The Value of Business Networks

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Abstract

We construct the topology of business networks across the entire population of private firms in Pakistan, and estimate the value that network membership brings in enhancing bank credit and improving financial viability. We link two firms together if they have a common director, and find that the resulting topology includes a "super-network" comprising 5% of firms but over one-half of all bank credit. We estimate the value of joining the super-network by instrumenting network membership with "incidental" entry and exit of firms over time. Network membership increases total external financing by 16.5%, reduces propensity to enter financial distress by 9.7%, and better insures firms against industry and location shocks. These benefits are stronger when firms connect through more powerful network nodes, and newly networked firms are more likely to start new banking relationships with banks already lending to its super-network neighbors.

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Economic organization is deeply embedded in networks and informal contractual arrangements, especially in emerging markets. It has long been argued that networks substitute for missing markets and hence add value to network participants (e.g. Leff 1976, 1978, and 1979). However, empirical evidence on the topology and value of networks remains scant. This paper uses a novel data set to construct network formation in the entire universe of firms in Pakistan, and estimates the value that network membership brings in improving the firm's access to credit and it's financial viability.

A meaningful analysis of the structure of business networks, and the value networks bring, is faced with at least three main hurdles. First, one needs data on the entire population of firms in the economy in order to construct networks in a satisfactory manner. For example, most data sets cover only publicly listed companies, while private firms form an overwhelming majority of business enterprises. Therefore any network analysis limited only to public firms is likely to miss many important links running through the economy via private firms, particularly in emerging markets. Second, business networks are the cumulative result of strategic choices that firms make when forming relationships. Therefore one must be careful in separating the causal effect of networks from the possibly spurious effect of networks absorbing firms with certain unobserved characteristics. Finally, network theory repeatedly points out that network benefits depend critically on *where* in the network one is connected to. One therefore needs credible measures of network strength, such as the "power" of a node, in order to try and understand the process through which networks bring value.

We address these challenges by using a firm level data set that covers in essence the universe of over 100,000 firms in Pakistan over a four year period. The data comes from the central bank of Pakistan that supervises the banking sector, and contains information on each firm's lending relationships, credit history, and importantly the identity of its board of directors. We construct networks of firms by joining firms with common directors, i.e. inter-locked boards, and follow *changes* in these networks at a six-monthly frequency over a period of 4 years. The time-series changes in network structure enable us to track entry and exit of firms from different networks.

The networks formed through inter-locked boards reveal a striking result. There is a single powerful "super-network" that comprises over 5,000 firms and borrows two-thirds of aggregate bank credit. In fact the super-network is so dominant, that the next largest network is almost one-hundredth its size. Network theory suggests that such a "giant component" is possible even without any central coordination, i.e. that a decentralized process of local link formations can also lead to such a structure.

In such a case, one would expect that the network would be very robust in the sense that it would not be reliant on any particular nodes i.e. there is no critical central hub and there would be built in "redundancy" so that nodes would connect through multiple pathways. Our closer examination of the super-network supports this: the overall structure and dominance of the super-network remains even with different link definitions (two directors in common etc.), and the exclusion of even highly connected firms and directors. The super-network displays "small-world" properties - despite having over 5,000 firms, the average path distance between any two firms is 6.5 links - it has a intermediate degree of clustering (clustering coefficient of 0.65), and a low degree of centralization/hubs (0.02 centralization coefficient).

We focus our attention on the super-network and investigate whether this network brings any real value to its member firms in terms of access to external finance and financial viability. As mentioned earlier, the challenge is that network entry is a bilateral choice and may be driven by unobserved characteristics. We deal with the time-invariant firm characteristics that determine network participation by using firm fixed effects and estimate the effect of network membership on firms entering/exiting the super-network. However, time-varying firm attributes are also likely to be an issue. For example, firms with better growth prospects might be more likely to join the network. We deal with these concerns in two ways. First, we match firms by size, industry and location, and non-parametrically account for time trends common to firms with similar attributes by using time interacted with firm type fixed effects. Second, we look at and control for pre-network-entry trends to see if firm entering the network were on statistically different trajectories (and vice versa for firms exiting the network).

Our alternative approach for addressing potentially endogenous entry (exit) of firms is based on instrumental variable estimation. We instrument firm entry/exit into the super network through "incidental" entrants and exitors. These are firms that enter the super-network *not* because of any changes in their board of directors, but because of changes in the board of directors of a neighboring firm that they were already linked to. In other words, one of their neighboring firms entered the super-network. and this gives the firm incidental access to the super-network. The IV estimate is valid under the assumption that incidental entrants are not systematically selected. We show that this is true on all observed attributed. For example, incidental entrants are not any different from non-entrants in their cohort in terms of size, growth, or credit history.

Both non-parametric and IV estimates show that network membership significantly improves credit access and financial viability. Network membership increases access to bank credit by 16.6%, and decreases propensity to enter financial distress by 1.7 percentage points (or by 9.7% of the base default rate).

While isolating the particular channels through which the network provides benefits is harder, we explore further results that offer suggestive evidence. In terms of financial access, we find that the benefits of network membership are accumulated through both the intensive and extensive margins: firms increase their average borrowing from old banking relationships, and also form new banking relationships. The new banking relationships are more likely to be formed with banks that already have a lending relationship with one of the immediate super-network neighbors of the newly networked firm. This result suggests that network links provide valuable information to banks when forming new relationships.

We also investigate whether network benefits depend on the "power" of the connecting firm. We measure both power of a firm when it is out of the super-network and when it is in. The former allows us to capture whether the super-network acts as a substitute or complement to a firm's pre-existing power. The latter captures whether it matters where a firm connects once it enters the network. We measure power of a connecting node in a number of different ways, including number of direct links to other firms/directors within the network, the strength of these neighbor firms and also an analogous measure to the "google page-rank".

For financial access, we find that firms benefit more from entry when they connect to more powerful parts of the super-network. However, while entry into the super-network is beneficial for all firms, a firm benefits less if it was already powerful i.e. entry into the super-network is a substitute to a firm's pre-existing power. This is not surprising if the mechanism is access to banks' by leveraging ones' neighbor firms, since one would expect that there are diminishing returns to this.

The results on financial distress offer an interesting contrast. While there is little robust evidence that the benefits of entry vary in terms of where a firm connects in the network, entry into the super-network acts as a complement to a firm's pre-entry power. Firms which are already powerful when they are out of the network, see greater drops in financial distress. This hints that the mechanism in lowering default rate may be quite different from improving financial access. While the latter is likely to reflect leveraging one's network neighbor's links/reputation with lenders, the former may be more about directly benefitting from one's neighbor's through internal insurance/credit/business contacts type flows since one may expect the more powerful to better take advantage of their network neighbor's resources. As further evidence for the importance of these internal flows, we also find that networked firms are better insured against industry and local demand shocks than non-networked firms.

Overall our results highlight the value that business networks bring in terms of gaining access to external financing, improving financial viability, and providing better protection against common shocks. These benefits are not distributed uniformly across the network, but depend critically on both the firm's pre-existing power, and on where in the network a firm is connected to. Our focus on estimating network value in terms of access to credit and financial viability has long been considered an important benefit of networks. For example, Leff 1978 and Lamoreaux 1986 emphasize the importance of networks in accessing credit in early American history.

While there has been considerable work in network theory (see Jackson 2004 for an excellent summary), empirical work has largely lagged behind. Ours is the first study to our knowledge that provides a detailed account of the entire network structure in an economy, and then estimates the value that participation in the network brings to firms.

We see our paper as providing three key contributions relative to the existing empirical literature on networks.[1] First, we use the entire population of firms in an economy to construct networks rather than any specific subset. We can thus be reasonably confident that we are not missing any important set of network connections from our sample. Second, earlier work on business networks focused on estimating *cross-sectional* differences between networked and non-networked firms due to data limitations. While this analysis has been important in documenting differences across networked and non-networked firms, there remain concerns that the differences might be driven by unobserved firm-specific attributes that determine both network membership and the firm outcome of interest. Our paper on the other hand analyzes time-series changes in network membership for a given firm. We can thus use firm fixed effects to take out firm-specific fixed factors influencing network membership. We also address additional concerns of time-varying unobservables (at firm level) by using time series controls as well as incidental entry and exit as instruments.

[1] Prominent examples in this lieterature include: Grief (1993) who examines the role that networks of traders played in overcoming barriers to international trade such as weak international legal system and informational asymmetries. Feenstra et al (1999) who find that networks matter for explaining differences in quality and variety of exports across South Korea, Taiwan and Japan. Hoshi, Kashyap and Scharfstein (1991) who show the importance of networked firms in getting access to credit in Japan. Hochberg et al (2007) who show that better-networked VC funds are correlated with better performance. Khanna in a series of papers also examines the structure and importance of business groups (see Khanna, 2000, for a review).

The third key contribution of our paper is that we do not treat the network as one homogenous entity. It has been repeatedly pointed out by sociologists (e.g. Burt 1992, Granovetter 1973) as well as economic theorists (e.g. Jackson and Wolinsky 1996, Johnson and Gilles 2000, Belleflamme and Bloch 2002, Calvo-Armengol and Jackson 2001, Kranton and Minehart 2002) that not all nodes and links within a network are created equal. Hence the value of a network to its members is not uniformly distributed but depends critically on where, and with whom a firm is connected to. Moreover, firms of different initial power may benefit differentially from the network. While previous studies could not test for such heterogeneity of network effects,[2] we are able to do so due to our ability to observe both pre-network entry and intra-network variation in a firm's (network) power.

I Defining Business Networks

A. Data

We use two data sets in this paper, both coming from the central bank of Pakistan that supervises and regulates the entire banking sector. The first data has information on the board of directors for all borrowing firms in Pakistan from 1999-2003 at a six monthly frequency, and the second has detailed loan level information on these firms from 1996 to 2003 at quarterly frequency. We describe each of these below:

(i) Board of Directors Information

The central bank of Pakistan maintains a list of the board of directors of all firms borrowing from any bank in the country. We have this data from 1999 to 2003 at a six-monthly frequency for well over a hundred thousand firms that represent the universe of all borrowing firms in Pakistan. The data records the full name, father's name, national identification card (NIC) number and percentage of equity held for each director of a firm at a point in time.

Since we ultimately want to link two firms together if they have the same director in common, it is important to uniquely identify individuals in our board of directors data set. The NIC number issued by the government serves this purpose as it is unique to every individual. However, reporting of the NIC number is not mandatory and as such this information is missing or incomplete around 16% of

[2] A recent review article by Rauch and Hamilton (2001) makes the same point.

the time. When we do not have NIC information, we identify and track individuals over time and across firms by matching an individual's full name *and* their father's name (or husband as the case may be). We deliberately choose a strong criteria for matching director names so as not to incorrectly connect two firms together. Our matching criteria gives us a total of 261,069 unique directors for 139,526 firms in our sample. In our final sample, we drop very small firms with less than Rs.500,000 (~US $8,500) of borrowing at the beginning of our sample period since these firms have very noisy loan amounts going from positive to zero amounts frequently. Exclusion of these firms leaves us with a total sample of 105,917 firms.

(ii) Firm Borrowing Information

We also have quarterly information on a firm's borrowing from every bank that it borrows over a seven year period from 1996 to 2003. The original data is at the level of a loan (i.e. firm-bank pair) and traces the history of firm borrowing with information on the amount of the loan (principal and interest) outstanding, and how much of the outstanding amount is in default. The outstanding loan amount is further broken down into different categories such as term loans, working capital, etc. The default amount starts appearing in our data set as soon as a loan payment is overdue by 30 days or more. Although the original data is at the level of the loan, for most of our analysis we aggregate loans of a given firm across it's lenders at a given point in time. Since the director data is available at 6 monthly frequencies from 1999 to 2003, we only use the loan data that corresponds to these time periods.[3]

In terms of data quality, our personal examination of the collection and compilation procedures, as well as consistency checks on the data suggest that it is of very good quality. Our data was part of a large effort by the central bank to setup a reliable information sharing resource that all banks could access. Perhaps the most credible signal of data quality is the fact that all banks refer to information in our data on a daily basis to verify the credit history of prospective borrowers. For example, we checked with one of the largest and most profitable private banks in Pakistan and found that they use the information about prospective borrowers explicitly in their internal credit scoring models. We also ran several internal consistency tests on the data such as aggregation checks, and found the data to be of high quality. As a random check, we also showed the data from a particular branch of a bank

[3] We use 1998 data to construct lagged measures of loan growth and change in default.

to that branch's loan officer who confirmed the authenticity of the data related to his portfolio.

