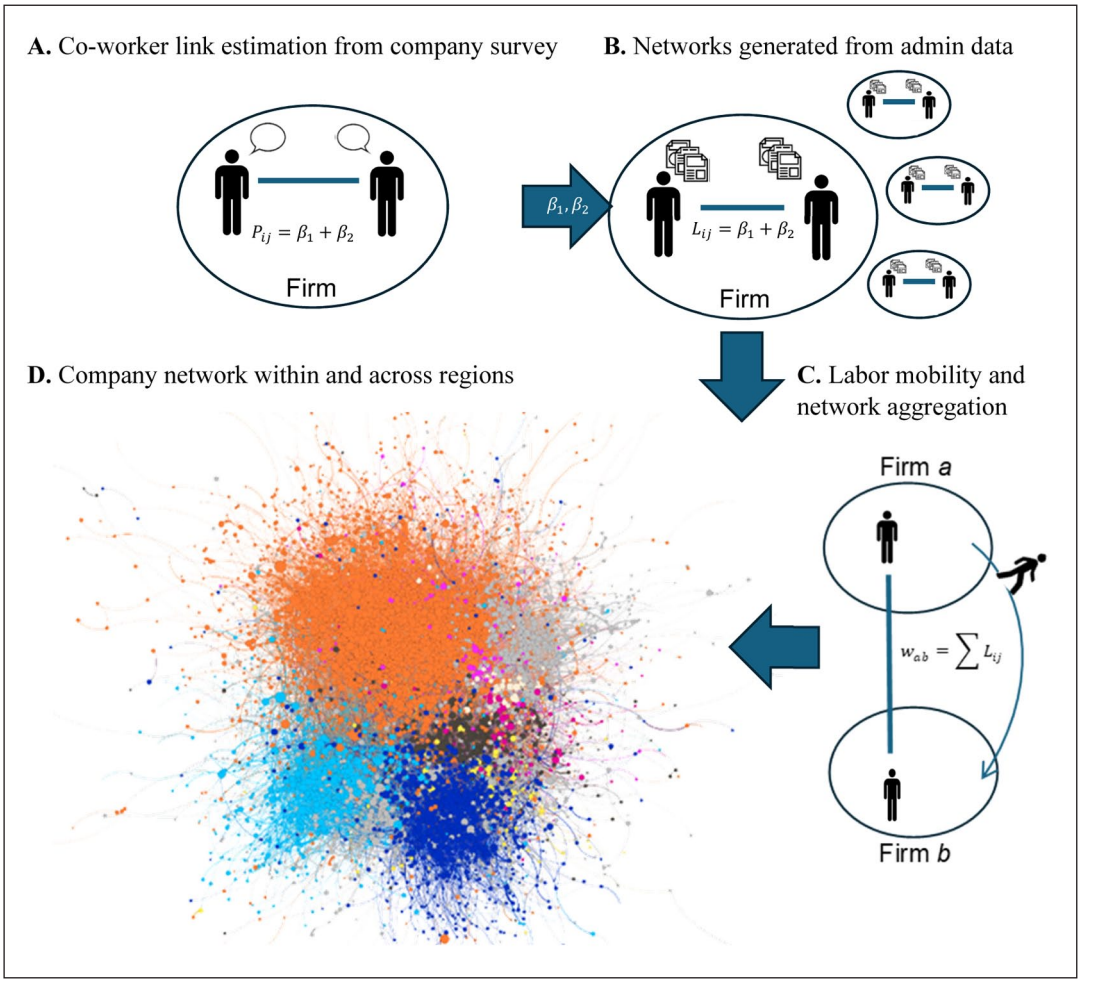


Figure 1. Process of co-worker network generation. (a) Estimation of co-worker ties using survey data is the first step. (b) Generating co-worker ties within firms, using parameters from (a). (c) Following co-worker ties after mobility. (d) This process generates a dynamic and complex network.
Node colors depict regions.

the probability that two employees are linked by an advice link that represents directed information flow ($P_{ij} \neq P_{ji}$), using the formula:

$$P_{ij} = \gamma_0 + \gamma_1(Z_{i\epsilon f}, Z_{j\epsilon f}) + C_{ij} + S_f + \varsigma_f + \varepsilon_{ijf} \quad (1)$$

where i and j are employees at firm f, Z refers to their characteristics regarding age, gender, and education, C_{ij} is the number of years that employees i and j have worked together previously, S_f is the number of employees at firm f, ς_f is the random intercept of firm f assumed to be normally distributed, and ε_{ijf} is the error term. The equation is estimated by a logistic regression. We have chosen the random intercept model instead of the fixed effects model because it allows for firm specificities in the variation but does not require firm-specific parameters, which are not possible to replicate in the network simulation. The survey questions to map the advice, social and cooperation networks within companies are presented in Supplemental Appendix 1, together with a description of further information collected.

We have estimated the likelihood of co-worker links in all three layers we mapped in the survey: advice-, collaboration-, and friendship networks (Figure 1(a)) and also a multilayer network that contains links from all three network layers. We found that homophily in terms of gender, level of education, and age strongly influences tie creation in all layers that have been frequently reported previously (McPherson et al., 2001). Longer mutual time spent within the same workplace increases the probability of information flows, while firm size has a negative impact on establishment of ties. Tie probability estimations are summarized in Supplemental Table A1.

