



THE UNIVERSITY *of* EDINBURGH

Edinburgh Research Explorer

Proximity and its Impact on the Formation of Technical Networks of Product and Process Innovation

Citation for published version:

Golra, O, Rosiello, A & Harrison, R 2018, 'Proximity and its Impact on the Formation of Technical Networks of Product and Process Innovation' Paper presented at 4th Geography of Innovation Conference, Barcelona, Spain, 31/01/18 - 2/02/18, .

Link:

[Link to publication record in Edinburgh Research Explorer](#)

Document Version:

Publisher's PDF, also known as Version of record

General rights

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.



Proximity and its Impact on the Formation of Technical Networks of Product and Process Innovation

Owais Anwar Golra^{a*}, Alessandro Rosiello^b, and Richard T. Harrison^c

University of Edinburgh
Business School, 29 Buccleuch Place, EH89JS, Edinburgh, UK.

*Email: owaisanwargolra@gmail.com,

*Phone: +447563557556

Abstract:

Informal networks among manufacturing firms play an important role in the transfer of knowledge in industrial clusters. Proximity facilitates the networking process, however our understanding is limited about the relationship between proximity dimensions and different types of innovation networks. Particularly, it is unclear how proximity dimensions shape the technical networks of product innovation and process innovation? We studied these networks in the Lahore textile cluster in Pakistan, and found significant influence of four dimensions of proximity on the process of network formation. Notably, the impact of cognitive, social, and organisational dimensions of proximity was found to be stronger for process innovation network than for product innovation network. Contrarily, the geographic proximity plays more important role in the network formation for product innovation than process innovation.

Keywords: Networks, Proximity, Innovation, Knowledge Flows, Clusters

1. Introduction:

The notion of proximity emerged in the 1990s, especially to study the phenomena of the creation, organisation and diffusion of innovation, and knowledge (Knoben and Oerlemans 2006). Although the studies on proximity and the geography of innovation grew tremendously over the last 25 years (Torre and Wallet 2014; Ferru and Rallet 2016), recent years have seen stability in their growth and it appears that this field has reached its saturation point. This is because the original objectives of the proximity research programme, which were set approximately three decades ago, have largely been achieved (Ferru and Rallet 2016). Ferru and Rallet (2016:p102) revealed that 13,733 articles published between 1990 and 2015 in the business; economic; geography; and urban studies, have used the key words ‘proximity and innovation’ in the main body of text.

Despite, large amount of empirical evidence gathered by proximity scholars, there are still interesting questions unanswered in the field of proximity dynamics (Balland, Boschma et al. 2015), geography of innovation and organisation of firms’ innovative activities (Ferru and Rallet, 2016:p117). First of all, the proximity framework has largely ignored the relationship between different types of innovation, and multiple dimensions of proximity. For instance, an

interesting question to explore is, whether radical innovation or incremental innovations are influenced in the same way by the dimensions of proximity, networks structural properties and the attributes of actors (Boschma, Balland et al. 2015). Similarly, Ferru and Rallet (2016) suggested to study the organisational choices related to product and service innovation, and their impact on the spatial configuration of the innovation process.

Second important and overlooked area of research is the integration of multidimensional proximity framework in multiple network research setting. Prior studies mainly focused either on single dimension of proximity (Heringa, Horlings et al. 2014) or multiple proximity dimensions, and cooperation in single network (Aguilera, Lethiais et al. 2012). The exception is Balland, Belso-Martinez et al. (2016), who have studied different dimensions of proximity and two types of networks in an integrated framework. The authors provided empirical evidence that multiple proximity dimensions influence technical and business advice network in a different manner. They further argue that cognitive and geographic proximity plays significant role in explaining the formation of technical advice network, whereas the impact of these dimensions on the formation of business advice network is not significant. Their findings suggest that conclusions based on single network studies may be incomplete and biased because, on the one hand, a firm may prefer to collaborate with geographically proximate partner to acquire a specific type of knowledge (e.g. tacit). On the other hand, firms may prefer to collaborate with geographically, as well as, cognitively proximate partner when the required type of knowledge is complex (Balland and Rigby 2017). Therefore, an integrated approach is imperative to draw useful conclusions for cluster policy development and to contribute to the proximity and network literature.

Finally, plethora of studies have used formal relational data i.e. research projects, joint publications, patents, contracts/deals etc., to study the impact of multiple dimensions of proximity on network formation (Agrawal, Kapur et al. 2008; Broekel and Boschma 2011; Balland 2012; Balland, De Vaan et al. 2012; Boschma, Balland et al. 2014; Boschma, Marrocu et al. 2015; Lazzeretti and Capone 2016) and very few have investigated informal relational data in multi-dimensional proximity framework (Molina-Morales, Belso-Martínez et al. 2015; Balland, Belso-Martínez et al. 2016). Particularly, in the developing countries context, such type of studies have been rare (Geldes, Felzensztein et al. 2015). We believe this will be unique contribution in literature because application of multidimensional proximity as determinant of informal networks in developing countries perspective is scarce, particularly, application in case of regional cluster is not yet fully explored.

Therefore, in this paper, we respond to the prior call for further research and explore the relationship between multidimensional proximity and multiple networks (Balland, Belso-Martínez et al. 2016) in an integrated framework. We address the aforementioned research gaps by investigating the role of four different dimensions of proximity framework, (Boschma, 2005) namely social; organisational; cognitive and geographic, in shaping the formation of two different types of innovation networks in a developing country's regional context. The two networks were composed of the technical advice linkages established by the firms for the development of new products and new processes in a textile industrial cluster in Pakistan. The key contribution of this paper lies in the proximity relations and geography of innovation

literature (Torre and Wallet 2014; Shearmur, Carrincazeaux et al. 2016) that, according to our knowledge, overlooked the formation of different types on innovation networks and their relationship with the geographic and non-geographic dimensions of proximity.

We have excluded the institutional dimension from our analytical framework because it is not relevant in our research setting. Our sample of firms only includes the local textile manufacturers from different stages of the textile value chain, and they all work under the umbrella of similar institutional rules. Therefore, institutional proximity is not considered.

The structure of the paper is as follows. The next section stresses the importance of innovation, network and proximity concepts, and explains, why proximity might be important to study the network of product and process innovation? In section three, we present our research propositions. The data and methodology is presented in Section four, and results are discussed in the fifth section. We conclude in the last section with limitations of current study and suggestions for future research.

2. Innovation, Networks and Proximity:

Innovation is the most important engine for economic growth of firms and regions, however the prerequisite to produce innovation is the capability to learn and create new knowledge (Boschma 2005). New knowledge can be created through trial, error and experimentation process individually or it can be created by joint action of different actors through networking process (Cantner and Graf 2011). Both knowledge and the networks are extremely important for the successful performance of firms and regions (Zaheer and Bell 2005; Arikan 2009). Knowledge is considered as the most valuable source of innovation and hence competitive advantage for the firms (Grant 1996). In order to remain competitive in the market, firms need to regularly update their stock of knowledge by combining the existing knowledge with the new knowledge (Kogut and Zander 1992). Firms can create new knowledge internally, however it is nearly impossible, to produce all components of knowledge required for the development of new products or services internally (Arikan 2009). Secondly, creation of new knowledge through in-house R&D can sometime be more costly than the benefits it may deliver, hence firms may acquire the required knowledge externally (Van Wijk, Jansen et al. 2008). Firms can acquire external knowledge through several mechanisms such as buying required knowledge from the appropriate market, outsourcing research project to other firms, buying license or patent, and hiring people with required knowledge (Cantner and Graf 2011).

In a regional context, one of the most important mechanisms that firms use to acquire external knowledge is via informal contacts. Several studies have provided empirical evidence that firms do share significant amount of knowledge with one another through informal networking process (Giuliani and Bell 2005; Powell and Grodal 2005; Giuliani 2006; Boschma and Ter Wal 2007; Morrison 2008). The two very important drivers of the network formation are network endogenous effects (Glückler 2007) and individual attributes of actors (Cohen and Levinthal 1990; Giuliani and Bell 2005; Giuliani 2013) which means actors tend to collaborate with others, either based on their position in the network (e.g. degree centrality), or according to their individual characteristics e.g. (size, absorptive capacity). Nonetheless, proximity has been acknowledged as an important and third driver of network formation (Boschma, 2005;

Torre and Rallet, 2005). Balland, Belso-Martínez et al. (2016) argue that firm level attributes and network endogenous effects are important though, the notion of proximity plays a central role in explaining the formation and dynamics of, especially, technical networks.

Boschma (2005) proposed an analytical framework based on five key dimensions of proximity. He suggested that actors interact with each other because of social proximity between them or embeddedness in the social relations (Granovetter 1985). Social relations are important but they are not always present, therefore actors often tend to collaborate because of their organizational proximity to each other, which refer to as the similarity in terms of organizational routines and structures. For instance, employees working in the same organisation are more likely to seek advice from one another instead of seeking help from the employees of other organisations. However, sometime the required advice, knowledge or information is neither available from the social contacts nor from the other colleagues inside the organisation, therefore employees search for partners outside the organisation who can provide the required knowledge. Here, cognitive proximity plays important role in facilitating interaction, which refer to as similarity in terms of knowledge bases of partners (Nooteboom 2000). In addition to the above three forms of proximity, actors cooperate because of similarity in norms and institutions in which they are embedded (Edquist 1997). Boschma (2005) termed it as the institutional proximity. Finally, geographic proximity is defined in terms of the co-location or nearness in geographic distance, which means actors interact with other close located actors.

