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Original Article

Leveraging the digital layer: the strength of weak and strong ties in bridging geographic and cognitive distances

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Abstract

Firms may seek non-redundant information through inter-firm relations beyond their geographic and cognitive boundaries (i.e., relations with firms in other regions and active in different fields). Little is known about the conditions under which firms benefit from this high-risk/high-gain strategy. We created a digital layer of 600,000 German firms by using their websites' textual and relational content. Our results suggest that strong relations (relations with common third partners) between firms from different fields and inter-regional relations are positively associated with a firm's innovation level. We also found that a specific combination of weak and strong relations confers greater innovation benefits.

Keywords: digital layer; weak and strong ties; proximity; innovation.

JEL classifications: C81, D83, L14, O31

1. Introduction

Firms build on different types of relations (e.g., scientific and supply-chain collaborations) as knowledge-sourcing channels to seek the knowledge and expertise required to solve problems, remove bottlenecks, and innovate (Haus-Reve, Fitjar, and Rodríguez-Pose 2019). Economic geography literature suggests that firms seek knowledge, resources, and skills from proximate peers (Boschma 2005; Torre and Rallet 2005; Boschma and Frenken 2010; Balland, Boschma, and Frenken 2015, Balland, Boschma, and Frenken 2022; Torre and Gallaud 2022). However, the knowledge and expertise required may be only available in geographically distant places or possessed by firms in different fields (i.e., cognitively distant ones). Also, firms have varying capacities to identify, absorb, and employ the knowledge required to innovate and solve problems. The proximity framework suggests that two firms close in multiple proximity dimensions (e.g., geographical and cognitive) can form inter-firm relations more easily. However, the proximity paradox implies that relations among firms that are too proximate provide minimum benefit for innovation (Boschma and Frenken 2010; Broekel and Boschma 2012; Balland,

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Boschma, and Frenken 2022). Although establishing geographically and cognitively distant relations exposes firms to non-redundant information, the literature remains agnostic about the conditions under which firms benefit from this high-risk/high-gain knowledge-sourcing strategy.

Economic geographers have discussed the importance of dyadic (i.e., two firms being proximate or not) and triadic (i.e., two firms being connected with a third common partner or not) factors in inter-firm relations (Balland, Boschma, and Frenken 2015; Balland, Belso-Martínez, and Morrison 2015; Ter Wal 2014; Ter Wal et al., 2016; Balland, Boschma, and Frenken 2022). However, scholars only recently claimed that these two levels should be viewed in one integrated framework. Recent debates in proximity literature suggest that the benefit of inter-firm ties between two firms depends on already-established relations (Balland, Boschma, and Frenken 2022).

This recent approach in the proximity debate speaks to the criticism of dyadic atomism by stressing that the connections between two firms are influenced by their direct and indirect connections to other actors. The portfolio perspective goes beyond the dyadic nature of proximity dimensions to understand better how inter-firm relations are formed. Importantly, this approach provides a better understanding of how inter-firm relations that share a third common partner (i.e., strong ties), as opposed to those without a third common partner (i.e., weak ties), may assist firms in innovating through interaction with firms in other regions or different fields.[1] Although the relevance of weak and strong ties in knowledge transfer and knowledge creation has been widely discussed in sociology, innovation studies, and network science, the notion of weak and strong ties has not been fully integrated into the proximity framework in economic geography (Granovetter 1973; Burt 1992, 2005; Aral and van Alstyne 2011; Aral 2016; Vedres 2021).

We integrate this perspective in the proximity literature (Balland, Boschma, and Frenken 2022) with the modes of innovation literature (Jensen et al., 2007) and argue that the knowledge exchange between two firms in different technological communities requires flexibility to handle the complexity of transferring tacit knowledge. These relations require a greater channel bandwidth that a higher degree of clustering can provide, that is, creating inter-firm relations with strong ties (Aral 2016). Similarly, two firms can exchange standardized and less complex knowledge pieces through channels with a smaller bandwidth (Aral 2016). Thus, weak inter-firm relations may better facilitate exchanging this type of knowledge (Mudambi 2008; Wu et al., 2008).

We used the Mannheim Enterprise Panel (MUP), comprising a list of German firms with their information and URL addresses. We created a digital layer of German firms by scraping their web texts and hyperlink relations. Next, we built on advancements in machine learning to approximate the firms' innovativeness (Kinne and Lenz 2021; Abbasiharofteh et al., 2023), specifically via an artificial neural network that analyzes web texts and predicts a product-innovator probability. Moreover, this study also pulled hyperlinks from 633,523 firms' websites and constructed a network of inter-firm relations based on 1,363,305 reciprocated hyperlinks.

The results show that the inter-firm relation types (i.e., strong versus weak) are a reliable predictor of firms' innovativeness. More precisely, strong relations connecting firms across different technological communities are positively associated with firms' innovation levels. However, both strong and weak inter-regional (WIR) relations are beneficial for innovation. The results also suggest that the joint effects of strong relations across technological fields and WIR relations more strongly relate to a firm's innovation level than other relation-type combinations.

The structure of this article is as follows. Section 2 reviews the notion of weak and strong ties and discusses them in the context of inter-firm knowledge transfers. Section 3 highlights the relevance of relational web data reflecting inter-firm relations and focuses on the empirical approach of the article. Section 4 presents and discusses the results. Section 5 highlights the main results and limitations and discusses methodological contributions and potential policy implications.

2. Knowledge transfer through weak and strong inter-firm relations

Knowledge sourcing is an interactive process in which firms acquire the knowledge and expertise necessary to overcome bottlenecks and solve problems. Effective knowledge sourcing expands the knowledge pool available for sharing and enhances firms' innovation levels (Weitzman 1998; Fleming 2001).

[1] Note that the term *strong tie* is equivalent to structurally embedded ties. We use the terms relations and ties interchangeably.

Evolutionary and relational approaches in economic geography have fostered an upsurge in empirical studies that investigate knowledge sourcing as a path-dependent process (Bathelt and Glückler 2003; Boschma and Martin 2010). Empirical evidence suggests that two firms are more likely to exchange knowledge if they colocate (geographical proximity), use similar technologies (cognitive proximity), and share a common collaboration partner (triadic closure) (Giuliani 2007, 2013; Molina-Morales et al. 2015; Lazzeretti and Capone 2016; Abbasiharofteh and Dyba 2018; Capone and Lazzeretti 2018; Giuliani, Balland, and Matta 2018; Juhász and Lengyel 2018; Abbasiharofteh and Broekel 2021; Simensen and Abbasiharofteh 2022). Although proximate firms tend to interact more easily, the potential benefits for innovation drop if proximity exceeds a certain threshold (Boschma and Frenken 2010; Broekel and Boschma 2012). However, establishing inter-firm relations with firms in other regions or different technological communities may enable firms to tap into diverse external knowledge sources. The proximity paradox emphasizes that the high-risk/high-gain knowledge-sourcing strategy, if successful, contributes to firms' innovativeness by exposing them to non-redundant information (Broekel and Boschma 2012).

Although many empirical studies have investigated the impact of proximity dimensions on the formation of inter-firm relations (for a review, see Balland, Boschma, and Frenken 2022), less attention has been paid to the conditions under which firms' innovativeness benefits from geographically or cognitively distant inter-firm relations. To address this gap, we underline a critical element of innovation processes: the nature of exchanged knowledge (Asheim and Coenen 2005; Boschma 2005; Asheim and Gertler 2006; Jensen et al., 2007).