Next, we extrapolate the predictions from the survey to all ICT firms in Sweden using administrative employer–employee data. The logic of this step is generative rather than representative: we do not assume that the network structure observed in the 16 surveyed firms in Umeå is itself representative of the Swedish ICT sector, but rather that the behavioral mechanisms generating ties, mainly homophily, are general and can be re-applied to the composition and size of every other firm. This is the principle underlying methods that reconstruct complete networks from sampled, egocentric relational data: because the social processes that produce ties are largely local, networks of different size and composition can be simulated from locally estimated tie-formation parameters (Krivitsky and Morris, 2017; Krivitsky et al., 2011; Smith, 2012). Our procedure therefore combines the tie-formation parameters estimated on the survey (Supplemental Table A1), which confirm previous studies, with the actual demographic composition and size of each firm in the administrative data. Homophily in age, gender, and education is among the most robust regularities documented across organizational settings (Lee et al., 2019; McPherson et al., 2001); because its strength is known to vary with group size and composition (Currarini et al., 2009), we explicitly let these dimensions, together with firm size, condition advice-seeking.

This procedure rests on two assumptions. The first, set out above, is that the determinants of tie formation reflect general mechanisms of workplace network formation rather than firm-specific idiosyncrasies. The second is that homophily is persistent over time: although the role of similarity in within-firm information networks can shift as firms evolve, homophily is typically found to be stable (e.g. Mollica et al., 2003). More recent approaches emphasize the dynamic nature of group formation in organizations (Kossinets and Watts, 2009), which we return to as an avenue for future research. Generating national co-worker networks from survey-based relational data nonetheless entails limitations regarding external validity and organizational heterogeneity, which we discuss in the concluding section.

We start the network simulation by using equation (1) to assign tie probabilities to all employee-employee dyads within each firm based on the observed characteristics of the dyad and of the firm (Figure 1(b)). We then draw a random number from a uniform distribution with range between 0 and 1, establishing a tie when the result from the random draw is smaller than the estimated probability for the dyad (see equation (A1) in Supplemental Appendix 1 for the formula). For the sake of simplicity, we assume now that ties do not dissolve once formed and trace them over the subsequent years until *i* or *j* reached the age of 65 (see Lengyel and Eriksson, 2017), but we will test networks with time decaying edge-weighting and the termination of old ties as well (similar to Eriksson and Lengyel, 2019). The network density of simulated networks for all companies in the administrative data and that of the observed networks in the survey data all fall within the same range (Figure A1, Supplemental Appendix 1), showing that our procedure generates realistic networks.

Ties are kept fixed even if one or both co-workers in the dyad left the workplace (Figure 1(c)). Such inter-firm mobility enables us to generate a dynamic network of firms in which two firms are connected if there is a past network connection between any of their workers (Figure 1(d)). The weight of a tie between two firms equals the number of such connections between their workers. Formally, the weight between firms a and b are $w_{ab,t} = \frac{1}{2}\sum_{ij,t}\left(L_{ij,t} + L_{ji,t}\right);\ i \epsilon\, a,\ j \epsilon\, b$, where L is the simulated link between individuals i who works for firm a and j who works for firm b in year t. In this final step, we generate undirected networks between firms taking the average of directed firm-firm links to keep network indicators simple.

This above process yields a growing network (except the robustness test that terminates old edges) because we add but do not delete individual edges year-by-year unless the worker exits the data (due to death, moving abroad etc. when we can no longer trace individuals in administrative data). Such growing networks are desirable as they have been proven useful in fixed-effect panel regression specifications (Abbasiharofteh et al., 2023; Eriksson and Lengyel, 2019; Tóth and Lengyel, 2021). This process creates dynamic inter-firm networks in which two firms may be connected even if they do not exchange workers directly, as long as at least two of their workers have shared a workplace in the past (Lengyel and Eriksson, 2017).

Variables

In this paper, the dependent variable MEANINC is to represent firm performance and is defined as the workplace-level average salary. Wages are widely treated as the best available proxy for worker and firm productivity: at the worker and plant level, pay closely tracks measured productivity (Combes et al., 2008; Hellerstein et al., 1999), and more productive, profitable, and innovative firms systematically share these rents with their employees through higher pay (Abowd et al., 1999; Kemeny and Storper, 2015). Further, value added, or other usual proxies for performance like innovativeness, is registered in Sweden on firm level (organization) and not for each given workplace in the firm. Although most firms in this sample are single-plant firms, which we specifically focus on in some of the regressions, we also include workplaces that belong to larger firms with many branch-plants. Hence, for these workplaces, income is the most readily available proxy for performance and therefore we also use the term firm although in some cases the unit of analysis is a workplace within a firm. To assess the relationship between network position of firms and their performance, we measure wage-level as the logarithm of mean monthly income of all employees, calculated by dividing the annual income from wage and employment-related transfers (e.g. parental leave, sick leave) by 12. Hourly compensation from work is unfortunately not available in our data, therefore we resort to this procedure. Income values were adjusted for inflation as of 2016 prices in Swedish crowns (10 SEK is equivalent to about 1 USD).

