Social and Economic Networks: An Investigation of Retailer Networks in Lahore & their Impact on Enterprise Performance

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Abstract

A detailed study of a market in Lahore was conducted to create a map of the socioeconomic network of different retailers located in this particular area. The aim was to distinguish various ways in which these individual sellers were connected to one another, and then investigate how these network ties affected their economic lives. As opposed to developed economies where economic exchange is buttressed by formal market institutions, developing economies often depend on personal relationships between different economic actors for business transactions. This study looks at how networks allow entrepreneurs to navigate through a business environment that is troubled with sluggish and costly information transfer, prohibitive terms of credit, and feeble (often exploitative) formal institutions that are a detriment to contract enforcement. This research uses a respondent driven sampling method to obtain comprehensive social network data through extensive structured interviews with sellers of water pumps and motors in the Brandreth Road area of Lahore. Information on 6 different types of relationships, from who respondents took advice from, to who they shared information, and inventory with were obtained to construct a network of connections representative of the many ways in which retailers in these markets engage with and benefit from one another. Each individual seller's centrality in these networks was then determined to confirm that more central players in the market had a significantly different demographic makeup than their less central counterparts, and that they leveraged this position to secure more favorable terms of exchange for themselves: more central sellers paid significantly less for borrowed inventory, and did so with a significantly relaxed repayment schedule. Centrality, however, had an unexpected impact on the sellers' joint purchases arrangements, where less central sellers in the market reported receiving significantly larger discounts on jointly purchased supplies.

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Introduction

Social networks affect our well being in innumerable ways. Network-related research shows that social relations are central to understanding the spread of information about public health, employment opportunities, and microfinance products (e.g., Kremer and Miguel (2007), Beaman and Magruder (2012), Banerjee et al. (2013)). Furthermore, networks are deemed critically important in facilitating the adoption of new technologies (Conley and Udry, 2004), enhancing the trade of goods and services (Fafchamps and Minten (1999), Kuepié et al. (2014)), and enabling access to finance (Biggs, Raturi and Srivastava, 2002). These social connections also serve as vehicles for informal insurance and risk sharing (e.g., Bloch, Genicot and Ray (2008), Bramoullé and Kranton (2007)).

For long, the study of social networks has been restricted to the realm of sociology and anthropology where research has largely centered on learning how network ties are established and what role they play in providing structure to social life. Although, some industrial sociologists have been emphasizing the ability of informal networks to effectively displace formal organization practices and structures since the 1950s, the idea of the impact of social relations on economic activity has only recently begun to constitute a rapidly growing field of research in economics (Smith-Doerr and Powell (2005), Jackson (2008)). This increase in interest is largely a result of the increased availability of data and coinciding advances in computer technology, which now allow economists to build better models of human behavior and explain how different bonds of affiliation between community members facilitate economic exchange (Jackson, 2014).

Idealized views of market transactions that are captured by most traditional economic theories appear unfit to explain interpersonal relationships built around cooperation, willful commitment and, at times, altruism – features that are a hallmark of most socioeconomic exchange in the developing world. The assumption that economies comprise of a large number of self-interested, semi-anonymous actors who are perfectly informed, trade solely on the basis of price data, and come together in settings where contracts are fully specified and easily and costlessly enforced fails to appreciate the complex, dynamic and interdependent nature of economic transactions in developing countries. This deficiency is particularly felt in countries like Pakistan that present extremely challenging economic and sociocultural environments where weaknesses in collateral and bankruptcy laws, and inefficient, deeply mistrustful judicial & civil law enforcement bodies hamper access to credit and jeopardize enforcement of contracts.[1]

Given these market asymmetries and the absence of well functioning formal institutions, social networks allow economic actors to cooperate and function in a business environment where contracts are not effectively enforced, access to credit is difficult, and information transmission is slow and costly. This is made possible as social networks affect the spread and quality of information, act as a source of reward and punishment, and provide a governance structure by creating trust among participants. Resultantly, this increases efficiency by making decision-making less unwieldy, reducing search and monitoring costs, ensuring compliance and reciprocity, and improving flexibility –factors that then spur development by creating new growth opportunities (Uzzi (1997), Granovetter (2005)).

As we realize that production, trade, and consumption of goods and services occurs in social settings where the pattern and nature of interactions shape, and in turn are shaped by, economic activity (what literature refers to as embeddedness), it becomes imperative for effective economic policy design to be predicated upon a firm understanding of social network architecture. The position of individual agents in networks, their neighborhood, and the construction of the network overall are crucial in learning how connections form, transfers occur, relationships evolve, and order is maintained within a community of connected actors.

The next section will focus on reviewing literature that analyzes the theoretical and empirical justifications of the impact of social networks on economic behavior. This will be followed by the methodology used to create and study networks in this study. The paper will conclude by presenting the results obtained from this research and offering an explanation based on both anecdotal evidence gathered during interviews, and social network literature as to the role network relationships play in shaping economic outcomes in this market.

[1] As per the World Bank's "Doing Business (2016)" report, Pakistan ranks 133rd out of 189 countries in the world on a legal rights index measuring the ability of laws to broaden access to credit. Its contract enforcement ranking is even weaker (155 out of 189), taking 993.20 days to enforce commercial contracts and costing 23pc of the claims value. The country fares poorly on both accounts versus the South Asian average.

Literature Review

In recent years, economists have studied the function of social networks in untangling a number of economic questions. Here, we look at a few these questions concerning labor market outcomes, inter-firm relations, social learning and diffusion, trade credit, and contract enforcement. Moreover, major insights from theory and evidence on how network structure affects economic behavior and outcomes will also be discussed.

Social Networks in Labor Markets

The role of social networks in shaping labor market outcomes is worth examining since it effectively illustrates why networks should matter to economists and why it's important to utilize network theory to model markets (Jackson, 2008). The general perception around the existence of informal institutions is that they serve to address market failures that emerge in the absence of well functioning formal institutions, a distinctive feature of economic environments in the developing world. However, evidence shows that a large proportion of jobs are found and filled through networks, regardless of the geographic location and skill level of workers. Early research shows nearly 30pc-50pc of jobs were made known and/or filled via use of personal contacts (e.g., Myers and Schultz (1951), Granovetter (1974), Holzer (1987), Campbell and Marsden (1990), and Montgomery (1991)).

Social networks in labor markets are seen to address the joint problems of imperfect information and adverse selection that create inefficiencies and inconvenience workers and firms in various settings. Calvo-Armengol and Jackson (2004) present a theoretical model of how information regarding job vacancies is transmitted through a network. Here, individual workers have personal connections and the aggregate of these connections gives rise to a social network. Members of the network then randomly receive information about new job openings. The unemployed take up the job while those already in employment pass this new job information to their out-of-work friends and acquaintances.

The abovementioned study makes two main propositions: first, the employment status of all members of the social network is positively correlated. This is because it is assumed that individuals with a better employment status are more likely to pass on new job information to friends (as they are less likely to want the job for themselves). The second major contribution made by Calvo-Armengol and Jackson (2004) is that the probability of finding a job declines with the duration of unemployment. This is called duration dependence and is seen to arise since it is suggested that the longer a person remains unemployed the less likely that members of his social network are employed, which makes it ever less probable that new job information will be passed along to this unemployed agent. Resultantly, the probability of the unemployed person of moving into employed status is lowered (Calvo-Armengol and Jackson, 2004).

Munshi (2003) uses data from the Mexican Migration Project to confirm the existence of informal information networks in the U.S. labor market. He shows that a migrant is much more likely to be employed and hold a higher paying job when she is a member of a larger network. These results are robust and statistically significant. Munshi (2003) uses individual fixed effects, and random variation in rainfall to instrument for the size of the migrant network to overcome the identification problem that troubles researchers while establishing causality of network effects. Thus it can be conclusively said that networks play an important role in the modern economy: A greater pool of established migrants (i.e., a larger social network) provide both job referrals for other (newer) migrants - resulting in above average employment levels – and channel them into higher paying jobs, whereby significantly improving labor market outcomes.

The information problem of costly search can as easily apply to firms. This causes employers to rely on employee networks for referrals since firms are unable to ascertain the ability of new recruits. Montgomery (1991) takes on modeling this problem of adverse selection in labor markets. Here, workers know their own ability, of which potential employers are ignorant. However, working in a firm discloses information about the workers' ability to the firm. In case of a job opening, the firm can either advertise the vacant position in the relevant media and/or ask current employees to recommend someone for the job. This gives purchase to the idea that firms with high ability workers expect their present workers to nominate individuals of comparable or higher ability, versus firms whose workers are of low ability. This difference in expectations is seen as the reason why some firms hire via referrals while others choose to approach the market for their hiring.

Beaman and Magruder (2012) use evidence from a lab experiment in Kolkata, India to confirm that indeed some high ability workers have useful information on the abilities of other members in their social network and can in fact successfully screen for their employers. Nevertheless, the results observed in Beaman and Magruder (2012) also reveal that individuals rely on their network for multiple contexts and thus externalities from one context to another may create incentives that counter the employer's objective (e.g., high ability workers may refer poorly qualified friends if are members of a network where altruism or reciprocity of favor exchange dominates). The experiment corroborates this belief by showing that high performance individuals nominate other high performance individuals only when properly incentivized. Here, this incentive takes the form of a performance-based bonus that the original participant receives for referring a worker of higher ability. This use of incentives to align employee and employer objectives via social networks in the workplace is also seen in Castilla (2005), Mas and Moretti (2009), and Bandiera, Barankay, and Rasul (2009),

The above survey of literature highlights that social networks benefit labor markets in three important ways: they minimize search costs for those seeking employment (Calvo-Armengol, 2004); they help firms economize on monitoring costs since referees induce co-workers to exert high effort (Kugler (2003), and Castilla (2005)); and they use screening by employees to reduce asymmetric information that is embedded in the hiring process (Montgomery (1991), and Munshi (2003)). However, reliance on networks for job search and hiring can also lead to persistent wage inequalities (Calvo-Armengol and Jackson, 2004).

Social Networks & Firm Performance: Embedded Ties, Trade Credit and Contract Enforcement

In addition to facilitating job search and hiring, social networks also prove effective in enhancing firm competitiveness. In a classic study of 23 entrepreneurial firms in the Women's Better Dress sector of the garment industry in New York City, Uzzi (1997) finds that the structure and quality of network ties between manufacturers and contractors has strong implications for mechanisms that contribute to key performance outcomes. By doing so he essentially addresses the theoretical indefiniteness of embedded relationships introduced by Granovetter (1985).

Nadvi's (1998) work on the Sialkot surgical goods cluster in Pakistan closely mirrors the results obtained by Uzzi in his study of the New York garment industry. It is also the rare Pakistan specific study of whether social networks influence economic behavior.

