

# The Value of Business Networks

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## Abstract

Developing countries are marked by the prevalence of informal business networks. Many believe that these networks facilitate information sharing, trade, and contractual enforcement in weak institutional environments. However estimating network benefits remains difficult due to data limitations, and identification concerns. This paper uses ownership data on all (but the very small) private firms in Pakistan to construct business networks involving 100,000 firms. We link two firms together if they have a director in common, and document the presence of a super-network in the economy. It comprises 5% of all firms, is over a 100 times larger than the next largest network and obtains more than half of all bank credit. We then investigate the economic value that membership to the super-network brings by exploiting entry (exit) of firms over time into the network. We identify the causal effect of network membership through a number of tests, including instrumenting network membership with “incidental” entry / exit of firms. 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. When forming new banking relationships, entering firms are also more likely to select banks that already have existing relationships with adjoining firms. We also find that consistent with theories of strategic network development, benefits of memberships are stronger when firms connect through more powerful network nodes.

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A distinguishing feature of economic organization in emerging markets is the importance of networks and informal contractual arrangements. It has long been remarked that networks offer a substitute to missing markets, and bring value to network members by providing access to factors of production that they would not otherwise get (Leff 1976, 1978, and 1979).

However, despite the ubiquitous nature of business networks in emerging markets, we continue to lack a clear understanding of how extensive such networks are, and what value they bring to networked firms.<sup>1</sup> The first hindrance is the availability of relevant data. Most data sets in emerging markets cover only publicly listed companies. Since private firms form an overwhelming majority of business enterprises, missing information on private firms precludes a meaningful analysis of business networks. Second, networks - particularly business networks - are the cumulative result of strategic choices that firms make when forming relationships. Endogenous entry into networks implies that one must be careful in separating the causal effect of networks from the possibly spurious effect of networks absorbing firms with certain unobserved characteristics. Finally, as network theory repeatedly points out, network benefits can depend critically on *where* in the network one is connected to. Therefore one needs measures of intra-network strength (such as the power of a node) to test some of the more detailed predictions of network theory.

This paper uses a data set that attempts to overcome some of the above hurdles in investigating the value of networks. The data set comes from the central bank of Pakistan, and includes information on a firm's borrowing from the banking sector, and its default history. It covers the universe of all - but the very small - private firms in Pakistan, and contains information on the identity of each firm's set of directors. We adopt a commonly used definition of networks, i.e. inter-locked boards, and construct links between firms to generate a spatial networks of over 100,000 firms. Furthermore, we can follow *changes* in these networks at six-monthly frequency over a period of 4 years, enabling us to track network entry and exit of firms.

The networks formed through inter-locked boards reveal a striking result. There is a single powerful "super-network" that comprises over 5,000 firms and borrows over 55% of aggregate bank credit. The structure of this super-network is very stable, and robust to a number of checks such as link definitions, and exclusion of certain types of firms and directors. The super-network is so dominant, that the next largest network is almost one-hundredth its size.

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<sup>1</sup>The literature on business groups (Khanna et. al.) does highlight related aspects but even this literature does not get at the more diffuse networks of business relations and is mostly restricted to looking at large/public firms.

We focus our attention on the super-network and investigate whether this network brings any real value to its member firms in terms of access to external finance. The primary concern here is that network entry is endogenous, and differences between networked and non-networked firms, particularly in the cross-section, might be driven by spurious unobserved firm characteristics.

We therefore exploit the time-series dimension, and look at what happens to the same firm over time as it enters or exits the super-network. While the time-series approach controls for any time-invariant differences across networked and non-networked firms, there remains the worry that entry (or exit) of a firm is correlated with unobserved (time-varying) firm attributes that independently influence a firm's access to finance. For example, growth firms with greater propensity to increase borrowing in the future may also be more likely to join an existing business network.

We address such concerns of firm-specific time-varying determinants of network entry (or exit) in three steps. First, we match firms by size, industry and location to take out time trends. Second, we look at pre-entry trends to see if firm entering the network were already on an upward trajectory (and vice versa for firms exiting the network). Finally, concerns about spurious selection of firms into a network are greater for firms that directly link to the network. We therefore separately estimate the network effect for the sub-set of firms that *indirectly* join the network. These are firms that enter the super-network *not* because of any changes in their board of directors, but because of changes in the board of directors of a neighboring firm that they were already linked to. We refer to such firms as “incidental” entrants and exitors.

We find that network entry significantly improves credit access and performance. Network membership generates an increase in bank credit of 16.6%, and a decrease in the propensity to enter financial distress of by 1.7 percentage points (or by 9.7% of the base default rate). Network benefits are generated both through the intensive and extensive margin - firms not only increase their average borrowing but are also able to access new banks, particularly those banks which are creditors of one of the firms they are directly connected to in the super-network. The result is not driven by time-varying size, industry or location effects, and the estimated network benefits appear sharply *post* network-entry. They are also robust to instrumenting network entry / exit with incidental entry and exit.

These series of tests strongly suggest the presence of network benefits in terms of better access to external finance. This conclusion receives further support when we investigate whether network

benefits depend on the power of the connecting node within the network. Power can be measured by a firm's number of direct links to other firms within the network, the strength of these neighbor firms (in terms of the number of directors and creditors they have), and the average link quality (in terms of the overall borrowing and default rates of their neighbor firms). We find that network benefits in terms of loan access are larger when entrants link to nodes that are more powerful along all these dimensions.

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

Our results on lower default rates for firms that join the network already suggest that the value networks may generate is real. This is particularly relevant given that related work in Pakistan (Khwaja & Mian 2005) shows that politically connected firms obtain rents by being able to default on their loans. Moreover, our results show that once firms enter network, not only are they more likely increase private creditors as compared to government lenders, but their total borrowing share from the former increases. Given that government banks in the Pakistani context are likely to be more inefficient and rent-providers (see Khwaja & Mian 2005 and Mian 2006), this further strengthens the view that networks add real value. Relatedly, we also find that firms in super network are also less volatile and better insured against macro shocks and this insurance increases when these firms enter the super network.

Our results show that in addition to what one normally thinks of as business groups – a closely coordinated group of firms – more loosely yet very stably knit firm networks also play an important role in emerging economies. Not only are such networks robust and prevalent, but they generate large and real value for member firms.

# I Related Literature

The analysis of networks in economics has largely been theoretical thus far (see Jackson 2004 for an excellent summary). In contrast, sociologists have devoted a lot more energy to the study of networks and their impact on individual and social decision making. Granovetter (1985) coined the term “embeddedness” to reflect that economic behavior can be so constrained by social relations, such as networks, that viewing it in the neoclassical tradition of anonymous self-interested agents would be misleading. Unlike the traditional market based analysis where decentralized prices govern everything, an analysis embedded in networks pays a lot more attention to whom you are linked to, even if such relationships hold no legal or formal authority.<sup>2</sup>

Sociologists have been documenting the prevalence of networks in a wide range of social situations. For example, Sorensen and Stuart (2004) describe networks in entrepreneurship in the US, Strachan (1976) provides one of the best sources on business networks in Latin America, and White (1974) gives an account of the origins of business groups in Pakistan.

