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Proximity and its impact on the formation of product and process innovation networks among producer firms

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Abstract:

Informal networks among manufacturing firms play an important role in the transfer of knowledge in industrial clusters. Proximity facilitates the networking process; however, empirical evidence on the relationship between multiple proximity dimensions and different kinds of innovation networks is scarce, especially in developing economies. Using multiple regression quadratic assignment procedures (MRQAP), this paper studies the relationship between four proximity dimensions and innovation networks for new product and new process innovations in the Lahore textile cluster in Pakistan. Our findings suggest that both geographic and non-geographic proximity dimensions show a distinct impact on product and process innovations networks.

Key words: Networks, Proximity, Innovation, Industrial Clusters, Developing Economies

JEL Codes: D85; L14; 018; R12

1. INTRODUCTION

While individual level attributes and network endogenous structures are important drivers of network formation, proximity dimensions as a dyadic level mechanism play a crucial role in facilitating collaboration and knowledge transfer activities (Torre and Wallet, 2014; Broekel and Mueller, 2018; Guo et al., 2021).

However, proximity studies predominantly focus on analysing singular relations among actors and overlook the role of different types of proximity dimensions in multiple relations (Quatraro and Usai, 2017; Maghssudipour et al., 2020). Given this, our study addresses the importance of proximity in explaining multiple network formation. We build on recent studies that have demonstrated that different aspects of proximity distinctively impact multiple types of knowledge and collaborative interactions in the innovation process (Balland et al., 2016; Capone and Lazzeretti, 2018; Mattes 2012).

Furthermore, different proximity dimensions are inter-related (Torre and Wallet, 2014) in a substitutive way or complementary manner, and tend to co-relate and co-evolve in a network. For instance, an actor connected to a cognitively proximate actor may also be geographically close to that actor (Broekel, 2015). In this case, the realised link is characterised by both cognitive and geographic proximity. Similarly, geographically proximate actors may also be socially connected to one another (Boschma, 2005) and socially close actors may also have similar cognitive domains (Balland et al., 2014). These relationships are complementary in character because the link characterised by two proximities together is more likely being realised than the link that is solely characterised by one proximity dimension. Otherwise, the relationship is substitutive when being proximate in one dimension helps to overcome missing proximity in another dimension (Huber 2012; Broekel, 2015; Fitjar et al., 2016). Bignami et al. (2020) argued that different types of knowledge activities require different geographical logics. For instance, the number of collaborations is more influenced by geographical distance in - cognitively close areas than in cognitively distant areas. Similarly, Ferretti et al. (2022) argue that the micro-geographical proximity plays a distinct role in intra-cluster linkage formation owing to distinct type of knowledge exchanged among firms, information asymmetries, and trust mechanisms inside cluster boundaries. While these studies have highlighted the significance of establishing collaboration among partners at the right distance, it is still unclear how multiple proximity dimensions co-evolve and co-relate in multiple networks having distinct characteristics. Although we expect that the overlap and substitution mechanisms operate distinctly in multiple networks, ours is the first study of on the complementary and substitution effects of all proximity dimensions on different knowledge or innovation networks.

Moreover, there have been a number of prior studies of the double-sided impact (or an inverse 'U-shaped' relationship) of proximity dimensions on innovation networks (Heringa et al., 2014 and Koo, 2020): while proximity is critical for facilitating interaction between actors, too much proximity or distance can be detrimental to learning and innovation (Boschma, 2005). Therefore, collaborating partners should be located at an optimal distance (i.e., not too close, and not too far) from one another across proximity dimensions to achieve the best learning and innovation outcome (Broekel and Boschma, 2012; Fitjar et al., 2016). However, little is known about the double-sided impact of proximity dimensions on multiple networks.

We explore these issues using four of Boschma's (2005) proximity dimensions (geographic, social, organisational, cognitive and institutional proximity), which are the main forces behind inter-organisational learning and the innovation process (Hansen and Mattes, 2018). Process innovation in a firm is defined as a new or significantly improved production or process technology [involving activities ranging from internal quality control measures, optimum use of equipment for operation, improvements in equipment and processes] that leads to an increased performance of the production process. Product innovation is a new or significantly improved product [involving new product designs, input materials and features] introduced commercially to meet a user or a market need[i]. This paper analyses the process of linkage formation among actors and investigates whether and how different proximity dimensions influence the creation of product innovation links or process innovation links among actors.

Further, prior research on product and process innovations suggests that they embody different knowledge characteristics (Gopalakrishnan et al., 1999; Wong et al., 2008; Krzeminska and Eckert, 2015). While process innovation knowledge is relatively more complex, systemic and context specific, product innovation knowledge is relatively concrete, autonomous and more observable (Hatch and Mowery, 1998; Casanueva et al. 2013; Un and Asakawa, 2015). Given these two distinctive knowledge characteristics, we explore the extent to which different proximity dimensions may play distinctive roles in facilitating R&D collaborations for product and process innovations.

Much of the research on proximity and multiple networks has been conducted in developed economies and remains empirically underexplored in the context of traditional industry clusters in emerging economies (Geldes et al., 2015; Park and Koo, 2020). Industry clusters are relevant for studying multidimensional proximity and multiple relations because firms within clusters tend to have greater interactions with other local firms than they do with firms outside the cluster (Contreras Romero, 2018). These interactions, in turn, facilitate multiple types of information and knowledge flows among variety of clustered firms (Maghssudipour et al., 2020). Accordingly, given that context matters (Gertler 2003) and that specific industry studies are essential for better understanding the correlation between proximity dynamics and innovation networks (Mattes, 2012; Davids and Frenken, 2017), the empirical setting for this study is the Lahore textile cluster, comprising a variety of textile producer firms involved in knowledge exchanges, economic exchanges, and social interactions to develop innovations.

