How Does The Director's Social Network Matter? Evidence From Structure Estimation

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Abstract

Board interlocked networks (i.e. boards are connected by interlocked directors–individuals who are officers and/or directors at two or more firms) are ubiquitous in Asian countries and even in developed economies. In this paper, I evaluate the impact of board interlock networks on directorship market outcomes and firm values by estimating a dynamic structural model. The model features endogenous network formation and network learning and predicts that, under certain restrictions, the structure of board interlock networks can fully reveal previously unidentified objectives (e.g. whether the board is the firm value maximizers or social alliance to the CEO). The model's parameters are estimated by applying Bayesian Markov-Chain-Monte-Carlo methods to longitudinal interlock network data of U.S. and Chinese public traded firms over ten years. I find that social network connections in both countries are important in determining who gets which directorship. Specifically, the possibility of obtaining board seat increases by 30-150 times if the director has a tie to the hiring board, while other variables (e.g. director's demographic characteristics, the performance of his current firm, his professional title, his compensation, how often the director attends a board meeting, etc.) have negligible effects. I also find that boards discount the value of directors with a large number of outside directorships, indicating a desire for effective monitors. Finally, I find that in the U.S., interlock connections decrease firms' values pre-Sarbances-Oxley Act (SOX) and increase post-SOX. Overall, this model provides the first study in the dynamic relationship between board interlock network, director appointment and firm value.

Keywords: Board interlocks, board networks, structural model, Bayesian Methods
JEL Classifications: G34 D85

1 Introduction

Practitioners and researchers have long recognized that corporate boards often recruit new directors through their social ties. Board interlocked networks are ubiquitous in Asian countries and even in developed economies(e.g. U.S.A. and French. See Tirole (2006),Leonhardt (2000)). What role does the director's social network play in the process of director appointment? More precisely, does the board look for social alliance? Alternatively, do they look for effective monitors, and social network is used to only reduce information asymmetries regarding the potential candidate? In this paper, I attempt to shed some lights on these questions by developing and testing a dynamic structural model that accesses how the board recruits directors and how it matters for firm value.

Social theory analysis, which has been applied by many papers on financial issues[1], are basically reduced-form regressions in which director's network positions and neighborhood properties are used as if they were exogenously determined attributes. Drawing clear inferences from such reduced-form regression is difficult for two reasons. First, different measures of a director's social network (e.g. one subset of researchers studies social ties between boards and CEOs[2], and another subset investigates directors who hold multiple board seats[3]) are correlated. For instance, directors who hold multiple board seats are more likely to know the current CEO before joining the firm. Focusing on one measure while ignoring the others will lead to biased predictions. Second, extensive research in both sociology literature and the economics literature has shown that social network is itself based on individual choices motivated by utility maximization (see Jackson (2009) for a survey). In our analysis, the "interlock network" is formed endogenously when firms strategically hire their outside directors from the other firms. Ignoring this will cause the "joint endogeneity problem"–"director-board matching is

[1] see e.g. Hochberg, Ljungqvist, and Lu (2007),Hochberg, Ljungqvist, and Lu (2010) for venture capital network, Carhart (1997) for the network of mutual fund managers

[2] see e.g. Shivdasani and Yermack (1999); Hwang and Kim (2009), Adams and Ferreira (2007)

[3] see, e.g. Stuart and Yim (2010), Fich and Shivdasani (2006), Ferris, Jagannathan, and Pritchard (2003), Larcker, Richardson, Seary, and Tuna (2005).

not random, hence board characteristics are often endogenously related to firm outcomes" (Hermalin and Weisbach (2003),Adams, Hermalin, and Weisbach (2009)).

These challenges lend themselves to a structural estimation approach. Following the literature on evolutionary game theory (Hojman and Szeidl (2008), Kandori, Mailath, and Rob (1993), Snijders (2001)), I build a network formation model featuring a group of heterogeneous firms (i.e. firms which are different in their size and performance), a large pool of potential directors, a network of directors who are connected by their social ties and a "interlock network" where firms are connected by interlocked directors[4]. All seats on the board are subject to a risk of breakdown, endogenously determined by the characteristics of each board (e.g. boards with younger directors are less likely to face a vacancy). Ties in the interlock network represent direct communication channels created by mutual consent of the two linked directors (or firms through their interlocked directors) and through which information may flow. The information includes not only the private information about the firm, but also the job information on the board. Boards thus partly rely on reference from current directors to gather information about potential directors, or from public information to evaluate them. The model also allows the board to learn their own preference over time by adding an error term to their preference. The choice of certain directors is based on the expected rewards that he can bring to the board. For example, firm-value-maximizing boards may want strong monitors, while personal-value-maximizing boards may like to do a favor to their friends. As a result, not only the "skills" of directors, but also their social network will impact their appointment to a new board. The first finding of this model is that in equilibrium, under certain restrictions, the structure of board interlock networks can fully reveal previously unidentified objectives (e.g. whether they are firm value maximizers or social alliance to the CEO).

The intuition behind this finding can be illustrated in Figure 1. This figure shows interlock networks

[4]In the empirical part, these two networks coincide

formed by boards with three different preferences. In industry A, boards select their outside directors randomly from other firms; Industry B, boards like directors from the best performed firm– firm 10; and in industry C, they hire their directors only through current directors's social network, or through "friend of a friend". As I can see, these three networks show different structures. For example, the number of triangles (three firms are linked with each other) in network C is much higher than that in industry A and B. In fact, a large literature in network formation (see Jackson (2009) for a survey) has shown that the networks in industry A and B cannot produce a cluster coefficient ($\frac{\text{Number of formed triangles in the network}}{\text{Potential number of triangles}}$) as high as that in the real world (i.e. network in industry D in Figure 1). Jackson and Rogers (2007) shows that for homogenous agents, the real network can be better explained by a mixture of the networks of industry A and C, while our model, after adding heterogeneity to boards and directors, shows that the real network is a mixture of all three networks in industry A, B and C.

I then extend the model by allowing directors to take decisions that influence the firm value. Specifically, interlocked directors will give suggestions to the management team based on their experience from other firms (Fracassi (2009), Stuart and Yim (2010), Bizjak, Lemmon, and Whitby (2009)). The second finding of the model is that, if the board's goal is to maximize the firm value, then interlock connections should increase firms' values. This prediction follows the literature in network learning (see e.g. Gale and Kariv (2003)). Namely, more-connected firm has more observations to update their beliefs (Bayesian learning), hence will be more closed to the true state.