However, there has been very limited empirical work among economists that looks at the effect of networks on economic outcomes. Grief (1993) examined the role that networks of traders played in overcoming barriers to international trade such as weak international legal system and informational asymmetries. Feenstra et al (1999) find that networks matter for explaining differences in quality and variety of exports across South Korea, Taiwan and Japan. Hoshi, Kashyap and Scharfstein (199?) show the importance of networked firms in getting access to credit in Japan. Hochberg et al (2007) show that better-networked VC funds are correlated with better performance. However, all of this literature involves a cross-sectional comparison of firms, and the concern is that unobserved firm attributes might determine both entry into the network as well as firm performance.

An important contribution of our work relative to existing literature is that we explore the benefits of networks in a sample that represents the entire economy over time. This enables us to pay particular attention to identification by focusing on the entry and exit of same firm from a network over time, and isolating “incidental” entrants and exitors that are less susceptible to concerns of spurious correlation.

Second, as Rauch and Hamilton (2001) point out in their recent review of literature on networks, some of the richer elements of the sociology of networks remain unexplored by economists. For example, certain nodes in the network are likely to be more important as centers of power than others (referred

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<sup>2</sup>This distinction between network and market-based analysis is also made by Podolny and Page (1998) among others.

to as “structural holes” by Burt (1992)). Similarly, not all network links are equivalent as they can differ in quality and strength (e.g. Granovetter 1973). Economic theorists have highlighted very similar predictions as well (see e.g. Jackson and Wolinsky (1996), Johnson and Gilles (2000), Belleflamme and Bloch (2002), Calvo-Armengol and Jackson (2001), Kranton and Minehart (2002)). However, there is no empirical work that tests whether such intra-network variation in node and link-strength is relevant for economic outcomes.

Our use of inter-locked directorates to define networks has a long tradition among social scientists (e.g. Mintz and Schwartz 1985; Stokman et al. 1985; Scott 1987). Similarly our focus on access to finance as one of the important benefits of networks is in-line with a number of historical studies that have suggested the same (see e.g. Leff 1978 and Lamoreaux 1986 on the importance of networks in accessing credit in early American history).

## II Defining Business Networks

### A. Data

We use two new data sets in this paper. The first has directorship information for all borrowing firms in Pakistan from 1999-2003 and the second has detailed loan level information for all corporate loans given out by banks in Pakistan from 1996 to 2003. Both data sets were provided by the Credit Information Bureau (CIB) at the State Bank of Pakistan (SBP). We describe each of these below:

#### (i) Board of Directors Information

The Credit Information Bureau maintains a list of the board of directors of all firms borrowing at any given period from any formal lending institution. Our data consists of all such firms borrowing from 1999 to 2003 at a frequency of every six months and represents the universe of all firms borrowing from the formal financial sector during this 4 year period. This database uniquely identifies each firm by a specific code allowing us to match firms over time and to the loan level database. However, we should note that unlike firms, board of director members are not given a unique code and therefore an important part of our analysis was to first identify unique directors in the database. With hundreds of thousands of names in the data set, this is not a trivial task.

The database provides the full name, national identification card (NIC) number and full father’s

name for every board of director of the firm and this allows us to also uniquely identify directors over time and across firms. In order to do so we utilize an algorithm that identifies directors by first exactly matching on the NIC number of the director since this number does not suffer from the usual spelling variation common when Urdu names are recorded in English. In case the NIC numbers do not match, we ensure that the two individuals are not classified as the same (even if their names match). However, in case the NIC number information is missing or obviously incorrect (i.e. is not of the required length and format etc.), we then match individuals if both their full name and father's (or husband as the case may be) full name matches exactly. Finally, if two individuals are reported as directors for the same firm (over time), we also allow for a looser match by matching on the director's full name alone. Given this strict match algorithm it is more likely that we will under-match rather than over-match and therefore we may overestimate the total number of distinct directors in the sample or more pertinent to our analysis, may underestimate the extent of board interlocks amongst firms in the economy. However, we have conducted robustness exercises using different matching algorithms to identify unique directors and our analysis remains robust to doing so.

In addition the database provides information on the percentage of firm equity the directors' own. This data provides us with a total of 139,526 unique borrowers and after we have carried out our director matching algorithm, 261,069 unique directors.

## **(ii) Firm Borrowing Information**

The loan-level data is unique both in terms of its coverage, and detail. We have quarterly information on every firm borrowing from the banking sector in Pakistan. The data is at the level of the loan (firm-bank pair) and traces the history of lending with information on the amount of the loan (principal and interest) outstanding by different loan types (fixed, working capital, etc.), and default amounts.

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. CIB was part of a large effort by the central bank to setup a reliable information sharing resource that all banks could access. Perhaps the most credible signal of data quality is the fact that all banks refer to information in CIB on a daily basis to verify the credit history of prospective borrowers. For example, we checked with one of the largest and most profitable private banks in Pakistan and found that they use CIB

information about prospective borrowers explicitly in their internal credit scoring models. We also ran several internal consistency tests on the data such as aggregation checks, and found the data to be of high quality. As a random check, we also showed the data from a particular branch of a bank 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. To do so, we define firm links based on whether two firms share a common director or not (i.e. a board interlock). A firm network is the set of firms that are connected to each other through such inter-locked boards. Figure I illustrates the hypothetical construction of a network where each link represents a common director between two firms (the number on the link indicates the number of shared directors if there are more than one). This example considers an economy with 8 firms, firm A to H, and a total of 15 directors, director 1 to 15. Linking firms if they share a director produces two distinct networks in the economy and two firms, G and H, that are not connected to any one else (i.e. form a singleton network). Note that even though the four firms A through D are in one network, they are not all directly connected to each other. While firms A, B and C are all linked to one another (although through different directors), firm D is only linked indirectly to firms A and B through its direct link to firm C. Larger networks may be linked through even longer chains of such indirect links.

Firms within a network may also vary by how “important” they are in the network. Thus firm C is important in the network because it has the most number of firm’s directly connected to it. Similarly, firm links may vary in their “strength” such as the number of common directors. Thus while the network of firms A through D is larger, the two firm network of firms E to F may be “stronger” in the sense that these two firms share three directors. Moreover, networks may differ in their shapes from “totally connected” networks where all firms are connected to each other (a two firm network like that of firms E and F is by definition totally connected) to a “star” shaped network where all firms in the network are connected (only) through one crucial firm (had firm A and B not been connected directly, our four firm network would have been a “star” network). We will make use of such attributes and structures in analyzing networks in our data.

Figure II illustrates the distribution of firms across the different network sizes. Almost two-thirds of the firms in the data are not linked to any other firm and the other third are a member of some

network. One interesting fact is the distribution of the networks. While, most of the networks have between 2 and 100 firms, there is one “super-network” composed of 7102 firms. In comparison, the second largest network is only formed by 85 firms.

Another interesting fact is how total lending is distributed across the single - i.e. non-networked - firms and the networked firms. While single firms represent 64% of total firms in our sample, they account for only 20% of total lending. On the other hand, the super network, formed by 5% of total firms, borrows 55% of total lending! The economic significance of the super network is clearly substantial.

