The Value of Business Networks

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Abstract

We construct the topology of business networks across the population of firms in Pakistan, and estimate the value that network membership brings to access to bank credit and improving financial viability. We link two firms if they have a common director, and find that the resulting topology includes a "super-network" comprising 5% of all firms but accessing two-thirds 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. Network firms improve financial access both by borrowing more from existing lenders and new ones, particularly those already lending to its super-network neighbors. We also find substantial heterogeneity in network benefits - they vary both in terms of where a firm connects to in the network, and its pre-existing network strength.

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Economic organization is deeply embedded in networks and informal contractual arrangements, especially in emerging markets. It is often argued that networks substitute for missing markets and hence add value to network participants (e.g. Leff 1976, 1978, and 1979). However, understanding the topology of business networks and estimating the value that networks bring to member firms remains difficult. This paper uses a novel data set to identify network structures in the universe of firms in Pakistan, and estimates the value that network membership brings in improving a firm's access to credit and its financial viability.

A meaningful analysis of the structure of business networks, and the value networks bring, is faced with at least three significant challenges. First, one needs data on the entire population of firms in the economy in order to construct an accurate topology of networks. Most data sets cover only publicly listed companies. Since private firms form the overwhelming majority of business enterprises, any network analysis limited to public firms is likely to miss many important links, 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 selection 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. One therefore needs to be able to examine such heterogeneity by utilizing credible measures of network strength, such as the "power" of a node, in order to better understand the process through which networks bring value.

We address these challenges using firm level data that covers 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 that have common directors, i.e. have inter-locked boards, and follow *changes* in these networks at a six-month interval 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 "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. The super-network has a diffuse network structure and does not rely on any single hub of nodes to keep the structure intact. It displays “small-world” properties in that despite having over 5,000 firms, the average distance between any two firms is 6.5 links. It has a reasonably high degree of clustering (clustering coefficient of 0.65), and a low degree of centralization/hubs (0.02 centralization coefficient). These characteristics suggest that the super-network is the result of a decentralized process of local link formations, rather than the outcome of any central coordination.

We investigate whether the super-network brings any real value to its member firms in terms of access to external finance and financial viability. The challenge is that network membership is an endogenous outcome and may be driven by unobserved characteristics. Thus cross-sectional differences between networked and non-networked firms are likely to suffer from such selection effects that make it harder to isolate the causal effect of network membership. We first deal with the time-invariant firm characteristics that determine network membership by using firm fixed effects and estimate the effect of network membership on firms entering/exiting the super-network, i.e., by exploring the panel structure of our data, we can compare the *same* firm’s outcomes when it is in the network, compared to when it is not.

We find that network membership significantly improves credit access and financial viability. Network membership leads to an increase in bank credit by 16.6%, and decreases the propensity to enter financial distress by 1.7 percentage points (or by 9.7% of the base default rate).

While firm fixed effects go a long way in addressing selection concerns, time-varying firm attributes may also influence network membership and therefore pose an additional identification concern. For example, firms with better anticipated growth prospects might be more likely to join the network. We deal with these concerns using two separate methodologies. First, we match firms by size, industry and location, and non-parametrically account for time trends common to firms with similar attributes by using firm-type interacted with time fixed effects. We also control for pre-network-entry trends to see if firms entering/exiting the network were on statistically different trajectories.

Our second 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 they were already linked to. For example, consider firms A and B with three directors each and only one director, director 1, in common. Both firms are initially not in the network. Now suppose that firm B enters the super-network either because one of its existing directors - other than director 1 - is invited to be on the board of a super-network firm, or because it gains an additional director who also sits on the board of a super-network firm. In either case, we consider Firm B has "directly" entered the network. Firm A however, also "incidentally" enters the network - not because one of its directors was selected to join a super-network firm or because it got a new director, but simply because it happened to be connected to a firm (B) which entered the network.

Instrumenting network entry (exit) with "incidental" entrants (exitors) gives us an unbiased estimate of the impact of super-network membership under the assumption that incidental entrants are not systematically selected. We show this to be a reasonable assumption based on examining observed attributes. Specifically, incidental entrants are not any different from non-entrants in their cohort in terms of credit growth and change in financial health, prior to incidental entry into the super-network. We should caution though that, to the extent a firm is selected to be a part of the super-network on account of not just its own anticipated growth prospects but also its pre-entry neighbors' prospects, then one may still have time-varying selection concerns. These concerns are likely to be less significant since they are one-stage further along the potential selection story.

Our estimates for both the value of network membership on financial access and financial distress remain robust to the non-parametric and IV estimates. The former specification shows little change. While the estimates are somewhat smaller for incidental entrants (12.8% percent increase in financial access and a 1.5 percentage point drop in financial distress) they remain relatively large. Moreover, these changes likely reflect the heterogeneity in the extent to which network benefits accrue as evidenced by our results below.

We are also able to shed light on how these benefits accrue both by examining the source of the benefits and heterogeneity of the network membership effect.

Examining the source shows that the increase in bank credit is both due to an increase in average borrowing from old banking relationships, and also due to the formation of 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 suggests the importance of a "reference channel" i.e. that network links provide valuable information/value to banks particularly when these links are to their existing clients.

We examine heterogeneity of the network membership effect by investigating whether network benefits depend on the "power" of the connecting firm. We measure both the 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 to 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 for a firm's pre-existing power. This is not surprising if the mechanism, as suggested previously, is access to banks by leveraging one's 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 that are already powerful when they are out of the network see greater drops in financial distress. This hints that the mechanism for lowering default rate may be quite different from improving financial access. While the latter is likely to reflect leveraging one's network neighbors' connections with lenders, the former may be more about directly benefiting from one's neighbors through internal insurance/credit/business contacts type flows since one may expect the more powerful to better take advantage of their network neighbors' 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.

The role of business networks in improving firm performance and access to bank credit has also been emphasized in the context of early American history by scholars such as Leff 1978 and Lamoreaux 1986. While there has been considerable work in network theory (see Jackson 2004 for an excellent summary), empirical work in financial markets has largely lagged behind. Our paper provides three key contributions relative to the existing empirical literature on networks.[1] First, we use the entire

[1] Prominent examples in this literature include: Grief (1993) who examines the role that networks of traders played in overcoming barriers to international trade, such as weak international legal systems 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

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 important network connections in our analysis.

Second, earlier work mostly focuses on estimating *cross-sectional* differences between networked and non-networked firms, making it difficult to control for unobserved firm-specific attributes that determine both network membership and the outcome of interest. Our paper uses time-series changes in network membership for a given firm and can thus use fixed effects to address (unobserved) firm-specific factors influencing network membership. We also address additional concerns of time-varying firm-level unobservables through non parametric controls and instumental variables.

A third contribution of our paper is that we do not treat the network as a 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. Moreover, firms of different initial power may benefit differentially from the network. Finally, the relative importance of these factors may depend on the particular outcome being examined since that may reflect different mechanisms through which network benefits accrue. While previous studies have rarely examined 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. We should caution though, that while our methodology is able to make progress in identifying the benefits that accrue from network membership, these changes may reflect either/both an increase in the supply of bank credit as banks become more willing to provide credit to firms with stronger connections, and/or an increase in the demand for credit by firms as access to stronger business networks makes them more productive. In fact, our results suggest that both factors may be at play.

(see Khanna, 2000, for a review).

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

I Defining Business Networks

A. Data

We use two data sets in this paper, both from the central bank of Pakistan. The first data has information on the board of directors for all borrowing firms in the economy from 1999-2003 at a six month frequency. The second has detailed loan level information on these firms over the same period at a 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-month frequency for well over a hundred thousand firms that represent the universe of all borrowing firms in the economy. 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 a 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 this information is missing or incomplete around 16% of 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 full name (or husband in the case of married women). We deliberately utilize a stringent criteria for matching director names so as not to incorrectly connect two firms. 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, frequently going from positive to zero amounts. Exclusion of these firms leaves us with a total sample of 105,917 firms. The results are qualitatively similar even if these firms are included.