In order to estimate this model, I use a structural estimation approach, following the empirical methods used for strategic network formation (Christakis, Fowler, Imbens, and Kalyanaraman (2010)) or in statistics, the Actor Based Models (Snijders (2001),Steglich, Snijders, and Pearson (2007)). The model's parameters are estimated by applying Bayesian Markov-Chain-Monte-Carlo methods to longitudinal interlock network data of U.S. and Chinese public traded firms over ten years (1996-2006),

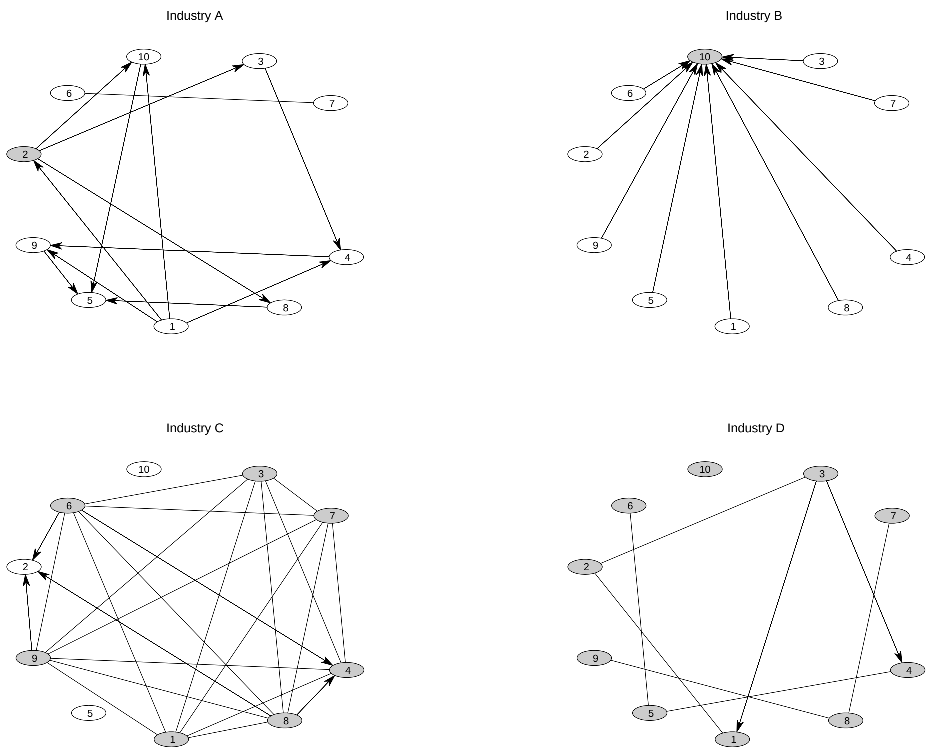

Figure 1: Four Industries With Different Network Structures

Each node presents a firm and each link shows that there is a shared director between these two firms. In industry A, links are built randomly; In industry B, links are built following "preference attachment" property, i.e., they all link to one firm because they all prefer this firm to others; Links in industry C is built through "friends of friends", i.e.,two nodes will form a link if they share the same friends; Links in industry D is the real business network of 10 U.S.firms.

in combination with data on the firm performance in the network. There are two sets of parameters to be estimated: the "selection parameters" that represents a board's preference for directors with certain characteristics and the "influence parameters" that represents the influence of directors on firm policies, or firm value. The special property exploited in this paper to deal with the "joint endogenous problem" is the time order that is basic to causality (Stuart and Yim (2010)): selection means that an earlier configuration of attributes of boards and directors leads later on to a change in a director-board match; whereas the influence means that an earlier configuration of a director-board match leads later on to a change in firm's values.

I find that social network connections are important in determining who gets which directorship.

Specifically, the possibility of obtaining a board seat increase by 30-150 times if the director has a tie to the hiring board, while other variables (e.g. director's demographic characteristics, the performance of his current firm, his professional title, how often the director attends a board meeting, etc.) have negligible effects. I also find that boards discount the value of directors with a large number of outside directorships, indicating a desire for effective monitors. Finally, I find that interlock connections decrease firms' values pre-Sarbances-Oxley Act (SOX) and increase post-SOX.

The paper is organized as follows: Second 2 is literature review. Section 3 presents the model of the formation process of the board interlock network. In Section 3 model predictions and hypotheses are developed. Section 4 presents and interprets the estimated parameters. Section 5 concludes.

2 Literature Review

While there is a large empirical literature on interlocked directors[5], this represents one of the first attempts at using an economic model to study the formation of the interlock network and to quantify the potential effects of the impact of the interlock network on shareholder value. As we discuss later, our model is consistent with several existing empirical findings, and the model produces new, untested predictions.

Our paper contributes to the literature on determinants of board appointments, where most research does not take director's social network into consideration (see e.g. Fich (2005), Booth and Deli (1996),Brickley Jeffrey and James (1994), Fich and Shivdasani (2006), Linck, Netter, and Yang (2009), Fahlenbrach, Low, and Stulz (2010)). As a consequence, they will get biased predictions. Most important, they miss one dimension of reputation that faced by directors: the private reputation ("soft" dimension) that is only observed within the social network of CEOs and directors (Adams, Hermalin,

[5]Davis (1996) on diffusion of poison bills,Khurana (2002) on CEO search, Cohen, Frazzini, and Malloy (2008) (2008) on mutual fund manager's performance, (2009)Bizjak, Lemmon, and Whitby (2009) on the spread of options backdating

and Weisbach (2009)).

Our paper also contributes to a large literature relating characteristics of the board, such as board size and fraction of outside directors, to firm performance, and corporate decisions. Recently, papers on director's social networks start to find ways to solve the endogeneity problems associated with the director's network studies. For example, Adams and Ferreira (2009) found that the proportion of women on boards increases the CEO performance-turnover sensitivity even after controlling for the proportion of outside directors, which suggests that the proportion of female outside directors – Directors outside of the "old boy network"–is a proxy for board independence. Stuart and Yim (2010) check the causal relation of director interlock on firm's go private decisions by exploiting the sequence of events in the data.

From a theoretical point of view, our model combines the approach to network formation introduced in Jackson and Rogers (2007) with the approach to the study of learning in the social network developed in Gale and Kariv (2003). On one hand, the main drawback of the existing literature on strategic network formation is that the benefits that players obtained when belonging to a certain network are primitives of the model. That is, the architecture of the director's network influences which director the board wants to hire, but it does not influence other decision variables of the board, such as the provision of effort in monitoring, collecting information to advise the management team and alike. On the other hand, the existing literature on network learning assumes that the network of relations is given and focuses on how the location of a player in the network affects his behavior. In many instances, both dimensions are endogenous: individuals form connections with others depending on their behavior and the behavior of individuals depends on the social network. This paper shows that the combination of these two approaches yields a tractable framework and sharp predictions.

Regarding the empirical part, Christakis, Fowler, Imbens, and Kalyanaraman (2010) and Steglich, Snijders, and Pearson (2007) are the most similar with respect to the estimation of strategic network formation. Their models focus on friendship formation, whereas mine focuses on the director interlock network, which is different from friendship formation in many ways. For example, interlock network is basically a bipartite network, in which the tie is between firms and directors, while friendship is between two persons.

3 A Model of Network Formation

In this section, I will present a dynamic model to analyze the formation process of the interlock network. The model features a group of heterogeneous firms, a large pool of potential directors, an interlock network where firms are connected by sharing the same individuals on their board and a director's social network (such as friends, college mates, etc.). The composition of the interlock network will change if one of the firms recruits new directors or changes its corporate policies. Our aim is to study whether firm's preference over directors with certain characteristics can be reflected on the network's structure in equilibrium, and how the corporate policies depend on the new directors on the board. The model is tailored to fit our empirical estimation and to highlight the main economic force at play.