So far, proximity framework has been broadly studied to explain the formation of economic networks (Boschma et al, 2014), collaboration networks (Balland, 2012), innovation networks (Capone and Lazzeretti, 2016), knowledge networks (Broekel and Boschma, 2012), marketing networks (Geldes et al., 2015) and technical networks (Balland et al, 2016). Scholars have found significant, nevertheless inconsistent influence of all proximity dimensions in the network formation in different situations. Specifically, proximity dimensions have been found to impact the different types of networks (i.e. technical and business network) in a different manner (Balland et al., 2016).

There is evidence that the configuration of both product and process innovation networks is different from each other (Gemünden, Ritter et al. 1996), which means suppliers, customers, and competitors etc., each plays different role in the development of process and product innovations. For instance, Antonelli and Fassio (2016) showed (in their empirical study on the role of external knowledge) that, on the one hand, the interaction of innovators with their suppliers favours the generation of technological knowledge for process innovations, whereas on the other hand, the interaction of innovators with their customers favours the generation of technical knowledge for product innovations. Research also shows that the structure of external knowledge absorption for product innovations is different from that of the process innovations (Bogers and Lhuillery 2011), therefore we can argue that firms interact with different external partners when they seek technical advice to develop process innovations and product innovations. We can also assume that if the type of partners and their relative importance in the two innovation networks is different from one another, then the relational characteristics

between the nodes of the two networks may possibly be different from each other in various dimensions, e.g. geographic, cognitive, organisational, social and institutional.

3. Research Propositions:

3.1 Proximity, and the Formation of Product and Process Innovation Networks:

Different dimensions of proximity may impart differentiated impact on the formation of product and process innovation networks. Because, first of all, the characteristics of knowledge needed to develop product innovations is different from that of process innovations (Gopapakrishnan, Bierly et al. 1999), due to which actors may require different coordination mechanisms to deal with different level of complex and tacit knowledge. Secondly, the organisation of innovation process for the development of these two innovation types may also be different from one another. For instance, the development of a product usually involve several process technologies and each of these technologies can also be used to develop other products, hence there does not exist a one to one relationship between technological process innovations and product innovations (Granstrand and Sjölander 1990). Westerlund and Rajala, (2010) revealed in their study on firms' learning orientation and network collaboration, that, explorative learning orientation facilitate collaboration with new partners when the focus is to introduce product co-innovations. On the contrary, exploitative learning orientation promotes process innovations but discourages the collaboration with new partners. This is because the firms prefer to stay with existing network partners and do not search for new partners in process co-innovation (Westerlund and Rajala 2010).

As suggested above that the network formation between firms can be influenced by the characteristics of knowledge involved in the innovation process. Gopapakrishnan, Bierly et al. (1999) argue that the knowledge required to develop process innovation is complex, tacit and systematic, whereas product innovation require simple (less complex), explicit and autonomous knowledge. An increase in the complexity of knowledge makes its transfer less easy and creates coordination problems between partners (Van Wijk and Jansen 2008). Aguilera, Lethiais et al. (2012) noted that the importance of non-geographic dimensions of proximity increases with the increase in level of coordination between partners. For instance, higher number of coordination steps may involve higher number of personnel expertise and therefore may require proximity in cognitive and organisational dimensions to smooth the coordination mechanism. Besides, it was argued that, an increase in the tacit-ness of knowledge increases the need of higher level of proximity between partners (Von Hippel 1998; Maskell and Malmberg 1999), because geographical proximity facilitates information and knowledge sharing through frequent interactions, especially when knowledge is tacit, complex and sticky (Bathelt, Malmberg et al. 2004). Van Wijk and Jansen (2008) claimed that, although, the difficulty of knowledge transfer increases with the increase in its complexity; tacit-ness; and specificity, high geographic proximity to the source can at least minimise the coordination problems.

Geographic Proximity

From the above discussion, we can conclude that both geographic and non-geographic proximities are important to reduce coordination problems in the transfer of complex knowledge and to facilitate collaboration between partners, however geographic proximity may play more important role because it facilitates face to face communication and therefore enhance level of trust between partners. *Geographical proximity* or spatial proximity is generally associated with the notion of space, territory, locality and physical closeness (Knoben and Oerlemans, 2006). In other words, it is the spatial distance between two agents and usually operationalized in terms either physical distance between partners or geographic co-location (Anguilera et al., 2012). As mentioned earlier, the two partners located at close geographic proximity are more likely to have frequent interactions, which can improve the level of trust between them. Consequently, this can minimise the coordination problems during the diffusion of even complex knowledge. As we know that process knowledge is complex than the product knowledge, and its diffusion and transfer may be more difficult than the product knowledge, therefore geographic proximity between partners is necessary for successful transfer of process knowledge. (Balland and Rigby 2017) have recently investigated the importance of geographic proximity in the diffusion of complex knowledge. They have shown that the likelihood of the diffusion of complex knowledge increases with the decrease in geographic distance between partners, however decrease in geographic distance between partners decreases the diffusion of complex knowledge. Their research further suggest that the less complex knowledge can be diffused easily at both shorter and longer geographic distance. On the contrary, Sorenson et al (2006) argue that complex knowledge is less likely to diffuse between partners even if the interacting partners are located at close proximity. From the above points, we can say that geographic proximity may be equally important for both product and process knowledge diffusion, however increase in geographic distance may create problem for the transfer of complex knowledge between partners. Therefore, the impact of geographic proximity on the network formation of process innovations and product innovations may be same.

Social Proximity

'Social proximity' is referred to as the social embeddedness in relations between agents (Knoben and Oerlemans, 2006). Its origin is generally considered as the embeddedness literature (Granovetter 1985). It is mainly related to the notion of trust, based on kinship, friendship and past collaborations (Boschma, 2005; Broekel and Boschma, 2012). Boschma (2005) pointed out that in a cooperation, which is based on informal linkages, it is not market contracts that favour knowledge exchange rather it is trust that facilitates smooth flow of knowledge among partners, especially when the knowledge is in tacit form. Therefore, social proximity may be more important for process innovation knowledge than product innovation knowledge. It is because the process innovation knowledge is more tacit than the product knowledge. In a similar way, social proximity may facilitate the knowledge flow when the knowledge is complex, because of trust and friendship based relations, actors are more likely to help each other in order to minimise the coordination problems cause due to complexity.

Cognitive Proximity

Cognitive proximity is important for the interfirm network formation because similarity in knowledge base and shared skills is critical to properly understand the knowledge of partners. The complex knowledge may transfer (comparatively) easily between cognitively close partners than cognitively distant partner. (Balland and Rigby 2017) argue that complex knowledge is more valuable and more difficult to produce than simple knowledge, and its diffusion becomes even more difficult when the knowledge bases of the two collaborating partners are not close to each other. Sorenson et al (2006) claimed that the complex knowledge is less likely to diffuse either. As we know that the process innovation knowledge is more complex therefore cognitive proximity between partners can enhance the diffusion of complex knowledge. Contrarily, the product innovation knowledge is simple, therefore firms can easily acquire simple knowledge from the partners or sources which are even less cognitively proximate to them. From this discussion, we can posit that cognitive proximity play more important role in the network formation of process innovation knowledge than product innovation knowledge.

Organisational Proximity

Organisation proximity is also important for the network formation because firms prefer to interact with others who are working under similar organisational structures. The similarity in rules, procedures, practices, routines, structural equivalence, mechanism of coordination, and the set of interdependencies, all are related to the concept of organisational proximity (Boschma, 2005; Anguilera et al., 2012). As we know that the complex knowledge need higher level of coordination between cooperating partners for its successful transfer and diffusion. This higher level of coordination can be achieved if the collaborating partners have similar organisational and governance structure. For instance, subsidiaries of multinational companies or a large parent organisation often follow the same organisational routines and procedures, therefore we can expect better coordination between two sisters firms than between two firms that belong to different organisational groups. Due to similarity in the governance structure, organisational procedures and mechanism of coordination, these actors become organisationally proximate. Actors may prefer to collaborate with more organisationally proximate partners when want to develop process innovations, because complex and tacit knowledge seeks higher level of coordination, which is more likely between partners with close organisational proximity. In case of product innovation knowledge which is simple and codified, less organisationally proximate partners may also prefer to collaborate with each other.

From the above discussion, we can therefore posit that, although, proximity to the external source in all dimensions is important for both product and process innovation networks, it may be more crucial for process knowledge than product knowledge, because process knowledge is more complex, systemic and tacit (Gopapkrishnan et al. 1999). In other words, the likelihood that firm will successfully establish a knowledge linkage with its external knowledge source or another partner depends, first of all, on the type of knowledge and/or innovation, and secondly, on the proximity between the exchange partners in multiple dimensions. The more the complexity and tacit ness of knowledge, as in case of process knowledge, it is more likely that

the knowledge linkage will be established between more proximate partners. Moreover, process innovators tend to work more closely with external partners to develop new technological solutions (Von Hippel 1998). Contrarily, product innovation knowledge is simple, codified and autonomous, therefore proximity dimensions play relatively less important role in facilitating knowledge linkages between partners. Nevertheless, some similarity is still required in the knowledge bases of partners to collaborate on product development, and of course social and organisational proximity is also necessary at some extent. Finally, close location to the other source can definitely effect the collaboration in case of product innovation development.