(ii) Firm Borrowing Information

We also have quarterly information on a firm's loan from any bank it borrows from over a seven year period from 1996 to 2003. The 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 to a given firm across its lenders at a given point in time. Since the director data is available at 6 month 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 an effort by the central bank to set up a reliable information sharing resource that all banks could access. A credible signal of data quality is that all banks refer to this information on a daily basis to verify the credit history of prospective borrowers. Our checks with one of the largest and most profitable private banks in Pakistan revealed 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 it to be of high quality. As a random check, we also showed the data from a particular branch of a bank 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 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 (labeled 1 through 15).

Interlocked 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.

[3] We use 1996-1998 data to construct lagged measures of loan growth and change in default.

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

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.

We apply the principle outlined in Figure I to construct networks at a point in time. Doing so gives us eight snapshots of the structure of business networks in Pakistan - once for every six months from 1999 till 2003. We can thus observe not only how networks evolve over time but also isolate the entry and exit of individual firms from specific networks. Almost two-thirds (66,140) of firms are never linked to any other firm at any point in time. The remaining third of firms belong to multi-firm networks in at least some of the periods (Table I, Panel A). The size distribution[5] of multi-firm networks reveals a striking pattern in every period. Network size varies from 2 to 85, followed by a single "super-network" of over three thousand firms.[6]

The size of the super network as well as the identity of firms belonging to the super network changes over time due to the addition or removal of directors from firms, or firm death/birth. There are 2,838 firms that are always part of the super-network, and 2,457 firms that belong to the super-network for some (but not all) of the periods. Panel A in Table I shows the distribution of firms by network size along with some summary statistics. While about 5% of firms (5,295) belong to the super-network at some point in time, the share of these firms in total bank credit is 65% signifying the relative economic importance of the super-network. 34,482 out of the remaining firms belong to networks of size 2 through 85 at some point in time during our sample period. These firms collectively borrow about 21% of total bank credit, with the remaining (15%) bank credit going to non-networked firms.

Figure IIa illustrates the super-network by taking a union of the super-networks over the eight 6-month periods. 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 at some point in time. The large number of firms and high density of links in

[5] The size of a network is defined as the number of firms constituting the network.

[6] The super-network size varies somewhat in each time period, but remains within two and a half to three thousand firms.

the super-network make it difficult to see the intra-network details in Figure IIa. We therefore zoom into a couple of different areas of the super-network to provide more clarity as to what the network structure looks like. Figure IIb zooms in to an area closer to the "core" of the super-network.[7] 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 in to a more peripheral area of the super-network where firms have a lot fewer connections to other firms.

Figures IIa-c highlight a couple of important super-network characteristics. The network is quite strongly interconnected with no single "hub" firm (or a small subset of firms) holding the entire network together. The number of links per firm is small even in the core of the super-network (Figure IIb). Moreover, robustness tests shows that even after the removal of firms that have the most number of links, the super-network retains its overall structure (see appendix for more details on this and other related checks regarding the robustness of super-network structure). A second feature reflected in the figures is that there is heterogeneity in the strength with which a firm is connected to the super-network. Some firms hang on to the super-network with one or two connections, while others are very strongly interconnected with multiple links. Similarly, some firms are connected to more "powerful" firms within the super-network than others.

Panel B in Table I provides summary statistics on various measures of "power" of a firm. We present summary statistics of power measures only for firms that enter or exit the super-network during our sample period. The reason for this restriction is that we identify the effect of super-network membership off of time-series variation provided by these firms. We separately provide power measures for when a firm is in the super-network and when it is out.

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 neighbors' 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

[7] 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.

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 it's 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 it's in and out of the network) and the average of its neighbors google rank measures.

A number of network statistics suggest that our super-network displays "small-world" properties. The average distance (number of links) between any two firms is 6.5 links, surprisingly close to the canonical "six degrees of separation" example. The maximum distance between any two firms in the network is 23, which is quite low given the total size of the network. The network displays a reasonably high degree of clustering, with a clustering coefficient of 0.65. A maximum clustering coefficient of one reflects that 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, the super-network has a very low 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). The network statistics, coupled with the visual evidence shown in Figure II suggests that the super-network is a consequence of decentralized matching across firms rather than a set of coordinated centralized actions.

II Empirical Methodology

A. Basic Setup

Given the remarkable economic status that the super-network enjoys in the credit market, we investigate the effect of membership specifically in the super-network on a firm's credit market outcomes. While firms may also benefit from membership in the smaller networks as well, focusing on the super-network allows us to more readily use our methodology of comparing a firm's outcomes when it enters the super-network relative to when the same firm is out, and also provide estimates for incidental entrants.[8] To the extent that the estimates vary for different sized networks, our results are therefore about the value of network membership in the super-network.

Before outlining the methodology, we should note that business networks can enhance both the

[8] While one could define both even in smaller networks, the sample of firms that (incidentally) enter and exit such smaller networks is too small to permit a feasible analysis.

supply and demand for credit. For example, access to the super-network may provide firms with important business opportunities, credible market information, and effective contractual enforcement which in turn should increase firm productivity and demand for credit. Similarly, banks may be more willing to lend to firms with network connections because such connections provide banks with credible information about firms, and also enable the bank to better monitor them. Banks may therefore be willing to increase the supply of credit as firms enter strong business networks. We want to emphasize that while some of our specific results suggest the relative importance of these two channels, our focus is on estimating the *aggregate* effect of entering the super network, whether driven by changes in the supply or demand for credit.

The difficulty in identifying the aggregate effect of entry into the super-network is that firms that enter the super-network might be systematically different from firms that do not. Thus any observed difference between networked and non-networked firms may be driven by spurious unobserved "selection" factors rather than a direct effect of network membership.

Consider a network with n nodes, where each node represents 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 establish a link with an existing network node. 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.

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 a selection equation that specifies whether and when a firm enters the super-network. Let h_{it} denote the hazard rate that firm i enters the network at time t, conditional on not having entered already. 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. An example of incidental factors is social ties that do not influence firm performance but help a firm gain entry. We assume that 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.

π_{it} evolves through a stochastic process such that 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 may not be independent across firms or over time. The difficulty in identifying the direct benefits of network entry for firm i. can be seen in Equation (1).

Let Y_{it} reflect a 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 $ENTRY_{it}$ itself is a function of π_{it} through equation (1), we have the usual simultaneity/omitted variable problem.

B. Non-parametric controls and Instrumental Variables

We address for the possibly spurious effect of π_{it} on $\widehat{\beta}_1$ using two separate types of approaches.

The first approach uses non-parametric controls to absorb firm specific factors that might determine network entry and may independently affect firms' credit market performance as well. A key component of π_{it} that influences 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.[9]

However, this still leaves open the concern that firms are more likely to enter the network at certain points in time when, for example, the industry they belong to happens to get a series of positive shocks. We make another non-parametric adjustment to account for such time-varying productivity factors by including the interaction of firm-type fixed effects with time fixed effects (α_{kt}) in (2) in addition to the level firm-fixed effects. Firm type, k, in our regressions includes firm location, size decile and industry.

More generally β_1 may be influenced by other *time-varying* firm-specific 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 of the firm. While we do not observe such firm-specific shocks, if these shocks were influential then *conditional* on entry in t, a firm should have a higher growth trajectory for Y prior to t.

Thus one can test whether β_1 is driven by time-varying shocks to firm productivity by including lagged growth rate of Y_{it} and checking if β_1 drops substantially. The combination of non-parametric and lagged growth rate controls gives us the following estimation equation:

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

where α_i are firm fixed effects and α_{kt} are firm-type (k) interacted with date fixed effects.[10]

Our second approach type for addressing potentially endogenous entry into the super-network is based on instrumental variables. A limitation of equation (3) is that it does not make it explicit *which* specific factors are causing a firm to enter the network and so leaves open the possibility that a firm-specific time-varying factor may influence both network membership and the outcomes of interest. In the terminology of the hazard function (1), ideally we would like to instrument entry with an incidental parameter x_{it}.

[9] 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.

[10] 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 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 at it is differenced out.

We propose such an instrument based on the "incidental" entry of some firms into the super-network. There are two distinct ways in which a firm can gain entry into the super-network: *direct* and *incidental*. We can utilize Figures IIIa-d, based on our actual data, to illustrate the difference between the two.