Our primary contribution is to the emergent literature on proximity dynamics and multiple networks (Balland et al., 2016; Capone and Lazzeretti, 2018) by demonstrating that different types of proximity, with their different knowledge characteristics, distinctively shape the formation of product and process innovation networks. Knowledge is heterogeneous and multifaceted, assumes a variety of shapes in different situations, and hence cannot simply be transferred seamlessly like a parcel to other actors (Mattes, 2012). Creating a balance between proximity and knowledge heterogeneity is, thus, a major challenge for innovating firms. Explicating the link between multiple proximity types and different types of knowledge (product vs process) can help firms foster a deeper and more differentiated understanding of this relationship (Davids and Frenken, 2017). We also respond to the recent calls for studying the overlap/substitution mechanism among proximity dimensions (Fitjar et al., 2016; Cao et al., 2019). While prior work provides evidence of overlap/substitution-innovation mechanism among geographic and non-geographic proximity dimensions in collaborative projects (Broekel, 2015; Hansen, 2015; Crescenzi et al. 2016), we show that overlap/substitution mechanism among proximity dimensions differently operate across multiple networks (Balland et al., 2016; Leszczyńska and Khachlouf, 2018). Finally, this study contributes to the scarce literature on the role of networks in traditional industries in emerging economies (Nadvi and Schmitz, 1999; Geldes et al., 2015; Maghssudipour et al., 2020).

The structure of the paper is as follows: section two presents our theoretical framework and research propositions. The empirical context, data and methodology are presented in section three; and the results are discussed in section four. Section five concludes the paper with the limitations of the current study and suggestions for future research.

2. Proximity and multiple network formation

The principle of relatedness – the pattern of interrelated knowledge links between technologies, skills and sectors (Frenken and Boschma, 2007) – has become an increasing focus of attention, establishing that firms prefer to co-locate in technologically compatible clusters to benefit from improvements in their own technology from the technology and location of other firms (Bond-Smith and McCann, 2019). Given that firm innovation is a branching process, the development of new innovations by a firm is a function of both technological, geographical and other proximities (Boschma, 2005) and the densities of related varieties (Kali et al., 2013), and is influenced by the structure of the network itself (Alshamsi et al., 2018), including the development of proximity-related path dependency effects (Frenken and Boschma, 2007) and peer effects (Kelchtermans et al., 2020).

Against this background, several empirical studies have applied Boschma's (2005) proximity analytical framework- which includes geographic, social, organisational, cognitive and institutional proximities (Table 1)- to explain the inter-organisational learning, innovation and collaboration process (Broekel and Mueller, 2018; Hansen and Mattes, 2018; Guo et al., 2021). Moreover, recent empirical studies maintain that organisations are simultaneously embedded in multiple relations (Shipilov, 2012; Balland et al., 2016; Maghssudipour et al., 2020) and that the relative importance of proximity dimensions depends on the characteristics of the relationship that is being analysed and the knowledge that flows through these relationships. These knowledge flows may be distinguished in multiple ways based on the ease of codification and complexity of the knowledge. For instance, technical knowledge is complex compared to business/market knowledge and therefore has a distinct relationship with proximity dimensions during knowledge sharing and network formation (Balland et al. 2016). Specifically, while cognitive and geographic proximity plays a significant role in explaining the formation of technical advice networks, their impact on forming business advice networks is not significant. Similarly, Quatraro and Usai (2017) observe that depending on the codifiability of knowledge flows, proximity dimensions can play a unique role in facilitating linkage formation. While examining the effect of the proximity dimension on co-citations, applicant-inventor links and co-inventorship, they find that technological proximity has a more substantial positive effect on citation links. In contrast, physical contiguity shows the highest impact on co-inventorship collaborations. Further, Capone and Lazzeretti (2018) show that only geographic proximity has a positive and significant effect on friendship, innovation and technical advice networks. Other scholars examine the relationship between analytical, synthetic and symbolic knowledge bases and different proximity dimensions (Mattes, 2012).

For instance, Davids and Frenken (2017) show that while analytical knowledge production requires high cognitive proximity between partners, permanent co-location is crucial for the production of synthetic knowledge.

Insert Table 1 here

2.1 Proximity as a determinant of product and process innovation networks

This paper maintains that different proximity dimensions have distinct impacts on creating product and process innovation networks because these two innovation types embody different knowledge characteristics (Krzeminska and Eckert, 2015; Un and Asakawa, 2015). In this study, we predominantly focus on the four crucial dimensions - the codifiability of knowledge (imitability), the location of knowledge (substitutability), the degree of novelty (rareness), and the underlying knowledge base- in developing product and process innovations (Table 2).

Insert Table 2 here

In terms of the codifiability of knowledge dimensions, the role of a firm is to facilitate the codification, integration and transfer of knowledge in a manner that results in an innovation (Nonaka, 1994). However, it is not easy to imitate, transfer and replicate knowledge in a different setting (Hatch and Mowery, 1998; Wong et al., 2008) because knowledge resides in the skills of individuals, and the routines of firms and individuals cannot precisely express to others what they know (Balland et al., 2016). Second, knowledge is difficult to substitute because it is subject to complexity, system interdependence, and causal ambiguity (Saviotti, 2009; Un and Asakawa, 2015). Even when a competitor tries to substitute how something works and how the firm arrives at that solution, its underlying logic is rarely clear. Third, knowledge is rare because its distribution across individuals and organisations is imperfect (Gopalakrishnan et al., 1999). As a result, no two or more individuals or firms have the same set of knowledge (Un and Asakawa, 2015). This brings with it a high level of complexity, which can cause dynamic coordination failures among actors in scheduling, teamwork, knowledge exchange and related issues (Mattes, 2012). Finally, knowledge is distinguished as analytical, synthetic and symbolic types (Asheim and Coenen, 2005). Analytical mainly refers to know-why and is needed to explain empirical phenomena. This knowledge is highly codified. Synthetic knowledge refers to know-how, which is more tacit, and is needed to solve a practical problem. Symbolic knowledge refers to the knowledge of cultural codes underlying cultural industries and is used to produce cultural meanings.