Another argument regarding the relationship between proximity and the types of innovation network is that proximity may positively influence process innovation relations between firms in industrial districts, because firms situated in clusters share common understanding of technical problems due to similarity in their production systems (Callois 2008) and production conditions (Bathelt, Malmberg et al. 2004). The common problem solving increases the similarity between the knowledge bases of cooperating partners and hence reduces the cognitive distance between them, which consequently facilitates interaction. Additionally, the frequent face to face interaction between clustered firms increases the level of trust and social proximity between firms. On the one hand, the increase in trust level, positively influence the collective efficiency of clustered firms because of the shared pool of resources developed due to co-location; social proximity; and cognitive proximity (Callois, 2008). On the other hand, these proximity dimensions may be negatively associated with product innovations, because diverse knowledge and new ideas are more important for introducing new products (ibid), hence firms may search for partners outside their close geographic boundaries, as well as from different technological domains, to obtain diverse information.

To summarise, we expect the role of proximity in facilitating the formation of both process and product innovation networks, nevertheless its role may be more important in the formation of process innovation network as compared to product innovation network, because the transfer of complex knowledge may need more frequent interactions between partners for its successful and smooth transfer. Also due to similarity in production systems amongst clustered firms, they may prefer to cooperate more on process related issues than product development matters. Hence, we assume that the different dimensions of proximity will influence the two networks in a different way and we submit our two prepositions as follows;

Proposition 1: The multiple dimensions of proximity facilitate the formation of both the technical networks of process innovations, and product innovations.

Proposition 2: The magnitude or impact of the cognitive, social and organisational dimensions of proximity on the process innovations network is higher than the product innovations network. However, the impact of geographic proximity remains the same for both product and process innovations networks.

4. Data and Methodology:

4.1. Research Setting:

Textile Industry of Pakistan & Lahore Textile Cluster:

The context of this empirical study is a textile cluster in the city of Lahore, Pakistan. Lahore is the second most populous city in Pakistan with the total population of around 10.6 Million in 2016 (Demographia 2017). The city is hub of many industries including textile and clothing. Textile Industry is considered as the backbone of the economy of Pakistan. It contributes to around 54% of the total country's exports, employs 40% of the industrial workforce and also accounts for 8% of the total GDP (O. A. Golra, A. Luqman et al. 2011; Pakistan Textile Policy 2014-19). The industry is scattered across the country in the form of several clusters. The most prominent textile industrial clusters are located in the cities of Lahore; Faisalabad; Sheikhpura; and Sialkot in the province of Punjab, and Karachi; Sukkur; and Hyderabad in the province of Sindh.

According to a census of manufacturing industries conducted by the Pakistan Bureau of Statistics (PBS) in 2005-06, the city of Lahore accounts to approximately 18% of the total textile and clothing manufacturing firms in the province of Punjab and about 10% in Pakistan (Pakistan Bureau of Statistics 2005). The census results reported 131 textiles and 39 wearing apparel firms from Lahore, and the number of workers employed by these firms were reported to be between 200 and 350 on average¹. These firms are involved in almost all stages of the textile value chain i.e., yarn manufacturing, knitted and woven fabric manufacturing, dyeing, printing and finishing of fabric, and apparel, and made-ups manufacturing. Further, they are clustered mainly in four different locations, i.e. Raiwind-Manga Road, Ferozepur Road, Bhaiperu-Multan Road, and Defence Road as shown in Figure 1. Lahore textile cluster is the home to some of the most prominent textile firms and/or their subsidiaries that are leading the textile industry in Pakistan.

Most of these firms have set-up R&D, product development and design departments in Pakistan, and some of them have established these departments in London and Istanbul (Nabi and Hamid, 2013:25-26). Others have hired highly paid foreign consultants, mostly from Turkey (because Turkey is quite advance in denim jeans & apparel washing), in order to develop difficult samples and also to train the local staff. Because of this initiative of large firms, local workers in these firms are improving their technical skills and indirectly the other firms in the local cluster are also improving their capabilities because of knowledge spill over

¹ In our data, the minimum number of employees reported by firms are 500 and maximum are 13000. On average, each firm employ approximately 1834 workers. We surveyed those firms that are registered with APTMA, because only organised firms are granted APTMA's membership. There is large number of un-organised firms operating in the country which makes it difficult to verify their information from any other source. Therefore, in order to apply the whole network approach, we limit our survey to only those firms that are registered with APTMA. Therefore, our full population of active firms is 73 in total instead of 170 that was reported by the PBS manufacturing census 2005-06. Moreover, in the last 10 years several firms ran out of business due to severe energy crisis, which was also highlighted in the latest Textile Policy document of the Government of Pakistan (Textile Policy 2014-2019, 2015).

effect caused by the geographic proximity to the leading firms or co-location in the same cluster.

Another important, however informal, mechanism of knowledge transfer between firms is the strong presence of the community of textile engineers or graduates, which belong to the oldest Textile University (i.e. NTU, Faisalabad) in the country. The university was established in 1959 and since then its graduates have been serving the textile industry of Pakistan. It is believed that they retain control over the technical and business operations of more than 80% of the textile firms in Pakistan. They are commonly recognised as “Textilians”, “BSc’s” or “Manawala Graduates”, and because of this affiliation and social embeddedness among “Textilians”, the knowledge produced in innovative firms reaches the other local textile firms. The similar embeddedness phenomena is prevalent also at the entrepreneurial level, as most of the textile firms owners are actually relatives of each other and they also advice each other on new investment decisions. Another very important aspect is that large number of firms in textile industry are owned by small number of families or clans in the country (Faheem, 2005; Haque, 2007), and therefore several firms belong to a single larger group of companies. Due to this reason, the knowledge circulation often remains within the sister companies due to organisational boundaries set up by the central head offices of the parent company.

The purpose of discussing the context is to highlight the importance of the social relations and also their potential role in facilitating the transfer and circulation of knowledge in local clusters. In this context, we have designed our study to investigate the knowledge transfer mechanism between firms in the textile cluster in Lahore. Particularly, to investigate the role of proximity dimensions in shaping the knowledge networks between clustered firms.

-----FIGURE A HERE -----

4.2. Data

In order to investigate the impact of different dimensions of proximity on the inter-firm knowledge transfer mechanism for the development of new products and processes, we collected micro level data from the Lahore textile cluster. The data was collected through face to face interviews from the personnel responsible for the management of production operations, and the development of new products and processes.

In our study, the survey was not based on a sample of firms and data was collected from all active large scale textile firms located in the four municipalities in the city of Lahore. The list of firms were obtained from the website of All Pakistan Textile Mill Association (APTMA). According to the list, there are 84 large textile firms operating in the city of Lahore. During the pilot study, we were informed by the managers of pilot firms that, not all firms in the APTMA list are active, number of firms had shut down their operations due to severe energy crisis. Therefore, we surveyed only those firms that were active at the time of data collection. Our final list consists of 73 firms in total.

Prior to our final data collection exercise, we also conducted pilot study during the month of October and November 2015. Based on the results of pilot study, we revised our survey and interview questionnaires. Final data collection was then started in May 2016 and finished in September, 2016. As mentioned above, fieldwork was based on interview based survey design. We conducted interviews with managers of 73 firms to collect primary relational and firm level attribute data, in order to create dependent and explanatory variables. We also collected secondary data from other sources, such as; company websites; government websites and trade association websites. These sources helped us in the construction of remaining explanatory and control variables. Another purpose of this exercise of data collection was to triangulate the data obtained via face to face interviews. Following Giuliani and Bell (2005), and Boschma and Ter Wal (2007), we used roster recall methodology (Wasserman and Faust 1994) to collect our relational data. We also mixed roster recall methodology with free-recall approach, and allowed the firms to add the names of other advice seekers and givers, which are not mentioned in the roster. The next section will explain the operationalisation of key variables.

4.3 Operationalization of Variables

4.3.1 Explanatory Variables:

Geographic Proximity (geoprox):

This variable has been operationalized in the studies by measuring the distance between firms in either kilometres, logarithm kilometre, travel time or by the co-location in the same geographic area (Balland, 2012; Broekel and Boschma, 2012; Balland et al., 2014; Molina-Morales et al., 2015 among others). Following Broekel and Boschma (2012), we measure geographic distance by calculating the natural logarithm of distance in kilometres between the two firms. We then inversed the natural logarithm of distance to get the measure for the geographic proximity (Boscham, Balland et al. 2014). We expect a positive sign in our results because the increase in proximity increases the likelihood of collaboration between firms, which means firms are more likely to seek advice from other firms that are located at a close geographic distance.

Cognitive proximity (cogprox):

Cognitive proximity is also measured by scholars in different ways. Mostly, it is measured by using the similarity in the NACE codes (Molina-Morales, Belso-Martínez et al. 2015; Usai, Marrocu et al. 2017). Some scholars have operationalised it by measuring the similarity in the technological and knowledge base. We have measured it following Broekel and Boschma (2012) by calculating the cosine similarity index between the eight technologies involved in the local textile cluster. This is in fact a measure of industry or technology relatedness. We have consulted Pakistan Standard Industrial Classification (PSIC) 2010 to collect information on the industry codes. We then used the following formula to calculate the cosine similarity index between the eight technologies involved in the textile industry²;

² Pakistan Standard Industrial Classification (PSIC) and the definition of each class can be found here; http://www.pbs.gov.pk/sites/default/files/other/PSIC_2010.pdf

$$\text{Cosine}\Theta, S_{ij} = \frac{\sum aikbjk}{\sqrt{\sum aik^2 \sum bjk^2}}$$

Where i, j and k are technologies. In above equation, aik and bjk are the technology vectors of organisations. In our sample, firms are involved in more than one technologies. For example, the highest number of firms are involved in spinning (26%), followed by 25% and 15% firms in processing and weaving technologies respectively. Cosine similarity informs us about the technology overlap between the two knowledge sharing partners.