Figure IIIa shows a set of firms before they enter the super-network, and figure IIIb shows the same firms after they have joined the super-network. The three firms in figure IIIa are connected through a line because they each have a director in common, but there is no director common to all three. Figure IIIb shows that two firms (colored as white) directly join the super-network. Examining the data shows that this is because their common director is invited to sit on the board of an existing network firm. The third firm, colored in yellow, enters the network *incidentally* as none of its directors is invited to sit on the existing super-network (or any new directors join its board).

Figures IIIc-d depict another example of incidental and direct entry into the super-network, where the nature of the direct entry is slightly different. Instead of the direct entrant's director being invited to sit on a networked firm's board, in this case the direct entrant firm has a new director join it from a super-network firm. As in the previous example, the three firms have a common director and are thus linked to each other. One of the firms (#106) adds a new director who already happens to sit on the board of one of the super-networked firms. Thus firm #106 enters the super-network directly, while firms #104 and #105 (colored in yellow) join the super-network incidentally since none of their directors are invited to sit on a super-network firm, nor do they add a new (super-network firm) director.

We analogously define incidental exits, i.e., firms that exit the super-network indirectly because one of the firms they are connected to experiences either a removal of a super-network firm director from its board, or one of its directors no longer sits on the board of another super-network firm.

While these figures highlight the two different ways in which a firm can enter (exit) directly into a super-network - a firm can either have one of its directors to sit on the board of an existing super-network firm (e.g. firms #100 and #101 in figure IIIb), or it can have one of the directors of a super-network firm to sit on its board (e.g. firm #106 in figure IIId) - we only highlight this to make it clear who the incidental entrants are, i.e. firms that enter (exit) indirectly because they enter without anything that happens on its board (neither does it add (loose) a new super-network firm board member, nor do any of its existing directors join (leave) the board of a super-network firm).[11]

We use incidental entry/exit into the super-network as an instrument for entry/exit. Incidental entrants/exitors likely serve as appropriate instruments because these firms join/leave the super-network without any direct change in the composition of their board, or a change in the list of firms that their directors belong to. Therefore, to the extent these incidental firms are not joining/leaving 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, estimating the impact of network membership on them provides unbiased estimates. In fact we show in the results section that incidental entrants are observationally identical before entry in terms of loan growth, and changes in credit history to firms in similar-sized smaller networks that end up not being selected into the super-network.

While we could literally instrument for network membership using incidental entry/exit, given that the proposed instrument effectively just excludes a subset of firms that change network membership, this is analogous to separately estimating the impact on incidental and direct entrants, i.e. we augment the previous specification and estimate:

$$Y_{it} = \alpha_i + \alpha_{kt} + \alpha_t + \gamma * \triangle Y_{i,t-1} + \beta_1 ENTRY_{it} + \beta_2 ENTRY_{it} * Direct_i + \varepsilon_{it} \tag{4}$$

where $Direct_i$ indicates a firm which ever directly enters/exits the super-network and β_1 is our coefficient of interest (the analogous IV estimate) since it isolates the impact on the incidental entrants/exitors.

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. 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.

[11] While one could separate incidental entrants, based on which of the two types of direct entry their connecting firm experiences, we don't do so. This is both because of sample size limitations, but also because there is no clear reason to think this would improve identification i.e. it is not clear whether one form of direct entry faces a stronger selection problem than the other.

III Estimating Network Benefits

We use two measures of firm performance in the credit market to estimate the impact of super-network membership. 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 viable, and hence less likely to enter financial distress.

Before presenting the regression estimates Figures IVa-b illustrate what happens to these two measures of firm performance as a firm enters the super-network during our sample period. Since the analysis is done in event-time, with time of entry defined as time zero, we take out economy wide aggregate effects (at industry and size level) before plotting data over the event-time horizon.

Figure IVa shows a discrete jump in total bank credit of about 6% as a firm becomes a 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, lending credibility that our regressions estimates are unlikely to be biased. Since our unit of time is 6 months, the figure plots what happens to firms up to two years before and after firm entry.

Figure IVb shows 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, the 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 the 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 rigorously in fully specified regression analysis below.[12]

[12] The magnitude of the effect on bank credit and financial distress in figures is smaller than in the regressions later on because we only focus on a smaller sample of "single entry" and "single exit" firms for whom a timeline makes sense. The regressions utilize a larger sample by also including firms that enter/exit more than once.

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,[13] and the sample size is restricted to non-defaulting firms. By definition, firm fixed effects estimate the value of the super-network only for firms that change their network membership during our sample period. We nonetheless use the entire sample to estimate coefficients because the total sample is needed for appropriately estimating time effects and their interactions with firm attributes.

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 is robust to the inclusion of these controls. Another variant of the size-decile interacted with time fixed effects is to include the network size of the firm when it is out of the super-network as fixed effects, and interact these fixed effects with time dummies. Adding these controls (regression not shown) gives very similar results (a 0.19 coefficient).

The coefficient on network entry in Table II is identified off of 2,457 firms that change their network membership during our sample period. Column (3) makes this explicit by first 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).

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 loan growth should reduce or eliminate the estimated coefficient on network entry. However, column (5) shows that including 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

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

correlation in loan growth, it is not differentially higher for firms that enter the super-network.

Column (6) separates entry into (and exit from) the super-network into "direct" and "incidental." We do so by creating a dummy variable "direct entrant/exitor" and interacting it with $InNetwork$. *Direct entrant/exitor* is one if a firm enters/exits the network directly and zero if it enters/exits incidentally. Thus the coefficient on the $InNetwork$ term reflects the value of being in the network on the incidental entrants (our "instrumental" variable estimate), and the effect on the direct entrants/exitors is this coefficient plus that on the interaction term. As explained in the methodology section, incidental entrants/exitors into the super-network are less likely to suffer from endogenous entry/exit concerns since they are entering/exiting because of another firm's decision.

The results in column (6) show that the effect of network membership on firms that enter/exit "incidentally" 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 mentioned previously, it could also 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.

Does incidental entry provide appropriate instruments?

Incidental entry (and exit) provides an appropriate instrument for network entry (exit) if the occurrence of incidental entry is orthogonal to other time varying factors that might influence firm performance and hence bank credit. It is reasonable to expect that any concerns of positive correlation between determinants of network entry and firm performance over time would be significantly lower for incidental entrants relative to direct entrants. However, we also provide direct empirical evidence showing that there are no significant differences on observables between incidental entrants and similar non-entrant firms.

A firm can enter the super-network incidentally only if it is connected to some other firms, one of which enters the super-network directly. This implies that the probability of entering incidentally increases monotonically with the size of the network that a firm belongs to before entry into the super-network. Therefore the natural comparison cohort of firms belonging to a network of size k at time $t-1$, that enter the super-network incidentally at time t, is the set of non-entrant firms at time t that also also belong to a network of size k.

Figure Va illustrates some sample networks of various sizes k that end up entering the super-network. While a few of the firms in each network enter directly, the remaining firms enter incidentally. Figure Vb illustrates a comparison sample of firms. These are firms that also belong to various networks of size k. However, the difference is that these networks never enter the super-network. As an example, consider the two networks with $k = 12$ in figure Va and Vb respectively. For the sake of argument, suppose that one of the firms in Va network enters directly, with the remaining entering incidentally. If incidental entry is truly driven by "luck," then the eleven firms that happen to enter the super-network incidentally in figure Va should be no different (on average) than the twelve firms in $k = 12$ network in figure Vb that did not enter incidentally.

We check whether this is true more broadly in our data by using network-size fixed effects and comparing incidental firms prior to super-network entry with their relevant cohort firms. We check for differences on our two key performance metrics, growth in bank credit and changes in default status. The result shows that there is no difference between incidental firms and firms that do not enter the super-network in either of the two metrics. The difference in growth rate of bank credit between incidental entrants and non-entrants belonging to same-sized networks is less than 0.5% and insignificant (t-stat of 0.2). Similarly, the difference in changes in default rate is less than 0.04% and insignificant (t-stat of 0.14). The change in default rate can be seen as a measure of firm performance over time. For example, if incidental entrants were improving prior to network entry, then they should have (relatively) declining propensity to be late on their loan repayments. However, this is not the case.[14]

B. *Effect on Financial Viability*

Table III repeats the analysis of Table II using financial distress as the outcome of interest. The number of observations in Table III is larger because it includes observations for firms that are currently in default. Table II, on the other hand, only includes observations that are not currently in default since we are interested in measuring active current borrowing of a firm.

