CORPORATE NETWORKS AND PEER EFFECTS IN FIRM POLICIES: EVIDENCE FROM INDIA *

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ABSTRACT

This paper identifies the effect of corporate network peer groups on firm policy decisions such as investment, executive compensation and expenditure on R&D. Using panel data for all publicly listed companies in India, I construct time-varying corporate networks based on interlocking directorates. Identification of dynamic network peer effects, which arise due to endogenous association, is achieved by exploiting natural breaks in network evolution that exogenously change the composition of peers. These breaks occur as a result of local network shocks – deaths and retirements of shared directors – that are stochastic in nature and external to the network formation process. I find significant network peer effects that are associated positively with firms' investment strategy and executive compensation. In addition, I use detailed stock level breakdown of investments for each company, to show that for any two companies, the probability of investing in the same stock at any given time is increasing in the strength of their network ties. Finally, I explore heterogeneity in peer effects by distinguishing between network peers who belong to the same industry from those that do not and find a greater effect of across-industry network connections.

KEYWORDS: Social Interaction Models, Corporate Finance and Governance, Development

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1 INTRODUCTION

Firms interact with other firms, within the same industry and across, in various ways. These interactions can be both market and non-market based. Examples of market-based interactions include formal intra-industry agreements among competing firms (cartels) or resource-sharing alliances (strategic partnerships). Non-market based interactions occur when firms interact with other firms informally; by entering into board interlocks or through shared social connections between employees, among other things. In both cases, such social interactions often influence firm policy decisions in accordance with their peers. Instances of such behaviour are quite pervasive; a firm may gain information from another firm about strategic investment opportunities or may simply mimic it's within industry competitors' marketing strategy to maintain its market share. While a multitude of models, mainly theoretical, have investigated this phenomenon, there is little empirical evidence to validate such effects.

This paper uses firm level panel data for all publicly listed companies in India, covering the period 1998-2010, to estimate peer effects in corporate policies. Peer effects refer to the broad class of externalities that arise when a firm's own behaviour is responsive to the behaviour as well as the characteristics of other firms in its chosen reference group. I examine whether peer effects operate on firm managerial policies such as corporate market investment and executive compensation. I construct peer groups using interactions that occur within and across industry, through corporate networks based on interlocked directorates. Mizruchi (1996) defines an interlocking to occur "...when a person affiliated with one organization sits on the board of directors of another organization" (pg. 1). These networks are longitudinal in nature and change over time due to entry and exit of directors. I also consider whether a firm is influenced by its industry level peers i.e. a set of all other firms that share the same industry classification[1]. Manski (1993) notes that the 'informed specification of reference groups is a necessary prelude to analysis of social effects' (pg. 536). Corporate networks based on interlocked directorates provide a frequent and important channel for social interaction amongst firms. There is a large literature that documents how firms choose to strategically interlock with other firms, with the consequence that corporate networks are often endogenously determined[2].

A central contribution of this paper is the identification and estimation of peers effects in endogenously formed networks. The identification of peer effects encounters well known problems laid out in Manski (1993). Manski lists three effects that need to be distinguished in the analysis of peer effects. The first type are endogenous effects which arise from a firm's

[1]Both network and industry level peer provide different environments and mechanisms for the propagation of peer effects. Industry level peers are commonly associated to provide competitor driven peer influence in the "keep up with the Joneses" tradition, while network peers provide a monitoring, information and learning based explanation of peer influence.

[2]In Section 2, I review both the causes and consequences of board interlocks.

propensity to respond to the *outcomes* of its peers. For example, a firm is inclined to invest more if it observes its peers investing heavily. The second are so-called contextual effects which represent the propensity of a firm to behave in some way as a function of the exogenous characteristics of its peer group. For instance a firm is able to spend more on investment independently of its own profits if it receives some positive externalities from its peers' profits[3]. The third type are so-called correlated effects which describe circumstances in which firms in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional arrangements, i.e., firms within the same industry may behave similarly due to common industry-specific shocks. This means that there are unobservables in a group which may have a direct effect on observed outcomes. The main empirical challenges, therefore, consist in (1) disentangling *contextual* effects, from *endogenous* effects and (2) distinguishing between *social* effects, i.e., exogenous and endogenous effects, and *correlated* effects. Identification of network based peer effects is confounded by additional problems of self-selection and endogenous network formation.

In this paper I present a novel strategy that exploits both the structure and inter-temporal variation of the corporate network to identify network based peer effects. The structure of the network implies that the pattern and magnitude of social interactions are non-linear in nature which allows me to distinguish the endogenous peer effect from the exogenous peer effect. Secondly to mitigate bias associated with non-random selection, in addition to differencing out firm fixed effects, I use natural breaks in network evolution which arise from local network shocks that are stochastic in nature and external to the network. In this setting, local network shocks are in the form of deaths/retirement of directors that severs a tie between two firms and/or exit of any peer firm. Loss of peers with high outcome values is likely to reduce the average in the next period (net of other endogenous deletions and additions) because they are no longer part of the peer group. Therefore, for every firm, I use average outcomes of those peers who have been lost due to death/retirement related director exits to instrument for its average peer outcomes in the next time period. I control for the direct effect of director exits due to deaths/retirement on the outcome and require only that there be no systematic differences in director exits that break interlocks and those that do not (i.e. director exits of unconnected directors). The identification assumptions are violated if firms choose to strategically replace the lost directors with directors of equally well connected companies. To ensure that this is not the case, I estimate a simple difference-in-difference regression and find no significant effect of a director death/retirement shock to a firm in the past period on its probability of forming a new link. Finally, to purge out correlated effects, I control for common time-varying shocks that occur both across industry and business group by employing industry by business group by time fixed effects. As an extension, I also estimate peer effects from a firm's 'global' network of interaction wherein a

[3]This is especially the case with firms that have a common ownership structure wherein profits could be tunnelled between firms to fund each other's investment activities (Bertrand, Mehta, and Mullainathan 2002).

firm's peer group consists of both its direct links (examined before) and its indirect links as obtained through the corporate network.

I analyze the impact of peer interactions on the following firm policies: investment, executive compensation and current R&D expenditure. I make a distinction between two types of investments, corporate investments in marketable securities (henceforth corporate market investment) and physical capital expenditure. I focus mainly on corporate market investments for two reasons[4]. Firstly, there has been an increasing trend over the last decade whereby firms have increased their holdings of liquid assets in marketable securities, either with a view to procure strategic equity stakes or to smoothen their risk portfolio[5]. Secondly, there is a large theoretical literature that focuses on social interactions in finance, particularly investments, through models of herding and information cascades. In these models, investment decisions may be influenced by observing the decisions of others and this leads to a convergence or divergence of behaviour. Behavioural responses of such kind are more likely to be dynamic in nature and involve taking decisions on expenditure items that can be easily modified. Corporate market investments satisfy this criterion because in contrast to physical capital expenditure, they are more liquid and managerial decisions on portfolio adjustment tend to be more flexible. If social interactions influence investment decisions, then it has important implications for investor welfare because it may contribute to clustered financial activity.
I also focus on executive compensation because pay-scales are closely monitored by the firm's board of directors. Many CEO's themselves are directors on boards of other firms. Potentially this could mean either that networked CEO's are more likely to collude and influence each other's pay or at least have access to information on the setting of other CEO's pay scales. The recent phenomena of rising CEO pay, that has been popularly termed the "Lake Wobegone Effect"[6] to reflect the fact that no firm wants to admit to having a CEO who is below average, is indicative of this aspect (Hayes and Schaefer 2009). Actions such as these, which are in part influenced by social interactions, could lead to a distortion of performance related pay scales.

Overall, I find evidence for positive network based peer spillovers. An increase of one standard deviation in network peer investment leads to an increase of 0.16 standard deviations in the growth of own firm investment. Similarly an increase of one standard deviation in network

[4] I also explain peer effects in capital expenditure but due to the lumpiness of physical investment, I transform capital expenditure into a dummy variable which is equal to one if there is investment in capital/infrastructure and zero if not.

[5] For example Brown (2009) argues that this form of investment is not merely equivalent to a simple store of cash; rather it serves as value enhancement. He finds evidence firms may use market investment as a risk management tool as well as to manage future financial commitments and payout policy. Allen and Phillips (2000) examine block equity ownership patterns of US corporations and note that, among other things, purchasing corporations could be able to effectively monitor or influence management since they are in possession of superior knowledge relative to other shareholders.

[6] "Where's the stick?", The Economist, October 2003; "Are India CEO's Overpaid", Business Today, July 2007; "Do Indian CEO's Overpay Themselves", Rediff Business, October 2009.

peer executive compensation leads to an increase of 0.05 standard deviations in the growth of own firm executive compensation. For investment, I also use detailed stock-wise breakdown of investments for each company, and show that for any two companies, the probability of investing in the same stock at any given time is increasing in the strength of their network ties. In order to further understand the mechanisms driving the aggregate peer induced outcome increase, I disaggregate the network into two further groups: network peers who are in the same industry as the firm and network peers who are not. The reason for separating peer effects using these pre-defined groups is to distinguish between the different types of interactions that a firm can have even within its given network. I take insight from economic theory and argue that interactions amongst industry peers are competitive in nature whereas strategic interactions with firms not in the same industry are more benevolent in nature. Therefore, if information is the channels through which these peers effects dissipate then it is likely that a firm will ignore information received from its competitors and there will be no industry network peer effects. However a finding of positive industry network peer effects indicate that firms could potentially be mimicking the behaviour of its competitors[7]. I find that for both market investment and executive compensation, industry network peer effects are close to zero while non-industry network peer effects are positive and significant. Finally, I find positive industry peer effects for market investment and R&D but not for executive compensation. Comparing industry peer effects with overall network peer effects (consisting of both network peers from same industry and network peer from different industries), I find that for market investment network peer effects dominates whereas the opposite is true for R&D investment.

The paper is most closely related to the small but growing body of literature that provide evidence for corporate peer effects. In recent work, Leary and Roberts (2010) show that corporate financial policies are highly interdependent. Taking the industry as the peer reference group, they identify peer effects by using idiosyncratic shocks of peer firms as instruments and find that a one standard deviation change in industry based peer firms' leverage ratios is associated with an 11% change in own firm leverage ratios. They argue that these effects are consistent with models of learning and show that smaller, more financially constrained firms exhibit 'more pronounced mimicking tendencies'. Fracassi (2008) using data on board interlocks[8] in the United States provides further evidence that firms are influenced by their social peers when making corporate policy decisions. He finds that more social connections

[7] I also distinguish between industry peer effects i.e. the effect of peers in a firms industry and overall network peer effect (containing both industry and non-industry within network peers). The disaggregation of peer effects into industry peers and non-industry peers is different from above because the former seeks to understand how even within the network firms differentially respond between industry and non-industry peers.

[8] Other work relating to corporate networks via board interlocks include Khwaja, Mian, and Qamar (2011) who estimate the value of corporate networks in Pakistan and find that membership in a highly clustered component of a network increases total external financing and better insures firms against industry and location shocks.

two companies share with each other, the more similar their level and change of investment behaviour is over time. In the same context, Bouwman (2011) finds that governance practices are propagated across firms through a network of shared directors. She shows that these network effects lead to a convergence in governance practices because of the influence of directors who sit on the boards of different firms. In relation to firm compensation policy, Shue (2011) exploits random assignment of MBA students to sections within classes at Harvard Business School and finds that executive compensation and acquisitions strategy are significantly more similar among graduates from the same section than among graduates from different sections within the same class.

The paper contributes to the empirical literature on firm level social interactions by providing evidence for the presence and importance of both network and industry based peer effects in a developing country setting. The Indian context is different from other developed country settings such as the United States and United Kingdom which have been the focus of previous literature, because corporate governance rules are less stringent and more informal in India (see Estrin and Prevezer (2011)). For instance while there are clear cut regulations in the United States that restrict intra-industry interlocks, no such rules apply in India. As such the policy implications for a finding of positive peer effects through corporate interlocks are more profound. Firstly, it has implications for the formulation of corporate governance regulations depending on whether such effects are considered desirable or not. Secondly, from a policy perspective, (only) endogenous peer effects have the capacity to generate multiplier effects. Positive and significant network peer effects in firm market investment, wherein a firm's decision to invest is influenced by the aggregate investment behaviour of its peers, have the ability to propagate asset bubbles or contribute to financial clustering. A vast literature examining financial herding and information cascades find evidence on correlated trading, both at the institutional & individual level[9] (Seasholes 2011). The peer interactions framework complements this literature by providing precise mediums through which such correlated trading decisions could be influenced. For example, as discussed in the paper, distinguishing between market-based peer effects (industry peers) from non-market based peer effects (corporate networks, shared educational associations etc.) allows us to determine the appropriate reference group through which these social multiplier effects emanate (if any). Likewise, firms influencing each other on executive compensation policies have the effect of distorting performance oriented pay-scales. CEO's of firms are likely to be paid much above their marginal product only to ensure that a particular standard, as determined by their peers, is met.

The rest of the paper is organized as follows: Section 2 defines the construction of industry and

[9]See Allen and Babus (2009) for an excellent review of financial networks and its implications; see also Ozsoylev (2003) for a good theoretical understanding on how social networks may lead to clustered financial decision making.

network reference groups. Section 3 discusses the identification strategy which is translated into the specification of the empirical model presented in the same Section. The data used is described in Section 4. Section 5 discusses the results and Section 6 provided further robustness results. Section 8 concludes.

2 CORPORATE NETWORK

Firms can potentially be influenced by two types of peer firms – those that it considers its competitors and those with whom it shares an affiliation of sorts. As stated before, in this paper I consider corporate network & ownership related peer groups. I also provide evidence considering industry based peer groups. Below I provide definitions for each.

Corporate Network Affiliation: This type of affiliation comes from firm relationships fostered through interlocked board of directorates or corporate networks. An interlocking directorate occurs when a director of the board of one firm sits on the board of another. This means that two firms share a direct link in the corporate network if they share a shared director. A firm can have one or more directors who sit on the boards of other firms. Indian corporate governance regulations mandate that a director sit on no more than fifteen firms at a time. Corporate networks evolve over time due to link additions and deletions from shared director entry & exits. Interlocked boards provide an important source of information about a firm's network. A firm can also have connections based on shared education background of executives, past employment of employees but my data does not allow me to distinguish such potential connections. The networks defined in this paper are based purely on firm relationships through interlocked boards. As pointed out earlier, many authors find evidence of similarities in corporate behaviour of firms that are linked through this type of a corporate network. I discuss below the relevance of interlocked directorates.

Mizruchi (1996) provides a review of board interlocks where he describes the origins and features of common board interlocks in the United States. He highlights three factors, among other reasons, that help explain the formation of interlocks: collusion, monitoring and social cohesion. The intent to collude between competitors as a means of restricting competition may lead to the formation of interlocks. This is evident for instance through the findings that most interlocks occur within a specific industry (Pennings 1980). The second reason is that interlocking provides for a means to co-opt and monitor sources of environmental uncertainty. Firms tend to employ board seats as devices to monitor other firms and their organizational decision making suggesting that interlocks can act as instruments of corporate control. A wide range of literature has found evidence suggesting that interlocks are positively associated with firm profitability (Baysinger and Butler 1985; Burt 1983). It is unclear however, whether this is due to the fact that firms tend to monitor each other effectively though interlocks or that profitable firms tend to interlock more. Finally, interlocks can occur as a result of social

cohesion wherein individuals are invited to sit on boards of firms due to their past associations (social, educational etc.) with other board members.