The seminal contribution of Jensen et al. (2007) defines and juxtaposes two distinct innovation modes. The first, known as the science, technology, and innovation (STI) mode, includes the creation and application of codified scientific and technical knowledge. The second, the doing, using, and interacting (DUI) mode, comprises informal and experience-based knowledge exchange. The STI mode primarily relies on the codified knowledge of know-what and know-why types of knowledge, whereas the DUI mode is based on the tacit knowledge of know-how and know-who (Haus-Reve, Fitjar, and Rodríguez-Pose 2023).

Moody (2011) claims that if the nature of knowledge makes it hard to transfer, strong ties may need to link actors to benefit from in-group cooperative effects. Similarly, Aral (2016) and Aral and van Alstyne (2011) argue that strong ties benefit an information environment with multiple topics and rapidly changing information. Bruggeman (2016) and Wu et al. (2008) extend this research by empirically showing that strong ties are better channels for transferring complex knowledge. Multiple empirical studies support this theoretical argument by showing the advantages of creating strong ties (Hansen 1999; Uzzi 1997; Uzzi and Spiro 2005; Lingo and O'Mahony 2010; Obstfeld 2016). Building on these empirical findings, Aral (2016) suggests a modern strength-of-weak-ties theory that acknowledges previous pioneering works (Granovetter 1973; Coleman 1988; Burt 1992) and considers the content's specificity in the knowledge transferred.

Economic geographers argue that the increasing pace of advancement and complexity in technologies call for a more intense tacit knowledge exchange (Broekel 2019; van der Wouden 2020). As a result, knowledge sourcing more often leads to a situation in which "we can know more than we can tell" (Polanyi 1966). To meaningfully communicate tacit knowledge, Nelson (1989) and Krackhardt (1992, 1999) underline the importance of strong ties, which are mutual and embedded in a clique (also known as Simmelian ties). These scholars argued that strong ties are associated with transcending individual interests and reducing bargaining power and conflict within groups. Thus, strong knowledge ties related to the normative power of groups may contribute to innovation by facilitating tacit knowledge transfer through trust building, altruistic reciprocity, and lower transaction costs (Heider 1958; Coleman 1988).

Broekel (2019) shows that relations between firms in different fields have increasingly hampered the benefit of such relations. This implies that knowledge does not spread among firms if the cognitive distance between them exceeds a certain threshold (Nooteboom 2000). Firms tend to collaborate with other firms operating in the same or related economic activities. As a result, one might expect to observe denser inter-firm relations among firms involved in the same technological community and relatively fewer inter-community relations (Fig. 1). Besides that, the path-dependent nature of knowledge sourcing increases the likelihood of forming intra-community ties (Boschma 2005; Glückler 2007; DiMaggio and Garip 2011; Tóth and Lengyel 2021). Thus, inter-community ties might need wider

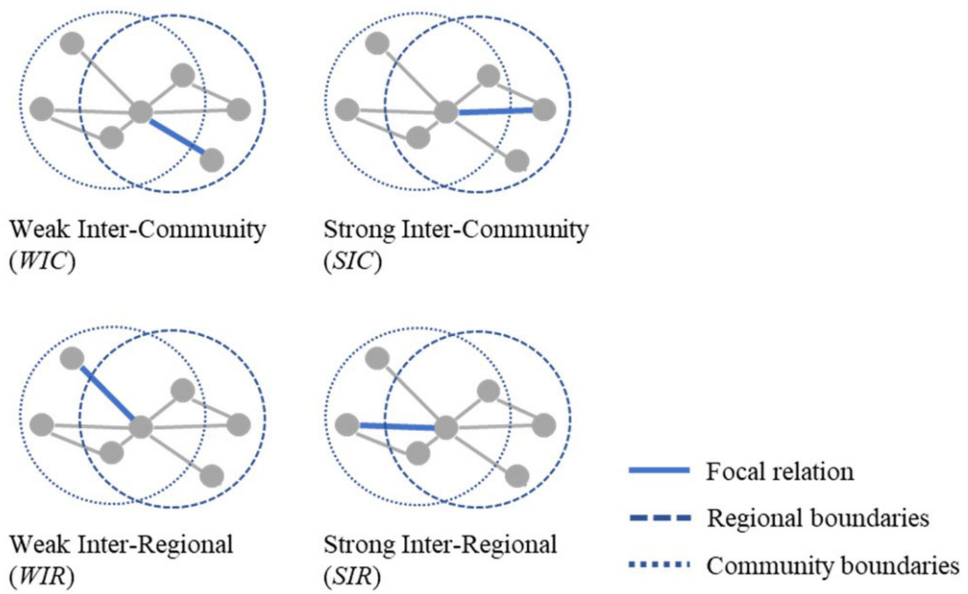

Figure 1. Schematic illustration of the four bridging types.

bridges (i.e., strong ties) to counterbalance the negative effect of cognitive distance. Explicitly, Tortoriello and Krackhardt (2010: 168) claim that "mere bridging is not enough" and indicate that innovative activities need strong relations to enable firms to exchange knowledge effectively. Therefore, one can expect strong ties to enhance the effectiveness of tacit and complex knowledge transfer (Aral and van Alstyne 2011; Aral 2016). Following these lines of argument, we hypothesize that:

Hypothesis 1a. Strong inter-community (SIC) relations are positively associated with innovation in firms.

Hypothesis 1b. Weak inter-community (WIR) relations are not positively associated with innovation in firms.

The impact of colocation on innovation has been discussed since Marshall's work (1890), in which he claimed that firms benefit from various aspects of colocation, summarized as sharing, matching, and learning mechanisms (Duranton and Puga 2004). Classical studies provide empirical evidence of the multiple benefits of the colocation of firms (Porter 1990; Saxenian 1994; Audretsch and Feldman 1996). However, more recent economic geography studies (Fitjar and Rodríguez-Pose 2016) imply that colocated firms do not equally benefit from Marshallian externalities (Giuliani 2007). Colocation is effectively an enabler factor through which firms can transfer and disseminate tacit knowledge (VonHippel 1987; Gertler 2003).

Although geographical proximity facilitates mutual interactions and learning, too much geographical proximity may exhaust the potential sources of novelty and excessive lock-in effects (Glückler 2013; Torre and Gallaud 2022). Firms may strategically establish inter-regional relations to counterbalance the negative externalities associated with too much geographical proximity. However, the nature of exchanged knowledge determines whether firms can successfully absorb and employ the knowledge transferred from distant places. Knowledge codification (i.e., expressing knowledge in numbers, diagrams, text, etc.), standardization, and education and training enable firms to transfer knowledge more effectively over greater distances (Gertler 2003; Jensen et al., 2007). In other words, the exchange of codified knowledge helps two firms connect at great geographic distances, which makes regular face-to-face meetings and spontaneous informal encounters impossible. Therefore, we conjecture while the exchange of tacit and complex knowledge remains highly local, firms can more effectively exchange codified and less complex knowledge through inter-regional relations. This conjecture resonates with recent empirical findings.

Several economic geography studies support our conjecture. Mewes (2019), Balland et al. (2020), Balland and Rigby (2016), and Balland et al. (2022) show the geographic concentration of atypical, complex, and inventive economic activities perhaps because such activities require a greater degree of tacit knowledge exchange.