Social proximity (socProx):

This variable has also been defined by scholars in different ways. In our research context, we have operationalised it as a binary variable based on the affiliation of the top management personnel with the National Textile University (NTU), Faisalabad. We asked the respondents about the university affiliation of the head of the department, and if both the top manager of collaborating firm has obtained his/her degree from NTU then the variable takes the value 1 and otherwise 0. We adopt this idea from Broekel and Boschma (2012) who measured the social proximity between the firms based on their past affiliation with the Fokker Company. We name this variable, ‘*socprox-same univ*’. Secondly, we have also asked information about the last three employers of the respondent, if any of the last three employers are same between the two connected partners then it will show a sign of social proximity. We name this variable, ‘*socprox-past employer*’

Organizational proximity:

This variable has also been defined by scholars in different ways. We have operationalised it following (Balland et al., 2014) and consider it as a binary variable. It will take the value 1 when both firms are owned by the same group of companies and otherwise 0. As explained above that most of the textile firms are owned by few large groups, therefore we have chosen this method.

4.3.2 Dependent Variables:

Network for Product Innovation

This variable is operationalize on the basis of links between actors established to share knowledge for product innovations. We follow Broekel and Boschma (2012) in the operationalization of this variable, because our main purpose is to estimate the importance of different dimension of proximity on the likelihood that two actors are connected for the purpose to share the product innovation knowledge. It takes the value 0 when there is no link and the value 1 when there is a link. The question seek information for directed graph unlike Broekel and Boschma (2012) who assumes presence of link when one of the partner identifies a link.

Network for Process Innovation

This variable is operationalize on the basis of links just like the product network, but this link is based on the knowledge related to process innovations. Following Broekel and Boschma (2012) our main purpose is to estimate the importance of different dimension of proximity on the likelihood that two actors are connected for the purpose to share the process innovation

knowledge. It takes the value 0 when there is no link and the value 1, when there is a link. The question seek information for directed graph unlike Broekel and Boschma (2012) who assumes presence of link when one of the partner identifies a link.

4.4 Method & Model

Multiple Regression Quadratic Assignment Procedure (MRQAP)

Our focus is to understand the relational intensity of knowledge exchange between two actors. Different models can be used to study the relational data (Broekel, Balland et al. 2014), however we will use multiple regression quadratic assignment procedure (MRQAP) to explain the formation of linkages between firms because the MRQAP is useful where research interest focuses exclusively on the effects of explanatory variables (predictors) and not on modelling the network as such or on structural dependencies (Snijders 2011). In our paper, we are interested to study the impact of four dimensions of proximity (as explanatory variables) on the formation of product and process innovation networks (dependent variables).

MRQAP is a logit or OLS regression model that uses permutation method to assess the statistical relevance and consider the inherent interdependencies of relational variables (Broekel and Hartog 2011). The choice of OLS or Logit model depends on the availability of data in hand. If the data is valued, then OLS is more appropriate, otherwise for binary data (0/1) Logit model should be the preferred choice (Broekel et al, 2014). Our data is primarily binary, and the dependent variables are the dyadic relations that takes the value '1' when the relation exist between partners and otherwise it takes the value '0' when the relation is absent. In our model, all explanatory variables are in the form of binary relational data except cognitive and geographic proximity, which are relational data though, but these are continuous variables. We have chosen MRQAP model in our study because this model is recommended and useful when the dependent variables are in binary data format, as ours.

The working principle of QAP regression model (Krackardt 1987) is a permutation or randomization based semi parametric test of dependence between two matrix of same size i.e. rows and columns. MRQAP model is specifically designed to study the data in which the dependent and independent variables are not vectors, and de facto (n*n) matrices. The dependent variable (a matrix) is regressed by one or more independent variables (matrices) using OLS or Logit model depending on the type of data (Broekel et al, 2014). The p-value or the significance of the test is estimated by permuting the rows and columns of the matrices thousands of times. The logic of doing this is to compare the observed relationship among dependent and independent matrices against the distribution of relationships obtained via permuting the rows and columns thousands of times (Dekker, Krackhardt et al. 2007; Borgatti, Everett et al. 2013).

MRQAP model also has several limitations. The most important is that one cannot directly incorporate node level and structural level attributes into the model. However, node level attributes can be incorporated into the model by converting the attribute level data into relational level data based on the similarity or distance between two connecting partners' attributes of interest (Broekel and Hartog, 2011). In our study, primary interest is to study the

impact of different proximity dimensions, which are in the form of four n*n matrices, on the formation of linkages between firms particularly for product and process developments. We have also included several node level variables in our model after converting them into a relational variable by using the method suggested by Borgatti et al (2013). We did that to improve the fit of our model. The basic model is given below in equation 1 and 2;

$$Y1ij = Odds = P/1-P = e^{\beta_0 + \beta_1x1ij + \beta_2x2ij + \beta_3x3ij + \beta_4x4ij + \beta_5x5ij}$$

$$Y1ij = Ln (P/1-P) = \beta_0 + \beta_1x1ij + \beta_2x2ij + \beta_3x3ij + \beta_4x4ij + \beta_5x5ij \text{ ----- Equation 1}$$

Y1ij = Dyadic link between 'i' and 'j' for product innovation

b1= Geographic Distance, b2=Cognitive Proximity, b3= Organisational Proximity, b4=Social Proximity (Work), b5 = Social Proximity (University)

$$Y2ij = Odds = P/1-P = e^{\beta_0 + \beta_1x1ij + \beta_2x2ij + \beta_3x3ij + \beta_4x4ij + \beta_5x5ij}$$

$$Y2ij = Ln (P/1-P) = \beta_0 + \beta_1x1ij + \beta_2x2ij + \beta_3x3ij + \beta_4x4ij + \beta_5x5ij \text{ ----- Equation 2}$$

Y2ij = Dyadic link between 'i' and 'j' for process innovation

β1= Geographic Distance, β2=Cognitive Proximity, β3= Organisational Proximity, β4=Social Proximity (Work), β5 = Social Proximity (University)

The following section presents the result of QAP logit regression model applied to investigate the relationship between proximity dimensions and the network formation for product and process innovation. Broekel and Boschma (2012) applied this model to investigate the impact of proximity dimensions on the knowledge network of Dutch Aviation Industry. They used Double Dekker Semi-Partialling MRQAP technique, however the interpretation of this approach is a bit tricky and not straight forward (see Borgatti et al, 2013:132), and hence one cannot claim that an increase in one unit of X variable is associated with a certain increase in the odds of that case being a 1 on the dependent variable. To have such interpretation, logistics regression model (LRQAP-logistic regression quadratic assignment procedure) is recommended by Borgatti et al (2013). Therefore, we have used Logit model in our study. Our dependent variable is dichotomous variable (i.e. the likelihood of the presence of a link between two firms) and this model is most reasonable when the dependent variable is dichotomous i.e. 0/1.

5. Results:

5.1. Descriptive Statistics:

Table 1 reports descriptive statistics on firm level characteristics, such as their size (number of employees), legal status (whether firms are private limited companies, or public limited companies (whose shares can be bought by the general public), age (number of year since the firm was localised), organisational structure (whether it is an independent firm, part of a textile group, or part of a multi-sector group), Export level (whether firm is a significant exporter or not). Finally, the table provides information on the technology profile of firms (the number of firms involved in each textile technology as per Pakistan Standard Industrialisation

Classification System)³. The numbers in technology profile exceeds the total number of firms in the sample, because several firms are involved in more than one technology. In some cases, two technologies always go together and therefore the number of firms appear in the data exceeds the sample size. The other way round, last section in the table provides the profile of each technology and the number of firms involved in each technology class. Table 2 reports the proximity variables and the range of data points.

-----Table 1 & 2 here -----

Figure 2 and 3 shows the technical networks of product and process innovations, respectively. The nodes are the firms in the network and the size of nodes represents the absorptive capacity of the firms. The focus of current paper is not to discuss the composition and effect of absorptive capacity therefore we will not discuss it in detail. Figure 4 and 5 shows the technical networks of product and process innovations and this time the nodes sizes represent the innovation count of each firm. The number of edges (links) in the process and product innovation networks are 259 and 206, respectively. The density of product and process networks are 0.039 and 0.049, respectively.

-----Table 3 here -----

-----Fig 1,2,3,4 here-----

5.2 Results of the Regression Model:

First of all, we computed the correlation between the product and process innovation network. The results obtained from QAP correlation are reported in table 4. The correlation between the two networks is 0.45 i.e. 45%, which means that 55% of the underlined network connections are different in the two networks. This provides us the opportunity to further investigate the choices of partner selection of firms during the process of new product development or process improvement.