The super-network is robust to a number of sensitivity checks. For example, the super-network is not driven by a few “universal directors” who sit (nominally) on the boards of many firms concurrently. Such directors may exist if government or large creditors automatically get a few seats as board of directors. The super-network is also robust to the exclusion of directors who do not hold equity in the firm. Therefore our network definition can also be viewed as equivalent to common ownership definition.

We also get similar patterns (i.e. the emergence of a dominant super network) if we make the definition of “links” stricter and only connect two firms if they have *two* directors in common. The super-network is also very stable over time, and does not change much if we remove firms with the most number of links. The latter result shows that super-network is not driven by a few “star nodes” to which everyone else is connected. Instead the connections within the super-network appear quite diffused. These robustness tests are described in the appendix (for more detail see Khwaja, Mian Qamar 2005).

### III Empirical Methodology

Given the dominance of super-network in our data both in terms of aggregate lending going to it, and also in terms of the size of the next largest network, we restrict our analysis of network benefits to firms that are part of the super-network at some point.

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

While there is a burgeoning literature on how networks form, survive and evolve over time (see

Jackson 2004 for an excellent review), a full model of network formation is beyond the scope of our paper. Instead we take the  $n$ -node network as given, and estimate the impact of network membership on the *marginal* firm joining the network. The purpose of sketching the conceptual framework is to illustrate the empirical identification concerns and how we attempt to deal with them.

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

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

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

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

Since we will be concerned with potential identification issues arising from  $\pi_{it}$  in estimating the value of networks, we focus on productivity dynamics. Consider the evolution of  $\pi_{it}$  to be determined by a random walk process where each firm starts with a firm specific productivity  $\bar{\pi}_i$  in period 0, and then evolves according to  $\pi_{it} = \pi_{i,t-1} + \nu_{it}$ .

Equation (1) illustrates the difficulty in identifying the direct benefits of network entry for firm  $i$ . Let  $Y_{it}$  reflect some measure of firm performance 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:

$$Y_{it} = \alpha + \beta_1 ENTRY_{it} + \varepsilon_{it} \quad (2)$$

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  $\beta_1$  is that outcomes  $Y_{it}$  are likely to depend on not only network membership,  $ENTRY_{it}$ , but also firm productivity,  $\pi_{it}$ . Since  $ENTRY$  itself is a function of  $\pi_{it}$  through equation (1), we have the traditional simultaneity problem.

To the extent that one can observe  $\pi_{it}$ , one could directly control for it in (2). While we will do so,  $\pi_{it}$  can admittedly reflect many attributes. For example, it may signify the efficiency with which a firm translates inputs into output, or it may signify the ability of a firm to get cheap inputs through an economic, political, or strategic advantage. However, in this case the simultaneity problem can still be avoided if we identify  $ENTRY$  using the incidental factors  $x_{it}$  in a firm's hazard rate, rather than the variation driven by firm productivity,  $\pi_{it}$ .

We therefore both utilize non-parametric controls and also directly construct “incidental” reasons for joining the network. The non-parametric approach first includes firm fixed effects,  $\alpha_i$ , in (1). Firm fixed effects absorb any time-invariant productivity differences across firms (i.e.  $\bar{\pi}_i$ ), and force comparisons within the same firm over time. While firm fixed effects take care of any beginning of sample differences in firm productivity, one may be concerned that firms differ along time-varying productivity shocks as well. While we cannot include firm interacted with time fixed effects since that would leave no variation, we can non-parametrically allow for firm-*type* specific time trends, where firm type is firm location, size decile and industry. We do so by including time interacted with firm types dummies in (2).

However, one may still be concerned that  $\beta_1$  can still be biased due to the idiosyncratic firm-specific permanent shocks,  $\nu_{it}$ , to productivity. For example, a given firm is more likely to join a network when it receives a positive permanent shock to its productivity. Since the positive shock to productivity independently increases outcome  $Y_{it}$  as well,  $Y_{it}$  and  $ENTRY_{it}$  can be spuriously correlated even for the same firm over time.

Given the specific firm productivity dynamics we introduced, *conditional* on entry in period  $t$ , a firm is more likely to have had a positive sequence of permanent shocks in the past (relative to the

firm fixed effect of productivity that is already absorbed out). Thus one can test whether  $\beta$  is driven by the permanent shock to firm productivity by including lagged values of  $Y_{it}$  and checking if  $\beta_1$  drops substantially. Intuitively, if firms on an upward trajectory are more likely to join the network then the outcome of interest should be on an upward trajectory even prior to the firm joining the network. Alternatively, if networks have a direct effect on the outcome then we should expect a sharper increase in outcome *post* entry.

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

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

where  $\alpha_i$  and  $\alpha_{kt}$  are firm and firm-type ( $k$ ) interacted with date fixed effects. The firm types are size decile, location, and industry.

Finally, we also construct an instrument that tries to mimic firm entry due to exogenous shocks denoted by  $x_{it}$  in (1). There are two distinct ways in which a firm can enter the network: One of its directors can sit on the board of a networked firm (or vice versa), or the firm’s board and directors experience no change but one of the firm’s non-networked neighbor firm connects with the network. We classify the former as *direct entrants*, and latter as *incidental entrants*. The incidental entrants are *not* joining the network because of a direct change in their board members or a direct act by one of their directors. One can therefore plausibly argue that shocks to the productivity of an incidental entrant are not responsible for network entry. Since we include firm fixed effects and define a firm as an incidental only if all its entries/exits were incidental, this instrumentation strategy is equivalent to separately estimating the impact of network entry separately on the incidental entrants.

Since network theory generates predictions that the value generated by a network depends on the “strength” of a connection, we also present further specifications which allow for such heterogeneity. Specifically, we estimate:

$$Y_{it} = \alpha_i + \alpha_{kt} + \beta_1 ENTRY_{it} + \beta_2 ENTRY_{it} * X_i + \varepsilon_{it} \quad (4)$$

where  $X_i$  is a variety of measures of the (average) strength of a firm’s connections when it is in. The strength measure include the number of neighbors a firm has, the numbers of directors and lenders these neighbors have.

## IV Estimating Network Benefits

Since our estimation strategy outlined above explores entry and exit of firms over time, we exclude the very small firms from our analysis as time-series data is very noisy for these firms (e.g. repeatedly going from zero to positive borrowing amounts and vice versa). We therefore drop firms with less than Rs.500,000 (~US \$8,500 ) of borrowing at the beginning of our sample period, and are left with a total sample of 105,917 firms.

Table I provides the summary statistics for our main sample of firms. 5,295 firms belong to the largest super-network, and account for two-thirds of total bank credit within this sample. 2,838 of the super-networked firms always remain part of their network during our sample period. The remaining 2,457 firms are out of the super-network at some point during the sample, and thus have the necessary time-series variation that we need to identify the benefit of network membership.

The remaining 100,622 firms are never part of the super-network. 66,140 of these are stand-alone firms that do not share a director with any other firm, while the remaining 34,482 firms are part of much smaller networks as described in the network description section. While our coefficient of interest on network benefits is identified off of the sample of firms that go in and out of the super-network over time, we keep the rest of the firms in sample as well to control for economic shocks at various levels such as time, industry, firm size and firm location.