B. Network Description

We use information on firm directors to construct networks and link two firms together if they share a common director (i.e. have interlocked boards).[4] Figure I illustrates the hypothetical construction of a network through this process. There are 8 firms in the example (A through H), and a total of 15 directors sitting on the board of these firms (labelled 1 through 15).

Inter-locked board linkages produce two distinct networks and two firms (G and H) that are not connected to anyone else. The largest network consists of firms A through D, where firms A, B and C are linked to each other directly and firm D is linked to firms A and B indirectly through its direct link with C. Thus firms in the same network may be linked to each other through long chains of indirect links.

A second feature to take away from Figure I is that firms within a network vary by how "important" they are in the network. For example, firm C is important in the network because it has the most number of firms directly connected to it (3 firms). Similarly, links between firms can vary in their "strength". For example, firms E and F are connected to each other through three directors (the number on the link represents the number of directors generating the link). We shall exploit such heterogeneity in the strength of network nodes and links to test if the strength of connections is also important in determining the advantage that networks bring to connecting firms.

Applying the principle outlined in Figure I to our firm level data reveals an interesting network topology. Almost two-thirds (66,140) of the firms are not linked to any other firm, while the remaining third belong to multi-firm networks (Table I, Panel A). The multi-firm networks range mostly in size between 2-firm networks and upto networks of 85 firms[5]. However, there is one network that is many times larger than the second largest network of 85 firms. We refer to this as the "super-network".

The super-network consists of 5,295 firms that are all connected to each other either directly or indirectly through chains of inter-locked boards. Although the share of firms belonging to the super-network is close to 5%, the share of these firms in total bank credit is 65%. Another 21% goes to firms belonging to networks of sizes 2 to 85 firms, and the remaining 15% goes to singleton firms. Thus

[4] Our use of inter-locked directorates to define networks has a long tradition among social scientists (e.g. Mintz and Schwartz 1985; Stokman et al. 1985; Scott 1987).

[5] Within firms of network size 2 through 85, 74% belong to networks of size 2 through 4, 18.4% to networks of size 5 through 10, and the rest to networks of size 11 through 85.

the economic significance of super-networked firms is much greater than their sheer number in the economy.

Since the super-network enjoys a remarkable economic status in the credit market, we investigate the value that membership into the super-network brings to firms. We focus on firms that enter or exit the super-network over time in order to identify the impact of super-network on firm performance in the credit market. Out of the 5,295 firms that are part of the super-network at some point during our sample period, 2,838 firms are always part of the super-network and the remaining 2,457 firms enter and/or exit the super-network during our sample period. The high level of turnover within the super-network over time thus provides us with unique time-series variation to estimate the impact of super-network membership.

Figure IIa provides a visual map of the super-network by aggregating over our sample period i.e. we pool the time dimension. Firms that always remain inside the super-network are represented by black dots, while firms that enter and/or exit the super-network are represented by red dots. Firms are linked if they share a common director. The large number of firms and high density of links in the super-network makes it difficult to see the intra-network details in Figure IIa. We therefore zoom into a couple of different area of the super-network to provide more clarity as to what the network structure looks like. Figure IIb zooms into an area closer to the "core" of the super-network.[6] While each dot represents a firm, the number inside the dot represents the number of firms that the firm is connected to. Figure IIc zooms into a more peripheral area of the super-network where firms have a lot fewer connections to other firms.

Figures II highlight a couple of important super-network characteristics. The network is quite strongly inter-connected with no single "hub" firm (or a small sub-set of firms) holding the entire network together. Even in the core of the network, there are firms with not that many links, and even the most linked firm is not large enough to be a major/critical hub. Moreover, there are often multiple pathways connecting two firms. These features offer graphical evidence for the robustness of the super-network: it is not surprising that the removal (or death) of a few firms is unlikely disintegrate the network structure. Second, the graphs also show there is heterogeneity in how strongly differently

[6] The graphs were plotted using a graphing software (CITE) used by sociologists. The software computes the "centrality" of every node before deciding whether to place a node in the center or at the periphery. Thus for example an important node with many connections to other firms within the network is likely to be placed closer to the core of the network structure. On the other hand a node with a few connections is more likely to sit at the periphery of the network structure.

firms are connected within the super-network. While some firms hang on to the super-network with one or two connections, others are very strongly inter-connected with multiple firms. In fact, it is interesting to note that while most of the firms that enter/exit the network over time are in the periphery, such firms can also enter/exit near the core of the network.

Panel B in Table I provides summary statistics on various measures of "power" of a firm. Since we are interested primarily in firms that enter/exit the network (we identify the network effect only of these firms) we present (average) measures of power for when the firm is out of the super-network and when it is in the super-network. The simplest power measure is the number of other firms that a firm is directly connected to. On average a firm in the super-network is directly connected to 5.38 other firms. These direct connections drop to 3.08 when a super-networked firm drops out of the network. Similarly, the number of directors that a firm is linked to (through neighboring firms) drops from 34.7 to 9.49. Number of Neighbor's lenders is defined as the banks (not counting the firm's own lenders) that the firm's neighbors are borrowing from. Finally, we also construct a measure of the firm's strength in the network using the algorithm put forth by Google to rank the relative strength of web pages. This "Google Rank" captures the importance of a firm iteratively in terms of how many firms its linked to and how important those firms are in terms of how many firms they are linked to and so on. We use both the direct Google rank measure of the firm (when its in and out of the network) and the average of it's neighbors google rank measures.

While figure II provides visual evidence of the network being strongly interconnected, we conduct more formal tests of network integrity as well. We find that the super-network is robust both to the exclusion of "super-firms" (firms which many direct links) "super-directors" who sit (nominally) on the boards of many firms concurrently. Such directors may exist if government or large creditors automatically get a few seats as board of directors. The network is also robust to removing certain types of directors such as those that do not hold equity in the firm or are likely to be government appointed directors (identified as directors that sit on government owned firms).

We also get similar network characteristics (i.e. the emergence of a dominant super network) if we make the definition of "links" stricter and only connect two firms if they have *two* directors in common. The super-network is also very stable over time. This once again shows that the super-network is not driven by a few "star nodes", but is instead a diffused collection of inter-locked firms. We describe these robustness checks in greater detail in the appendix.

In addition to the visualization, some commonly used network statistics can provide a sense of the structure as well. The super-network displays "small-world" network properties in the sense that the average distance (number of links) between any two firms is 6.5 links - firms really do face only six degrees of separation from one another. The maximum distance between any two firms in the network is also surprisingly low - 23. Furthermore, the network displays an intermediate degree of clustering - a clustering coefficient of 0.65. A network has the maximum clustering coefficient of one if each node is fully connected to every two nodes around it. It has a clustering coefficient of zero if all nodes are connected through a chain of single links to one another. Finally, as is apparent from the network graphs - the super-network displays a very low degree of centrality - a centralization measure of 0.02. A network obtains a centralization coefficient of 1 if each node is connected to the other through one central hub (a "hub and spoke" network). This is not surprising, since our zooms of even the core part of the network showed that there were few significant "hubs". All of these statistics suggest that one should not think of this network as driven by some central players that coordinate the action of most of the firms in the network, but rather a more decentralized structure where firms most connect to their neighbors, yet still do so in a manner that they are not to far from any other members of the network.

Since our identification strategy exploits time-series changes in super-network membership for individual firms, we also provide visual evidence for the manner in which firms enter the super-network over time. Figure IIIa depicts some sample structures of firms before they enter the super-network. It is meant to emphasize the fact that firms are often part of smaller networks before joining the super-network. Figure IIIb shows some sample structures of other networked firms that never join the super-network. The point to take away from Figures III is that network structures of firms that do enter the super-network and those that do not are often very similar.

Figure IV illustrates the difference between direct and incidental entrants in our paper. Figure IVa illustrates a sample network of firms before they enter the super-network, and figure IVb shows the same set of firms after they join the super-network. The three firms in figure IVa are connected through a line because they each have a director in common, but there is no director common to all three. Figure IVb shows that two firms (colored as white) have a director in common who joins the super-network. Thus the two white firms are direct entrants into the super-network. However, the third firm, colored in yellow, enters incidentally as none of its directors chose to sit on the existing super-network (or vice versa). Figure IVc and IVd shows another example of entry into the super-network by a network of three firms. However, this time only one of the firm is a direct entrant, and the other two are incidental. The direct entrant (colored in white) has a director not common with the other two firms who starts to sit on the super-network board.

II Empirical Methodology

Our primary objective is to identify the effect of membership into the super-network on a firm's credit market outcomes. If access to the super-network provides a firm with important business opportunities, credible market information, and means for effective contractual enforcement, then we would expect firm performance and demand for bank credit to rise after entry into the super-network. Similarly, if being related to the super-network provides banks with more credible information and better monitoring technology vis a vis a firm, then we would expect the supply of bank credit to go up as well. These factors can in turn affect the firm's financial health, especially if network membership also provides access to internal capital/insurance markets and business connections.

However, the empirical difficulty in identifying these effects is that entry into the super-network might effect a firm's performance not because of any direct impact of the super-network, but because firm's with better characteristics or better future potential are more likely to enter the super-network. We set up this identification problem in this section, and then highlight our approach for isolating the causal impact of super-network membership on firm performance and credit market outcomes.

Consider a network with n nodes, where each node reflects a firm. Two nodes are linked if they have a director in common, and all nodes in the network are ultimately connected to each other through such links. We denote individual nodes with N_m where m varies from 1 to n.

There is a burgeoning literature on how networks form, survive and evolve over time (see Jackson 2004 for a review). However, a full model of network formation is beyond the scope of our paper. We therefore take the $n - node$ network as given, and estimate the impact of network membership on the *marginal* firm joining the network.

Suppose firm i attempts to join the network every period t by trying to convince an existing network node to establish a "link" with it. Such a link can be established if one of the board members of firm i starts sitting on the board of a networked firm. Alternatively the link can be established if a director of an already networked firm starts to sit on firm i's board. For simplicity we assume that once a link is formed, it lasts forever.

In order to estimate the direct benefits of network membership, a key question is: What determines *which* firm i enters the network, and *when*? Network entry is determined by the selection equation that specifies whether a firm enters the super-network, and when. Let h_{it} denote the "hazard rate" that firm i enters the network at time t, conditional on not having entered already. What should h_{it} depend on? Without much loss of generality, we assume that h_{it} depends on expected firm productivity, π_{it},and "incidental factors", x_{it},that are orthogonal to firm productivity (for example, social ties that do not influence firm performance but help a firm gain entry). In particular, firms with higher expected productivity and "better" incidental factors are more likely to enter the network:

$$h_{it} = \Phi(\pi_{it}, x_{it}, \eta_{it}) \tag{1}$$

where Φ is a cumulative distribution function and η_{it} is an i.i.d random component. For simplicity we assume separability of these factors.

Since we will be concerned with potential identification issues arising from π_{it} in estimating the value of networks, we focus on productivity dynamics. Suppose π_{it} evolves through a random walk process where each firm starts with a firm specific productivity π_{i0} in period 0, and then evolves according to $\pi_{it} = \pi_{i,t-1} + \nu_{it}$. ν_{it} is a firm specific productivity shock every period, and does not have to be independent across firms or over time.