Similarly, Mudambi's (2008) study shows that companies in knowledge-intensive industries tend to identify and control the "creative hearts" of the production process and outsource other activities. Activities associated with the former are geographically concentrated, whereas the latter are geographically dispersed. Mudambi uses the case of the iPhone as an example to show Apple geographically clusters basic and applied R&D, design and commercialization, and marketing in the USA and disperses somewhat standardized activities, such as chip manufacturing and assembly lines, in South Korea and Taiwan.

Considering the structural properties of inter-firm relations, Aral (2016) and Aral and van Alstyne (2011) suggest that actors benefit from weak ties most if an environment entails few topics and slowly changing information. Weak ties are not embedded in a clique (also known as non-Simmelian ties). The seminal work of Granovetter (1973) points toward the structural properties of weak ties, which provide actors with non-redundant information. Granovetter defines weak ties as relations that connect parts of a given network not already connected (i.e., structural holes). Burt (1992) builds on the strength-of-weak-ties theory and shows that actors who bridge structural holes are more likely to tap into diverse knowledge sources. This mechanism may work because occupying such network positions enables actors to monitor and control the flow of information, consequently, giving them access to diverse information (Reagans and Zuckerman 2001; Burt 2004). Bruggeman (2016) and Wu et al. (2008) provide evidence that simple knowledge transfers better through weak ties. The modern strength-of-weak-ties theory implies that geographically distant relations are beneficial when they focus on fewer and less complex themes that firms can absorb and use more easily (Aral 2016). This may explain the recent empirical findings of Balland and Boschma (2021), which indicate that inter-regional relations benefit firms in regions with complementary capacities. Thus, we argue that weak ties are particularly beneficial for nonlocal inter-firm relations that channel rather focused, standardized, and less complex knowledge pieces (Fig. 1). We suggest the following hypotheses.

Hypothesis 2a. WIR relations are positively associated with innovation in firms.

Hypothesis 2b. WIR relations, compared to strong inter-regional (SIR) ones, are more strongly associated with innovation in firms.

Innovation performance requires novel and useful combinations of existing knowledge and ideas (Weitzman 1998; Fleming 2001). Through this process, firms recombine the absorbed knowledge through different channels. Organizational learning literature suggests that innovative firms can benefit from exploration and exploitation as complementary processes (Tushman and O'Reilly 1996; Hoang and Rothaermel 2010). Perri, Silvestri, and Zirpoli (2021) review knowledge base and industrial dynamics studies in the management literature and suggest that tacit and codified knowledge complements (and does not substitute) one another in the innovation process. Similarly, Jensen et al. (2007) demonstrate that companies that integrate both STI (relying on codified knowledge) and DUI (relying on tacit knowledge) innovation modes are more inclined to introduce new products or services than those heavily dependent on a single mode.

In economic geography, scholars argue that knowledge production can be seen as an optimal combination of close and distant relations (Oinas 1999; Schilling and Phelps 2007; Breschi and Lenzi 2016; Whittle, Lengyel, and Kogler 2020). Conceptually, Bathelt, Malmberg, and Maskell (2004) discuss the advantages associated with the coexistence of local and global relations to source different types of input for innovation (i.e., local buzz and global pipelines). Bathelt, Malmberg, and Maskell (2004: 46) stress that "it seems reasonable to assume that the information that one cluster firm can acquire through its pipelines will spill over to other firms in the cluster through local buzz." According to Aarstad, Kvitastein, and Jakobsen (2016), however, local interactions influence exclusively the innovativeness of small- and medium-sized enterprises. Moreover, firms' sourced knowledge from distant areas may function as "external stars" and not contribute to knowledge generated from other places (Morrison 2008; Giuliani, Balland, and Matta 2018).

To reconcile the concepts of local buzz and global pipelines with empirical findings, we alternatively argue that the coexistence of WIR relations and SIC ties contribute to innovation in firms. Ter Wal et al. (2016) show the benefits of combining such relation types because they provide access to diverse inputs. They argue that the shared interpretive schema eases the interpretation of knowledge exchanged via weak specialized ties. In contrast, shared third-party ties (i.e., strong ties) facilitate interpreting cognitively distant knowledge in closed diverse networks. Therefore, we conjecture that firms benefit most from concurrently creating SIC and WIR inter-firm relations. Based on this rationale, we predict that:

Hypothesis 3: The joint effects of SIC and WIR relations are more strongly associated with firms' innovation than a combination of other relation types.

3. Empirical approach

3.1 Data

In economic geography, quantitative empirical studies investigating the processes of knowledge sourcing mostly use secondary data on patents, scientific publications, and R&D projects (Bettencourt, Lobo, and Strumsky 2007; Lobo and Strumsky 2008; Strumsky and Lobo 2015; Breschi and Lenzi 2016; Juhász and Lengyel 2018; Abbasiharofteh and Broekel 2021; Balland et al. 2020). Although these studies have contributed immensely to the understanding of how firms create, maintain, and dissolve knowledge ties, more recently, scholars have called for the use of alternative firm-level databases to address unresolved research questions in economic geography (Duranton and Kerr 2018; Fritsch, Titze, and Piontek 2020).

The Internet "can be thought of as a self-organizing social system: individuals, with little or no central oversight, perform simple tasks: posting web pages and linking to other Web pages" (Mitchell 2009: 10). Hyperlinks are considered the "basic structural element of the Internet" (Park 2003: 49). They allow users to take different paths throughout the Internet, revealing other communication structures among people, organizations, and institutions.

Heimeriks and van den Besselaar (2006) found that "web data can be meaningful in mapping the aspects of knowledge production" on how linking patterns reflect research field development in scientific organizations. Vaughan, Gao, and Kipp (2006) found that inter-firm hyperlinks represent business relations. Abbasiharofteh et al. (2023) analyzed the hyperlink network of 600,000 German firms and also found that most hyperlinks represent business relations.

In this study, we created a digital layer of German firms. We built on the MUP of 2019 that covered all firms in Germany and is updated semiannually. MUP includes firm-level information, including web addresses (URL), of 1,155,867 firms (URL coverage of 46%). Prior analyses of this dataset (Kinne and Axenbeck 2018, 2020) show that comparatively low URL coverage was found, for example, in the subgroup of young and small companies. In contrast, companies with more than twenty-five employees were almost completely covered. We geocoded firms based on their postal addresses (five-digit level) and street names.

For each firm, we scraped the web text and hyperlinks of a maximum of twenty-five (sub-)webpages. These web pages were not randomly selected but follow a simple process. Preference was given to (sub-)webpages written in German with the shortest URL. The latter was intended to ensure that more general (top-level) content was downloaded. For example, "company.com/about-us" would be downloaded before "company.com/news/2019/august." After we excluded erroneous downloads and potentially misleading redirects, 633,523 firms remained in the dataset.

We then constructed a directed network of firms based on the hyperlinks on their websites (3,062,670 ties). In using these hyperlinks as a proxy for knowledge-sourcing ties, we took a more conservative approach. We included only reciprocated ties in the network (1,363,305 ties). This means a tie exists between firm A and firm B only if both firms have hyperlinks to each other's websites. This approach aligns with the rationale behind weak and strong ties. Two firms are strongly tied (Simmelian tie) if they are reciprocally connected to each other and at least one common firm (Krackhardt 1999). Accordingly, two firms are weakly tied (non-Simmelian tie) if they are reciprocally connected to each other and not reciprocally connected to one or more common firms. Figure 2 shows the locations of all firms in the digital layer dataset and a sample of hyperlink connections between them.