Panel A in Table I shows that firms that are part of the super-network are on average much larger than firms outside the network. Firms within the super-network also tend to be much better in terms of financial default, particularly those that are permanently part of the network during our sample period. Such large differences between super-networked and other firms strongly suggest that selection into the network systematically depends on firm characteristics and that such selection must be taken seriously into account when estimating the direct benefits of network membership.

Panel B presents summary statistics for various measures of node and link strength that we use in this paper. The simplest is the number of other firms that a firm is 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. We also measure a connecting node's strength by aggregating the total lending going to the firms connected to that node.

### A. *Effect on External Finance*

Column (1) of Table II estimates (3) with only firm and date fixed effects. The dependent variable is log of total external credit of a firm. The sample size is restricted to non-defaulting firms. Moreover, the sample is forced to be balanced by imputing 0 borrowing by a firm if it does not enter in our database in a given time period.

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 (Table I) is much larger, 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) then adds size decile, industry, and firm city location fixed effects, all interacted with time fixed effects to completely absorb shocks at the size, industry or location level at any point in time. The estimated effect of network entry increases with the inclusion of these controls.

Column (3) supplements column (2) by including lagged values of firm external borrowing. This addresses concerns arising from network entry of firms that simultaneously experienced a positive productivity shock. The small though positive sign on lagged borrowing does suggest that firms that passed borrowing does positively influence a firm's ability to borrow more in the future. Column (4) allows for more extensive past history effects by including two (six monthly) period lags as well. The effect of network entry remains qualitatively unchanged.

The coefficient of interest on network entry in Table II is being identified off of the firms that actually change their network membership during our sample period. There are 2,457 such firms. Column (5) makes this explicit by firm demeaning the data using all of the fixed effects in column (2), and then estimating the network entry effect on the demeaned data, using only the 2,457 firms that change network membership status. Column (6) includes firm-type interacted with tie fixed effects and shows that the results are robust even when allowing for type specific time shocks even in the restricted sample.

The inclusion of firm fixed effects; size, industry and location interacted with date fixed effects; pre-entry growth trends provides strong evidence that the results of Table II can be plausibly attributed to a causal effect of network entry on firm external financing. We will provide further evidence to support this later, but first we test if network entry also leads to better firm performance, as proxied

by the propensity to enter financial distress.

### *B. Effect on Firm Performance*

Table III replicates all of the columns of Table II, except that the dependent variable is firm default rate rather than total external credit. The number of observations in Table III is larger because now (by definition) we include observations that are currently in default, whereas Table II only included observations that were not currently in default (since we were interested in measuring active current borrowing of a firm).

Column (1) estimates the basic specification with firm and time fixed effects and shows that firms reduce their propensity to enter financial distress by about 1.7 percentage points once they enter the network. Given the base default rate for firms that enter or exit the network, the drop in financial distress represents about a 9 to 10 percent improvement. Column (2) controls for shocks at the size, industry or location level at any point in time and shows little change in the estimates.

Columns (3)-(4) supplement column (2) by including lagged values of firm default rates. Note that while the coefficient on a firm being in the network does drop to 1.1 percentage points, it is still highly significant. The drop is not surprising if one considers that once a firm defaults on a loan it is likely that this default increases in the near future.<sup>3</sup> In other words, such negative productivity shocks, even if isolated, are likely to have continued impacts for the next few periods.

Columns (5)-(6) restrict to the sample of firms that actually change their network membership during our sample period and show, as expected, that the results hold in this sample.

### *C. Incidental Entrants*

While the results in Tables II and III provide evidence that network membership does *lead* to greater borrowing and lower likelihood of financial distress, one may still worry that firms that just received a positive productivity shock are granted entry into the network and so our results are still confounded by this contemporaneous selection effect. While such explanations are harder to rule out, the “incidental” entry approach outlined in section III offers a solution.

Firms that enter the network incidentally i.e. not account of a direct change in the directors (either

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<sup>3</sup>Since the panel is no longer balanced, controlling for lagged default rates leads to a sample drop as well as lagged firm default rates are not defined if the firm was not borrowing in the lagged periods. However, we did ensure that the coefficient change is not driven by the sample change but in fact it is effected because of the inclusion of the lagged default rate controls.

in terms of a new director from the super-network joining its board or one of its directors sitting on the board of a super-network firm), are less likely to have experienced such a simultaneous positive productivity shock. Therefore by restricting our estimates to such firms only we can purge out some of these direct time-varying selection effects. However, we should caution that if productivity shocks are correlated across neighbor firms than this argument weakens.

Columns (1)-(3) in Table IV repeat the tests of columns (2)-(4) in Table II, but this time separately looks at the effect on *incidental entrants*, which are unlikely to suffer from the unobserved productivity shock concerns highlighted in section III. The results indicate that even incidental entrants experience large and statistically significant increase in external credit when joining the network. The network entrant effect on incidental entrants is slightly less though at 12.8%, which is to be expected both given the likely sign of the initial endogeneity bias and if there is any heterogeneity of impact since this incidental firms enter in a “weaker” manner.

Columns (4)-(5) repeat these tests but for default rate and again show that incidental entrants experience large drops in default rates once they are in the super-network.

Together with Table II-III, the results in Table IV provide compelling evidence for a causal positive impact of network membership. We now turn to explore this value both in terms of its provision channels and whether there is variation in who gets to benefit more.

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

We know that network entry leads to an increase in external financing. Table V investigates whether this increase is on the intensive or extensive margins. Column (1) uses average bank borrowing as the dependent variable, as opposed to total borrowing across all banks (for a given firm) in Table II. The result indicates that average bank borrowing, which reflects the intensive margin, also goes up as a result of network entry. However, the coefficient is smaller than the corresponding coefficient in column (2) of Table II, suggesting that part of the increase in financing comes from getting access to more banks within a network.

Using total number of banks of a firm as the dependent variable, column (2) confirms the extensive margin effect of network entry as well. On average network entry leads to an increase of 0.13 banks per firm. Columns (3) and (4) show that most of the increase in the extensive margin comes from private rather than government banks. The share of firm borrowing from government banks actually

decreases by 1.3% as a result of network entry. Given earlier evidence in Khwaja and Mian (2006) that government banks are more likely to lend for political reasons and private for economic, these results suggest that network brings in economic value for entrants.

If informational and enforcement advantages of network are responsible for the increase in external financing, especially the increased access to new banks, then when forming new banking relationships, entrants should be disproportionately more likely to borrow from banks of their new network links. Column (5) confirms this by showing a sharp increase in the borrowing from bank of immediate neighbors.

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

As section III explained, network theory suggests that the benefits of network depend on where in the network one is connected to. In particular, if an entrant connects to a more “powerful” node, then network benefits are likely to be larger. However, what is less clear is whether a firm that is relatively powerful to begin with, benefits more or less from network membership i.e. is the network a complement or substitute to firm “power”.

We examine these questions in Table V by using five different measures of power. The first measures the number of firms an entrant is directly connected to when joining a network. The second is the number of directors one gains direct access to by joining a network. Third is the total number of creditors your neighboring firms have access to. Fourth is the aggregate size of firms an entrant is connected to, and fifth is the average credit default history of a firm’s neighbors.