More importantly, for the purposes of this paper, there are many consequences of such board interlocks. Mizruchi (1996) lists several and reviews evidence against each. Mainly, it is argued that board interlocks lead to a heightened sense of corporate control whereby firms used the board interlock to extended their control on their partner firms' policy decisions. Executive compensation is typical example of such a policy decision. Guedj and Barnea (2009) use data on directors who served on the boards of S&P firms and find evidence that firms whose directors are more central in the network, pay their CEO higher and that CEO pay is less sensitive to firm performance. Another consequence of board interlocks is of 'network embeddedness' i.e. interlocks connect multiple firms with each other and therefore provide a standpoint from which to view how a firm's relations with other firms affect its corporate behaviour (Mizruchi 1996). A seminal contribution in this perspective comes from Cohen, Frazzini, and Malloy (2008) who document connections between mutual fund managers and corporate board members via shared education networks. They find that portfolio managers place larger bets on connected firms and perform significantly better on these holdings relative to their nonconnected holdings. In similar vein, Hochberg et al. (2007) find that better-networked Venture Capital firms experience significantly better fund performance where they measure connections through syndication relationships. Stuart and Yim (2010) exploit the sequential timing of receiving private equity offers and provide evidence to show that that companies which have directors with private equity deal exposure gained from interlocking directorships are approximately 42% more likely to receive private equity. This is indicative of gains from peer influenced information transmission in a network of interlocked boards.

Business Group Affiliation: In India, most firms are also organized into 'business groups' which is defined as a set of firms managed by a common group of insiders. The firms affiliated to business groups are single entities with individual production processes however it is quite common to find firms within such business groups sharing directors with each other. Since the nature of social interactions amongst firms sharing a business group are akin to that through board interlocks, I supplement the peer reference group to incorporate peers from same business group affiliations as well. The appendix contains more details about business groups in India.

Industry Affiliation: Finally to examine heterogeneous peer effects, I also distinguish between the set of corporate network peers that belong to the same industry and those that do not. An industry affiliation of a firm is based, very simply, on a shared industrial classification. I use classifications given by the National Industrial Classification (NIC) which is the standard classification system for economic activities in India. The NIC groups together economic activities which are akin in terms of process type, raw material used and finished

goods produced. The classification does not make any distinctions according to the type of ownership or type of economic organization, and except in some cases the c1assification does not distinguish between large scale and small scale (GOI 2004). Basically firm affiliation into the same industry can indicate how well as firm responds to policies of its peers who are producing the same output as itself.

3 IDENTIFICATION OF PEER EFFECTS

The identification of peer effects is notoriously difficult as explained by Manski (1993) and Moffitt et al. (2001)[10]. Manksi noted that within a linear framework without additional information, it is impossible to infer from the observed mean distribution of a sample whether average behaviour within a group affects the individual behaviour of members of that group. In other words, the expected mean outcome of a peer group and its mean characteristics are perfectly collinear due to the simultaneity induced by social interaction. The main challenges, therefore, consist in (1) disentangling *contextual* effects, i.e., the influence of exogenous peer characteristics on a household's observed outcome, and *endogenous* effects, i.e., the influence of peer outcomes on a household's outcome, and (2) distinguishing between *social* effects, i.e., exogenous and endogenous effects, and *correlated* effects, i.e., firms in the same network may behave similarly because they are alike or share a common environment.

3.1 THE REFLECTION PROBLEM

This fundamental identification problem, termed *reflection problem* by Manski, makes it clear that within a linear-in-means model, identification of peer effects depends on the functional relationship in the population between the variables characterizing peer groups and those directly affecting group outcomes. In such a setting, if all individuals interact in a similar way in groups of the same size, then it is impossible to recover the parameter on the endogenous peer effect because it is perfectly collinear with the mean exogenous characteristics of the group. However under special settings, wherein the social interactions are not homogenous within or across a group, it is possible to identify both the endogenous and exogenous peer effects. Lee (2007) was first to show formally that the spatial autoregressive model specification (SAR), widely used in the spatial econometrics literature, can be used to disentangle endogenous and exogenous effects. Lee notes that in a SAR model, identification of endogenous and contextual effects is possible if there is sufficient variation in the size of peer groups within the sample. As stressed by Davezies et al. (2009), Lee's identification strategy crucially requires knowledge of peer group sizes and at least three groups of different size. Bramoullé et al. (2009) propose an encompassing framework in which Manski's mean regression function and Lee's SAR specification arise as special cases. They show that endogenous and exogenous effects can be distinguished through a specific network structure, for example the presence

[10]For a summary of the literature see also Blume and Durlauf (2005).

of intransitive triads within a network. Intransitive triads describe a structure in which individual i interacts with individual j but not with individual k whereas j and k interact[11]. In both cases it is possible to identify endogenous and exogenous effects separately because the variation in the magnitude of social interactions, either through group size variations or through a network structure, produces exogenous variations in reduced form coefficients across groups that allow us to recover the endogenous effect.

In this paper, I use a rich panel of all publicly listed firms in India and estimate peer effects in reference groups that have a non linear social interaction structure. This structure emerges when interaction do not occur symmetrically, i.e. not everyone is related to everybody else, even within sub-populations in the same way. A well known example of such a structure is a social network. In a social network each person is linked to a select set of people but no to the entire network directly. In the firms context, it means that each firm is linked to a set of firms though shared directors and in turn their peer firms have further connections, other than the target firm. An example of such a firm network is given below – denote a network, in the form of an *adjacency matrix*[12], as $\mathbf{W}$ –:

	1	2	3
1	0	1	0
2	1	0	1
3	0	1	0

Here, Firm 1 shares a director with Firm 2 (and therefore is connected to it) but not with Firm 3. Similarly, Firm 2 is connected with Firm 1 and also with Firm 3. The matrix $\mathbf{W}$ represents the *global network* of all social interactions[13]. Within this global network we can define a local network which is a set of all firms that any given firm is *directly linked* to. I use the local network as the relevant peer group. In the above example, Firm 1's local network or peer group is Firm 2 whereas Firm 2's peer group is Firm 1 and Firm 3. In this section I use the terms local network and peer group interchangeably. In section I also consider interactions through indirect links thereby accounting for the entire global network. The structure of such peer groups are heterogeneous both across firms at a given time and within firms over time due to movements of directors on the board. The across firm non-linearity

[11] This particular network structure produces exclusion restrictions which achieve identification in the same way as exclusion restrictions achieve identification in a system of simultaneous equations.

[12] A common way to represent connectivity of network graphs is through a $n \times n$ binary symmetric matrix called an adjacency matrix. The adjacency matrix is non-zero for entries whose row-column indices correspond to a link between two individuals/firms and zero for those that have no links. Operations on the adjacency matrix also yield additional information about the network such as degree, clustering etc. For more on adjacency matrices and properties of network graph see Kolaczyk (2009).

[13] This type of a network/graph is also called an 'affiliation network'/'bipartite graph'. An affiliation network refers to the set of binary relations between individuals/entities (firms) that belong to a common group or participate in common events (shared directors).

in interactions due to the asymmetric nature of the peer interaction allows us to distinguish the endogenous effect. The *structure* of the network ensures that the endogenous peer effects are *identified*, i.e. the parameters can be separately recovered.

Denote the set of firms as i $(i = 1, ..., n)$, y_{it} denotes the outcome of firm i at time t and x_{it} is the firm's exogenous characteristic[14] at time t. Let **N denote the global network** of all interactions and η **the local networks**[15] that are contained within N. Each firm's peer group, its local network η, is of size n. By assumption firm i is excluded from its peer group. We assume that our sample of size n_t is i.i.d. and from a population of networks with a fixed and known structure. We distinguish between three types of effects: an agent's outcome y_{it} is affected by (i) the mean outcome of her peer group (endogenous effects), (ii) her own characteristics, and (iii) the mean characteristics of her peer group (contextual effects):

$$y_{it} = \beta \frac{\sum_{j \in \eta_{it}} y_{jt}}{n_{it}} + \gamma x_{it} + \delta \frac{\sum_{j \in \eta_{it}} x_{jt}}{n_{it}} + \varsigma_t + u_{it} \tag{1}$$

or, as is common in the peer effects literature:

$$y_{it} = \beta \overline{y}_{-it} + \gamma x_{it} + \delta \overline{x}_{-it} + \varsigma_t + u_{it} \tag{2}$$

Hence, β captures endogenous effects and δ contextual effects. Time fixed effects are represented by ς_t. We require strict exogeneity of x_{it} with respect to u_{it}. Note that we do not require the residuals u_{it} to be homoscedastic or normally distributed.

Omitting the time subscripts for clarity, denote $\mathbf{W^N}$ as the global network peer interaction matrix. Any i, j element within it is represented by w_{ij}^N. It is row-standardized such that $w_{ij}^N = 1/n_{ij}$ if firm i and j have a board interlock, i.e. share a director, and 0 otherwise. I use $\mathbf{W_i^N}$ to denote the ith row vector which is used to represent a firm i's local network[16]. Its pre-multiplication with the column vector $\mathbf{y}$ produces a firm specific peer average denoted by $\mathbf{W_i^N y_t}$, i.e. it is the same as $\overline{y}_{-i}$. Rewriting Eq. (2) we now get[17]:

$$y_{it} = \beta \mathbf{W_{it}^N y_t} + \gamma x_{it} + \delta \mathbf{W_{it}^N x_t} + \varsigma_t + u_{it} \tag{3}$$

[14] For ease of notation, in this section, I represent only one exogenous characteristic but the empirics take into account many exogenous characteristics that are described later.

[15] This terminology is consistent with much of the literature on statistical networks and discussed in Bramoullé et al. (2009).

[16] $\mathbf{W_i^N}$ is the ith row of the $n \times n$ matrix $\mathbf{W^N}$. When post multiplied by $\mathbf{y_t}$ whose dimension is $n \times 1$, it produces a 1×1 firm specific peer average.

[17] The use of time dependent weights matrices is not uncommon in the social networks literature. Doreian and Stokman (1996) refers to Eq. (3) as a 'processual model' and use it to detect contagion in social networks. In the spatial econometrics literature, recent work by Lee and Yu (2011) also develops quasi-maximum likelihood estimation of spatial dynamic panel data models where spatial weights matrices can be time varying.

The reduced form of Eq. (3) is given by (Lee and Yu 2011):

$$\mathbf{y_t} = (I - \beta \mathbf{W_t^N})^{-1}(\gamma \mathbf{x_t} + \delta \mathbf{W_t^N} \mathbf{x_t} + \varsigma_t) + (I - \beta \mathbf{W_t^N})^{-1} \mathbf{u_t} \tag{4}$$

3.2 NON RANDOM SELECTION

The main problem with estimating network based peer effects is that the network is endogenously formed. Endogenous tie formation will also typically induce a correlation between unobserved shocks of the firm and the firms' peers. This is especially the case when similar group of firms share directors. To see this, decompose the error from Eq (3) in the following parts:

$$u_{it} = \mu_i + \nu_{it} + \varepsilon_{\eta t} \tag{5}$$

μ_i represents all time invariant firm level unobservables, ν_{it} contains time varying firm unobservables and $\varepsilon_{\eta t}$ contains shocks/unobservables that are common to a firm's local network at any given time t. In such a case a non-zero coefficient on the peer influence variable could mean that these firms behave in a similar fashion because they share similar attitudes (and have sorted themselves based on that) rather than the fact that network members are influencing each other (Epple and Romano 2011). Firstly, I employ a first-differences specification to eliminate any time invariant firm unobservable, μ_i, that may be correlated with selection or correlated unobservables. First differencing Eq (3), we get:

$$\triangle y_{it} = \beta \triangle \mathbf{W_{it}^N} \mathbf{y_t} + \gamma \triangle x_{it} + \delta \triangle \mathbf{W_{it}^N} \mathbf{x_t} + \triangle \varsigma_t + \triangle u_{it} \tag{6}$$

I retain time fixed effects in this specification to capture common time specific trends. The parameter β represents the contemporaneous effect of peer firms. The model, therefore, captures the effect of changes in peer firms' contemporaneous outcomes on the change in a firms' outcome. It is possible however that instead of responding to contemporaneous outcomes, firms respond to the permanent component associated with their peer firms' outcomes. For example, Mas and Moretti (2009) use data from a supermarket chain and estimate productivity spillovers. In their model, the peer function takes the form where workers respond to the permanent productivity of their peer workers and over time changes in the composition of peers enables the identification of such effects. However as noted by them in the paper, both model (permanent and contemporaneous) are ex-ante possible (Mas and Moretti 2009). As in their paper, I am unable to distinguish between the effects of the two models, simply because estimating fixed effects would entail employing a peer group composition or local network fixed effect which is infeasible in the case of endogenous networks. Therefore the estimates obtained in this paper could in part be reflecting some effect of firms' response to permanent rather than contemporaneous outcomes.

Given Eq (6), we are still confronted with the challenges of mitigating bias arising from time varying unobservables that might influence selection into the network or time varying unobservables, such as common productivity shocks, that are correlated with the peer effect. I first take up the issue of network selection and return to the problem posed by correlated effects in the next sub-section.

To tackle the selection bias, I make use of natural breaks in dynamic networks that are independent of any selection process. The idea of using exogenous variation in networks to isolate the endogenous component of the peer effect is similar to using class size variation brought about due to exogenous movement of students across schools. In the network context, it would mean having to look for local network shocks that break (or append) a tie but are external to the network or its formation. Such shocks would bring a reduction or increase in the network average outcome depending on the quality of the tie being broken (or appended) and will be uncorrelated to both the propensity to form ties and aggregate network level unobservable that affect any agents' outcome. Identifying peer effects using variations in the composition of groups is well established in the social interactions literature (Hanushek et al. (2003); Hoxby (2000)). However the strategy of using naturally induced variation in group composition to instrument for peer effects that arise from endogenously formed groups is relatively novel. Hoxby and Weingarth (2005) use policy based reassignment of students into schools to estimate peer effects in education. The authors use the average outcomes of past period peers following reassignment, disallowing and excluding from this average other endogenous movement of students, as an instrument for the endogenous peer effect. In similar spirit but taking a different approach, Waldinger (2010) uses dismissals of scholars in the Nazi era as a source of exogenous variation in the peer group of scientists staying in Germany to identify peer effects in scientific publications. He uses the past period dismissal induced reduction in peer quality to instrument for the present period peer average. Finally, Cooley (2007) uses introduction of student accountability policies in North Carolina public schools as an exogenous 'utility shifter' for identifying peer spillovers in education[18]. The author uses the percentage of students held accountable in any given year to predict average peer achievement in the classroom. The assumption is that the percentage of students in danger of failing is independent of both group level and individual level unobservables. The common underlying idea for the identification strategy pursued in the papers discussed above, as well as in this paper, is the use of an exclusion restriction in the form of an exogenous shock that is able to alter the composition of groups or/and the peer averages.

In what follows, I provide the assumptions that describe the properties of a valid exclusion restriction such as the one described above:

[18]The policy required that students perform above a certain level in order to be automatically promoted to the next grade. This meant that classrooms with a high percentage of students in danger of failing were more likely to increase their aggregate achievement because students close to failing would put in more effort (and therefore increase achievement) so as to get promoted.

(A1) There exists a variable, representing a stochastic network shock, D_{it-1} that changes the response of firm i to choose the optimal outcome[19] *and* the composition of peers, $\mathbf{W^N_{it}}$, in the next period.

(A2) The variable D_{it-1} induces a shift in both the endogenous and exogenous peer averages in the next period depending on the quality of peer loss given by, $\mathbf{W^D_{it-1}y_{t-1}}$[20] (endogenous peer average shifter) or $\mathbf{W^D_{it-1}x_{t-1}}$ (exogenous peer average shifter).