2.1.1 Characterising product and process innovation knowledge, and associating that with proximity dimensions

Our analysis of the two innovation types based on knowledge dimensions discussed above follows four stages. Firstly, we argue that product and process innovations differ in knowledge codification, which requires distinct imitation capabilities from competitors (Krzeminska and Eckert, 2015). Product innovation tends to be easier to imitate because the knowledge is embodied in the product *per se* (Utterback and Abernathy, 1975), thus providing an explicit and more apparent objective for competitors to imitate. Consequently, competitors can reverse engineer a product's components and system more efficiently. In contrast, process innovation tends to be difficult to imitate because the process is internal to the firm, more tacit and obscure, and thus not easy to codify (Hatch and Mowery, 1998). The firm could restrain competitors from entering its facilities, thus limiting the ability of competitors to imitate process innovation. Therefore, high proximity in geographical and non-geographical dimensions among partners is crucial for a smooth transfer when the tacit component in the knowledge is high. (Guo et al., 2021).

Secondly, the location of the knowledge for product and process innovation differs, requiring unique capabilities by competitors to substitute the innovation. Product innovation knowledge is generally located in a quasi-independent unit such as an R&D unit, with teams of experts focusing predominantly on technological aspects of new products, which partially limits the substitution by competitors with a different skillset. In contrast, process innovation tends to be more systemic and interdependent (Gopalakrishnan et al., 1999), which requires coordination among different units to implement change in the process. The causal ambiguity and context-specific nature of process innovation make its substitution difficult (Un and Asakawa, 2015). Thus, replicating process innovation in a different user setting can be challenging for competitors. Therefore, firms that require advice on solving complicated production problems may prefer to interact with partners who are situated in the same territory (Gertler, 2003), share common 'codes' of communication (Balland et al., 2016) and to whom they also have trustful social relations (Nilsson, 2019). Thus, the likelihood of firms being linked to proximate partners may be higher when the knowledge is context-specific, systemic and complex (Aguiléra et al., 2012; Laursen et al., 2016).

Thirdly, product and process innovation differ significantly in the accepted degree of novelty, or rareness. Product innovation focuses on achieving a degree of radicalness, through interacting with diverse knowledge sources, to serve customers' unique and unmet needs. Thus, the learning that product innovation aims for is exploratory, with new ideas and concepts to be incorporated into a new product (Wong et al., 2008). In contrast, process innovation focuses more on achieving some degree of incremental innovation, with the process being improved evolutionarily to reduce costs as well as to increase product quality (Un and Asakawa, 2015). Thus, the learning that process innovation aims to achieve is more exploitative in nature, with improvements on existing concepts and ways of doing things. These learning strategies can also impact the way firms form ties with their partners (Menzel et al., 2017). For instance, when the learning orientation of firms is explorative, they tend to collaborate with technologically different and, geographically and organisationally distant partners for acquiring state of the art knowledge to achieve radical innovation goals (-Shkolnykova and Kudic, 2021). In contrast, when the learning orientation is exploitative, as in case of process innovations, firms closely work with organisationally and geographically proximate, established and familiar partners to develop innovations and work out production-related practical problems (Davids and Frenken, 2017).

Fourthly, product and process innovation may be distinguished based on underlying knowledge base (Asheim and Coenen 2005). This framework has been used predominantly to classify industries in terms of ideal-type knowledge underlying their innovation process (Mattes, 2012). More recently, Davids and Frenken (2017) have used it to classify knowledge at different stages in an innovation process. They demonstrate that research stage requires more analytical knowledge to guide the search process, development stage draws on synthetic knowledge to solve production problems and marketing stage requires more of the symbolic knowledge to get a new product accepted by the users. Product innovation tends to achieve aesthetical and design attributes in products which require symbolic knowledge. In contrast, a new process innovation requires mobilising synthetic knowledge to enhance production efficiencies by reducing production cycles in existing systems. Organisational and geographic proximity have been found to play a crucial role in solving production problems, while cognitive and institutional proximity is crucial in the product development stage. Similarly, geographic proximity is less important for developing symbolic knowledge, whereas the production of synthetic knowledge requires permanent co-location.

Insert Figure 1 here

In sum, we argue that, although all proximity dimensions are important for both product and process innovation networks, they may be more crucial for the latter than the former predominantly because of the difference in the knowledge characteristics of the two innovation types (Figure 1). Thus, we hypothesize that:

H1: Geographic proximity and non-geographic forms of proximity (cognitive, social, and organisational) are positively associated with the formation of both the product and process innovation networks.

H2: The impact of geographic and non-geographic forms of proximity (cognitive, social, and organisational) are expected to be higher in the process innovations network than the product innovations network.

2.2 Complementary and substitution mechanisms of proximity, and product and process innovation networks

We also examine whether proximity dimensions are related to one another in a similar or distinct manner in multiple networks. Prior work suggests that both the geographic proximity and non-geographic forms of proximities can have a substitution as well as complementary/overlap relationship (Huber, 2012; Hansen, 2015). In a substitution mechanism, one form of proximity may compensate for other forms of proximities, for instance, geographically distant relationships are based on non-geographical types of proximity (Broekel, 2015; Fitjar et al., 2016), and geographic proximity is found to have a substitution relationship with social and cognitive proximities (Crescenzi et al., 2016). In complementary/overlap mechanisms, one form of proximity may facilitate other forms of proximities and vice versa, suggesting that geographical proximity and non-geographical proximity are positively correlated (Fitjar et al., 2016). For instance, Hansen (2015) found a strong overlap relationship between geographic and social proximity.

Since geographic and non-geographic forms of proximity may have a substitution and overlap relationship with one another (Broekel, 2015), it is essential to investigate how these mechanisms operate in multiple networks. We examine whether geographic and non-geographic forms of proximities substitute or complement in product and process innovation networks, i.e., when geographic proximity interacts with social or cognitive proximity in the formation of product innovation-related linkage formation, what happens when the same interaction occurs in a process innovation-related linkage formation. Hansen (2015) demonstrates that geographically distant partnerships combined with higher cognitive, organisational and institutional proximity are beneficial for product innovation. Similarly, Fitjar et al. (2016) show that collaboration with partners having a medium-to-low level of geographic and non-geographic distance is associated with significantly higher levels of product innovations. Moreover, Davids and Frenken (2017) suggest that geographic and non-geographic proximities play a distinct role in facilitating different stages in the new product development process. Analytical knowledge production requires high cognitive proximity between partners, synthetic knowledge requires high geographic proximity and symbolic knowledge production requires high institutional proximity among partners. We therefore hypothesize that:

H3: The complementary and substitution mechanism of geographic and non-geographic forms of proximity impact product and process innovation networks in a distinct manner.