We separately construct these power measures for when a firm is in the network and when it is put of the network. The coefficient on the former interacted with when a firm enters the super-network, shows how much more a firm gains when it enters the network by connecting to more powerful nodes. In contrast, the coefficient on the out-of-network firm power measure and network entry, estimates whether more powerful firms gain more or less from the network.

Table VI first examines these results for firm borrowing. The results in columns (1) through (5) show that regardless of the measure of power used, an entrant generally gains more benefit when it connects to a more powerful node in the network. In contrast, the evidence seems to support the “networks as substitutes” explanation since firms that are more powerful to begin with, tend to gain relatively less when they enter the super-network.

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

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

#### *F. The Insurance Benefits of Networks*

Table VIII tests whether networks also provide insurance benefits in addition to increasing credit growth and improving firm performance. We do so by testing how networked firms respond to economic shocks hitting their industry or city, *relative to* non-networked firms. We do so by first identifying the “sister” firms to a given firm in terms of whether these firms share the same city or industry with the given firm. We then construct a proxy for shocks facing the firm’s city/industry sisters, by averaging the default rates these sister firms experience each period. To the extent that a firm is affected by shocks to its city/business sisters, its default rate will positively covary with its sister’s 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/industry sister’s shocks.

Column (1) runs precisely this test and reveals stark and strong insurance results: While non-network firms are 56 and 63 percent more likely to default if their city and/or business sisters default, networked firms are entirely immune to their sister firms’ shocks. Note that the specification includes firm and time fixed effects. Column (2) focuses only on the super-network firms that actually exit and enter the network during our data period (i.e. the 2,457 firms we restrict to in Column (5) of Table II) and shows the same (though slightly smaller) insurance patterns for these firms.

Columns (3)-(4) 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, 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. Column (3) first shows the impact of the sample restriction to firms that enter and exit the network and already the magnitude of the business-sister insurance provided by network firms is no longer present due to the sample drop. Nevertheless, Column (4) runs the test and shows that indeed for shocks to their city-sisters, a networked firm is better insured when it enters the network, compared to when it was out.

## V Concluding Remarks

What might be the economic rationale for benefits of network membership? One possibility is improvement in an entrant's loan demand, while another is improvement in its loan supply. In an environment characterized by weak markets, business networks The collective effect of these advantages could be higher sales and hence higher loan demand.

Conversely network advantages can also lead to increased loan supply, even if the (latent) demand for loans remained unchanged. It is well known that banks in emerging markets are very conservative in extending credit and demand high rates of pledgeable collateral due to fears of strategic default and adverse selection (see e.g. Liberti and Mian 2006). Access to business networks through credible links, such as cross-ownership, relaxes these credit supply constraints since banks can lean on the network to discipline borrowers and gain information. There is plenty of qualitative field evidence in Pakistan that loan officers pay first-order attention to a firm's network affiliations when making loan approval decisions.<sup>4</sup>

Separating whether network benefits are due to changes in loan demand or changes in loan supply is difficult. For example, the reduction in propensity of financial distress could be due to a reduction in strategic default (loan supply effect), or due to an increase in firm sales (loan demand effect).

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<sup>4</sup>This is also common among other emerging markets such as India, Argentina, etc.

Similarly, the increase in loan amounts may be driven by changes in demand or supply. There is some suggestive evidence however that part of the benefits are due to loan supply effects. For example, the increase in external financing is more likely to take place through banks that are existing lenders of the network nodes an entrant joins. However, more research is needed in trying to understand the economic mechanisms that bring about network benefits.

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

## VI Appendix: Structure of the “Super-Network”

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

### A. *Network Pattern Link Robustness*

In the paper we defined the link between two firms as having at least one director in common. In order to check the robustness of the network pattern above, we employ four alternative ways of identifying links between firms. The different panels in Appendix Figure I show the distribution of firm network sizes for each of these definitions. Importantly, it shows that the general network pattern - that of a super-network that is orders of magnitude larger than the next network remains. The four alternate link definitions used are:

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

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

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

(iv) Excluding individual borrowers: Finally, we test our network distribution by excluding individual/small borrowers. To do so we excluded all the firms that have only one director on their board. This restrictive condition left us with only 35% of the total number observations since a lot of the single firms are now excluded. As expected, only 53% of total firms are now not part of any network. However, both the distribution of firms and total lending across the different networks remains fairly stable when using this new group definition.

## *B. Super-Network Structure*

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

### **Large Nodes?**

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

We do the same exercise but now see whether there are firms that are connected to lots of other firms and that can explain the network: a "royal firm". Appendix Figure 2 shows the distribution of all firms in the super-network of the number of firms a given firm is linked to (including itself). 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. Appendix Figure IV shows this more systematically by graphing the histogram and kernel density for the distribution of the proportion of firms in the biggest and second biggest networks after the above exercise of excluding each director one by one. 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. As before, Appendix Figure V illustrates the effect of excluding one firm on the size of the two biggest networks. Regardless of which highly-linked firms is excluded over 99,5% remain in the super network while the second largest group has less than 0.4% of the firms.

### **“Important” Clusters?**

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

We start by removing clusters of directors. In order to do so, we eliminate all directors that sit on the board of more than a given number of firms. We start with a threshold value of 51 (i.e. remove all directors who sit on the board of equal to or more than 51 firms and recomputed the network structure) and then lower this threshold in steps of 2. We are interested not only in the number of

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

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

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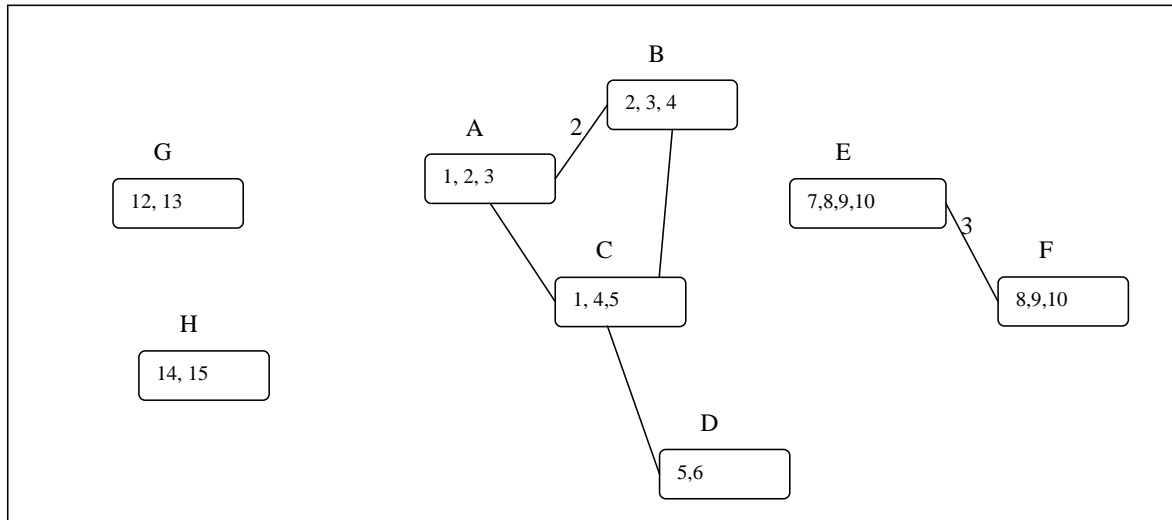
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**Figure I: Constructing Networks**