3.1 Setup

There are two finite and disjoint sets of players: firms and directors. The set of firms is given by N, and the set of directors siting on firm's board is given by M. A tie exists between board i and director j if j is a member of board i. Given a finite set of firms N and directors M, a bipartite graph on N and M is an $N \times M$ matrix $\mathbf{G}$ where entry g_{ij} indicates whether a tie exists between firm i and director j. The obvious notation is that $g_{ij} = 1$ indicates the presence of a tie and $g_{ij} = 0$ indicates the absence of a tie. In addition, the set of all edges is denoted by E, i.e. $E \equiv \{(i, j)|g_{ij} = 1, \forall i \in N, j \in M\}$.

Denote the interlock network observed in each year as $\mathbf{G}(t_i), t_i = 1996, 1997, ..., 2006, i = 1, 2, ..., 11$.

The interlock network is a result of firms' recruitment decisions, hence endogenously determined by their board of directors. Another endogenous variable in our model is firm's corporate policies, such as investment policies, financial policies, governance policies. Specifically, I assume that each firm $i, i \in \{1, 2, ..., N\}$ has a list (vector) of S (endogenously determined) corporate policies $B_i = \{b_{i,1}, ..., b_{iS}\}$. The collection of all firms' attributes is $\mathbf{B} = \{B_1, B_2, ..., B_N\}$. And the value of B I observed in each year is denoted as $\mathbf{B}(t_i), t_i = 1996, 1997, ..., 2006, i = 1, 2, ..., 11$.

I also assume that each firm $i, i \in \{1, 2, ..., N\}$ can be identified by a vector of A (exogenous) attributes $X_i = \{x_{i,1}, ..., x_{iA}\}$. The collection of all firms' attributes is $\mathbf{X} = \{X_1, X_2, ..., X_N\}$. In the empirical part, firms' attributes include their size (book value and market value), performance (ROA, market return and Tobin's Q) and corporate policies (investment policies, leverage policies and CEO compensation policies). Similarly each director can be characterized by his attributes Y_i. This Y_i includes director's socialeconomic characteristics (gender, age and seniority), their professional titles as well as their social network. Since a person's social network(friendship, college mates) is usually formed over their life time and hence can be viewed as exogenously given.

3.2 Timeline and Basic Assumptions

Assuming time is continuous, the evolution procedure of interlock network can be represented by a continuous-time stochastic procedure. Its formation process is modeled as an evolutionary game among all the firms. The timeline of the game is as follows:

At an endogenously determinant rate λ_i (the replacement rate) [6], a firm i faces a vacancy on its

[6] For the model specification it should be noted that the social time which determines the speed of change of the network is not necessarily the same as the physical time elapsing between consecutive observation moments. Given the absence of the extraneous definition of this social time, it is not a restriction to set to 1 the total time elapsed between each pair of consecutive observations.

board. After observing the current interlock network and the characteristics of all potential directors, the board of firm i needs to make two decisions: 1)Should they appoint new directors? If yes, which directors to choose? 2)Should they change firm's management policies? If yes, will these actions improve the firm value? These decisions are made according to the board's utility, given their information. Since all firms have to re-evaluate the network if any other firms change their ties, the model must be dynamic.

In order to make the model tractable, I borrow the following four commonly used assumptions from the evolutionary game theory literature (Hojman and Szeidl (2008), Kandori, Mailath, and Rob (1993), Snijders (2001)):

The complete information assumption Firms and directors have complete information on the current network shape and the characteristics of each player in the network.

The inertia assumption At any single moment in time, only one firm is active and she only updates one of her network ties or one of the corporate policies.

The myopia assumption When firms change their outgoing relations or policies, they act myopically, namely, they maximize their utility conditioning on previous period network G_t.

The mutation, or experimentation assumption there is a small probability that firms change their strategies at random.

The general principle of these assumptions is to decompose the observed transitions from one firm-director interlock network in one year to the next year as a sequence of unobserved small changes, so called "micro–steps", and specify each year's observed network and the firm's policy to be repeated observations embedded in an endogenous network formation process, which is modeled as a Markov process constructed from the smallest possible steps, with transition probabilities determined by firm's needs for changes in board and policy and firms' preferences. Since firms can only do one thing at one time, the network formation process and policy changing process can be viewed as independent processes. Moreover, the small changes in each micro step will be referred to as *network micro steps* and *policy micro steps* respectively. In the following discussion, I will focus on the network micro steps. All the arguments can be directly applied to the policy micro step.

3.3 A Markov Chain Representation of the Endogenous Network Formation Process

The model description given above defines $(\mathbf{G}(t), \mathbf{B}(t), \mathbf{X}(t), \mathbf{Y}(t))_{t\in[1,T]}$ as a continuous-time Markov process with Q-matrix or intensity matrix (e.g., Norris, 1997) for $g \neq g_0$ given by

$$q_{ij}(g, g(i \hookrightarrow j)) = \lambda_i(g) Pr(g_{ij}^t = 1 | g_{-ij}^{t-1}, X, Y)$$

where $\lambda_i(g)$ is the replacement rate and $Pr(g_{ij}^t = 1|g_{-ij}^{t-1}, X, Y)$ is the possibility for firm i to hire director j. (From now on, I will drop X,Y in utility function for brevity)

The rate $\lambda_i(g)$ indicates how frequently the firms recruit outside directors or change her policies in one year. It may depend on events such as whether firm's have a vacancy on her board, the CEO met an interesting guy during conference, there is an innovation that one director heard from other firm, etc. It's formal definition is as follows:

Definition 1

$$\lambda_i(g, X) = lim_{dt\to 0} \frac{P(g_{ij}(t+dt) \neq g_{ij}(t) \text{ } for \text{ } some \text{ } j \in \{1, ..., N\} \, | G(t) = g)}{dt}$$

The possibility $Pr(g_{ij}^t = 1|g_{-ij}^{t-1})$ depends on firm's preference over director j. When the firm hires a director j, she receives an additional direct net benefit u_{ij}. The direct utility includes both costs and benefits, and it may be negative. In many models, this component is parameterized as $u_{ij} = b_{ij} - c_{ij}$, where b_{ij} indicates the (gross) benefit and c_{ij} the cost of forming the additional link g_{ij} . I use the notation u_{ij} for the net benefit that does not require assumptions on the cost function. Given the present state g of the network, the network that results when the single element g_{ij} is changed into $1 - g_{ij}$ (i.e., from 0 to 1 or from 1 to 0), is denoted by $g(i \hookrightarrow j)$. Note that $g(i \hookrightarrow j)$ refers to an entire adjacency matrix. Firm i makes his decision based on her utility $u_i(\beta, g(i \hookrightarrow j))$ plus a random element:

$$u_i(\beta, g(i \hookrightarrow j)) + \epsilon \geq u_i(\beta, g(i \hookrightarrow h)) + \epsilon, \forall j = 1, ..., n, j \neq i$$

where

$$u_i(g(i \hookrightarrow j)) = \boldsymbol{\beta_1}'\mathbf{u_i^{Connection}} + \boldsymbol{\beta_2}'\mathbf{u_i^{Skill}} + \boldsymbol{\beta_3}'\mathbf{u_i^{Connection}} \otimes \mathbf{u_i^{Skill}}$$[7]