-----Table 4.1 & Table 4.2 here-----

-----Table 5 here -----

-----Table 6 here -----

-----Table 7 here -----

The R-square value for the LRQAP model for process network is 0.20 and also highly significant (p-value is less than 0.001), which shows that 20% of the linkage formation in the network of process innovation can be explained by our model. The coefficient for technological or cognitive proximity shows the highest value (3.047) among all proximity dimensions followed by the coefficients of organisational (2.47) and social proximity-past-employer (2.039) respectively. Both significant at p-value 0.001. The second variable for social

³ Pakistan Standard Industrial Classification, PSIC Rev.4 (2010)
http://www.pbs.gov.pk/sites/default/files/other/PSIC_2010.pdf

proximity-same-university (0.534) is also positive and significant at p-value 0.001. The geographic distance is negative (0.423) and significant at p-value 0.05. However, we cannot compare the relative magnitude of these explanatory variables because some are continuous and others are dichotomous variables.

On the other hand, the R-square for product network is 0.12 and is significant at p-value 0.001, which shows approximately 12% of the linkage formation in the network of product innovation can be explained by our model. Similar to the relationship between proximity and process network, the coefficients for product network follow the same pattern, however the value of coefficients are comparatively weaker for product network. For product network, the technological proximity shows the highest value (2.45) among all proximity dimensions followed by the coefficients of organisational (1.98) and social proximity-past-employer (1.33) respectively. Both significant at p-value 0.001. The second variable for social proximity-same-university (0.52) is also positive and significant at p-value 0.01. The geographic distance is negative (0.65) and significant at p-value 0.01.

Among the other control variables in the model, joint R&D and being an exporter both are significant at p-value 0.05 for both process networks, however the coefficient for joint R&D is slightly stronger for product innovation network than process network. Nevertheless, the coefficient of being an exporter is positive and significant for process network and interestingly it is negative for product network, which implies that the export oriented firms that are involved in product innovations are less likely to collaborate with other export oriented firms. Taking into consideration the memberships of trade associations, alter-memberships in the trade associations is not likely to facilitate linkage formation both in the product and process network. Finally, absolute difference in the qualification level of senior managers is negative and significant (p-value =0.06) for process network, which shows more qualified managers do not interact with less qualified managers, however it is not significant in case of product network.

We have also tested the impact of all these explanatory variables on the formation of technical networks. We constructed this technical network by combining the product and process innovation networks. By this way we can further strengthen the support to the hypothesis of the role of knowledge characteristics in process of network formation. Table 8 presents the results of the impact of proximity dimensions on the network formation of technical network. Table 9 illustrates comparison between the three networks. The results suggest that with the increase in the complexity of knowledge the magnitude of the coefficient for proximity variables rises and vice versa. This is true for the social, organisation and cognitive dimensions of the proximity framework. On the contrary, the magnitude of geographic proximity increases with the decrease in the complexity of the knowledge, as in our case the coefficient is higher for product network than the other two networks. This implies that when the knowledge becomes more complex and tacit the need for proximate partner becomes imperative in all proximity dimensions except geographic proximity.

-----Table 8 -----

-----Table 9 -----

6. Discussion and Conclusion:

We find that geographic, organizational, social, and technological proximity dimensions, all significantly influence the formation of product and process innovation networks, nevertheless the impact on process innovation network is quite stronger than the impact on product innovation network as expected (see table.6 and 7), however the influence of geographic proximity is higher on the formation of product innovation network. Our findings suggest that, on the one hand, firms in mature and traditional clusters are more likely to share knowledge about process related developments and problems, and help each other in achieving higher production efficiencies. On the other hand, the knowledge sharing is less common in product development issues. As argued in our paper, the process knowledge is more complex, tacit and systematic than the product knowledge that is simple, codified and autonomous, hence we come to the conclusion that firms prefer to collaborate with more socially, cognitively and organisationally proximate partners when their focus is on process innovation development. Although the role of geographic proximity is important for network formation in both networks, but firms prefer to collaborate with geographically proximate partners in the development of product innovation than the process innovation. Contrary to the suggestions of Sorenson et al (2006) we find that geographic proximity facilitates the diffusion of complex knowledge. Our study partially supports the findings of Balland and Rigby (2017) who suggest that the geographic proximity facilitates the diffusion of complex knowledge whereas increase in the geographic distance decreases the diffusion of complex knowledge. We find positive and significant results for the impact of geographic proximity in the transfer of complex, tacit and systematic knowledge such as in case of process innovations, however the magnitude of the coefficient is lower than the product innovations, which means that the firms are more likely to collaborate with or seek advice from other geographically proximate partners when their focus is on the development of simple, codified and autonomous knowledge as in case of product innovations. The main reason for these contradictory findings may be the context of both studies. Our study is based in Pakistan, a developing country and also the industry context in our case is a mature textile industrial cluster, whereas their study is based USA and their focus is not on a single industry. This issue is recently highlighted by scholars that the context of the study plays an important role in the proximity dynamics and therefore it should not be ignored.

In our study, the non-geographic proximity seems more important because of the context. As explained in the research setting in this paper, social proximity is highly important. Because of strong social relations both at entrepreneurial and managerial level, firms seek technical advice from other partners for the development of both process and product innovations. Again, the impact is higher for process network because of the complexity and tacitness of the knowledge. As the complex knowledge is not easy to transfer, firms share knowledge with more socially proximate partners. In addition to that organisational proximity also plays a very important role in the diffusion and transfer of technical knowledge. Firms seek advice from sister firms for the development of both product and process innovations. Our results show that complex and tacit knowledge is even not easier to transfer within the same organisation and technical personnel often seek advice from more organisationally proximate partners when they deal

with problems related with the process innovations. Organisational proximity is also important for the transfer and diffusion of process knowledge but again the magnitude is less because of simplicity and explicitness of the product related knowledge. Finally, in our research setting, the role of cognitive proximity is the most important in the circulation of knowledge within the cluster boundaries. Its magnitude is again lower for the product knowledge but this time the reason seems not the competition between complexity and simplicity. The product innovations demand knowledge from the diverse sources therefore firms are more likely to seek advice from cognitively less proximate partners. However, some level of cognitive proximity is necessary to understand the new knowledge. On the contrary, the process knowledge require coordination with more proximate partners because process knowledge is systematic and to minimise coordination problems higher level of technological proximity between different production systems is important.

Implications

This research will have implications for both R&D managers working in manufacturing firms and policy makers involved in policy formulation for clusters. Reichstein and Salter (2006) argue that firms may focus on product or process innovation depending upon the competition in the market. In this regard, the managers adopt different strategies to compete in the market and make different strategic choices about different types of innovations. Therefore, the match between the type of innovation and proximity to external source of knowledge is essential for implementing successful innovation strategies (Antonelli and Fassio 2016). The managers whose are focusing on developing new processes or products may need to consider their proximity to the external source of knowledge before making any strategic move. For instance, on the one hand, if the firms' proximity to the source is low and the knowledge to be acquired is complex then they should first put efforts to reduce the level of proximity or to search for partners that are not too distant in proximity dimensions in order to ease the transfer of required knowledge. On the other hand, if the knowledge required is not too complex and it can be easily acquired from the external source then firms' managers may not need to worry too much about the proximity issue. Similarly, policy makers may be interested in creating more jobs in clusters by introducing diverse industrial units, or they may be interested to increase the efficiency of existing clusters to enhance economic performance. In any case, policy makers may need to be informed that how much proximity among actors in multiple dimensions is necessary for balancing the efficiency effect with employment, growth and diversity, consequently best policy can be formulated.

Our research is not without limitations. First of all, we have focused on a single cluster and therefore future research should replicate this study into different research setting and should collect data from more than one cluster at a time, to observe whether the impact of proximity dimensions on the formation of product and process innovation differs in a similar way, as we have found, so that a consistent theory of proximity and innovation networks can be suggested.

References:

Agrawal, A., D. Kapur, et al. (2008). "How do spatial and social proximity influence knowledge flows? Evidence from patent data." *Journal of urban economics* **64**(2): 258-269.