A caveat of using firm-level income as dependent variable is that our networks are generated from workers' mobility between firms, and mobility can be directly related to wage levels. First, high wage-levels usually attract productive workers, while low levels may generate higher turnover-rates (e.g. Christensen et al., 2005; Holtom et al., 2008). Second, attracting workers with high human capital generates positive knowledge spillovers, which leads to higher productivity and wage levels (Boschma et al., 2009; Poole, 2013). To keep track of these mechanisms, we control for the mobility of the workers, more precisely, for the incoming and outgoing human capital. We follow the method of Abowd et al. (1999) to measure human capital. This process includes the estimation of individual wage with level of education, field of education, age and age squared, and worker-level and firm-level fixed-effects. Individual human capital can then be calculated as the sum of the predicted observable traits and the worker-level fixed-effects (Csáfordi et al., 2020). Finally, we calculate the incoming human capital, HC-IN, and the outgoing human capital, HC-OUT, by summing the individual human capital values of the incoming and outgoing workers in the given year. The process is described with formulas in Supplemental Appendix 2.

The main network variable is STRENGTH, defined as the sum of individual co-worker links that the company has with other firms. This indicator is decomposed into STRENGTH DIRECT, which is the sum of co-worker links that are preceded by inter-firm labor mobility, and STRENGTH INDIRECT, which is the sum of co-worker links with companies that had never been linked to the firm by mobility (Figure 2(a)). These latter links are also generated by labor mobility (for instance, co-workers who made a connection at firm *a* might move to firm *b* and firm *c* establishing such indirect links) but can reflect inter-firm connections that are independent from direct knowledge flows embedded in the mobile worker. We find that the sum of indirect ties is comparable to direct ties (Figure 2(d)).

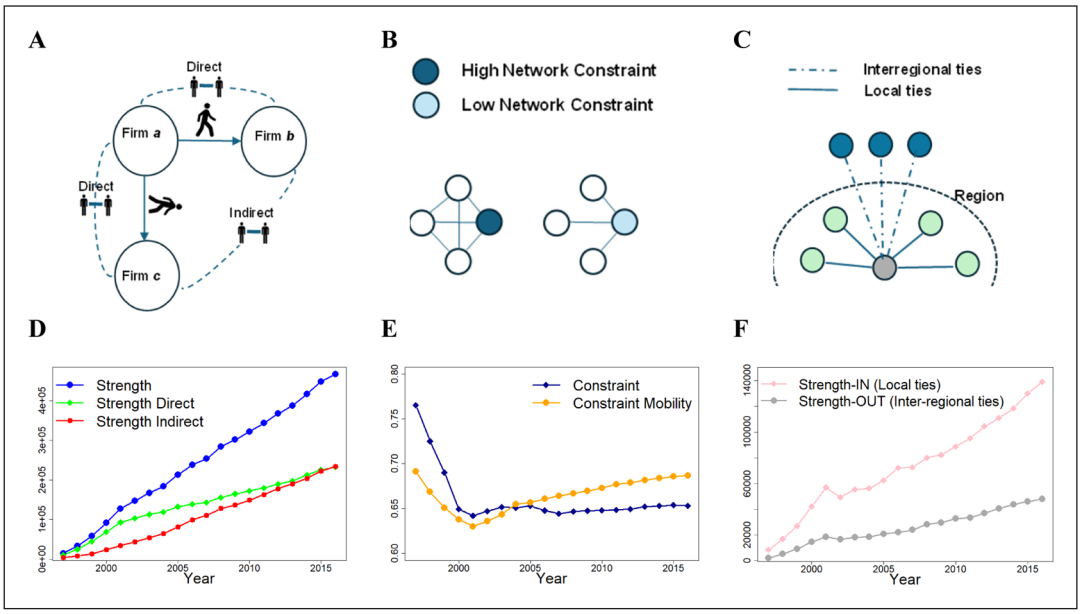


Figure 2. Firm-level variables of the co-worker network. (a) The co-worker network is decomposed to a segment where there is a direct mobility link between companies, and to another one, in which firms are only indirectly linked by mobility. (b) Network constraint quantifies the cohesiveness of firm-level co-worker networks. (c) Co-worker networks are decomposed to links within the region and links to other regions. (d) The steady growth of indirect co-worker ties keeps this network segment at similar size compared to direct co-worker links. (e) After a turbulent start in the co-worker network generation, average constraint is stable and is at the same level like the constraint measured in the mobility network. (f) The co-worker network is dominated by local links but the number of interregional links are also growing over time.

Next, we quantify the cohesiveness of firm networks with the CONSTRAINT indicator (Burt, 1992), which is high if there are dense connections among firms linked to the focal firm and low if these connections are sparse (Figure 2(b)). This measure is widely applied to capture the so-called structural holes in networks that signal access to diversity. Besides measuring CONSTRAINT of the co-worker network, we construct a network of firms in which they are linked by labor mobility to disentangle the role of co-worker networks from mobility networks. Then, CONSTRAINT MOBILITY is constructed in an identical way, to control for the possibility that diverse co-worker networks are simply artifacts of the structure of the labor mobility network. The average values of CONSTRAINT and CONSTRAINT MOBILITY are comparable across the period (Figure 2(e)). Calculation of the variables is described in detail in Supplemental Appendix 2.