Both authors make comparable discoveries and narrate that inter-firm relations in their respective settings exhibit characteristics of structural embeddedness, a concept that refers to how the quality and network architecture of material exchange relationships shapes economic outcomes (Uzzi, 1997, p. 36). In both contexts we learn that rivalry and cooperation are not mutually exclusive, that relationships in these settings are typified by: trust, (i.e., the belief that network members will not behave opportunistically), fine grained information transfer (the exchange of proprietary/tacit information versus banal price/quantity data shared in impersonal relationships) and lastly, joint problem solving arrangements, such as the establishment of a dry port to ameliorate customs handling difficulties by the otherwise competitive members of the Sialkot cluster (Nadvi, 1998).

This pooling of resources to address complex problems, and not being hindered by search for competitive terms of exchange across many relationships, boosts coordination, helps resolve problems in real-time, and allows firms to predict, respond to and capitalize on new market opportunities with greater speed and efficiency.

Social networks in these diverse environments rely on repeated interactions and long-lasting relationships to provide a policing system to ensure contract compliance, encourage cooperation, and make available a rich repository of technical and personal information that aids problem solving and underpins reputational knowledge. Additionally, embedded relationships allow firms to become more responsive to stimuli, make decision-making less complex, increase learning and reduce production errors (Uzzi (1997), Nadvi (1998)). Resultantly, given that resources are no longer spent on monitoring, control and detailed negotiation, transaction costs are significantly reduced.

Although, the above case studies offer rich data for creating theoretical building blocks, and undertaking an exhaustive examination of the nuances of inter-firm ties, they provide little in the way of generalizability. A key conceptual problem with establishing network effects is that the network itself may be endogenous, a result of some unobservable characteristics of firms or individuals, making it difficult to establish causal relations between networks and outcomes (Goyal, 2009). However, it is shown that use of detailed network data, as will be used in this study, allows for robust estimations of network effects (Bramoullé, Djebbari and Fortin, 2009).

Ayako, Maytous and Yasuyuki (2014) exploit the time structure of data to make definitive and causal inferences regarding the effects of business collaboration networks on the growth in sales and skill levels of a tailor cluster in rural Ethiopia. Here, collaboration networks are identified by asking firms to nominate other tailoring firms they most closely work with within a year, the location of these firms, and the nature of the relationship they enjoy with one another (e.g., do they share credit, information, raw materials, etc.). Two firms are linked if either reports the flow of resources to the other. The study further uses the concepts of directional ties to estimate the impact of direct and indirect network links between firms in the cluster. Results show that direct collaboration links, as measured by the number of incoming ties for each firm, have a significantly positive impact on sales and the time efficiency component of the skill level. But skill levels have no significant impact on sales. These results remain consistent in both OLS, and fixed and random effects estimations. Discussion reveals that business networks contribute to sales growth through improving availability of inputs and sharing of works, and to skill augmentation through the diffusion of knowledge within the cluster (Ayako et al, 2014).

Fafchamps and Minten (1999) illustrate the role personal relationships play in the trade of agricultural products in Madagascar. They find that more successful traders make exhaustive use of embedded ties, and are better connected versus their less successful counterparts. Traders exploit their networks to secure information on prices and market conditions, obtain credit, negotiate and enforce contracts, and mitigate risks, whereby enhancing productivity. In a later study, Fafchamps and Minten (2002) account for endogenous network effects, and confirm that a traders' network structure and her location within that structure has a significantly positive impact on traders' profits, particularly in terms of providing better access to trade and commercial credit.

Trade credit, i.e., credit offered by suppliers, is an important source of finance in markets where creditor protection is weaker, and is relatively prevalent in countries with worse legal institutions (Burkrat and Ellingson, 2004). Supplier credit is often granted on the basis of repeated, ongoing relations and thus social networks rather than availability of collateral is seen to determine access to this form of finance. McMillan and Woodruff (1996) show that trade credit is provided to those customers whose reliability can be assessed by the supplier through their business network. Social networks thus enable a firm's access to credit by providing suppliers with information on customers they haven't previously dealt with, these extensive information flows allow each individual to know how others have behaved in the past. Additionally, networks discourage rule violations through the threat of sanctions and reputational loss. In their study on how ethnic networks facilitate economic exchange, Biggs et al. (2002) find that credit relations with suppliers were established on the basis of personal or mutual contacts, and market reputation. Moreover, networks perform both a screening and monitoring function, with members easily and costlessly evaluating credit worthiness of other members of the network through direct inspections and/or by 'asking around.' Engelberg, Gao and Parsons (2012) show that information and monitoring advantages accorded through by social networks can result in firms receiving formal bank credit at markedly lower rates even in the developed world.

Social Networks in Learning and Diffusion

Social networks can also prove effective in favoring innovation and shaping the diffusion of new technologies. Research shows that instead of adopting new technologies randomly or through expert recommendations, individuals who adopt technology quickly often do so by evaluating the returns of the innovation via their social network. Conley and Udry (2010) use detailed survey data to define each individual's information neighborhood to study the influence of social networks on the farmers' input decisions. This study benefits from two main innovations: first, it uses direct data on the flow of information to distinctly define the information neighborhood of each farmer and not rely on geographic proximity alone to estimate results. This helps to distinguish network effects from those occurring as a result of unobserved spatially correlated shocks. And second, the authors exploit the time structure of their data to account for the endogeneity problem of social networks. Results show that a farmer alters his fertilizer use in response to news of fertilizer productivity in his information neighborhood, and more so if the news originates from experienced farmers and farmers who are as wealthy as him. These findings are robust to the inclusion of other information metrics. Thus it can be conclusively said that both information and the links that generate/broadcast information are of value to farmers, and that social learning influences cultivation decisions.

Banerjee, Chandrasekhar, Duflo, and Jackson (2013) use network data from a set of Indian villages to analyze the diffusion of microfinance and understand what drives participation in the program. Here too the authors make use of rich network data that provides information on 13 different types of relationships among villagers to learn why participation rates vary so significantly across villages. Findings suggest that participating households are much likely to inform their friends about the availability of microfinance than non-participating households. Thus having a high fraction of participating friends raises an individual's probability of hearing about microfinance, revealing that peer effects in this setting operate via raising awareness about microfinance. The study uses two new approaches (the reduced-form and the structural approach) to determine the channels that influence the diffusion of microfinance, and subsequent participation in the program, respectively. The reduced-form approach in particular is employed to investigate how the network position of those initially contacted by the microfinance firm, their centrality, affects participation rates. It is learned that initially contacted individuals who are more eigenvector central have a significant impact on subsequent participation rates in their respective villages. This confirms that the position of individual nodes, and how these nodes are connected to one another in a network – the network structure - has important implications for economic decisions.

Network Structure and Economic Behavior

Jackson, Rogers and Zenou (2015) identify four major network characteristics that are fundamental to understanding how networks impact economic behavior. These are: the centrality of nodes, clustering, homophily patterns, and degree distribution. The first two characteristics are grouped under micro or local properties of networks while the last two come under macro or aggregate characteristics of network structure. Social learning and diffusion in particular are impacted by the macro patterns of a network (Jackson, 2014).

Degree distribution (or network density) is the most basic macro feature of any network. Denser networks, in terms of average number of connections, are said to result in more sizeable diffusion, ceteris paribus (Jackson et al, 2015). This is because in a denser network a given individual comes into contact with other individuals more frequently, and highly connected individuals are then seen to serve as hubs that play an important role in the diffusion of information (Banerjee et al., 2013).

Alatas, Banerjee, Chandrasekhar, Hanna, and Olken (2014) use network information from over 600 Indonesian villages to estimate how network structure influences social learning. They find that network position and density is correlated with how much people know about other people in the village.

In addition to network density, there is another fundamental characteristic of network structure that has far reaching implications concerns the way in which agents with similar attributes are linked together. Actors in economic interactions have certain relevant attributes such as age, gender, ethnicity, income, etc., that is seen to be highly correlated with other actors they have dealings with. This tendency of similar actors to be linked to other similar actors is referred to as homophily and has profound consequences for behaviors in a network. For e-g in Banerjee et al. (2013), strong patterns of association by caste designation are observed in a network of connections based on whether households borrow rice or kerosene from one another. Jackson (2014) reports that the frequency of links among pairs of households is 0.089 when both households belong to the same caste while in case of dissimilar castes this number is 0.006. Such patterns of segregation could clearly hinder the process of diffusion that begins in one clique from going mainstream as in a well integrated network diffusion of an idea or technology may never move beyond the group it is initially introduced to. Beyond diffusion, homophily is seen to explain why individuals that are linked in a network have a propensity to make decisions that are correlated beyond to what could be explained by their other characteristics (Jackson et al., 2015). This dependence of behavior among connected individuals that homophily helps highlight can be critical to designing effective policy interventions. For e-g it might be more effective to target education subsidies in a manner that takes advantage of these embedded segregation patterns in a community rather than on a person-by-person basis (Calvo-Armengol and Jackson, 2014).

The literature on social networks has paid particular importance to the role of "central" agents in influencing economic behavior and outcomes. Central actors have been shown to be useful in driving participation rates in microfinance programs, disseminating information, enforcing contracts, affecting educational attainment, etc. (Chandrasekhar et al. (2013), Ballester et al. (2006), Breza et al. (2015), Calvo-Armengol et al. (2009)). In these varied settings it is learned that central agents derive their usefulness by their ability to influence their immediate neighbors by their actions/beliefs, who in turn influence those closely connected to them whereby setting off a network wide chain of effects. This ripple effect of influence is particularly meaningful in understanding the power of centrally positioned individuals in networks with complementarities at play (for e-g where a central person affects an individual's decision to acquire more education as well as the decision of others connected to the individual who is initially influenced).

Breza, Chandrasekhar, and Larreguy (2015) use evidence drawn from trust games conducted as part of a lab experiment in 40 Indian villages to measure the effectiveness of central third parties in enforcing contacts. They find that central agents are valuable in discouraging rule violations because of two main reasons. First, they are able to share information of an actor's indiscretion more widely with other members of the network whereby inflicting severe reputational harm on those that behave unfairly. Second, central agents are in a position to credibly administer direct punishments on defecting parties since they may face less blowback from fined actors versus less central, unimportant agents who are entrusted to act as arbiters. Their results confirm that assigning central actors to the roles of arbiters brings about significant gains in efficiency further showing that in the absence of formal contacts agents who are more centrally situated in a network have repeated interactions with other agents and are more able to enforce punishments. Resultantly, importance within a network may allow actors to successfully substitute for formal contracting institutions (Breza et al., 2015).

The ability of central agents to effectively disseminate information is also seen to be effective in driving up savings, as is shown by Breza and Chandrasekhar (2015) in a follow up experiment. Here it is learned that assigning network central peer monitors to participants significantly drives up savings by an additional 14pc.