- Aguilera, A., V. Lethiais, et al. (2012). "Spatial and Non-spatial Proximities in Inter-firm Relations: An Empirical Analysis." *Industry and Innovation* **19**(3): 187-202.
- Antonelli, C. and C. Fassio (2016). "The role of external knowledge(s) in the introduction of product and process innovations." *R&D Management* **46**(S3): 979-991.
- Arikan, A. T. (2009). "Interfirm knowledge exchanges and the knowledge creation capability of clusters." *Academy of Management Review* **34**(4): 658-676.
- Balland, P.-A. (2012). "Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry." *Regional Studies* **46**(6): 741-756.
- Balland, P.-A., J. A. Belso-Martínez, et al. (2016). "The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity?" *Economic Geography* **92**(1): 35-60.
- Balland, P.-A., R. Boschma, et al. (2015). "Proximity and innovation: From statics to dynamics." *Regional Studies* **49**(6): 907-920.
- Balland, P.-A., M. De Vaan, et al. (2012). "The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007." *Journal of Economic Geography* **13**(5): 741-765.
- Balland, P.-A. and D. Rigby (2017). "The geography of complex knowledge." *Economic Geography* **93**(1): 1-23.
- Bathelt, H., A. Malmberg, et al. (2004). "Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation." *Progress in human geography* **28**(1): 31-56.
- Bogers, M. and S. Lhuillery (2011). "A functional perspective on learning and innovation: Investigating the organization of absorptive capacity." *Industry and innovation* **18**(6): 581-610.
- Borgatti, S. P., M. G. Everett, et al. (2013). *Analyzing social networks*, SAGE Publications Limited.
- Boschma, R. (2005). "Proximity and innovation: a critical assessment." *Regional studies* **39**(1): 61-74.
- Boschma, R., P.-A. Balland, et al. (2014). The formation of economic networks: A proximity approach. *Regional development and proximity relations*: 243-266.
- Boschma, R., P.-A. Balland, et al. (2015). The geography of interfirm knowledge spillover in biotechnology. *The economics of knowledge, innovation and systemic technology policy*. F. Crespi and F. Quatraro, Routledge. **6**.
- Boschma, R., E. Marrocu, et al. (2015). "Symmetric and asymmetric effects of proximities. The case of M&A deals in Italy." *Journal of Economic Geography* **16**(2): 505-535.
- Boschma, R. A. and A. L. Ter Wal (2007). "Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the South of Italy." *Industry and Innovation* **14**(2): 177-199.
- Broekel, T., P.-A. Balland, et al. (2014). "Modeling knowledge networks in economic geography: a discussion of four methods." *The annals of regional science* **53**(2): 423-452.
- Broekel, T. and R. Boschma (2011). "Knowledge networks in the Dutch aviation industry: the proximity paradox." *Journal of Economic Geography* **12**(2): 409-433.
- Broekel, T. and M. Hartog (2011). "Explaining the structure of inter-organizational networks using exponential random graph models: does proximity matter." *Papers in Evolutionary Geography*(11.07).
- Callois, J.-M. (2008). "The two sides of proximity in industrial clusters: the trade-off between process and product innovation." *Journal of Urban Economics* **63**(1): 146-162.
- Cantner, U. and H. Graf (2011). "15 Innovation networks: formation, performance and dynamics." *Handbook on the economic complexity of technological change*: 366.
- Cohen, W. M. and D. A. Levinthal (1990). "Absorptive capacity: A new perspective on learning and innovation." *Administrative science quarterly*: 128-152.
- Dekker, D., D. Krackhardt, et al. (2007). "Sensitivity of MRQAP tests to collinearity and autocorrelation conditions." *Psychometrika* **72**(4): 563-581.

- Demographia (2017). "Demographia World Urban Areas 13th Annual Edition, April 2017 (4), pp-18 (Available at: <http://demographia.com/db-worldua.pdf>)."
- Edquist, C. (1997). Systems of innovation: technologies, institutions, and organizations, Psychology Press.
- Ferru, M. and A. Rallet (2016). "Proximity dynamics and the geography of innovation: diminishing returns or renewal?" Handbook on the Geographies of Innovation: 100.
- Geldes, C., C. Felzensztein, et al. (2015). "How does proximity affect interfirm marketing cooperation? A study of an agribusiness cluster." Journal of Business Research **68**(2): 263-272.
- Gemünden, H. G., T. Ritter, et al. (1996). "Network configuration and innovation success: An empirical analysis in German high-tech industries." International Journal of Research in Marketing **13**(5): 449-462.
- Giuliani, E. (2006). "The selective nature of knowledge networks in clusters: evidence from the wine industry." Journal of economic geography **7**(2): 139-168.
- Giuliani, E. (2013). "Network dynamics in regional clusters: Evidence from Chile." Research Policy **42**(8): 1406-1419.
- Giuliani, E. and M. Bell (2005). "The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster." Research policy **34**(1): 47-68.
- Glückler, J. (2007). "Economic geography and the evolution of networks." Journal of Economic Geography **7**(5): 619-634.
- Gopalakrishnan, S., P. Bierly, et al. (1999). "A reexamination of product and process innovations using a knowledge-based view." The Journal of High Technology Management Research **10**(1): 147-166.
- Granovetter, M. (1985). "Economic action and social structure: The problem of embeddedness." American journal of sociology **91**(3): 481-510.
- Granovetter, M. (1985). "Economic action and social structure: the problem of embeddedness." American journal of sociology: 481-510.
- Granstrand, O. and S. Sjölander (1990). "Managing innovation in multi-technology corporations." Research Policy **19**(1): 35-60.
- Grant, R. M. (1996). "Toward a knowledge-based theory of the firm." Strategic management journal **17**(S2): 109-122.
- Heringa, P. W., E. Horlings, et al. (2014). "How do dimensions of proximity relate to the outcomes of collaboration? A survey of knowledge-intensive networks in the Dutch water sector." Economics of Innovation and New Technology **23**(7): 689-716.
- Knoben, J. and L. A. Oerlemans (2006). "Proximity and inter-organizational collaboration: A literature review." International Journal of Management Reviews **8**(2): 71-89.
- Kogut, B. and U. Zander (1992). "Knowledge of the firm, combinative capabilities, and the replication of technology." Organization science **3**(3): 383-397.
- Krackardt, D. (1987). "QAP partialling as a test of spuriousness." Social networks **9**(2): 171-186.
- Lazzeretti, L. and F. Capone (2016). "How proximity matters in innovation networks dynamics along the cluster evolution. A study of the high technology applied to cultural goods." Journal of Business Research **69**(12): 5855-5865.
- Maskell, P. and A. Malmberg (1999). "Localised learning and industrial competitiveness." Cambridge journal of economics **23**(2): 167-185.
- Molina-Morales, F. X., J. A. Belso-Martínez, et al. (2015). "Formation and dissolution of inter-firm linkages in lengthy and stable networks in clusters." Journal of Business Research **68**(7): 1557-1562.
- Morrison, A. (2008). "Gatekeepers of Knowledge within Industrial Districts: Who They Are, How They Interact." Regional Studies **42**(6): 817-835.
- Nooteboom, B. (2000). Learning and innovation in organizations and economies, OUP Oxford.
- O. A. Golra, A. Luqman, et al. (2011). "Strategy for Introducing Nanotechnology in Textile Industry of Pakistan." International Journal of Chemical and Environmental Engineering **2**(4): 276-283.

- Pakistan Bureau of Statistics (2005). Census of Manufacturing Industries (CMI) 2005-06. Islamabad.
- Pakistan Textile Policy (2014-19). Ministry of Textile Industry, Government of Pakistan.
- Powell, W. W. and S. Grodal (2005). "Networks of innovators." The Oxford handbook of innovation **78**.
- Reichstein, T. and A. Salter (2006). "Investigating the sources of process innovation among UK manufacturing firms." Industrial and Corporate Change **15**(4): 653-682.
- Shearmur, R., C. Carrincazeaux, et al. (2016). Handbook on the Geographies of Innovation, Edward Elgar Publishing.
- Snijders, T. A. B. (2011). "Statistical Models for Social Networks." Annual Review of Sociology **37**(1): 131-153.
- Sorenson, O., J. W. Rivkin, et al. (2006). "Complexity, networks and knowledge flow." Research Policy **35**(7): 994-1017.
- Torre, A. and F. Wallet (2014). Regional development and proximity relations, Edward Elgar Publishing.
- Usai, S., E. Marrocu, et al. (2017). "Networks, Proximities, and Interfirm Knowledge Exchanges." International Regional Science Review **40**(4): 377-404.
- Van Wijk, R., J. J. Jansen, et al. (2008). "Inter-and intra-organizational knowledge transfer: a meta-analytic review and assessment of its antecedents and consequences." Journal of management studies **45**(4): 830-853.
- Von Hippel, E. (1998). "Economics of product development by users: The impact of "sticky" local information." Management Science **44**(5): 629-644.
- Wasserman, S. and K. Faust (1994). Social network analysis: Methods and applications, Cambridge university press.
- Westerlund, M. and R. Rajala (2010). "Learning and innovation in inter-organizational network collaboration." Journal of Business & Industrial Marketing **25**(6): 435-442.
- Zaheer, A. and G. G. Bell (2005). "Benefiting from network position: firm capabilities, structural holes, and performance." Strategic management journal **26**(9): 809-825.

Table.1 Descriptive statistics

<i>Characteristics</i>	<i>Number of firms (%)</i> <i>(n=73)</i>
<i>Qualification (Respondent degree)</i>	
Non-Engineering	8 (11%)
Engineering Degree	52 (71%)
Engineering + Business	13 (18%)
<i>Size (Sqrt-number of employees)</i>	
Minimum	20.0
Maximum	83.6
Standard Deviation	15.6
<i>Firm Age (Years since creation)</i>	
Less than 10 years	17 (23%)
Between 10 to 20 years	30 (41%)
More than 20 years	26 (36%)
<i>Organisational Structure</i>	
Independent Textile Firm (not part of group)	15 (21%)
Part of Textile Group only	18 (25%)
Part of Textile + Multi-sector group	40 (55%)
<i>Export Profile</i>	
Not significant exporter (<50% exports)	33 (45%)
Significant Exporter (>50% exports)	40 (55%)
<i>Sender-Memberships of Trade Associations</i>	
Minimum	0
Maximum	12
Standard Deviation	2.25
<i>Joint R&D</i>	
Minimum	0
Maximum	1
Standard Deviation	0.425
<i>Technology Profile (PSIC Code)</i>	
Spinning (1311)	37 (26%)
Weaving (1312)	21 (14%)
Textile Processing (1313)	36 (25%)
Knitting (1391)	8 (6%)
Home Textile Made-ups (1392)	7 (5%)
Embroidery work (1399)	13 (9%)
Apparel & Garments excl. Knitted (1410)	18 (12%)
Knitted Apparel & Garments (1430)	5 (3%)

Table 3. Proximity Variables-Descriptive Statistics

Sr. No.	Proximity Dimension (Matrix)	Variable Type	Min	Max	Std. Dev
	Cognitive Proximity (CogProx)	Continuous	0	1	0.388
	Geographic Proximity (Inverse of Log-distance)	Continuous	1.822	0	0.422
	Organisational Proximity (Orgprox)	Dichotomous	0	1	0.136
	Social Proximity (Socprox-uni)	Dichotomous	0	1	0.495
	Social Proximity (Socprox-exp)	Dichotomous	0	1	0.0819

Table 3. Density of product and process network

	Std. Dev	No. of Ties	Avg. Degree	Density N=5000 (obs)
Product Network	0.196	206	2.88	0.039
Process Network	0.216	259	3.55	0.049
Technical Network (Combined)	0.251	355	4.86	0.068

Table.4.1 QAP Correlation between product and process network

Network type	Std. Dev	Pearson Correlation N=5000 (obs)
Product vs Process Network	0.0149	0.45*** (0.000)

Significance in parenthesis

Table.4.2 QAP Correlation between Technical⁴, Product and Process network

Network type	Std. Dev	Pearson Correlation N=5000 (obs)
Product vs Technical Network	0.0148	0.75*** (0.000)
Process vs Technical Network	0.0148	0.84*** (0.000)

Significance in parenthesis

⁴ We combine the network of product and process innovation network and name it as Technical Network.