**Table I: Summary Stats**

Panel A							
Firm Type	Number of Firms	Log Loan Size		Default Rate		Initial Borrowing (000s)	
		mean	sd	mean	sd	mean	sd
Super-Network - Always In	2,838	9.59	3.11	10.97	28.32	191,142.5	1,021,052.0
Super-Network - In and Out	2,457	8.50	2.86	17.87	35.44	81,396.3	478,365.8
Other Network Firms	34,482	7.24	2.47	16.91	35.16	9,386.2	66,847.4
NonNetwork Firms	66,140	6.52	2.13	28.13	40.30	3,969.2	79,609.3

Panel B			
Firm Power Measures			
	mean	sd	
No.of Firm Neighbours When In	5.38	5.79	
No.of Firm Neighbours When Out	3.08	2.40	
No.of Neighbours' Directors When In	34.71	70.73	
No.of Neighbours' Directors When Out	9.49	14.11	
No.of Neighbours' Lenders When In	10.58	10.95	
No.of Neighbours' Lenders When Out	4.89	4.73	
Log Ave. Loans of Neighbours When In	9.65	2.04	
Ave. Log Loans of Neighbours When Out	6.14	4.32	
Ave. Def Rate of Neighbours When In	0.15	0.27	
Ave. Def Rate of Neighbours When Out	0.12	0.25	

**Table II: Effect of Network Entry on Total External Borrowing**

<b>Dependent Variable is Log of Firm External Borrowing</b>	(1)	(2)	(3)	(4)	(5)	(6)
InNetwork	0.166 [0.043]***	0.184 [0.043]***	0.181 [0.042]***	0.181 [0.042]***	0.154 [0.043]***	0.171 [0.043]***
Lagged LogLoan			0.02 [0.002]***	0.021 [0.002]***		
2-period lagged LogLoan				-0.003 [0.002]		
Constant	6.536 [0.021]***	6.54 [0.022]***	6.452 [0.022]***	6.456 [0.022]***	1.092 [0.023]***	0.822 [0.023]***
Fixed Effects	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	286,034	286,034	286,034	286,034	12,053	12,053
R-squared	0.59	0.6	0.6	0.6	0.44	0.36

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

Table III: Effect of Network Entry on Firm Financial Distress

Dependent Variable is Financial Distress	(1)	(2)	(3)	(4)	(4)	(4)
InNetwork	-1.728 [0.350]***	-1.632 [0.351]***	-1.07 [0.284]***	-1.242 [0.310]***	-1.689 [0.349]***	-1.614 [0.348]***
Lagged Def Rate			0.426 [0.004]***	0.39 [0.005]***		
2-period lagged Def Rate				0.038 [0.004]***		
Constant	16.216 [0.155]***	16.482 [0.161]***	12.091 [0.166]***	15.082 [0.196]***	0.308 [0.191]	0.708 [0.191]***
Fixed Effects	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business
Observations	397416	397416	313411	254576	15043	15043
R-squared	0.86	0.86	0.88	0.88	0.1	0

This Table shows the Effect of Network membership on Firm Default Rates. Column (1) estimates the basic specification. Column (2) add firm-type interacted with time FEs. Columns (3)-(4) add lagged dependent variable controls. Sample size drops as firms may not be borrowing in previous periods and so default rate is missing for such firms. Columns (5)-(6) replicate Columns (1)-(2) in the restricted sample of firms that move in and out of the network. Robust standard errors are in parentheses with \* significant at 10%; \*\* significant at 5%; and \*\*\* significant at 1%

**Table IV: Effect of Incidental Network Entry**

	LHS: LogLoan			LHS: Default Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
InNetwork	0.128 [0.059]**	0.128 [0.059]**	0.128 [0.059]**	-1.502 [0.464]***	-1.005 [0.391]**	-1.154 [0.427]***
Lagged LHS		0.02 [0.002]***	0.021 [0.002]***		0.426 [0.004]***	0.39 [0.005]***
InNetwork * Non-Incidental	0.126 [0.085]	0.12 [0.084]	0.12 [0.084]	-0.284 [0.702]	-0.138 [0.563]	-0.186 [0.614]
2-period lagged LHS			-0.003 [0.002]			0.038 [0.004]***
Constant	6.542 [0.022]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	6.454 [0.022]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	6.458 [0.022]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	16.477 [0.161]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	12.088 [0.167]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	15.078 [0.196]*** Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Fixed Effects						
Observations	286,034	286,034	286,034	397416	313411	254576
R-squared	0.6	0.6	0.6	0.86	0.88	0.88

This Table shows the impact of network membership on "incidental" entrants - those who entered indirectly because one of their neighbor's experienced a change. Column (1) estimates the base specification for firm borrowing with interacted firm-type and time FEs. Columns (2)-(3) add lagged dependent variable controls. Columns (4)-(6) repeat these using default rate as the dependent variable. Robust standard errors are in parentheses with \* significant at 10%; \*\* significant at 5%; and \*\*\* significant at 1%

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

	(1)	(2)	(3)	(4)	(5)
	Average Loan Size	Total number of creditors	%age credit from government banks	%age credit from private banks	Fraction of Creditors Common with Immediate Neighbours creditors
InNetwork	0.139 [0.041]***	0.137 [0.018]***	-0.014 [0.003]***	0.025 [0.005]***	0.206 (0.007)**
Constant	6.412 [0.021]***	1.041 [0.004]***	0.294 [0.002]***	0.51 [0.002]***	0.426 (0.007)**
Fixed Effects	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business type
Observations	286034	286034	286034	286034	
R-squared	0.57	0.86	0.9	0.86	0.74

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

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

<b>Dependent Variable is Log of Total External Borrowing</b>	(1)	(2)	(3)	(4)	(5)
InNetwork	0.18 [0.043]***	0.179 [0.043]***	0.174 [0.042]***	0.177 [0.042]***	0.174 [0.044]***
InNetwork * No.of Firm Neighbours(std) When In	0.099 [0.040]**				
InNetwork * No.of Firm Neighbours(std) When Out	-0.045 [0.041]				
InNetwork * No.of Neighbours' Directors(std) When In		0.075 [0.027]***			
InNetwork * No.of Neighbours' Directors(std) When Out		-0.074 [0.043]*			
InNetwork * No.of Neighbours' Lenders(std) When In			0.077 [0.038]**		
InNetwork * No.of Neighbours' Lenders(std) When Out			-0.133 [0.043]***		
InNetwork * Ave. Log Loans of Neighbours(std) When In				0.074 [0.049]	
InNetwork * Ave. Log Loans of Neighbours(std) When Out				-0.138 [0.045]***	
InNetwork * Ave. Def rate of Neighbours(std) When In					-0.063 [0.064]
InNetwork * Ave. Def rate of Neighbours(std) When Out					0.003 [0.065]
Constant	6.54 [0.022]***	6.54 [0.022]***	6.54 [0.022]***	6.541 [0.022]***	6.54 [0.022]***
	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm
Fixed effects	Business type	Business type	Business type	Business type	Business type
Observations	286034	286034	286034	286034	286034
R-squared	0.6	0.6	0.6	0.6	0.6