We also decompose STRENGTH to STRENGTH-IN (local) and STRENGTH-OUT (inter-regional) elements. While local ties have been found in earlier work to be important for big industry-regions that accumulate large knowledge bases, extra-regional ties are considered to provide access to new knowledge (Eriksson and Lengyel, 2019). In our case, the co-worker network is dominated by local ties but the number of inter-regional ties is also growing over time (Figure 2(f)).

The ICT industry in Sweden is dominated by male software developers, and the country does not differ significantly from other developed economies in the gender pay gap (Fortin et al., 2017). Therefore, we include the PERCFEMALE variable that captures the fraction of women in the firm. To capture the impact of co-worker networks on firms at their specific stage over this period, we include FIRMSIZE, which is the number of workers in the company in each year. Further, to quantify whether co-worker networks operate differently in regions where the number of firms in the industry

are growing compared to regions where it is not, we include INDSIZE, which is the absolute number of ICT firms (as defined in 3.1) in the region. While the exact definitions of clusters vary in the literature, our definition is based on the arguments of Kemeny and Storper (2015) that the absolute number of firms in a regional industry rather than the relative number (e.g. versions of locations quotients) best proxies the potential for substantial externalities to occur. Finally, we include region-level indicators that can capture the impact of agglomeration economies that are external to the firm. EMPLOYMENT denotes the total number of employees and REGWORKPLACES stands for the number of workplaces in the region. These indicators aim to quantify urbanization economies and the fact that larger agglomerations provide bigger benefits for firms. MEANREGTURNOVER is the mean of labor turnover among all firms in the region and aims to control for local market characteristics that might impact the ICT industry through the demand for information and communication services. Finally, we control for the average age of firms in the region MEANFIRMAGE to capture the life cycle of the ICT cluster in the region. This is important because the industry has gone through a dynamic boost during the analyzed period, but this growth was unequal across Sweden (Martynovich and Henning, 2018). Descriptive statistics and correlation of variables can be found in Supplemental Appendix 2.

Estimation framework

When estimating firm performance by the network characteristics and the above controls, we used firm-level fixed-effect linear panel regressions to control for unobserved heterogeneity across firms. Thus, due to the within-estimation, we can assess whether firm-performance increases over time as they achieve more favorable network characteristics. Since future wage levels at firms are greatly determined by past realizations of wages, we add the previous year's wage level to the right-hand side of the equation. Accordingly, we estimate the following regressions:

$$y_{a,t+1} = \propto + y_{a,t} + Controls_{a,t} + RegControls_{r,t} + NET_{a,t} + \xi_a + \varepsilon_{at} \quad (2)$$

where $y_{a,t}$ represents MEANINC, *Controls* include HC-IN, HC-OUT, FIRMSIZE, INDSIZE, PERCFEMALE, and *RegControls* stands for EMPLOYMENT, MEANFIRMAGE, MEANREGTURNOVER, REGWORKPLACES. *NET* includes network variables STRENGTH, STRENGTH DIRECT, STRENGTH INDIRECT, STRENGTH-IN, STRENGTH-OUT, CONSTRAINT, and CONSTRAINT MOBILITY. ξ_a stands for firm-level fixed-effects, and ε_{at} is the error term. The models contain year dummies to control for time-specific events that influence all observations but are specific to certain years (e.g. macroeconomic trends and economy-wide changes in policy). This model (2) is then followed by an extension, in which we included the interactions of the network variables with the firm size[2] and regional industry size to test Hypotheses 3–4. Finally, fixing all other variables at their means, we calculate the marginal effects of the *NET* variables at different levels of FIRMSIZE and INDSIZE to examine these effects in more detail.

Robustness tests

Besides the advice network documented in the main text, we repeat the network generation exercise running identical variable creation and regressions for the social and collaboration networks, applying the parameters from the collaboration-, and friendship tie estimations. The results of these alternative networks and their overlap are reported in Supplemental Appendix 3. Furthermore, we also generate networks in which the weight of the co-worker tie is decreasing over time after the event of labor mobility (we test a quick and a slow time-decay specification as well) and one network in which co-worker ties are eliminated after 5 years following labor mobility. Results of these time-inflated networks are reported in Supplemental Appendix 4. Because the generation of the individual level co-worker network

Table 1. Firm performance (mean income) and coworker networks decomposed by labor mobility.

	Model 1	Model 2	Model 3	Model 4
Variables	All firms	All firms	Turnover filter	Single plants
MEANINC (lag)	0.305*** (0.002)	0.305*** (0.002)	0.301*** (0.003)	0.289*** (0.003)
HC-IN	0.006*** (0.001)	0.006*** (0.001)	0.003* (0.001)	0.006*** (0.001)
HC-OUT	0.001 (0.001)	−0.001 (0.001)	−0.002 (0.002)	−0.004* (0.002)
INDSIZE	0.057*** (0.006)	0.057*** (0.008)	0.062*** (0.007)	0.052*** (0.008)
FIRMSIZE	0.009* (0.004)	0.008 (0.004)	0.040*** (0.007)	0.019** (0.006)
STRENGTH	0.028*** (0.002)			
$STRENGTH^{direct}$		0.016*** (0.002)	0.015*** (0.003)	0.014*** (0.003)
$STRENGTH^{indirect}$		0.022*** (0.002)	0.019*** (0.003)	0.022*** (0.006)
Constant	1.737*** (0.065)	1.745*** (0.065)	1.695*** (0.079)	1.798*** (0.094)
Region controllers	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	195,239	195,239	164,363	101,879
R-square	0.108	0.108	0.101	0.099
Mean VIF	6.48	6.41	5.80	6.67

Fixed effects regressions with time dummies and regional controllers (unreported), 1996–2016. Standard errors in parentheses.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

includes a randomization step, we have repeated the panel regression estimations for 20 simulated realizations of the advice network and obtained pooled coefficient and standard error estimates by applying Rubin's rules (Rubin, 2004) for pooling parameter estimates. The description of the pooled coefficient and standard error calculation can be found in Supplemental Appendix 5.