Ostensibly, the concept of centrality is fairly uncomplicated: researchers only look at actors that are at the "center" of a network. However, identifying precisely what is meant by "center" is rather challenging. The different measures of centrality employed in this study, the relevance of each measure, and the survey instrument used to determine the overall structure of the network in this study are looked at in detail in the following section.

Methodology

This section includes details on the data collection methods used to establish network links between different retailers that were interviewed during the course of this study. It also covers how the given data was processed to create network maps. These network maps help illustrate the various dimensions along which retailers in this particular market are connected to one another, and how a given retailer's connectivity (his centrality) varies (if at all) in different contexts. Descriptions of the various constructs of centrality (Degree, Ego-betweenness) are also detailed in this unit.

To construct social network data, detailed structured interviews were conducted with thirteen (13) retailers about their social and economic interactions with other retailers located in and around the Brandreth Road area of Lahore. The individual questionnaire used to acquire this information is included at the end of this study (see: Appendix A). This survey was adapted from Banerjee, Chandrasekhar, Duflo, and Jackson's (2013) study on how network relationships affect participation in a Microfinance program rolled out in the villages of India.

The core of this survey is a set of questions about the enterprise owner's relationship with other retailers in the market along the following dimensions: (i) people the respondent gives (takes) advice to (from); (ii) people the respondent shares (receives) information with (from); (iii) people the respondent jointly purchases supplies with; (iv) people the respondent shares inventory with; (v) people the respondent borrows (lends) money from (to); and, lastly, (vi) people in the market the respondent has accepted in the role of a guarantor for money transactions, and/or a mediator to help resolve disputes.

Retailers who nominated people they share and/or jointly purchase inventory with were asked for information on the terms of exchange of these transactions. Additionally, those interviewed were also asked for opinions (open-ended) on how different relationships emerge, how they strengthen (or turn sour), and why are they considered important for the success of their business. Furthermore, demographic data on both the enterprise owner (age, education, experience, etc.) and the enterprise (age of business, number of employees) was recorded.

The survey concluded with a section on the subjective measures of enterprise performance, & the institutional environment in which these businesses function. Since the study included retailers that acted more or less like micro entrepreneurs, the paper operates on the assumption of De Mel et al (2009) that these enterprise owners will have knowledge and figures concerning all aspects of the business. Kueipé, Tenikue, & Walther (2014) explain that these declarative measures of performance are considered robust, and are also preferred over detailed disclosures of sales and expenses in developing countries such as Pakistan largely because sellers here are wary of divulging sensitive performance data due to high levels of tax evasion. Also, inconsistent accountancy measures across sellers make comparative assessments difficult to execute using formal sales data (Kueipé et al, 2014).

The questions on institutional environment sought details on whether retailers in this market banked with formal financial institutions and their degree of interaction with these institutions (whether they save with these banks, undertake loans, and/or use mobile banking options, etc.).

This study symmetrizes the networks that have been derived from this data, i.e., two retailers are considered to be connected to one another if at least one of them lists the other as a contact in response to any of the six (6) tie eliciting questions detailed previously. This technique allows one to generate comprehensive maps of ties among retailers along multiple dimensions of connections, and has been used extensively in recent research, particularly in papers that helped give shape to the questionnaire proposed for this study (e.g., Conley and Udry 2010, Banerjee et al. 2013, Breza et al 2015, Chandrasekhar et al 2015).

Data here was collected using the snowball sampling method (details of which are outlined in the Data section that follows). Under this method information is first obtained from a single, focal retailer (the ego) who nominates a group of individuals he is linked to in response to a network question. The individuals listed by this ego are referred to as its alters (who are then contacted and asked to report their alters). If we get information on one of these alters then we get to know a great deal about both individuals (nodes) of that link, and about further links along the network. However, if the named person is not interviewed, then our information about that link is quite limited and we know nothing about further connections along the network (Conley and Urdy, 2004).

Following Jackson (2008), once the network data was collected, the connections between various sellers were denoted as follows: Let $N = \{1, 2,\ldots, n\}$ be a finite set of nodes (here, sellers). By $g_{ij} \in \{0,1\}$ we denote a link between sellers i and j, where

$$g_{ij} = \begin{cases} 1, & \text{if there is a link between } i \text{ and } j \\ 0, & \text{otherwise} \end{cases}$$

A network, g, is then defined as a set of nodes N with links between them. This can be represented in graph form in an adjacency matrix (G), where an entry in the matrix G, corresponding to a particular pair of nodes (i, j), signifies the presence or absence of a connection between i and j.

Accordingly, using the data gathered from the survey, an adjacency matrix, like the one described above, was constructed for each specified dimension listed previously.

A total of six (6) matrices were constructed altogether.

The rows and columns of each matrix included the distinct serial number assigned to each ego and the alters it nominated. The snowball sampling method adopted demands researchers to be mindful of each node that was already named (Illenberger & Flötteröd, 2012). This stipulation ensured that no same individual was allocated two different serial numbers. Consequently, a roster of retailer names (and other relevant contact information) from each interviewed retailer was maintained and tracked to identify common nodes and safeguard against duplicates.

The entries corresponding to each cell in the matrix were then coded '0' or '1' on the basis of whether a link existed between two given retailers or not. The matrices were constructed under the assumption that any given retailer is not related to himself so the diagonal of these matrices are all set to '0' (Hanneman & Riddle, 2005).

The Whole Network Matrix was generated by following Banerjee et al. (2013) and taking the union of all six (6) individual matrices, i.e. a link between two retailers (nodes) is said to exist if either one nominates the other along any one dimension, whereby ensuring that all relevant connections between these particular retailers are effectively captured. This is helpful given that this study was only able to interview thirteen (13) individual retailers so teasing out all possible links helps arrive at a network that is representative of the many different interactions that occur between a pair of retailers in this particular market. Once all adjacency matrices are constructed and a Whole Network Matrix formed, individual network maps are generated for all six (6) matrices and the Whole Network Matrix. The central most retailers are then identified using these network maps.

Lastly, these centrality measures are used to analyze how more connections and/or social closeness economically benefits (if at all) retailers in this particular market. Under the assumption that position in a network impacts a given retailer's exchange relationships, it is hypothesized that more central retailers are able to arrive at relatively favorable terms of trade as compared to other retailers that rank lower in terms of their centrality in the whole network. Additionally, the study also looks at how demographic and enterprise characteristics of members of this network relate to their respective centrality scores.

Measuring Centrality

Centrality is one of the most studied concepts in social network analysis and may reflect a node's potential power, prestige or influence within a network. Resultantly, once the network maps were generated, the next step was to find out which sellers lay at the core these different networks and hence wielded most influence given different contexts. Centrality measures have important implications, from how information spreads in a network to a node's effectiveness as an arbiter in various transactions. Although, a outwardly straightforward concept, we want to identify sellers that are at the "center" of the networks that emerge, but determining what one means by "center" can be fairly complex. Numerous measures of centrality have been developed, but, as presented in Jackson (2008), these are categorized into four main groups: a) Degree centrality, b) Closeness centrality, c) Betweenness centrality, and d) Eigenvector-related centrality. Our focus shall remain on two of the four measures identified.

Degree centrality is a basic measure of centrality that simply counts how many connections a particular node has – here: the total number of retailers in this market a particular seller is linked to along the various dimensions under study. Following Jackson (2008), node *i's* degree (d_i) in network *g*, is defined as:

$$d_i(g) = \#\{j : g_{ji} = 1\} = \# N_i(g)$$

This measure of connectivity helps capture a given node's popularity and can be seen as an index of its communication activity (Rusinowska, Berghammer, De Swart, & Grabisch, 2011). Literature shows that network actors with more linkages are able to extract benefits in two basic ways: by enhancing their competitive position, and reducing uncertainty (Kranton & Minehart, 2001). This is so because having a larger pool of connections allows actors to (i) turn to more people to help fulfill resource needs, i.e., experience and improved availability of inputs, and, (ii) insulate themselves from difficulties that may plague a particular link in their network (Kranton & Minehart, 2001).

However, impact in a network varies with setting. In Pakistan, where contracts are hard to write and enforce, evaluating a seller's importance in terms of his ability to write contracts and have them enforced, i.e., broker deals between other sellers, may prove to be much more relevant. Measuring the betweenness centrality of sellers allows one to identify which retailer lies between a lot of other retailers in a world where it's important to broker deals. Here, the betweenness centrality of a retailer will show the number of times a given retailer in this market lies between the shortest paths between different pairs of retailers.

Following Borgatti (2005), and Jackson (2008), we determine a given node's betweenness by calculating the fraction of times a node needs a particular node (one's whose centrality is being measured) to reach another node through the shortest path. By summing this fraction through all pairs of nodes in the network we arrive at the betweenness score for the node in question. Higher the betweenness centrality for a particular seller, the more prominent and essential that seller is in the network.

Specifically, the betweenness centrality of a seller *k* will be as follows:

$$\sum_{i}\sum_{j}\frac{g_{ikj}}{g_{ij}}, \qquad i \neq j \neq k$$

where, g_{ikj} is the number of shortest paths between seller *i* and seller *j* that pass through seller *k*, and g_{ij} is the total number of shortest paths between seller *i* and seller *j*. Hence, betweenness basically counts the total fraction of all paths between all pairs of nodes that use a node's (here, seller *k*'s) exclusive position to reach one another. This measure of centrality will help capture the significance of indirect connections between two sellers through a directly connected seller. This betweenness measure is calculated for each individual seller in each of the six sub networks and in the whole network.

Both centrality measures utilized in this study are significantly positively correlated to one another (*p*-value = 0.0004) and hence are not incorporated together in regressions to avoid multicollinearity between the two. This positive correlation is illustrated in Figure 5 (Appendix C). All network maps with nodes sized by betweenness centrality are also included in the Appendix to this study.

Data

Market Background

The study uses data gathered from structured interviews with sellers of water pumps and motors in and around the Brandreth Road area of Lahore. Brandreth Road is home to the largest industrial goods market in Pakistan and, arguably, one of the largest in South Asia. Trading relationships here can date back to the pre-partition era with many businesses being offshoots of older family owned businesses, even if independently run at present.

Of the retailers interviewed for this study, many previously manufactured water pumps themselves but given the glut of low cost Chinese imports nearly all have made the shift from producer to trader. However, these sellers' past experience as manufacturers still informs a lot of their present business since they seem to have an intimate knowledge of the construction of the items they sell. After sales service includes repair and maintenance work and is increasingly valued given the rise in trading of second-hand, refurbished machinery. Some retailers even act as consultants for clients helping them customize their purchase and assist in the procurement of specialized equipment whose knowledge is a direct by product of their previous line of work.