(A3) Conditional on $(x_{it}, \varepsilon_{\eta t})$, ν_{it} is independent of D_{it-1}.

(A4) Conditional on (x_{it}), $\varepsilon_{\eta t}$, ν_{it} are jointly independent of $\mathbf{W^D_{it-1}y_{t-1}}$, $\mathbf{W^D_{it-1}x_{t-1}}$.

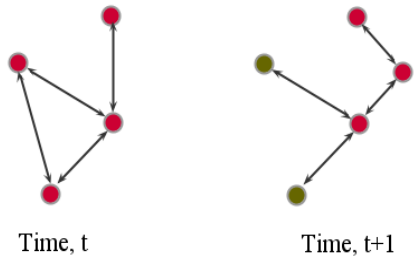
(A1) ensures that there are no direct spillovers from the network shock D_{it-1}. This means that D_{it-1} affects the composition of peers and is capable of having a direct effect on the outcome but only by changing the response of the firm in reaction to the event. Note that the change in peer composition shifts *both* the exogenous and endogenous peer averages requiring, still, a non-linear social interaction structure that allows for separability of the exogenous and endogenous peer average *shifters*. In a linear-in means model this type of an exclusion would be ineffective, since neither the exogenous/endogenous peer effects nor the exogenous/endogenous peer shifters are individually separable. (A2) clarifies this by indexing the network shock to be firm specific i.e. it represents a *local network* shock. (A3) requires that the shock be uncorrelated with firm specific unobservables in the next time period.

Death or retirements of directors which induce a pair-wise break in links, present this sort of a local network shock in the given context. A death or retirement of a director has two potential effects. It can directly affect the behaviour/outcome of the firm due to a loss of an employee and his/her productive input to firm policies. Indirectly, if the firm participates in board interlocks and shares the director it would result in a broken link. In this case, if the firm loses opportunities to interact (through board interlocking) with a high quality firm it would result in a reduction in overall network average in the next period i.e. the loss of a firm with high outcome values in period t leads to a reduction in the average in period $t+1$. I control for the direct effect of director deaths/retirement and use this death induced reduction to average outcomes due to broken firm linkages as an instrument. This implies that identification requires only that there be no systematic differences in director exits that break interlocks and those that do not (i.e. director exits of unconnected directors). The first stage will essentially compute a differences-in-differences estimate for those firms that experienced the shock in each time period. As an example, consider the following figure (below): the network in time t evolves to a new structure in time $t+1$. Two links have

[19] Note that D_{it-1} does not directly enter a standard production function.

[20] Superscript D indicates the subset of past period peers who have been lost as a result of shock D_{it-1}. $\mathbf{W^D_{it-1}y_{t-1}}$ can also be written as $\overline{y}^D_{-it-1}$ indicating the average outcomes of peers who have been lost. I describe in detail the construction of the peer average shifters in the subsequent pages.

been broken and one new link has been appended. However, only one link has broken due to a shared director death/retirement (in green) – I identify, only this type of pair-wise link deletions.



The objective is to construct a variable that can predict the gain or loss to the next period average, $t+1$, due to deaths/retirements induced link exits. $\mathbf{D_{it}}$ is a binary variable that indicates whether firm i experiences death or retirement of one or more directors. At given time t, let $\mathbf{W^D_{it}}$, denote the subset of past period peers who have been lost as a result of shock D_{it}; its elements are defined as follows:

$$w^D_{ij,t} = \begin{cases} 1 & \text{if i and j lose a } \underline{\text{shared}} \text{ director due to } D_{it}, D_{jt} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Endogenous Effects: To instrument for the endogenous peer effect in time t I use the average outcomes of lost peers (due to death/retirement of shared directors) in time period $t-1$, given by $\mathbf{W^D_{it-1}y_{t-1}}$. This variable measures the 'quality' of peer loss.

Exogenous Effects: Similarly, to instrument for the exogenous effects I use the average exogenous characteristics of lost peers, given by $\mathbf{W^D_{it-1}x_{t-1}}$.

With these as instruments I estimate the following system using two stage least squares. Explicitly controlling for the direct effect of the shock D_{it-1} in Eq. (6), the equation of interest is given by:

$$\triangle\, y_{it} = \beta \triangle \mathbf{W^N_{it}y_t} + \gamma \triangle x_{it} + \tau \triangle D_{it-1} + \delta \triangle \mathbf{W^N_{it}x_t} + \triangle \varsigma_t + \triangle u_{it} \tag{8}$$

The first stage equations for the endogenous and exogenous peer variables are:

$$\begin{aligned} \triangle \mathbf{W^N_{it}y_t} &= \theta^{f1} \triangle \mathbf{W^D_{it-1}y_{t-1}} + \vartheta^{f1} \triangle \mathbf{W^D_{it-1}x_{t-1}} + \gamma^{f1} \triangle x_{it} + \tau^{f1} \triangle D_{it-1} + \triangle \varsigma^{f1}_t + \triangle u^{f1}_{it} \\ \triangle \mathbf{W^N_{it}x_t} &= \theta^{f2} \triangle \mathbf{W^D_{it-1}y_{t-1}} + \vartheta^{f2} \triangle \mathbf{W^D_{it-1}x_{t-1}} + \gamma^{f2} \triangle x_{it} + \tau^{f2} \triangle D_{it-1} + \triangle \varsigma^{f2}_t + \triangle u^{f2}_{it} \end{aligned} \tag{9}$$

Finally, identification requires that the quality of peer loss ($\mathbf{W^D_{it-1}}(.)$) be independent of both

ν_{it} and $\varepsilon_{\eta t}$ as maintained in Assumption (A4)[21]. Independence with ν_{it} could be violated for instance if firms choose to strategically replace the lost directors with directors of equally well connected companies. This could be if firms that witnessed shared director deaths are more likely to form new links in the next period. In section (6.1) I verify that this is not the case and that the effect of a shared director death is insignificant in predicting the probability of new links. Moreover, I am able to control for the direct effect of director deaths/retirement on the firm's outcome since not all deaths/retirements are of shared directors. I discuss the independence of $\varepsilon_{\eta t}$ and the constructed instrument in the following subsection.

3.3 CORRELATED EFFECTS

The presence of correlated unobservables within a firm's local network could bias the peer effects estimates. Correlated effects could arise due to a number of reasons such as common productivity shocks (if the peer firm was in the same industry as the target firm), change in business group policies ((if the peer firm was in the same business group as the target firm) or other shared director related shocks. I can classify local network peers of any firms into three types: those that belong to the same Industry (I), those that belong to the same business group (G) and the remaining that do not belong to either the firms' industry or business group ($\not{I}\ \not{G}$). On average 62.45% of network links are peers who belong to the same industry or same business group. Using this property and to clarify the issue more, I further decompose the error by dividing $\varepsilon_{\eta t}$ into three parts:

$$\varepsilon_{\eta t} = \varepsilon^{I}_{\eta t} + \varepsilon^{G}_{\eta t} + \varepsilon^{\not{I}\not{G}}_{\eta t} \tag{10}$$

where $\varepsilon^{I}_{\eta t}$ represents the industry level common unobservables, $\varepsilon^{G}_{\eta t}$ represents the business group level common unobservables and $\varepsilon^{\not{I}\not{G}}_{\eta t}$ represents the residual. To eliminate the first two terms I use *both* industry by year and business group by time fixed effects. The resulting specification is (omitting the first stage):

$$\triangle y_{it} = \beta \triangle \mathbf{W^N_{it}} \mathbf{y_t} + \gamma \triangle x_{it} + \tau \triangle D_{it-1} + \delta \triangle \mathbf{W^N_{it}} \mathbf{x_t} + \triangle \varsigma_t + \triangle \phi_{It} + \triangle \tau_{Gt} + \triangle \nu_{it} + \triangle \varepsilon^{\not{I}\not{G}}_{\eta t} \tag{11}$$

where ϕ_{It} and τ_{Gt} represent industry by year and business group by time fixed effects that

[21] An easy way to see that it holds is to examine the instrument validity condition[22]; omitting the individual subscript and first difference operators:

$$\begin{aligned} E[(\mathbf{W^D_{t-1}} \mathbf{y_{t-1}})' \mathbf{u_t}] &= E[(\mathbf{y_{t-1}})' (\mathbf{W^D_{t-1}})' \mathbf{u_t}] \\ &= E[\underbrace{(\mathbf{y_{t-1}})'}_{A} \underbrace{((\mathbf{W^D_{t-1}}) \mathbf{u_t})}_{B}] = 0 \end{aligned}$$

Using the fact that that the network W^N and therefore W^D is symmetric, a simple reformulation of the original exclusion shows that the validity condition holds because the average disturbances of lost peers in **time t** (vector B) are uncorrelated with the vector of own outcomes in **time t − 1** (vector A). See Appendix A.1 for details.

will be estimated. This specification also allows us to control for both industry and business group level fundamentals that may be driving the outcome of interest[23]. The remaining correlated unobservable, $\varepsilon_{\eta t}^{\mathcal{I}\mathcal{G}}$, are not systematically related to any firm specific pre-defined group. Even then, the identification strategy pursued in this paper will provide consistent estimates of the peer effects since past period peers that dropped out due to death of shared directors are no longer in the peer group of the next period and therefore do not share the same unobserved shocks/correlations.

4 DATA

My primary source of data is the PROWESS database provided by the Center for Monitoring of the Indian Economy (CMIE). Prowess includes annual report information for around 29,000 companies in India from 1989 to the present year. It provides detailed balance sheets, financial statements, industry information and group affiliation for each firm, corporate ownership data, share prices, and other relevant data for publicly traded Indian corporations. In this paper, I use an (un-balanced) panel of all Indian private sector firms that are publicly listed firms – both on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE)– from the period 1997-2010. As in other papers (Khanna and Palepu 2000, Bertrand, Mehta, and Mullainathan 2002), I rely on CMIE classification of firms into group and nongroup firms, and of group firms into specific group affiliation which is based on a "continuous monitoring of company announcements and a qualitative understanding of the group wise behaviour of individual companies" (CMIE 2010, pg. 4). For identifying industry affiliation, I use information on the principal line of activity of the firm and use the National Industry Classification (NIC) code accorded to them. This is similar to the SIC classifications of firms in the UK and US. The PROWESS data also provides detailed information on the directors serving on the board of each firm, along with information on the number of board meeting attended, salary, directors' fee etc. The listing of these directors is unique within each time period and I undertake and exhaustive matching exercise to ensure uniqueness even across time periods.

My second source of data comes from a Bombay Stock Exchange led initiative called Directors' Database (www.directorsdatabase.com) and maintained by Prime Database of India. The data contains individual as well as firm level information on all directors including the directors educational qualifications; the directors position in the board (for example promoter director, managing director, non-executive director, independent director, etc.); whether the

[23]Note that given the panel dimension of my data which contains ten time periods and about two thousand industry and business groups, I am only able to estimate full industry by year and business group by year fixed effects in separate specifications. However, to estimate both industry and business group by time fixed effects, I define a time period as two year spells and interact them with both industry and business groups indicators to estimate industry by year and business group by time fixed effects. While slightly restrictive, this is the most feasible alternative to capture industry and group time invariant shocks together.

director satisfies the definition of being independent according to the guidelines laid by out by the Securities and Exchange Board of India (SEBI); the other public and private firms in which the director is a board member. Importantly, it contains separate information about cessations of every director in the boards of all listed firms which includes the name of each director who ceased to be a board member, the date of such cessation and the reason for such cessations (end of nomination, resignation, demise etc.) (Chakrabarti et. al, 2010).

Based on the above two data sources I construct time-varying networks for the all the listed firms in my data-set. Figures (1) & (2) provide a summary of the network topology and its evolution over time. I find, consistent with many studies (see Kossinets and Watts 2006), that these network graphs experience a fair amount of stability over time. Figure (1) shows that the degree and clustering coefficient witness a slight upward trend. Figure (2) summarizes the number of director appointments & cessations for each firm along-with the corresponding link additions and deletions. On average about 4.5 links are deleted/lost and 1 new link is added. The last panel in this figure also shows the average number of death/retirement related lost links (approximately 0.5 links) in each time period. Death and retirements related link deletions account for about 10% of all link deletions.

The outcome variables that I use for analysis are defined as follows. Market investment is defined as the sum of all firm investments in equity shares, preference shares, debt instruments (issued by the government or by non-government entities, or of short-term or long-term nature), mutual funds and approved securities. Investments made by investment companies that are engaged entirely, or essentially, in the business of purchase and sale of securities for making profits from these are not included in this data field. Investments of such companies are treated as stock in trade and not investments. For robustness I consider also investments made by the company in only securities that are listed on securities exchanges; such securities are called "quoted" securities[24]. Executive compensation is the remuneration paid to company executives and it includes the amount of salary paid, contribution to provident fund, value of perquisites, performance linked incentive to whole time directors and also the commission paid to them. It does not include the sitting fees paid to the directors for attending board meetings. Capital Expenditure is measured as the total expenditure incurred during the setting up of a new plant or a new project up to the date of the commercial production. Current R&D expenditure is measured by the total outlay of the company on research and development during the year on its current account.

I use a fairly parsimonious specification to control for other firm exogenous characteristics. Specifically, I include total profit before depreciation, interest, tax and amortisation; total book value of assets (in logs); total sales of a company (in logs). All the control variables are

[24]Investment in mutual fund is also treated as quoted investment even if not listed on the exchanges as their fair price is available and are easily marketable

lagged by one year. I also control for the number of director exits. This refers to the number of directors who have left the company in the previous time period. Toe measure scale effects I also include a total network size variable that measures the number of direct links i.e. the number of other firms with whom it shares common directors.

5 RESULTS

I now report results of industry and network peer effects on firm policies. I first provide descriptive evidence that peer groups matter. Figures (4) & (3) present nonparametric plots of a firms' investment expenditure against the average industry and network peer averages of the same. In both graphs firms' investment expenditures are increasing in their peers' performance. Note also that this positive relation is approximately linear for both industry and network averages. Table (1) provides summary statistics over all time periods for the variables used in the analysis.

5.1 NETWORK PEER EFFECTS

Corporate Market Investment: Table 2 shows the results for peer effects in corporate market investment from estimating Equation (3) using OLS and the two stage least squares using the instrument described in Section 3.2 above. Both the outcome variable and the endogenous peer variable are in logs. In the following results I control for the assets of each firm but in unreported results I also asset normalize the investment variable; the results are unchanged. Column (1) shows OLS results not accounting for potential bias in selection or unobserved network shocks. There is a positive and statistically significant coefficient associated with the endogenous peer effects. Other control variables are also statistically significant: a change in profits, assets and sales are all associated with a positive growth in corporate market investment as expected. I now discuss the instrumental variable results. Column (2) reports the first stage of the two stage least squares procedure. Recall that the instrument I use is the average outcome of death induced deleted links in the past period, $\mathbf{W^D}$ *Mkt. Invst.* An exits of peers with high outcome values is likely to reduce the average in the next period (net of other endogenous deletions and additions) because they no longer contribute to this average. The first stage results confirm this; a one unit increase in the average investment of lost peers (due to death/retirement) leads to a 6.4% reduction to the next period average investment (of existing network peers). The coefficient is statistically significant at 1%. This result suggests that firms are unable to immediately replace dead/retired directors with equally well connected new directors so as to restore their links. Moreover, the instrument is highly informative as the first stage F statistic is 124.2. Therefore the endogenous peer effect is not 'weakly' identified[25].

[25] "Weak identification" arises when the excluded instruments are correlated with the endogenous regressors, but only weakly.