Table 5. QAP Correlation relational variables

ID	QUAL	JNT-R&D	SND-MBRSHIP	RCV-MBRSHIP	EXPORTER	COGPROX	INV-LOG-DIST	ORGPROX	SOCPROX-UNI	SOCPROX-EXP
QUALIFICATION	1.00									
JNT-R&D	0.04	1.00								
SND-MBRSHIP	-0.07	0.12**	1.00							
RCV-MBRSHIP	-0.07	0.14***	-0.014***	1.00						
EXPORTER	0.02	0.11***	0.02**	0.03***	1.00					
COGPROX	-0.001	0.02	-0.05**	-0.003	0.31***	1.00				
INV-LOG-DIST	0.04	-0.02	0.01	-0.001	-0.08***	-0.13***	1.00			
ORGPROX	-0.03	0.10***	0.02	0.04**	0.07***	0.06**	-0.15***	1.00		
SOCPROX-UNI	-0.12***	0.17***	0.05**	0.05***	-0.01	0.03*	-0.14***	0.04**	1.00	
SOCPROX-EXP	-0.03	0.06***	0.01	0.03**	0.04**	0.14***	-0.04**	0.05**	0.07***	1.00

*sig at 0.1, **sig at 0.05, *** sig at 0.001

Table 6. QAP logistic regression model: process network

	Coefficient	Odds Ratio	Sig	
Intercept	-6.989	0.003		
Qualification (Absdiff)	-0.251*	0.778	0.08	
Joint-R&D (Matching)	0.346*	1.413	0.09	
Memberships (Sender Effect)	0.062*	1.064	0.05	
Memberships (Receiver Effect)	0.124***	1.132	0.004	
Exporter (Matching)	0.318**	1.375	0.04	
Cognitive Proximity	3.407***	30.17	0.001	
Geographic Proximity (inv-dist)	0.481**	1.618	0.02	
Organisational Proximity	2.429***	11.34	0.001	
Social Proximity (Same-Univ.)	0.447**	1.564	0.01	
Social Proximity (Past-employer)	1.957***	7.077	0.004	
<i>Overall fit of the logistic regression model</i>				
	R-square	LL	Observations	Permutations
	0.201***	-743	5255	5,000

*sig at 0.1, **sig at 0.05, *** sig at 0.001

Table.7 QAP logistic regression model: product network

	Coefficient	Odds Ratio	Sig	
INTERCEPT	-6.694	0.004		
Qualification (Absdiff)	-0.081	0.922	0.366	
Joint-R&D (Matching)	0.706**	2.025	0.012	
Memberships (Sender Effect)	0.038	1.038	0.196	
Memberships (Receiver Effect)	0.115**	1.122	0.013	
Exporter (Matching)	-0.234*	0.792	0.119	
Cognitive Proximity	2.704***	14.937	0.001	
Geographic Proximity (inv-dist)	0.709**	2.032	0.002	
Organisational Proximity	1.969***	7.162	0.001	
Social Proximity (Same-Univ.)	0.443**	1.557	0.02	
Social Proximity (Past-employer)	1.270***	3.562	0.001	
<i>Overall fit of the logistic regression model</i>				
	R-square	LL	Observations	Permutations
	0.124***	-687	5255	5,000

*sig at 0.1, **sig at 0.05, *** sig at 0.001

Table 8. QAP logistic regression model: Technical Network (Combined process and process network)

	Coefficient	Odds Ratio	Sig	
Intercept	-6.178	0.003		
Qualification (Absdiff)	-0.197	0.822	0.148	
Joint-R&D (Matching)	0.420**	1.522	0.043	
Memberships (Sender Effect)	0.048	1.049	0.115	
Memberships (Receiver Effect)	0.141***	1.151	0.001	
Exporter (Matching)	0.062	1.064	0.308	
Cognitive Proximity	2.919***	18.514	0.001	
Geographic Proximity (inv-dist)	0.615**	1.850	0.006	
Organisational Proximity	2.158***	8.652	0.001	
Social Proximity (Same-Univ.)	0.388**	1.474	0.008	
Social Proximity (Past-employer)	1.765***	5.839	0.001	
<i>Overall fit of the logistic regression model</i>				
	R-square	LL	Observations	Permutations
	0.188***	-989	5255	5,000

*sig at 0.1, **sig at 0.05, *** sig at 0.001

Table 9. Comparison of QAP logistic regression model: Technical Network, Process Network and Product Network

	Technical Network	Process Network	Product Network	
	Coefficient	Coefficient	Coefficient	
Intercept	-6.178	-6.989	-6.694	
Qualification (Absdiff)	-0.197	-0.251*	-0.081	
Joint-R&D (Matching)	0.420**	0.346*	0.706**	
Memberships (Sender Effect)	0.048	0.062*	0.038	
Memberships (Receiver Effect)	0.141***	0.124***	0.115**	
Exporter (Matching)	0.062	0.318**	-0.234*	
Cognitive Proximity	2.919***	3.407***	2.704***	
Geographic Proximity (inv-dist)	0.615**	0.481**	0.709**	
Organisational Proximity	2.158***	2.429***	1.969***	
Social Proximity (Same-Univ.)	0.388**	0.447**	0.443**	
Social Proximity (Past-employer)	1.765***	1.957***	1.270***	
<i>Overall fit of the logistic regression models</i>				
	R-square	R-square	R-square	Permutations
	0.188***	0.201***	0.124***	5,000

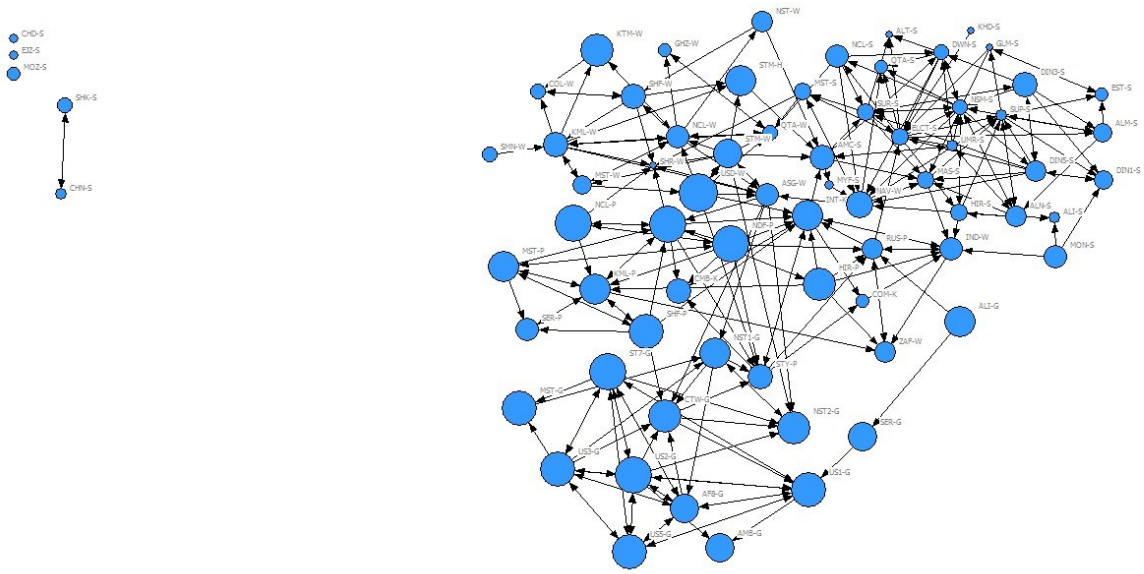


Figure 1 Process Network (Node Size Represents Absorptive Capacity)

