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GLOBAL CONNECTIONS AND THE STRUCTURE OF SKILLS IN LOCAL CO-WORKER NETWORKS

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ABSTRACT

Social connections that reach distant places are advantageous for individuals and firms by providing access to new skills and knowledge. However, systematic evidence on how firms work up global knowledge access is still missing. In this paper, we analyse how global work connections relate to differences in the skill composition of employees within companies. We gather survey data from 10% of workers in a local industry in Sweden and complement this with digital trace data to map co-worker networks and skill composition. This unique combination of data and features allows us to quantify global connections of employees and measure the degree of skill-similarity and skill-relatedness to co-workers. We find that the workers with extensive local networks typically have related skills to others in the region and to their co-workers. Workers with more global ties typically bring in less related skills to the region. These results provide new insights to the composition of skills within knowledge intensive firms by connecting the geography of networks contacts to the diversity of skills accessible through them.

JEL codes: D85, J24, J61

Keywords: Co-worker networks, skills, relatedness, global connections, survey, online social network

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Globális kapcsolatok, munkatársi kapcsolathálók és a dolgozók készségei

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ÖSSZEFOGLALÓ

A nagy távolságokat áthidaló kapcsolatokon keresztül a cégek új készségekhez és ismeretekhez férhetnek hozzá, melyek előnyösek mind a dolgozók, mind a cégek számára. Egyelőre azonban nem találhatunk szisztematikus kutatásokat arról, hogy a globális tudáshoz való hozzáférés hogyan épül be vállalatok működésébe. E tanulmányban azt vizsgáljuk, hogy a globális kapcsolatok hogyan függenek össze a munkavállalók készségeinek szerkezetével a vállalatokon belül. Egy észak-svédországi klaszter dolgozói körében végzett kérdőíves felmérési adatait online kapcsolatháló adatokkal kapcsoltuk össze, így feltérképezve a munkatársak kapcsolathálóit és a készségeik jellemzőit. Az adatok e kombinációja segítségével számszerűsítjük a munkavállalók helyi globális kapcsolatait, és a készségeik hasonlóságának és közelségének mértékét. Eredményeink alapján a kiterjedt helyi hálózatokkal rendelkező munkavállalók inkább hasonló képességekkel rendelkeznek, mint a térség más munkavállalói és mint saját munkatársaik. A globálisabb kapcsolatokkal rendelkező munkavállalók viszont általában eltérőbb készségeket hoznak a régióba. Eredményeink új információt nyújtanak a tudásintenzív cégek készségeinek összetételéről, összekapcsolva a kapcsolathálók földrajzi vonatkozását az ezeken keresztül elérhető készségek diverzitásával.

JEL: D85, J24, J61

Kulcsszavak: Munkatársi kapcsolathálók, készségek, közelség, globális kapcsolatok, online kapcsolathálók

1. INTRODUCTION

Understanding the role of networks, in the various domains of social and economic life, is one of the central challenges of today's science (e.g. Borgatti et al. 2009, Lazer et al. 2009). Social networks are proven to inform us about how information spreads (Bakshy et al. 2012, Helbing et al. 2015), about the role of social influence on individual behaviour (Aral and Nicolaides, 2017, Ugander et al. 2012), and the impact of social network structure on the performance of teams (Guimera et al. 2005, Vedres, 2017), among others.

Despite recent years' advancement in Big Data, most of our knowledge on social networks is still based on either small samples and case-studies, or large-scale analyses, thus neglecting the very geography inscribed in all socio-economic relations (Fernandez and Su, 2004). Nevertheless, the spatial structure of networks is decisive for understanding the role of networks in society. For example, social connections that reach distant places, compared to more local connections, are commonly perceived to be crucial in the generation of wealth for individuals, firms, and communities by providing access to opportunities and diverse knowledge (Bailey et al, 2019, Eagle et al, 2012, Eriksson and Lengyel, 2019, Fitjar and Rodriguez-Pose, 2011). However beneficial so-called "long ties" might be, these distant, and presumably weak, ties are highly dependent on the local capacity to absorb and internalize external information. Research on information flows and innovation, for example, show that distant ties tend to be most beneficial when also combined with cohesive local networks that can efficiently process complex information (Aral, 2016, Bathelt, et al. 2004, Granovetter, 1973, Ter Wal et al. 2016, Tóth and Lengyel, 2019).

The skills and knowledge of the workforce are defining assets of the firm and are directly related to internal and external collaboration. We have ample evidence that firm performance depends extensively on how skills of employees are combined (Abdulkareem et al, 2018, Boschma et al 2009; Dibiaggio et al 2014). The efficiency gains generated by division of labour in the firm and the consequent skill specialization naturally depend on the extent of knowledge resided in the firm that fosters specialization of employees (Neffke, 2019) but is counterbalanced by coordination costs that also increase with the extent of knowledge (Becker and Murphy 1992). Firm specialization itself is also seen as a net outcome of the advantages of focusing on special tasks in the firm and the costs of transferring this special knowledge to the outside world (Kogut and Zander 1993). Although transferring knowledge across firm boundaries usually comes with extra costs, inter-firm collaborations enable specialized firms to access complementary resources (Madhok 2002) or external sources of information (e.g., Tortoriello and Krackhardt, 2010). However, previous research on advice networks in local industries found that firms tend to collect knowledge from co-located firms that are similar to them in terms of knowledge or applied technologies (Balland et al. 2016, Juhász and Lengyel

2018). It is widely accepted in economic geography that network formation driven by technological similarity threatens local economies with a scenario of lock-in that harms productivity and resilience (Boschma and Frenken, 2010, Grabher, 1993, Hassink, 2010). In this understanding, global links can feed local dynamics by adding new varieties of skills (Bathelt and Turi, 2011, Glückler, 2007).

Previous research explored the combination of firms' existing skills with new skills by investigating flows of skilled labour (Breschi and Lissoni 2009; Eriksson and Lindgren, 2009). The conclusive claim is that complementarity of incoming workers' skills and the skills already present in the firm boost performance (Boschma et al, 2009, Csáfordi et al, 2020, Ter Wal et al. 2016). At the individual level, complementary skills within the firm is found to increase wages (Neffke 2019). In this body of literature, geography plays an important role because distant knowledge flows via labour mobility bring in additional novelty arising from the differences of geographical locations (Boschma et al 2009).