Column (1) 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.

[14] There is some evidence that direct entrants are on a better trajectory, justifying the focus on incidental entrants. Credit growth for direct entrants is 3% faster, while propensity to enter default declines by 0.4. However, these differences are marginal in significance, with t-stats of 1.24 and -1.37 respectively.

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 by including firm type interacted with time fixed effects 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 as expected show that the result holds in this sample as well.

Column (5) includes lagged changes in financial distress,[15] 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 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 better interpret these results as reflecting a causal 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 other plausible definitions of network connections. Section I.B and the appendix highlight some alternative definitions of network formation and showed the emergence of a super-network in all definitions. We now test if the results of Tables II and III also hold under these alternative network definitions.

We first reconstruct networks after dropping all those directors that are nominated by the government to sit on boards. These directors, identified as those who are on government firm boards, constitute 5% of directors in the super-network firms. 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.

[15] 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)

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 interconnected firms. The size of super-network reduces from 5,295 firms to 4,782 firms once we exclude such directors. However, repeating our main regressions with bank credit and financial distress as outcome variables in Columns (1) and (2) of Table IV shows that our results are robust to the formation of network links without government directors.

Our second robustness check 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, Columns (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 the 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.

In addition to these three alternatives, we also checked and confirmed the robustness (regressions not shown) of our results in Tables II and III to network definitions which exclude firms with only a single director, exclude small firms, and exclude firms with missing national identity card information on directors.

D. Who provides the increase in external finance?

Where does the increase in bank credit as a result of super-network membership come from? It could either come from banks that already have a relationship with the entering firm (the intensive margin), or 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) in Table V 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. One may ask why entry into the super-network would increase credit from existing relationships. If a firm already has a relationship with a bank, one may think that the bank has sufficient information and control over the firm to enhance its credit even prior to network entry. However, as already mentioned, entry into the super-network could very well increase the demand for bank credit if firms now have better business connections to seek useful information and enforce informal contracts more effectively. Thus our estimates should not necessarily always be interpreted as an expansion in supply of credit.

Column (2) tests if entry into the super-network also leads to an increase in total banking relationships. 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 more than a 10% increase in the number of banking relationships per firm.

What drives the increase in bank credit obtained by networked firms? Specifically, one may ask whether 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 also suggests another test for whether the value gained due to network membership represents rent seeking. The earlier work finds that rent seeking is primarily concentrated within government banks while 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 comes 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 to a real economic advantage provided to entering firms rather than rent seeking.

One explanation for the increase in bank credit due to network entry is that banks are more willing to lend to a firm if they already have a relationship with the firm's new network neighbors. If a firm's new neighbors help it secure credit, we should see a disproportionate share of the credit from new lenders coming from its neighbors' banks. Column (5) in Table V tests this prediction. We construct a variable that captures the relative share of additional credit coming from an entering firm's new network neighbors. This variable is zero when a firm is out of the super-network. When a firm enters, the variable is constructed as follows: Let A be the total credit coming from all new banking relationships post network entry. Let B be the total credit coming only from those new banking relationships, where the bank is an existing creditor of one of the new neighboring firms of the entrant. Then $\frac{B}{A}$ captures the share of new credit coming from those first-time lenders who already have a relationship with the entering firm's new neighbors. We normalize this ratio by subtracting what it would have been if new banking relationships were formed at random. This "random chance" ratio, $\frac{\overline{B}}{\overline{A}}$, is the total lending portfolio of all new banks lending to an entering firm' neighbors (but not the firm itself) divided by the total lending portfolio of all banks the firm was not borrowing from before. The normalized ratio, $Y = \left(\frac{B}{A} - \frac{\overline{B}}{\overline{A}}\right)$, forms the dependent variable in Column (5).

If a disproportionate amount of credit from new banking relationships comes from a firm's new neighbors, then Y should be positive post entry. Column (5) shows that this is indeed the case. Since the variable Y is only defined for firms that are part of the super-network, the data in Column (5) is restricted to firms that are part of the super-network at some point in time.

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

As network theory repeatedly argues, network benefits are unlikely to be equally shared. Network benefits may vary depending on an entrant's pre-existing power and where in the network it 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 the power of connections. 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 the super-network. 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 captures 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 it's 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 its neighbors' google rank measures.

We construct each of the power measures 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 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. Moreover, 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 and therefore what mechanisms that generate network value may be at play. While it is hard to identify a precise mechanism for why these two effects may be so different, the previous results suggest that a firm's borrowing reflects more on the networks strength vis-a-vis lenders (and hence acts as a substitute to pre-existing power). In contrast, a firm's ability to avoid financial distress, may depend relatively more on whether a firm is powerful enough to seek insurance from other firms in its network. The latter suggests 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, et al). The insurance benefit of networks could be due to multiple reasons. Networks may help insure one another 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 that 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 examine 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 in financial distress (default rate) 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 its status is the same over time, i.e. if it's 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 separately 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) restrict 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[16] 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.

[16] 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.

Thus Column (3) 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 the universe of firms in an emerging economy, identify the presence of a robust super-network, and provide estimates of the value generated by a firm joining this network. The latter is made possible by exploiting time-series variation in network membership for a given firm and by utilizing incidental entrants/exitors from the network as an additional, and likely exogenous, source of variation in network membership. Moreover, we present results on how the network benefits vary across firms that differ both in their own and their immediate neighbor's pre-existing strength, shedding light on the mechanisms through which the network adds value.

While isolating the impact of network membership is clearly a challenge in the literature that this paper attempts to deal with, and exploring alternate methodologies, particularly those that can utilize close to or actual experimental variation in network membership, would allow one to make further progress, our results also point to several other empirical directions that solicit further enquiry.

While we present results that examine the heterogeneity of network benefits, there is clearly more work that can be done in this area - particularly in being able to test for some of the predictions of network theory that have so far eluded empirical work. Our findings show that while some of these predictions are borne out - such as network benefits (in terms of financial access) increasing in the strength of the node one connects to, this may be quite different for other forms of network benefits, such as financial distress, where our findings indicate that the strength of the connecting node is less crucial. This contrast is even starker when examining how the network benefit varies by the firm's pre-existing power. While entry into the super-network acts as substitute in terms of financial access, it is acts as a complement in terms of financial distress.

These differences suggest that the network generates benefits through a variety of channels, and these channels vary in their importance for different firms and for the specific benefits being sought. One interpretation of the contrasting results in how a firm's pre-existing strength affects its ability to draw on the network is that the financial access margin relies more on the network's influence/value vis-a-vis lenders and hence acts as a substitute to pre-existing power, i.e. firms that have relatively little influence over/reputation with creditors leverage their network's influence/reputation more. In contrast, while a firm's propensity to enter into default is likely affected by its relationship with external creditors, it may even more important depending on its relative influence over other firms in its network. To the extent that this relative influence is greater for more powerful firms, this may explain why pre-existing strength acts as a complement to network membership, i.e. the more powerful firms are better able to obtain insurance from others in their network. Therefore exploring such heterogeneity - across firms, connecting nodes and a wider range of outcomes - informs us regarding the channels that generate network benefits and in turn better makes us able to understand the nature of the underlying market frictions in these economies that allow networks to add value.

More broadly, this begs the question as to whether the benefit networks provide is a concern from a broader welfare perspective. Is a highly networked economy a sign of inefficiency and hence a feature that diminshes as the economy develops, or is it that networks persist, perhaps changing form, as the economy grows? 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. However, to the extent that networks complement/augment the efficiency of markets, their continued presence is instead desirable. Yet 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 into the network can thus have positive externalities for the society as a whole.

Given this multitude of questions, it is not surprising there is a burgeoning empirical literature on analyzing networks. While this literature has focused on social and labor market networks, new datasets and methodologies, such as those used in this paper, should allow further progress in understanding the structure, role and evolution of financial networks.

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 define 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 (2008) for details) on the distribution of firm network sizes for each of these definitions show that the general network pattern holds: There is always a super-network that is orders of magnitude larger than the next network. 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.