Data Collection

As is the case with traders in developing countries, sellers in this market are not easily convinced to share proprietary information regarding their business operations. Furthermore, the sheer breadth of potential connections between any two retailers can make it difficult to identify meaningful relationships that would arguably have an effect on their economic outcomes. As Jackson (2008) shows, a group of 10 people can have 45 different possible relationships among themselves, with 2^{45} potential networks that can be present in this society of just 10 people. This study uses a respondent driven sampling technique, which itself is a type of snowball sampling method, to approach retailers in this particular market. My choice of market and segment was primarily based on convenience but driven by certain facts informed by literature. I wanted to look at a market that: (i) had history, where sellers would have been operating for a substantial amount of time whereby allowing for relationships to have matured enough to matter, and (ii) contained sellers of similar products so I could make a comparable analysis between multiple retailers of the same kind of goods but with varying network positions within the market they inhabited.

Data Description

The study interviewed a total of 13 individual sellers over a 7-month period to create a network between 34 different sellers in the market. Between these 34 sellers, there is a potential of $2^{34(33)/2} = 2^{561}$ undirected networks to be present. Each interviewed seller and his nominated list of connections was assigned a serial number. This helped achieve two purposes: first, as literature demanded, it helped keep track of and distinguish between respondents and non-respondents. This was important because assessments regarding the position of nodes in a network can only credibly be made for those actors who were in fact interviewed (Illenberger & Flotterod, 2012). It would be inaccurate to say that a non-respondent has only one connection (a degree of 1) in the network since that seller was never interviewed. However, the non-respondents cannot be eliminated from my analysis entirely since interviewed sellers in fact list them as connections and hence these links help determine the position of surveyed retailers in the network. Given the sensitive nature of the information gathered in the study it is safe to say that no single retailer had the incentive to divulge more information than was really necessary since all participants were aware that their listed contacts would be requested to participate, i.e., there is no logical reason for retailers to overstate their connections and inflate popularity. Also, given that I had an established member of the actual network serving as a recruiter the motivation to lie and misrepresent links is substantially lowered since information about network links among different members can be easily verified through the network itself as, shown in the next section, information travels fast here.

The second purpose for assigning unique serial numbers to all sellers in the market was that it helped depersonalize their information as was assured to them during the course of this study.

The data is summarized in Table 1 below.

Variable	Observations	Mean
Demographics		
Age	13	46.92
Business Age	13	17.538
Experience	13	28.154
No. of workers	13	4.23
Start-up finance - % of retailers		
Personal savings	13	85%
Gift from family/friends	13	69%
Some loan from friends/family	13	23%
Ownership - % of retailers		
Sole Proprietorship	13	77%
Family-owned	13	23%
Factors important for success - % of retailers		
Personal reputation & relationships	13	92%
Access to credit	13	77%
Granting credit	13	85%
Trust	13	100%
Relevance of network relationships		
Likelihood of sharing credit with unknown retailer	13	1.85
Creditworthiness assessed by:		
% who get info from direct inspections	13	77%
% who get info from other retailers	13	85%
% who get info from mobolizing employee network	13	92%
Dispute resolution method		
Take cheating party to court	13	0%
Involve local leaders	13	85%
Do nothing & discontinue relationship	13	15%
Seek outside "assistance" & recoup partial cost	13	46%
Repercussions of cheating		
Dispute with one sharing partner strains ties with others	13	62%
Dispute with one sharing partner would become known to others	13	85%
Would never transact with retailer who has cheated a trading partner	13	69%
Retailers will tighten terms of exchange if news of my cheating spreads	13	85%
Maintaining long-term relationships with trading partners only way to ensure favorable sharing agreements	13	77%

Table 1. Summary Statistics.

The average retailer is nearly 50 years old, has a secondary school education, and has been operating his present business for almost 2 decades. These businesses are small and largely owner owned and managed, with 77% of surveyed firms identifying as sole proprietorships with an average of 4 employees. Consistent with businesses in much of Pakistan, the major source of start-up finance here was the owner's personal savings, although 69% of entrepreneurs report receiving some financial help in the form of gifts from friends and family, while 23% cite receiving a form of start-up loan from friends or family. No interviewed seller reported receiving a bank loan to set up his business. The total figure for all these sources is greater than 100% since retailers were allowed to choose more than one source of start-up finance that they used.

The potential relevance of networks is made known as one learns that, on a scale of 1 to 10, this set of surveyed retailers will rarely ever share credit with a seller they have no prior interaction with. This number is only slightly higher for unknown retailers with who interviewed sellers would share inventory with (2.28). This preference for sharing inventory rather than money was also made known in discussions where sellers confided that sharing inventory was more desirable than sharing money since inventory has a higher probability of being recovered and investment recouped as opposed to a cash loan whose recovery may require one to hire "muscle" and incur inflation related losses.

Further proof of the role of networks here is communicated in the fact how a whopping 92% of surveyed sellers attribute success in this market to the personal reputations and relationships one nurtures here. In contrast, only 77% of those interviewed deem access to credit as a vital ingredient for success. These numbers, coupled with the ones explained above, allude to how having fewer connections and/or inferior standing in this market could prove as a possible barrier to progress.

The screening and contract enforcement functions of social networks are also made apparent in this table: 85% of respondents said that they would talk to other retailers in the market to make assessments about the credit worthiness of an unknown seller prior who approaches them for credit. This shows that network members in this market act as screeners for one another and also how enough information regarding others' businesses is known to connections to make an educated evaluation. In discussions respondents revealed foot traffic at a potential borrower's shop to be an important indicator of how well his business is doing; lenders want to make sure that this seller is not idle all day. Greater social interaction or having more connections would prove advantageous in communicating such information to potential lenders and facilitate flow of credit. Other important markers of stability included the number of orders that are dispatched, and the frequency with which a given seller replenishes stocks. Retailers reported that the best way to learn these bits of information about any seller were through people this seller employed and other retailers he shared inventory with. This helps clarify why 92% of those surveyed cite their employee network as a preferred tool for gathering information on other seller's in the market.

According to the World Bank Doing Business report (2016), enforcing commercial contracts in Pakistan takes nearly 993 days on average and costs 23% of the claims value. The country ranks 151 globally out of 189 countries in terms of contract enforcement (Doing Business 2016, 2016). This inefficiency of the courts is reflected in the apparent distrust sellers place in the ability of the judiciary to resolve any impending disputes. No single respondent in this study considered taking any legal recourse against those who reneged on exchange agreements. Most of the retailers interviewed expressed unguarded disgust for the country's judicial system and reported how even lawyers recommend approaching politically connected individuals in the market for dispute resolution. A sizeable number of surveyed retailers (46%) report, "seeking assistance" from certain "specialists" to help recoup disputed sums of money. However, majority of those interviewed approach market leaders for settling any conflicts that may emerge within this market area.

Furthermore, 77% of those surveyed agree that maintaining long-term relationships with trading partners is the only way to ensuring favorable sharing agreements between retailers in the market. Many here disclosed that making timely payments to trading partners is one way of building and maintaining strong ties in this market. One respondent narrated how he would always reimburse/repay a lender of inventory/money 15 days prior to when these fees became outstanding, regardless of how long he had been engaged in such transactions with the respective seller, since this allowed him to borrow large amounts whenever he wanted.

Empirical Estimation & Results

This section uses network data to construct and analyze network maps. These maps are then used to compute degree and betweenness centrality measures detailed previously to study how a particular retailer's position in this network is determined, and whether he extracts any economic benefits by virtue of this position. The analysis makes uses of retailers' centrality in the Whole Network, and the Joint Purchases and Inventory Sharing sub-networks since the economic outcomes of interest (the terms of exchange a retailer is able to secure from his network partners) are subject to his association with other retailers along these two dimensions. A further analysis of the cumulative impact of a retailer's position in all different sub networks – his centrality scores in the Whole Network – on his enterprise performance is also carried out. I use ordinary least squares (OLS) to estimate these simple regression equations.

Network Maps

Using responses to different tie eliciting questions, adjacency matrices were constructed to express the presence or absence of links between retailers along the six dimensions summarized in the preceding segment. Network maps were then generated for each individual matrix. Following Banerjee et al (2013), a union of all six matrices was used to construct a Whole Network Matrix (and a corresponding network plot of this matrix too was then generated). Since the aim of the study is to essentially help determine how network relationships benefit retailers in this particular market setting, connections between sellers were established using factors that would facilitate informal transfers between retailers in a developing country context. These transfers are particularly relevant for a country such as Pakistan where information and enforcement problems, coupled with a preference for entering into unregulated transactions to evade taxes, have led to burgeoning informal finance markets (Qadir, 2005).

Whole Network Matrix

The Whole Network Matrix was generated using a union of all six individual sub matrices that specified whether two retailers exchanged advice, information, or inventory with one another, or if they made any joint purchases of supplies with a particular retailer, or identified a retailer as having acted as a guarantor of transactions between them and other retailers and/or helped resolve market disputes. The Whole Network is reproduced below (Figure: 1).

The network comprises of 34 nodes (read: sellers) and a line between two nodes is representative of a link between them along any of the six different dimensions outlined previously. The network graph is undirected, i.e., symmetric – a link between two sellers is said to exist if either nominates the other as a contact, a technique similar to that used by Banerjee et al. (2013), Chandrasekhar et al. (2013), and Breza et al. (2015) in different studies outlined in the literature review section. The numbers next to the nodes are distinct serial numbers that were assigned to these sellers, and the size of nodes is indicative of the number of connections that they have, i.e., their degree centrality (with the largest square having the most number of links).

(Insert figure 1)

Figure 1. Whole Network Matrix Map**.** The figure represents 34 nodes (retailers) as squares with six dimensions of possible links between two nodes. The size of each square indicates the degree centrality of a given node, i.e., the total number of retailers reported to be linked to a given retailer. Nodes with matching colors have the same degree.

Looking at Figure 1 we can make certain observations about the properties of this particular network (these network properties are summarized in Table 1.1 below). There are a total of 34 nodes (retailers) in this whole market network, and as is evidenced by the one giant component, all of these retailers are connected to one another through at least one of the relationships mentioned previously. However, there do seem to be differences in the degree centrality (the number of connections each retailer has) of different nodes. This degree centrality of nodes ranges from 1 to 12, i.e., the most connected retailer in this market (Retailer # 10 in Figure 1) is linked to 12 other sellers. On average, a retailer in this particular market network is connected to 2.82 other retailers. This range of degree centrality of nodes (and their average degree) is even higher if we only focus on those individuals that were directly interviewed for this study, i.e., only focus on the ego-vertices (for reasons outlined in the Data section). In that case, degree centrality ranges from 3 to 12, i.e., the least connected retailer, in terms of degree, is linked to 3 other retailers along the different dimensions under consideration in this study. Furthermore, each interviewed retailer, on average, is reportedly linked to 5 other sellers in the market.