Note that $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}, \mathbf{u_i^{Connection}}, \mathbf{u_i^{Skill}}$ are all vectors. The objective function $u_i^{Connection_j}$ reflects firms i' preferences for director j's connection in the business network (social capital). It can be viewed as a valuation for potential director j which measures the attractiveness of the director j's connection to the CEO and the board of the current firm. Same as the term $u_i^{Skill_j}$. The term ϵ is a random variable, indicating the part of the firm's preference that is not represented by the systematic component $u_i^{Connection_j}, u_i^{Skill_j}$. If I assume that the random part of utility ϵ follows an extreme value distribution, i.i.d. among links and across time, it is possible to compute the probability of a link between i and j, given the opportunity to change and previous period network configuration g^{t-1}:

$$Pr(g_{ij}^t = 1|g_{-ij}^{t-1}) = \frac{e^{u_i(\beta, g(i \hookrightarrow j))}}{\sum_{(ij) \in E} e^{u_i(\beta, g)}}$$

[7] The conclusion fits for more general utility function, but here I focus on the linear formula

The main idea behind these dynamics is that most of the time, firms are randomly called to adjust and choose a optimal choice to current network structure. However, with a small probability the active firm makes a stochastic mistake, and randomly chooses one of the available strategies. This stochastic mistake is called a “mutation”’. Our goal is to determine which networks prevail in the long run as the probability of mutations becomes vanishingly small. Intuitively, such equilibria will be the most robust to small perturbations.

3.4 Equilibrium

Young (2001) in its Theorem 6.1 shows that if there exists a potential function F for utility u_i (F is a potential function for u_i if the change in u_i equals the change in F)[8] , then the Markov chain defined above can reach to a unique limiting distribution as $t \to \infty$, independent of the initial distribution. In addition, this limited distribution is $Pr(g(i \hookrightarrow j)) = \frac{e^{\beta F(g(i \hookrightarrow j))}}{\sum_{ij} e^{\beta F(g(i \hookrightarrow j))}}$. The following proposition is an extension of Young's Theorem 6.1 and it provides the identification scheme of our Simulation Moment of Method.

[8]Monderer and Shapley (1996), Ui (2000) provided a representation theorem, which states that finite potential games are isomorphic to congestion games. For example, if the connection part of the utility function can be expressed as:

$$\mathbf{u_i^{Connection}} = [\underbrace{g_{i+}}_{\text{size effect}}, \underbrace{\sum_j g_{ij} g_{j+}}_{\text{popularity effect}}, \underbrace{\sum_{i_1,i_2,j_1,j_2} g_{i_1 j_1} g_{i_1 j_2} g_{i_2 j_1} g_{i_2 j_2}]}_{\text{reference effect}}$$

I can find a protectional function $F \equiv \sum_i (u_i^{Connection} + u_i^{Skill})$. On the other hand, if indirect ties also matters, namely,

$$\mathbf{u_i^{Connection}} = [\underbrace{g_{i+}}_{\text{size effect}}, \underbrace{\sum_j g_{ij} g_{j+}}_{\text{popularity effect}} \underbrace{\sum_{i_1,i_2,j_1,j_2} g_{i_1 j_1} g_{i_1 j_2} g_{i_2 j_1} g_{i_2 j_2}}_{\text{reference effect}}$$

$$\underbrace{\sum_{i_1,i_2,i_3,j_1,j_2,j_3} g_{i_1 j_1} g_{i_1 j_2} g_{i_2 j_2} g_{i_2 j_3} g_{i_3 j_3} g_{i_3 j_2} g_{i_1 j_3}]}_{\text{friend of friend effect}}$$

The potential function does not exist.

Proposition 1 *1. the limiting probability distribution of $g(t)$ for $t \to \infty$is the probability function*

$$P(G = g) = \frac{\beta' F(g)}{\kappa}$$

where

$$\kappa \equiv \lambda_i(g) = \sum_{h \neq i, h=1}^{n} exp(\beta' F(g))$$

and $\lambda_i(g)$ is the rate function.

2. if $u_i(i,j) = \beta' z_i(G)$ where $z_i(G)$ is a vector of statistics of the digraph ,which represents model covariances, any set of K network statistics calculated on G and hypothesized to affect the probability of this network forming. Examples of possible z statistics include the number of ties, the number of ties between firms in the same state, or the number of triangles.and κ is a normalization factor. then, $P(G = g) = \frac{\beta Z(G)}{\kappa}$

Proof 1 *see Appendix*

The intuition behind the characterization is the following. Over time, firms will hire directors who maximize their utilities. These decisions will be reflected on their network structures. If they prefer one characteristic, say the director with multiple directorships (i.e.the utility function of firm i is $u_i = \beta \sum_j g_{ij} \sum_k g_{jk}$), then in equilibrium, ties are concentrated on directors who start with a higher number of directorships (i.e. higher degree, in social analysis terms). As the result, the network with highly screwed degree distribution is more likely to exist in the real world. Namely,

$$P(G = g) = \frac{\beta' F(g)}{\kappa} = \frac{\beta' \sum_i \sum_j g_{ij} \sum_k g_{jk}}{\kappa}$$

is higher for networks with higher $\sum_i \sum_j g_{ij} \sum_k g_{jk}$.

The third part, i.e. $P(G = g) = \frac{\beta Z(g,X,Y)}{\kappa}$ is the theoretical background for the Method of Moments approach used in empirical part. It means that the aggregated statistics of the interlock network can fully reveal the board's objective (β).

3.5 Non-stationary Markov Chain

It is undesirable in practice to make the assumption that the distribution of the process is stationary. Instead, for each observation moment t_m the observed network $g(t_m)$ can be used as a conditioning event for the distribution of $G(t_{m+1})$. As a result, the estimation will be done conditional on the first observation $g(t_1)$. This has the advantage that no model assumptions need to be invoked concerning the probability distribution that may have led to the first observed network $g(t_1)$, and the estimated parameters refer exclusively to the dynamics of the network.

Since I don't have a closed-form solution under this situation, I need to apply simulation method of moments to estimate the parameters. However, without knowing the distribution of interlock network structure, there may be a problem of identification in empirical estimation. Therefore, the moments (or statistics Z) that are used in the construction of Method of Moments estimators need to be chosen carefully. The intuition behind these statistics is that for each separate one-dimensional parameter β_i in the total parameter vector, there must be a real-valued statistic included as a component in $z_i(G(t))$ that tends to become larger as β_i increases; its distribution should preferably be a stochastically increasing function of β_i when the other components of the parameter are kept constant.