Labour mobility is of course not independent from collaboration networks (Tzabbar et al. 2018). As employees keep social relations with former co-workers, labour mobility creates social networks between firms. Recent contributions have quantified the probability of co-worker relationships within regions (Lengyel and Eriksson 2017) and then showing that the internal networks in industry-regions largely determine whether more diverse or specialized linkages to other sectors and regions are promoting growth (Eriksson and Lengyel 2019). Hence, social relations, that is the main mechanism enhancing interactive learning (Arrow 1962) and also tend to be the most localized type of interaction (Singh 2005), is likely to be highly influential in structuring the skill combination of firms. However, data limitations have so far prevented us from understanding how global knowledge access matches the skill-composition of co-worker networks within firms. The literature on knowledge flows has neither assessed the origin of skills, nor gone beyond formal knowledge captured by educational degrees or industry experience.

The aim of this paper is therefore to make a systematic analysis of how the structure and skill-content of social networks within firms match with local and global networks, respectively. To address this problem, we first investigate how the skills of employees are related in the advice network within firms and in an online social network across firms. Subsequently, we turn to the relationship between the geography of social networks and skills. The aim of the paper is summarized in two research questions.

Research Question 1: Do co-workers' skills predict information networks within firms?

Research Question 2: Do workers who have extensive global connections offer new skills to the firm compared to workers who are embedded in local networks?

Extensive previous research has assessed the evolution of organizational advice networks, arguing that tie formation in these networks is driven by status and individual characteristics (eg. Lazega and Van Duijn 1997, Agneessens and Wittek 2012), value similarity (Lazega et al. 2012), or team membership (Brennecke and Rank 2016). However, extensive research on the skill structure within firms and advice networks is still missing. An exception is Brennecke and Rank (2017) that investigates how knowledge of inventors – measured by the technological profile of their patent portfolio – in a large firm influence their connections in their advice network. They find that knowledge similarity facilitates the formation of advice relations, while diverse individual knowledge increases the probability of being asked, and decreases the probability of asking advice from a colleague.

Our contribution to this literature is twofold. First, we assess how skills of co-workers in general – without focusing on inventors – are related to advice networks in the firm and across firms in the region. Second, we explore the interplay of the distant social connections and the skill structure in local co-worker networks.

This analysis is made possible by collecting survey data at the firm level and combine it with online data. We ask all employees of 16 ICT (Information, communication and technology) firms in Umeå, Sweden (representing 10% of the local industry) to name their co-workers whom they collaborate with, socialize with, or ask professional advice from. Additionally, we asked for respondents' permission to collect public information from their LinkedIn profiles. These data collection techniques allow us to quantify the geographical reach of the connections (Park et al. 2019) and to measure the skill complementarity of co-workers based on how similar and related their skills are (Neffke and Henning, 2013).

We find that co-workers are more likely to be linked in the advice network if their skills are similar or related. A further result suggests that workers with extensive local networks typically have skills that are related to peers in the region and to co-workers within the firms. On the contrary, workers with a high fraction of distant ties have skills that are only loosely or not related to the skills of connections in the region and in the firm. Finally, we find that shared education abroad is more important for creating global ties than foreign work experience. These results provide new insights to the composition of skills within knowledge intensive firms by connecting the geography of networks and the similarity or diversity of skills.

2. DATA AND METHODS

We collected network data of 214 IT workers in 16 ICT firms using a workplace survey in Umeå, Sweden. Besides being part of a knowledge-intensive industry, the ICT cluster in Umeå is located in a relatively peripheral position (ca 1000 km north from the capital of Stockholm) and yet unusually connected to the rest of the world due to the existence of a fast-growing

university. This makes it a good case for studying the importance of distant ties in providing skill diversity to local industries.

Our firm sampling population consisted of all ICT firms with main offices in the Umeå region and more than 10 IT workers. A list of ICT companies with offices in the Umeå region was obtained from a local business incubator (Uminova). Of 77 companies in the list, 17 were excluded because they had less than 10 IT workers on their payroll and 24 were excluded because their main office were not in the Umeå region. Of the remaining 36 companies, 14 declined to collaborate, and six companies wanted to collaborate but were not able to do so during our fieldwork period. This resulted in 16 out of 36 companies that matched the sample requirements being surveyed, yielding a 44.4% response rate on the firm level. Within firms, our response rate of employees exceeded 80% in every firm.

The survey included questions on demography (gender, country of birth), on the job (current position at the firm, department, promotion), satisfaction with different aspects of the work, and on co-worker networks. In respect to network questions De Lange, Agneessens and Waeye (2004) analysed 17 questions used in organizational network studies, and revealed three main dimensions using factor analysis: advice, social support – companionship, and friendship. Considering time constraints and sensitivity, we chose three questions that had similar logic, but tapping different dimensions: information, socialization, and cooperation, and asked them using the full roster method¹. In this study focus on advice networks (asking for professional advice), as advice is related to direct information channels.

Based on respondents' consent to access their LinkedIn profiles we collected detailed information about their skills, employment and education histories. Our LinkedIn subscription allowed us to collect similar data from the network connections of the respondents, including location. Due to some incomplete surveys and missing variables, we collected complete skills data for 150 respondents, and connections, education and work histories for 125 respondents.

¹ The questions' wordings were the following in our study: 1. Who are the people you need to collaborate with in your current projects in order to get your work done? Pick as many of your co-workers as you like. (Click on a name to select and click again to de-select.) 2. Who are the people who give you important information to get your current projects done? Pick as many of your co-workers as you like. 3. Who are the people you socialise with outside of work-related situations? Pick as many of your co-workers as you like.

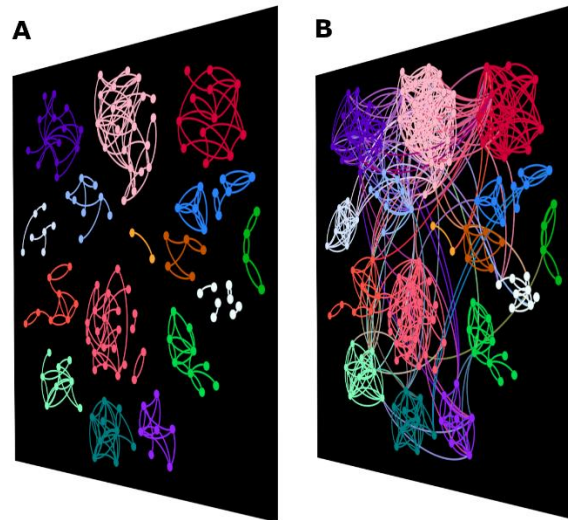


Figure 1.

Connections of respondents. (A) Connections in the information networks within firms. Colours represent firms. (B) LinkedIn connections added to advice network. The colour of inter-firm edges is set on a dyadic level as the interpolation of nodes' colour. LinkedIn connections concentrate within firms, but a significant number of them bridge across firms in the cluster.