The network map also gives us other insights about the connectivity of retailers in this market. For e-g, it can be shown that, on average, a message has to be passed between 3 people to reach the other person in this whole market network. This is referred to as the average distance between nodes. Shorter average distances are associated with faster diffusion of information among network members (Borgatti, Everett, & Johnson, 2013).

The map and its associated signatures summarized above show that there is enough interaction between retailers in this market for information to spread fast. These network properties help explain responses of retailers to objective questions regarding the flow of reputational information in this market: for e-g 85% of interviewed retailers report that they would assess the creditworthiness of an unknown retailer through other retailers in the market (i.e., by tapping their network connections), while 92% would mobilize their workers to seek out relevant information on the potential, unknown borrower, versus 77% who would opt for direct inspection of an unknown borrower's business. This apparent role of networks as reservoirs of information is well documented in literature (McMillan and Woodruff, 1999; Conley and Udry, 2004; Banerjee et al., 2013), and illustrates why 92% of surveyed retailers here consider "personal reputation and relationships" to be an important factor of success in this particular market and line of business, even more so than "access to credit" (77%) and "granting credit" (85%).

Furthermore, analysis of the neighborhood of leaders in this market (here, the top two nodes with the most connections, Retailer # 10 and Retailer # 6, respectively) shows that people farther away from central nodes have fewer connections (p-value = 0.000), and exhibit higher clustering (p-value = 0.011). In network parlance, clustering is how often nodes that a particular node is connected to are in fact linked to one another (Jackson, 2008). The overall clustering coefficient for this network is equal to 24, i.e., in this network if one retailer is linked to two others, those two linked retailers, on average, are also connected to one another nearly a quarter of the time. Having neighbors that aren't directly connected to one another lends importance to nodes that then act as bridges or "brokers" between such indirectly connected actors, as Jackson (2008) makes apparent in his discussion of Padgell and Ansell's paper on the rise of the Medici family in 15th century Florence.

Network	Network Size	Degree Range	Average Degree	Average Distance	Clustering Coefficient	Most Central Retailer
(1) Whole Network	34	1-12	2.82	3	24%	#10
(2) Joint Purchases Network	15	1-3	1.83	1.6	44%	#4 & #19
(3) Inventory Sharing Network	15	1-5	2.08	2.8	22.2%	#6
(4) Guarantor/Mediator Network	16	1-6	1.3	1.4	13.6%	#10

Table 1.1 Network Properties

Joint Purchases Network Matrix

The Joint Purchases (Sub)-Network Matrix was generated in response to who the surveyed retailer jointly purchases supplies with in the market. A network link is said to exist between two retailers if either one nominates the other in response to the above question. A network map of the Joint Purchases Network Matrix is shown in Figure 2 below.

(Insert figure 2)

Figure 2. Joint Purchases Network Matrix Map**.** The figure represents 34 nodes (retailers) as squares with a line between two retailers if they jointly purchase supplies with one another. The size of each square indicates the degree centrality of a given node, i.e., the total number of retailers connected to a particular seller along the specified dimension. Nodes with matching colors have the same degree.

The Joint Purchases (JP) network map shown above is a fairly fragmented network and is made up four different connected parts along with 17 nodes that are not linked to any other node in the network. Such detached nodes are termed as isolates in network jargon (Hanneman & Riddle, 2005). The degree centrality of nodes ranges from 0 to 3, with a retailer jointly purchasing supplies, on average, with 0.59 other retailers. Those retailers who made active joint purchases cited the benefit they receive from bulk buying and more supplier options as a major factor for entering into these arrangements. The central retailers in this sub-network also happened to be those who have relatively newer businesses as opposed to the more prominent retailers identified in the Whole Network map. For e-g the most central seller in Figure 1 (Retailer #10) has a degree centrality of 1 in this JP network, whereas Retailer #4 and Retailer

#19 who otherwise have markedly lower links relative to Retailer #10 in the Whole Network are ranked first in terms of degree centrality in this JP network. Interviews with sellers revealed that entering into joint purchase arrangements resulted in the exchange of a lot of exclusive information (particularly regarding customers' identities, their purchase patterns and the terms of payment negotiated with them) that can become a cause for concern and thus keep retailers from connecting with many others in the market along this dimension. The intimate nature of JP arrangements is confirmed by how 83% of retailers who jointly purchase supplies with others describe their relationship with such people as "Close" as opposed to "Purely commercial" (17%) or "Impersonal" (0%). Furthermore, the overall clustering coefficient for the JP network is much higher than that seen in the Whole Network: Here, if one retailer jointly purchases supplies with two others, those two linked retailers, on average, also jointly purchase supplies with each other nearly 45% of the time. But central most retailers in the JP network still have lower than average individual clustering coefficients. For e-g: Retailer #4 and Retailer #19's neighbors are only connected to one another 33% and 17% of the time, respectively. Therefore, influence through brokerage is still expected to be relevant in such a network.

Inventory Sharing Matrix

The Inventory Sharing (Sub)-Network Matrix was generated in response to who in the market did surveyed retailers turn to if needed to borrow inventory. A link between two retailers is said to exist if either identifies the other as a connection in reply to the above question. A network map of the Inventory Sharing Matrix is shown in Figure 3 below.

(Insert figure 3)

Figure 3. Inventory Sharing Network Matrix Map**.** The figure represents 34 nodes (retailers) as squares with a line between two retailers if they share inventory with one another. The size of each square indicates the degree centrality of a given node, i.e., the total number of retailers connected to a particular seller along the specified dimension. Nodes with matching colors have the same degree.

The Inventory Sharing (IS) Sub-Network map above, though fragmented, is characterized by one large connected part linking the majority of the interviewed retailers. This again is an undirected graph of 34 retailers where ties are symmetrical, and the number of connections that each node has ranges from 0 to 5. Here, Retailer #6 is seen to be the most central actor with 5 different retailers he shares inventory with in the market. Retailer#10, who is most influential in terms of total links in the aggregate of all 6 sub-networks (the Whole Network Matrix) ranks second here with 4 links. In this particular network a retailer, on average, shares inventory with 0.765 other sellers in the market, nearly 30% more people than those an average retailer jointly purchases supplies with. The IS network is also characterized by a relatively low overall clustering coefficient (21.4%) as compared to both the Whole Network and the JS Network. Here, Retailer #10's connections share inventory with one another only 10% of the time, whereas Retailer #6's connections share inventory with one another 20% of the time, a fact that is bound to be reflected in differences in their respective influence as brokers in this network.

Relationships in the IS network are seen affect reputations of network members in this market as more than 60% of surveyed retailers report that a dispute with one sharing partner will adversely impact their relationship with other retailers in the market. This negative feedback is significantly more pronounced for retailers with fewer connections in this network (*p*-value = 0.032). In contrast, degree centrality in this network doesn't significantly impact a retailer's decision to not interact with other network members who have cheated a trading partner (*p*-value = 0.28). This would mean that people here believe in the independent verification of claims made against retailers in their network. This assessment seems fair since interviews with retailers reveal that even though they would become "cautious" of dealing with supposed cheaters they will "investigate the matter fully" before restructuring the nature of their relationship with those who are accused of violating sharing agreements.

Having more connections in this network did appear to be advantageous in that more central retailers narrated that they felt confident about their standing in the market and were of the opinion that in case of disputes other retailers in the market would give more weight to their side of the story. Such anecdotes seem to hold up since retailers with more connections were significantly more likely to agree to the statement that other sellers would "refuse to trade with a retailer who has cheated me" (*p*-value 0.027).

Given how surveyed retailers (ego-vertices) in this IS network, on average, are connected to 2.08 other retailers along this particular dimension, it's unsurprising that network members believe news of tricksters would be widely disseminated in the market: here, over 80% agree that dispute with one trading partner would become known to others in the market, and nearly 85% believe that duping network members will have repercussions in such that their terms of exchange with other trading partners would be negatively affected as their reputation as a cheater is cemented.

Guarantor/Mediator Network Matrix

The Guarantor/Mediator (GMR) (Sub)-Network Matrix was generated in response to who surveyed retailers have turned to (or would do so in the future) in the market to help act as a guarantor for trading arrangements with other retailers and/or as a mediator to resolve network disputes in the market. A directed link between two retailers is said to exist if one retailer has accepted (or would accept) another retailer in the roles just outlined. This particular social network question helps identify retailers who are truly considered to bear most influence in this market. Breza et al. (2015) confirm that for individuals to be accepted in roles where they successfully help enforce agreements it is necessary for them to be able to widely spread information about those who renege (so their future terms of exchange in the network are impacted) and carry out punitive actions without any fear of retribution. Individuals with such traits occupy central positions in any social structure & identifying them is key to making accurate assessments about where power lies in a network. The GMR network matrix map for retailers in this particular market is shown in Figure 4 below.

(Insert figure 4)

Figure 4. Guarantor/Mediator Network Matrix Map**.** The figure represents 34 nodes (retailers) as squares with a directional tie between two retailers if one seller identifies the other as someone he has accepted (or will accept) as a guarantor/mediator in the market. The size of each square indicates the in-degree centrality of a given node, i.e., the total number of retailers that identify a particular seller as a guarantor/mediator. Nodes with matching colors have the same degree.

The in-degree centrality is simply the number of incoming ties to a particular retailer in this market, and is the most uncomplicated measure of popularity in a network (Jackson, 2008; Ayako et al., 2014). The surveyed retailers in this market nominate a total of 9 individual retailers who they would accept (or have accepted) in the role of a guarantor/mediator. Of these, Retailer #10 has the most number of incoming ties (6), closely followed by Retailer #7 who has an in-degree centrality of 5. This characterization of these respective actors is consistent with their background information. Retailer #7 is union president of this particular market and hence a natural choice for this role. Retailer #10, however, has the more interesting backstory: he is one of the first people to have set up shop in this particular section of the market. He is known for his philanthropic work and has reportedly run multiple successful charity drives for the Internally Displaced Populations in Pakistan's war-torn tribal belt, collecting as much as Rs.1.1 million at a recent event during Ramadan. Other people in the area report that he has been repeatedly offered to become the head of the country's ruling party's local traders wing but has refused due to his apolitical nature. However, having close ties to the ruling party in both Punjab (Pakistan's largest province) and the Centre buys one tremendous influence and helps explain why most would choose this particular retailer to enforce their trading agreements.

Determinants of Centrality

The following equation is estimated to determine whether a retailer's position in this market is shaped by the individual characteristics of both the retailer and his enterprise:

$$C_i = B_0 + B_1 D_i + e_i \quad (1)$$

The prediction is that more centrally located sellers in this market have a different demographic makeup than their less central counterparts.