Under all these alternate definitions the network structure remains similar with the existence of a “super-network” that is orders of magnitude large than any other network. Not surprisingly, the third definition is the most restrictive with over 90% of the firms not linked to any other firm when using it. However, even in this case 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. 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 (2008) 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 (2008) 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.

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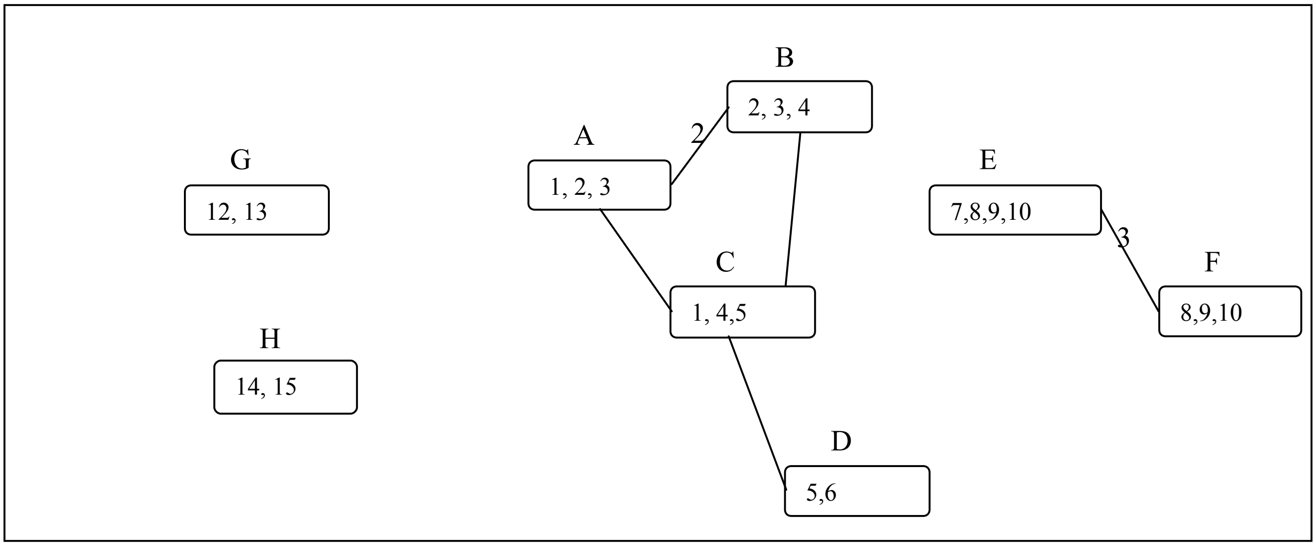

Figure I. Constructing Networks. This figure illustrates the hypothetical construction of a network. There are 8 firms in the example (A through H), and a total of 15 directors sitting on the board of these firms (labeled 1 through 15). Interlocked board linkages produce two distinct networks and two 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.

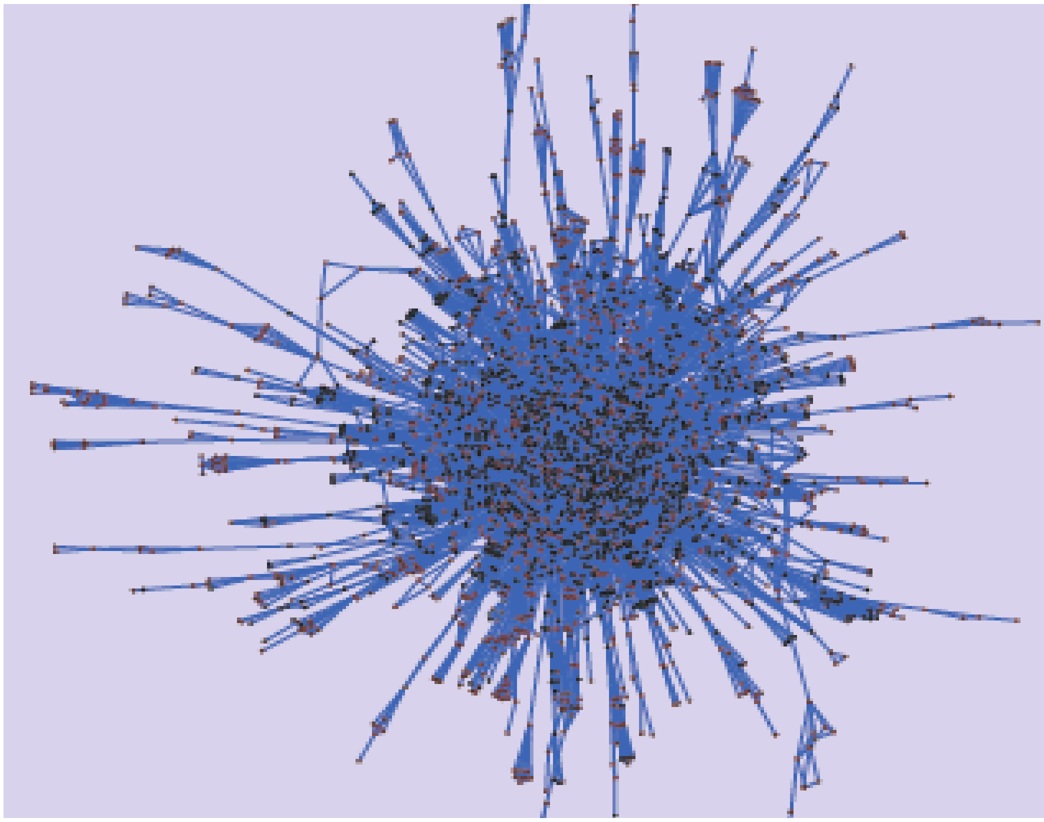

Figure IIa. The super-network. Firms that always remain inside the super-network are represented by black dots, while firms that enter and/or exit the super-network (In-out firms) are represented by red dots. Firms are linked if they share a common director.

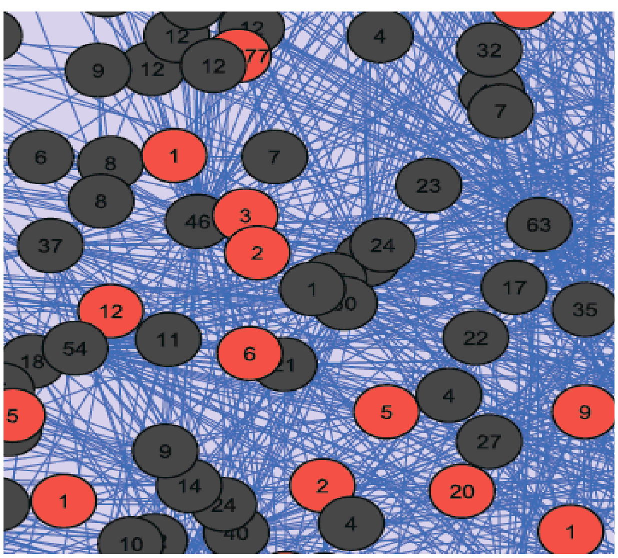

Figure IIb. Zoom View #1. This figure is a zoom view near the "core" of the super-network. While each dot represents a firm, the number inside the dot represents the number of firms that the firm is connected to.

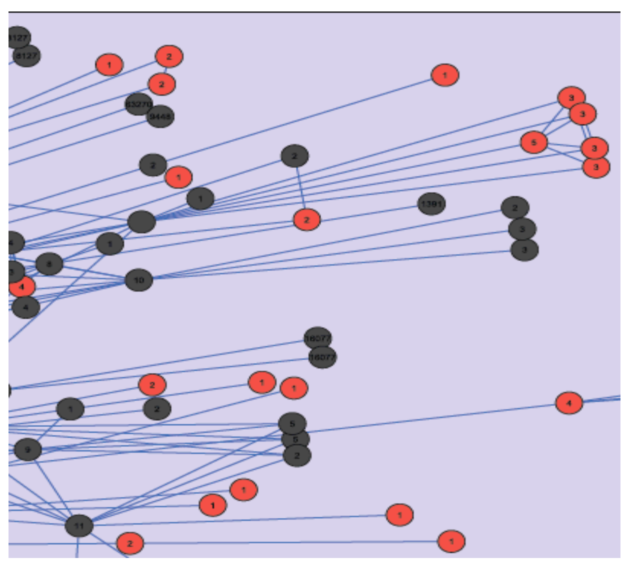

Figure IIc. Zoom View #2. The figure zooms into a more peripheral area of the super-network where firms have fewer connections to other firms than they do near the "core."