3. RESEARCH CONTEXT, DATA AND METHODOLOGY

3.1 Research setting

The empirical context of our study is the textile cluster in Lahore. This is an appropriate context because it typifies a traditional industry (Peerally and Cantwell, 2006) where external economies increase with spatial agglomeration and firms are geographically concentrated within the industrial cluster (Nadvi and Schmitz, 1999). Knowledge externalities and localised interactions among cluster firms help them in coping with the challenge of innovation and knowledge creation (Guerrieri and Pietrobelli, 2004). In textile sector, process innovations are basically the introduction of quality and productivity control methods, and time and process control methods that are primarily embodied in the machinery, while product innovations are categorised as improving products' aesthetic and design attributes or the utilizing new innovative input materials (Peerally and Cantwell, 2006). Cluster firms are embedded in multiple horizontal and vertical linkages, which play a crucial role in new products and processes development, thus providing ideal setting to studying research questions related to multiple linkages (Pietrobelli and Barrera, 2002).

We chose Lahore because it is the second most populous city in Pakistan with a total population of around 11.07 million (Demographia, 2018). The city accounts for about 10% of the entire textile and clothing firms in the country (Pakistan Bureau of Statistics, 2013). These firms are involved in almost all stages of the textile value chain: spinning; knitting and weaving; dyeing and printing and finishing of fabric; and apparel and made-ups. They are located in four different locations or geographical zones in Lahore: Raiwind-Manga Mandi (zone 1), Bhai Peru (zone 2), Ferozepur Road (zone 3) and Defence Road (zone 4).

Studying the role of proximity in facilitating cooperation among local firms in Lahore cluster is important for several reasons. First, prior research on industrial clusters in Pakistan suggests that most firms in the country are located in industrial clusters (Nadvi and Schmitz, 1999; Fayyaz et al., 2008) and hence they are more likely to have greater inter-firm cooperation with each other as compared to outside firms (Rehman, 2016; Contreras Romero, 2018).

Second, a strong culture of cooperation and support exists among cluster firms in Pakistan's textile and clothing sector (Ghani and Fayyaz, 2007; Rehman, 2016) at both the managerial and ownership level. At the ownership level, a small number of Pakistani family groups own several textile firms which facilitates inter-organisational interactions among different units in a group. Prior work on family business management suggests that the embeddedness of firms in entrepreneurial family relations is an important factor that facilitates the transfer of specialised knowledge as a distinctive asset (Del Giudice et al., 2011) by promoting trust and cooperation among these firms in the local cluster (Nilsson, 2019). This relational embeddedness also nourishes the organisational and cognitive proximity among firms owing to their association with a single parent company (family group).

At the managerial level, there is an informal culture of support and collaboration among firms' managers (textile engineers) for solving technical as well as other industrial problems, as most of these managers are graduates of the oldest textile institute in the country, the National Textile University[ii]. This existence of "old boys' networks" is likely to influence knowledge sharing and collaboration activities among managers (Broekel and Boschma, 2012), facilitating social and cognitive bonding among these managers.

The context of Lahore textile cluster is relevant to study product and process innovation networks. First, the fact that firms in Lahore textile cluster are involved in all stages of the textile value chain indicates firms' involvement in the manufacturing of variety of textile products and processes in the local cluster. This provides an opportunity to observe multiple types of interactions among these different kinds of firms, highlighting the crucial role of technological proximity in facilitating/hindering inter-firm cooperation. Second, Pakistan is a collectivistic cultural society (Hofstede et al., 2010, Merkin, 2016) and such societies promote interdependence among individuals (actors) for learning and development of new knowledge. Owing to the collectivistic nature of Pakistani society we expect that local firms are more likely to cooperate with one another for developing products and processes innovations. However, we expect that the distinct nature of product (explicit) and process (tacit) innovations will distinctively impact inter-firm collaborative activities. As pointed out by Gertler (2003, p.78), "*tacit knowledge can only be shared effectively between two or more people when they also share a common social context: shared values, language, and culture*", while explicit knowledge can be easily transferred in the written form and does not require high-level of coordination (Dhanaraj et al., 2004). Nevertheless, it will be interesting to investigate whether firms having strong embeddedness in social context collaborate differently for products and process-related innovation developments. Third and last reason for choosing Lahore textile cluster for this study is that Pakistan [Lahore] is a country [city] having weak institutional bases/setting and prior network studies suggest that informal networks among actors play even more crucial role in innovation creation, particularly, in weak institutional settings (Zhang et al, 2018). Therefore, we believe that considering Lahore textile cluster for studying the product and process innovation network is appropriate because it will provide an opportunity to observe enough interactions among local players to understand dynamics of multiple network formation.

3.2 Data collection

In order to investigate the impact of different dimensions of proximity on the formation of product and process innovation networks, we collected primary data at the firm level in the Lahore textile cluster. This was done via face-to-face interview-based survey from the personnel responsible for the management of production operations and the development of new products and processes because the most important source of knowledge in a firm is the personal knowledge networks of senior-level managers (Huber, 2012). Prior to interview-based survey, participants were provided with an information sheet and a consent form. Subsequently, they were requested to sign and date the consent form to demonstrate their understanding of the informed consent and the research purpose, and to seek their willingness to participate in the research study. To ensure confidentiality and anonymity, each participant was given a pseudonym and it was ensured that no results will be associated to any specific organisation or a person. Ethical level 1 approval was taken from the research ethics committee of the University of Edinburgh Business School prior to fieldwork.

In our study, the survey was not based on a sample of firms. Instead, data was collected from local textile firms in the cluster who are registered with All Pakistan Textile Mills Association (APTMA). As per APTMA member's directory, 84 textile mills were based in Lahore. Before data collection, we showed the list to some of local industry managers in Lahore cluster who informed us that a few of firms in the list are inactive and have not been in operations for a while. Therefore, we decided to gather information from only those firms (73) which were active during the study period. In total, we surveyed 73 firms in Lahore. However, we also conducted a pilot study before the actual data collection exercise to test our instrument as well as to identify the key informants in the textile firms. In addition to the interview-based survey data, we collected information from secondary data sources, such as companies' annual reports, various government reports, industry reports and websites of companies and other departments.