Advice networks within firms and additional LinkedIn connections across respondents are displayed in Figure 1. Ties in the advice networks are directed. This implies that there might be two edges between two nodes in case both respondents indicated the other as a source of information (Fig. 1A). Although the number of respondents vary considerably between 3 and 25, these networks are relatively similar in terms of edge density (mean equals 0.21 with a 95% confidence interval of [0.14; 0.28]) and average path length (mean equals 1.61 with 95% confidence interval [1.34; 1.88]). In Fig. 1B we add the LinkedIn connections to the advice networks and show that employees are linked to workers in other firms. Moreover, there are co-workers who are not linked in the advice network but are connected on LinkedIn.

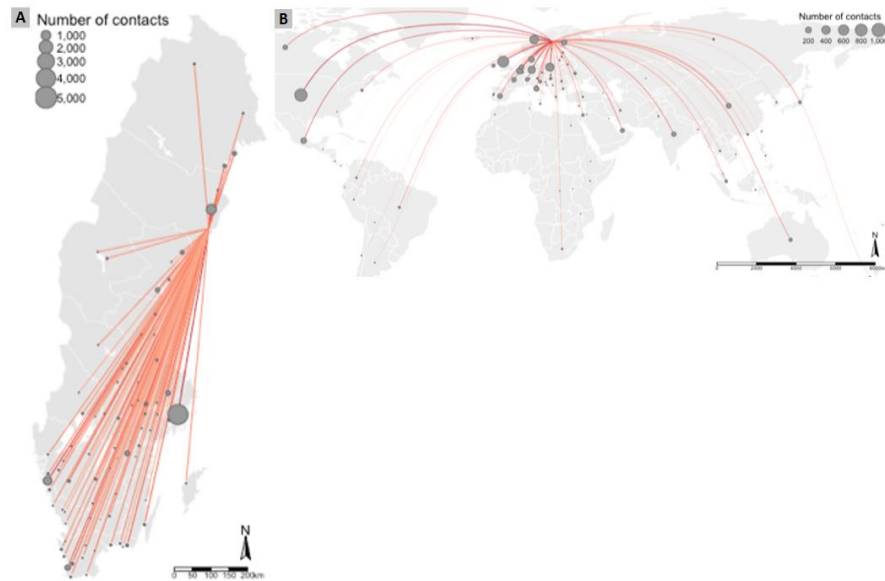


Figure 2.

Geography of respondents' national (A) and global (B) networks. Node sizes represent number of connections. The region has a diverse connection portfolio in Sweden and is mostly connected European countries. However, Umea experts have many connections in the USA and other large countries.

To assess the spatial dimension of links, we divide the connections collected from LinkedIn profiles to three geographic categories: local (Umeå), national (rest of Sweden), and global (outside Sweden). The geography of their global and national connections is displayed in Figure 2 A and B. As depicted from the figure, proximity clearly shapes the geography of the networks. The largest number of links is, hardly surprising, to the capital city of Stockholm. Although the other two metropolitan regions (Gothenburg in the West and Malmö in the South) indeed both have a significant number of connections, the neighbouring city of Skellefteå in the North also stands out. Looking at the global (international) connections, although the single country with the most connections is the US, the nearby European countries (UK, Norway, Poland) dominate.

Based on the respondents LinkedIn profile it is then possible to collect the skills of our respondents. We observe 2639 skill listings from 150 observed respondents, leading to 847 different skills being represented in the dataset. This means that one person has on average 17.6 skills; the minimum is two, and the maximum 46 skills for a person. The most popular skill is possessed by 76 respondents, however, an average skill is only possessed by 3.11 people (Table 1).

We have information on the location of LinkedIn contacts for 125 respondents. They have 57.7 local, 73.1 Swedish non-local and 41.2 foreign contacts on average. Considering all LinkedIn contacts, respondents have 172 connections on average (Table 1).

Table 1.

Summary statistics of respondents' skills and LinkedIn connections

	Skills		LinkedIn connections by respondents			
	Skills by respondents	Frequency of skills	Local	National	Global	Total
Mean	17.6	3.11	57.7	73.1	41.2	172.0
SD.	8.93	6.75	61.0	109.5	97.2	191.7
Min.	2	1	2	0	0	3
Max.	46	76	311	761	582	998
N	150	847	125	125	125	125

The skills of the workers are analysed using two types of measures. First, we define the similarity of skills between workers using the Jaccard measure (the number of common skills between two workers divided by the total number of skills they have together):

$$J_{pq} = \frac{|S_p \cap S_q|}{|S_p \cup S_q|}, \quad (\text{Eq. 1})$$

where J_{pq} is the similarity measure between individuals p and q , S_p and S_q are their skill-sets, respectively.

Second, we assess how related their *non-similar* skills are by using a co-occurrence based approach. In this technique, we define two skills related if they often occur together in the skill-profiles of individuals. This is quantified based on the ratio of how often they occur together in the profiles compared to what we expect by random chance, applying the measurement of Teece et al. (1994) that originally was developed for product portfolios within firms:

$$t_{ij} = \frac{C_{ij} - \mu_{ij}}{\sigma_{ij}}, \quad (\text{Eq. 2})$$

where t_{ij} is the relatedness measure, C_{ij} is the observed number co-occurrences of the skills, μ_{ij} is the expected value of co-occurrence in case of random distribution of the skills, and σ_{ij} is its standard deviation assuming binomial distribution. The formula of expected co-occurrence is $\mu_{ij} = \frac{n_i n_j}{K}$ and of standard deviation is $\sigma_{ij}^2 = \mu_{ij} \frac{1-n_i}{K} \frac{K}{K-1}$, where K is the number persons, and n is the observed frequency of the skill.

Figure 3 represents the relatedness landscape of the skills using the definition of Equation 2. Similar skills cluster together, which we build upon when grouping and labelling these groups by characteristic features of included skills. Interestingly, management-related skills (e.g. Public relations and Decision making) are not related to engineering (eg. System design, Database, Engineering) or analytical skills (e.g. Visuals, Analysis and modelling), but more to Finance and Sales. Strongly related skill groups are, for example, Finance and Sales, Artificial Intelligence (AI) and Investments and Business Intelligence. Audio is in itself a rather distinct

group of skills that is not very connected to other ICT skills while Knowledge management has a transcending character.