Null Hypothesis 1: Demographic features of the retailer and his enterprise have no impact on a retailer's centrality in the Whole Network.

Alternate Hypothesis 1: Demographic features of the retailer and his enterprise have an impact on a retailer's centrality in the Whole Network.

Equation (1) is estimated for both a retailer's degree and betweenness centrality to ascertain whether certain demographic characteristics of the retailer and his enterprise are more relevant than others in helping explain the importance of a particular retailer in a specific context. Regressions are run here with the dependent variable (C_i) being the overall centrality of a retailer in terms of degree, and betweenness in the Whole Network. The independent variables of interest in both regressions remain the same and are represented by the vector of demographic covariates of both the retailer and his enterprise (D_i) namely, the log transformations of: the age of the retailer (Lage), the age of the business (Lbage), the experience of the retailer (Lexperience), the size of the business, as proxied by the total number of workers, both full and part time, the retailer employs (Lworkers), and the level of education of the retailer (Education). The results of these regressions are shown in Table 2 and Table 3.

Table 2: Degree Centrality and Demographics

	(1) DEGREE	(2) DEGREE	(3) DEGREE	(4) DEGREE	(5) DEGREE
Lage	10.85*				
	(1.99)				
Lbage		5.21**			
		(2.38)			
Lexperience			6.29*		
			(1.94)		
Lworkers				6.47	
				(1.67)	
Education					-0.076
					(-0.1)
Constant	-37.40	-9.74	-15.87	-3.87	5.18
	(-1.76)	(-1.56)	(-1.47)	(-0.72)	(2.65)
Observations	13	13	13	13	13

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. DEGREE is a discrete dependent variable that measures the total number of links a particular retailer has in the Whole Network Matrix. Sellers with the greater number of links are said to be more central. Of the independent variables, the age of the retailer (Lage), the age of the business (Lbage), the years of experience a retailer has (Lexperience), and the number of workers a seller here employs (Lworkers) is in logs. Education is a categorical variable and corresponds to the maximum level of education attained by a retailer. OLS estimates of the various demographic characteristics are reported in 5 separate regressions to avoid mullticollinearity between variables since most are significantly positively correlated to one another.

The results shown in Table 2 imply that sellers who are older, or have more experience, or whose business has been in operation longer tend to have a significantly larger number of connections in this market. Meanwhile, the maximum level of education a retailer has attained, and the size of his business (as measured by the number of people he employs) has no significant bearing on how well connected he is in this market. The log of business age (Lbage) seems to be the most significant predictor of the size of network links in this market. However, our analysis can't confirm whether remaining in business longer resulted in this expansion of a retailer's network or having more connections in the market helped prolong the existence of businesses run by more centrally located retailers.

Table 3 shows OLS estimates of equation (1) but with the dependent variable (C_i) now measuring whether a given seller is a crucial connector laying on most shortest paths linking other sellers in the market, i.e., a retailer's betweenness centrality. The different demographic predictors (D_i) are identical to those used in Table 2 above and are computed in the same way. The results present an interesting foil to the relationships observed in Table 2. Business age is still the most significant correlate of centrality in this context but a retailer's age though positively related to a seller's betweenness centrality is no longer a significant determinant of how much influence a seller has in the market. In contrast, the size of a retailer's business, as measured by the total number of workers he employs, has a positively significant impact on his ability to act as an intermediary between two sellers in this market, i.e., his betweenness centrality. Individuals with higher betweenness centrality derive influence from their ability to control the flow of information in their network (Jackson, Rogers, & Zenou, 2015). Interviews with sellers in this market showed that they considered their employees to be a vital source of information, with 92% of surveyed sellers reporting that they would gather relevant information regarding the business operations of unknown retailers by mobilizing their employee network. Furthermore, it is pertinent to mention that some employees in this market have been working here for a substantial amount of time. One such worker had been employed on Brandreth Road for nearly 2 decades. That's slightly more than the average age of businesses surveyed in this network. Some sellers in the Information Sharing sub network cited another such worker, who had previously apprenticed with the Union President and now managed a business of his own in the area, as a contact. He, although, is not made a part of the analysis since was engaged in the industrial tools business. These examples indicate that workers in the market have well-established networks of their own and could arguably provide important informational advantages to employers and facilitate their roles as brokers. A larger employee network could also help sellers transmit news of reneging retailers more widely across the market; this ability to broadcast such information to a large number of people is cited as an important reason as to why some people in the network are more well placed to effectively mediate disputes or enforce agreements than other less central individuals (Breza et al., 2015). Causality here too is hard to pin down.

Education has no significant affect on the importance of a particular retailer in this network. However, a retailer's experience has a positively significant impact on his betweenness centrality. This is identical to what we saw in Table 2 and indicates that sellers in this market are potentially able to leverage their working experience to extract more influence in terms of both direct and indirect connections.

Table 3: Betweenness Centrality and Demographics

	(1) BET	(2) BET	(3) BET	(4) BET	(5) BET
Lage	353.74 (1.73)				
Lbage		187.91** (2.34)			
Lexperience			241.80* (2.10)		
Lworkers				270.72* (2.00)	
Education					-5.72 (-0.21)
Constant	-1288.73 (-1.61)	-439.03 (-1.93)	-710.16 (-1.85)	-279.20 (1.49)	105.71 (-1.66))
Observations	13	13	13	13	13

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. BET is a continuous dependent variable that measures the number of shortest paths between all pairs of sellers that pass through a given seller (one whose betweenness is being measured). A seller who lies on many shortest paths among all pairs of sellers is said to be most central in this market. A retailer's age, his experience, the age of his business (bage), and the number of workers he employs (size of the business) are measured in logs. Education is a categorical variable measuring the maximum level of education a retailer has attained. OLS estimates of the various characteristics are reported in 5 separate regressions to avoid mullticollinearity between variables since most are significantly positively correlated to one another.

Joint Purchases and Centrality

This part of our analysis will focus on learning whether a seller's position in the Whole Network, as determined by his degree and betweenness centralities, has any significant consequences for the terms of exchange he's able to secure for the resources he shares with other retailers in the market. The following equation is estimated to model the impact of a retailer's position on his economic outcomes of interest:

$$Y_i = B_0 + B_1 C_i + B_2 Z_i + e_i \quad (2)$$

The prediction here is that retailers with more central positions in the Whole Network will be able to secure more favorable terms of exchange for shared resources in the market. We will model this effect for terms of exchange secured in the Joint Purchases, and Inventory Sharing sub networks in particular. Regression results will be presented both in tabular and graphical form.

Null Hypothesis 2: Having a high centrality score in the Whole Network does not affect a seller's terms of exchange that he secures for shared resources.

Alternate Hypothesis 2: Having a high centrality score in the Whole Network affects a seller's terms of exchange that he secures for shared resources.

Table 4 shows the OLS estimates for the first of these models. In this model our outcome of interest is the discount a particular seller receives upon jointly purchasing supplies with other retailers in his network. This is Y_i in equation (2) and is measured in response to the question "*How much less would you pay, on average, if you jointly purchased Rs.100, 000 worth of supplies*?" Responses to this query were coded as a categorical variable ranging in magnitude from 0 to 4 with 0 being set equal to the response "*pay same*" and 4 being set equal to paying *"> 40% less*" on jointly purchased supplies in the market. No retailer in the Joint Purchases sub network reported receiving zero discount, i.e., paying same, for jointly purchased supplies. As a matter of fact, retailers in this sub network reported paying 10%-20% less, on average, for jointly purchased supplies.

The results shown in Table 4 imply that a seller's position in the Whole Network does in fact significantly affect the amount of discount he allegedly receives by jointly purchasing supplies with other retailers in his network but not in the expected direction. Given the significant positive correlation between both degree and betweenness centrality measures (*p*-value = 0.000) regression results for the impact of each is reported independent of one another to avoid multicollinearity.

Having more connections in the Whole Network is associated with paying significantly more for Rs.100, 000 worth of jointly purchased supplies. Similarly, laying on more shortest paths connecting all pairs of sellers in the market too has a significantly negative bearing on the terms of exchange secured in this context. Columns (3) and (4) in Table 4 confirm that this significantly negative impact of a seller's betweenness centrality on the reported discount he receives on jointly purchasing supplies is robust to the inclusion of other covariates. This negative relationship between discount received and the degree and betweenness centrality scores of sellers in the Whole Network is also represented in Figure A and Figure B below.

To understand the reason why more centrally located retailers in this market report receiving lower discounts on jointly purchased supplies of Rs. 100,000, it is important to mention that some retailers prefaced their nominations to the "*who do you jointly purchase inventory with*" question with the confession that they don't make joint purchases as often since they've either had a bad experience (a retailer shared that the person he jointly purchased goods with once ended up learning a great deal about one of his major clients and attempted to poach this said client), or, as is the case with more central players in this market, disclose offering increasingly customized options to clients with own set of technicians who modify pump and motor designs to the customer's' needs. This apparent disinterest of central players in collaborating with other actors in this network to make joint purchases is also illustrated in the Joint Purchases Network Map (Figure 3) where we saw that the most central retailer in the overall Whole Network sees his degree centrality score fall from 12 to 1, while retailer # 4, who otherwise is comparatively less connected in the Whole Network, is seen to collaborate with the most number of other retailers along this dimension.

Given this trend it could be surmised that the more central sellers might feel less inclined to enter into such arrangements, and thus their reported benefit from these purchases is subdued. Additional analysis shows that younger businesses are seen to report receiving significantly higher discounts (p-value = 0.024).

Table 4: Joint Purchases and Centrality

	(1) Discount JP 100k	(2) Discount JP 100k	(3) Discount JP 100k	(4) Discount JP 100k
DEGREE	-0.20*			
	(-2.14)			
BET		-0.01**	-0.01*	-0.0062*
		(-2.34)	(-2.00)	(-2.15)
Lage			0.15	0.79
			(0.07)	(0.34)
Education				-0.28
				(-1.05)
Constant	3.19	2.70	2.13	-0.31
	(5.98)	(8.37)	(0.25)	(0.04)
Observations	12	12	12	12

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. Discount JP 100k is a categorical dependent variable with a value ranging from 0-4 that measures the amount of reported discount a seller receives on jointly purchasing Rs. 100, 000 worth of supplies with other retailers in his network. A higher value for this variable corresponds to sellers reportedly paying less for jointly purchased supplies. DEGREE and BET measure the degree and betweenness centrality of individual sellers in the manner detailed in methodology section. The age of the seller is measured in logs (Lage). Education is a categorical variable measuring the maximum level of education a retailer has attained.