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

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

Dependent Variable is Firm Financial Distress	(1)	(2)	(3)	(4)	(5)
InNetwork	-1.605 [0.351]***	-1.578 [0.350]***	-1.588 [0.350]**	-1.593 [0.349]***	-1.582 [0.338]***
InNetwork * No.of Firm Neighbours(std) When In	0.22 [0.349]				
InNetwork * No.of Firm Neighbours(std) When Out	-1.028 [0.342]***				
InNetwork * No.of Neighbours' Directors(std) When In		0.093 [0.276]			
InNetwork * No.of Neighbours' Directors(std) When Out		-1.384 [0.381]***			
InNetwork * No.of Neighbours' Lenders(std) When In			0.554 [0.307]*		
InNetwork * No.of Neighbours' Lenders(std) When Out			-1.334 [0.381]***		
InNetwork * Log Ave. Loans of Neighbours(std) When In				-0.326 [0.357]	
InNetwork * Log Ave. Loans of Neighbours(std) When Out				-0.794 [0.387]**	
InNetwork * Ave. Def rate of Neighbours(std) When In					1.938 [0.568]***
InNetwork * Ave. Def rate of Neighbours(std) When Out					-3.144 [0.545]***
Constant	16.479 [0.161]***	16.475 [0.161]***	16.476 [0.161]***	16.479 [0.161]***	16.484 [0.161]***
	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business	Firm, Time, Time*FirmLocation, Time*FirmSize, Time*Firm Business
Fixed effects	type	type	type	type	type
Observations	397416	397416	397416	397416	397416
R-squared	0.86	0.86	0.86	0.86	0.86

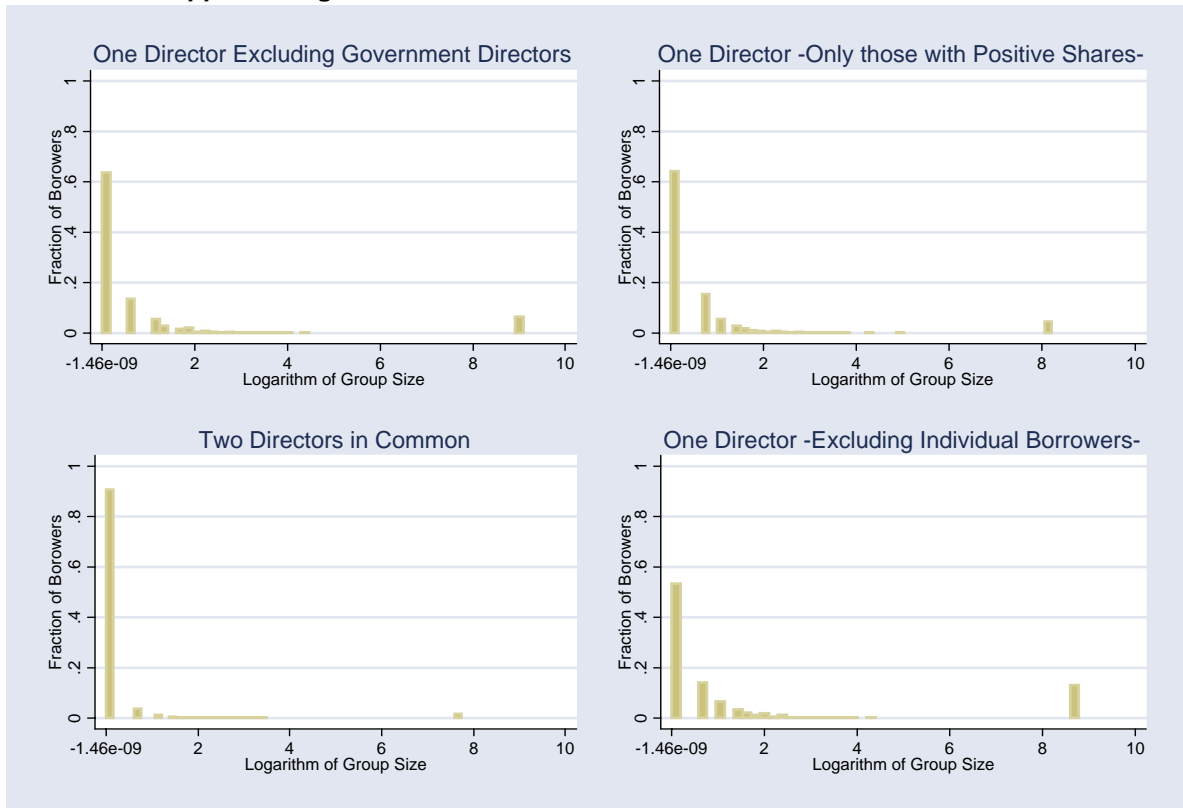
This Table examines heterogeneity in the network impact on a firm's default rate. Each column examines how the network value differs along a different measure of a firm's "power" both when it is out of the network and In the network. Column (1) uses the number of firms an entrant is directly connected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

**Table VIII: Networks and Insurance**

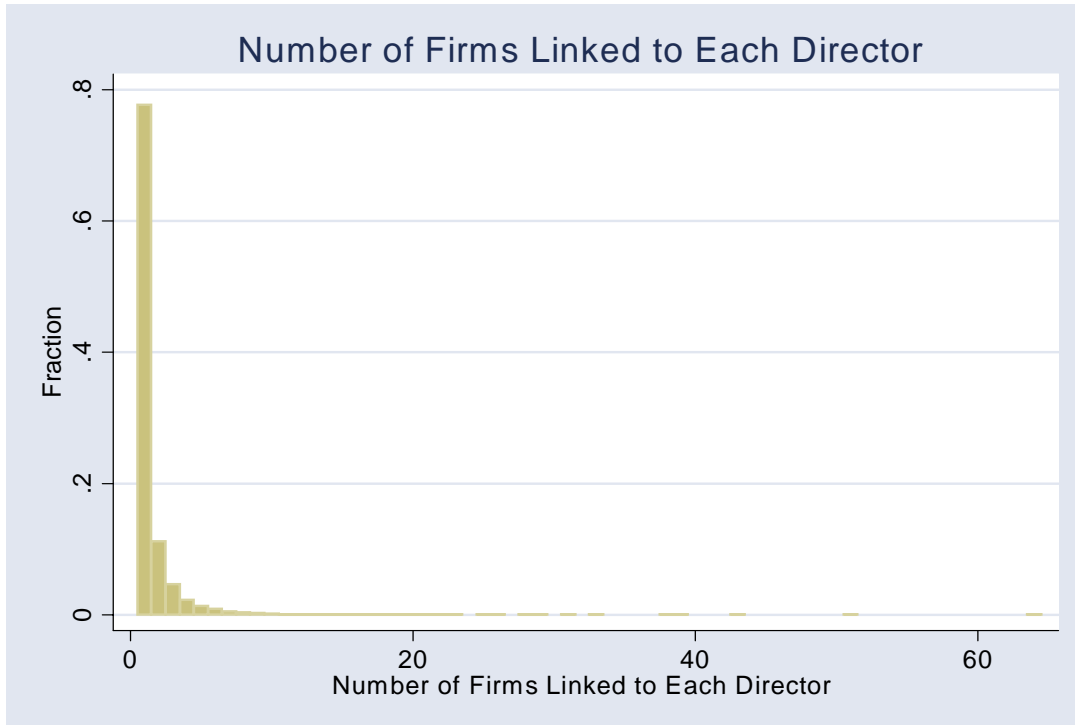
	(1)	(2)	(3)	(4)
CitySisterDR	0.558 [0.006]***	0.545 [0.006]***	0.607 [0.006]***	0.607 [0.006]***
BusinessSisterDR	0.633 [0.012]***	0.553 [0.012]***	0.514 [0.019]***	0.516 [0.019]***
CitySisterDR* Super- Network Firm	-0.564 [0.020]***			
BusinessSisterDR* Super- Network Firm	-0.505 [0.021]***			
CitySisterDR* In&Out Super- Network Firm		-0.424 [0.030]***	-0.348 [0.045]***	-0.311 [0.049]***
BusinessSisterDR* In&Out Super-Network Firm		-0.394 [0.031]***	-0.051 [0.062]	-0.075 [0.065]
InNetwork				0.015 [0.015]
InNetwork*CitySisterDR* Super-Network Firm				-0.139 [0.053]***
InNetwork*BusinessSisterD R* Super-Network Firm				-0.006 [0.048]
Constant	-0.14 [0.002]***	-0.134 [0.002]***	0.042 [0.004]***	0.041 [0.004]***
Controls				
Fixed Effects	Firm, Time	Firm, Time	Firm, Time	Firm, Time
Observations	1315562	1315562	973839	973839
R-squared	0.76	0.76	0.83	0.83