Column (3) & Column (4) report second stage results under different specifications. Generally, the results show a large increase in the coefficient of peer effects. Now, an increase of one standard deviation in a firm's network peers has almost twice the effect on the change in writing skills it had when using OLS. An increase of one standard deviation of the endogenous effects leads to an increase of 0.16 standard deviations in the growth of market investment. All the conditioning variables, remain statistically significant throughout. Note that the coefficient on the director exit is statistically insignificant which would imply that exits of directors have no direct independent effect on the outcome.
Column (5) reports results that include contextual effects. For corporate market investment, none of the contextual effects are significant. The endogenous peer effect is still statistically significant and slightly larger in magnitude. This is not however the general pattern and in other results I discuss the interpretation of contextual effects where they are found to be significant. Finally, Column (6) adds scale effects separately. The average network peer effect implicitly captures the scale effect since it normalizes the peer total by network size. I control for the firm size by including firm sales; therefore if larger have more directors and hence larger networks, the sales variable will potentially already capture some effect of the network size. Even then, there might be concern that the size of the network directly enters the model and so I calculate in each period the number of local network peers that a firm is linked with and include this in the regression. The network size variable is endogenous due to the above mentioned concerns of non random selection into the network and the existence of other unobservables. Here again, I rely on the death/retirement induced local network shocks and instrument network size in the current period with the number of firms lost due to death/retirements of common directors in the previous period. In unreported results, I find that the instrument is significantly negatively correlated with the endogenous network size variable as expected. Column (6) shows that the network size variable is not significant, after controlling for firm size, endogenous and exogenous peer effects. Table (6) further strengthens the results by eliminating industry and business group specific shocks. I find that both the magnitude and significance of the endogenous peer effects, as reported in Column (1) of Table (6: A & B) remain unchanged even after accounting for industry by business group by time fixed effects.

Executive Compensation: Table 3 shows the results for peer effects in executive compensation. As before, both the outcome variable and the endogenous peer variable are in logs. Column (1) shows OLS results not accounting for potential bias in selection or unobserved network shocks. There is a positive and statistically significant coefficient associated with the endogenous peer effects. Both, a change in assets and sales, are associated with a positive growth in executive compensation. Column (2) reports the first stage of the two stage least squares procedure. The first stage results show that a one unit increase in the average compensation of lost peers (due to death/retirement) leads to an 8.9% reduction to

the next period average. The coefficient is statistically significant at 1% and the instrument is strongly correlates with the endogenous variable (Cragg Donald F statistic in the first stage is 178.946). Column (3) & Column (4) report second stage results under different specifications (as above). Generally, the results show a large increase in the coefficient of peer effects. An increase of one standard deviation of the endogenous effects leads to an increase of 0.05 standard deviations in the growth of executive compensation.

Column (5) reports results that include contextual effects. It shows that the average profits of peer firms negatively effects the growth of executive compensation of any given firm, however the coefficient is quite small and close to zero. In general, the interpretation of contextual effects is fraught with ambiguity. Cooley (2009) provides a detailed discussion on the specification and interpretation of contextual effects in the classroom/child learning context. She argues that higher values of peer exogenous characteristics might reduce own outcome values if there are positive spillovers from endogenous peer effects and we condition on this. For instance, extending the argument in the firm setting, consider a firm whose executive compensation levels are increasing in its peer's compensation levels as well as own profits. This implies that *controlling for the firm's own profits and peer firms' compensation levels* any increase in peer profitability should decrease own compensation levels. This is because the firm will require an increase in effort from its own executives to match up to the profits of its peer firms (and therefore reduce compensation until effort is increased and profit is matched), for any given own profit level and peer compensation level. Apart from peer firm profits I find no other significant contextual effects. Finally, Column (6) includes scale effects separately however the coefficient on network size is not significant. As before, I account for industry and business group level unobservable in Table (6). Column (2) of Table (6: A & B) reports these results and I find similar results to those reported above.

Capital Expenditure & R&D expenditure: Table 4 reports results for peer effects in capital expenditure and it is quite similar to the market investment results (in the final contextual effects specification) discussed before. Interestingly, the endogenous peer effect on capital expenditure is positive but statistically significant only with the inclusion of contextual effects. Table 5 reports results for peer effects in current R&D expenditure. I find no significant network effects in current R&D expenditure in either of the specifications.

5.2 HETEROGENEITY

In order to distinguish between the different types of peers *within local networks*, I disaggregate the overall peer effect between industry network peers and non-industry network peers. This is important because there may be differences in how a firm *responds* to the behaviour of peer firms within the network who belong to its own industry compared to those that do not belong to the same. The disaggregation also helps establish channels though which peer effects operate if we assume that the nature of interactions are distinct and separable between

the two sets of peers[26]. Although the precise qualitative nature of peer effects is hard to pin down, it is possible to distinguish the different types of interactions between the groups using some insight from economic theory. Economic theory on firms typically considers interactions amongst industry peers to be competitive. In contrast firm strategic alliances are theorized to be benevolent and more collaborative in nature. There is an extensive literature on such network based firm interactions wherein firms collude and cooperate to share information and resources (Goyal and Moraga-Gonzalez (2001); Belleflamme and Bloch (2004)). This implies that if corporate peer effects are based on information diffusion, firms may be less willing to trust information received from industry network peers (as compared to non-industry network peers) and as a result not respond to the behaviour of this set. However if one were to find positive and significant peer effects from industry network peers then it could potentially imply that, keeping with the competitive spirit, firms *mimic* behaviours of these peers.
In Section 7.2 I distinguish between effects of industry peers which comprise all other peers in a firms industry and distinguish it from the overall network peer effect (containing both industry and non-industry within network peers). The present exercise is different from Section 7.2 in that it tests for the differences in peer effects only *within* the overall network – between industry network peers and non-industry network peers. In a sense this distinction precludes any comparison between industry and overall network peer effects because network peers also contain industry peers and vice versa. I therefore first seek to understand how even within the network firms differentially respond between industry and non-industry peers.

Table 7 reports results that decomposes the peer effects as discussed. I present results only on market investments and executive compensation since these are the two outcomes for which I do find significant peer effects. The first two columns of both outcomes report the two first stage results. Recall that the instrument is the average past period outcomes of delinked peers due to death/retirement. In order to find separate peer effects by industry and non-industry peers, I also decompose the instrument to separate loss to the average next period outcome due to delinked industry peers and those due to delinked non-industry peers. Both the instruments work well in predicting the two outcomes and are orthogonal to each other. An exit of industry network peers with high outcome values reduces the industry network average in the next period and has no effect on the non-industry network average in the next period. The same applies for non-industry network peer exits. In general the joint Cragg-Donald F-stat is high implying that both instruments are strong and informative. I now focus on discussing peer effects from different sources. The results show that in both cases, industry network peer effects ($\mathbf{W^{NI}}$) are statistically insignificant while non-industry network peer effects ($\mathbf{W^{NN}}$) are positive and significant. An increase of one standard deviation of the *endogenous non-industry network peer effects* leads to an increase of 0.16 standard

[26]There is recent and growing literature that identifies the mechanisms of peer effects by decomposing its effect between pre-defined groups of interest. See Cohen-Cole and Zanella (2008) and Lavy and Schlosser (2007) as examples.

deviations in the growth of market investments and 0.05 standard deviations in the growth of executive compensation. The coefficient on endogenous industry network peer effects is close to zero. This indicates that the bulk of network peer effects derive from a firms association with other non-industry firms. However a firm can have interactions with a wide range of firms within its own industry outside of its corporate network. It is therefore important to account and distinguish these market based interactions from the non-market based interactions (corporate networks) discussed up till now. This is developed further in Section 7.2.

5.3 INVESTMENT: STOCK LEVEL ANALYSIS

In order to pin down the exact nature of corporate market investment peer effects, I make use of detailed information on each stock that a company has invested in over several years[27]. The previous section established that companies are influenced by their peers in their choice (nature and volume) of stock market investment. I refine the result now by tracking stock-wise activity of every firm in relation with its networked and industry peers over time. Specifically I estimate whether, for any two companies, the probability of investing in the same stock in any given time periods is increasing in the strength of their network ties. Denote the set of stocks of any company i at time t as R_{it}. I match the set of stocks for every pair in the sample (R_{it} and R_{jt}) to see whether there is at least one stock that is common to both. Let $\varnothing$ denote a null set indicating that there is no common stock between a pair of matched stocks; the equation of interest is:

$$Pr(R_{it} \cap R_{jt} \neq \varnothing) = \beta_1 N_{ijt} + \beta_2 I_{ijt} + \gamma X_{it,jt} + \varepsilon_{ijt} \tag{12}$$

I estimate pair-wise or dyadic regressions where the unit of analysis is a pair of two companies i and j[28]. The dependent variable is binary taking the value 1 if both i and j have invested in the same stock in time period t. *Network Strength*, N_{ijt} indicates the value of connection between i and j and ranges from zero to one. It is equal to the inverse of path distance in the global network between i and j – zero indicates no connection and one indicates direct connection. All other values mean that i, j are connected but through a series of intermediate links. I also includes a vector of pair-specific controls (differences in their profits, sales and assets), $X_{it,jt}$. Finally I also capture whether the probability of investing in the same stock is correlated with sharing a common industry, I_{ijt}. I use a dyadic framework for analysis because it allows incorporating the several thousands of stocks that exist in the entire sample, matching effectively the stock sets of different companies. Although this framework is unable

[27]Detailed stock information is available for bulk of the listed companies in PROWESS only from the year 2006. Data for previous years exist but only for a selected few companies. Therefore in order for the results to be representative of the publicly listed sample as well to make the analysis computationally feasible I use only the years 2006-2010 for analysis

[28]Standard errors are adjusted using the QAP procedure to account for pair-wise dependence.

to distinguish whether company j is influenced by company i to invest in the same stock, it is informative of the *similarity* in the patterns of stock-wise investment of both companies. I also instrument for the potential endogeneity of the network strength variable by using director exits due to death and retirement. This follows the same idea as all previous analysis, wherein I use a variable that takes the value one if there are any common directors over the network between i and j who have died or retired in the previous time period to instrument for the strength of network tie between i and j in the current time period.

Table (8) reports results from this analysis. Column (1) reports simple OLS results. It shows that an increase in network tie between i and j from zero to one increases the probability of investing in the same stock by approx. 9%. Absolute differences in both profits and assets also increase the probability of investing in the same stock. It is interesting to note that sharing the same industry (indication of industry peers) also increases the probability of investing in the same stock – by about 4%. Since the occurrence of investing in the same stock is quite low[29] across the whole universe of dyads, I also employ a rare events a logit estimator to account for the underestimation in the probabilities associated with such an event. I follow the procedure outlined in King and Zeng (2001) to estimate bias-corrected parameter estimates and standard errors[30]. The results show that network strength effect is associated with a coefficient of 1.63. this means that a change in network strength from 0 to 1 (no connection to direct connection) increases the probability of investing in the same stock by 11%. The relative risk associated with this change (of 0 to 1) on the probability of same stock investment is 4.56 log-odds. Column (3) incorporates pair fixed effects to control for pair specific correlated unobservables; network strength still remains positive and significant. Finally I report instrumental variable results. The first stage, Column (4), shows that a global network shared director exit (due to death/retirement) in the previous period is associated with a fall in network strength of about 0.05 units and this effect is statistically significant[31]. The second stage results, both random effects and fixed effects show a positive and significant effect of network strength, much higher in magnitude compared to the OLS results, on the probability of investing in a similar stock.

[29] Investment in same stock takes the value 1 in approx 4% of dyad-year observations.

[30] Briefly, the method incorporates three corrections into ordinal logistic regression: choice based sampling giving greater weight to positive events, prior correction on the dependent variable based on the representation of the positive event within the population and amplification of the probability by a correction factor. For more details on this procedure see King and Zeng (2001).

[31] The instrument also satisfies the criteria for a strong informative instrument; the first stage Cragg Donald F statistic is over 100.

6 SENSITIVITY ANALYSIS

6.1 THREATS TO IDENTIFICATION

Identification of network effects relies solely on the occurrence of death/retirement related local network shocks being witnessed by the firm. The validity of the instruments could be violated for instance if firms choose to strategically replace the lost directors with directors of equally well connected companies i.e. firms that witnessed a shared director death are more likely to form new links in the next period. In order to test if this is the case or not, I run a simple difference-in-difference regression comparing the network dynamics of firms that lose connections due to death/retirement induced director exits to other firms. The objective is to determine whether firms that experience death/retirement shock in time $t-1$ are more likely to form new links in time t. Table (9) reports results on this regression. I find no significant effect of a death shock in the past period on the probability of forming new links and this result holds even after controlling for other firm level factors (sales, assets etc.). The results also show that all the time fixed effects are jointly highly significant in predicting the propensity to form new links. This suggests that there the increasing trend over time to form new links is independent of whether a firm experiences link reduction due to death/retirement shocks.

6.2 NETWORK MEASUREMENT: MONTE CARLO

Throughout the analysis I measure inter-firm network connections between all listed companies in India. However it is true that the directors of each listed company also serve on boards of non-listed companies. Since these non-listed companies are not part of the sample, the network omits linkages between listed and non-listed companies thereby inducing a potential measurement error. In this section, I provide some Monte Carlo evidence to assess the sensitivity of my results to such network related measurement error. To do so I consider a population of two types of firms: listed and non-listed[32]. The objective is to compare an estimated value of the parameter obtained from 'sampling' a network to the true population parameter. Here, a sample network refers to a subset of the original population network from drawing a sample of all listed companies.

There are three types of links in the population: links between a pair of listed companies ('*listed links*'), links between a listed company and non-listed company ('*mixed links*') and

[32]Note that here the population is assumed to derive from the set of all directors that serve on boards of listed companies. The simulations deal with sampling issues caused by partial enumeration of links from a bipartite graph (defined in Footnote 13). Therefore I consider the list of directors to represent the entire universe of groups or events, and assess the measurement error induced by omitting links (and therefore firms) that share common affiliation with any of these directors. This type of measurement issue is also commonly referred to as the 'Boundary Specification' problem in relation to bipartite graphs (Kossinets 2006). In particular, I abstract from the possibility that there are additional 'non-listed links' due to non listed companies sharing common directors who do not serve on the boards of listed companies. This exercise is beyond the scope of this paper but is an interesting research agenda for the future.

links between a pair of non-listed companies ('*non-listed links*'). To assess the bias arising from partially enumerating links of listed companies, I use controlled network topology driven Monte Carlo experiments similar to Páez, Scott, and Volz (2008). Details of the procedure are outlined in the Appendix A.2. In the first experiment I control the density of listed links (henceforth listed-density), measured as the proportion of listed links to the total number of links in the population, and the sample size i.e. the proportion of listed companies in the sample, in order to simulate various population networks. I then extract the sample networks (all listed links) to estimate the peer effect parameter and compare it to the true population parameter. Table (13) reports results from these simulations. Overall, I find that this type of measurement error induces a *downward bias* i.e. the estimated parameters tend be lower than the true population parameter. Figure (5) plots a heat-map of the root mean square errors (henceforth RMSE). It shows that, for $\beta = 0.2$, the values of RMSE increase as the listed-density and size fall; higher values of RMSE are indicated by (progressively) dark shades of blue. For most the RMSE is quite low but increases sharply only at listed-density lower than 0.1. At this level and for a sample size equal to 20% of the population, the RMSE is 0.08. The maximum RMSE, 0.40, is reached with a sample size of 10% and listed-density of 3%. In the second experiment, I explore bias associated with a homophillic tendency to form links. Homophily in this context arises when listed firms are more likely to form links (or share directorates) with other listed firms. Higher homophilic tendency should decrease the extent of measurement error because it limits the extent of mixed link omissions. Therefore even at low listed link densities, a sufficiently high degree of homophily can reduce the extent of bias. To examine this, I introduce an additional topological parameter, degree of homophily, and vary it to arrive at different network configurations. The homophily parameter measures the distribution of links that listed companies have between listed links (intra-group links) and mixed links (inter-group links). For example a value of 0.5 indicates that 50% of all links that listed companies have are amongst themselves. Table (14) reports results from varying the homophily parameter at a given level of sampling size and listed-density. There is a downward bias even in this case. Figure (6) summarizes the results; it shows that at $\beta = 0.2$ and sample size of 20% , the bias steadily increases as the homophily parameter and listed-density fall.