We also collected relational data using roster recall methodology. In this method, each firm was provided with a complete list (roster) of the other firms in the cluster. Thus, we asked respondents to choose from a roster of 73 firms to which respondents regularly asked for technical advice. Other scholars have already used this methodology to collect relational data (Balland et al., 2016). This approach is particularly useful for the collection of whole network data because it reduces selectivity bias in the responses of personnel owing to memory effects (Molina-Morales et al., 2015).

3.3 Estimation model

The data analysis involved testing for the impact of proximity dimensions on innovation collaboration. Among the four network-modelling techniques suggested by Broekel et al. (2014), this study employs multiple regression quadratic assignment procedures (MRQAP). MRQAP model continue to be a widely used network regression technique in the innovation and management research (Park and Koo, 2020; Briseño-García et al., 2022; Huo et al., 2022; Zagenczyk and Powel, 2022). It employs a permutation method to assess the statistical significance and interdependencies of relational variables (Broekel et al., 2014). Relational variables describe the link between two actors, i.e., the extent to which they are distinct, similar, or share specific attributes (Broekel and Boschma, 2012).

A predominant characteristic of relational data is the lack of independence among observations, which limits the use of standard regression techniques (Dekker et al., 2007). The difference between standard regression and the MRQAP model is that the former demands independence of observations, while the latter technique is capable of dealing with the lack of independence among observations (Scott and Carrington, 2014). Hence, in the MRQAP model both the dependent and independent variables are n x n relational matrices instead of vectors (Broekel and Boschma, 2012). In order to test the hypothesis using MRQAP, multiple relational matrices (as explanatory variables) are used to predict a dependent relational matrix (Robins et al., 2012). Snijders (2011) argues that MRQAP is useful when the focus of research is exclusively on the effects of predictor variables.

The p-value or the significance of the test is estimated by permuting the rows and columns of the matrices thousands of times (Dekker et al., 2007). The model fit and regression coefficients of the observed data are compared to coefficients obtained through extensive permutation of rows and columns (Pinheiro et al., 2016). For example, if an initially estimated coefficient value remains greater than 95% of the estimates obtained through permutations, the original coefficient estimate is considered as significant at 0.05 level (Borgatti et al., 2013). In this study, we employ MRQAP, 'semi-partialling plus' method because it is considered robust in dealing with multi-collinearity problems associated with MRQAP analysis (Dekker et al., 2007). In the present study, QAP routines were performed with 5000 permutations.

The basic form of the MRQAP model is estimated using the following equation:

$$\boldsymbol{Y_{ij}} = \boldsymbol{Ln}\left(\frac{\boldsymbol{Y}}{\boldsymbol{1-Y}}\right) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 X_1} + \sum_{i=2}^{5} \boldsymbol{\beta_i X_i} + \boldsymbol{\beta_6 X_6} + \boldsymbol{\varepsilon} \qquad (1)$$

Where**:**

'$\boldsymbol{Y_{ij}}$' is the dependent socio-matrix or network; and

X_1 'geographic proximity', X_2 'cognitive proximity', X_3 'organisational proximity', X_4 'social proximity (work)', X_5 'social proximity (university)', and X_6 'controls' and ε is the error term. The size of these coefficients provides the measure of the relative importance of each of the proximity dimensions on the likelihood of tie formation.

3.4 Variables Description

3.4.1 Dependent variables

In our sample 38% (28) firms reported that they have successfully developed product innovations in the recent past and/or are involved in product innovation-related activities, while 83% (61) firms reported that they have successfully introduced a process innovation in the recent past and/or are involved in process innovation-related activities as shown in table 4. In this study, the dependent variable is the product and process innovation network which can be represented as binary $n*n$ graphs $x = (x_{ij})$, where $x_{ij}=1$ when actor *'i'* discloses a technical advice link to actor *'j',* otherwise $x_{ij}=0$. Our first dependent variable is a *73*73* socio-matrix for *'product innovations network'*, which is a dichotomous variable and indicates whether firm *'i'* or *'j'* mention the other as a source of technological knowledge for new products development. Similarly, our second dependent variable is a *73*73* socio-matrix for *'process innovations network'*.

To gather relational data, we asked the following two questions:

a) *When you need technical advice on product development/innovation, to which of the local firms mentioned in the roster do you turn?*

b) *When you need technical advice on process improvement/innovation, to which of the local firms mentioned in the roster do you turn?*

Figure 2a and 2b provide the graphical representation of process and product innovation networks respectively.

Insert Figure 2 here

3.4.2 Explanatory variables

Geographic proximity refers to nearness between partners in terms of territory, space and physical distance (Boschma, 2005). We computed the natural logarithm of the distance between firms and subsequently inverse the distance to obtain the proximity variable (Boschma et al., 2014). This was done by subtracting each value with the maximum value. Eventually, our maximum value for geographic proximity is between 0 for the most distant firms and maximum for the most proximate ones. The formula for geographic proximity between firm '*i*' and '*j*' is as follows:

$$\text{Geographic Proximity}_{ij} = \text{Maximum distance} - \ln(\text{distance}_{ij})$$

Prior studies have measured *cognitive proximity* either using the similarity in the NACE codes (Molina-Morales et al., 2015; Usai et al., 2015), or similarity in the technological and knowledge base of firms (Broekel and Boschma, 2012; Quatraro and Usai, 2017a). Following Broekel and Boschma (2012), we measure cognitive proximity by calculating cosine similarity index between firms' technology profiles as defined in the Pakistan Standard Industrial Classification (PSIC)[iii]. In other words, it is the technological proximity between firms. We used the following formula to calculate the cosine similarity index[iv] between the eight industrial/technological codes associated with the textile industry,

$$\text{Cosine Similarity (A, B)} = \cos(\theta) = \frac{A \bullet B}{\|A\|\|B\|} \quad (2)$$

The final value estimates the cosine of the angle between the two vectors. A cosine value of 0 means that two vectors are at 90 degrees and have no match, while a cosine value of 1 means two vectors are at 0 degrees and have a perfect similarity (Kellstedt and Whitten, 2018). For instance, total eight PSIC technology codes appear in our data. To calculate the similarity index, we created a two-mode matrix (73 x 8) having firms in rows and PSIC codes in columns. We assign 1 to a cell when a firm 'i' is involved in a particular technology 'j', else assign 0. A firm may be involved in one technology only or several technologies simultaneously. Formula in equation 2 calculates the cosine similarity index (continuous variable) of each firm in the matrix. Table 3 provides information on the technology profiles of firms, i.e., the number of firms involved in each textile technology as per the PSIC codification system.