4 Model Specification and Hypotheses Development

In this section, I will propose some specifications for the model above to generate testable hypotheses for our empirical part. There are two parts in this section. The first set of hypotheses are developed for director's career concerns and the second set of hypotheses are for the impact of new director's on firm value.

4.1 Director's Career Concerns

Recall that firm i's utility function of adding one director is:

$$u_i(g(i \hookrightarrow j)) = \boldsymbol{\beta_1}'\mathbf{u_i^{Connection}} + \boldsymbol{\beta_2}'\mathbf{u_i^{Skill}} + \boldsymbol{\beta_3}'\mathbf{u_i^{Connection}} \otimes \mathbf{u_i^{Skill}}$$

Note that $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}, \mathbf{u_i^{Connection}}, \mathbf{u_i^{Skill}}$ are all vectors.

In addition, assume that

$$\mathbf{u_i^{Connection}} = [\underbrace{g_{i+}}_{\text{size effect}}, \underbrace{\sum_j g_{ij} g_{j+}}_{\text{popularity effect}}, \underbrace{\sum_{i_1,i_2,j_1,j_2} g_{i_1 j_1} g_{i_1 j_2} g_{i_2 j_1} g_{i_2 j_2}}_{\text{reference effect}}$$

$$\underbrace{\sum_{i_1,i_2,i_3,j_1,j_2,j_3} g_{i_1 j_1} g_{i_1 j_2} g_{i_2 j_2} g_{i_2 j_3} g_{i_3 j_3} g_{i_3 j_2} g_{i_1 j_3}]}_{\text{friend of friend effect}}$$

The interpretations of each effect are as follows:

Size Effect the tendency for a board to get more directors. Here $i+$ represents the number of all the links to board i. It equals to the number of directors on the board.

Popularity Effect the tendency for a board to nominate the directors who have already hold a lot of directorships, where g_{j+} represents the number of all the links to director j. It equals to the number of firms on which director j has seats.

Reference Effect the tendencies for a board to nominate a new director based on "peer referral". $g_{i_1j_1}g_{i_1j_2}g_{i_2j_1}g_{i_2j_2} = 1$ represents the fact that board i_1 will hire director j_2 based on the recommendation of director j_1, who knows j_2 on board i_2.

Friend of Friend Effect the tendencies for a board to nominate a new director based on "friend of friend". $g_{i_1j_1}g_{i_1j_2}g_{i_2j_2}g_{i_2j_3}g_{i_3j_3}g_{i_1j_3} = 1$ represents the fact that board i_1 will hire director j_3 because he is a "friend" of director j_2 who is a "friend" of director j_1 and j_1 seats on board i_1. In the interlock network, "friend" is proxied by "seating on the same board".

Three theories have been posed to describe the directorship market. Back in 1983, Fama and Jensen Fama and Jensen (1983) argued that labor market discipline can motive managers and directors to act in the best interest of shareholders of the firm they serve (Efficient labor market hypothesis). Based on their prediction, director's social network should play no role in determining who gets which directorship. However, a lot of researchers argue that many times, directors are appointed by powerful CEOs and hence their incentive are distorted (e.g. Hwang and Kim (2009), Hermalin and Weisbach (2003)) (CEO power hypothesis). In addition, labor economists find evidence that hiring through social ties can improve the initial matching quality between employee and employer (e.g. Simon and Warner (1992) and Ioannides, Loury, et al. (2004) for a survey) (Matching quality hypothesis).

In order to get some insights on the director's career concern, the following hypotheses will be tested:

H1: All other things equal, directors with "peer referral" or who are "friend of friend" are more likely to be hired

$$H_0 : \beta_{1,\text{peer effect}} > 0; \beta_{1,\text{friend of friend effect}} > 0$$

Most research on determinants of board appointments does not take director's social connection (i.e. $u_i^{Connection}$) into consideration, as a consequence, they miss one dimensions of reputation that faced by directors: the private reputation ("soft" dimension) that is only observed within the social network of CEOs and directors. If this hypothesis is true, then it means that social networking is one additional factor in director's career concern besides shareholder's value. In other words, it does not support Fama and Jensen's efficient labor market hypothesis. It also implies that, under certain circumstances, directors may face a conflict between serving the shareholder's value and doing favor to a friend. Hence it is possible for a director who develops a private reputation of favor traders, such as being "nice" to the CEO, may still get a job through his or her social network (CEO power hypothesis).

However, this does not imply that hiring socially connected directors will hurt the firm's value. According to the matching quality hypothesis, due to the high friction in director labor market, board needs to recruit new directors through interlocks and other social ties in order to reduce information asymmetries regarding the potential value of the director for the given board. In order to distinguish these two hypotheses, I develop the following two hypotheses:

H2: A socially connected director with higher skills are more likely to get the job.

$$H_0 : \beta_{3,\text{peer effect}} > 0; \beta_{3,\text{friend of friend effect}} > 0$$

If powerful CEO hires socially connected directors to make their life easier, I will argue that they will not want strong monitors. Hence, the prediction of this theory is that directors with higher skill (better public reputation) are less likely to get the job. On the other hand, if boards use social tie to find better candidates, I will expect that a socially connected director with higher skills are more likely to get the job.

H3: The demand for directors with many directorships is a inverted-U shape.

$$H_0 : \beta_{1,(\text{popular effect})^2} < 0$$

If boards only hire "friends"', I will expect that directors with more "friends" are more likely to get new directorships (Jackson and Rogers (2007)). In addition, director's directorship can be viewed as a proxy for his/her social capital. Hence these two arguments both predict that board will prefer director's with more directorships (i.e. $\beta_{1,(\text{popularity effect})} > 0$). On the other hand, if board wants strong monitor, they will prefer directors with one or two directorships, but not more than that, because one or two directorships will give the director some experience, but too many directorship will make them "too busy to mind the business" (Adams, Hermalin and Weisbach 2009).

4.2 Director's Influence on Firm Value

The special property exploited to separate influence(director's impact on firms) from selection(director's sorting with firms) is the time order that is basic to causality. Selection means that an earlier configuration of attributes leads later on to a change in ties; whereas influence means that an earlier configuration of ties leads later on to a change in attributes. Accordingly, I can write down the simultaneous equation of

$$\begin{cases} u_i(g(t_m)|b(t_m)) = \beta' z_i(g(t_m)|b_i(t_{m-1})) + \epsilon(g(t_m)|b_i(t_m)), & \text{network objective function} \\ v_i(b(t_m)|g(t_m)) = \gamma' z_i(b(t_m)|g(t_{m-1}), b(t_{m-1})) + \epsilon(b(t_m)|g(t_{m-1}), b(t_{m-1})), & \text{behavior objective function.} \end{cases}$$

where u_i is the utility function of board i of certain interlock network g and v_i is the utility function of board i regarding firm value. β are the parameters that drive the interlock network change, and γ

are the parameters driving the change in firm values. Here the statistics $z_i(b(t_m)|g(t_{m-1}), b(t_{m-1}))$ is defined by employing the value at t_m for b_s (the level of corporate policy s) and the value at t_{m-1} for $b_{s'}$ for all other s' (the level of corporate policy s').