To assess the significance of these results, I construct a quasi-population network from the observed data. I am able to do this this because the data provides information on all non-listed companies that a director of any listed company serves on. After including these non-listed companies, I construct an approximate population network. I find that listed companies represent about 15% of the full list of companies. The proportion of listed links to total links is approximately 0.7, while the degree of homophily is 0.18. Assuming that the true population parameter lies between 0.2 and 0.3, I can expect the extent of bias to be quite negligible; if anything, the peer effect coefficient should be slightly greater than what

is estimated. Moreover if we consider inference to be based on a population containing only listed firms then the presence of links with non-listed firms enter the regression framework as an omitted variable – average outcome of non-listed peers. My instrumental variables strategy mitigates the effect of bias from such an omitted variable because the instrument is uncorrelated with the omitted variable [33].

7 ALTERNATIVE PEER REFERENCE GROUPS

7.1 GLOBAL NETWORK INTERACTIONS

In this section, I account for global network interactions. Recall that a global network is the entire graph of social interactions, both though direct connections and indirect connections. Multiple local networks comprised solely of direct connections are all nested within the local network. Until now I have restricted interactions to occur only though local networks. However, it is possible that a firm's peer group consist of not only direct connections but also indirect connections. To this extent, I construct a firm's peer group by linking into all the firms that it is directly or indirectly related to. Respecting the topology of the network, I give direct connections the highest weight whilst calculating the average. To calculate weights in the global network I use a common network statistic, the path distance. In the firm network, we say that a path exists between firm i and j if they are connected either directly or though a sequence of other firms. The path distance then is defined as the length of the shortest path between them. For example, the path distance between two firms that are directly connected is one; path distance between two firms that are connected by an intermediary firm is two. The global network peer average is therefore just a weighted average of outcomes of all peers where the weights are given by the inverse of the path distance.

It is useful to understand how the instrument is applicable even in this context. In the previous section we had used average outcomes of the death induced deleted links in the previous time period to instrument for average peer outcomes in the current period. In this case we had only considered death induced deletion of links between two firms that are directly connected. In the global networks we can visualize multiple such instances wherein bilateral links are being broken due to death/retirement of shared directors. Consider three firms i, j and k. i & j and j & k are directly connected. If j & k break a link due to death/retirement of a shared director then, in the global interactions case, even i is affected because the broken link results in reducing the *strength* of network connections for i. The advantage of this is that the instrument is still valid and we no longer have to rely on only bilateral link losses. The disadvantage is that the measure is prone to a lot of noise. While we know that firm j & k have lost a link, it is not necessary the strength of connection between

[33] The results in Table (7) are an indication of this as it shows that decomposition of the instrument produces two instruments that are orthogonal to each other given the superability of peer effects.

i & k would reduce because it is possible that in the next period i directly links with k. The informativeness of this instrument then relies on the perturbations in connection patterns not deviating significantly (apart from the death induced deletions) from the previous state.

Table (10) reports results on the global peer effects. While the coefficients on investment and executive compensation peer effects remain positive and statistically significant, they are much larger in magnitude compared to the local networks based specification. An increase of one standard deviation of the endogenous effects leads to an increase of 0.19 (as compared to 0.16 in the local networks case) standard deviations in the growth of market investment. Similarly, an increase of one standard deviation of the endogenous effects leads to an increase of 0.15 (as compared to 0.06 in the local networks case) standard deviations in the growth of executive compensation.

7.2 INDUSTRY PEER EFFECTS

I also account for peer interactions through a shared industry affiliation and contrast it with the network peer effect. Identification in this case is through partially overlapping groups using peers-of-peers as an exclusion, wherein some 'peers of peers' do not affect an individual directly but only through his or her own peers. I use the exogenous characteristics of an industry peers business group to identify endogenous peer effects. The exclusion restriction is valid since the business group's peers (or peers-of-peers) are not directly connected to the target firm. Appendix A.3 details the identification strategy used to estimate industry based endogenous peer effects. Table 11 reports industry level peer effects. Note that all specifications include time fixed effects. I report results for market investment, executive compensation and current expenditure in R&D. I omit reporting results on other control variables for brevity. Column (1) shows OLS results, Column (2) IV results and Column (3) IV results with contextual effects. I do not report the first stage results, however I provide both the Cragg-Donald first stage F statistic and the joint significance of the excluded peer averages (instruments). I first discuss Panel A of Table 11 that reports results on corporate market investment. I find that both the OLS and the IV coefficients are positive and statistically significant although the IV coefficient is much larger in magnitude than the OLS. I find that a one standard deviation increase in the industry peer average investment is associated with a 0.27 standard deviation increase in growth in own investment. The significance of the coefficient disappears when I include contextual effects. Note that the first stage instruments are all jointly significant and are strongly correlated with the endogenous variable Panel B reports results on executive compensation. I find no statistically indicants industry peer effects vis-*à*-vis compensation. Industry Peer effects in current R&D expenditure is reported in Panel C. In contrast to network peer effects, I find that industry R&D expenditure significantly increases the firm's own growth of the same. A one standard deviation increase in the industry peer average R&D expenditure is associated with a 0.34 standard deviation

increase in growth in own R&D expenditure and this effect is significant at 5%. Moreover, this effect holds even with the inclusion of contextual effects. The finding of positive industry peer effects for R&D but not for executive compensation is not surprising since there is substantial heterogeneity in performance and compensation policies amongst industry peer whereas R&D intensity is generally concentrated within certain industries.

To distinguish between the network and industry peer effects I include both the peer averages in a parsimonious specification. Table (12) reports results for this specification[34]. The results show that network peers matter for market investment more than industry peers. In contrast, firms respond to the behaviour of industry peers in decisions on current R&D expenditure. The results hold even after controlling for industry by business group by time fixed effects.

8 CONCLUSION

This paper presents evidence on contemporaneous peer spillovers from firm social interactions. Using firm level panel data I examine whether peer effects operate on firm policies viz. investment, executive compensation and R&D expenditure. I find substantial evidence for positive network based peer effects. My identification strategy exploits both the structure and the inter-temporal variation of firm networks to estimate endogenous peer effect, distinguishing it from other exogenous and correlated peer effects as well as from issues of non-random selection. I use information on director exits caused by deaths/retirements of shared directors to exploit the incidence of natural breaks in the network. Using average outcomes of those peers who have been lost due to death/retirement related director exits to instrument for a firm's average peer outcomes in the next time period I find that an increase of one standard deviation in network peer investment leads to an increase of 0.16 standard deviations in the growth of own firm investment. Similarly an increase of one standard deviation in network peer executive compensation leads to an increase of 0.05 standard deviations in the growth of own firm executive compensation. I find positive industry peer effects for market investment and R&D but not for executive compensation. I also compare industry peer effects with overall network peer effects and find that for market investment network peer effects dominates whereas the opposite is true for R&D investment. Further I show that these peer effects hold even when considering the 'global network' of any firm i.e. considering both direct links and indirect links to other firms. The results found in this paper have significance not only for the understanding of inter firm dynamics but also for designing optimal corporate governance regulations. Directors who sit across the boards of various companies can conduit information and influence firm strategy and policy in similar ways without requiring the firms to collude or form an alliance by more formal, market-based means.

[34] I only report results on market investment and expenditure in current R&D because I find that the instruments set is not strongly correlated with the endogenous regressors of the other outcomes

As mentioned earlier, other studies that investigate peer effects in the firm context (but in the US context) also document evidence on positive peer spillovers influencing a range of corporate policy decisions. For instance, in the corporate network case, Fracassi (2008) finds that an increase in the strength of social connections shared by any two firms reduces the differences in their pattern of investment behaviour by 0.02 units i.e. it makes them their investment patterns more similar. On the other hand, for industry peer groups, Leary and Roberts (2010) find that one standard deviation change in industry based peer firms' leverage ratios is associated with an 11% change in own firm leverage ratios[35].

In order to further understand the mechanisms driving the aggregate peer induced outcome increase, I also present evidence on network peer effects disaggregated by within network industry peers and non-industry peers. Using insight from economic theory I argue that a firm's link to its industry peers is more competitive in nature whereas its links to its non-industry peers are relatively more benevolent. I find that for both market investment and executive compensation, industry network peer effects are close to zero while non-industry network peer effects are positive and significant. This implies that the bulk of the network peer effects derive from a firm's strategic alliances that are inter-industry rather than intra-industry. Also this might suggest that information rather than mimicking is the mechanism underlying the peer driven influence. However these results are only suggestive of the quality and mechanisms of peer spillovers. More research, perhaps experimental, is needed to pin down the precise channels by which peer effects operate.

It is important to emphasize that while the focus of this paper has been to provide evidence on the existence of peer effects in different firm interaction settings, a full account of what determines corporate policies would need to take other factors into account. For example if firms are responding to some information received by their peers then a richer model will be needed to account for the filtering and updating mechanism that firms employ to take their decisions, using both their own and their peers' information signals. This is related to ambiguity in decision making since a firm will perceive substantial noise to be associated with signals received from all their peers. Such a model will also be able to distinguish between models of herding versus cascading by seeking to understand whether a firm ignore their own private signals in preference for their peers' or not. Detailed data providing dynamic information on the sequence of firms' investment in particular stocks to undertake this exercise.

[35]Interestingly my results are also similar in magnitude to studies that investigate peer interactions amongst students and households. For students in general, studies have found that a one standard deviation increase in test scores of peers increases the students own test score by around 0.1 to 0.3 standard deviations. Other studies on household retirement behaviour, crime, also find peer effects in a similar range. The extent of literature needed to be referred for this is quite large so I direct the reader to an excellent review on social interactions by various authors in the Handbook of Social Economics (Behabib, Bisin, and Jackson (eds.) 2011)

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A APPENDIX

A.1 EXCLUSION RESTRICTION

Endogenous network formation biases OLS estimates though the presence of selection specific unobservables. Recall that the elements w_{ij}^N, of the *endogenous* network adjacency matrix take the value one, if there is a link between firms i and j, and zero otherwise. Each binary element w_{ij}^N can be thought of as representing an underlying (latent) index function by which firm i derives a utility from linking with firm j. This utility can be influenced by many factors, both observable and unobservable. Let c_{ij} denote those factors that are unobservable to the econometrician and possibly correlated with individual errors u_i. This leads to biased estimates of the endogenous peer effect, $E[(\mathbf{W_t^N y_t})'\mathbf{u_t}] \neq 0$, because among other things, the elements of $\mathbf{W_t^N}$ are correlated with $\mathbf{u_t}$ through link formation specific unobservables, $c_{ij,t}$. To mitigate this concern I make use of random shocks – death/retirement of directors – to the observed network. As before, $\mathbf{D_{it-1}}$ is a binary variable that indicates whether firm i experiences death or retirement of one or more directors in $t-1$. Peers/links lost due to the shock are contained in the matrix $\mathbf{W^D}$, whose elements $w_{ij,t-1}^D$ take the value one if firm i and j lose a <u>shared</u> director due to $D_{it-1}, D_{jt-1} = 1$ and zero otherwise.

To prove that the exclusion restriction holds I use the fact that the endogenous network $\mathbf{W^N}$ and the shock induced matrix $\mathbf{W^D}$ are symmetric and that the errors are independent of the shock. Symmetry implies that $(\mathbf{W_{t-1}^D})\prime = \mathbf{W_{t-1}^D}$. Further, both $\mathbf{W^N}$ and $\mathbf{W^D}$ are row-normalized which means that the row sums are equal to one. Row-normalization also implies, following Geršgorin's theorem, that all eigenvalues of $\mathbf{W^N}$ are less than or equal to one in absolute value. This ensures that $|\beta| < 1$ which in turn implies that all eigenvalues of $\beta\mathbf{W^N}$ are less than one in absolute value (Kelejian and Prucha 1998). This allows us to use a series expansion, $(I - \beta\mathbf{W^N})^{-1} = \sum_{k=0}^{\infty} \beta^k (\mathbf{W^N})^{\mathbf{k}}$ (Horn and Johnson 2005), that gives us the following result (omitting the first difference operators):

$$
\begin{aligned}
E[(\mathbf{W_{t-1}^D y_{t-1}})'\mathbf{u_t}] &= E[(\mathbf{y_{t-1}})'(\mathbf{W_{t-1}^D})'\mathbf{u_t}] \\
&= E[(\mathbf{y_{t-1}})'\left((\mathbf{W_{t-1}^D})\mathbf{u_t}\right)] \\
&= E[((I - \beta\mathbf{W_{t-1}^N})^{-1}(\gamma\mathbf{x_{t-1}} + \mathbf{u_{t-1}}))'\left((\mathbf{W_{t-1}^D})\mathbf{u_t}\right)] \\
&= E[\underbrace{(\sum_{k=0}^{\infty} \beta^k (\mathbf{W_{t-1}^N})^{\mathbf{k}} \mathbf{u_{t-1}})'}\ \underbrace{\left((\mathbf{W_{t-1}^D})\mathbf{u_t}\right)}]
\end{aligned} \tag{13}
$$

To show that Eq. (13) is equal to zero, it is sufficient to show that $\mathbf{W_{t-1}^D u_t} = 0$. The vector, $\mathbf{W_{t-1}^D u_t}$ represents the averages disturbances of lost peers in the next time period. The occurrence of the combined shock, D_{it-1}, D_{jt-1} is independent of u_{it} as maintained

in Assumption (A3)[36]. This implies that $w^D_{ij,t-1}$ is stochastic and independent of both u_{it} and link formation specific unobservables, $c_{ij,t}$. Since $\mathbf{u_t}$ is orthogonal to the probability of death/retirement shock and therefore to the probability of $w^D_{ij,t-1}$, it can be seen that $E(\mathbf{u_t}|w^D_{ij,t-1}) = E(\mathbf{u_t})$. Using this fact we have:

$$\begin{aligned}
\mathbf{W^D_{t-1}u_t} &= \begin{bmatrix} w^D_{11,t-1}u_{1t} + w^D_{12,t-1}u_{2t} + \ldots + w^D_{1n,t-1}u_{nt} \\ w^D_{21,t-1}u_{1t} + w^D_{22,t-1}u_{2t} + \ldots + w^D_{2n,t-1}u_{nt} \\ \vdots \\ w^D_{n1,t-1}u_{1t} + w^D_{n2,t-1}u_{2t} + \ldots + w^D_{nn,t-1}u_{nt} \end{bmatrix} \\
&= \begin{bmatrix} E(\mathbf{u_t}|w^D_{1j,t-1} = 1) \\ E(\mathbf{u_t}|w^D_{1j,t-1} = 1) \\ \vdots \\ E(\mathbf{u_t}|w^D_{1j,t-1} = 1) \end{bmatrix} \\
&= \begin{bmatrix} E(\mathbf{u_t}) \\ E(\mathbf{u_t}) \\ \vdots \\ E(\mathbf{u_t}) \end{bmatrix} = 0
\end{aligned} \tag{14}$$

To sum up, the exclusion only requires that the there be no systematic pattern in the occurrence of link loss.