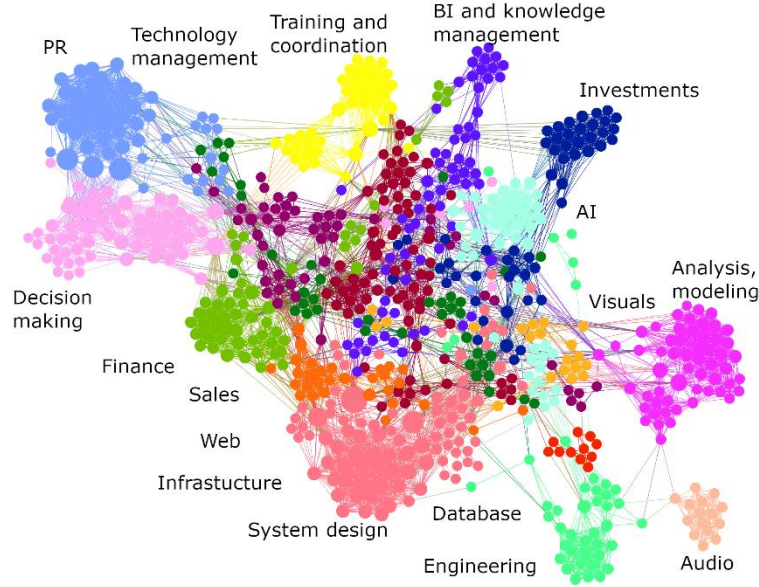


Figure 3.

Map of the relatedness of the skills. Nodes represent skills, edges represent relatedness values with a threshold of $t_{ij} > 2$. Colors represent communities detected by the Louvain algorithm. Similar skills tend to cluster together.

Having defined the relatedness of the skills, we measure the degree of skill-relatedness R_{pq} between every pair of individuals p and q by taking the average relatedness for each combinations of person-skills:

$$R_{pq} = \frac{\sum_{i \in S_p} \sum_{j \in S_q, i \neq j} t_{ij}}{|S_p||S_q| - 2|S_p \cap S_q|}, \quad (\text{Eq. 3})$$

where S_p and S_q are the skill-sets of p and q .

When measuring skill-similarity and relatedness of skills from LinkedIn data, we must be aware that skill-sets displayed on LinkedIn can be endogenously correlated with LinkedIn networks. On the platform users can add their own skills, but skills can also be added via “endorsement”. In this case the platform asks one’s connections to endorse the individual with a set of suggested skills, and the exact algorithm of this recommendation system is not publicly available but might influence the tie-creation.

3. RESULTS

2.1 3.1 SKILL-RELATEDNESS AND CO-WORKER NETWORKS

Figure 4 contains distributions of average relatedness (4A-B) and similarity (4C-D) of individuals with colleagues in the firm and with colleagues who are connected. Figure 4A illustrates that the average relatedness between co-workers in the same firm is higher than between random persons in the sample not being co-workers. Further, we find that the relatedness of skills between those who are connected on LinkedIn does not differ from relatedness of co-workers. Zooming into relations within firms in Figure 4B; we find that individual workers who are connected in the advice network are more skill-related on average than those who were not connected in the advice network. We can observe similar patterns regarding skill similarity. Co-workers within firms tend to have more similar skills than non-connected workers in different firms (Figure 4C). Hence, while there is a high degree of similarity and relatedness of skills between co-workers, which is expected given the formation of creative and more productive teams (Becker and Murphy 1992, Brennecke and Rank 2017; Neffke 2019), this is also the case concerning social connections reported on LinkedIn. Furthermore, employees tend to ask advice from co-workers having more similar skills (Figure 4D). In other words, workers are more likely to be connected to persons with related skills than to any random person, both within the workplace but also to other firms and regions.

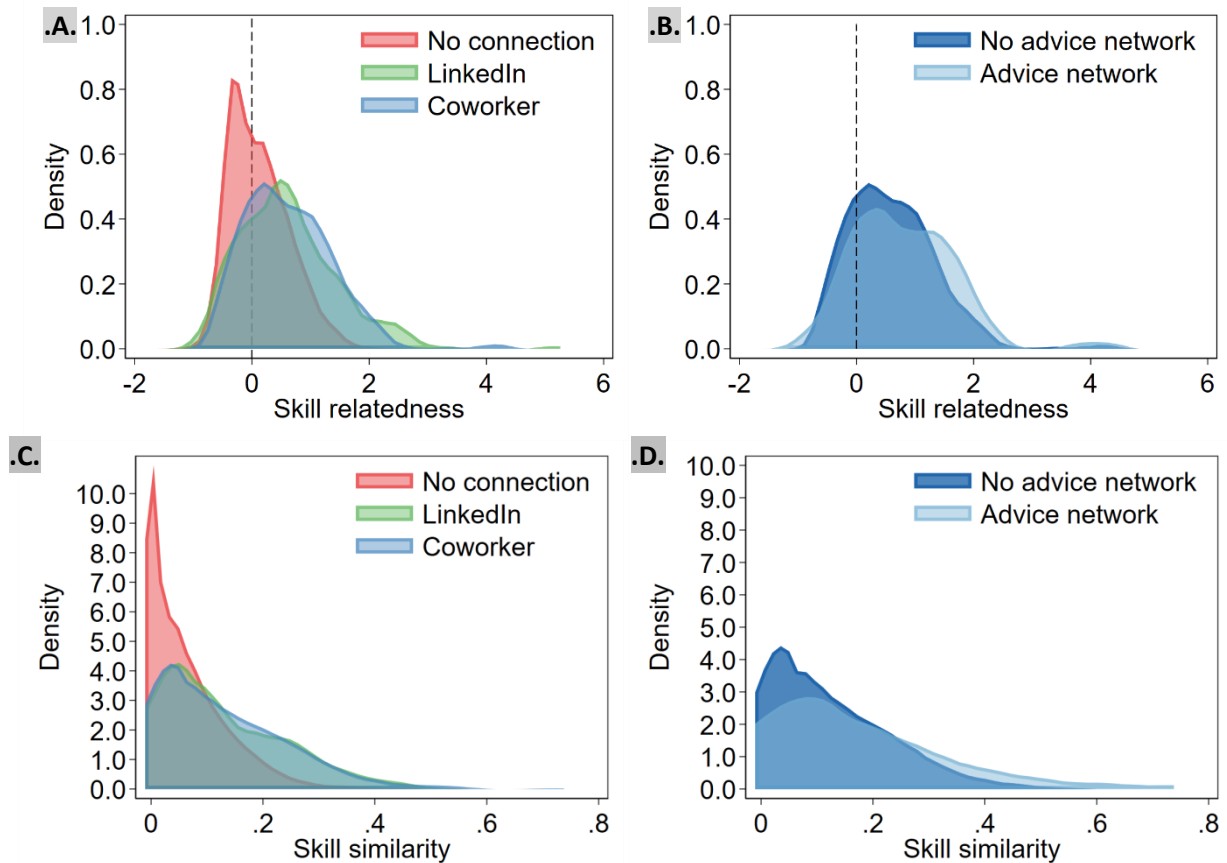


Figure 4.