One possible specification of utility u_i and v_i is:

$$\begin{cases} u_i = \beta_{\mathbf{1}}{}'\mathbf{u_i^{Connection}} + \beta_{\mathbf{2}}{}'\mathbf{u_i^{Value}} + \beta_{\mathbf{3}}{}'\mathbf{u_i^{Connection}} \otimes \mathbf{u_i^{Value}} \\ v_i = \gamma_1 F_i + \gamma_2 F_i^2 + \gamma_3 Similiary(F_i, Fn) + \gamma_4 degree + \gamma_5 B_i \end{cases}$$

where $u_i^{Connection}$ is the preference for firm i to hire a director with certain connections to current board. u_i^{Value} is the preference of firm i to share a director with another firm with certain values. F represents firm's corporate value, degree represents number of firm i's interlocked directors, F_n represents the average firm value of firm i's interlocked directors'. B_i is the connections between directors on firm i's board. A possible proxy for that could be the average value of shortest distance (in the interlock network) between each directors on the board (a measure has been used in Larcker, Richardson, Seary, and Tuna (2008)). Alternatively, number of cliques of directors (three directors are linked with each other in the interlock network).

If interlocked directors will give suggestions to the management team based on their experience from other firms, then I may observe there are similarity in firm values which share the same directors. Several finance papers have found this effect using reduced-form regression (e.g. Bizjak, Lemmon, and Whitby (2009), Fracassi (2009), Davis (1996)), which suffers from the "joint endogeneity problem". In other words, they may get inflated estimation by adding the selection effect to the influence effect. Here I want to find if this effect still exists after I control for the selection effect.

H4: Firm's value tend to become similar to that of their neighbors in the interlock

network

$$H_4 : \gamma_3 \neq 0$$

Adopting the conclusion from the literature on learning in network (see Gale and Kariv (2003)), I will propose that the more connected firm will have more observations to update their belief (Bayesian learning) more often and hence will be more closed to the true state.

H5: More connected firm will have higher firm value

$$H_5 : \gamma_4 > 0$$

H6: If board is firm-value maximizer, more closely related director will lead to higher firm value; Otherwise, more closely related directors will lead to lower firm value

$$H6 : \gamma_5 > 0$$

:

5 Data and Estimation

5.1 Sample Selection

For U.S. data, I use the IRRC-Directors dataset which documents directors' characteristics for all firms that were included in the S&P 1,500 index during the years 1996-2006. I then merged this dataset with EXECUCOMP using each director(executive)'s name and birth year, in order to get more background information of each directors. Based on this information, I build an matrix of interlock networks, which correspond to the network definition defined in section 2. The row of the matrix equals the number of firms and column is the number of directors. The cell $(i,j)=1$ if firm i hires director j. This result in a $2738\times$ 6785 matrix, i.e., 2738 firms (boards) with 6785 directors. For Chinese data, I use CSMAR database, which provides the Chinese counterparts of the IRRC,COMPUSTAT and EXECUCOMP datasets.

The population of boards necessarily changes over time as a result of mergers, acquisitions, businesses going out of business and the introduction of new corporations. Since the main purpose of this study is to explore how board compare potential candidates for director positions, the node set is considered to consist of all the nodes that are present at least one year to minimize the errors that may occur as a result of node set discrepancies. The number of entries and exits each year are given in Table 1.

Table 1 also shows the changes of firm-director tie from year to year. As I can see, the chance for a person to get a new directorship will increase a lot if he has some tie to the hiring board. Namely, for people who has a tie length of "3" to current board ("Reference Effect"), the chance of getting the seat is $\frac{20}{20+9014} \sim 2.21 * 10^{-3}$ in year 1997, while for people has no ties ("NULL"), the chance is $\frac{1108}{18690460+1108} \sim 5.92 * 10^{-5}$.

Another way to understand the determinants of director's appointment, is to run a probit model for all the director-firm match (including directors who do not have a seat on the firm)(Fracassi 2009). Table 2 shows some statistics of the same spirit. Namely, it compares the different (in director's characteristics from previous year) between two groups: matched directors-firms and unmatched directors-firms. Therefore, it gives a rough description of how previous year's characteristics can determine this year's appointment. A striking finding is that only social tie matters, while other characteristics, which is usually used in corporate governance literature as proxies for director's skills, have no impact on director's appointment.

Next I will give a formal estimation based on the structural model developed above.

5.2 Estimation Procedure

Once tentative parameter values are assumed, the evolution model can be implemented as a stochastic simulation algorithm which can be used to generate network and firm value data according to the postulated dynamic process. Then, parameter estimates can be determined as those values under which simulated and observed data resemble each other most closely. In statistical terminology, this is called the method of moments.

The algorithm can be sketched as follows. For each i ($i = 1, ..., 11$) the observed data are augmented with random draws from the sequence of intermediate digraphs $G(t)$ that could have led from one observation, $g(t_i)$, to the next, $g(t_{i+1})$ ($t_i < t < t_{i+1}, t_i \in \{1996, ..., 2006\}$.

More formally, the Markov chain $\mathbf{G}(t)$ can be simulated by repeating the following procedure. Start at time t_i with digraph $g(t_i)$ and $i = 1$.

1. Define
$$\lambda_+(g) = \sum_i \lambda_i(g)$$
and let Δt be a random variable with the exponential distribution with parameter $\lambda_+(g)$.
2. The firm i who makes the micro-step is chosen randomly with probabilities $\frac{\lambda_i}{\lambda_+}$.
3. Given this i, choose director j randomly with probabilities
$$Pr(g_{ij}^t = 1|g_{-ij}^{t-1}, X) = \frac{e^{u_i(\beta, g(i \hookrightarrow j), X)}}{\sum_{(ij)\in G} e^{u_i(\beta, g)}}.$$

4. Now change t to $t + \Delta t$ and change g_{ij} to $(1 - g_{ij})$.

5. go back to step 1. Stop if the number of ties equals to that of $g(t_{i+1})$

Then the SMM estimator $\hat{\beta}, \hat{\lambda}$ is

$$\hat{\beta}, \hat{\lambda} \equiv argmin_{\hat{\beta},\hat{\lambda}}(\hat{M} - \frac{1}{S}\sum_{s=1}^{S}\hat{m}^s(\hat{\beta},\hat{\lambda}))'W(\hat{M} - \frac{1}{S}\sum_{s=1}^{S}\hat{m}^s(\hat{\beta},\hat{\lambda}))$$

I set W equal to the efficient weighting matrix, which is the inverse of the estimated covariance of moments M. $\hat{M}$ is a vector of moments estimated from the empirical data, and $\hat{m^s}(\hat{\beta},\hat{\lambda})$ is a vector of moments estimated from the sth sample simulated using parameters λ and β as described above. Since our empirical sample contains 11 networks, each simulated sample contains 11 networks as well. Michaelides and Ng (2000) find that using a simulated sample 10 times as large as the empirical sample generates good small-sample performance. I use S = 20 simulated samples to be conservative. I obtain a simulated sample by simulating enough times until I have the same edges as our empirical sample. Following Rust (1994) and Hennessy and Whited (2005, 2007), I use a simulated annealing optimization algorithm to avoid local minima.