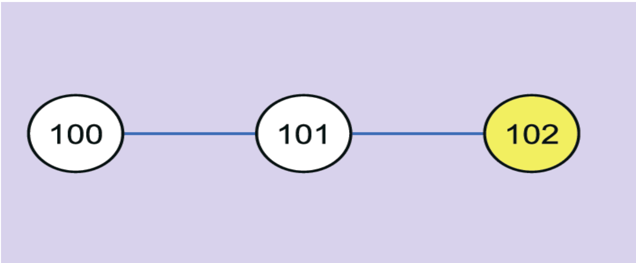

Figure IIIa. Sample network of In-out firms. This figure illustrates a sample network of firms *before* they enter the super-network. The three firms are connected through a line because they each have a director in common, but there is no director common to all three.

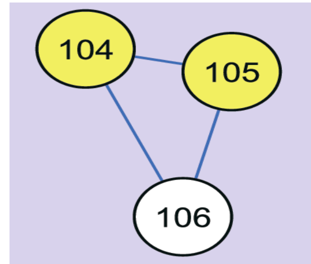

Figure IIIc. A second sample network of In-out firms *before* they enter the super-network. The three firms are connected as a triangle because there is a single director who is on the board of each of the three firms.

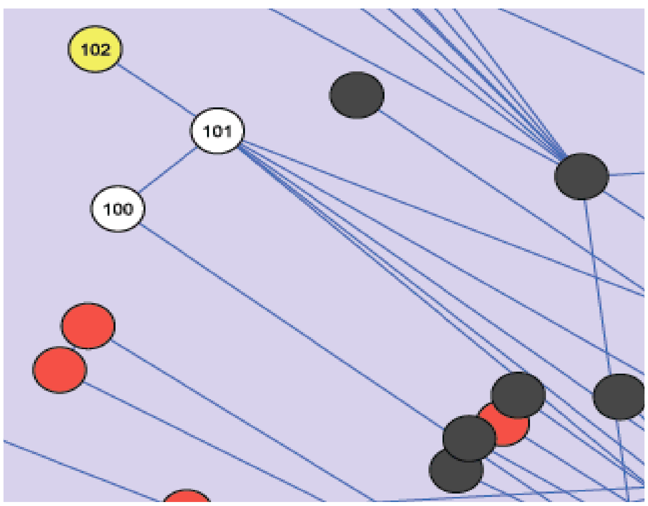

Figure IIIb. The figure shows firms in Figure IIIa once they have entered the super-network. Two firms (colored as white) have a director in common who joins the super-network. Thus the two white firms are *direct* entrants into the super-network. The third firm, colored in yellow, enters *incidentally*.

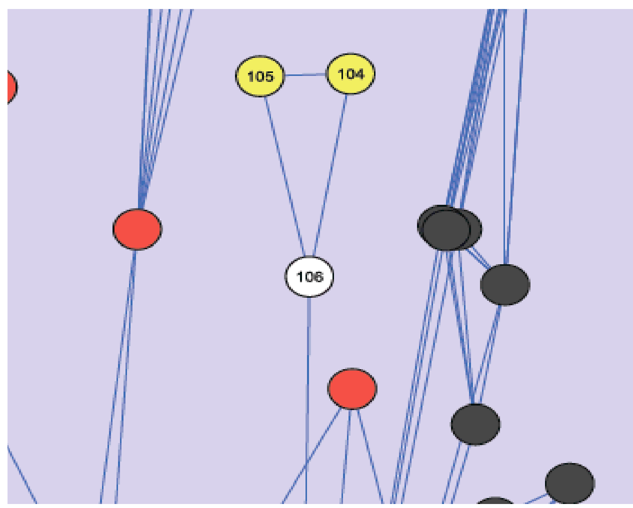

Figure IIId. The figure shows firm in Figure IIIc once they have entered the super-network. One firm (colored as white) enters the super-network *directly* as it has a director (who is not common with the other two firms) who starts to sit on the super-network board. However, the other two firms, colored in yellow, enter *incidentally*.

Note: The numbers inside firms are simply firm identifiers.

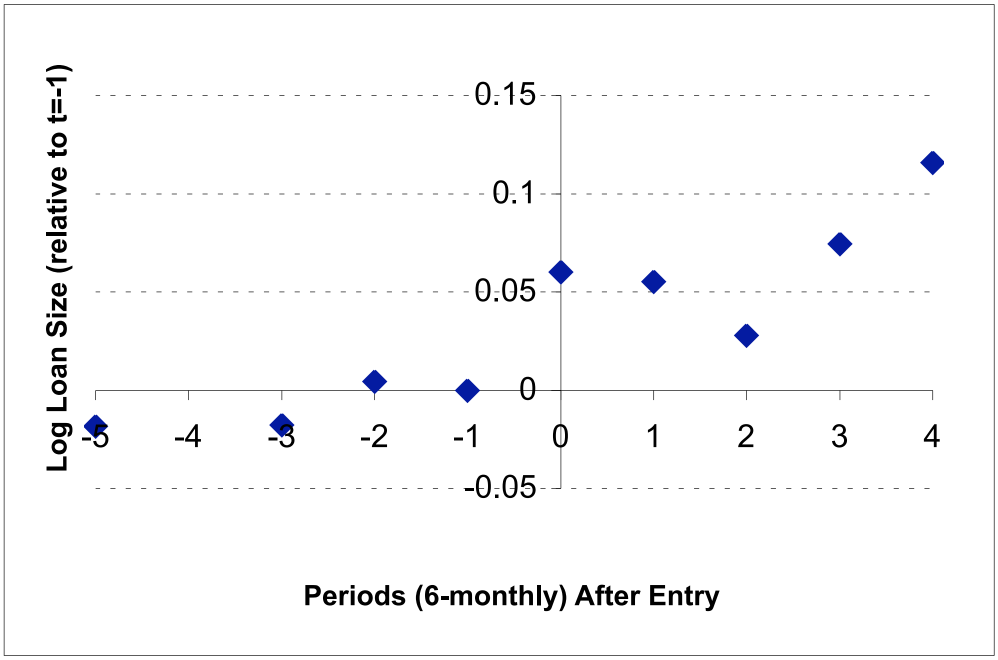

Figure IVa. Log loan size (relative to t=-1) against periods (6-month) after entry. This figure depicts what happens to the log of total firm credit from the banking sector as a firm gains entry into the super-network. We follow the same firm over time, and take out economy wide aggregate shocks (at industry and size level) by taking out firm and time interacted with sector fixed effects.

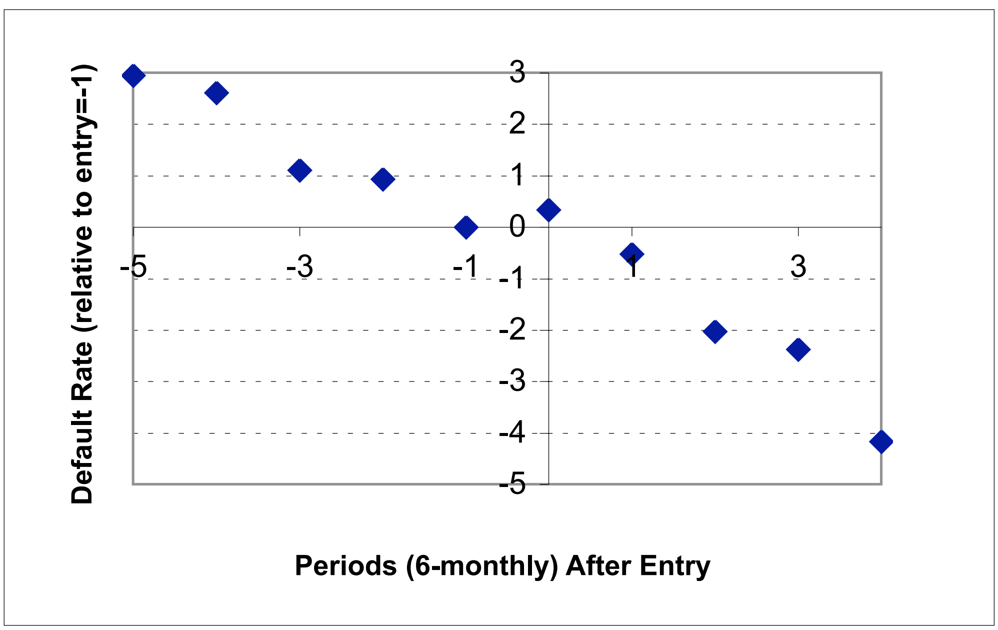

Figure IVb. Default rate (relative to t=-1) against periods (6-month) after entry. This figure depicts what happens to the default rate of a firm as it gains entry into the super-network. We follow the same firm over time, and take out economy wide aggregate shocks (at industry and size level) by taking out firm and time interacted with sector fixed effects.