Insert Table 3 here

Social proximity is the embeddedness of partners in trustful relations (Nilsson, 2019) which is measured in two ways in this study. Our first measure is based on university affiliation that is shown to be an important driver of network formation (White, 2011). It is a binary variable, which takes the value '1' if managers/directors of collaborating firms have graduated from the same university, and '0' otherwise. We name this variable as 'social proximity (university)'. For the second measure, we sought information on the past employers of each respondent. It is also a binary variable which takes the value 1 when collaborating partners share employment history, and 0 otherwise. We name this variable as 'Social proximity (work)'. For these two measures, we follow the approach adopted by Broekel and Boschma (2012) who argued that an existence of "old boys' networks" is likely to influence knowledge sharing and collaboration activities among managers. If two different respondents have studied or worked together in the past at the same place, then we assumed that they are socially proximate to each other.

Organisational proximity refers to similarity in terms of organisational routines, rules, procedures, and structures among collaborating partners (Aguiléra et al., 2012). It is also a binary variable in our study. It takes the value 1 when collaborating firms belong to a single parent organisation or the same industrial group, and 0 otherwise.

In order to test the double-sided impact or an inverted U-shaped relationship, we applied the quadratic terms to only the cognitive and geographic proximity dimensions for two reasons. First, these two are continuous variables while organisational and social are binary variables in our study and testing quadratic term of binary variables will yield the same results as a of a non-quadratic term. Second, following most proximity studies, we also consider cognitive/technological (Mowery et al., 1998; Nooteboom et al., 2007; Broekel and Boschma, 2012) and geographic (Heringa et al., 2014; Park and Koo, 2020) dimensions for testing non-linear relationship.

3.4.3 Control variables

First, we control for the following dyadic variables: *age; size; joint R&D activities* of the firm; the *manager's qualification*, as these tend to affect the propensity to build networks (Fitjar et al., 2016); *export performance* as export-oriented firms may be more likely to cooperate with other similar firms (Giuliani, 2010); and *trade memberships* of firms, as Houghton et al. (2009) argue that memberships in a trade association are an important type of external network. We measure and operationalise these control variables as follows. We measure firm *age* by performing the square root of the total years in operations, which is converted into a graph/matrix using absolute difference, firm *size* by calculating natural log of the number of employees and converted into a matrix by summing up ages of two firms, *joint R&D* by asking whether a firm indicates involvement in joint research projects. While 76% (55) of firms are involved in joint R&D projects, only 27% (20) firms reported that they have a dedicated R&D department. We measure *managers' qualifications* according to their level of education and convert them to a matrix using absolute difference, firm's *export performance* as whether a firm is an exporter or not. Our results indicate that 54% (40) of firms are involved in exporting products. The *trade memberships* of firms were measured through counting their participation in maximum trade associations and converted to matrix using sender/receiver effect. Table 4 presents the descriptive statistics of the dyadic explanatory and control variables, and Table 5 presents the correlation among the main proximity variables. These correlation results are in line with previous research (Balland et al., 2016), which find a weak correlation among the proximity dimensions.

Insert Tables 4 and 5 here

4. RESULTS AND DISCUSSION

This section presents the results of the paper and discusses the impact of different proximity dimensions on the formation of product and process innovation networks. Table 6 presents the structural descriptive statistics of the two innovation networks. The density of the process network (0.049) is slightly higher than the density of the product network (0.039) indicating higher interaction for process innovation-related advice. In other words, density represents the number of established linkages of the total possible linkages in a network. In this study, the number of edges (links) in the process and product innovation networks are 259 and 206 respectively of the total possible 5256 linkages. The average degree of process and product innovation networks is 3.55 and 2.82 respectively, which indicates that firms ask process innovation-related advice from approximately four different firms, while they ask product innovation-related advice from about three different firms.

Insert Table 6 here

To test the relationship between proximity dimensions and innovation networks, we perform MRQAP logit regression analysis methodology (Dekker et al., 2007) and test four models. Table 7 and 8 show the results of the MRQAP analysis for the process innovations network and product innovation network respectively as the dependent variables. In our analysis, all parameter estimations are based on 5000 permutations. For robustness check, we follow the advice of Pinheiro et al. (2016) and Borgatti et al. (2013) and re-ran all models using LRQAP analysis. Subsequently, we compared the results of LRQAP with MRQAP estimation procedures by checking the direction and significance level of coefficients. Borgatti et al. (2013) suggested that if both routines signalled the same independent variables as significant or non-significant then the results are valid and robust. We found the same significance level and direction of all coefficients. Moreover, we have tested our model with different permutations to ensure that results are reliable and robust.

Insert Tables 7 and 8 here

Our results in models 1 and 3 indicate that the parameter estimates of both geographical, and non-geographical proximity dimensions (social, organisational, and cognitive) are positive and significant for both networks. These results confirm our research hypothesis, *H1*. The pseudo R-square and other goodness of fit statistics reveal that both models perform well in explaining the likelihood of linkage formation among firms for the exchange of product and process related knowledge. These findings are consistent with prior work that suggests a positive and significant relationship between multidimensional proximity and network formation (Aguiléra et al., 2012; Balland et al., 2016; Laursen et al., 2016; Guo et al., 2021).