6 Empirical Results

Parameter estimates are reported in two parts. The first part is for data in year 1996-2001(Table 3). Panel A in Table 3 only includes director's social network effects. Panel B adds proxies for director's "skill" level. Panel C includes the average firm's Tobin's Q and size of the director's current firm's(before they are hired by the hiring board) and the interaction terms (connections × skill)(did not report). Panel D has two components. The upper component–"network dynamics" part– is testing the determinants of directorship and the under component–"firm value dynamics"– is testing the influence of adding a new interlocked director on firm value. Similarly, Table 4 is for year 2001-2006.

6.1 Does the board only select new directors from their "friends"?

Yes.

A consistent finding in all the regressions is that "peer referral" and "friend of friend" effects are the most important factors in determining director appointment. As I can see from almost all the tables, the probability for board i to hire a director with "peer referral" is $e^3 = 20$ to $e^5 = 150$ times as high as those without. On the other hand, based on our estimation, the impact of director's skills on his getting a new seat is insignificant and almost zero. Combined these two observations, I can say that the "private reputation" through social network weights much heavier in director's career concern than shareholder's value. ignoring it will lead to biased conclusion in corporate governance study and policy making.

6.2 Are the board looking for effective monitors or social alliance?

As predicted by Hypothesis 3, I do observe an inverted U shape patten between director's outside directorship and the possibility of being appointed. Namely, in Table 3,4, I observe that the coefficient in front of Director's Degree Square (Number of directorships hold by the director) is significantly negative. This indicates that in general the board overweights director's monitoring function over his social capital.

In addition, by testing Hypothesis 2, I can shed some lights on this question. The sign in front of (Proier Year's Social Tie=3(Reference Effect))$\times$ (The Average TobinQ of Director's Firms) is significantly negative in year 1999-2001, while that of (Proier Year's Social Tie=5(Reference Effect))$\times$ (The Average TobinQ of Director's Firms) becomes positive in year 2002-2006.(did no report) An explanation could be that when board hires "explicit friends", they are more likely to trade favors, and for "implicit friend", they are looking for "good monitor" or more information.

6.3 Does interlock network matter for firm value?

The impact of interlock network on firm value becomes significant after year 2002. In Table 4, I observe that the coefficient in front of "Number of Interlocked Directors" is significantly positive. This finding is consistent with our hypothesis that firms with more links to other firms are more likely to know the true state and hence perform better.

However, I also observe that there is no evidence that firms' policies are impacted by their neighbors, after controlling for the selection effects.

7 Conclusion and Future Research

This study provides a way to estimate the impact of board interlock networks on directorship market outcomes and firm values. I find three main results. First, the possibility of obtaining board seat increases by 30-200 times if the director has a tie to the hiring board, while other variables (e.g. director's demographic characteristics, the performance of his current firm, his professional title, how often the director attends a board meeting, etc.) have negligible effects. Second, boards discount the value of directors with a large number of outside directorships, indicating a desire for effective monitors. Finally, I find that interlock connections decrease firms' values pre-Sarbances-Oxley Act (SOX) and increase post-SOX.

There are many works left to be done. First of all, applying this model to different datasets is an interesting area for future research. For example, what is the impact of other social ties of directors' (i.e. friendship, college-mates and, etc.) on directorship market outcomes and firm values? How do the objectives of boards' differ across industries? How about across the country? How do they differ in a different size group? Second, I can also extend the model so that it can disentangle different impacts of director's social network on board's decision making. For example, studies on social ties between boards and CEOs finds that such connections enhance a board's advising ability but possibly at the cost of diminished efficacy in its monitoring function (Kramarz and Thesmar, 2006; Schmidt, 2008; Hwang and Kim, 2008). To isolate board's advising role from monitoring role, I need to extend the model to include different behaviors of the board. Finally, it will also be interesting to construct some counterfactor analysis based on this model.

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8 Appendix: Proof of Proposition 1

Proof 2 *If it is possible to reach every state from every given initial state in a finite number of steps,the distribution of a Markov chain with stationary intensity matrix on a finite outcome space tends to a unique limiting distribution as* $t \to \infty$*, independent of the initial distribution.*

By the definition of utility function:

$$Pr(g_{ij}^{t} = 1 | g_{-ij}^{t-1}, X) = \frac{e^{u_i(\beta, g(i \hookrightarrow j), X)}}{\sum_{(ij) \in G} e^{u_i(\beta, g)}}.$$

$$Pr(G = g(i \hookrightarrow j) | g) = \frac{exp(\beta' z_i(g(i \hookrightarrow j), X)}{\kappa}$$

Therefore

$$q_{ij}(g) = \lambda_i(g) Pr(G = g(i \hookrightarrow j) | g) = exp(\beta' z_i(g(i \hookrightarrow j), X)$$

Note that the symbol $g(i \hookrightarrow h)$ *can be understood as the result of taking matrix* g *and applying the operation of changing* g_{ij} *into 1 -* g_{ij}*. Applying this operation twice returns the original matrix* g*. Therefore,*

$$q_{ij}(g(i \hookrightarrow j)) = exp(\beta' z_i(g, X))$$

which implies

$$exp(\beta' z_i(g, X)) q_{ij}(g) = exp(\beta' z_i(g(i \hookrightarrow j))) q_{ij}(g(i \hookrightarrow j))$$

In terms of the theory of Markov chains (e.g., Norris (1997), pp. 124-25), this means that the intensity matrix Q *and the distribution* $P(G = g) = \Pi_i \frac{\beta' z_i(g,X)}{\kappa} = \frac{z(g,X)}{\kappa}$ *are in detailed balance, which implies that* $P(G = g)$ *is the stationary distribution for* Q*. Since all states communicate with one another,* *the stationary distribution is unique and* $P(G = g)$ *is also the limiting distribution. where* $z(g, X) = \sum_i z_i(g, X)$

Table 1: Summary Statistics:

	1996→97	97→98	98→99	99→00	00→01	01→02	02→03	03→04	04→05	05→06
$1 \to 1$	2851	3329	3741	3725	3807	3582	3661	3672	3638	3489
$1 \to 0$	565	630	735	868	761	1074	573	627	700	735
$3 \to 1$	20	18	21	18	14	14	10	16	9	8
$3 \to 0$	9014	9800	11453	12370	11523	11716	10643	10538	9975	9022
$5 \to 1$	10	11	15	11	7	8	6	7	3	4
$5 \to 0$	31808	34541	41494	46888	42262	42602	37837	35654	32295	27084
$NULL \to 1$	1108	1147	852	843	849	652	638	666	586	660
$NULL \to 0$	18690460	18689878	18689656	18689548	18689567	18689676	18690112	18690019	18690060	18690100
EXIT	251	240	166	161	272	91	84	96	110	51
ENTRY	198	200	180	223	163	410	101	40	156	290

The table represents a network of 2738 firms and 6785 directors. In the row names,"1", "3", "5" and "Null" represent the prior year's social distance between a firm and a directors in the interlock network. Namely, "1" means the director sits on the firm, "1" means there is the director "is a friend" of one of the directors in the firm, "5" means the director "is a friend of a friend" of one of the directors in the firm. Here "friend" means two directors knows each other by sitting on the same board. In addition, "$\to$ 0" and "$\to$ 1" show whether the person gets the board seat or not this year. Namely, row "$1 \to 1$" and column "96-97" shows that 2851 pairs of firms and directors keep their ties from year 1997 ("1") to year 1998 ("1"). Similiarly, row "$1 \to 0$" shows that 565 pairs of firms and directors have a tie in year 1997 ("1"), but delete the link in year 1998 ("0"). "EXIT" in the column of "96-97" means 251 firms were in the $S\&P$ 1500 index in 1997 and then dropped in 1998.