Average relatedness (A-B) and similarity (C-D) of skills between pairs of respondents.

(A, C): Comparison of LinkedIn connections (green) | Co-workers in firms (blue) | none (red). (B, D) Co-workers in the firms connected in advice network (light blue) | not connected in advice network (dark blue). Findings indicate highly similar or related skills between employees who work at the same firm, are connected on LinkedIn, and especially, if they ask advice from each other.

To analyse the statistical significance of these results, one has to consider that similarity and relatedness are measured for each dyad, while we actually observe connections on the individual level. Therefore, to obtain correct estimates, we used cross-classified multilevel models (Skrondal and Rabe-Hesketh 2004, Snijders and Bosker 2011), where level 1 represent the dyads, and level 2 the individuals. Multilevel models (in econometrics these models are labelled as clustered standard error models) are to analyse data when individual observations are clustered within groups. In this case, we have fewer observations for the group level variables than for individual ones, therefore standard errors tend to be under-estimated in OLS specifications and significance levels are lower (Snijders and Bosker 2011). Indeed, when

estimating OLS models we obtain similar results but also slightly more significant estimates. Cross-classified data structure is a specific case when observations are classified by intersections of overlapping groups. Furthermore, advice-seeking behaviour as well as skills may be correlated with individual attributes. Therefore, we include work experience, type of job (junior professional, senior professional or manager), gender, and firm size as control variables to our models. Accordingly, we estimate the following equation:

$$L_{pq} = \alpha + \beta_1 R_{pq} + \beta_2 J_{pq} + \gamma \mathbf{Controls}_p + \xi_p + \xi_q + \varepsilon_{pq}, \text{ (Eq. 4)}$$

Where $L_{pq} = 1$, if person p asks advice from person q and 0 otherwise, while ξ and ε are the error terms on the individual and on the dyad level respectively.

Table 2 reports the estimates for the network of asking advice in professional matters within the firm. Having more related skills (Column A) or more similar skills (Column B) increase the likelihood of tie-formation. In this sense, the answer for our first research question is that skill similarity does predict advice relations and related skills also predict advice relations. However, once the share of the same skills is controlled for, the relatedness of the non-similar skills does not have an additional impact on this (Column C). This implies that while concentrations of complementary skills in a firm allow both specialization and (related) diversity that induce individual wage premiums as well as firm performance (Boschma et al 2009; Neffke 2019), the more qualitative content of co-worker interactions tend to be between employees with similar skills. Hence, on the scale of the firm complementary skills induce spillovers although the more direct information flows are between similar agents. The significant random effects on the individual (1) and individual (2) levels indicate that dyadic variance is clustered by the individuals, which justifies the choice of multilevel approach.

Table 2.

The impact of skill relatedness and skill similarity on links in the advice seeking networks

Dependent variable:	Link in advice network		
	(A)	(B)	(C)
Independent variables:			
Skill relatedness	0.0321** (0.0134)		-0.0213 (0.0202)
Skill similarity		0.400*** (0.0970)	0.517*** (0.147)
Constant	0.0803 (0.0658)	0.0742 (0.0656)	0.0809 (0.0660)
Controls ¹	YES	YES	YES
<i>Random effects</i>			
Individual (1)	0.0163*** (0.00376)	0.0168*** (0.00384)	0.0170*** (0.00388)
Individual (2)	0.00426* (0.00228)	0.00372* (0.00220)	0.00361* (0.00218)
Dyad	0.0746*** (0.00410)	0.0738*** (0.00405)	0.0737*** (0.00405)
Observations (dyads)	910	910	910

Notes: coefficients (standard errors in parentheses) of cross-classified multilevel models.

¹ Controls: work experience (years), type of job (junior professional, senior professional or manager), gender and firm size

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

2.2 3.2 SKILL-RELATEDNESS AND THE GEOGRAPHY OF CO-WORKER TIES

The degree of skill similarity and relatedness vary depending on where these connections are located. Considering the geography of networks, on the one hand, a higher share of local contacts is associated with a higher relatedness of skills to other respondents in our sample ($r=0.16$, $p<0.001$), and a higher skill similarity ($r=0.19$). On the other hand, the share of global contacts correlates negatively with relatedness of skills to other people ($r= -0.14$), as well as with skill similarity to other people ($r= -0.16$). Similar results can be found *within firms* for skill similarity: The skills of those who have more global contacts tend to be less similar to the skills of their present co-workers, while skills of those who have more local contacts tend to be more similar. Consequently, not only are global contacts more likely to introduce additional skill-variety in itself, the persons having these contacts are also less similar to their co-workers and hence act as a bridge between localized knowledge and more global knowledge. A trade-off discussed in the conceptual cluster literature (c.f., Bathelt et al 2004), but to our knowledge never been systematically empirically shown for a detailed regional cluster (Bathelt and Turi 2011). Figure 5 illustrates these findings regarding relatedness and similarity of skills of all

respondents (Figure 5A, C) and of co-workers (Figure 5B, D). Here we separate between two categories of workers: few global contacts (0%, representing the lowest quartile) versus many global contacts (>15%, the highest quartile).