Since system GMM does not produce a valid specification for our data, likely because firm wages exhibit persistent dynamics, we test regressions without controlling for persistence using the lag of the dependent variable among the estimators (Supplemental Appendix 6). Nonlinear relationships between the explanatory variables and the independent variables are reported in Supplemental Appendix 7. Finally, we exclude highly correlated regional variables, the inclusion of which are theoretically motivated, to mitigate the risk of multicollinearity in Supplemental Appendix 8.

Results

We test our four hypotheses by running three main models, reported in Tables 1 to 3. The estimation approach for each table follows the same logic with a first model containing the main variable of interest together with firm- and region-level control variables (firm-level controls are only displayed in Table 1, while region-level controls are not reported). These initial specifications are then supplemented by additional models using interaction terms and/or separate estimates on different sub-samples.

Table 1 reports the findings related to hypothesis 1 by testing how the firm-specific sum of coworker links to other firms (STRENGTH) influences firm performance when controlling for several other determinants of firm performance as specified in previous section. Our findings indeed suggest that an increasing number of such links is positively correlated with firm performance (defined as higher average incomes). As shown in Model 1 and 2, this network effect is positively significant regardless of whether aggregated (Model 1) or decomposed into ties directly preceded by inter-firm labor mobility and ties that do not correspond to direct mobility (Model 2). The findings also hold true when we filter out the companies that have the highest and the lowest 5% in terms of employee

Table 2. Firm performance (mean income) and cohesion of coworker networks.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	All firms	All firms	Old firms	Young firms	Turnover filter	Single plant
INDSIZE	−0.000	0.004	0.018*	−0.018*	0.001	0.015
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.008)
FIRMSIZE	0.009***	0.004	−0.002	0.017***	0.043***	0.020***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.008)	(0.004)
STRENGTH	0.005**	0.005**	0.007**	0.000	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
CONSTRAINT	−0.027**	−0.078***	−0.053*	−0.118***	−0.029***	−0.134***
	(0.009)	(0.017)	(0.025)	(0.023)	(0.008)	(0.022)
CONSTRAINT × *FIRMSIZE*		0.024***	0.015	0.040***	0.011**	0.034***
		(0.006)	(0.009)	(0.010)	(0.004)	(0.004)
Constant	2.173***	2.178***	1.898***	2.610***	2.408***	2.084***
	(0.060)	(0.060)	(0.083)	(0.120)	(0.101)	(0.085)
Firm controllers	Yes	Yes	Yes	Yes	Yes	Yes
Region controllers	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	48,714	48,714	20,779	27,935	29,846	33,030
R-square	0.246	0.246	0.293	0.210	0.157	0.194
Mean VIF	5.80	5.63	6.11	5.28	5.02	5.70

Fixed effects regressions with time dummies and controllers (unreported), 1996–2016. Standard errors in parentheses.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

turnovers, to test whether frequent job moves bias the result (Model 3), and when we limit the observations to single-plant firms (Model 4). In all, this confirms Hypothesis 1 and even suggests that while mobility is positively correlated to firm performance (c.f., Breschi and Lissoni, 2009; Eriksson and Lindgren, 2009), the externalities derived from indirect flows are of greater magnitude.

Next, we expand the results in Table 2 by adding information on the diversity of links to the number of ties displayed in the previous table. Since CONSTRAINT captures the density of links to the focal firm, our findings suggest that an increasing diversity (negative sign) of ties is beneficial for firm performance. To address Hypothesis 2 that a diversity of ties, as compared to cohesiveness, is of particular relevance among small and new firms (young firms are defined by birth in or later than the year 2000) that may need to compensate for the lack of size by having several diverse connections, Models 3–4 presents the corresponding interaction effects. Here, a few noticeable differences should be mentioned. First, we see a negative parameter for CONSTRAINT, but a positive interaction term with size (Model 2). As made visible in Figure 3, this entails that small and large firms benefit from different network positions: for smaller firms, a diversity of ties (low constraint) is more beneficial while the performance of larger firms is enhanced by more closed network positions. Considering old and young firms separately (Models 3–4), we see that small and young firms enjoy externalities from diverse ties, which is exactly what we expected in our second Hypothesis 2. Together with the above-mentioned main effect, this confirms our second Hypothesis that diverse rather than cohesive coworker networks enhance firm performance, particularly for small *and* new firms, filtering out high- and low-turnover companies, and zooming in to single-plant companies leaves the results unchanged (Model 5–6). In Models 3–6, we also control for labor mobility ties and CONSTRAINT