Following the work of Tsamenyi et al. (2010), we classified inter-firm hyperlinks into three main categories: joint venture (e.g., joint research), outsourcing (e.g., training, advice-seeking, and marketing), and supply-chain relations. Based on the data structure, we added one more category to those

Figure 2. Visualization of firm locations and the intensity of inter-firm hyperlink connections at the national level.

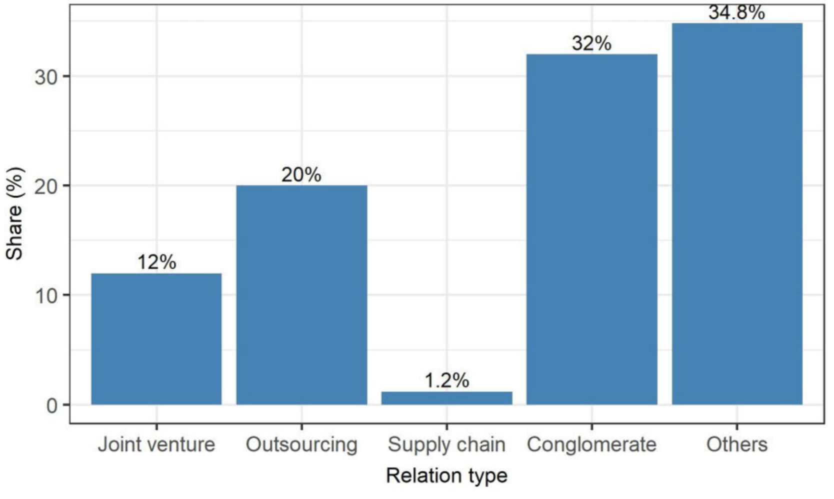

Figure 3. Classifying randomly selected inter-firm hyperlink relations.

suggested by Tsamenyi et al.—links among firms within a conglomerate. We manually checked and classified 500 randomly selected hyperlinks based on a webpage's title and hyperlink ambient texts. For instance, *Firm X [hyperlink] and Firm Y [the citing firm] formed a partnership … giving both parties a great …* In this case, we manually tagged the hyperlink as a joint venture relation based on the information the hyperlink ambient text provided. Figure 3 shows the result of our manual check. Notably, the other category consists of heterogeneous relations that do not fall into any of the four main

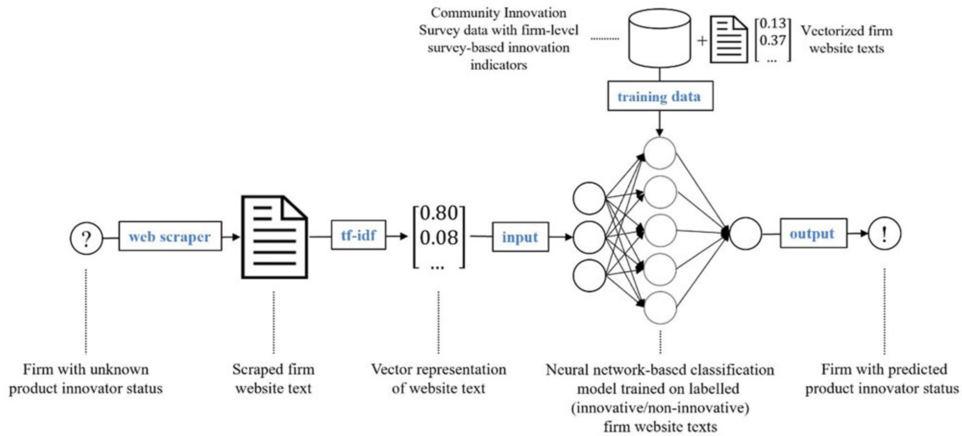

Figure 4. Schematic representation of the InnoProb model for evaluating text from corporate websites. Adapted from Kinne and Lenz (2021).

categories. Developing a method to classify 1,363,305 mutual hyperlinks is beyond the scope of this study, and we leave this to future research.

3.2 Dependent variable

3.2.1 Web-based innovation indicator

We approximate firms' innovativeness by estimating *InnoProb*, as suggested by Kinne and Lenz (2021). *InnoProb* corresponds to "predicted product innovator probability," estimated by a web-scraping method in which an artificial neural network assesses firms' web texts (see Fig. 4). The artificial neural network acts as a text classification model, which analyzes the input texts and then outputs *InnoProb* values for each firm. More precisely, it estimates the likelihood of the examined texts originating from a company that has launched new or significantly improved products to the market in the past three years and can, therefore, be considered a "product innovator" per the Oslo Manual (OECD 2018). The training process centers on the German Community Innovation Survey (CIS), which ascertains whether a company has introduced new or significantly improved products or services within the previous 3-year period, including innovation types both new to a firm and new to the world.

3.2.2 InnoProb training phase

Kinne and Lenz (2021) trained a model through the web texts of German companies that participated in a traditional innovation survey. They utilized the German CIS, which asked about 12,000 companies about their innovation activities, including whether they are product innovators. For the *InnoProb* model-training stage, all texts from the surveyed companies' websites were downloaded, vectorized according to the *tf-idf* (term frequency-inverse document frequency) scheme (e.g., see Manning, Raghavan, and Schutze 2009), and used, along with the information on whether the company is a product innovator, as training data for a deep neural network (Kinne and Lenz 2021).

In this study, we utilized the algorithm developed by Kinne and Lenz (2021) for the same digital layer dataset. To follow their suggested procedure, we used the *tf-idf* algorithm to transfer each document into a sparse vector of fixed size V, where V is the size of a dictionary consisting of all words found in the entire text corpus. We restricted our dictionary to words with a minimum document frequency of 1.5 per cent and a maximum document frequency of 65 per cent (popularity-based filtering), resulting in a dictionary size V of 6,144 words. Each entry in a document's *tf-idf* vector corresponds to a word in the dictionary, representing that word's relative importance in the document (i.e., website). A zero value represents words that do not occur in a given document. The intuition behind the *tf-idf* method is that ubiquitous words in documents should be weighted less than less common words because rare words are more useful as discriminators.

The deep neural network consists of four hidden layers with intermediate dropout layers designed to improve the network's generalization by ignoring (dropping) neurons during training. The first hidden layer of the network consists of 250 neurons, the following two hidden layers consist of only five

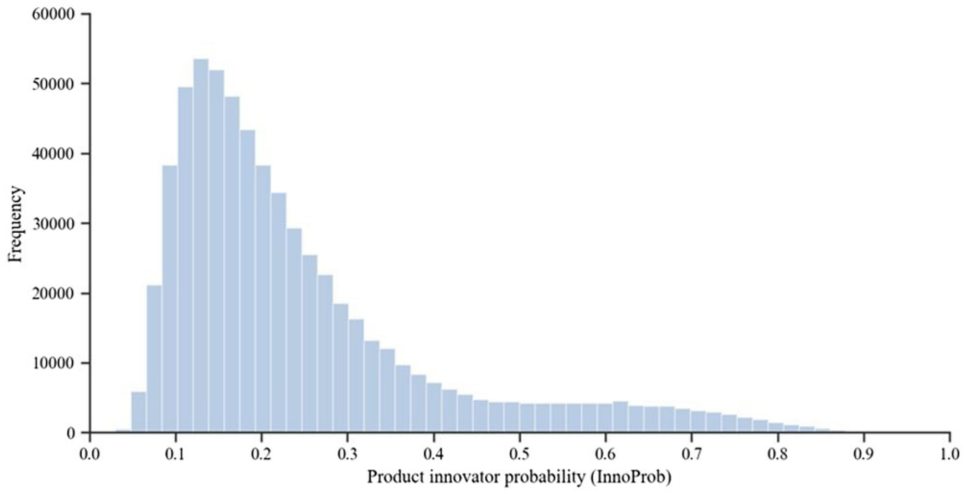

Figure 5. Distribution of product innovator probability (*InnoProb*) scores.

neurons each (the bottleneck), and the fourth and final hidden layer contains 125 neurons. We used scaled exponential linear units as activation functions in the hidden layers. The output layer of the network consists of a single neuron with a sigmoid activation function, a common approach in obtaining an output between zero and one from a neural network in binary classification tasks. We used the usual Adam optimization algorithm for the stochastic optimization of the network weights.