Equation (1) illustrates the difficulty in identifying the direct benefits of network entry for firm i. Let Y_{it} reflect some measure of firm performance in the credit market that we can use to calculate the benefits of network membership. Our paper uses two such measures, (i) access to external finance (which is also closely related to firm sales and inventory), and (ii) propensity to enter financial distress. Suppose we estimate the benefits of network membership by comparing the performance of networked and non-networked firms through the equation:

$$Y_{it} = \alpha + \beta_1 ENTRY_{it} + \varepsilon_{it} \tag{2}$$

where $ENTRY_{it}$ is an indicator variable for whether firm i is part of the super-network in period t. The key concern regarding identification of β_1 is that outcomes Y_{it} are likely to depend not only on network membership, $ENTRY_{it}$, but also firm productivity, π_{it}. Since $ENTRY$ itself is a function of

π_{it} through equation (1), we have the traditional simultaneity problem.

We control for the possibly spurious effect of π_{it} on $\widehat{\beta}_1$ in three steps. First, a key component of π_{it} influencing entry into the network is the initial productivity level of a firm, π_{i0}. While we do not observe this parameter, we can completely absorb it from the estimating equation by including firm fixed effects α_i in (1). Firm fixed effects account for any level differences in productivity across firms[7]. However, a second concern is that firms of certain type, such as those belonging to a specific industry, are more likely to enter the network over time because that industry happened to get a series of positive shocks to productivity. Therefore our second adjustment for unobserved productivity factors is to include firm-*type* specific interacted with time fixed effects (α_{kt}) in (2). Firm type, k, includes firm location, size decile and industry.

A third remaining concern is that β_1 is may be influenced by idiosyncratic firm-specific permanent shocks, ν_{it}. For example, a given firm is more likely to join a network after it receives a series of positive permanent shocks $\{\nu_{it}\}$ that may be unrelated to the sector, city, or size decile that the firm belongs to. Although we do not observe such firm-specific shocks, if such shocks are influencing both network entry as well as the outcome of interest, then there is a simple prediction that we can test in the data.

In particular, suppose a sequence of idiosyncratic positive shocks to firm productivity make the firm more likely to enter the super-network, and also increase firm outcome of interest Y_{it}. Then *conditional* on entry in period t, a firm should have a higher growth trajectory for Y prior to t. Thus one can test whether β_1 is driven by idiosyncratic permanent shocks to firm productivity by including lagged growth rate of Y_{it} and checking if β_1 drops substantially. Alternatively, if entry to the network is predominantly driven by incidental factors then firm outcome of interest would jump up post entry rather than trend upwards prior to entry into the network.

Combining all these controls together provides the following semi-parametric estimation equation:

$$Y_{it} = \alpha_i + \alpha_{kt} + \gamma * \triangle Y_{i,t-1} + \beta_1 ENTRY_{it} + \varepsilon_{it} \tag{3}$$

where α_i are firm fixed effects and α_{kt} are firm-type (k) interacted with date fixed effects.[8]

[7] Panel A in Table I shows that firms that are part of the super-network are on average much larger, and have much lower default rates than firms outside the network. Such fixed time-invariant differences between networked and non-networked firms are absorbed away by the firm fixed effects.

[8] Since (3) is a fixed effects regression, we need to be careful in including lagged depedent variables. Including levels of lagged dependent variable would be problematic since the lagged term would be correlated with the fixed effect. While

While equation (3) controls for potentially spurious firm specific factors influencing entry as well as the outcome of interest, it does not make it explicit *which* specific factors are causing a firm to enter the network. In the terminology of the hazard function (1), ideally we would like to instrument entry with some incidental parameter x_{it}.

We propose one such incidental factor that determines firm entry into the network. As figure III illustrated a firm can enter the super-network in one of two ways. It can enter the network "directly" through a change in its board of directors, or a change in the boards that one of its directors sits on. Alternatively, it can enter the network "incidentally" if one of the firms it is linked to directly enters the network.

Such incidental entrants are *not* joining the network either because of a direct change in their board members or a direct act by one of their directors. It is therefore less likely that incidental entrants are joining the super-network through an active decision of their own or in terms of our terminology, due to unobserved (to us) changes in their productivity. In fact we show in the results section that incidental entrants are observationally identical (in terms of loan growth pre-entry, credit history etc.) to their cohort firms that end up not being selected into the super-network. We can therefore separately estimate the effect of entry on incidental entrants or equivalently, "instrument" for entry using a dummy for whether the entry was incidental or not.

We should note though that to the extent that there is heterogeneity in the impact of network entry - and our results show that there is - this procedure will likely to give us lower estimates since the incidental entrants are (by definition) entering in a less powerful part of the network. However, since this would bias us towards not finding a result, we view our incidental entry estimate as a lower bound of the true impact of entry. In fact, to an extent, the same reasoning suggests that even our primary specification would provide lower bound estimates. It is likely that the firms that gain the most from the network never leave it and therefore, given our methodology excludes these firms (since we use firm fixed effects), we are not including the (larger) network value these firms obtain in our estimates.

one could correct for this using Arellano-Bond style corrections, our specification uses lagged *growth* of the dependent variable. We do so since we believe this is a more appropriate correction i.e. we are concerned about controlling for a firm's growth trajectory. Since this lagged term is in changes (i.e. $Y_{i,t-1} - Y_{i,t-2}$), the immediate concern that it is correlated with the fixed effect is not present (it is differenced out).

III Estimating Network Benefits

We use two measures of firm performance in the credit market to estimate the impact of super-network on member firms. The first is total borrowing from the banking sector. As explained earlier, the value provided by a network can increase both the supply and demand for bank credit for a firm. Our second measure of performance is financial viability, or the ability of a firm to prevent financial distress (defined as being late on loan payments for over 30 days). Any improvement in firm growth and profitability due to network access should make a firm more financially viabile, and hence less likely to enter financial distress.

Figures Va and Vb present evidence on the evolution of our two measures of firm performance before and after membership into the super-network. Figure Va depicts what happens to the log of total firm credit from the banking sector as a firm gains entry into the super-network. We follow the same firm over time, and take out economy wide aggregate shocks (at industry and size level) by taking out firm, and time interacted with sector fixed effects.

Figure Va shows a discrete jump in total bank credit of about 6% as a firm becomes member of the super-network, and then it gradually increases over time. Importantly there is no significant upward trend in bank credit prior to entry into the super-network. Our unit of time is 6 months, thus the figure plots what happens to firms upto two years before and after firm entry.

Figure Vb show the corresponding graph for firm financial distress, and shows a gradual decline in financial distress post entry into the super-network. Given the nature of the financial distress variable, any improvement in financial viability due to network entry will only show gradually as lower probability of financial distress. It is thus reasonable that unlike bank credit, probability of financial distress does not jump quickly after entry, but rather starts to decline at a faster rate. There is no significant trajectory in financial distress path in the year and a half prior to network entry. However, there does appear to be a drop in financial distress before that period. Whether this truly depicts a selection concern will be tested more rigourously in fully specified regression analysis below[9].

[9] The magnitude of the effect on bank credit and financial distress in figures is smaller than in the regressions because we only focus on"single entry" and "single exit" firms for whome a time line makes sense.

A. *Effect on External Finance*

Column (1) in Table II estimates (3) with firm and date fixed effects. The dependent variable is log of total external credit of a firm,[10] and the sample size is restricted to non-defaulting firms. Although with firm fixed effects we estimate the value of super-network only for firms that change their network membership during our sample period, we use the entire sample when estimating coefficients. The reason for this is that the rest of the sample is still useful for properly estimating the time effects, as well as firm-type interacted with time fixed effects.

Column (1) shows that when a firm is in the super-network it is able to increase its borrowing by 16.6%. Recall that the cross-sectional differences between firms that are in the super-network versus those that are not in any network is much larger (Table I), suggesting that it is important to control for differences across firms when estimating benefits to network membership. Nevertheless the value generated by the network is substantial even once such selection is accounted for.

Column (2) adds size decile, industry, and firm city location fixed effects, all interacted with time fixed effects to completely (non-parametrically) absorb shocks at these levels at any point in time. The estimated effect of network entry increases with the inclusion of these controls. The coefficient of interest on network entry in Table II is being identified of the firms that actually change their network membership during our sample period. There are 2,457 such firms. Column (3) makes this explicit by firm demeaning the data using all of the fixed effects in column (1), and then estimating the network entry effect on the demeaned data, using only the 2,457 firms that change network membership status. Column (4) does the same but first demeans the data using all the fixed effects in column (2) and shows that the results are robust even when allowing for type specific time shocks in the restricted sample.

Column (5) supplements column (2) by including lagged growth of firm external borrowing. As explained in the methodology section, doing so tests whether firms which are already on an upward trajectory are more likely to enter the super-network. If this were the case then including lagged bank borrowing should reduce or eliminate the estimated coefficient on network entry. However, column (5) shows that including the lagged growth in bank credit does not change the estimated coefficient on network entry. The small positive sign on lagged borrowing growth suggests that while there is positive serial correlation in loan growth, it is not differentially higher for firms that enter the super-network.

[10] We set this value to 0 when a firm is not borrowing. Excluding these observations provides qualitatively similar results.

Column (6) separates entry into (and exit from) the super-network into “direct” and “incidental”. We do so by creating a dummy variable "direct" and interacting it with the variable of interest $InNetwork$. Thus the coefficient on the $InNetwork$ term reflects the value of being in the network on the incidental entrants, and the effect on the Direct entrants is this coefficient plus that on the interaction term. Recall, that direct entrants are those that enter the super-network either because one of the directors that belongs to the super-network starts to sit on its board, or because one of its directors starts to sit on the board of a super-networked firm. Incidental entrants on the other hand are firms that just happened to be linked to a firm that directly connects to the super-network. As explained in the methodology section, incidental entrants into the super-network are less likely to suffer from endogenous entry concerns since they are entering because of another firm’s decision.

The results in column (6) show that the effect of network membership on incidental firms is still positive and significant. Although the magnitude of the effect on incidental firms is smaller, it is only weakly statistically different from the overall effect of network membership on entering firms. The smaller effect on incidental entrants may reflect a correction of the endogeneity bias. However, as we discussed earlier, it is also quite reflect heterogeneity in the impact of network membership since incidental firms enter in a weaker manner. Column (7) includes lagged bank credit and shows no significant change in the coefficient on incidental entry.

B. *Effect on Financial Viability*

We next repeat the analysis of Table II using financial distress as our outcome of interest in Table III. The number of observations in Table III is larger because now we include observations that are currently in default, whereas Table II only included observations that were not currently in default since we were interested in measuring active current borrowing of a firm. We repeat the analogous specifications to those in Table II.

Column (1) in Table III estimates the basic specification with firm and time fixed effects. The propensity to enter financial distress goes down by 1.7 percentage points when a firm is part of the super-network. Given the average default rate for firms that enter or exit the network, the drop in financial distress represents about a 9.5 percent improvement. Column (2) controls for shocks at the size, industry or location level at any point in time and shows little change in the estimates. Columns (3) and (4) restrict to the sample of firms that actually change their network membership during our sample period and show that as expected the result holds in this sample as well.

Column (5) includes lagged changes in financial distress,[11] and columns (6) and (7) separately estimate the effect for direct and incidental entrants/exitors. Our results remain quite robust regardless of the specification with the coefficient of interest remaining between 1.5 to 1.95 percentage points.

Taken together, the results in Tables II and III show that membership into the super-network is greatly beneficial for firms in terms of increasing bank credit and improving financial viability. Given our controls, such as firm fixed effects and firm-type interacted with time fixed effects, as well as our focus on firms that enter due to incidental factors, we can interpret these results as reflecting a direct effect of super-network membership on firms.

C. Robustness to network definition

Our results thus far were based on networks constructed by joining two firms if they have a director in common. One could question if our results are sensitive to alternative plausible definition of network connections. We have already mentioned possible alternative definitions of network formation in section I.B, where we showed the emergence of a super-network regardless of the definition of network formation. We now test if the results of Tables II and III also hold under the different network definitions.