Table 3. Firm performance (mean income) and coworker networks within and across regions.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	All firms	All firms	Old firms	Young firms	Turnover filter	Single plant
INDSIZE	0.055*** (0.006)	0.059*** (0.006)	0.067*** (0.008)	0.040*** (0.008)	0.086*** (0.007)	0.054*** (0.008)
FIRMSIZE	0.018*** (0.004)	0.025*** (0.005)	0.032*** (0.006)	0.057*** (0.007)	0.082*** (0.008)	0.034*** (0.006)
$STRENGTH^{IN}$	0.021*** (0.002)	−0.004 (0.009)	0.002 (0.011)	0.001 (0.014)	0.003 (0.016)	−0.007 (0.014)
$STRENGTH^{OUT}$	0.019*** (0.002)	0.038*** (0.009)	0.048*** (0.012)	0.021 (0.014)	0.075*** (0.017)	0.038*** (0.014)
$STRENGTH^{IN} \times$ *FIRMSIZE*		−0.002 (0.001)	−0.006*** (0.002)	−0.003 (0.003)	−0.001 (0.004)	−0.001 (0.002)
$STRENGTH^{OUT} \times$ *FIRMSIZE*		−0.005** (0.002)	−0.008*** (0.002)	−0.004 (0.003)	−0.019*** (0.005)	−0.005 (0.003)
$STRENGTH^{IN} \times$ *INDSIZE*		0.004*** (0.001)	0.005*** (0.001)	0.002 (0.002)	0.004* (0.002)	0.004* (0.002)
$STRENGTH^{OUT} \times$ *INDSIZE*		−0.001 (0.001)	−0.001 (0.001)	0.000 (0.001)	−0.001 (0.002)	−0.001 (0.002)
Constant	1.741*** (0.065)	1.720*** (0.065)	1.043*** (0.086)	2.097*** (0.137)	2.426*** (0.082)	1.773*** (0.094)
Firm controllers	Yes	Yes	Yes	Yes	Yes	Yes
Region controllers	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	195,239	195,239	66,614	128,625	164,363	101,789
R-square	0.108	0.108	0.209	0.076	0.010	0.098
Mean VIF	6.03	8.69	9.52	8.33	6.77	8.95

Fixed effects regressions with time dummies and controllers (unreported), 1996–2016. Standard errors in parentheses.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

in the labor mobility network to test the potential relationship between labor mobility and co-worker network constraint.

Finally, we assess the geography of ties by decomposing STRENGTH (the sum of both direct and indirect co-worker connections) into an intra-regional and an inter-regional component (Table 3). Based on these findings, we cannot support arguments advocating for either local or global linkages. Instead, Model 1 suggests that on average both matters almost equally. Nevertheless, depending on the size of the firm and the degree of agglomeration, the role of local and non-local ties varies depending on firm-specific capacities and local spillovers. First, Model 2 shows that local ties are particularly important in large industry clusters where, presumably, the concentration of industry-specific knowledge is high. This indicates that local ties are an integral part of growing industry clusters which supports previous accounts arguing for the need of dense networks in large agglomerations to avoid information overload (e.g. Eriksson and Lengyel, 2019). The main effect of the local ties is insignificant here, but that corresponds with a hypothetical region with zero firms. From Figure 3, it could be confirmed that within-industry ties indeed have a positive and significant impact basically on all the relevant range of regions, but it is more pronounced in the larger ones. Therefore, hypothesis 4 can be