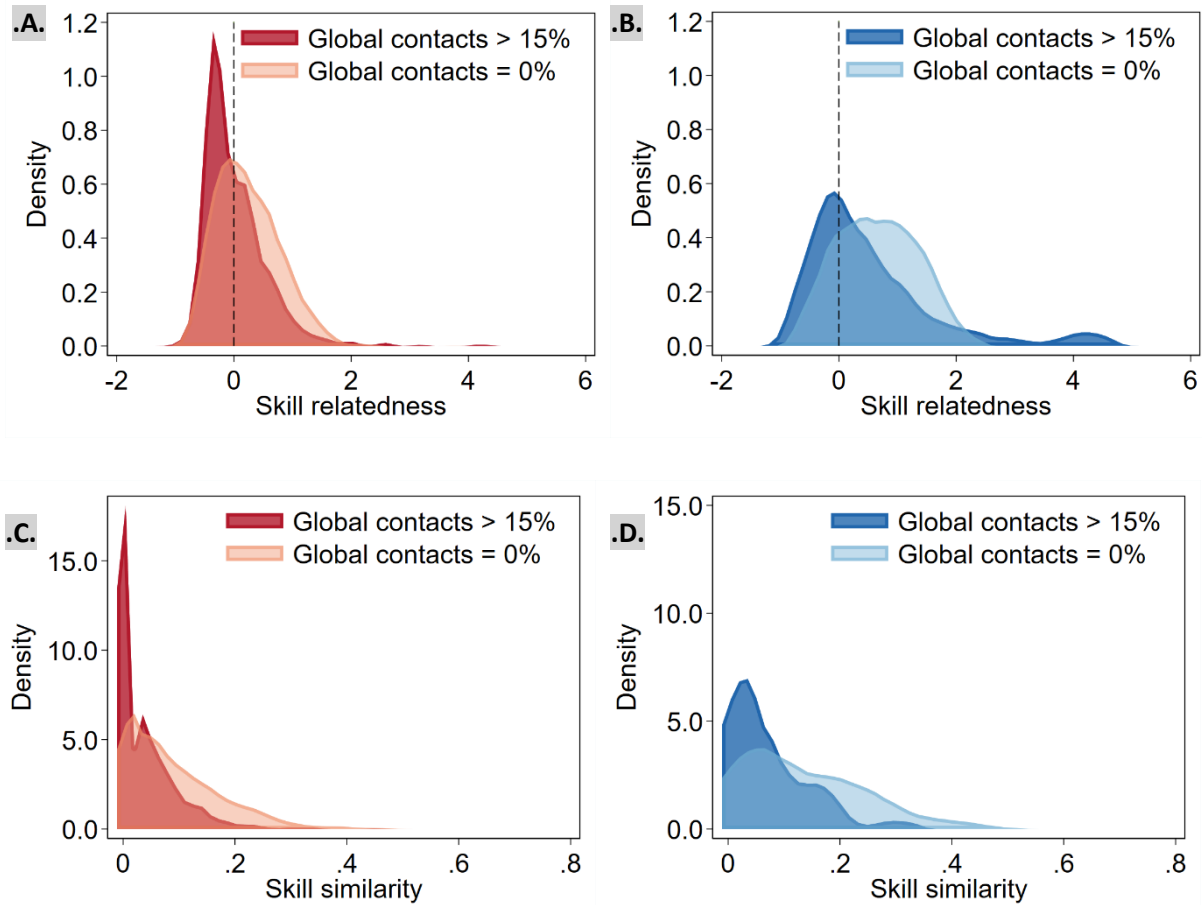


Figure 5.

Average relatedness (A-B) and similarity (C-D) of skills of persons with low | high share of global contacts. (A, C): All respondents, (B,D): Co-workers within firms. Findings suggest that similarity and relatedness of skills of workers to everyone else in the firm and the region is low in case the the individual has many global contacts.

To test the statistical significance of the findings reported in Figure 5, we estimate two additional cross-classified multi-level regressions:

$$R_{pq} = \alpha + \beta_1 LOC_p + \beta_2 GLOB_p + \beta_3 N_p + \gamma \mathbf{Controls}_p + \xi_p + \xi_q + \varepsilon_{pq}$$

(Eq .5a)

$$J_{pq} = \alpha + \beta_1 LOC_p + \beta_2 GLOB_p + \beta_3 N_p + \gamma \mathbf{Controls}_p + \xi_p + \xi_q + \varepsilon_{pq}$$

(Eq .5b)

In both equations, *LOC* denotes the share of local contacts within the person's LinkedIn connections, and *GLOB* represent the share of contacts outside Sweden. *N* represent the size of the individual's network on LinkedIn, and *Controls* include gender, work experience, job type and firm size.

We estimate both regressions on two samples. First, we consider all potential pairs of our respondents. The results obtained from these models are reported in Table 3 Panel A. Second, we restrict the sample to those dyads, where both persons work at the same firm (Table 3 Panel B).

The estimates suggest that a higher share of local contacts is associated with higher skill similarity *and* skill-relatedness to co-workers as well as to other ICT workers in the region. Once the share of local contacts is considered, having a higher share of global contacts (instead of national ones) is only significant in the model on skill-relatedness of all workers without individual- and firm-level control variables (Table 3 Panel A column 1). Nevertheless, the models are conclusive about our second research question, suggesting that globally embedded professionals' skills are less similar and less related compared to skills of locally embedded ones. The fact that the parameter of global contacts is not significant in column 2 indicates the presence of selection effects as certain positions tend to be more globally oriented². For example, having high share of global connections is positively correlated with being in managerial position. This confirms previous findings suggesting that hiring practices, especially more global-oriented employees, allow firms to tap into global sources of knowledge and thereby reduce the risk of cognitive inertia (Hassink 2010).

In fact, as indicated above, if at all being impactful, a high share of global contacts implies a greater diversity of skills. Having many connections, disregarding the type of skills involved, is also associated with lower skill similarity and skill relatedness to other workers in the region. In all, this suggests two dimensions of local knowledge formation. First, workers in a local industry with a relatively high local network density tend to have a distinct set of skills and competences. Secondly, a large network, consisting of high shares of non-local links, is more likely to bring new types of skills to the region. Hence, regional clusters (in this case ICT) develop distinct local capabilities that might be different from similar activities in other regions. In the conceptual literature, this is usually referred to untraded interdependencies that facilitate localized learning (Storper 1997; Malmberg and Maskell 2002). To avoid inertia and potential lock-in effects (Grabher 1993) it is therefore essential to also have global gatekeepers that can act as knowledge pipelines (Bathelt et al 2004) as well as being able to recruit more global-oriented employees (Hassink 2010).

² In addition, *N*. of observations is somewhat lower in the equations including controls. This is due to the survey data collection that left control variables missing in many cases.

These findings correspond to our expectations and verify that workers' local social connections are strongly related to the skill-set accumulated within the firm or the region. On the contrary, those workers who have established global connections in the past tend to deviate most from the local skill-set. Taken together the results presented in Figures 4 and 5 and Table 2, distant connections are important sources for accessing new skills in closely related local co-worker networks. Hence, as proposed in previous studies, a mix of local buzz and extra-local linkages is crucial for continuous renewal and competitiveness (Bathelt et al 2004; Bathelt and Turi 2011).

Table 3.

The impact of geography of networks on skill relatedness and skill similarity.