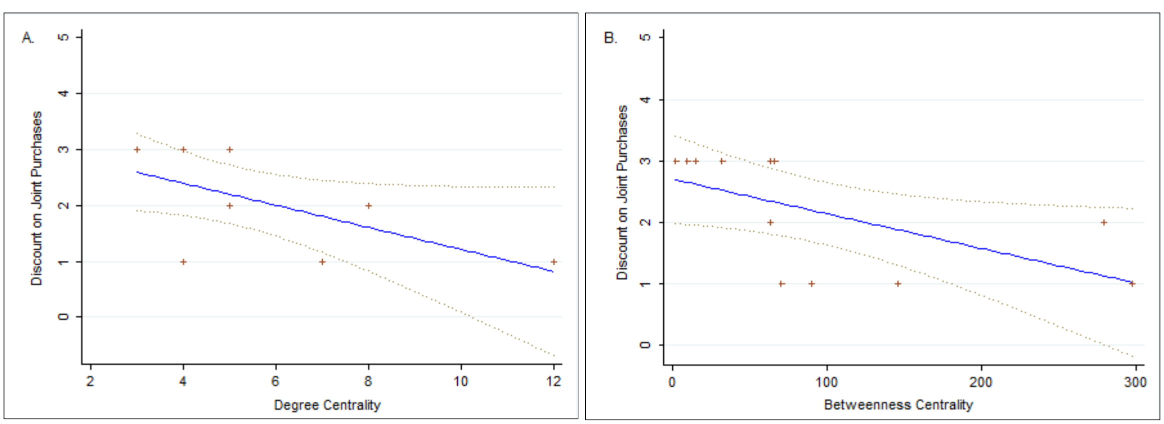

Figure A. Retailers with more connections reportedly receive significantly smaller discounts on joint purchases of Rs.100, 000 of supplies.

Figure B. Retailers who lie on many shortest paths among other pairs of sellers in the market (have higher betweenness centrality) report receiving significantly smaller discounts on joint purchases of Rs. 100, 000 worth of supplies.

Inventory Sharing and Centrality

In this model there are two outcomes of interest: namely, the inventory payment schedule (IPS), and the payments for inventory (PINV). Table 5 shows OLS estimates for the impact a seller's position in the Whole Network, and the Inventory Sharing sub-network, has on a respective seller's IPS. This is Y_i in equation (2) and is measured in response to the question "*What is the maximum number of days you have, on average, before you begin making payments for borrowed inventory*?" Responses to this question are coded in the form of a categorical variable that ranges from 0-4 where 0 means a seller, on average, has to begin to pay for borrowed inventory "*0 to 15 days*" after he first borrows it, and a response of 4 would communicate that a seller, on average, has to begin to pay for borrowed inventory "> *6 months*" after he first borrows it.

As expected, being better connected in the Whole Network gives retailers the freedom to pay for shared inventory at a later date, i.e., a higher degree centrality score is seen to be significantly positively correlated with a more flexible repayment schedule. A graphical representation of this relationship is supplied in Figure C. Surveyed retailers mentioned that they usually pay (or would ideally pay) for borrowed inventory once they receive proceeds for the respective sale. It could be argued that retailers who are afforded a lax repayment schedule can also extend the same latitude to their customers. Retailers cited 'Granting credit to customers" as an important variable for success in this market, more so than gaining "Access to credit" (85% versus 77%, respectively). So less flexible terms of repayment could end up having an adverse impact on a retailer's bottom line. One interesting finding of this network is that the inventory payment schedule has a positive and significant relationship with the number of employees a firm employs in this market (p-value = 0.02). This is consistent with what we find in trade credit literature where larger firms are able to secure more favorable terms of exchange. But, again, it would be inaccurate to make a causal assessment here since being offered more flexible repayment terms could in turn have allowed these sellers to become large and not the other way round.

A retailer's betweenness centrality in the Whole Network, however, has a positive yet insignificant bearing on the terms of his inventory repayment schedule in this market. When asked to rank their response about whether these surveyed retailers would be willing to share inventory with unknown retailers in the market on a scale from 1 to 10, retailers, on average, were seen as reluctant to enter into such sharing arrangements with previously unknown retailers. The average score awarded to the preceding question was roughly 2. This could help explain why being directly connected to other individuals in the Whole Network is seen to bring significant value in terms of securing a flexible inventory repayment schedule while having more indirect links in the Whole Network appears to be unavailing.

During interviews sellers confided that one of the indicators of an unknown retailer's wealth that they focus on when assessing his creditworthiness is the frequency with which he replenishes his stock. The underlying assumption here being that going through your given stockpile of supplies at a greater pace will be a signal of a healthy business. Another aspect sellers focused on was on ascertaining that the business received a lot of traffic and the retailer wasn't lying idle. In general questions regarding whether sellers knew of any specific attributes of people they shared inventory with, and whether this figured in their decision to share inventory with these people, many responded in the affirmative and said they were "more comfortable to deal with people we know". Sellers related that they "knew where these people lived" and even if the house they lived in was a permanent residence. Having a "permanent" residence or place of business was seen to be a marker of reliability for these sellers since this confirmed that such people were less likely to renege as they had "roots in the area". Having these connections then almost serves as a way to overcome informational asymmetries that would keep detached actors from accessing these lines of credit. Also, it is not hard to see how a lot of such valued information would be conveyed to sellers that one periodically shares inventory with.

The above could also help explain why then sharing inventory with more retailers in the market, having a higher degree centrality in the inventory sharing network (INVDEG), and laying on most shortest paths among other sellers who in the market, i.e., having a higher betweenness centrality in the inventory sharing network (INVBET), could have significantly advantageous affects for more centrally located players in this sub network as confirmed in columns (3) and (4) of Table 5. Having more people to turn to for supplies would allow a central retailer to select to borrow from retailers who offer the most flexible repayment schedule, and also to not be affected by a slump affecting a particular retailer in his network. This expectation is consistent with the work of Kranton and Minehart (2001). Furthermore, sellers who act as connectors between other sellers in a context where they're essentially facilitating the improved availability of inputs can potentially use their privileged position to secure better deals for themselves.

Table 5: Inventory Payment Schedule (IPS)

	(1) IPS	(2) IPS	(3) IPS	(4) IPS
DEGREE	0.103* (2.15)			
BET		.00248 (1.70)		
INVDEG			0.204* (1.99)	
INVBET				0.0795* (1.96)

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. Inventory Payment Schedule (IPS) is a categorical dependent variable ranging from 0 to 4 that measures the number of days a seller has, on average, before he begins making payments for borrowed inventory. Paying for inventory at a later date would correspond to receiving a higher value on this variable. DEGREE is the total number of connections a retailer has in the Whole Network. BET is the betweenness centrality of retailers in the Whole Network. INVDEG measures how connected a seller is in the inventory sharing sub network in terms of the total number of retailers he is linked to in this network. INVBET measures the share of shortest paths among all sellers that pass through a particular seller (one whose centrality is being measured) in the inventory sharing sub network. A higher value across each independent variable translates into being more centrally situated in the market.

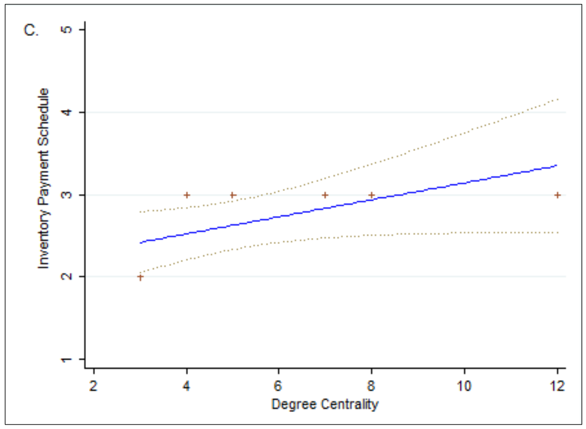

Figure C. Retailers that are connected to more people in the Whole Network are able to secure significantly more favorable repayment schedules for borrowed inventory.

Equation (2) was also estimated to model the effect of a seller's centrality on the price that he pays for shared inventory. The outcome of interest (Y_i) in this instance is Payments for Inventory (PINV) and is the response to the question "*How much more than wholesale price do you pay, on average, for borrowed inventory*?" The answer to this question is coded as a categorical variable ranging from 0 to 4 with 0 being assigned to retailers who report paying "*0%-5% more than wholesale price*" for borrowed inventory and 4 assigned to sellers who report paying "*retail price*" for borrowed inventory. A negative relationship between a retailer's centrality and the price that he pays for borrowed inventory is hypothesized. The OLS estimates for the observed relationship between centrality and pricing for shared inventory are shown in Table 6.

The results indicate that retailers with more direct links in the Whole Network pay significantly less for borrowed inventory. However, similar to what was witnessed in Table 5 previously, the Whole network Betweenness scores for retailers don't seem to impact the pricing of this exchange relationship. Although, retailers who share inventory with a larger number of retailers, and those retailers who are placed on most shortest paths among all pairs of retailers in the inventory sharing sub-network both reportedly pay significantly less for the inventory they borrow than their less connected counterparts in this market.

In contrast to the inventory payment schedule, additional analysis here shows that pricing for borrowed inventory is significantly negatively correlated with the age of the business in this market (*p*-value = 0.056). Furthermore, larger businesses (measured in terms of the number of employees) in this network again benefit from these exchange relationships by paying significantly less for inventory that they borrow (*p*-value = 0.098). Age of the retailer has no significant bearing on the price he pays for shared inventory in this network (*p*-value = 0.87).

Together these results indicate that those sellers who have been in the market longer and have a larger number of people working for them have been successful in developing profitable relationships in the market by utilizing their connections more efficiently. More centrally located sellers in this network are thus not only able to secure for their business an improved availability of inputs but are able to do so at significantly favorable terms of exchange.

Table 6: Payments for Inventory(PINV)

	(1) PINV	(2) PINV	(3) PINV	(4) PINV
DEGREE	-0.25* (-2.21)			
BET		-.01 (-1.57)		
INVDEG			-0.47* (-1.90)	
INVBET				-0.19* (-1.98)

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. Payments for Inventory (PINV) is a categorical dependent variable that measures "*How much more than wholesale price do you pay, on average, for borrowed inventory*?" Answers to this question are coded from 0 to 4 with higher values indicating that retailers paid increasingly more than wholesale price for inventory that they borrowed. DEGREE is the total number of connections a retailer has in the Whole Network. BET is the betweenness centrality of retailers in the Whole Network. INVDEG measures how connected a seller is in the inventory sharing sub network in terms of the total number of retailers he is linked to in this network. INVBET measures the share of shortest paths among all sellers that pass through a particular seller (one whose centrality is being measured) in the inventory sharing sub network. A higher value across each independent variable translates into being more centrally situated in the market.