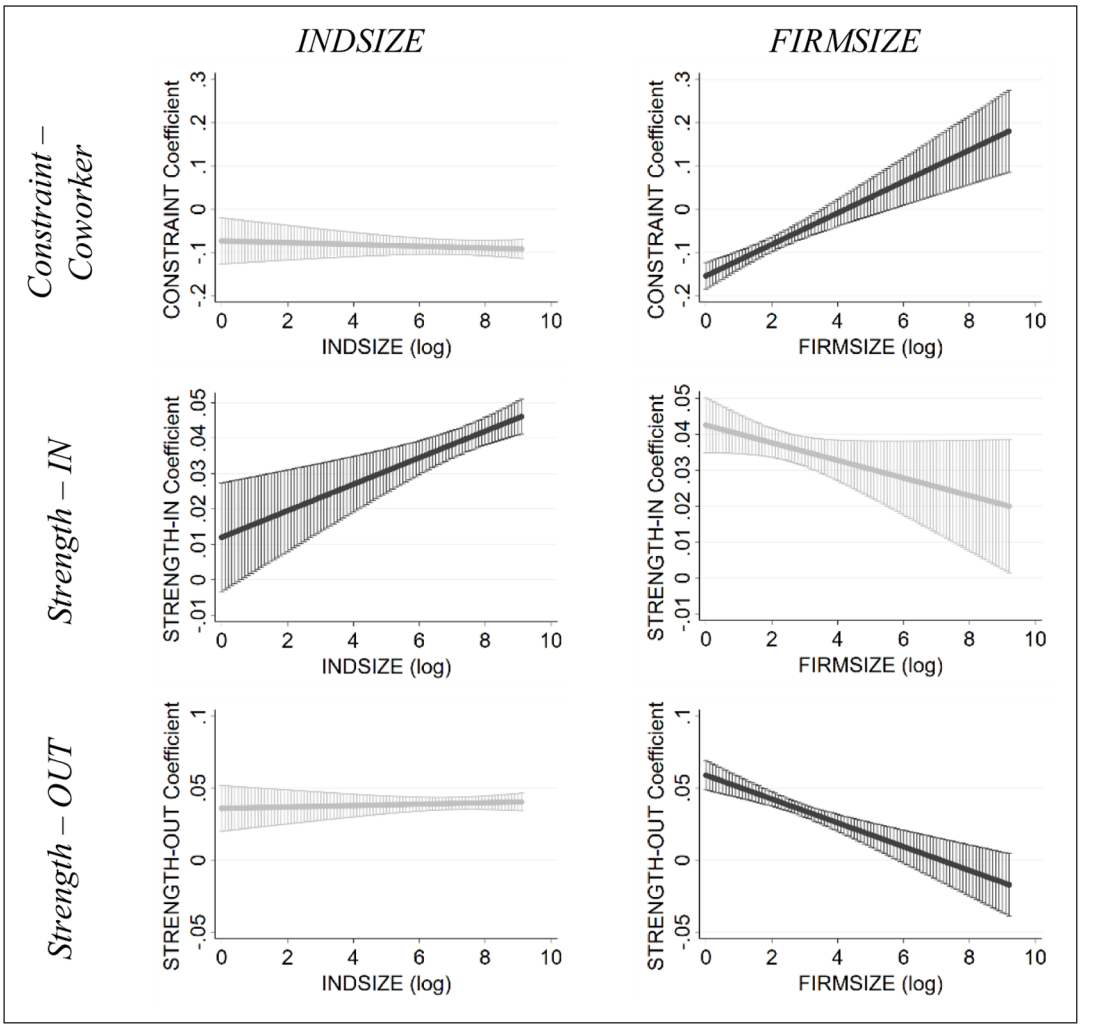


Figure 3. Marginal effects of network variables by the size of clusters (INDSIZE) and firms (FIRMSIZE). Dark gray graphs mark interactions significant in Tables 2 and 3 while light gray represent insignificant interactions. The turning points of significance by firm size is further analyzed in Supplemental Appendix 9.

confirmed as local networks enhance the performance of the involved firms, as stated in the literature (Storper and Venables, 2004), and especially so in regions where the number of ICT-firms are growing over time. Thus, the network component is an integral part of the assumed externalities derived from regional industry clusters.

Turning to the impact of local and distant ties for small and large firms, we see that while the main effect of inter-regional ties remains stable when introducing interaction terms, here also the size of the firm mitigates the role of inter-regional connections due to the already present internal capabilities. This shows, as is visible in Figure 3, that long-distance connections are highly beneficial for small firms, somewhat so for medium-sized ones, but not for large enterprises.

Considering new and old firms separately, however, we see that it is mainly older firms that enjoy such externalities (Model 3), while young firms are generally less influenced by the geography of ties (Model 4). Thus, we cannot fully confirm Hypothesis 3 that especially small and young firms profit

from distant ties. Our findings rather suggest that distant ties are more important for established SMEs than for newly founded start-ups. In addition, similar tendencies can also be observed for local ties. Small enterprises are especially already stable to the businesses that can utilize them, suggesting that these types of firms that may lack internal capacities can build a business operation where they "borrow size" from other firms via their networks. While trimming outlier firms regarding employee turnover does not change the overall picture (Model 5), single-plant companies seem to benefit mostly from inter-regional connections irrespective of their firm size (Model 6).

Our main findings are robust across network generations of social-, cooperation-, and multilayer network parameters (Supplemental Appendix 3), by decaying and terminating old co-worker links (Supplemental Appendix 4), and across 20 random realizations of the advice network (Supplemental Appendix 5). Results also hold when we do not include the lagged value of the independent variable among the estimators (Supplemental Appendix 6). We find that some of the explanatory variables are non-linearly related to firm growth but this does not change our main argument (Supplemental Appendix 7), neither does the exclusion of the highly correlated regional-level controllers (Supplemental Appendix 8).

Discussion

This paper analyzed how co-worker networks – formed through labor mobility and sustained through social relationships – shape firm performance in regional clusters. Drawing on survey-based data and nationwide administrative registers, we simulated dynamic co-worker networks across all Swedish ICT firms over two decades. This method enabled us to distinguish direct knowledge transfer via labor mobility (Almeida and Kogut, 1999; Breschi and Lissoni, 2009) from the broader externalities produced by enduring interpersonal connections (Agrawal et al., 2006; Casper, 2007).

Our results demonstrate that both direct and indirect co-worker ties significantly enhance firm performance. Even firms never connected by mobility can benefit when their employees share prior workplaces, indicating that social relationships can extend the learning effects of mobility beyond immediate hiring events. These findings support long-standing arguments about the social foundations of knowledge diffusion (Arrow, 1962; Granovetter, 1985) and confirm that social embeddedness within clusters matters as much as geographic proximity (Glückler et al., 2023; Storper and Venables, 2004).