PANEL A				
Dependent variable	All workers			
	Skill relatedness		Skill similarity	
Independent variables				
share of contacts global ¹	-0.188*	-0.114	-0.0255	0.293
	(0.102)	(0.103)	(0.0195)	(0.362)
share of contacts local ¹	0.209**	0.173*	0.0371*	0.517*
	(0.104)	(0.0964)	(0.0198)	(0.308)
N of connections ²	-0.283***	-0.0296***	-0.0056***	-0.0056
	(0.0097)	(0.0097)	(0.0019)	(0.0345)
Constant	0.147**	0.00564	0.0665***	0.418
	(0.0646)	(0.0838)	(0.0121)	(0.266)
Controls ³	NO	YES	NO	YES
<i>Random effects</i>				
Individual (1)	0.000996***	0.0177***	0.0246***	0.0337
	(0.000162)	(0.00361)	(0.00443)	(0.0346)
Individual (2)	0.00164***	0.0642***	0.0516***	0.0845**
	(0.000204)	(0.00862)	(0.00687)	(0.0403)
Dyad	0.00321***	0.237***	0.233***	0.466***
	(5.74e-05)	(0.00454)	(0.00415)	(0.0473)
Observations (dyads)	6,493	5,663	6,493	5,663
<hr/>				
PANEL B				
Dependent variable	Co-workers			
	Skill relatedness		Skill similarity	
Independent variables				
share of contacts global ¹	0.338	-0.114	-0.0135	0.293
	(0.389)	(0.103)	(0.0684)	(0.362)
share of contacts local ¹	0.649*	0.173*	0.0993	0.517*
	(0.350)	(0.0964)	(0.0647)	(0.308)
N of connections ²	0.0257	-0.0296***	-0.0058	-0.0056
	(0.0373)	(0.0097)	(0.0064)	(0.0345)
Constant	0.236	0.00564	0.0930**	0.418
	(0.210)	(0.0838)	(0.0384)	(0.266)
Controls ³	NO	YES	NO	YES
<i>Random effects</i>				
Individual (1)	0.0907**	0.0177***	0.00548***	0.0337
	(0.0444)	(0.00361)	(0.00145)	(0.0346)
Individual (2)	0.0716**	0.0642***	0.00199***	0.0845**
	(0.0353)	(0.00862)	(0.000718)	(0.0403)
Dyad	0.464***	0.237***	0.00618***	0.466***
	(0.0458)	(0.00454)	(0.000640)	(0.0473)
Observations (dyads)	6,493	5,663	310	303

Notes: coefficients (standard errors in parentheses) of cross-classified multilevel models.

¹ Reference: national contacts ² Scale of N. of connections is 100 links. ³ Controls: work experience (years), type of job (junior professional, senior professional or manager), gender and firm size. *** p≤0.01, ** p≤0.05, * p≤0.1

2.3 3.3 EXTENSION: THE ROLE OF EDUCATION AND WORK EXPERIENCE IN CREATING LOCAL AND GLOBAL CONNECTIONS

Professional contacts are not exogenously given to workers. They evolve during workers' education and work histories (Dahl & Pedersen 2004; Snijders, Lomi & Torló, 2013). Therefore, it is worth extending our analysis by examining how the location of workers' education and work experience shape the geography of networks and the degree of skill similarity and relatedness.

We divided education and work experience of employees into three categories: local, national or global, akin to the categorisation of LinkedIn connections in Table 1 and 3. This assignment is based on the minimum distance rule, meaning that in case the employee had both local and global education or work experience previously in her/his career, education or work experience are defined local.

In Figure 6, we illustrate the strong relation of the geography of network contacts with the geographical category of education (A), and its' much weaker relation with work experience (B). The more global (local) the education is, the more likely it is to have more global (local) connections. Work experience, however, has a smaller effect on the degree of local contacts, although global contacts naturally are slightly more common for workers having experience of working abroad.

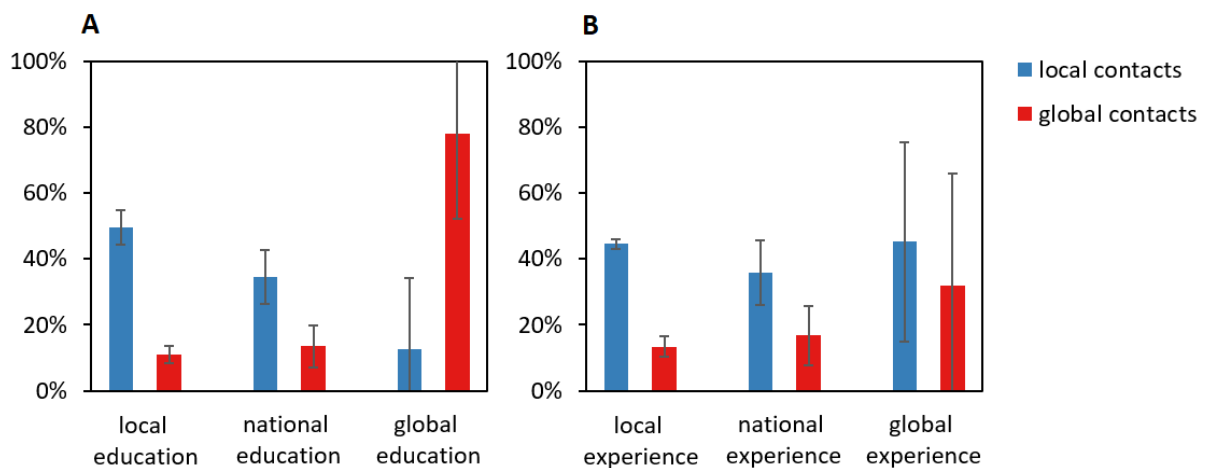


Figure 6.

Share of local and global contacts by education and work experience.

(A) Fractions calculated by education categories of workers. Bars denote mean and whiskers denote ± 2 standard errors. Individuals with global education have high share of global contacts, while individuals with local education have high shares of local contacts. (B) Fractions calculated by categories of work experience. Bars denote mean and whiskers denote ± 2 standard errors. Individuals with local work experience are embedded in local networks but global work experience does not make networks more global.

Again, by means of cross-classified multilevel models, we assess whether the geography of education and work experience not only influence the fraction of local vs global contacts, but the degree of skill similarity and relatedness. Our findings suggest that having a foreign education decreases skill similarity compared to having a national education. There is however no significant difference in the skill similarity and skill relatedness between different universities in Sweden. Workers educated in Sweden tend to have a higher degree of skill-relatedness to other workers compared to those educated abroad (Table 4, Column 1). We however find no significant associations between having foreign work experience and the skill composition (Table 4, Column 2), but having only local work experience increases relatedness of skills to other workers in the region.

Finding no effect of foreign work experience is not the result of controlling for having foreign education, since it is insignificant also when omitting that control (not reported in table). It can rather be the result of the weak correlation between work histories and the geography of networks. We however believe that the reason behind this is technical: if respondents did not update their LinkedIn profile recently, our measure for geography of the networks is not valid. We see that workers without any Swedish work experience report on average 40% local contacts, which may be explained by that those workers did not update their

profiles after coming to Sweden. On the other hand, education experience usually does not change after entering the labour force, therefore measuring education from LinkedIn is less sensitive to up-to-datedness of the profiles.

Table 4.