During the training phase, the model learns which words and word combinations characterize the texts of a product innovator. Notably, the input for the training phase relies solely on the textual content of websites without considering any information derived from the hyperlink network. Thus, measuring firms' innovativeness is not driven by the attributes of the hyperlinks (e.g., links to large or innovative firms) included on the firms' websites. After training, the model can assess the website texts of any (out-of-sample) firm and predict its product-innovator probability. These *InnoProb* scores range from zero (unlikely product innovator) to one (likely product innovator). Supplementary Appendix A provides a detailed account of the validation of *InnoProb*.

3.2.3 InnoProb as the dependent variable

For this study, we calculated the firm-level *InnoProb* scores for all 633,523 companies in our dataset (Fig. 5). Subsequently, we binarized these raw *InnoProb* scores using a classification threshold corresponding to the 90th percentile (0.5) to obtain a binary (dummy) dependent variable (*INNOVATIVE*). Compared to the recommended classification threshold of 0.4 by Kinne and Lenz (2021), we opted for a strict classification approach to minimize the share of false positives in the firms classified as innovative. As discussed later, we selected alternative thresholds for the *InnoProb* classification and replicated the empirical analysis.

3.3 Independent variables

The main variables of interest approximate the extent to which each firm is connected to others through weak and strong relations. We defined inter-regional relations as inter-firm hyperlinks that cross regional boundaries at the NUTS-2 level.

Identifying ties that connect firms from different technological communities is not straightforward. We built on a large body of empirical evidence in economic geography indicating that cognitive proximity is a driving force of inter-firm tie formation (Ter Wal 2014; Balland, Belso-Martínez, and Morrison 2015; Lazzeretti and Capone 2016; Juhász and Lengyel 2018; Boschma et al., 2023). This may be because combining similar knowledge is more straightforward, reduces uncertainty, and lowers adjustment costs (Hidalgo et al., 2018; Boschma et al., 2023). The knowledge base literature suggests that cognitively proximate firms establish relations as they are involved in similar associated networks and have access to specialized resources, skills, and competencies (Asheim and Coenen 2005). Other factors reinforce tie formation between cognitively proximate firms (Abbasiharofteh 2020). For instance, if two firms are indirectly linked through a common partner at time t_1, they likely will establish a relation at t_2. This translates into more ties between firms within a technological community and fewer relations across communities. From a network perspective, we expect densely connected segments of an inter-firm network to represent relations within communities. Similarly, relations between loosely connected communities illustrate the interactions of firms in different technological communities (Girvan and Newman 2002; Palla et al., 2005). A community detection algorithm[2] enabled us to identify firms' communities.

To measure the extent to which each firm weakly or strongly bridges distances, we use the *E-I index* suggested by Krackhardt and Stern (1988).

$$E - I\ index = \frac{E_i - I_i}{E_i + I_i} \tag{1}$$

E denotes the number of ties firm *i* has with firms that belong to groups other than the firm *i*'s group (i.e., different regions or technological communities). Accordingly, *I* represents the number of ties that *i* has with firms belonging to the same group (i.e., the same region or technological community). The minimum value corresponds to minus one if a firm has only within-group ties, and the maximum estimated value corresponds to one if a firm has only between-group ties. We estimated the bridging index for each bridging type separately. After estimating *SIR*, *WIR*, *SIC*, and *WIC*, we standardized the four variables by expressing them as z-scores[3] (mean: 0 and standard deviation: 1). This enables us to interpret the estimated coefficients of regression models more easily.

3.4 Controls

To ensure the robustness of our results, we constructed multiple control variables. Following similar empirical studies, we categorized controls into three groups: 1) network,[4] 2) firm, and 3) regional levels (Lobo and Strumsky 2008; Tortoriello and Krackhardt 2010; Breschi and Lenzi 2016; Balland et al., 2018; Bergé, Carayol, and Roux 2018; van der Wouden and Rigby 2019; Abbasiharofteh and Broekel 2021). Moreover, we included a set of dummy variables to control for the heterogeneities across forty-two sectors (i.e., Sector FE). Table 1 and Supplementary Appendix B provide a description and descriptive statistics of the variables, respectively.

4. Results and discussion

We investigated first the spatial dimension of firms' innovativeness (approximated by *InnoProb*). Figure 6 shows that large cities in western Germany are home to more innovative firms. In contrast, firms in regions in peripheral areas, especially in the former German Democratic Republic, are less innovative. This spatial pattern resonates with anecdotal evidence and empirical studies discussing Germany's still existing east–west divide (Fritsch and Slavtchev 2011; Abbasiharofteh and Broekel 2021). However, large cities in eastern Germany, such as Dresden, Greifswald, and Jena, score high on *InnoProb*. Firms in these cities may benefit from their agglomeration, large universities, and inter-regional, inter-firm relations.

Interestingly, the variance of *InnoProb* scores across regions strongly correlates with *InnoProb* average scores.[5] In other words, one observes a greater intra-regional inequality in innovation in more innovative regions on average. For instance, Munich and Münster are among the regions with the highest average and variance in *InnoProb* scores. This finding supports the conjecture that innovation is linked to increased intra-regional inequality (Boschma, Pardy, and Petralia 2023).

A wide range of studies shows that the centrality of firms in a knowledge-sourcing network is positively associated with firms' innovativeness (Giuliani and Bell 2005; Eriksson and Lindgren 2008; Chandler et al., 2013; Abbasiharofteh et al., 2023). Therefore, we explored the degree distribution of inter-firm relations (inter-firm hyperlinks). Figure 7 suggests that the degree distribution is highly

[2] We used the multilevel community detection algorithm because it is efficient (time complexity: $\mathcal{O}(N\ logN)$) and provides the most reliable results given the size of the investigated network (Yang, Algesheimer, and Tessone 2016).
[3] z-score = (x-$\bar{x}$)/sd(x), where $\bar{x}$ and sd(x) are the mean and standard deviation of x, respectively.
[4] To estimate network-level variables, we used the "igraph" R package developed by Csardi and Nepusz (2006).
[5] The regions' average and median values of *InnoProb* strongly correlate (Pearson correlation coefficient: 0.96).

Table 1. A short description of variables.