We first reconstruct networks after dropping all those directors that are nominated by the government to sit on boards of firm. 5% of directors in the super-network satisfy this criteria. Government directors may sit on the board of a firm for a couple of reasons. The government may appoint directors if a firm borrows significant capital from development finance institutions owned by the government, or if the firm belongs to an industry regulated by the government.

The removal of government directors for the purpose of network formation could be justified on the basis that government directors reflect the ability of a firm to access government financial institutions rather than an informal business network. Similarly a single government director sitting nominally on the board of many firms may artificially create a large pool of inter-connected firms. However, repeating our main regressions with bank credit and financial distress as outcome variables in columns

[11] The observations fall when we use lag change in default rate due to missing obervations. While this as not an issue in firm borrowing since a firm not borrowing is an observation, the issue is whether to include this observation in the default rate specification. Rather than doing so, we consider an observation on default rate to be mising in a quarter if the firm is not borrowing in the quarter. However, if we assume missing default means zero default, and re-run the regression, we get very similar result (coefficient of -1.39 vs. -1.63)

(1) and (2) of Table IV shows that our results are robust to the formation of network link without government directors.

Our second robustness check to the definition of network formation is the exclusion of directors that do not own any equity in the company. Since the ownership information for directors is missing many times, we lose about 45% of directors and the resulting super-network is much smaller now consisting of 2,010 firms. One could argue that the benefit of network is only passed on through links which actually have a real stake in the company. Columns (3) and (4) show that restricting attention to this definition of network links gives us very similar results.

Finally, column (5) and (6) radically change our definition of network formation by only counting links between firms if the firms have at least two directors in common. In other words, links have to be very strong between firms in order for firms to qualify as being connected to each other. The resulting super-network has 1,668 firms. The interesting result is that this stronger definition of networks gives us a much stronger result for bank credit, and slightly stronger result on financial distress propensity. The significantly stronger result on bank credit suggests that benefit of entry into the super-network is even stronger if a firm enters through stronger links (i.e. with at least 2 directors in common) and connects a super-network which itself is connected through the stronger definition of links.

D. *Who provides the increase in external finance?*

We have seen that entry into the super-network leads to an increase in bank credit. Therefore, a natural question is where does this increase come from? The increase in bank credit could come either from banks that already have a relationship with the entering firm (the intensive margin), or it could come from new banking relationships that the entering firm is able to form (extensive margin). Furthermore, to the extent that the entering firm is able to form new banking relationships, one would like to know the identity of these banks. For example, if the super-network provides more credible information to banks then one would expect that an entering firm is more likely to form relationships with banks that already lend to the super-network neighbors of the entering firm.

Column (1) tests for the effect of network entry on the average loan size of banks that are already lending to a firm at the time of entry into network. The average loan size increases by almost 14 percentage points. Why would entry into the super-network increase credit from existing relationships? If a firm already has relationship with a bank, does the bank not have sufficient information and control over the firm to enhance its credit even prior to network entry?

In answering these questions, it is important to keep in mind that the increase in bank credit that we estimate does not have to all come from an increase in supply of bank credit. As we have already discussed, entry into the super-network could very well increase demand for bank credit as well since the firm now has better business connections to seek useful information and enforce informal contracts more effectively. Thus our estimates should not necessarily be interpreted as an expansion in supply of credit, as they could reflect an increase in demand for credit by the firm. Having said that, access to the super-network could in principle also lead to an increase in supply from an existing relationship if the bank now feels more comfortable in extending credit due to better information and enforcement instruments. What is important for our interpretation, as we have argued in the methodology section, is that the increase in supply or demand of bank credit be driven by the access to super-network.

Column (2) next tests if entry into the super-network also lead to an increase in total banking relationships. The result indicates that entry into the network leads to an increase of 0.13 banks per firm. The average number of banking relationships for a firm that enters or exits the super-network during our sample is 1.2. Therefore the increase in banking relationships represents over a 10% increase over the mean number of relationships for these firms.

What drives the increase in bank credit obtained by networked firms? Specifically, do networks generate real value for member firms that banks then respond to, or are the network benefits driven more by greater access to rent-seeking opportunities. One can imagine both forces being stronger in emerging markets. In an environment with imperfect markets, networks could add real value by providing firms with better information, improved contractual enforcement, access to internal (credit) markets, and access to reliable customers and suppliers. Conversely, networks may also allow firms to exert political and relational influence over lenders in order to extract rents.

Our results on lower default rates for firms that join the network suggest that the value generated by networks is real. This is particularly relevant in the light of related work in Pakistan (Khwaja and Mian 2005) that shows that politically connected firms obtain rents by being able to default more on their loans. Thus a reduction in default rates makes it unlikely that the benefit of network membership leads to excessive rent seeking.

Our earlier work on rent-seeking due to political connections in Pakistan suggests another test for checking whether the value gained due to network membership represents rent seeking. We found that rent seeking is primarily concentrated within government banks and that private banks do not respond to political connections. Therefore if the increase in bank credit reflects real economic advantage then the increase should come predominantly from private banks. If the increase in bank credit instead came from government banks then one might suspect that it is due to rent-providing connections. Columns (3) and (4) show that the share of credit from government banks decreases, while the share from private banks increases as firms enter the super-network. These results corroborate the interpretation that super-network increases credit access due a real economic advantage provided to entering firms rather than rent seeking.

E. Do Network Benefits depend on the strength of the connecting node?

We discussed in the introduction that an additional implication of most network theories is that the benefits of network are not uniform for all network members. Network benefits may vary depending on both on the entrant's pre-existing power and where in the network one is connected to. For example, if an entrant connects to a more "powerful" node, then network benefits are likely to be larger. Similarly, an entrant which started off with more power may gain more or less from entry into the super-network depending on whether the super-network acts as a complement or substitute to the firm's pre-existing power. An advantage of our data set is that we can measure the intra-network heterogeneity in power of connections as well. This gives us the unique opportunity to test whether benefits to network membership depend on the power of the node that a firm connects to and whether the network acts as a complement or substitute to the firm's pre-entry power.

There are several possible measures of power that one can construct within a network. While they are likely to be related to each other, they all represent a somewhat different notion of power and so we present results for all of them. Our first measure of power of a node is given by the number of firms an entrant is directly connected to when joining a network at a node. The second is the number of directors one gains direct access to by joining a network. Since a firm can have multiple directors, the second measure is different from the first. Our third measure is the total number of creditors that are servicing the neighbors of a connecting firm. Finally, we also construct a measure of the firm's strength in the network using the Google algorithm that ranks the relative strength of web pages or in our case, firm-nodes in a network. This measure is quite different from the others since rather than just focusing on the immediate neighbors of a firm, it tries to capture the entire chain of linked firms in determining a firm's power. It does so by capturing the importance of a firm iteratively in terms of how many firms its linked to and how important those firms are in terms of how many firms they are linked to and so on. We use both the direct Google rank measure of the firm and the average of it's neighbors google rank measures.

We construct each of the power measure mentioned above separately for when a firm is in the network and when it is out of the network. The coefficient on the former interacted with firm entry shows how much more a firm gains when it enters the network in a more powerful part of the network. The coefficient on the interaction of out-of-network firm power measure and network entry estimates whether a firm with relatively more powerful connections to begin with gains more or less from the network i.e. is network entry a complement or substitute to its pre-existing power.

Table VI examines the results for firm borrowing. The results in columns (1) through (5) show that regardless of the measure of power used, an entrant gains more benefit when it connects to a more powerful node in the network. On the other hand there is also consistent evidence for the "networks as substitutes" idea. Firms that are more powerful to begin with, tend to gain relatively less when they enter the super-network. The magnitude of these effects is economically significant as well. For example, connecting to a node that is one standard deviation stronger in terms of the "google rank" leads to an almost 17% increase in bank credit.

Table VII repeats the exercise with financial distress as the dependent variable. Unlike loan amounts, whether a firm connects to more powerful nodes or not does not matter for financial distress. However, in sharp contrast to the results on borrowing, in terms of financial distress, network membership appears to be a complement to a firm's pre-existing "power": Firms that are more powerful initially see a greater drop in default rates when they enter the network.

While Tables VI and VII show that network value indeed varies across the power of the nodes a firm connects to or its pre-existing power, it also highlights that this heterogeneity may be quite different depending on what outcomes one considers. While it is hard to identify a precise mechanism for why these two effects may be so different, one could imagine than firm's borrowing reflects more on the networks strength vis-a-vis lenders (and hence acts as a substitute to pre-existing power), whereas a firm's ability to avoid financial distress, depends on whether a firm is powerful enough to seek insurance from other firms in its network. The latter suggest exploring possible insurance benefits on default rates more directly.

F. The Insurance Benefits of Networks

A commonly perceived benefit of networks and informal connections is that they help firms insure each other against common shocks (Khanna etc.). The insurance benefit of networks could be due to multiple reasons. Networks may help insure each other by providing access to each other's internal capital markets through instruments such as trade credit. Alternatively, networks may insure each other by giving preferential treatment in awarding contracts. Such preferential treatment can lessen the downside due to business cycle fluctuations. Finally, to the extent networks improve overall productivity of a firm, this by itself can lower sensitivity of firm performance to common shocks.

We test for the insurance benefits of network membership in Table VIII. We test how networked firms respond to economic shocks hitting their industry or city, *relative to* non-networked firms. The test is carried out by first constructing common shocks hitting an individual firm at a point in time. Common shocks are defined as aggregate changes financial distress at the level of a firm's city and industry. To the extent that a firm is affected by shocks to its city or business cohort, its default rate will positively covary with its cohorts' shocks. The test of whether the network provides insurance is if the default rate of firms that are members of the super-network covaries less with their city and industry cohorts' shocks. Since this test requires us to estimate covariances, in the first two specifications we make use of the full loan level data (1996 to 2003) rather than only restricting to those quarters where we have firm-director information. We are able to do so by extending our definition of whether a firm is in the super-network or not to previous quarter by assuming it's status is the same over time i.e. if its always in (enter/exits) the super-network during 1999-2003, it is always in (enters/exits) during 1996-1998 as well.

Column (1) runs this test and reveals some striking results. While non-networked firms are 56 and 63 percent more likely to default if their city and business cohort default respectively, networked firms are entirely immune to their cohort firms' shocks. Column (2) focuses only on the super-network firms that actually exit and enter the network during our data period (i.e. the 2,457 firms we restrict to in Column (3) of Table II) and shows the same (though slightly smaller) insurance patterns for these firms.

Columns (3)-(4) now restricts the sample to only the 1999-2003 period to address a potential selection concern. If firms are selected into networks precisely because they are the types of firms that are better able to insure themselves against shocks, then the results in columns (1) and (2) may be picking up such select firms. One way to address these concerns is to again take advantage of firms entering and exiting the network and ask whether the same firm is more insured when it is in the network as compared to when it is out. However, since this implies restricting the data to the quarters (1999-2003) where we have director information[12] we should note that since the insurance test relies on estimating how shocks covary, it necessarily imposes greater data constraints in terms of a long enough time-series to be able to estimate such shock covariances.

Thus Column (3) first shows the impact of the sample restriction by re-estimating Column (2) in the restricted sample where we actually have directorship information. While the city-sister shock insurance effect remains, we see that the sample drop results in a much weaker business-cohort insurance effect. Nevertheless, Column (4) runs the test and shows that indeed for shocks to their city-cohorts, a networked firm is better insured when it is in the network, compared to when it was out. This suggests that the insurance results are not likely to be driven by selection but indeed value generated by being a member of the super-network.

IV Concluding Remarks

This paper uses a novel dataset to construct business networks across firms in an entire economy. We use the commonly used definition of inter-locked boards to define links, and uncover the emergence of a robust super-network that absorbs more than half of all bank credit. The super-network is strongly inter-connected and raises the natural question of what benefits it generates for its members.