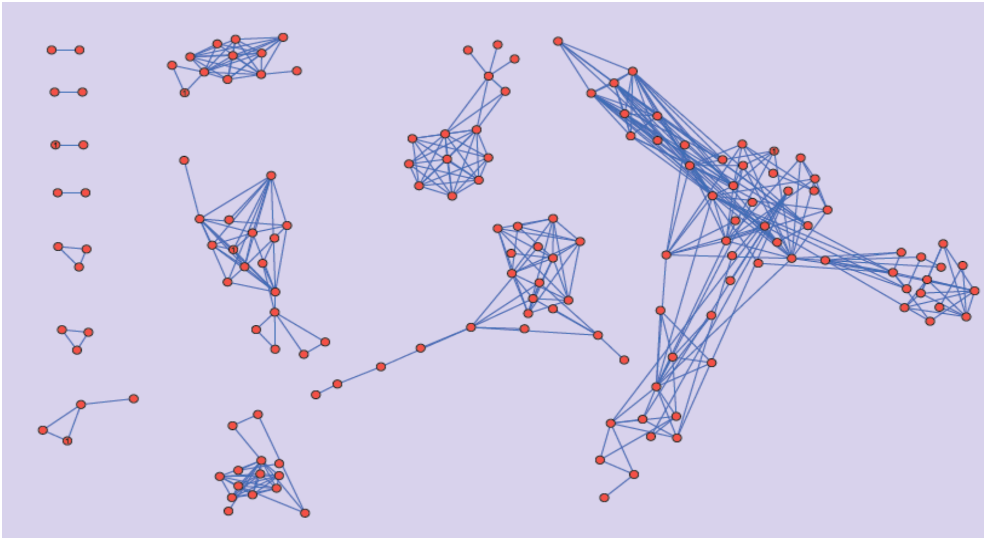

Figure Va. Sample structures of In-out firms when not in the super-network. This figure shows that firms are often part of smaller networks before joining the super-network.

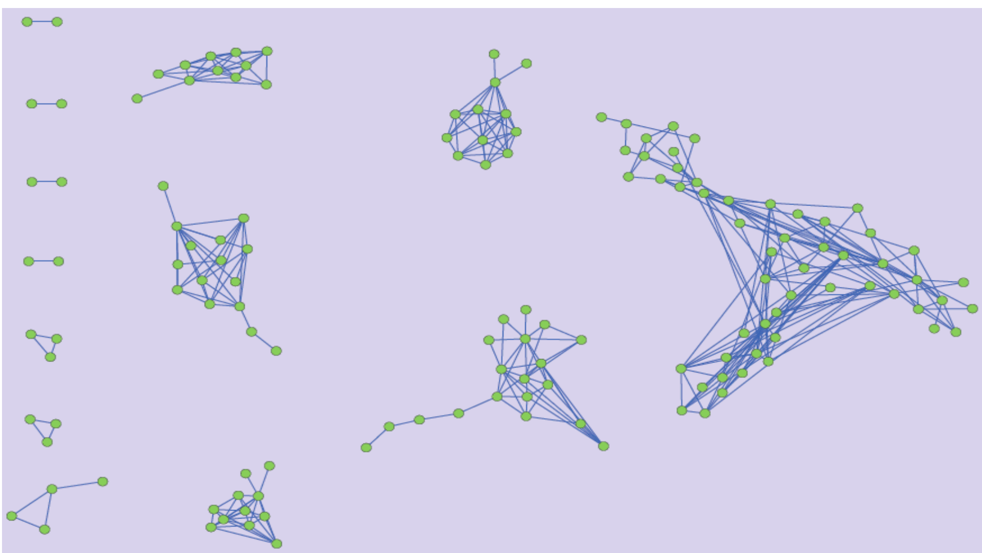

Figure Vb. Sample structures of Other Network firms. This figure shows some sample structures of firms which are in networks other than the super-network, and which never join the super-network.

Table I

Summary Statistics

This table presents statistics based on firms' connection to the super-network. In Panel A, we break firms into four categories: (1) Firms that are always in the super-network; (2) In-out firms which are in the super-network for some period of time in our sample, but not during all eight 6-month periods; (3) Other network firms which are never in the super-neteork but which do share directors with other firms; and, (4) Non-network firms which never share directors with any other firms. In Panel B, we examine how different measures of firm power change for firms moving in and out of the super-network. Measures of power include the number of neighbours a firm has, the number of these neighbours' directors, the number of lenders these neighbours have, the firm's own Google rank, and the average Google rank of the firms' neighbours (the Google rank is a power measure we construct based on the Google Pagerank algorithm).

Panel A: Statistics by Firm Type

			Log Loan Size		Default Rate		Initial Borrowing (000s)	
Firm Type	Number of Firms (Total = 105,917 firms)	%age of Total Bank Credit	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Super-Network - Always In	2,838	45%	9.59	3.11	10.97	28.32	191,143	1,021,052
Super-Network - In-out	2,457	20%	8.50	2.86	17.87	35.44	81,396	478,366
Other Network Firms (in networks of size 2 to 85)	34,482	21%	7.24	2.47	16.91	35.16	9,386	66,847
Non-Network Firms	66,140	15%	6.52	2.13	28.13	40.30	3,969	79,609

Panel B: Firm Power Measures

	Mean	St. Dev.
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
Google Rank of Neighbours When In	1.61	1.17
Google Rank of Neighbours When Out	0.83	0.62

Table II
Effect of Network Entry on Total External Borrowing

This Table shows the effect of network membership on firm borrowing. Dependent variable is log of firm borrowing, and sample is restricted to non-defaulting firms. Data in Columns (1)-(2), and Columns (5)-(7) include all firms in sample. Columns (3)-(4) replicate Columns (1)-(2) in the restricted sample of firms that move in and out of the super-network. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Basic" fixed effects are firm and time fixed effects. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not. "Direct Entrants" are firms that enter the super-network directly, i.e. either one of their directors starts to sit on the board of a super-networked firm, or a super-networked director starts to sit on its board.

	(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 Entrant/Exitor)						0.126	0.126
						(0.085)	(0.085)
Fixed Effects	Basic	Expanded	Basic	Expanded	Expanded	Expanded	Expanded
Observations	286,034	286,034	12,053	12,053	286,034	286,034	286,034
R-squared	0.59	0.60	0.44	0.36	0.60	0.60	0.60

Table III

Effect of Network Entry on Firm Financial Distress

This Table shows the effect of network membership on firm financial distress. Dependent variable is default rate. Columns (1) and (2) use the full sample of firms, while Columns (3)-(4) replicate Columns (1)-(2) in the restricted sample of firms that move in and out of the super-network. The number of observations reduces in Columns (5) and (7) because of the inclusion of lagged growth which is by construction missing for firms in their first period of data. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Basic" fixed effects are firm and time fixed effects. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not. "Direct Entrants" are firms that enter the super-network directly, i.e. either one of their directors starts to sit on the board of a super-networked firm, or a super-networked director starts to sit on its board.