A.2 MONTE CARLO SET UP

This section outlines the simulation procedure. I first simulate random networks with controlled network topologies. Consider the following population network, $\mathbf{W^P}$ with sub-subscripts l and z denoting listed and non-listed firms respectively:

$$\mathbf{W^P} = \left[\begin{array}{ccc|ccc} a_{1_l1_l} & \cdots & a_{1_ln_l} & b_{1_l1_z} & \cdots & b_{1_ln_z} \\ \vdots & (\mathbf{W^L}) & \vdots & \vdots & (\mathbf{W^M}) & \vdots \\ a_{n_l1_l} & \cdots & a_{n_ln_l} & b_{n_l1_z} & \cdots & b_{n_ln_z} \\ \hline b_{1_zn_l} & \cdots & b_{n_z1_l} & c_{1_z1_z} & \cdots & c_{1_zn_z} \\ \vdots & (\mathbf{W^M})' & \vdots & \vdots & (\mathbf{W^Z}) & \vdots \\ b_{1_zn_l} & \cdots & b_{1_z1_l} & c_{n_z1_z} & \cdots & c_{n_zn_z} \end{array}\right]$$

The matrix can be partitioned into four distinct block matrices with three different types of links. The first type of link concerns links between listed companies, 'listed links' (contained

[36]Specifically, Assumption (A3) states that D_{it-1} is independent of firm specific unobservables. However conditional on D_{it-1} the occurrence of a *combined shock*, which incorporates any other firm j, is independent of *both* firm specific and peer group level unobservables, given by the composite error term u_{it}.

in matrix $\mathbf{W^L}$); the second types of links are those between a listed company and non-listed company (contained in matrix $\mathbf{W^M}$); the third types of links are between a pair of non-listed companies, 'non-listed links' (contained in matrix $\mathbf{W^Z}$). The objective is to assess the performance of estimators when sampling only matrix $\mathbf{W^L}$ that contains listed links (elements $a_{.,.}$) from the population matrix $\mathbf{W^P}$. The simulation exercise generates several population networks each with different topologies. The two topological parameters that I control are, listed link density (henceforth listed-density), sample size and homophily. For example in the first experiment, I compare estimators between two population networks; one where the proportion of listed links (to the total number of links) is 0.3 and one where the proportion of listed links is 0.8. Overall, I vary the proportion of listed links over a range of 0.3 to 0.85 with increments of 0.5. For this application, I generate networks with $n = 500$ companies and also vary the number of listed companies amongst the 500; the size of the listed companies is varied over the range 25 to 150 in 25 step increments. Therefore for the first experiment, I have a total of 114 unique networks with controlled topolgies. Data for the experiment are generated using the following autoregressive model[37]:

$$\mathbf{y_n} = \beta \mathbf{W_n} \mathbf{y_n} + \gamma_0 \mathbf{l_n} + \gamma_1 \mathbf{x_n} + u_n \tag{15}$$

W_n is a $n \times n$ weights matrix, l_n is an n-dimensional column vector of ones's, $x_{n,i}$ is independently generated from a uniform distribution over the range [0, 10] for $i = 1, ..., n$ and $u_{i,n}$ are i.i.d $N(0, \sigma^2 = 0.5)$. The intercept term and the coefficient on the independent variable are set to 2.0 and 1.0, respectively. y_n is obtained using the reduced form of Eq. (15):

$$y_n = (\mathbf{I} - \beta \mathbf{W_n})^{-1} (\gamma_0 \mathbf{l_n} + \gamma_1 \mathbf{x_n} + u_n) \tag{16}$$

A total of 200 draws are obtained for the error terms and independent variable $\mathbf{x}$. Next, I draw a sample of all the listed companies in the population and extract the sample network which is a subset of the true population network (W) and captures only links amongst the listed companies. I use a generalized two stage least squares estimator as proposed in Kelejian and Prucha (1998). In order to asses the quality of the estimators in the simulations, I calculate the root mean squared error (RMSE) which is the square-root of the mean square error. The MSE for the parameter β is calculated is given by (Florax and Rey 1995):

$$MSE(\beta) = \Sigma_r \frac{(\hat{\beta}_r - \bar{\hat{\beta}})^2}{R} + \left[\frac{\Sigma_r (\beta_s - \hat{\beta}_r)}{R} \right]^2 \tag{17}$$

[37] I simulate the model with one exogenous variable and a constant for a single period for ease of exposition. However the results hold for a time dependent spatial autoregressive model as well, albeit with some further assumptions about the structure of errors and nature of serial correlations. For the simulated model I also assume that the weights matrix is exogenous in order to feasibly compare the true population parameter with the estimated one. The construction of the instrument although dependent on the weights matrix is invariant to the choice of the sample since the occurrence of death/retirement related breaks is orthogonal to the boundary imposed on the network.

where $\hat{\beta}_r$ is the estimate in replication r, $\bar{\hat{\beta}}$ is the mean of the estimate for all replications, β_s is the true value of the parameter, and R is the number of replications in the simulation experiment. The MSE combines both, the estimation variance as well as the bias of an estimate into a measure of goodness of fit.

In the second experiment, I follow the same procedure outlined above but vary each simulated network by an additional homophily parameter. This means that in addition to varying the proportion of listed links to the total number of links, I also control the relative distribution of listed links to mixed links in the population. I vary the degree of homophily over a range of 0.1 to 0.70 with increments of 0.20.

A.3 IDENTIFICATION OF INDUSTRY PEER EFFECTS

To identify peer effects specific to a firms' industry group, I construct the peer group of each firm as the set of all other firms who share the same NIC code or belong to the same business group. Even in this case, the resulting peer interaction structure is non-linear in nature because each firms set of industry plus business group peers are distinct. Firm i can be affiliated with all other firms in its industry but it is also affiliated to another set of firms that belong to its business group who may or may not be in the same industry. To see this, denote $\mathbf{W^I}$ as the industry based peer interaction matrix with $w^I_{ij} = 1/n_{ij}$ if firm i shares the same NIC code or belongs to the same business group as firm j and zero otherwise. This implies that matrix $\mathbf{W^I}$ has block diagonal elements of varying sizes. This brings about variation in reduced-form coefficients across industry groups of different size that ensures identification. The coefficient on the endogenous peer effect will be biased if firms' own policy decision influences their peers' decision or if there are common time varying group specific shocks that affect both the firm and the peer's behaviour. In order to find a causal effect, one would need an exclusion restriction that shifts the outcome of the firm independently of its peers. Therefore we need a valid exclusion restriction such that it affects the average behaviors of a firm's peer group but not the firm's behaviour directly.

Here the exclusion restrictions are derived from the peer interaction structure itself, specifically, the overlapping nature of affiliation. I exploit the overlap between a firm's industry based peer group (henceforth industry group) and its ownership based peer group (henceforth business group) to instrument for the endogenous peer effect. This identification strategy using peers-of-peers as an exclusion, wherein some 'peers of peers' do not affect an individual directly but only through his or her own peers, has been recently used by many authors. Bramoullé, Djebbari, and Fortin (2009) provide a general framework to show that endogenous and exogenous effects can be distinguished through overlapping sub-groups within a specific network structure[38]. In this setting, when firm i and j belong to the same industry

[38] Lin (2007) and Lee (2008) extend this model to a spatial autoregressive (SAR) framework where peer

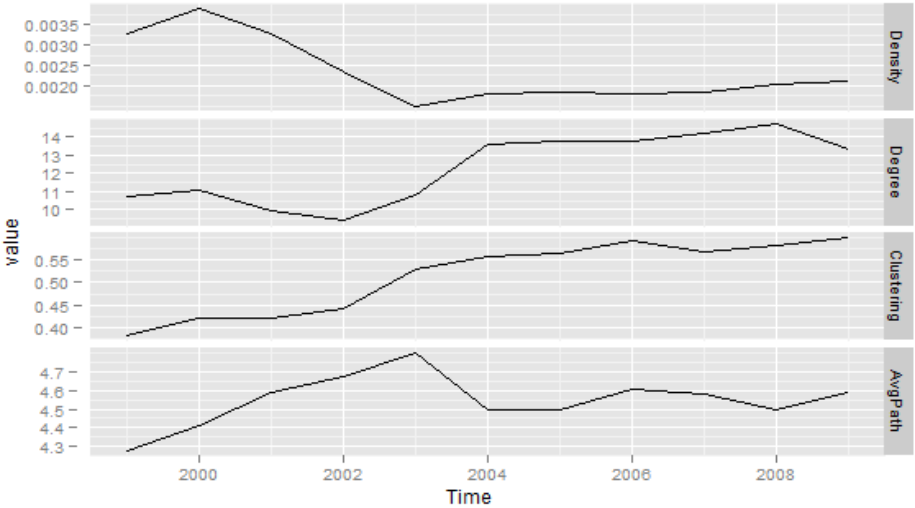
group, the exclusion corresponds to assuming that a firm i is not directly affected by firm $j's$ business group peers. I ensure that the characteristics of only those business group firms are used that share no affiliations (industry or business) with the target firm i. Firms that belong to $j's$ business group and are not associated with firm i form our excluded group, and the instruments are generated from their exogenous characteristics. As before, to mitigate the bias associated with selection into the industry, I employ a first differenced specification that eliminates firm specific unobservables that are constant over time. Using the row vector, $\mathbf{W_i^I}$ I obtain the following specification:

$$\triangle y_{it} = \alpha \mathbf{W_i^I} \triangle \mathbf{y_t} + \lambda \triangle x_{it} + \varphi \mathbf{W_i^I} \triangle \mathbf{x_t} + \triangle \chi_t + \triangle v_{it} \tag{18}$$

The set of excluded peers is contained in the matrix $(\mathbf{W^I})^\mathbf{2}$ and their exogenous characteristics are used as instruments for $\mathbf{W^I y}$. For convenience we denote the instrument set as $(\mathbf{W^{EX} x_t})$ where $\mathbf{W^{EX}} = (\mathbf{W^I})^\mathbf{2}$ refers to the network of excluded group (EG) or 'peers of peers'. Note that in this case the peer reference group does not change over time so the variation in peers' outcomes comes only from the changes in outcomes of a constant set of peers. As before, Eq. (18) is estimated by two stage least squares. The exclusion is informative because there is ample evidence that business groups are responsive to each other's shocks as well as profits (Bertrand, Mehta, and Mullainathan (2002); Gopalan, Nanda, and Seru (2007)).

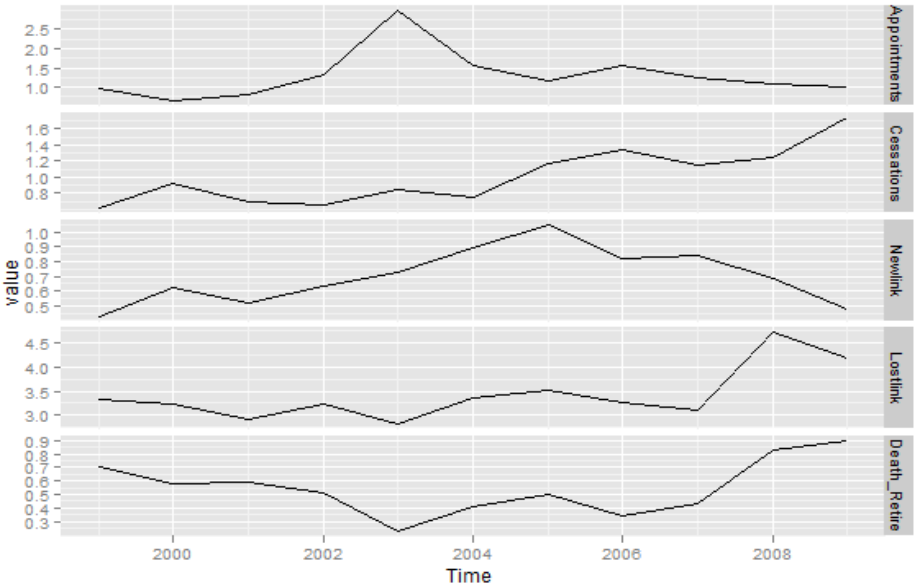
effects are captured by the spatial lag term. De Giorgi, Pellizzari, and Redaelli (2010) also show that in a context where peer groups do not overlap fully, it is possible to identify all the relevant parameters of the standard linear-in-means model of social interactions. See also Laschever (2009).

Figure 1: Network Topology Summary



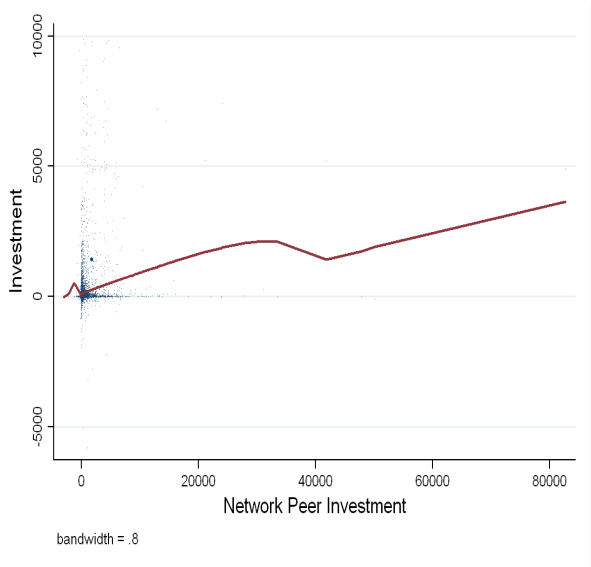
Note: The graph plots time series trends of the following network measures: *Density* - Proportion of links relative to total number possible; *Degree* - Total # links of any firm (averaged over all firms); *Clustering* - A measure of transitivity in link association i.e. whether two links of any firm are themselves directly linked; *AvgPath* - Distance between any two firms in the network (averaged over all firms).

Figure 2: Network Dynamics



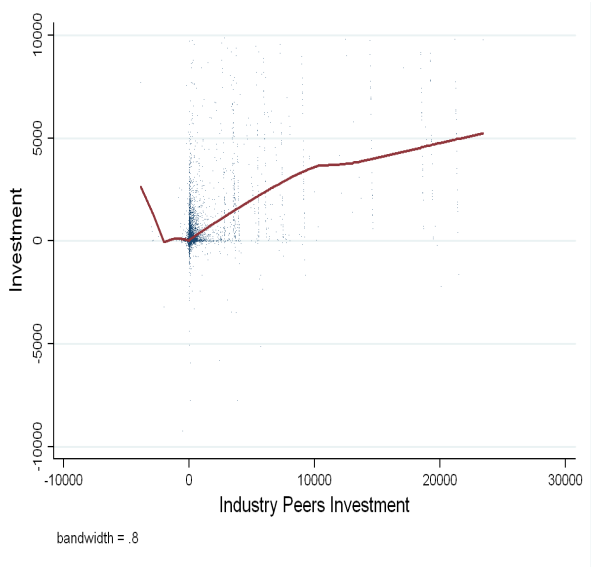
Note: The graph plots time series trends of network dynamics in a bipartite graph (following measures are averaged over all firms): *Appointments* - Total # of new directors appointed for any firm ; *Cessations* - Total # of director exits for any firm; *Newlink* - Total # of links added due to director appointments; *Lostlink* - Total # of links lost due to director exits; *Death_Retire* - Total # of links lost due to director exits from death or retirement.