The key difficulty in isolating the independent effect of network membership on firms is identification. Traditional studies estimating the impact of networks on firm performance have been restricted to cross-sectional comparisons. While results have proven to be a useful first start, they leave open the possibility that any observed differences might be driven by unobserved firm attributes that jointly determine firm performance and entry into the network. The advantage in this paper has been the availability of time-series variation in network membership at firm level. This allows us to focus on the entry and exit of firms over time, and control for a host of firm-specific and time varying factors. The construction of incidental entrants and exitors from the network provides an additional, and plausibly exogenous, source of variation in network membership.

[12] While we could plausibly impute whether a firm is of the type that enter/exits the super-network over time to previous quarters (as we did in Column (2)), it would be far less precise to impute whether such a firm is actually in or out in a particular quarter without having actual directorship data for that quarter.

Our results provide new insight into the direct effect of networks on firm performance. The increase in bank credit due to network membership signifies either an increase in firm demand for credit due to better business prospects, or an increase in the willingness of banks to lend to the same firm. Whether driven by demand or supply, the increase in bank credit signifies an improvement in firm performance. This is corroborated further by the fact that network membership also makes a firm more financially viable by reducing its propensity to enter financial distress. Network firms are also much better able to insulate themselves from shocks hitting their geographical regions or sectors.

An additional advantage of constructing networks from the group up was that we could also construct measures of intra-network strength at each network node. We could thus test for some common predictions of network theory that have so far eluded empirical work. Our findings show that while network benefits (at least in terms of financial access) typically increase in the strength of node one connects to, the effect varies by the firm's pre-existing power as well. While entry into the super-network acts as substitute in terms of financial access, it is acts as a complement in term's of financial distress. This suggests that the financial access margin relies more on the networks strength vis-a-vis lenders (and hence acts as a substitute to pre-existing power), whereas a firm's ability to avoid financial distress, depends on whether a firm is powerful enough to seek insurance from other firms in their network. Exploring such heterogeneity in network effects and the theoretical underpinnings of such effects should prove to be a useful inquiry in future work.

Where do we go from here? Showing that network membership brings benefits in a causal sense is a start, but there remain some important unresolved issues. A critical question is whether the high benefit of networks is a concern from a broader welfare perspective. If networks serve as a substitute to market failures (such as informational asymmetry, weak contractual enforcement etc.), then to the extent market failures can be corrected, it should be welfare enhancing to reduce the role of networks. Even if networks are essential, their effect on welfare depends on the nature of competition for entry into the network. For example, if networks are dominated by people of a particular background and membership to the network is essential for economic growth, then the less privileged groups will be at a great disadvantage. Entry of such less privileged groups into the network can thus have positive externalities for the society as a whole.

V Appendix: Structure of the "Super-Network"

The appendix describes the structure of the super network in more detail.

A. *Network Pattern Link Robustness*

In the paper we defined the link between two firms as having at least one director in common. In order to check the robustness of the network pattern above, we employ three alternative ways of identifying links between firms. The results (see Khwaja, Mian, Qamar (2005) for details) on the distribution of firm network sizes for each of these definitions show that the general network pattern - that of a super-network that is orders of magnitude larger than the next network remains. The three alternate link definitions used are:

(i) Excluding government directors: The rationale for excluding government directors is that in some cases they might just be political appointees sitting in boards of different firms. If this is the case, this could be a reason for having one big network.

(ii) Excluding all directors in a firm who do not hold equity in the firm: Being part of a firm's board of directors but not holding shares of the firm might imply that such a director is not a "real director" at least in terms of having the power to influence firm decisions. So it would be important to see how the network structure changes once such directors are excluded.

(iii) Consider links between two firms if they have at least two directors in common. This definition is extremely demanding since it only allows a link between two firms if they share two distinct directors. Not surprisingly this definition significantly increases the fraction of firms that have no links. In fact, over 90% of the firms are not linked to any other firm when using this new definition. Nevertheless,as the 3rd panel in the figure shows the structure of the network remains fairly stable. The super-network, while smaller, still includes over two thousand firms, borrows almost 50% of total lending and is 70 times bigger than the second largest network.

B. *Super-Network Structure*

Does the super-network present a dense structure with all firms connected to a lot/most of the others, a "royal family" where a few important firms act as links between all others, or a more diffuse structure? Could the network be explained by the presence of some popular directors that are linked to most of the firms? By analyzing different nodes, clusters of firms and directors we find that the network appears to be a fairly diffuse structure.

Large Nodes?

We first look at the super network and see if there are any "super directors" i.e. directors who hold positions on a large number of firms. Appendix Figure II shows for each unique director in the super-network, the distribution of the number of firm boards this director sits on. As the figure shows, there are not that many very popular directors. Less than 1% of the directors sit in the boards of more than 10 firms and 78% of the directors are appointed to the board of just one firm. While there are directors who serve on the boards of several different firms - some of them sit in over 60 different boards - this by itself can hardly explain the size of the super network.

We do the same exercise but now see whether there are firms that are connected to lots of other firms and that can explain the network: a "royal firm". We look first at highly networked firms and find that while firms do vary in the degree to which they are directly connected to other firms, the most connected firm has direct links with 215 firms in the network (less than 2% of the firms). On the other hand, most of the firms have links with only a few others. Out of the all the firms in the network, 75% of them have links with less than 10 firms. The analysis suggests that no firm constitutes a "royal node" but the network structure responds to a dense web of links across the entire network.

"Important" Nodes?

We then turn to examine how the super network holds up in terms of the "loss" of directors or firms in the network. We want to see if there is a crucial director or firm that can explain the web of links among firms in the super networks. In order to test this hypothesis, we take out -one by one- each director/firm that is important in terms of the number of firms the director or firm is linked to and then reconstruct the network using only the remaining directors/firms.

We first consider removing important directors. In 60% of the cases, doing so leads to absolutely no change: the director's removal does not create any new sub-networks but a single original super-network remains. While in 40% of the cases, the super network breaks into more subgroups, there always is a dominant network left orders of magnitudes larger than the second largest network. For example, when we take out one director that is linked to 43 firms, the super-network breaks into 17 different subgroups. Out of these 17 subgroups, the biggest network is still composed of 99.6% of total firms and borrows over 60% of total lending. In comparison, the second largest group has only 7 firms and accounts for less than 0.06% of total lending. In all cases, the biggest group is composed of 98.9%

to 100% of the firms in the super-network. In no case does the second maximum network size has more than 0.7% of total firms. The exercise suggests that the super-network is incredibly robust and remains unaffected even if we exclude highly linked directors.

A similar exercise can be conducted to see if what happens to the super-network if we exclude firms one by one. We exclude firms that are linked to 75 firms or more. In over 50% of the cases, excluding one firm does not change the structure of the super network at all. In the remaining, the biggest group still includes 99.5% of the firms in the original super-network and accounts for a similar share of total lending. Regardless of which highly-linked firms is excluded over 99,5% remain in the super network while the second largest group has less than 0.4% of the firms.

"Important" Clusters?

All the exercises conducted in the previous section point to the same general conclusion: there are no important nodes in the structure of the super-network. But what if there are important clusters of firms or directors? As in the previous section we are going to analyze how the structure of the super-network is affected when removing firm and director but instead of one by one, we remove all firms of directors (i.e. clusters) that are above a given threshold.

We start by removing clusters of directors. In order to do so, we eliminate all directors that sit on the board of more than a given number of firms. We start with a threshold value of 51 (i.e. remove all directors who sit on the board of equal to or more than 51 firms and recomputed the network structure) and then lower this threshold in steps of 2. We are interested not only in the number of distinct sub-networks that are formed once directors above a certain threshold are eliminated but what is the relative size and financial importance of the largest and second largest remaining groups. Our results (see Khwaja, Mian, Qamar (2005) for details) show that the super network does not break until we drop all directors directly related to more than or equal to 3 firms. By then, only 24% of the firms are still in the largest network although they still borrow slightly disproportionately more (33%). The remarkable thing to note is that even if we drop all directors who sit on the boards of five or more firms, while there are several hundred smaller networks, we still find that there one large sub-network that has 63% of the original super-network firms and that borrows 52% of total lending. Moreover what is interesting is that in all these cases (even when we drop directors who sit on 3 or more firms' boards) the second largest group remains extremely small - never greater than 1% of the firms and 0.5% in terms of lending share.

We can conduct a similar exercise but now dropping all firms above a certain threshold in terms of how many other firms they are linked to. We start with a threshold of 202 firms and lower the threshold in steps of 10. The same robustness is observed as when we drop clusters of directors. Our results (see Khwaja, Mian, Qamar (2005) for details) show that the super-network remains important even when we drop the top 500 or so firms (with links to 32 or more firms). In fact the network only significantly reduces in size once we eliminate the firms in the super network with 22 or more direct links to other firms. Even after dropping these more than 800 firms, the largest remaining network still has 35% of the remaining firms and 11% of total original lending. Moreover, this sub-network is more than ten times bigger than the second largest sub-network. It is only once we drop the top 2000 or so firms in terms of firm linkages (threshold of 12 or more links) that we find that the largest sub-network becomes small and comparable to the second largest sub-network. These results show that the super-network is indeed extremely robust to the loss of not only individual nodes but also clusters on important nodes.

References

Belleflamme, P. and F. Bloch (2002) "Market Sharing Agreements and Stable Collusive Networks" mimeo: University of London and GREQAM.

Calvo-Armengol, A. and Jackson, M.O. (2001) "Social Networks in Determining Employment: Patterns, Dynamics, and Inequality," forthcoming: American Economic Review,

Jackson, Matthew, 2004. "A Survey of Models of Network Formation: Stability and Efficiency," Chapter 1 in Group Formation in Economics; Networks, Clubs and Coalitions , edited by Gabrielle Demange and Myrna Wooders, Cambridge University Press, Cambridge U.K., 2004.

Jackson, M.O. and Wolinsky, A. (1996) "A Strategic Model of Social and Economic Networks", Journal of Economic Theory, 71, 44{74.

Johnson, C. and Gilles, R.P. (2000) "Spatial Social Networks," Review of Economic Design, 5, 273{300.

Kranton, R. and Minehart, D. (2002) "A Theory of Buyer-Seller Networks," American Economic Review.

Bala, V. and S. Goyal (2000), A Non-Cooperative Model of Network Formation, Econometrica.

Bala, V. and S. Goyal (1998), Learning from Neighbours, Review of Economic Studies.

Berglof, E. and E. Perotti. 1994. "The Governance Structure of the Japanese Financial Keiretsu." Journal of Financial Economics (36), 259-284.

Chandler, A. D. (1982). "The M-Form: Industrial Groups, American Style," European Economic Review, 19, 3-23.

Chang, S. J., and U. Choi. 1988. "Strategy, Structure, and Performance of Korean Business Groups: A Transactions Cost Approach." Journal of Industrial Economics. Vol. 37, No. 2: 141-158. December.

Collin, S-O. 1998. "Why are These Islands of Conscious Power Found in the Ocean of Ownership?: Institutional and Governance Hypotheses Explaining the Existence of Business Groups in Sweden." Journal of Management Studies 35(6): 719-746.

Dutta, B and M. Jackson (2003). "On the Formation of Networks and Groups," in Networks and Groups: Models of Strategic Formation, edited by B. Dutta and M. Jackson, Springer–Verlag, Heidelberg 2003.

Encaoua, D. and A. Jacquemin. 1982. "Organizational Efficiency and Monopoly Power: The Case of French Industrial Groups." European Economic Review (19), 25-51.

Feenstra, R., T.-H. Yang, and G.G. Hamilton. Nov 1993. "Market Structure and International Trade: Business Groups in East Asia". (ITI). NBER Working Pap 4536.

Fisman, R. and T. Khanna. 1998. "Facilitating Development: the Role of Business Groups". Working Paper.

Goto, A. 1982. "Business Groups in a Market Economy." European Economic Review (19), 53-70.

Granovetter, M.S. 1973. "The Strength of Weak Ties." American Journal of Sociology (78), 1360-1380. May.

Granovetter, M.S.. 1983. "The Strength of Weak Ties: A Network Theory Revisited." Sociological Theory, Vol. 1: 201-233.