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

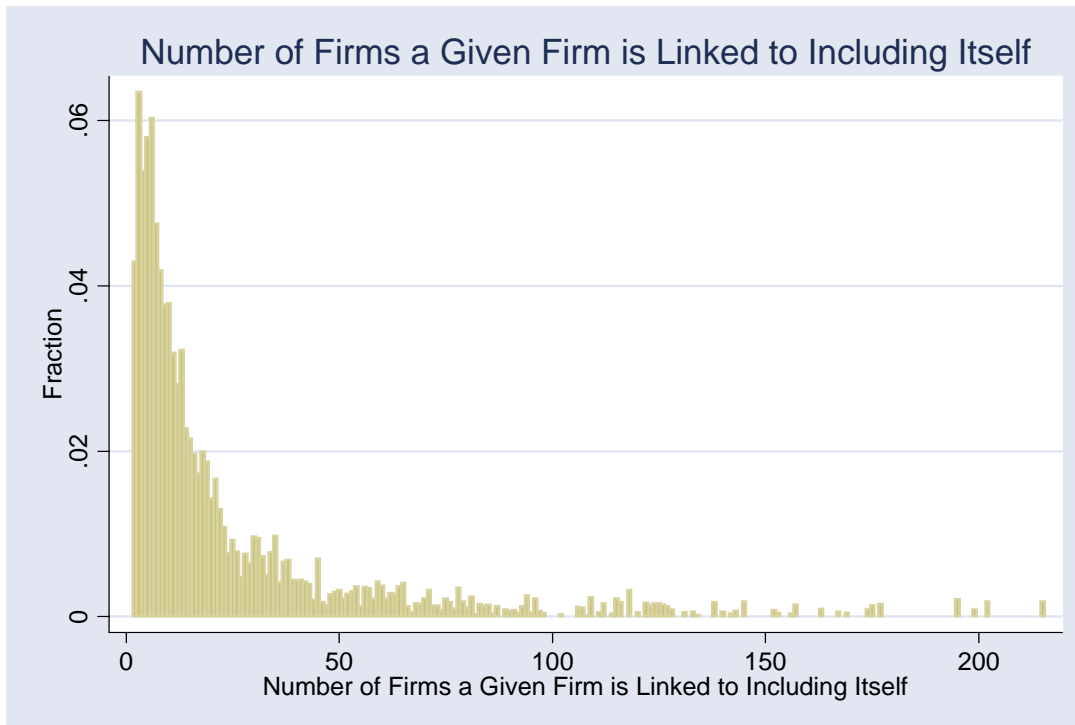
**Appendix Figure I: Network robustness to Alternative Link Definitions**



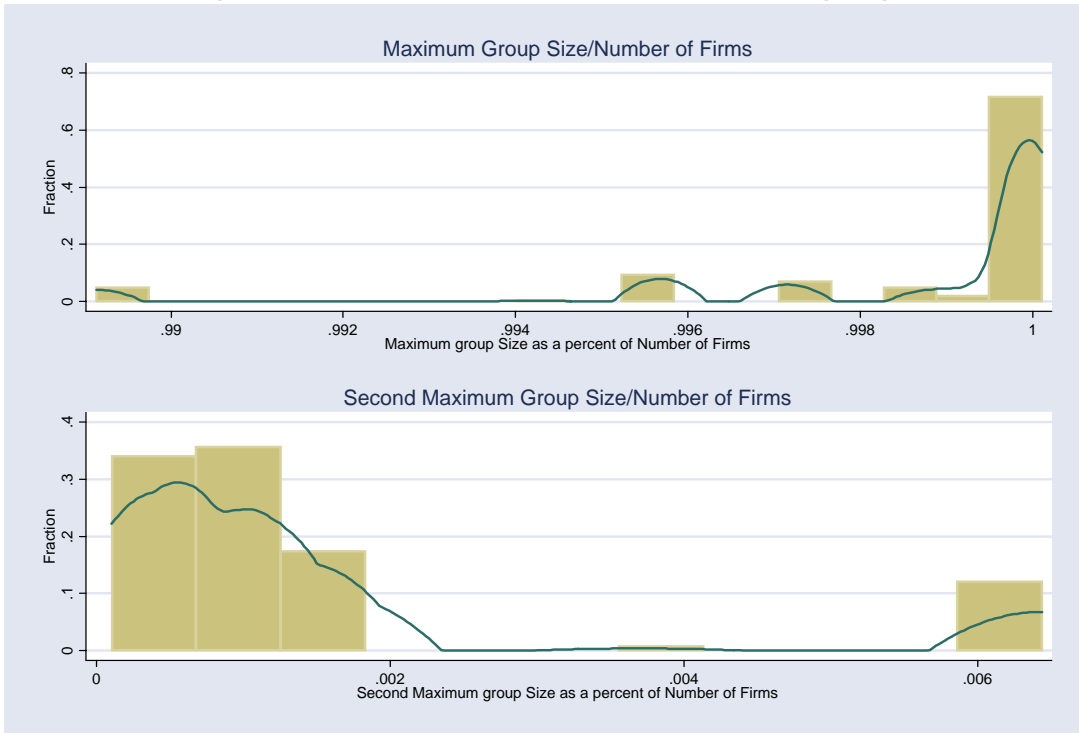
**Appendix Figure II: Director Power Distribution**



**Appendix Figure III: Firm Neighbours Distribution**



**Appendix Figure IV: Group Size Relative to Total Firms - Excluding Large Directors**



**Appendix Figure V: Group Size Relative to Total Firms - Excluding Large Firms.**