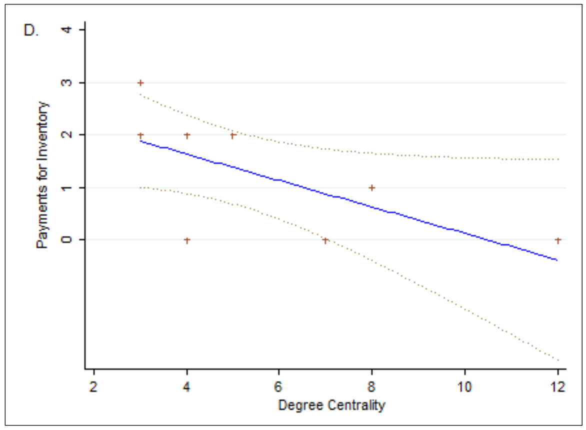

Figure D. Retailers who are connected to more other sellers in the market reportedly pay significantly less for borrowed inventory than those who have fewer connections in the Whole Network. This significant and negative relationship between centrality and pricing is represented in the figure above.

Enterprise Performance and Centrality

Equation 3 is next estimated to study whether the reported benefits of a seller's location in this network help in enhancing the overall performance of his business. Given the sheer reluctance of retailers to share hard sales and performance data in such developing country settings where tax evasion is rampant, the study uses a subjective measure of enterprise performance as its outcome of interest (Y_i) below:

$$Y_i = B_0 + B_1 C_i + B_2 Z_i + e_i \quad (3)$$

The dependent variable (SalesG) was originally intended as a categorical response (ranging from 0 to 6) to the question "*Over the last year, sales* have..." Retailer's were provided 6 different answers to choose from, with 0 indicating that sales had "*decreased*" as compared to last year, 1 showing that sales had "*remained the same*," and so on till 6, which signaled that sales had increased by "*more than 50%*". Results to this question, however, remained rather muted with retailers not showing much enthusiasm to report how they were doing as compared to this time last year. Many seemed cautiously content and qualified their answers by invoking thanks to God and his bounties. But most also mentioned that "business could be better". Ultimately, what I ended up with were just two responses testifying that sales had either "*decreased*" or "*stayed the same*" so I eventually coded this outcome as a binary dependent variable set equal to 0 if sellers reported a decrease in sales and equal to 1 if they said sales remain unchanged or increased over the last year. It should be said that the results obtained here should be seen as an understated representation of what's actually happening in the market.

The predictor variables in equation 3 are the two measures of a seller's centrality (C_i) in the Whole Network (Degree and Betweenness), and a vector of demographic covariates (Z_i) such as age of the business, size of the business, retailer's experience, etc., that have been analyzed throughout this study. The prediction is that retailers with higher degree and betweenness centrality in the whole network will make a more favorable assessment of their sales performance over the past year.

Null Hypothesis 3: A retailer's centrality in the Whole Network will have no impact on the subjective evaluation of his sales performance.

Alternate Hypothesis 3: A retailer's centrality in the Whole Network will impact the subjective evaluation of his sales performance.

The OLS estimates of this model are reported in Table 7 below.

Table 7: Enterprise Performance and Centrality

	(1) SalesG	(2) SalesG	(3) SalesG	(4) SalesG	(5) SalesG	(6) SalesG	(7) SalesG	(8) SalesG
DEGREE	0.0854		0.0365					
	(1.63)		(0.91)					
BET		0.00266*		0.00291*				
		(1.91)		(2.02)				
Education			0.197*	0.242*				
			(2.18)	(2.07)				
Lworkers			1.645**				1.998***	
			(2.82)				(3.40)	
Lage				-0.138	1.121			
				(-0.13)	(0.95)			
Lbage						0.698		
						(1.46)		
Lexperience								0.394
								(0.55)
Constant	0.189	0.371	-2.293	0.310	-3.760	-1.357	-2.124	-0.691
	(0.64)	(2.05)	(-3.09)	(0.07)	(-0.81)	(-1.00)	(-2.61)	(-0.29)
Observations	13	13	13	13	13	13	13	13

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note. SalesG is a binary dependent variable set to 0 if retailers report a decline in sales compared to last year, and 1 if sales are reported to have remained unchanged or increased over the last year. DEGREE is the total number of connections a retailer has in the Whole Network. BET is the betweenness centrality of retailers in the Whole Network. The number of workers (Lworkers), the age of the business (Lbage), the age of the owner manger (Lage), and the owner manager's experience (Lexperience) are all measured in logs. Education is a categorical variable measuring the maximum level of education attained by a retailer.

Results show that the number of connections a seller has in the Whole Network has no significant impact on the subjective assessment of his enterprise's performance. This ineffectiveness of degree centrality in predicting a retailer's assessment of his enterprise performance remains unchanged as we control for demographic variables that are not significantly correlated with DEGREE and hence pose no threat of multicollinearity, namely: a retailer's education and the size of his business (as measured by the number of workers he employs) in specification (3). Interestingly, the maximum level of education a retailer has obtained finally becomes a significant predictor of an outcome variable in this study. As seen in estimations of equations 1-2 previously, Education had no impact on a seller's ability to form links in this market or act as a connector between other sellers. However, now, we learn that Education when studied in unison with degree centrality and size of the business has a positively significant impact on a retailer's assessment of his sales performance over the previous year. Even though literacy rates here remain low with retailers on average having only acquired a secondary education at most, maintaining records, dealing with importers of machinery (in some instances directly engaging with Chinese suppliers online) and the technical aspects associated with selling such equipment can benefit from extra education, and eventually have a positive impact on business performance. The size of the business as measured by Lworkers in the model above has a consistently positive and significant impact on a retailer's reported sales performance across all specifications this variable is included in (3 & 7). The benefits associated with having more employees in this market have been well documented in earlier equations particularly in reference to securing favorable terms of inventory exchange so it is understandable why owners of larger businesses here that can procure inputs cheaply and with greater facility would be more buoyant about their performance. In fact, as seen in specification 7, the size of a business in this market is the single most significant factor that has an independent and positive impact on a retailer's subjective performance in this market.

A retailer's improved ability of acting as an effective intermediary between different sellers in the Whole Network, a facet that is captured by a higher betweenness centrality score in the Whole Network, has a positively significant impact on his reported subjective performance indicator. This effect remains robust to the inclusion of additional controls, as seen in specification 4. To function as an effective intermediary in this market it is important for sellers to be politically connected so as to credibly enforce agreements and not be intimidated from inflicting punitive costs on those who renege. This was learned both from literature and the discussions I had with sellers during the course of this study. Being more influential along this measure of connectivity would have to auger well for a seller's economic health since an elevated standing in the market is developed and not available to novice seller's who have recently set up shop in the area. Lastly, a retailer's age, the experience he has, and the age of his business seem to play no significant role in determining how well he's reportedly done over the previous year in terms of his sales performance.

Conclusion

The study used detailed structured interviews with water pump and motor sellers in the Brandreth Road area of Lahore to create comprehensive maps of how different retailers were linked to one another in the market along 6 main dimensions of interest: namely, information, advice, joint purchases, inventory sharing, money sharing, and dispute resolution. The role of social networks in helping ease the information, coordination, and enforcement problems that trouble developing countries such as Pakistan is being made increasingly well known but there are very few studies that investigate the impact of networks on economic outcomes in Pakistan. The relationships codified in this study were done so keeping in mind the nature of markets in Pakistan where lack of collateral and an ineffective judicial system makes it hard to write and enforce contracts and as a result restricts access to credit whereby limiting growth and constraining performance. Market participants here have been located in specialized markets such as the industrial goods market operating on Brandreth Road for a substantial amount of time and place considerable importance on developing the right reputation and then extracting benefits from the connections they form as a result. This was made known through the course of this study and the results of which are summarized in Table 1.

The study made use of a respondent driven sampling method that is mainly used to identify hidden sample frames, such as retailers in markets that engage in considerable tax evasion, as is the case in Pakistan, and are disinclined to share privileged information regarding their business operations with strangers. This method also helps collect data relatively cheaply and at a faster pace.

Once network links were constructed and respective maps generated, this information was used to evaluate the centrality of respective sellers in these individual networks and the aggregate Whole Network. Two separate measures of centrality (degree and betweenness centrality) were employed to gauge how influential each interviewed seller was in this market.

The results obtained show that more centrally located actors in this market have a different demographic makeup than their less influential counterparts. Sellers with more connections in the Whole Network are on average older, have more experience and have been in business longer. However, having these same attributes does not translate into sellers being central in both a degree and betweenness context. In fact, a retailer's age has no bearing on the number of shortest paths among all pairs of sellers that pass through him, i,e., his betweenness centrality. A seller's betweenness is more significantly impacted by the age of his business, his experience and the size of his business measured in terms of the total number of people he employs. The maximum level of education a retailer has in this market has no significant impact on his ability to form linkages or connect other sellers in these networks.

The findings in this study also confirm that a seller's location is an important predictor of the terms of exchange he secures for himself. On average, all other things remaining the same, sellers with higher degree centrality in the Whole Network and the Inventory Sharing sub network face significantly more flexible repayment schedules for borrowed inventory and pay significantly less for such supplies as compared to sellers with fewer connections in these networks. A seller's betweenness however is only a significant predictor of his terms of exchange in the Inventory Sharing sub network. The impact a seller's connectivity has on the amount of reported discount that he receives on jointly purchasing Rs. 100, 000 supplies with his network links is the opposite of what is predicted. It is learned that those with higher centrality in both degree and betweenness report receiving significantly less discount on their joint purchases than their less central counterparts, ceteris paribus. Reasons for this include presumably higher benefits of joint purchases being realized by younger businesses given their increased need to line up regular supplies as opposed to older, well-established businesses, which are seen to be the ones who are more centrally placed in these networks.

Lastly, it is learned that our hypothesized relationship between a subjective measure of enterprise performance (the reported change in sales over the last year) and a seller's centrality is confirmed for only those sellers who have higher betweenness centrality scores in the Whole Network. The significantly positive impact of a seller's central location along this measure is robust to the inclusion of additional demographic control variables. A seller's education too is seen to have a positive and significant affect on his reported sales performance.

In conclusion, the results of this study are able to confirm that different sellers of the same product in the same market do not have the same influence and this influence is developed over time and is associated with certain attributes of the seller and his enterprise. Additionally, sellers are able to leverage this power that comes with being better connected to secure certain benefits for themselves, here improved access to cheaply priced inputs, that arguably help them grow in size and influence. Causality here though is hard to establish due to inherent endogeneity problems. Also, it should be kept in mind that the results obtained in this study may not be generalizable to other networks in other markets and especially in other countries.

The strength of this paper is that it attempts to understand the empirical relevance of social networks in this particular market and confirms that improved connectivity has economic advantages that warrant closer study and better understanding.

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