Granovetter, M.S. 1985. "Economic Action and Social Structure: The problem of Embeddedness", American Journal of Sociology, 91 (Nov 1985).

Granovetter, M.S. 1994. "Business Groups." In N.J. Smelser and R. Swedberg, eds. Handbook of Economic Sociology. Princeton: Princeton University Press and New York: Russell Sage Foundation.

Granovetter, M.S. 1995. "Coase Revisited: Business Groups in the Modern Economy". Industrial and Corporate Change 4(1): 93-130.

Hochberg, Yael; Ljungqvist, Alexander and Yang Lu. 2007. "Whom You Know Matters: Venture Capital Networks and Investment Performance". Journal of Finance, ol LXII, No. 1, February 2007.

Hoshi, T., A. Kashyap, and D. Scharfstein. 1991. "Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups." Quarterly Journal of Economics (106), 33-60.

Khwaja, A. I., A. Mian, A. Qamar (2005). "Identifying Business Networks in Emerging Economies," Working Paper.

Khwaja, A. I., and A. Mian, (2005). "Do Lenders Favor Politically Connected Firms? Rent provision in an Emerging Financial Market," Quarterly Journal of Economics, Vol. 120, Issue 4, November 2005.

Khwaja, A. I., and A. Mian, (2006). "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market", Working Paper.

Jackson, M and A. Watts (2002). "The Evolution of Social And Economic Networks," Journal of Economic Theory, vol. 106, no. 2, pp 265-295.

Jackson, M and B. Rogers. '"The Economics of Small Worlds,"' forthcoming: Journal of the European Economic Association (papers and proceedings).

Keister, L. 1998. "The Emergence of Interorganizational Exchange: The Effects of Uncertainty, Firm Reputation and Cost on Resource Exchange in Chinese Business Groups." University of North Carolina and Ohio State University mimeo.

Keister, L. 2001. "Exchange Structures in Transition: Lending and Trade Relations in Chinese Business Groups. American Sociological Review, Vol. 66, No. 3: 336-360. June.

Khanna, T. and K. Palepu. 1999. "Policy Shocks, Market Intermediaries, and Corporate Strategy: the Evolution of Business Groups in Chile and India". Journal of Economics and Management Strategy. Vol 8, No. 2: 271-310. Summer.

Khanna, T. 2000. "Business Groups and Social Welfare in Emerging Markets: Existing Evidence and Unanswered Questions." European Economic Review (44) 748-761.

Khanna, T. and K. Palepu. 2000a. "The Future of Business Groups in Emerging Markets: Long Run Evidence from Chile." Academy of Management Journal. Vol. 43, No. 3: 268-85. June.

Khanna, T. and K. Palepu. 2000b. "Is Group Affiliation Profitable in Emerging Markets? An Analysis of Diversified Indian Business Groups." Journal of Finance. Vol 55, No. 2: 867-891. April.

Khanna, T. and J. Rivkin. 2000. "Ties that Bind Business Groups: Evidence from an Emerging Economy". Working Paper, Harvard Business School.

Khanna, T. and J. Rivkin. 2001. "Estimating the Performance Effects of Business Groups in Emerging Markets." Strategic Management Journal. 22: 45-74.

Khanna, T. and Y. Yafeh. “Business Groups and Risk Sharing around the World. Working Paper, Harvard Business School.

Leff, N. 1976. “Capital Markets in the Less Developed Countries: The Group Principle.” Pp. 97-122 In R. McKinnon, editor. Money and Finance in Economic Growth and Development. New York: Marcel Dekker, Inc.

Leff, N. 1978. “Industrial Organization and Entrepreneurship in the Developing Countries: The Economic Groups,” Economic Development and Cultural Change, 26 (July), 661-675.

Leff, N. 1979. “Entrepreneurship and Economic Development: The problem revisited”, Journal of Economic Literature, 17 (March), 46-64.

Lincoln, J. and M. Gerlach. 2002. Structure and Change in the Japanese Network Economy: The Form and Consequences of Business Networks. Forthcoming, Cambridge University Press.

Mian, A. (2006). “Distance Constraints: The Limits of Foreign Lending in Poor Economies”. Journal of Finance, Volume 61, Number 3, June 2006, pp 1465-1505(41).

Majluf, N., N. Abarca, D. Rodríguez, and L.A. Fuentes. 1995. “The Ownership of Economic Groups in Chile.” Pontifica Catholic University of Chile, Santiago, Chile mimeo.

Sorenson, Olav, and Toby E. Stuart. "Social Networks and Entrepreneurship." In Handbook of Entrepreneurship Research: Disciplinary Perspectives, edited by Olav Sorenson, Rajshree Agarwal and Sharon Alverez, 233-252. Kluwer Academic Publishing, 2004.

Strachan, H. (1976). Family and Other Business Groups in Economic Development: The Case of Nicaragua. New York: Praeger.

Watts, D. J., and S. H. Strogatz (1998). “Collective Dynamics of ’Small-World’ Networks,” Nature, CCCLXXXXIII, 440.

White, L.J. 1974. Industrial Concentration and Economic Power in Pakistan. Princeton: Princeton University Press.

Lamoreaux, N. (1986) “Banks, Kinship and Economic Development: The New England Case”. Journal of Economic History, 46 (3), 647-667.

Mintz, B. and M. Schwartz (1985) The Power Structure of American Business. Chicago: University of Chicago Press.

Stokman, F., R. Ziegler, and J. Scott (eds) 1985. Networks of Corporate Power: An analysis of ten countries. Cambridge: Polity Press.

Scott J. 1987. "Intercorporate Structures in Western Europe: A Comparative Historical Analysis of Business", in M. Mizruchi and M. Schwartz (eds) , Intercorporate Relations: The Structural Analysis of Business, pp 208-232. New York: Cambridge University Press.

Rauch, James and Alessandra Casella (eds), Networks and Markets. 2001. Russell Sage Foundation