Category	Type (range)	Method	Variable name
Explanatory variables	Continuous (−2.97, 2.27)	The number of external inter-firm relations (type: strong or WIR relations, or strong or WIC relations) subtracted by internal relations of the same type, divided by the total number of firm's relations of the same type (see Equation 1). These variables are standardized (mean: 0 and standard deviation: 1).	*SIR*
	Continuous (−1.80, 0.99)		*WIR*
	Continuous (−2.82, 3.32)		*SIC*
	Continuous (−1.01, 2.59)		*WIC*
Network level controls	Continuous (0.69, 11.85)	The log-transformed count of relations (reciprocal hyperlinks) a firm has; also known as degree centrality.	*DEGREE*
	Continuous (0.00, 18.95)	The log-transformed sum of *DEGREE* of a firm's neighbors.	*ALTER*
	Continuous (0.00, 1.00)	The probability that the neighbors of a firm are connected (Wasserman and Faust 1994).	*TRANSITIVITY*
Individual level control	Continuous (0.65, 6.93)	Age[a] of firms in years (log-transformed).	*AGE*
Regional level control	Dummy (0 or 1)	This variable takes the value of 1 if a firm is located in a metropolitan region (defined by Eurostat) and takes the value of 0 otherwise.	*METROPOL*
	Dummy (0 or 1)	This variable takes the value of 1 if a firm is located in the former East Germany (GDR) and takes the value of 0 otherwise.	*EAST*
	Continuous (0.00, 8.28)	The log-transformed count of firms within a 1 km radius around a given firm (all firms in the MUP dataset are considered, not only the ones in our network).	*FDENSITY*
	Continuous (8.41, 10.7)	The log-transformed count of firms in the NUTS-2 region, in which a given firm is located.	*RFDENSITY*

[a] A small number of companies have very large *AGE* values, which represent old family businesses and breweries.

skewed (average degree: 4.3, median: 2), implying few firms have numerous relations, whereas most firms have established few relations. This power law-like degree distribution resembles the networks created by the preferential attachment mechanism (Barabási and Albert 1999). We estimated logit models showing the positive relationship between firms' connectivity and patent holder status in the past 10 years (see Supplementary Appendix C). The finding aligns with Doloreux and Mattson's (2008) work, showing that incorporating external cooperation in innovation processes positively associates with firms' capability to create and introduce novel or enhanced goods, services, and processes. We also plotted the distribution of *InnoProb* stratified by sector (see Supplementary Appendix D). The descriptive statistics suggest that *InnoProb* follows a similar distribution pattern across industries, peaking around 0.12. However, Kolmogorov–Smirnov tests show that only a few sectors have statistically similar *InnoProb* distributions.

We estimated multiple logit models to investigate whether establishing WIR and SIC relations correlates with firms' innovation levels. Table 2 shows the results. The goodness of fit improves as more variables are introduced, and the full model provides the best fit. Because the results are consistent across all models and the full model (Model 6) provides the best goodness of fit, we interpret and discuss the full model results. This section analyzes the results related to the four independent variables of interest. Supplementary Appendix E reports and discusses the coefficients of controls.

The four variables relating to different inter-firm ties positively correlated with firms' product-innovator probability. However, the positive coefficient of WIC ties is not statistically significant. The presence of *SIC* relations significantly relates to firms' innovativeness, whereas we do not observe the

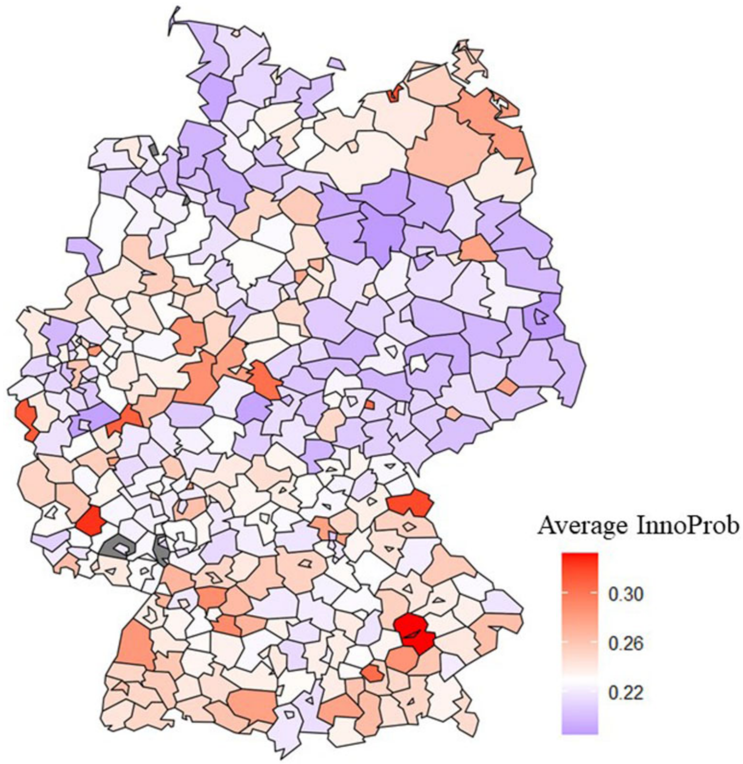

Figure 6. The average firms' *InnoProb* across NUST3 regions.

Note: The average and median values strongly correlate (the Pearson correlation coefficient: 0.96)

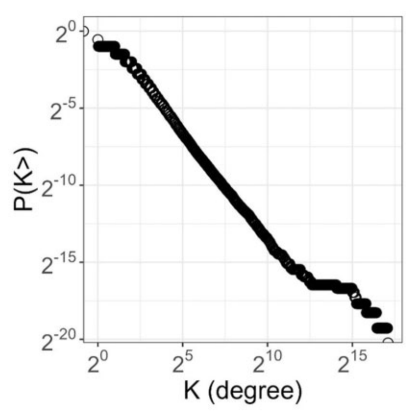

Figure 7. The degree distribution of firms' relations on the web on a log-log plot.

Note: *K* represents the number of relations (also known as degree centrality), and *P(K>)* denotes the probability of having *K* or fewer relations.

same association between *WIC* relations and the dependent variable. Though most economic geography studies focus on individual and regional factors to account for firms' innovativeness, the relevance of the meso-level (community level) is often ignored to some extent. A recent economic geography study discussed the importance of this level of analysis. It showed that collaborative ties among specialized and cognitively distant communities are critical for enabling regions to introduce unconventional innovations (Abbasiharofteh, Kogler, and Lengyel 2023). However, this study said nothing about which attributes of such inter-community ties may improve the quality of knowledge sourcing. Our

Table 2. Logit regression estimation results.