Importantly, the benefits of these networks vary by firm characteristics and regional context. Small and young firms profit most from diverse, non-redundant connections that bridge structural holes (Burt, 1992, 2004) and expose them to novel ideas (McEvily and Zaheer, 1999). Larger and more established firms gain more from cohesive and local ties that foster coordination and trust within established knowledge bases (Aral and Van Alstyne, 2011; Uzzi, 1997). Moreover, in expanding clusters where local knowledge stocks are growing (Eriksson and Lengyel, 2019; Menzel and Fornahl, 2010), local networks are especially valuable. In contrast, in peripheral or slower-growing regions, inter-regional ties compensate for limited local spillovers (Grillitsch and Nilsson, 2015; Lőrincz et al., 2020).

Despite these insights, the study has several limitations. The simulated co-worker networks rely on probabilistic tie inference rather than direct observation of all social interactions, which may introduce measurement noise. Our focus on wage-based performance captures one dimension of firm outcomes but may not reflect innovation or productivity effects. Furthermore, the analysis is limited to Sweden's ICT sector, and institutional differences may moderate these mechanisms elsewhere. Future research should test this framework in other industries and national contexts, integrate longitudinal survey data to refine and dynamically validate ties, and examine alternative outcomes such as innovation intensity or resilience. Several further limitations specific to our co-worker approach deserve emphasis, which we turn to next.

A first limitation concerns external validity. Our nationwide networks are generated by applying tie-formation parameters estimated on a survey of 16 ICT firms in a single Swedish city to the full population of ICT firms. We stress that this procedure does not assume that the surveyed firms are structurally representative of the sector; rather, it assumes that the behavioral regularities governing how co-workers form advice ties are general, and it combines these estimated regularities with the observed composition and size of every firm in the register data. This assumption is consistent with the robustness of homophily across organizational settings, but it remains an assumption: the strength of homophily may itself vary across regions, firm cultures, or industries beyond ICT, and the single-context calibration cannot capture such heterogeneity. Collecting comparable relational surveys across multiple places and sectors, and allowing tie-formation parameters to vary across them, is an important avenue for refining and stress-testing the approach.

A second limitation concerns the temporal structure of co-worker ties. Our networks treat the relationships that follow labor mobility as persisting after employees separate, which is central to the finding that even firms never linked by mobility can benefit when their employees share prior workplaces. The appropriate "memory" of such ties is, however, not pinned down by theory. We therefore re-generated the networks under slower and faster time decay of individual links and under a hard cutoff that deletes ties beyond a fixed tenure (Supplemental Appendix 4); the results are robust to these choices. Even so, our design does not model the formation and dissolution of ties as an explicit dynamic process. Richer longitudinal and dynamic network models that endogenize how co-worker relationships are created, maintained, and decay over careers would sharpen our understanding of how durable the social residue of mobility really is.

A third limitation concerns heterogeneity in labor mobility itself. We observe job moves but not their reasons, and workers who change employers frequently mechanically accumulate more co-worker ties, as also documented for mobility-based networks elsewhere (Lengyel and Eriksson, 2017). Because the motives behind mobility (e.g. promotion, displacement, or matching) plausibly shape the quality of the knowledge a tie carries, we cannot fully separate the value of connections from the selection of who moves and why. Linking co-worker networks to the causes of mobility, for instance through firm closures or other quasi-exogenous separations, is a promising direction for identifying the learning content of these ties more cleanly.

Notwithstanding these limitations, our results have practical and theoretical implications. The benefits of diverse, non-redundant networks are concentrated among smaller firms, while cohesive and local ties pay off for larger ones: the association between network cohesion and performance changes sign at roughly 27 employees, and the advantage of inter-regional ties fades only well into the medium-size range (Supplemental Appendix 9). For managers and cluster policy, this suggests differentiated advice that small firms and entrepreneurs gain most from cultivating bridging, cross-cluster relationships and from hiring that opens access to non-redundant knowledge, whereas larger, established firms benefit more from deepening cohesive local ties that support coordination and trust. Generic prescriptions to "network more" are therefore unlikely to serve SMEs and large firms equally well.

Theoretically, our findings bridge perspectives on labor mobility and network embeddedness to show that co-worker networks form an invisible yet persistent layer of inter-firm connectivity. These networks sustain the cumulative learning processes that underlie the success of clusters (Marshall, 1920; Porter, 1990), implying that regional competitiveness depends not only on the mobility of talent but on the social persistence of the networks that channel knowledge long after individuals change jobs. Co-worker networks are, however, only one of several channels through which firms in clusters learn from one another, alongside traded and untraded interdependencies, informal personal contacts (Dahl and Pedersen, 2004), and formal collaboration captured in patents and publications (Breschi and Lissoni, 2009). Because no prior study, to our knowledge, reconstructs co-worker networks at the firm and plant level on this scale, our results are best read as isolating this distinct, previously invisible channel rather than as ranking it against the others. Bringing these channels into a common

empirical setting by asking how co-worker ties complement or substitute collaboration and personal contacts in transmitting knowledge is, in our view, a promising research direction. Doing so would move the field from documenting individual channels toward mapping the full architecture of learning that makes clusters competitive.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. See Lőrincz et al. (2020) for details on the survey and discussions on representativity.
2. We also estimated alternative versions of equations (2) and (3) omitting the reference year's wage levels from the right-hand side. Results considering the parameters of interest became highly similar in these specifications from which we can conclude that adding the lagged dependent variable does not cause any severe issues of time-series correlation.

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