Figure I: Constructing Networks

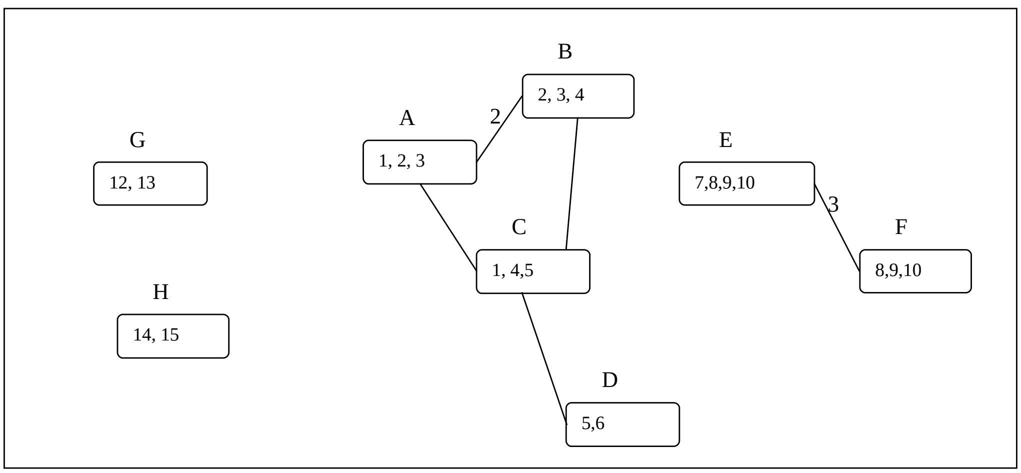


Figure 2a: The super-network in quarter 1 with In-out firms in re

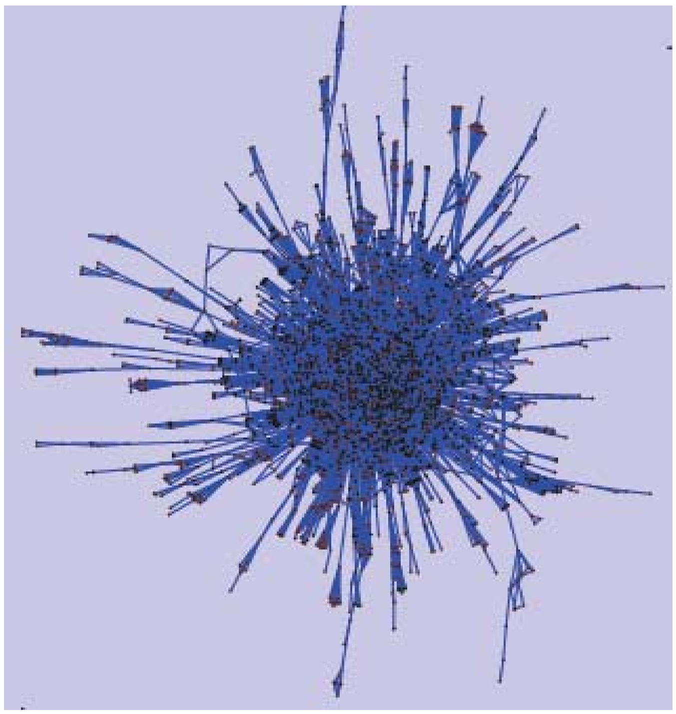


Figure 2b: Zoom View #1

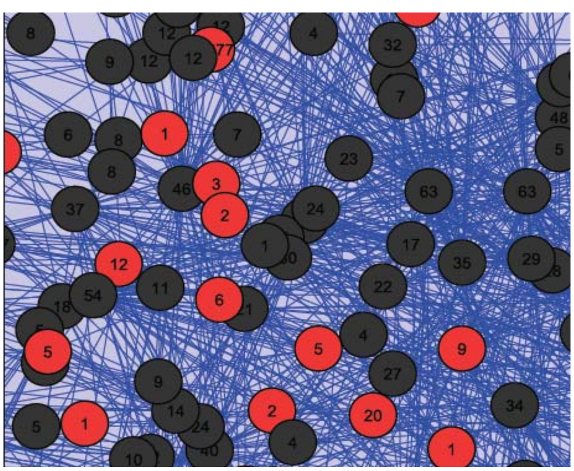


Figure 2c: Zoom View #2

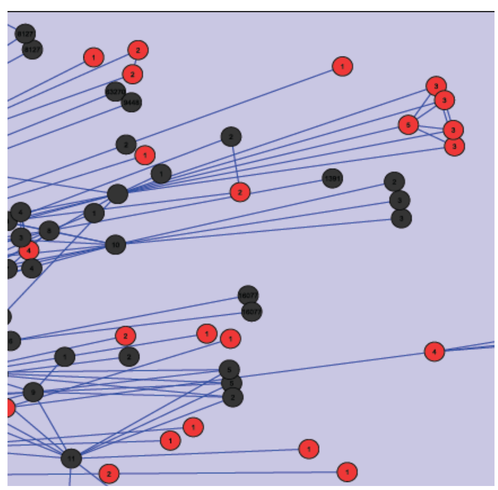


Figure 3a: Sample structures of In-out firms when not in the super-network

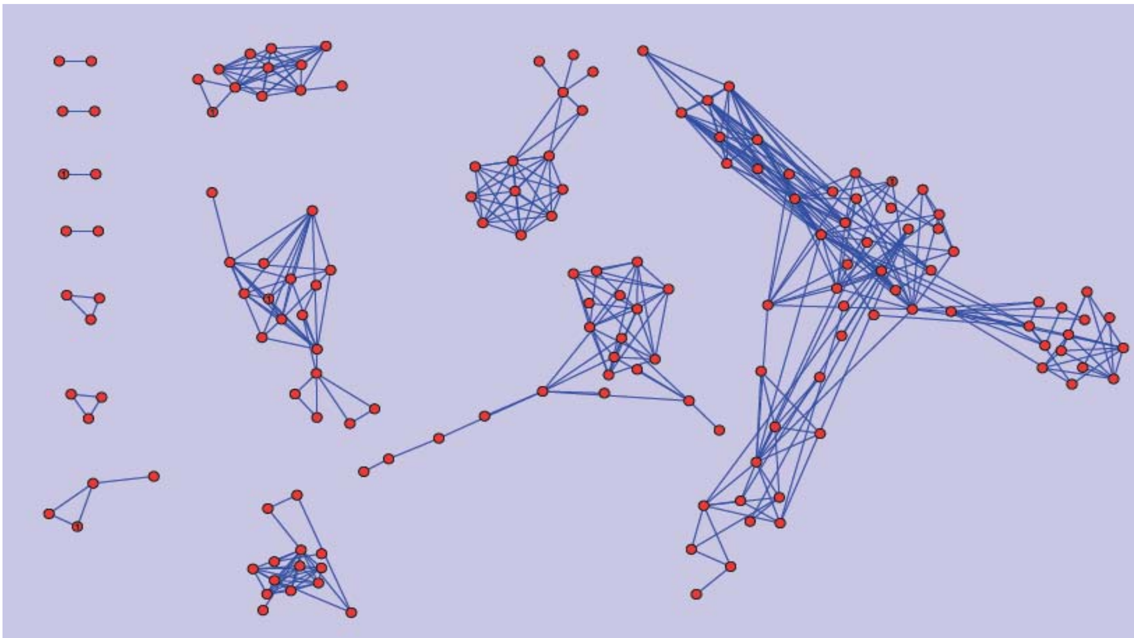
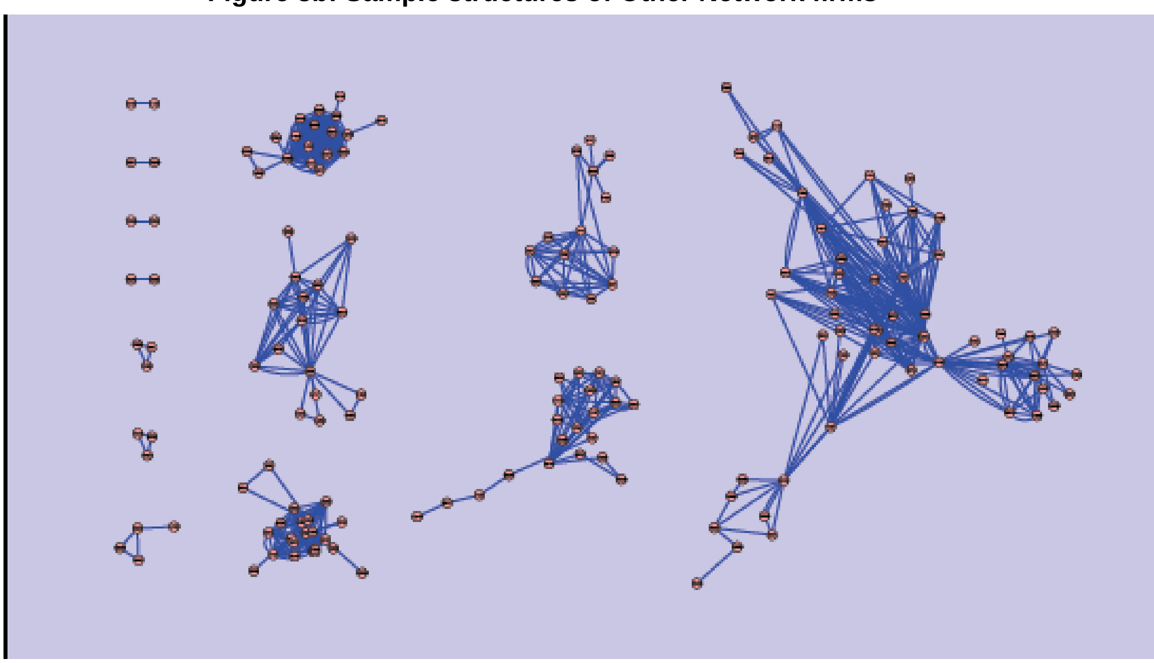


Figure 3b: Sample structures of Other Network firms



Figures 4a-d: Incidental (yellow) and Direct (white) Entrants

Figure 4a

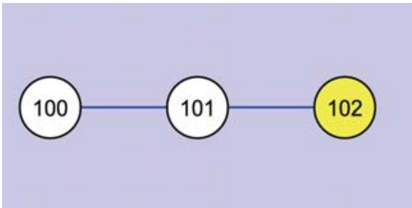


Figure 4c

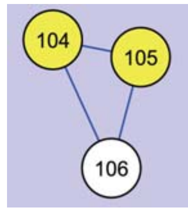


Figure 4b

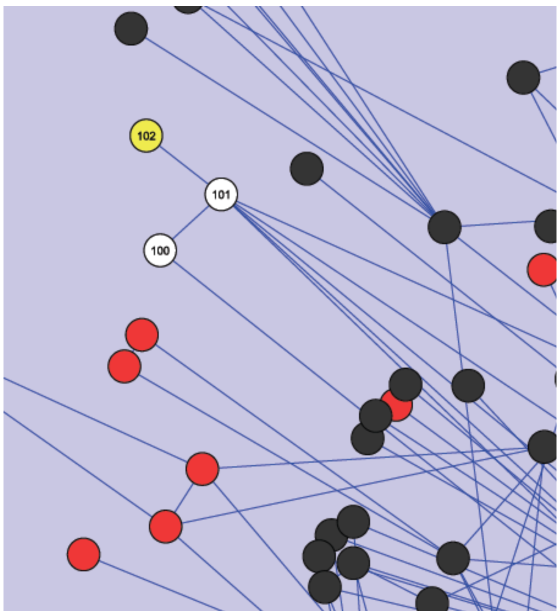


Figure 4d

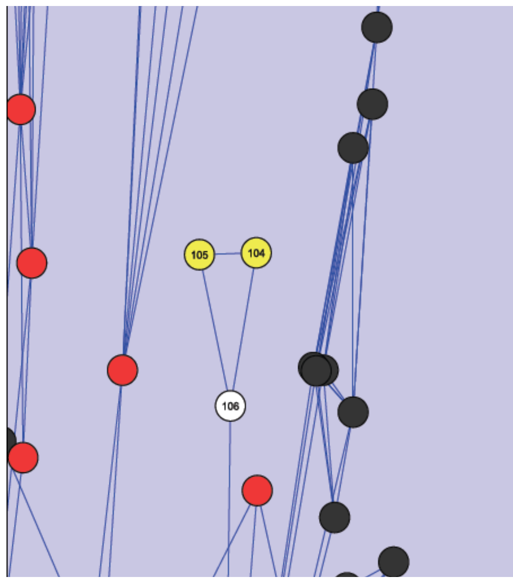


Figure 5a: Log Loan Size and (6-monthly) Period after Entry

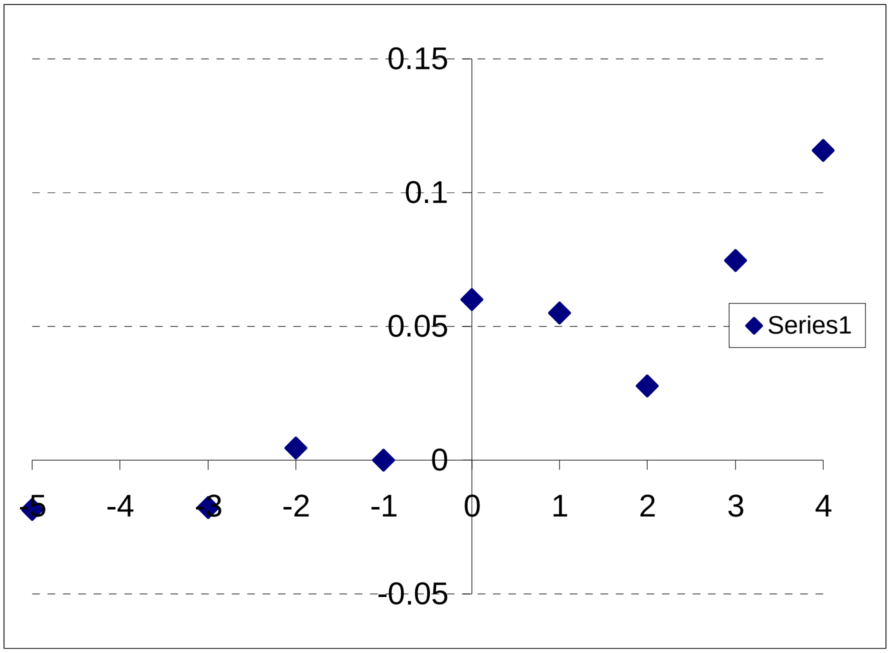


Figure 5b: DR and (6-monthly) Periods after Entry

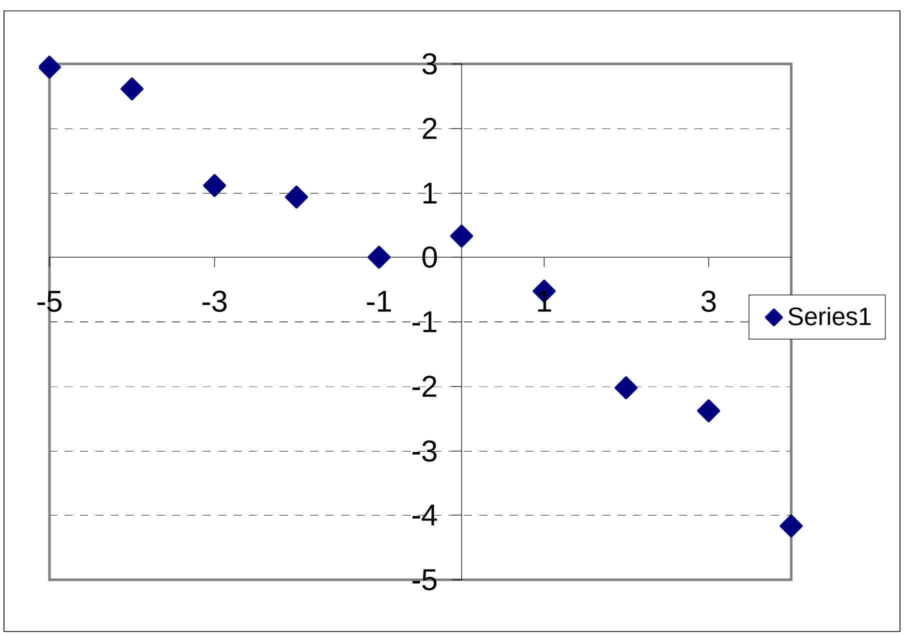


Table I: Summary Stats

Panel A

Firm Type		**Number of Firms**	**%age of Total Bank Credit**	**Log Loan Size**		**Default Rate**		**Initial Borrowing (000s)**	
				mean	sd	mean	sd	mean	sd
Super-Network - Always In		2,838	45%	9.59	3.11	10.97	28.32	191,142.5	1,021,052.0
Super-Network - In and Out		2,457	20%	8.50	2.86	17.87	35.44	81,396.3	478,365.8
Other Network Firms:		34,482	21%	7.24	2.47	16.91	35.16	9,386.2	66,847.4
	M1to4	25,523	10%	7.08	2.38	17.05	35.25	6,440.5	65,422.9
	M5to50	6,412	8%	7.64	2.62	17.53	35.80	17,695.2	71,932.1
	Mover50	2,547	3%	7.69	2.74	13.72	32.15	17,986.9	65,185.4
NonNetwork Firms		66,140	15%	6.52	2.13	28.13	40.30	3,969.2	79,609.3

Panel B

Firm Power Measures		
	mean	sd
No.of Firm Neighbours When In	5.38	5.79
No.of Firm Neighbours When Out	3.08	2.40
No.of Neighbours' Directors When In	34.71	70.73
No.of Neighbours' Directors When Out	9.49	14.11
No.of Neighbours' Lenders When In	10.58	10.95
No.of Neighbours' Lenders When Out	4.89	4.73
Google Rank When In	0.84	0.62
Google Rank When Out	0.74	0.56
Ave. Google Rank of Neighbours When In	1.61	1.17
Ave. Google Rank of Neighbours When Out	0.83	0.62