	Dependent variable: INNOVATIVE					
	(1)	(2)	(3)	(4)	(5)	(6)
SIR		0.1839***				0.1606***
		(0.0061)				(0.0062)
WIR			0.2045***			0.1901***
			(0.0069)			(0.0070)
SIC				0.0876***		0.0813***
				(0.0058)		(0.0059)
WIC					−0.0031	0.0039
					(0.0060)	(0.0061)
DEGREE	0.3605***	0.2742***	0.4124***	0.3702***	0.3618***	0.3395***
	(0.0073)	(0.0079)	(0.0075)	(0.0074)	(0.0077)	(0.0086)
ALTER	0.0057***	0.0077***	−0.0115***	0.0053***	0.0057***	−0.0090***
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0013)
TRANSITIVITY	0.0739***	−0.1871***	0.0965***	0.2280***	0.0776***	0.0061
	(0.0277)	(0.0298)	(0.0278)	(0.0295)	(0.0286)	(0.0326)
AGE	−0.3621***	−0.3567***	−0.3566***	−0.3600***	−0.3621***	−0.3500***
	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0069)
FDENSITY	0.1586***	0.1636***	0.1611***	0.1586***	0.1586***	0.1652***
	(0.0040)	(0.0041)	(0.0041)	(0.0040)	(0.0040)	(0.0041)
RFDENSITY	0.1888***	0.2068***	0.2110***	0.1909***	0.1888***	0.2269***
	(0.0105)	(0.0106)	(0.0106)	(0.0105)	(0.0105)	(0.0106)
METROPOL	0.1913***	0.1846***	0.1844***	0.1908***	0.1913***	0.1789***
	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)
EAST	−0.1695***	−0.1550***	−0.1675***	−0.1659***	−0.1695***	−0.1523***
	(0.0153)	(0.0154)	(0.0154)	(0.0154)	(0.0153)	(0.0154)
Constant	−5.9594***	−6.0129***	−6.1531***	−6.0160***	−5.9612***	−6.2329***
	(0.1676)	(0.1678)	(0.1679)	(0.1677)	(0.1676)	(0.1682)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	404,857	404,857	404,857	404,857	404,857	404,857
Log Likelihood	−114,082.6000	−113,609.9000	−113,630.4000	−113,970.5000	−114,082.5000	−113,150.9000
Akaike Inf. Crit.	228,265.2000	227,321.7000	227,362.8000	228,043.0000	228,266.9000	226,409.8000

*$P < .1$; **$P < .05$; ***$P < .01$

results suggest that firms benefit from inter-community relations only if such ties are strong (i.e., shared with at least a common third). These findings support Hypotheses 1a and 1b. As discussed earlier, because ties that cross technological communities might connect cognitively distant firms, this may increase uncertainty, interaction complexity, and the number of included topics. This finding resonates with the work of Aral and van Alstyne (2011), who argue that strong ties ("greater channel bandwidth" in their language) facilitate knowledge sourcing in such settings.

The share of SIR ties positively relates to firms' innovativeness. Moreover, our results show that the share of WIR ties more strongly correlates with the dependent variable than that of SIR ties. WIR ties may favor innovation more strongly because inter-regional ties are more effective channels at exchanging standardized or less complex knowledge (Fig. 8). However, the statistical difference between the magnitude of the effects of the two inter-regional variables becomes insignificant when we use alternative dependent variables or estimation techniques (see Supplementary Appendix G). Thus, the overall results provide partial support for the latter hypothesis.

We also investigated the joint effects of different inter-firm relations on innovation. Since interpreting the joint effects of dummy variables is more straightforward, we followed a common practice (Cattani and Ferriani 2008; Juhász, Tóth, and Lengyel 2020) and binarized our four variables, capturing bridging effects. More specifically, these transformed variables take the value of one if the value for the inter-firm relation type is greater than the 90th percentile of the original variable and zero otherwise.

Table 3 provides the results for six logit regression models covering all possible dyadic interaction terms between relation-type variables. The reported coefficients of our control variables are similar in

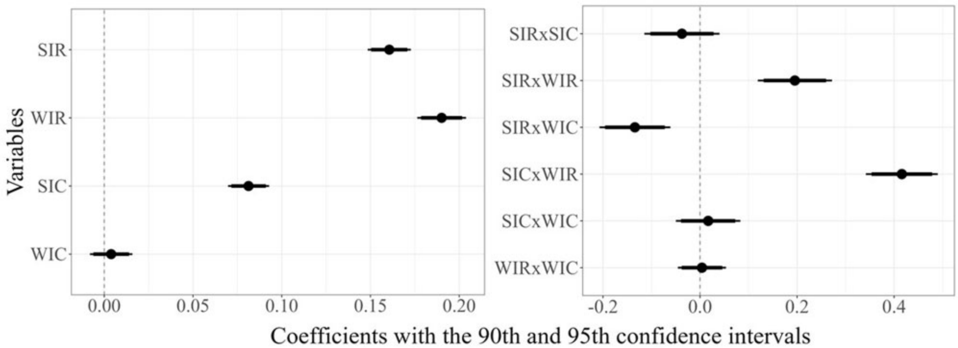

Figure 8. Regression coefficients and corresponding confidence intervals for the main variables of interest and their interactions.

Note: The visualization on the left side corresponds to the coefficients of Model 6 in Table 2, and the one on the right side represents the interaction coefficients reported in Table 3.

sign and significance to those presented above. Thus, we only report the coefficients that capture the effects and interactions of the variables of interest for brevity.

The results support Hypothesis 3, given that the combined effects of SIC and WIR ties relate more strongly to firms' innovation levels. More interestingly, the combined effects of SIR and WIC relations negatively correlate, meaning these two inter-firm relation types substitute the effect of each other. In contrast, SIC and WIR relations complement the effects of each other.[6] The theoretical argument and the empirical findings of economic geography studies point toward the importance of both relation types with firms in different regions as well as colocated ones (Oinas 1999; Nooteboom 2000; Bathelt, Malmberg, and Maskell 2004; Boschma 2005; Bathelt and Turi 2011; Breschi and Lenzi 2013). Our results contribute to this scholarly debate by suggesting that though inter-regional and inter-community relations foster innovation, inter-community relations' structural properties determine the effectiveness of such knowledge-sourcing efforts (Fig. 8).[7]

The complexity and type of knowledge exchanged between firms are not necessarily similar across industries (Asheim and Coenen 2005; Hidalgo and Hausmann 2009). Some industries are home to firms utilizing high-technologies (e.g., electronics and optics) or knowledge-intensive service firms (e.g., ICT services). In contrast, low-technologies (e.g., food production) or less knowledge-intensive services (e.g., real estate business) may dominate others. To explore such dissimilarities among sectors, we utilized the sector classification of Eurostat that groups industries into high- and low-technologies[8] and into less knowledge-intensive and knowledge-intensive services.[9] After classifying industries, we split the dataset into high-technology and knowledge-intensive firms and low-technology and less knowledge-intensive firms. Figure 9 shows no substantial difference between the two models. However, the only difference is that the correlation strength between *WIR* (i.e., WIR relations) and innovation decreases among firms in high-technology and knowledge-intensive service industries (Supplementary Appendix F includes a complete list of sectors and the full model). Although this result may come as a surprise, using a standardized system like the NACE classification to distinguish between firms is agnostic on firms' differences and subgroups within sectors. For instance, we cannot identify firms operating in novel market niches or emerging technological domains. Identifying such firms is beyond the scope of this article, and we encourage future research on this matter in the next section of the article. Moreover, our approach does not consider the significance of each type of inter-firm relation, scouring analytical, synthetic, and symbolic knowledge in varying innovation stages: research, development, and marketing (Davids and Frenken 2017).

[6] We also included all possible triadic and quadratic interaction terms (Supplementary Appendix G), and this finding remained robust across all specifications.
[7] The joint effects of strong inter-regional and weak inter-regional bridging ties also positively correlate with the dependent variable. However, the coefficient of this variable loses significance in an extended interaction model.
[8] For the sake of simplicity, we labeled high-technology and medium–high-technology industries as high-technology, and medium–low-technology and low-technology industries as low-technology.
[9] https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm (accessed: 18.04.2023)

Table 3. Logit regression estimation results with interaction terms.