Figure 3: Network Peer Investment and Firm Investment



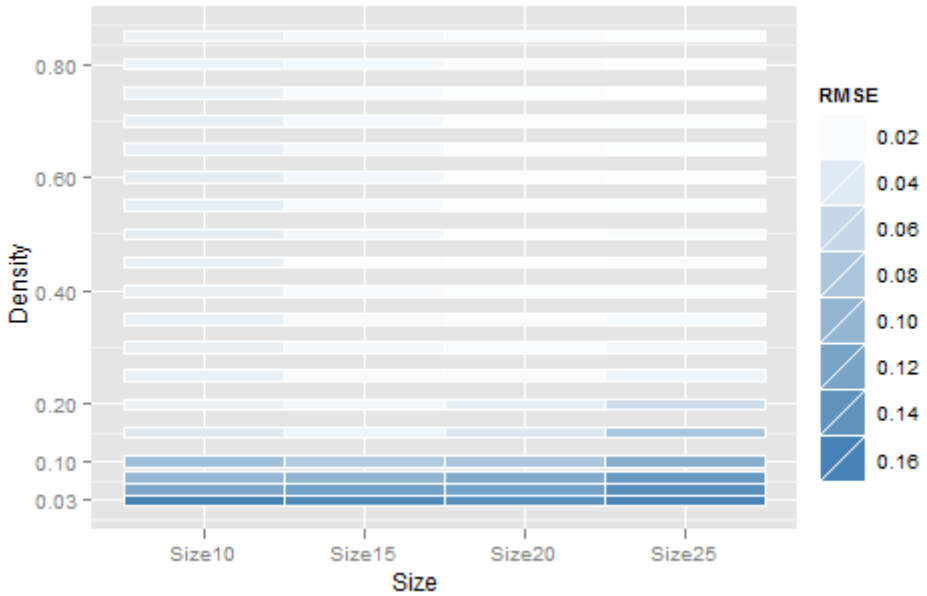
Note: The graph is a non-parametric plot of own firm market investment in relation to its network peers' market investment.

Figure 4: Industry Peer Investment and Firm Investment



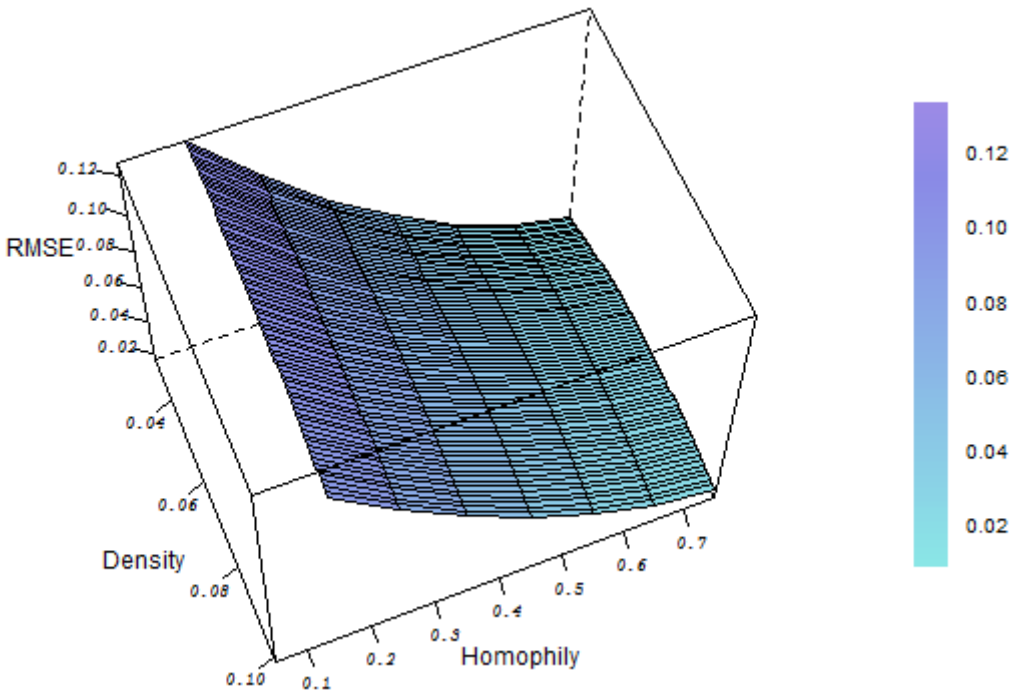
Note: The graph is a non-parametric plot of own firm market investment in relation to its industry peers' market investment.

Figure 5: RMSE for Network Simulations: Experiment 1, $\beta = 0.2$



Note: Each cell of the graph plots the RMSE associated with all given levels of Listed-density (Proportion of listed links to total number of links in the network) and Size (proportion of listed firms in the population).

Figure 6: RMSE for Network Simulations: Experiment 2, $\beta = 0.2$, Size=20%



Note: The three dimensional surface plot maps the distribution of the RMSE over two network topology parameters - Listed-density and Homophily (proportion of listed links relative to mixed links) for a sample size of 20% and a peer effect parameter of 0.2.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Median	75th Percentile
Market Investments	32166	1.35	1.89	0.48	2.06
Executive Compensation	32166	0.24	0.8	0.1	0.28
Capital Expenditure	32166	0.08	0.27	0	0
Current R&D Expnd.	32166	0.14	0.54	0	0
Sales (log)	32166	3.11	2.39	3.22	4.93
PBDITA	32166	107.14	953.33	2.89	20.91
Assets (log)	32166	3.97	2.03	3.76	5.26
Network Size	32166	6.4	10.23	3	8
# Links Lost (Death)	32166	0.29	0.95	0	0
Network Averages					
$\mathbf{W^N}$ Market Investments	32166	1.5	1.5	1.23	2.44
$\mathbf{W^N}$ Executive Compensation	32166	0.26	0.31	0.18	0.39
$\mathbf{W^N}$ Capital Expenditure	32166	0.1	0.18	0	0.18
$\mathbf{W^N}$ Current R&D Expnd.	32166	0.2	0.39	0	0.28
Industry Averages					
$\mathbf{W^I}$ Market Investments	32166	1.48	1.25	1.22	1.88
$\mathbf{W^I}$ Executive Compensation	32166	0.25	0.34	0.18	0.33
$\mathbf{W^I}$ Capital Expenditure	32166	0.09	0.15	0.01	0.13
$\mathbf{W^I}$ Current R&D Expnd.	32166	0.15	0.29	0.02	0.17
Instruments					
Local Network Shocks (Reduction from death induced link loss)					
$\mathbf{W^D}$ Market Investments	32166	0.24	0.94	0	0
$\mathbf{W^D}$ Executive Compensation	32166	0.04	0.17	0	0
$\mathbf{W^D}$ Capital Expenditure	32166	0.01	0.1	0	0
$\mathbf{W^D}$ Current R&D Expnd.	32166	0.02	0.21	0	0
Excluded Peer Averages					
$\mathbf{W^{EX}}$ Assets (log)	32166	5.03	1.39	4.98	5.83
$\mathbf{W^{EX}}$ Sales (log)	32166	3.92	1.47	4.21	4.88
$\mathbf{W^{EX}}$ PBDITA	32166	329.61	634.29	69.53	328.99

Table 2: Network Peer Effects: Corporate Market Investment

	(1) Mkt. Invst.	(2) $\mathbf{W^N}$ Mkt. Invst.	(3) Mkt. Invst.	(4) Mkt. Invst.	(5) Mkt. Invst.	(6) Mkt. Invst.
$\mathbf{W^N}$ Mkt. Invst.	0.020**		0.172*	0.149$^+$	0.232**	0.221*
	(0.005)		(0.068)	(0.079)	(0.088)	(0.094)
$\mathbf{W^D}$ Mkt. Invst.		-0.064**				
		(0.006)				
PBDITA	0.000*	0.000	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets (logs)	0.105**	0.062**	0.096**	0.132**	0.101**	0.096**
	(0.015)	(0.021)	(0.016)	(0.020)	(0.017)	(0.018)
Sales (logs)	0.040**	0.006	0.039**	0.035**	0.039**	0.040**
	(0.010)	(0.015)	(0.011)	(0.012)	(0.011)	(0.012)
# Director Exits	0.003	-0.010$^+$	0.005	0.004	0.006	0.008$^+$
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Growth Trajectory‡				-0.051**		
				(0.006)		
$\mathbf{W^N}$ PBDITA					-0.000	-0.000
					(0.000)	(0.000)
$\mathbf{W^N}$ Assets (logs)					-0.054	0.050
					(0.101)	(0.121)
$\mathbf{W^N}$ Sales (logs)					0.064	0.084
					(0.108)	(0.116)
Network Size						-0.017
						(0.011)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19644	19644	19644	15271	19644	19644
Cragg-Donald F			124.813	125.616	8.873	5.81

Notes:
1. $\mathbf{W^N}$ repesents local network peer averages.; $\mathbf{W^D}$ represents averages of past period links that have been broken due to death/retirement of shared directors
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. ‡ defined as the difference in outcome variable between period $t-1$ and $t-2$.
5. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
6. $^+$ indicates significance at 10%; * at 5%; ** at 1%.

Table 3: Network Peer Effects: Executive Compensation

	(1) Ex. Comp.	(2) $\mathbf{W^N}$ Ex. Comp.	(3) Ex. Comp.	(4) Ex. Comp.	(5) Ex. Comp.	(6) Ex. Comp.
$\mathbf{W^N}$ Ex. Comp.	0.053**		0.131$^+$	0.154$^+$	0.167$^+$	0.168$^+$
	(0.007)		(0.075)	(0.081)	(0.101)	(0.099)
$\mathbf{W^D}$ Ex. Comp.		-0.089**				
		(0.007)				
PBDITA	-0.000	0.000**	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets (logs)	0.069**	0.020**	0.068**	0.060**	0.069**	0.070**
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Sales (logs)	0.005$^+$	-0.002	0.006$^+$	0.012**	0.006$^+$	0.005$^+$
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
# Director Exits	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth Trajectory‡				-0.003$^+$		
				(0.002)		
$\mathbf{W^N}$ PBDITA					-0.000$^+$	-0.000$^+$
					(0.000)	(0.000)
$\mathbf{W^N}$ Assets (logs)					0.016	0.001
					(0.026)	(0.028)
$\mathbf{W^N}$ Sales (logs)					0.003	-0.001
					(0.030)	(0.030)
Network Size						0.003
						(0.003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19644	19644	19644	15271	19644	19644
Cragg-Donald F			178.946	179.066	8.88	5.61

Notes:
1. $\mathbf{W^N}$ repesents local network peer averages.; $\mathbf{W^D}$ represents averages of past period links that have been broken due to death/retirement of shared directors
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. ‡ defined as the difference in outcome variable between period $t-1$ and $t-2$.
5. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
6. $^+$ indicates significance at 10%; * at 5%; ** at 1%.

Table 4: Network Peer Effects: Capital Expenditure

	(1) Capex	(2) $\mathbf{W^N}$ Capex	(3) Capex	(4) Capex	(5) Capex	(6) Capex
$\mathbf{W^N}$ Capex	0.004		0.225	0.105	0.328^{+}	0.317^{+}
	(0.011)		(0.151)	(0.167)	(0.171)	(0.172)
$\mathbf{W^D}$ Capex		-0.084**				
		(0.008)				
PBDITA	0.000	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets (logs)	-0.001	0.003	-0.002	-0.003	0.002	0.001
	(0.005)	(0.003)	(0.005)	(0.006)	(0.006)	(0.006)
Sales (logs)	0.004	0.002	0.004	0.003	0.004	0.004
	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
# Director Exits	-0.002	-0.001	-0.002	-0.003^{+}	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Growth Trajectory‡				-0.083**		
				(0.006)		
$\mathbf{W^N}$ PBDITA					-0.000	-0.000
					(0.000)	(0.000)
$\mathbf{W^N}$ Assets (logs)					-0.094**	-0.073*
					(0.032)	(0.036)
$\mathbf{W^N}$ Sales (logs)					0.084*	0.089*
					(0.038)	(0.039)
Network Size						-0.004
						(0.004)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19644	19644	19644	15271	19644	19644
Cragg-Donald F			117.738	117.601	9.775	6.002

Notes:
1. $\mathbf{W^N}$ repesents local network peer averages.; $\mathbf{W^D}$ represents averages of past period links that have been broken due to death/retirement of shared directors
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. ‡ defined as the difference in outcome variable between period $t-1$ and $t-2$.
5. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
6. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.

Table 5: Network Peer Effects: Current Expenditure in R&D

	(1) R&D	(2) $\mathbf{W^N}$ R&D	(3) R&D	(4) R&D	(5) R&D	(6) R&D
$\mathbf{W^N}$ R&D	0.007		-0.036	-0.013	0.059	0.016
	(0.006)		(0.079)	(0.080)	(0.089)	(0.094)
$\mathbf{W^D}$ R&D		-0.071**				
		(0.007)				
PBDITA	0.000*	0.000	0.000*	0.000*	0.000^{+}	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets (logs)	0.020**	0.003	0.020**	0.022**	0.023**	0.019**
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Sales (logs)	0.003	-0.000	0.003	0.008*	0.003	0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
# Director Exits	0.000	-0.000	0.000	-0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth Trajectory‡				-0.084**		
				(0.006)		
$\mathbf{W^N}$ PBDITA					-0.000	-0.000
					(0.000)	(0.000)
$\mathbf{W^N}$ Assets (logs)					0.003	0.065*
					(0.027)	(0.032)
$\mathbf{W^N}$ Sales (logs)					-0.027	-0.010
					(0.032)	(0.035)
Network Size						-0.011**
						(0.003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19644	19644	19644	15271	19644	19644
Cragg-Donald F			122.915	123.20	8.80	5.77

Notes:
1. $\mathbf{W^N}$ repesents local network peer averages.; $\mathbf{W^D}$ represents averages of past period links that have been broken due to death/retirement of shared directors
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. ‡ defined as the difference in outcome variable between period $t-1$ and $t-2$.
5. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
6. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.