Table II: Effect of Network Entry on Total External Borrowing

Dependent Variable is Log of Firm External Borrowing	(1)	(2)	(3)	(4)	(5)	(6)	(7)
InNetwork	0.166	0.184	0.154	0.177	0.183	0.128	0.127
	[0.043]***	[0.043]***	[0.043]***	[0.043]***	[0.043]***	[0.059]**	[0.059]**
Lagged Loan Growth					0.012		0.012
					[0.002]***		[0.002]***
InNetwork-Direct			0.126	0.126			
			[0.085]	[0.085]			
Constant	6.536	6.54	1.092	0.82	6.516	6.542	6.518
	[0.021]***	[0.022]***	[0.023]***	[0.023]***	[0.022]***	[0.022]***	[0.022]***
Fixed Effects	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	286,034	286,034	12,053	12,053	286034	286034	286034
R-squared	0.59	0.6	0.44	0.36	0.6	0.6	0.6

This Table shows The Effect of Network membership on Firm Borrowing. Column (1) estimates the basic specification. Column (2) add firm-type interacted with time FEs. Columns (3)-(4) replicate Columns (1)-(2) in the restricted sample of firms that move in and out of the network. Column (5) estimates the base specification for "incidental" entrants. Columns (6) add lagged dependent variable controls to the base specification and Column (7) does so for the Column (5) specification. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table III: Effect of Network Entry on Firm Financial Distress

Dependent Variable is Financial Distress	(1)	(2)	(3)	(4)	(5)	(6)	(7)
InNetwork	-1.728	-1.632	-1.689	-1.62	-1.951	-1.502	-1.848
	[0.350]***	[0.351]***	[0.349]***	[0.348]***	[0.407]***	[0.464]***	[0.559]***
InNetwork-Direct						-0.284	-0.218
						[0.702]	[0.807]
Lagged DR Growth					0.167		0.167
					[0.004]***		[0.004]***
Constant	16.216	16.482	0.308	0.71	23.423	16.477	23.419
	[0.155]***	[0.161]***	[0.191]	[0.191]***	[0.195]***	[0.161]***	[0.196]***
Fixed Effects	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	397416	397416	15043	15043	254576	397416	254576
R-squared	0.86	0.86	0.1	0.002	0.86	0.86	0.86

This Table shows the Effect of Network membership on Firm Default Rates. Column (1) estimates the basic specification. Column (2) add firm-type interacted with time FEs. Columns (3)-(4) replicate Columns (1)-(2) in the restricted sample of firms that move in and out of the network. Column (5) estimates the base specification for "incidental" entrants. Columns (6) add lagged dependent variable controls to the base specification and Column (7) does so for the Column (5) specification. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table IV: Alternate Nework definitions

	LogLoan (1)	LogLoan (2)	LogLoan (3)	Def Rate (4)	Def Rate (5)	Def Rate (6)
InNetwork (Exclude Government Directors)	0.143			-1.582		
	[0.042]***			[0.353]***		
InNetwork (Exclude 0 equity Directors)		0.189			-1.392	
		[0.045]***			[0.361]***	
InNetwork (>=2 Directors In Common Links)			0.334			-1.903
			[0.057]***			[0.512]***
Constant	6.543	6.546	6.545	16.47	16.437	16.442
	[0.022]***	[0.022]***	[0.022]***	[0.161]***	[0.161]***	[0.161]***
Fixed Effects	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	286095	286407	286452	397416	397416	397416
R-squared	0.6	0.6	0.6	0.86	0.86	0.86

This Table shows the Robustness of the Network membership effect to different definition os network construction. Column (1) estimates it for networks constructed by exclduing all government director's. Column (2) uses a network defintion that excludes directors who are don't own equity in the firm. Column (3) examines networks where links are made between firms only if they have two directors in common. Columns (5)-(6) repeat the analogius exercise using firm default rates as the dependent variable. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table V: Decomposing the Effect of Network Entry on External Borrowing

	(1)	(2)	(3)	(4)
	Average Loan Size	Total number of creditors	%age credit from government banks	%age credit from private banks
InNetwork	0.139	0.137	-0.014	0.025
	[0.041]***	[0.018]***	[0.003]***	[0.005]***
Constant	6.412	1.041	0.294	0.51
	[0.021]***	[0.004]***	[0.002]***	[0.002]***
Fixed Effects	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	286034	286034	286034	286034
R-squared	0.57	0.86	0.9	0.86

This Table shows how the firm borrowing network effects arise. Column (1) considers the intensive margin and asks whether the increase comes from greater borrowing from pre-existing banks. Column (2) considers the extensive margin by examining whether network membership increases the number of lenders a firm is able to borrow from. Columns (3)-(4) seprately consider how the share of a firm's credit varies across government and private banks. Column (5) considers how the fraction of a firm's lenders that are common to its neighbor firms, changes with network entry. The Column (5) sample is the restricted sample of firms that move in and out of the network. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table VI: Heterogeneity in Network Benefit By "Power" of Connection

Power Measure	# Firm Neighbours	# of Neighbours Directors	# of Neighbour's Lenders	Own Google Page-Rank	Neighbour's Average Google Page Rank
Dependent Variable is Log of Total External Borrowing					
	(1)	(2)	(3)	(4)	(5)
InNetwork	0.18	0.179	0.174	0.177	0.178
	[0.043]***	[0.043]***	[0.042]***	[0.042]***	[0.042]***
InNetwork * No.of Firm Neighbours(std) When In	0.099				
	[0.040]**				
InNetwork * No.of Firm Neighbours(std) When Out	-0.045				
	[0.041]				
InNetwork * No.of Neighbours' Directors(std) When In		0.075			
		[0.027]***			
InNetwork * No.of Neighbours' Directors(std) When Out		-0.074			
		[0.043]*			
InNetwork * No.of Neighbours' Lenders(std) When In			0.077		
			[0.038]**		
InNetwork * No.of Neighbours' Lenders(std) When Out			-0.133		
			[0.043]***		
InNetwork * Google Rank (std) When In				0.167	
				[0.043]***	
InNetwork * Google Rank(std) When Out				-0.138	
				[0.045]***	
InNetwork * Ave. Google Rank of Neighbours(std) When In					0.021
					[0.043]
InNetwork * Ave. Google Rank of Neighbours(std) When Out					-0.148
					[0.043]***
Constant	6.54	6.54	6.54	6.54	6.54
	[0.022]***	[0.022]***	[0.022]***	[0.022]***	[0.022]***
Observations	286034	286034	286034	286034	286034
R-squared	0.6	0.6	0.6	0.6	0.6

This Table examines hetergoeneity in the network impact on a firm's borrowing. Each column examines how the network value differs along a different measure of a firm's ``power'' both when it is out of the network and In the network. Column (1) uses the number of firms an entrant is directly connected to when joining a network; Column (2), the number of directors one gains direct access to by joining a network; Column (3), the total number of creditors your neighboring firms have access to; Column (4), the firm's own google rank and Colun (5) its neighbours' average google rank. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table VII: Heterogeneity in Network Benefit By "Power" of Connection (measured by default rates)

	# Firm Neighbours	# of Neighbours Directors	# of Neighbour's Lenders	Own Google Page-Rank	Neighbour's Average Google Page Rank
Dependent Variable is Financial Distress	(1)	(2)	(3)	(4)	(5)
InNetwork	-1.605	-1.578	-1.588	-1.577	-1.631
	[0.351]***	[0.350]***	[0.350]***	[0.352]***	[0.351]***
InNetwork * No.of Firm Neighbours(std) When In	0.22				
	[0.349]				
InNetwork * No.of Firm Neighbours(std) When Out	-1.028				
	[0.342]***				
InNetwork * No.of Neighbours' Directors(std) When In		0.093			
		[0.276]			
InNetwork * No.of Neighbours' Directors(std) When Out		-1.384			
		[0.381]***			
InNetwork * No.of Neighbours' Lenders(std) When In			0.554		
			[0.307]*		
InNetwork * No.of Neighbours' Lenders(std) When Out			-1.334		
			[0.381]***		
InNetwork * Google Rank (std) When In				-0.308	
				[0.367]	
InNetwork * Google Rank(std) When Out				-0.808	
				[0.383]**	
InNetwork * Ave. Google Rank of Neighbours(std) When In					-0.628
					[0.254]**
InNetwork * Ave. Google Rank of Neighbours(std) When Out					-1.231
					[0.374]***
Constant	16.479	16.475	16.476	16.48	16.48
	[0.161]***	[0.161]***	[0.161]***	[0.161]***	[0.161]***
Observations	397416	397416	397416	397416	397416
R-squared	0.86	0.86	0.86	0.86	0.86

This Table examines hetergoeneity in the network impact on a firm's default rate. Each column examines how the network value differs along a different measure of a firm's ``power'' both when it is out of the network and In the network. Column (1) uses the number of firms an entrant is directly connected to when joining a network; Column (2), the number of directors one gains direct access to by joining a network; Column (3), the total number of creditors your neighboring firms have access to; Column (4), the firm's own google rank and Colun (5) its neighbours' average google rank. Robust standard errors are in parentheses with * significant at 10%; ** significant at 5%; and *** significant at 1%

Table VIII: Networks and Insurance

	(1)	(2)	(3)	(4)
CitySisterDR	0.558	0.545	0.607	0.607
	[0.006]***	[0.006]***	[0.006]***	[0.006]***
BusinessSisterDR	0.633	0.553	0.514	0.516
	[0.012]***	[0.012]***	[0.019]***	[0.019]***
CitySisterDR* Super-Network Firm	-0.564			
	[0.020]***			
BusinessSisterDR* Super-Network Firm	-0.505			
	[0.021]***			
CitySisterDR* In&Out Super-Network Firm		-0.424	-0.348	-0.311
		[0.030]***	[0.045]***	[0.049]***
BusinessSisterDR* In&Out Super-Network Firm		-0.394	-0.051	-0.075
		[0.031]***	[0.062]	[0.065]
InNetwork				0.015
				[0.015]
InNetwork*CitySisterDR* Super-Network Firm				-0.139
				[0.053]***
InNetwork*BusinessSisterDR* Super-Network Firm				-0.006
				[0.048]
city2Modtl	-0.32	-0.294	-0.379	-0.379
	[0.010]***	[0.010]***	[0.012]***	[0.012]***
business2Modtl	-0.441	-0.325	-0.297	-0.297
	[0.014]***	[0.013]***	[0.023]***	[0.023]***
city2BAlInodtl2		-0.141	-0.228	-0.227
		[0.032]***	[0.054]***	[0.054]***
city2BAloutodtl2		-0.25	-0.452	-0.452
		[0.035]***	[0.050]***	[0.050]***
business2BAlInodtl2		-0.182	-0.047	-0.047
		[0.030]***	[0.066]	[0.066]
business2BAloutodtl2		0.08	0.008	0.008
		[0.033]**	[0.076]	[0.076]
Bcity2NoSis		0.075	0.043	0.042
		[0.021]***	[0.033]	[0.033]
Bbusiness2NoSis		0	0	0
		[0.000]	[0.000]	[0.000]
Constant	-0.14	-0.134	0.042	0.041
	[0.002]***	[0.002]***	[0.004]***	[0.004]***
Controls				
Fixed Effects	Firm, Time	Firm, Time	Firm, Time	Firm, Time
Observations	1315562	1315562	973839	973839
R-squared	0.76	0.76	0.83	0.83

This Table considers evidence for insurance benefits provided by network membership. Columns (1)-(2) consider the full time-series data. Column (1) looks at all firms that were ever in the super-network. Column (2) focuses on only those super-network firms that enter/exit the network during our data period. Column (3) redoes Column (2) but by restricting the sample to firms where we can utlize the time variation induced by firms entering and exiting the network. This is done in order to be able to compare the results of Column (4) where we examine how network insurance varies for a firm when it is in thenetwork, compared to when that same firm is out of the network. Robust standard errors are in parentheses with * significant at 10%; ** significant at 5%; and *** significant at 1%