	Dependent variable: INNOVATIVE					
	(1)	(2)	(3)	(4)	(5)	(6)
SIR (dummy)	0.3130***	0.2548***	0.4127***			
	(0.0217)	(0.0212)	(0.0311)			
SIC (dummy)	0.1574***			0.0882***	0.1702***	
	(0.0200)			(0.0195)	(0.0269)	
WIR (dummy)		0.3251***		0.3105***		0.3518***
		(0.0145)		(0.0146)		(0.0169)
WIC (dummy)			−0.0134		−0.0263**	0.0270
			(0.0128)		(0.0132)	(0.0166)
SIR×SIC	−0.0372					
	(0.0395)					
SIR×WIR		0.1955***				
		(0.0390)				
SIR×WIC			−0.1341***			
			(0.0373)			
SIC×WIR				0.4159***		
				(0.0378)		
SIC×WIC					0.0168	
					(0.0339)	
WIR×WIC						0.0040
						(0.0253)
Constant	−6.0857***	−6.4398***	−6.0784***	−6.2920***	−5.9547***	−6.3630***
	(0.1679)	(0.1688)	(0.1679)	(0.1686)	(0.1677)	(0.1688)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	404,857	404,857	404,857	404,857	404,857	404,857
Log Likelihood	−113,894.5000	−113,624.2000	−113,923.1000	−113,656.4000	−114,025.8000	−113,773.2000
Akaike Inf. Crit.	227,895.0000	227,354.5000	227,952.2000	227,418.7000	228,157.5000	227,652.4000

*P < .1; **P < .05; ***P < .01

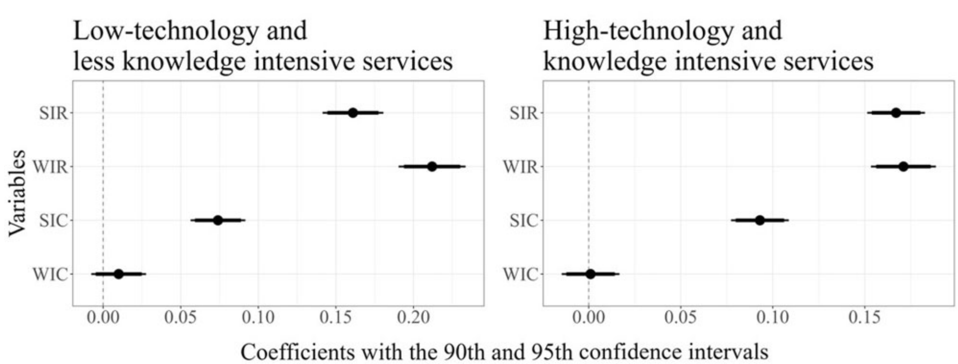

Figure 9. Regression coefficients and corresponding confidence intervals for two logit models.

We conducted several robustness checks. In these tests, we created alternative dependent variables based on different thresholds of the Innovation Probability Index (*InnoProb*). Also, we considered the overlap of bridging relations that cross geographic and cognitive boundaries. Moreover, we created two alternative cognitive distance variables and included multiple regional and network-related controls in the regression models. Finally, including multiple dummies for fixed effects in nonlinear models may provide biased coefficients (Gomila 2021). Thus, we estimated linear probability models (LPM) with clustered standard errors at sector, region, and metropolitan levels. The results of these checks did not substantially change after these specifications (see Supplementary Appendix G).

5. Conclusion

The proximity framework has provided a conceptual engine to analyze and understand the driving forces of inter-firm tie formation (Boschma 2005). Scholars discuss that interacting with firms from other regions or being active in another technological community (crossing geographic and cognitive boundaries) may foster innovation (Janssen and Abbasiharofteh 2022). To our knowledge, a necessary structural configuration for this relation type has not been empirically addressed. To this end, this article contributes to the ongoing scholarly discourse by showing empirically that only strong (versus weak) inter-community relations foster innovation, whereas both weak and SIR relations positively associate with innovation in firms. The results affirm Granovetter's (1973: 1378) argument that "treating only the strength of ties ignores, for instance, all the important issues involving their content."

In addition, firms' innovativeness relates more strongly to the combined effects of SIC and WIR relations. Building on recent scholarly debates in the proximity literature that adopt a multilevel approach, our study is among few efforts that provide empirical evidence on the relationship between the combined effects of proximities and triadic attributes of inter-firm relations (i.e., strong and weak ties) (Belso-Martínez et al., 2017; Juhász and Lengyel 2018; Hjertvikrem and Fitjar 2020).

Methodologically, this article integrates techniques developed in the machine-learning community to create a proxy for firms' innovativeness. Whereas multiple disciplines, such as computational social science, network science, spatial sciences, and applied economics, have started to benefit from machine-learning techniques (Muscoloni et al., 2017; Athey and Imbens 2019; Emmert-Streib et al., 2020; Storm, Baylis, and Heckelei 2020; Kopczewska 2021), economic geographers have, to some extent, overlooked the power of such techniques to mine and analyze much needed micro-level data (Duranton and Kerr 2018; Fritsch, Titze, and Piontek 2020). Economic geographers and regional studies scholars can take this study as a point of departure to enhance the diversity of available data and the methodological toolbox.

Having reviewed the main contributions of the article, this study is not free of limitations. We used a mutual inter-firm hyperlink network as a proxy for firms' knowledge sourcing. The digital layer includes a wide array of interactions ranging from supply-chain relations to research relations, each of which may contribute differently to innovation and may complement or substitute one another (Haus-Reve, Fitjar, and Rodríguez-Pose 2019). Thus, future research needs to study this issue by distinguishing various inter-firm relation types. Recent advancements in transformer-based machine-learning algorithms (e.g., Sentence Transformer Finetuning) enable researchers to classify inter-firm hyperlinks based on their ambient text (Tunstall et al. 2022). We also acknowledge that the digital layer does not capture informal relations that do not necessarily leave a digital footprint.

Moreover, given the structure of our training dataset, the deep neural network algorithm we developed is ambivalent about whether the innovation is new to a firm or the world and whether the innovation is based on high-technology and knowledge-intensive service industries. In other words, the estimated innovation indicator (*InnoProb*) represents a combination of all types of innovation. Therefore, we encourage future studies to distinguish between new-to-the-firm and new-to-the-world innovation types by using complementary datasets, such as firms' social media announcing new product launches or trademark filings (Abbasiharofteh, Castaldi, and Petralia 2022; Nathan and Rosso 2022).

Another limitation concerns the static nature of the network data. The data structure prevents us from investigating whether more innovative firms establish a specific type of relations or vice versa. Therefore, future studies should address this issue through a longitudinal digital layer.

This study provides timely advice for policies that target grand societal challenges. Policymakers may exploit the relevance of SIC relations in the context of place-based and mission-oriented innovation policies (Janssen and Abbasiharofteh 2022). These policies encourage collaborations among diverse stakeholders to discover untapped potential and solve grand societal challenges (Foray 2018; Mazzucato 2018; Hekkert et al., 2020). Our study suggests such collaborative efforts require a longer time span and more intense interactions to help stakeholders overcome the inertia caused by cognitive distance, leading to the exchange of tacit knowledge and cooperative impacts for firms.

Supplementary data

Supplementary data is available at *Journal of Economic Geography* online.

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