	(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)
Lagged Default Rate Growth					0.167***		0.167***
					(0.004)		(0.004)
InNetwork * (Direct Entrant/Exitor)						-0.284	-0.218
						-0.702	-0.807
Fixed Effects	Basic	Expanded	Basic	Expanded	Expanded	Expanded	Expanded
Observations	397,416	397,416	15,043	15,043	254,576	397,416	254,576
R-squared	0.86	0.86	0.1	0.002	0.86	0.86	0.86

Table IV

Alternative Network Definitions

This table shows the robustness of the network membership effect to different definitions of network construction. Specification A excludes all government directors. Specification B uses a network definition that excludes directors who do not own equity in their firms. Specification C examines networks where links are made between firms only if they have two or more directors in common. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not.

	Specification A		Specification B		Specification C	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log Loan	Default Rate	Log Loan	Default Rate	Log Loan	Default Rate
InNetwork	0.143***	-1.582***	0.184***	-1.414***	0.334***	-1.903***
	(0.042)	(0.353)	(0.045)	(0.363)	(0.057)	(0.512)
Constant	6.543	16.47	6.546	16.438	6.545	16.442
	(0.022)	(0.161)	(0.022)	(0.161)	(0.022)	(0.161)
Fixed Effects	Expanded	Expanded	Expanded	Expanded	Expanded	Expanded
Observations	286,095	397,416	286,407	397,416	286,452	397,416
R-squared	0.60	0.86	0.60	0.86	0.60	0.86

Table V

Decomposing the Effect of Network Entry on External Borrowing

This Table decomposes the effect of network entry on bank credit. Column (1) considers the intensive margin and looks at average loan size from 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) test whether new credit is disproportionately coming from government or private banks. Column (5) tests how much of a firm's additional credit when it enters the network comes from new lenders that are its neighbour firm's lenders. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not.

	(1) Average Loan Size	(2) Total number of creditors	(3) %age credit from government banks	(4) %age credit from private banks	(5) New Credit Share from Neigbours' Lenders
InNetwork	0.139***	0.137***	-0.014***	0.025***	0.120***
	(0.041)	(0.018)	(0.003)	(0.005)	(0.005)
Constant	6.412***	1.041***	0.294***	0.51***	0.211***
	(0.021)	(0.004)	(0.002)	(0.002)	(0.005)
Fixed Effects	Expanded	Expanded	Expanded	Expanded	Expanded
Observations	286,034	286,034	286,034	286,034	30,065
R-squared	0.57	0.86	0.9	0.86	0.88

Table VI

Heterogeneity in Network Benefit by "Power" of Connection

This Table examines heterogeneity in the network impact on a firm's borrowing. Dependent variable is log of firm borrowing. Each column examines how the network value differs depending on the (standardized) measure of a firm's "power" that is used (each measure is calculated when the firm is in the network and then when it is out of the network separately). Column (1) uses the number of neighboring firms one is directly connected to. Column (2) uses the number of directors one has direct access to. Column (3) looks at the total number of creditors the neighbors of a firm have access to. Column (4) is the firm's own Google rank. Column (5) is the average Google rank of the firm's neighbors. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not.

	(1)	(2)	(3)	(4)	(5)
InNetwork (IN)	0.18***	0.179***	0.174***	0.177***	0.178***
	(0.043)	(0.043)	(0.042)	(0.042)	(0.042)
IN * # Neighbors When In	0.099**				
	(0.040)				
IN * # Neighbors When Out	-0.045				
	(0.041)				
IN * # Neighbors' Directors When In		0.075***			
		(0.027)			
IN * # Neighbors' Directors When Out		-0.074*			
		(0.043)			
IN * # Neighbors' Lenders When In			0.077**		
			(0.038)		
IN * # Neighbors' Lenders When Out			-0.133		
			(0.043)		
IN * Google Rank When In				0.167***	
				(0.043)	
IN * Google Rank When Out				-0.138***	
				(0.045)	
IN * Avg. Google Rank of Neighbors When In					0.021
					(0.043)
IN * Avg. Google Rank of Neighbors When Out					-0.148***
					(0.043)
Fixed Effects	Expanded	Expanded	Expanded	Expanded	Expanded
Observations	286,034	286,034	286,034	286,034	286,034
R-squared	0.6	0.6	0.6	0.6	0.6

Table VII

Heterogeneity in Network Benefit by "Power" of Connection

This Table examines heterogeneity in the network impact on a firm's borrowing. Dependent variable is default rate. Each column examines how the network value differs depending on the (standardized) measure of a firm's "power" that is used (each measure is calculated when the firm is in the network and then when it is out of the network separately). Column (1) uses the number of neighboring firms one is directly connected to. Column (2) uses the number of directors one has direct access to. Column (3) looks at the total number of creditors the neighbors of a firm have access to. Column (4) is the firm's own Google rank. Column (5) is the average Google rank of the firm's neighbors. Robust standard errors are in brackets with * significant at 10%; ** significant at 5%; and *** significant at 1%. "Expanded" fixed effects include firm and time fixed effects, as well as size decile, industry, and firm city location fixed effects, all interacted with time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not.

	(1)	(2)	(3)	(4)	(5)
InNetwork (IN)	-1.605***	-1.578***	-1.588***	-1.577***	-1.631***
	(0.351)	(0.350)	(0.350)	(0.352)	(0.351)
IN * # Neighbors When In	0.22				
	(0.349)				
IN * # Neighbors When Out	-1.028***				
	(0.342)				
IN * # Neighbors' Directors When In		0.093			
		(0.376)			
IN * # Neighbors' Directors When Out		-1.384***			
		(0.381)			
IN * # Neighbors' Lenders When In			0.554*		
			(0.307)		
IN * # Neighbors' Lenders When Out			-1.334***		
			(0.381)		
IN * Google Rank When In				-0.308	
				(0.367)	
IN * Google Rank When Out				-0.808**	
				(0.383)	
IN * Avg. Google Rank of Neighbors When In					-0.628**
					(0.354)
IN * Avg. Google Rank of Neighbors When Out					-1.231***
					(0.374)
Fixed Effects	Expanded	Expanded	Expanded	Expanded	Expanded
Observations	397,416	397,416	397,416	397,416	397,416
R-squared	0.86	0.86	0.86	0.86	0.86

Table VIII

Networks and Insurance

This Table considers evidence for insurance benefits provided by network membership. The dependent variable is, for each column, the firm's own default rate. For each column, we examine how default rates covary with industry and city cohorts during common shocks. Columns (1)-(2) consider the full time-series data. Column (1) looks at the overall insurance effect for firms that are ever in the super-network. Column (2) separately estimates the insurance impact on the super-network firms that enter/exit the network during our data period. Column (3) repeats Column (2) but restricts the sample to the periods for which we have directorship information. This is done in order to be able to compare the results to those of Column (4) in which we examine how network insurance varies for a firm when it is in the network, 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%. "Basic" fixed effects are firm and time fixed effects. "InNetwork" is a dummy variable equal to one if a firm is in the super-network and equal to zero if a firm is not.

	(1)	(2)	(3)	(4)
City Default Rate	0.558***	0.545***	0.607***	0.607***
	(0.006)	(0.006)	(0.006)	(0.006)
Industry Default Rate	0.633***	0.553***	0.514***	0.516***
	(0.012)	(0.012)	(0.019)	(0.019)
City DR * Super-network Firm	-0.564***			
	(0.020)			
Industry DR * Super-network Firm	-0.505***			
	(0.021)			
City DR * In-out Super-Network Firm		-0.424***	-0.348***	-0.311***
		(0.030)	(0.045)	(0.049)
Industry DR * In-out Super-Network Firm		-0.394***	-0.051***	-0.075***
		(0.031)	(0.062)	(0.065)
InNetwork				0.015
				(0.015)
InNetwork * City DR * In-Out Super-Network Firm				-0.139***
				(0.053)
InNetwork * Industry DR * In-Out Super-Network Firm				-0.006
				(0.048)
Controls	City DR and Industry DR interacted with "Other-network Firm" separately.	City DR and Industry DR interacted with "Other-network Firm", and "Super-networked always in firm" separately.	City DR and Industry DR interacted with "Other-network Firm", and "Super-networked always in firm" separately.	City DR and Industry DR interacted with "Other-network Firm", and "Super-networked always in firm" separately.
Fixed Effects	Basic	Basic	Basic	Basic
Observations	1,315,562	1,315,562	973,839	973,839
R-squared	0.76	0.76	0.83	0.83