Table 6: Network Peer Effects: Fixed Effects

A. Industry-Group Fixed Effects

	(1) Mkt. Invst.	(2) Ex. Comp.	(3) Capex	(4) R&D
$\mathbf{W^N}$ Mkt. Invst.	0.164*			
	(0.066)			
$\mathbf{W^N}$ Ex. Comp.		0.167*		
		(0.070)		
$\mathbf{W^N}$ Capex			0.235	
			(0.144)	
$\mathbf{W^N}$ R&D				-0.022
				(0.074)
PBDITA	0.000	-0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Sales (log)	0.028*	-0.001	-0.001	-0.003
	(0.011)	(0.003)	(0.004)	(0.003)
Assets (log)	0.008	0.049**	-0.012$^+$	0.009$^+$
	(0.017)	(0.005)	(0.006)	(0.005)
# Director Exits	0.006	-0.001	-0.002	0.000
	(0.004)	(0.001)	(0.001)	(0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry-Group Fixed Effects	Yes	Yes	Yes	Yes
N	19644	19644	19644	19644
Cragg-Donald F	118.865	188.356	110.894	123.75

B. Industry-Group-Time Fixed Effects

	(1) Mkt. Invst.	(2) Ex. Comp.	(3) Capex	(4) R&D
$\mathbf{W^N}$ Mkt. Invst.	0.139*			
	(0.068)			
$\mathbf{W^N}$ Ex. Comp.		0.190**		
		(0.073)		
$\mathbf{W^N}$ Capex			0.241$^+$	
			(0.146)	
$\mathbf{W^N}$ R&D				-0.168$^+$
				(0.099)
PBDITA	0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Sales (log)	0.021	-0.005	-0.004	-0.002
	(0.013)	(0.004)	(0.005)	(0.004)
Assets (log)	-0.030	0.053**	-0.010	0.005
	(0.020)	(0.006)	(0.007)	(0.006)
# Director Exits	0.011*	-0.001	-0.001	-0.000
	(0.004)	(0.001)	(0.002)	(0.001)
Industry-Group-Time Fixed Effects	Yes	Yes	Yes	Yes
N	19644	19644	19644	19644
Cragg-Donald F	96.45	156.94	97.05	68.32

i) HAC robust standard errors in parentheses

Table 7: Network Peer Effects: Heterogeneous Effects

	Mkt. Invst.			Ex. Comp.		
	I: $\mathbf{W^{NI}}$	I: $\mathbf{W^{NN}}$	II: Mkt. Invst.	I: $\mathbf{W^{NI}}$	I: $\mathbf{W^{NN}}$	II: Ex. Comp.
$\mathbf{W^{NI}}$ Mkt. Invst.			-0.048			
			(0.158)			
$\mathbf{W^{NN}}$ Mkt. Invst.			0.131*			
			(0.065)			
$\mathbf{W^{NI}}$ Ex. Comp.						-0.117
						(0.195)
$\mathbf{W^{NN}}$ Ex. Comp.						0.182*
						(0.071)
$\mathbf{W^{DI}}$ Mkt. Invst.	-0.092**	-0.010				
	(0.013)	(0.022)				
$\mathbf{W^{DN}}$ Mkt. Invst.	0.004	-0.076**				
	(0.005)	(0.008)				
$\mathbf{W^{DI}}$ Ex. Comp.				-0.350**	0.005	
				(0.045)	(0.075)	
$\mathbf{W^{DN}}$ Ex. Comp.				0.007	-0.115**	
				(0.005)	(0.009)	
PBDITA	-0.000**	0.000	0.000	-0.000**	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales (log)	0.004	0.015	0.021	-0.001	-0.003	-0.005
	(0.012)	(0.020)	(0.013)	(0.002)	(0.004)	(0.004)
Assets (log)	-0.022	0.063*	-0.031	-0.001	0.017**	0.053**
	(0.018)	(0.030)	(0.020)	(0.004)	(0.006)	(0.006)
# Director Exits	-0.016**	-0.015*	0.010^{+}	-0.001	-0.001	-0.001
	(0.004)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)
Fixed Effects (Industry-Group-Time)	Yes	Yes	Yes	Yes	Yes	Yes
N	19644	19644	19644	19644	19644	19644
Joint Cragg-Donald F			23.227			30.324

Notes:
1. *I* refers to First stage of two stage least squares procedre while *II* refers to the second stage.
2. $\mathbf{W^{NI}}$ repesents local network averages of same industry peers; $\mathbf{W^{NN}}$ repesents local network averages of non-industry peers; $\mathbf{W^{DI}}$ represents averages of past period same industry links that have been broken due to death/retirement of shared directors; $\mathbf{W^{DN}}$ represents averages of past period non-industry links that have been broken due to death/retirement of shared directors
3. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
4. All control variables are lagged by one year.
5. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
6. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.

Table 8: Investment in Same Stocks

	(1) OLS	(2) Rare Event Adj.	(3) OLS FE	(4) IV: First	(5) IV RE	(6) IV FE
Network Strength	**0.091****	**1.655****	**0.017****		**0.638****	**1.187****
	(0.001)	**(0.011)**	**(0.001)**		**(0.245)**	**(0.401)**
Shared Director Exit†				-0.005**		
				(0.000)		
Diff PBDITA‡	0.322**	4.16**	0.132**	0.350**	0.074	-0.137**
	(0.0002)	(0.003)	(0.0006)	((0.0001)	(0.086)	(0.016)
Diff Assets (logs)	0.001**	0.053**	-0.002**	-0.004**	0.003**	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.0009)	(0.001)
Diff Sales (logs)	-0.0004**	-0.011**	-0.001**	0.0006**	-0.0005**	-0.001**
	(0.0000)	(0.0009)	(0.0009)	(0.0078)	(0.0000)	(0.0003)
Same Industry	0.044**	0.867**		-0.004**	0.049**	
	(0.000)	(0.009)		(0.0685)	(0.001)	
Time Fixed Effects	Yes	Yes	No	No	No	No
Pair Fixed Effecs	No	No	Yes	No	No	Yes
N	11798464	11798464	11798464	5759498	5759498	5759498
Cragg-Donald F					123.21	98.806

Notes:
1. The units of analysis in all specifications are dyads, i.e. a pair of two companies i and j. Standard errors are adjusted using the QAP procedure to account for pair-wise dependence. The dependent variable is binary taking the value 1 both i and j have invested in the same stock in time period t. *Network Strength* indicates the value of connection between i and j and ranges from zero to one. It is equal to the inverse of path distance in the global network between i and j – zero indicates no connection and one indicates direct connection. All other values mean that i, j are connected but through a series of intermediate links. Differences are in absolute terms due to the symmetric nature of the dyads.
2. ‡ coeffcient mutiplied by 10^6.
3. Column (2) adjusts coefficient estimates and standard errors to account for large non-events (zeroes) using the procedure outline in King and Zeng (2001). It is a logistic regression so the coefficient estimate can be interpreted as follows: A change in network strength from 0 to 1 (no connection to direct connection) increases the probability of investing in the same stock by 11%. The relative risk associated with this change (of 0 to 1) is 4.56 log-odds.
4. † is a dummy taking the value 1 if there are any common directors over the network between i and j who have died or retired in the previous time period. For this reason The IV regressions (Columns (3) - Column (6)) discard observations from the first year (2006) as its lag is not defined/missing.
5. Time fixed effects are not included when using pair fixed effects so as to preserve some variation in the dependent variable
6. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.

Table 9: Sensitivity Results: Probability of New Link

	(1) New Link	(2) New Link
Link Loss (Death)	-0.002 (0.008)	-0.003 (0.009)
Firm Controls	No	Yes
Time Fixed Effects	Yes	Yes
N	27084	21727
Joint Significance of Time F.E	645.14 (0.00)	540.80 (0.00)

i) HAC robust standard errors in parentheses

Table 10: Network Peer Effects: Global Network

	(1) Mkt. Invst.	(2) Ex. Comp.	(3) Capex	(4) R&D
$\mathbf{W^G}$ Mkt. Invst.	0.442*			
	(0.191)			
$\mathbf{W^G}$ Ex. Comp.		0.632^{+}		
		(0.394)		
$\mathbf{W^G}$ Capex			1.153	
			(1.023)	
$\mathbf{W^G}$ R&D				-0.341
				(0.503)
PBDITA	0.000	-0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Assets (log)	0.090**	0.065**	-0.003	0.022**
	(0.018)	(0.006)	(0.006)	(0.006)
Sales (log)	0.042**	0.006^{+}	0.004	0.003
	(0.011)	(0.003)	(0.004)	(0.003)
# Director Exits	0.008^{+}	-0.000	-0.001	-0.000
	(0.005)	(0.001)	(0.001)	(0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes
N	19644	19644	19644	19644
Cragg-Donald F	45.464	23.457	20.018	26.973

Notes:
1. $\mathbf{W^G}$ repesents *global* network peer averages
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
5. $^{+}$ indicates significance at 10%; * at 5%; ** at 1%.

Table 11: Industry Peer Effects

A. Mkt. Invst.

	(1) Mkt. Invst.	(2) Mkt. Invst.	(3) Mkt. Invst.
$\mathbf{W^I}$ Mkt. Invst.	0.043**	0.487^{+}	0.456
	(0.010)	(0.272)	(0.303)
$\mathbf{W^I}$ PBDITA			-0.000
			(0.000)
$\mathbf{W^I}$ Sales (log)			-0.006
			(0.025)
$\mathbf{W^I}$ Assets (log)			0.116**
			(0.044)
N	21727	17280	17280
Excl. Instruments Joint Significance		40.80 (0.00)	32.80 (0.00)
Cragg-Donald F		14.046	8.324

B. Executive Compensation

	(1) Ex. Comp.	(2) Ex. Comp.	(3) Ex. Comp.
$\mathbf{W^I}$ Ex. Comp.	0.032**	0.224	1.015
	(0.005)	(0.317)	(2.583)
$\mathbf{W^I}$ PBDITA			0.000
			(0.000)
$\mathbf{W^I}$ Sales (log)			0.020
			(0.071)
$\mathbf{W^I}$ Assets (log)			0.056
			(0.152)
N	21727	17280	17280
Excl. Instruments Joint Significance		6.58 (0.01)	0.24 (0.623)
Cragg-Donald F		6.536	1.23

C. R& D

	(1) R&D	(2) R&D	(3) R&D
$\mathbf{W^I}$ R&D	0.049**	0.690*	0.976*
	(0.012)	(0.302)	(0.448)
$\mathbf{W^I}$ PBDITA			0.000
			(0.000)
$\mathbf{W^I}$ Sales (log)			0.002
			(0.014)
$\mathbf{W^I}$ Assets (log)			0.027**
			(0.010)
N	21727	17280	17280
Excl. Instruments Joint Significance		38.91 (0.00)	15.09 (0.00)
Cragg-Donald F		14.31	5.43

i) Standard errors in parentheses

Table 12: Industry-Network Peer Effects

	(1) Mkt. Invst.	(2) Mkt. Invst.	(3) R&D	(4) R&D
$\mathbf{W^N}$ Mkt. Invst.	0.193*	0.146$^+$		
	(0.086)	(0.080)		
$\mathbf{W^I}$ Mkt. Invst.	0.237	0.016		
	(0.281)	(0.257)		
$\mathbf{W^N}$ R&D			-0.060	-0.016
			(0.114)	(0.127)
$\mathbf{W^I}$ R&D			0.690*	0.629**
			(0.318)	(0.184)
PBDITA	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Assets (log)	0.089**	-0.026	0.023**	0.004
	(0.019)	(0.022)	(0.006)	(0.007)
Sales (log)	0.035**	0.016	0.003	0.000
	(0.012)	(0.014)	(0.004)	(0.004)
# Director exits	0.007	0.012*	0.001	0.000
	(0.005)	(0.004)	(0.002)	(0.001)
Time F.E.	Yes		Yes	
Industry-Group-Time F.E.		Yes		Yes
N	15630	14172	15630	14172
Cragg-Donald F	10.688	14.414	10.482	13.204

Notes:
1. $\mathbf{W^N}$ repesents local network peer averages; $\mathbf{W^I}$ repesents industry peer averages.
2. PBDITA is the total Profit Before Depreciation, Interest, Tax and Amortisation; Assets in logs is total book value of assets; # Director Exits refers to the number of directors who have left the company in the previous time period; Network Size measures the number of direct links i.e. the number of other firms with whom it shares common directors.
3. All control variables are lagged by one year.
4. Standard errors (in parentheses) are adjusted for autocorrelation and arbitrary heteroscedasticity at the network level.
5. $^+$ indicates significance at 10%; * at 5%; ** at 1%.

Table 13: Monte Carlo Results: Experiment 1

Size	**Listed-density**	$\beta = 0$		$\beta = 0.1$		$\beta = 0.2$		$\beta = 0.3$		$\beta = 0.4$		$\beta = 0.5$	
		Mean	RMSE	Mean	RMSE	Mean	RMSE	Mean	RMSE	Mean	RMSE	Mean	RMSE
0.1	0.03	0.00	0.02	0.02	0.08	0.04	0.16	0.06	0.24	0.08	0.32	0.10	0.40
	0.1	0.00	0.03	0.05	0.05	0.11	0.09	0.17	0.13	0.23	0.17	0.29	0.21
	0.25	0.00	0.04	0.09	0.04	0.19	0.03	0.29	0.03	0.39	0.03	0.49	0.02
	0.5	0.00	0.04	0.11	0.04	0.20	0.04	0.30	0.03	0.40	0.03	0.50	0.02
	0.75	0.00	0.04	0.10	0.04	0.20	0.03	0.30	0.03	0.40	0.03	0.50	0.02
	0.85	0.00	0.04	0.10	0.04	0.20	0.03	0.30	0.03	0.40	0.03	0.50	0.02
0.2	0.03	0.00	0.01	0.03	0.07	0.06	0.14	0.08	0.22	0.12	0.28	0.14	0.36
	0.1	0.00	0.01	0.06	0.04	0.12	0.08	0.19	0.12	0.25	0.15	0.32	0.18
	0.25	0.00	0.02	0.09	0.02	0.19	0.02	0.28	0.02	0.38	0.02	0.48	0.02
	0.5	0.00	0.02	0.10	0.02	0.20	0.02	0.30	0.02	0.40	0.02	0.50	0.01
	0.75	0.00	0.02	0.10	0.02	0.20	0.02	0.30	0.02	0.40	0.01	0.50	0.01
	0.85	0.00	0.03	0.10	0.02	0.20	0.02	0.30	0.02	0.40	0.01	0.50	0.01
0.3	0.1	0.00	0.01	0.04	0.06	0.08	0.12	0.12	0.18	0.16	0.24	0.21	0.29
	0.25	0.00	0.02	0.08	0.03	0.16	0.04	0.24	0.06	0.33	0.07	0.41	0.09
	0.5	0.00	0.02	0.10	0.02	0.19	0.02	0.29	0.02	0.39	0.01	0.49	0.01
	0.75	0.00	0.02	0.10	0.02	0.20	0.01	0.30	0.01	0.40	0.01	0.50	0.01
	0.85	0.00	0.02	0.10	0.02	0.20	0.02	0.30	0.01	0.40	0.01	0.50	0.01

Table 14: Monte Carlo Results: Experiment 2

Size	**Listed-density**	**Homophily**	**RMSE** $\beta = 0$	**RMSE** $\beta = 0.1$	**RMSE** $\beta = 0.2$	**RMSE** $\beta = 0.3$	**RMSE** $\beta = 0.4$	**RMSE** $\beta = 0.5$
0.1	0.03	0.1	0.02	0.08	0.16	0.24	0.32	0.40
		0.3	0.02	0.05	0.10	0.15	0.20	0.25
		0.5	0.02	0.03	0.05	0.08	0.10	0.13
		0.75	0.02	0.02	0.02	0.02	0.01	0.02
	0.05	0.1	0.02	0.07	0.13	0.18	0.24	0.29
		0.3	0.02	0.06	0.10	0.15	0.21	0.25
		0.5	0.03	0.03	0.05	0.07	0.09	0.10
		0.75	0.02	0.03	0.04	0.05	0.06	0.08
	0.1	0.1	0.03	0.06	0.10	0.15	0.19	0.23
		0.3	0.03	0.05	0.09	0.13	0.18	0.21
		0.5	0.03	0.05	0.08	0.12	0.16	0.20
		0.75	0.03	0.03	0.03	0.03	0.02	0.02
0.2	0.03	0.1	0.01	0.07	0.14	0.21	0.28	0.35
		0.3	0.01	0.04	0.09	0.13	0.17	0.22
		0.5	0.01	0.02	0.04	0.06	0.08	0.10
		0.75	0.01	0.01	0.02	0.02	0.03	0.04
	0.05	0.1	0.01	0.07	0.14	0.21	0.28	0.35
		0.3	0.01	0.04	0.08	0.12	0.16	0.20
		0.5	0.01	0.03	0.05	0.08	0.10	0.13
		0.75	0.01	0.02	0.02	0.03	0.04	0.05
	0.1	0.1	0.02	0.06	0.12	0.17	0.22	0.26
		0.3	0.01	0.04	0.08	0.11	0.14	0.18
		0.5	0.02	0.02	0.04	0.05	0.06	0.08
		0.75	0.01	0.02	0.02	0.03	0.03	0.04