The impact of education and work experience on skill relatedness and skill similarity

Dependent variable:	Skill relatedness	Skill similarity
<i>Work experience</i> ¹		
Local	0.0868** (0.0419)	0.00995 (0.00880)
Foreign	0.138 (0.165)	0.0113 (0.0275)
<i>Education</i> ¹		
Local	0.0434 (0.0377)	0.00608 (0.00790)
Foreign	-0.296*** (0.113)	-0.0438* (0.0232)
N of connections ²	-0.0454*** (0.0090)	-0.0076*** (0.0019)
Constant	-0.0234 (0.0847)	0.0223 (0.0172)
Controls ³	YES	YES
<i>Random effects</i>		
Individual (1)	0.0150*** (0.00342)	0.000779*** (0.000150)
Individual (2)	0.0768*** (0.0102)	0.00204*** (0.000260)
Dyad	0.215*** (0.00454)	0.00327*** (6.90e-05)
Observations (dyads)	4,694	4,694

Notes: coefficients (standard errors in parentheses) of cross-classified multilevel models.

¹ Reference category: national. ² Scale of N. of connections is 100 links ³ Controls: work experience (years), type of job (junior professional, senior professional or manager), gender and firm size

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

CONCLUSIONS

The primary aim of this paper was to open the “black box” on the relation between firm-specific co-worker networks and external links across space to assess whether the geography of ties condition the degree of skill similarity. Our question is motivated by recent contributions arguing that firms and regions alike need to diversify their knowledge base in order to stay competitive and avoid cognitive lock-in (Grabher 1993, Boschma 2005). Combining detailed survey-data on the networks of 214 employees in 16 ICT-firms in the city of Umeå, Sweden, with automated online data collection on the professional networks of these individuals, we find that the geography of social connections indeed conditions the likelihood that firms (and hence regions) can access diverse knowledge.

Our findings suggest that there is a high relatedness of skills between co-workers compared to any random employee in the regional ICT industry. This finding supports the notion that firms develop certain capabilities that distinguish them from other firms in the industry (e.g., Penrose 1959). It is also consistent with the literature on knowledge specialization (Becker and Murphy 1992, Kogut and Zander 1993) and the resource-based approach of organization (Madhok 2002). We do however find here that the prevalence of complementarities is not only contingent on present co-worker networks, this also characterize professional networks via LinkedIn. Hence, workers are more likely to be connected to persons with related skills than any random person, both within the workplace, but also to other firms and regions. It is important to note that the observed correlation between the skills and being connected on LinkedIn can be positively biased by LinkedIn’s own recommendation algorithm.

Moreover, the geography of these ties also determines the degree of having access to diverse knowledge. Workers with more local contacts tend to be more similar to their co-workers and also have links to less diverse types of knowledge. This implies that recruiting key-personnel having broader national and global connections can act as a bridge to knowledge from those communities (c.f., Bathelt et al 2004, Hassink, 2010). This spatial dimension is also partly related to the size of the network as having more connections decreases skill similarity and skill relatedness to other workers in the region. This suggests that a large network, consisting of non-local links, is more likely to bring new skills to the region. For this global knowledge diversity to be absorbed and internalised in the local economy, a relatively coherent local knowledge base is required.

Finally, we show that the geographical location of education correlates with the geography of network contacts. Based on cross-classified multilevel models, we show that having a foreign education decreases skill similarity compared to local and national education. Considering relatedness of the non-similar skills, skills of the locally and nationally educated workers are the most similar to other workers in the region, while it is less related for those having foreign

education. These findings thereby suggest that ICT-related educations in general are relatively similar across different national universities compared to foreign educations. In particular, this suggests a team building mechanism based on “weak ties,” where existing team members manage complementary teams with related skills by hiring local peers known to have similar educations but lightly different skill specializations. In other words, this points towards the role of social networks to sustain matching externalities in industry-agglomerations (c.f., Eriksson and Lengyel 2019).

In sum, this research provides two distinct contributions. Compared to previous research on advice networks that identified the impact of formal positions and individual characteristics (eg. Lazega and Van Duijn 1997, Agneessens and Wittek 2012), value similarity (Lazega et al. 2012), local or global identification (Lomi et al. 2014) and team membership (Brennecke and Rank 2016) in network formation, we have shown that advice networks are formed along the skills of individuals. We thereby show that to develop mutual understanding and interactive learning, some similar or related skills are required between the two agents. Spatial proximity, as often assumed in the literature (Storper and Venables 2004), is simply not enough. In this aspect our conclusions are similar to Brennecke and Rank’s (2017) analysis of collaborations of patenting inventors at a high-tech firm. To the literature on knowledge flows in general, and labour mobility in particular, we have shown that the skill-content of such links is conditioned by the geography of contacts: More globally connected workers are more likely to both have more diverse skills and they are also connected to more diverse skills outside the firm compared to less globally connected co-workers in the firm. This is however greatly contingent on the type of job of the worker, as including such information by and large absorb the global “network effect”. Therefore, the positive impact of skill-similarity captured by education or industry experience in larger regions, not necessarily is a function of greater within-industry variety in larger regions (c.f., Timmermans and Boschma 2012). Instead, our results suggest that local networks offer access to complementary related skills beyond what can be captured by educational codes (degrees). For example, different skill-specializations within degrees. Hence, university networks may ease the matching of related skills through weak ties by giving additional information on the specialization of peers.

Although we explored interesting relationships between co-workers’ skills and their networks, this study is not without limitations and many questions remain open for further research. For example, the data used in this study is relatively small and confined to a specific geography and a specific industry. Having data on other ICT clusters could provide more robust estimates on what types of networks that matters where, while including more diverse industries may reveal different trends. Furthermore, although we have controlled for firm size, our sample is relatively homogenous, containing only small and medium sized companies. Therefore, examination of large MNEs may uncover further, or different mechanisms. As we

could see that some of these estimates are affected by the inclusion on individual attributes such as position in the firm and gender, further studies could delve deeper into these differences to help explain differences in, for example, career progression and collaboration patterns for men and women. Further, we have shown that skills and networks are related, but from the social network analysis perspective, it would be interesting to analyse how these two co-evolve over time. Having access to longitudinal data could allow more robust estimates controlling for both observed and unobserved individual attributes. In addition, from the organizational networks point of view, our findings may suggest that differences in the firms regarding how diverse or similar their workforce's skills are, imply different network structures, which support efficient cooperation. This could then be analysed in respect to wage formation and firm performance. For economic geography, our findings on the internal differences of skill-composition within firms would suggest that greater consideration needs to be taken when analysing within- and between-regional knowledge and information networks. Regional aggregates may actually reveal only fragments on the potential trade-offs between local and non-local links.

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