We also hypothesised a stronger impact of geographic proximity on the process innovations network as compared to the product innovation network. The coefficient [given in model 1 and 3 in Tables 7 & 8 respectively] for the process innovation network is slightly higher ($\beta = 0.58$) than the coefficient for the product innovations network ($\beta = 0.50$). However, both coefficients are significant at $p < 0.1$. This result suggests that firms are likely to seek advice from geographically proximate partners for process innovations (odds=1.8) and product innovations (odds=1.65) in nearly similar manner. These results weakly support our hypothesis *H2*. Our findings are in line with previous studies which suggest that geographic proximity facilitate the transfer of tacit knowledge in the innovation process (Gertler, 2003; Nilsson and Mattes, 2015; Laursen et al., 2016, Ferretti et al., 2022). Moreover, this finding is consistent with several studies that suggest that geographic proximity facilitates the transfer of not only tacit knowledge but also codified knowledge (Boschma, 2005)

Regarding the relationship among non-geographic forms of proximity, the coefficient of cognitive proximity is positive and significant for both the process ($\beta = 5.06$, $p < 0.001$) and product ($\beta = 2.712$, $p < 0.001$) innovations networks. As expected, the parameter estimate for the process innovations network is higher than the product innovations network. This result indicates that firms tend to link more with technologically similar partners when they seek advice on process innovations (odds=158) as compared to product innovations (odds=15), thereby confirming our research hypothesis *H2*. These results are also in line with other studies, which suggest that collaborative innovation activity is highest among cognitively proximate partners for exploitation-focused innovations (Dooley et al., 2015), which is the characteristic of process innovations.

Similarly, the coefficient for social proximity (work) is positive and significant for both the product and process innovations networks. As hypothesised in *H2*, the parameter estimates for the process innovations network ($\beta = 2.05$, $p < 0.001$) is relatively higher than that for the product innovations network ($\beta = 1.88$, $p < 0.001$). These findings are in line with previous studies that argue that the transfer of tacit knowledge requires high social proximity among partners (Dhanaraj et al., 2004). We also computed a second variable for social proximity (university), which is also positive and significant ($p < 0.01$) for both the process and the product innovation networks. However, the odds for establishing a tie is almost same for both product (odds = 1.68) and process (odds = 1.65) innovation networks suggesting that university alumni play an equally important role for different types of knowledge exchanges (White, 2011), thus reinforcing the importance of universities in contributing to 'institutional thickness' (Cao and Shi, 2020) and iterative learning for innovation through social proximity (Leszczyńska and Khachlouf, 2018).

Concerning organisational proximity, we find a positive impact on both networks. Since the magnitude of the parameter estimate is lower for the product innovations network ($\beta = 1.80$, p

< 0.001) than the process innovations network ($\beta = 2.49$, $p < 0.001$), indicating that the likelihood of tie formation between organisationally proximate partners is higher for process innovations (odds = 12) than product innovations (odds = 6.59). This result confirms our research hypothesis *H2*. Our study confirms the findings of previous studies, which suggest high organisational proximity facilitates collaboration and knowledge transfer (Davids and Frenken, 2017; Yao and Li, 2020).

Figure 3 graphically represents the parameter estimates of proximity dimensions for process and product innovation networks respectively. We also ran confidence interval overlap test to check the significant difference among coefficients of proximity variables. Except the social proximity (university) variable, coefficients of all other proximity variables significantly differ among product and process innovation networks as shown in tables 9 and 10.

Insert figure 3 here

Insert table 9 and 10 here

In addition to investigating a linear relationship among proximity dimensions and network formation, we tested for a potential non-linear relationship of geographic and cognitive proximity dimensions on product and process innovations networks. The results are summarised in models 1 and 3 in tables 7 & 8, respectively. We find that increased cognitive proximity (high technological overlap) has a negative ($\beta = -3.30$) and significant ($p < 0.05$) effect on tie formation for process innovations suggesting detrimental effect of too much cognitive proximity. Our findings contradict with some of the prior studies (Broekel and Boschma, 2012; Park and Koo, 2020), which did not find any non-linear effect of technological proximity. On the contrary, these findings are consistent with other studies that found a negative and significant impact of higher levels of technological overlap on the formation and maintenance of alliance partnerships (Mowery et al. 1998; Guo et al., 2021, Ferretti et al., 2022). We do not find any significant non-linear effect for product innovations network, suggesting a rather linear effect when the characteristic of the link is simple and explicit.

Moreover, we do not find any significant association between geographic proximity-squared term and the formation of product and process innovations networks, suggesting that too much geographical closeness has neither a beneficial nor a harmful effect on any type of tie formation in the given context. This result is in line with previous studies (Broekel and Boschma, 2012; Heringa et al., 2014; Fitjar et al., 2016; Park and Koo, 2020) who also find a linear effect of geographic proximity.

We also examine the overlap/substitution mechanisms among geographic and non-geographic forms of proximity, and product and process innovations networks. The results of the interaction terms are summarised in model 2 and 4 in table 7 & 8, respectively. In model 2, we find that, for process innovations network, only the interaction term of geographic and organisational proximity is negative (β = -1.05) and significant ($p < 0.05$), suggesting a substitution mechanism between these two proximity types. These results are in line with Hansen (2015) and Crescenzi et al. (2016), who found a strong substitution mechanism between geographic and organisational proximity dimensions.

By contrast, for product innovations network, interaction terms of geographic with organisational ($\beta = 0.79$, $p < 0.1$), cognitive ($\beta = 1.51$, $p < 0.01$) and social ($\beta = -1.37$, $p < 0.05$) proximity show significant results. The interaction effects of geographic with organisational and cognitive are both positive and significant, suggesting an overlapping mechanism, while the interaction of geographic and social proximity (work) shows a negative relationship, suggesting a substitution mechanism. Our results support hypothesis 3 as we find distinct relationship between proximity dimensions and, product and process innovation networks. These results are in line with prior work done by Crescenzi et al., (2016) on collaborative innovation; while these findings contradict with other previous studies conducted by Hansen, (2015) and Fitjar et al. (2016).