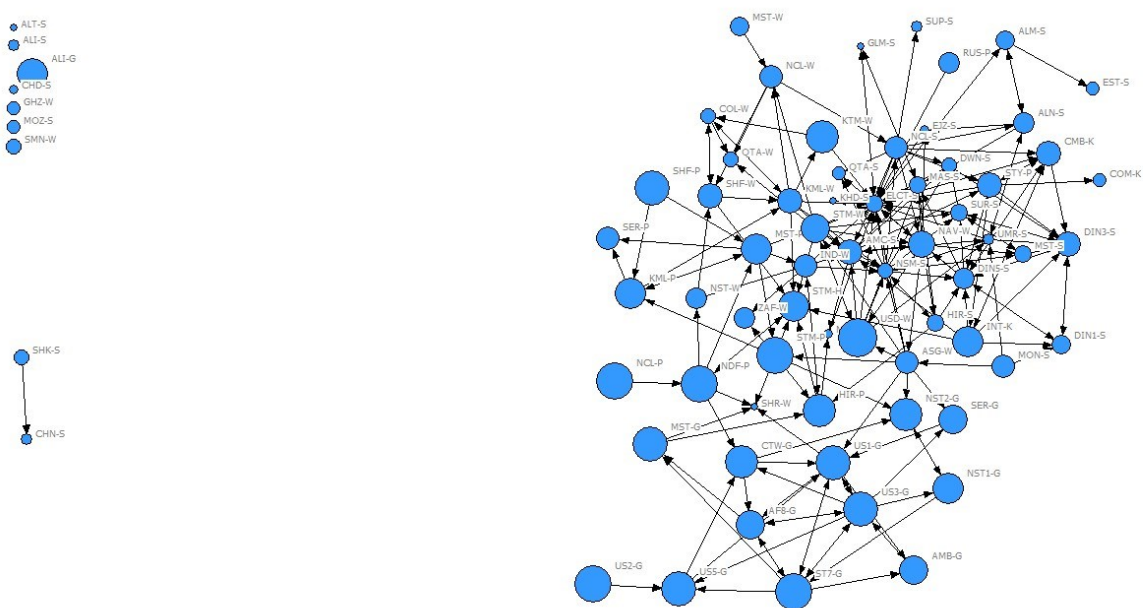


Figure 2 Product Network (Node size represents Absorptive Capacity)

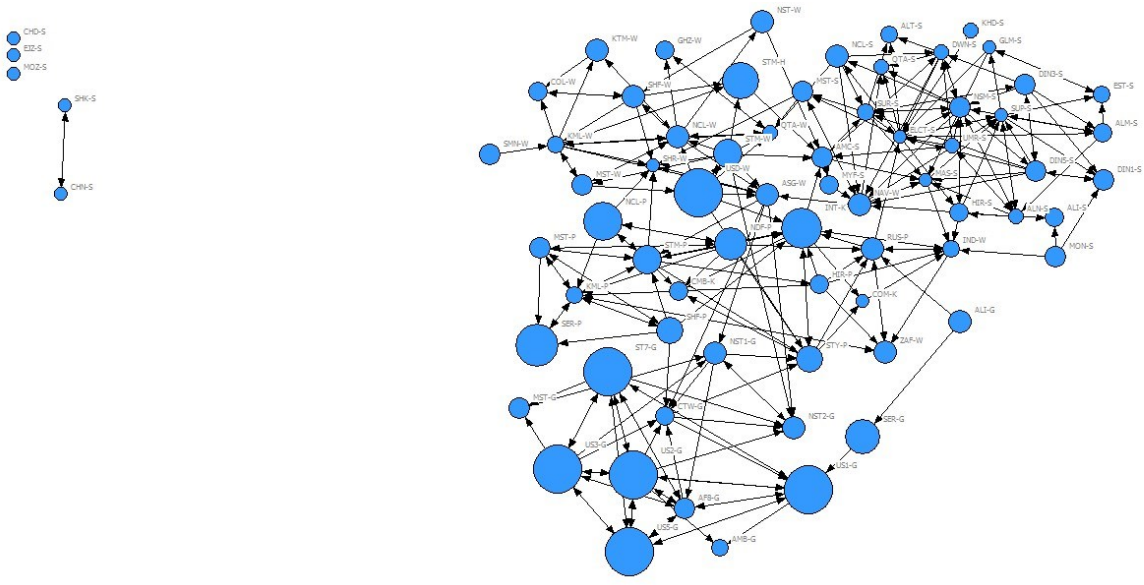


Figure 3 Process Network (Node size represents Innovation Count)

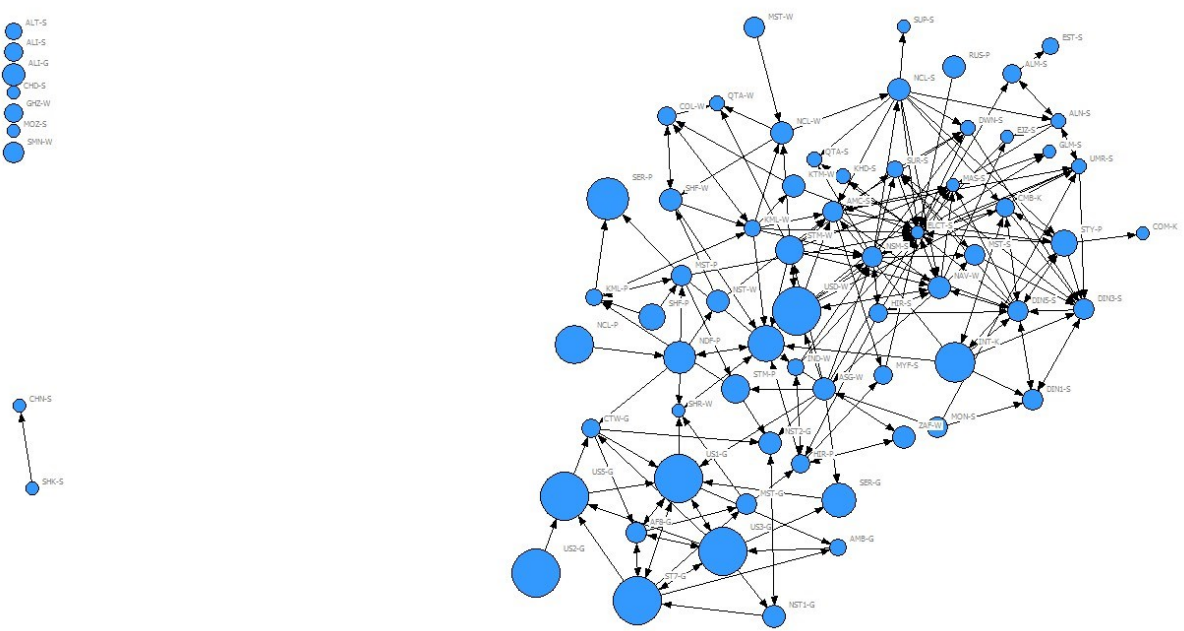


Figure 4 Product Network (Node size represents Innovation Count)

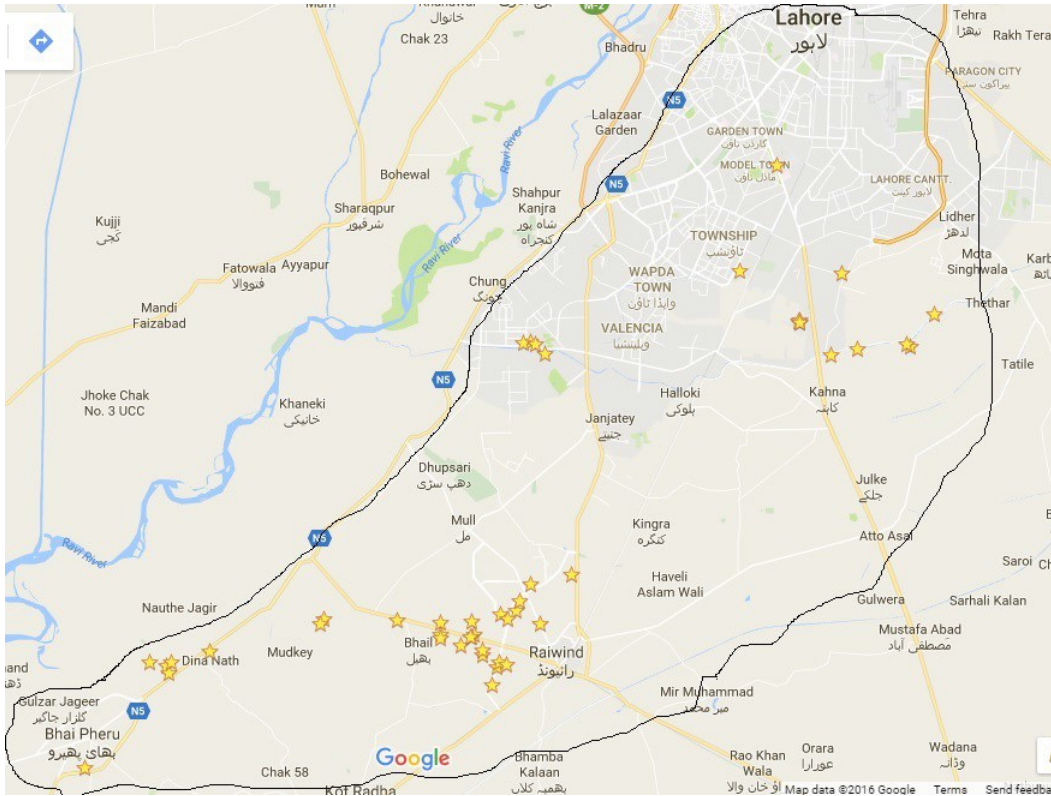


Figure A. TEXTILE FIRMS (STARS) SHOWN ON THE MAP OF THE CITY OF LAHORE

ⁱ We are aware that there can also be negative effects of these dense social relations, because they could drag clusters into lock-in situation by decreasing the level of diversity among firms' technological knowledge bases.