Regarding the control variables, we first note that a firm's export orientation propensity is positive ($\beta = 0.31$) and significant ($p < 0.05$) for the process network; however, it is negative (-0.26) for the product network ($p<0.1$), which implies that the export-oriented firms are more likely to collaborate with other export-oriented firms for process innovations than product innovations (Giuliani, 2010). Considering the impact of participation in *joint R&D activities*, this variable is positive (0.63) and highly significant ($p < 0.01$) only for product network. Finally, looking at memberships of trade associations, alter-memberships in the trade associations are not likely to facilitate linkage formation in the product network, whereas the coefficient for the process network is positive ($\beta = 0.06$) and significant ($p < 0.1$). On the contrary, if the receiver of the tie hold memberships in several trade associations, we find a significantly higher likelihood of tie formation both in the development of process ($\beta = 0.10$, $p<0.05$) and product innovation ($\beta = 0.10$, $p<0.05$).

5. CONCLUSION

This paper has looked at whether the impacts of geographic, organisational, social and technological proximity vary according to the type of innovation network, i.e., product and process innovation networks.

Our expectations were largely confirmed when it comes to analysing the positive relationship between proximity dimensions and the two innovation networks. We find significant results for both product and process innovations networks. Moreover, we find that the impact of geographic and non-geographic forms of proximities is relatively stronger in the process innovations network than the product innovations network. In particular, the impact of cognitive proximity is quite high. A possible explanation for this stronger impact of cognitive proximity dimensions on process innovations network may be the fact that innovation in traditional clusters is prevalently incremental or process-related (Dooley et al., 2015), owing to which managers and entrepreneurs in traditional industries participate in joint actions with other proximate partners, who are either using the same machinery/technology and also working in the same textile value chain, predominantly to solve machinery and production related issues or either to increase their production capacities and technical upgrading of production processes (Ghani and Fayyaz, 2007). Other possible reason for this high impact of proximity on process innovations network is that cluster firms share same language, culture and values, which is more conducive for transferring tacit (process) knowledge (Gertler, 2003; Nilsson and Mattes, 2015; Laursen et al., 2016). Final reason might be that, developing country firms require new forms of managerial knowledge and production practices to comply with international quality assurance standards which, in turn, require close cooperation among local firms for upgrading processes (Nadvi and Schmitz, 1999).

This study makes several contributions to the extant literature. First, we maintain that the mechanism of proximity and network formation operate distinctively across multiple networks (Balland et al., 2016; Quatraro and Usai, 2017; Davids and Frenken, 2017). We also find evidence that geographic and non-geographic dimensions may have substitution as well as overlap effect with each other (Crescenzi et al., 2016; Fitjar et al., 2016).

Second, we contribute to the literature that highlights the importance of having an optimal distance (proximity) among actors for technological collaborations (Mowery et al., 1998; Guo et al., 2021) and innovation creation (Boschma, 2005; Fitjar et al., 2016). Our study adds to prior work which suggests that collaboration with cognitively too close firms can result into knowledge homogeneity and locked-in phenomena (Nilsson, 2019), in turn, leading to withdrawal from cooperative partnership in future as these types of relationships bring limited economic value to partners (Guo et al., 2021). Therefore, it is always better to maintain a right distance between partners so that everyone being involved gets some benefits out of collaborations.

Third, we add to prior research on proximity and inter-firm cooperation in developing countries, which emphasise that non-geographic and geographic proximities are crucial in facilitating collaboration among clustered firms (Fayyaz et al., 2008; Geldes et al., 2015; Contreras Romero, 2018, Ferretti et al., 2022). Our findings suggest that cognitive and organisational dimensions, in addition to geographic and social proximities, are also crucial for technical advice sharing and innovation collaboration among clustered firms in developing countries (Boschma, 2005, Guo et al., 2021).

Our research is not without limitations. First of all, we have focused on a single industry cluster in a developing economy's context and its findings may not be perfectly applicable to clusters in developed economies. Therefore, future research should replicate this study to industry clusters in the developed economies to compare their outcomes with the findings of the current study. Second, we focus on a specific industry i.e., textile industry, which is a traditional industry, which is geared mainly at process innovations. Replication of this study into other technology sectors may yield different results owing to the complexity of innovation process for developing new product and process innovations in other sectors. Moreover, proximity effects are very strong in our paper. In particular, cognitive and organisational proximity coefficients are very strong. One possible reason might be that this study is conducted in a single industry cluster and some firms in our sample are subsidiaries of larger group of companies. On deeper inspection, companies are often involved in same textile technology (e.g., the spinning technology) and have not diversified into multiple businesses within textiles (e.g., spinning, garments and processing technology etc.), which is a limitation in our data. Another limitation might be that leading firms in the cluster tend to sublet a part of their larger orders to other independent firms (same technology) in the cluster consequently allowing them to jointly work on improvement/new development of products and processes, which is a possible cause of higher value of cognitive proximity.Therefore, future research should replicate this study into other industry clusters, which comprises of firms belonging to different industrial sectors, so as to better understand the proximity mechanism.

Third, we collected data only from those textile firms that are registered with APTMA and hence did not include other local textile firms in our study. Moreover, we only captured intra-cluster linkages among producer firms and did not capture extra-cluster linkages. We realise that limiting our sample to APTMA firms and only capturing intra-cluster linkages may not present the complete picture of innovation processes. Thus, while we situate our study in the micro-geographical proximity literature (Bignami et al., 2020; Feretti et al., 2022) which asserts that studying intra-cluster linkages is challenging because innovation-driven processes involve a variety of interactions among cluster members that are located at different geographical distances, we suggest that our findings should be interpreted with care in the sense that they only capture linkages among textile producers. Thus, future studies should study the relationship between producers and other actors inside cluster boundaries. Fourth, this study has analysed cross-sectional data, and is therefore unable to investigate the evolution of proximities and innovation networks in a dynamic manner. Thus, future studies should collect longitudinal data to probe whether and how the relationship between proximity and network evolves in a dynamic setting.

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[i] These definitions are commonly used in innovation measurement efforts, e.g. the OSLO manual or Community Innovation Surveys

[ii] National Textile University, Faisalabad http://ntu.edu.pk/ (accessed 13-05-2019)

[iii] http://www.pbs.gov.pk/sites/default/files/other/PSIC_2010.pdf (Last accessed 1st January, 2019)

[iv] We use UCINET6 software to calculate cosine similarity index