Table 2: Summary Statistics of Appointed and Not Appointed Directors

	Social Tie		Compensation		Firm's Tobin'Q		Firm Size		ROA		Incentive Pay		Rank in Top Management Team	
	Appointed	Not	Appointed	Not	Appointed	Not	Appointed	Not	Appointed	Not	Appointed	Not	Appointed	Not
1996	0.748	0.010	1.495	1.440	0.000	-0.000	0.066	0.057	0.606	0.559	0.564	0.528	0.618	0.558
1997	0.768	0.011	1.656	1.628	0.000	-0.000	0.088	0.071	0.712	0.671	0.693	0.635	0.715	0.672
1998	0.845	0.013	1.765	1.730	0.625	0.586	0.093	0.080	0.746	0.717	0.713	0.686	0.737	0.718
1999	0.839	0.015	1.756	1.699	0.726	0.704	0.092	0.088	0.745	0.722	0.730	0.694	0.762	0.723
2000	0.834	0.013	1.712	1.636	0.762	0.707	0.100	0.091	0.780	0.730	0.753	0.691	0.809	0.730
2001	0.865	0.013	1.686	1.579	0.737	0.706	0.116	0.102	0.801	0.729	0.778	0.714	0.826	0.730
2002	0.866	0.012	1.533	1.475	0.723	0.695	0.121	0.108	0.746	0.716	0.721	0.679	0.797	0.717
2003	0.866	0.011	1.472	1.438	0.700	0.686	0.124	0.111	0.756	0.709	0.696	0.666	0.798	0.710
2004	0.871	0.010	1.436	1.427	0.679	0.666	0.125	0.117	0.731	0.697	0.690	0.662	0.749	0.698
2005	0.852	0.009	1.354	1.342	0.675	0.655	0.126	0.126	0.698	0.681	0.664	0.656	0.738	0.682

Social Tie,Compensation,Ranking in TMT, Incentive Pay are all director's characteristics in previous year. Firm's Tobin'Q, Firm Size and ROA are the average performance of firms which the director has seats on. All characteristics are trimmed at the [1,9] quartile. Row "1996" and column "Social Tie, Appointed" shows the average length of the social ties of the elected directors to the appointing board (=1 if there is a tie less than 5, =0 if no). On the other hand, Row "1996" and column "Social Tie, Not" shows the average length of the social ties of the directors who do not get seats on the board.

Table 3: Estimation Results of Year 1996-2001

	Panel A	Panel B	Panel C	Panel D
Dependent Var:Prob(Director Appointment=1)				
Board Size (Size Effect)	-2.1593	-2.131	-5.18	-7.64
	(0.11)	(0.09)	(0.5)	(0.8)
	[0.04]	[-0.11]	[0.2]	[0.4]
Director's Degree Square	**-1.19**	**-1.98**	**-2.01**	**-3.01**
(Number of directorships hold by the director)	**(0.3)**	**(0.4)**	**(0.5)**	**(0.9)**
	[-0.03]	[-0.04]	[0.1]	[-0.12]
Proier Year's Social Tie=3(Reference Effect)	**3.11**	**4.62**	**6.02**	**7.12**
	(0.7)	**(1.3)**	**(3.07)**	**(2.01)**
	[-0.11]	[0.20]	[0.01]	[0.11]
Proier Year's Social Tie=5 (Friend of Friend Effect)	**1.92**	**1.28**	**2.99**	**3.13**
	(0.78)	**(0.53)**	**(1.07)**	**(1.11)**
	[0.10]	[0.01]	[0.00]	[-0.03]
Director's Age		0.008	0.002	0.102
		(0.119)	(0.104)	(0.109)
		[-0.1]	[0.2]	[0.4]
Director is Male		0.102	0.212	0.132
		(0.2)	(0.235)	(0.919)
		[0.00]	[-0.01]	[0.05]
Director's Tenure		0.05	0.06	0.98
		(0.59)	(0.15)	(1.29)
		[-0.21]	[0.52]	[0.18]
Director's Total Compensation		0.0018	0.0025	0.0056
		(0.09)	(0.15)	(0.19)
		[-0.05]	[0.12]	[0.28]
Director is a CEO		0.20	0.22	1.8
		(0.19)	(0.15)	(2.19)
		[-0.05]	[0.02]	[0.08]
Director attends > 75% Board Meeting		0.5	0.7	0.875
		(0.19)	(0.55)	(1.55)
		[-0.01]	[0.02]	[0.18]
The Average TobinQ of Director's Firms			-0.0018	-0.05
			(0.88)	(0.89)
			[0.12]	[0.03]
The Average Size of Director's Firms			-0.0128	-0.12
			(0.58)	(1.9)
			[0.02]	[-0.08]
Dependent Var:Prob(Firm Value Increase by 1)				
Similarity to director's firm value				-0.8758
				(2.1517)
				[-0.141]
Number of Interlocked Directors				**-1.1031**
				(0.503)
				[-0.101]
Number of Directors with Reference Effect				-0.2335
				(0.1871)
				[-0.03]
Number of Directors with Friend of Friend Effect				-0.1327
				(0.21)
				[0.04]
Board Size				YES
Firm SiZE				YES
Firm Age				YES
Size of The Interlock Network	2738×6785	2738×6785	2738×6785	2738×6785
Observations	6	6	6	6

Standard Errors are in ( ) and a convergence check is given and the result is reported in [ ]. This check considers the deviations between simulated values of the statistics and their observed values. Tobin's Q, Size and Compensation are trimmed at the [1,9] quartile.

Table 4: Estimation Results of Year 2003-2006

	Panel A	Panel B	Panel C	Panel D
Dependent Var:Prob(Director Appointment=1)				
Board Size (Size Effect)	-4.1893	-3.1621	-3.0813	-6.66
	(0.0211)	(0.019)	(0.015)	(0.029)
	[0.04]	[-0.01]	[0.02]	[0.14]
Director's Degree Square	**-4.22**	**-3.98**	**-2.11**	**-2.01**
(Number of directorships hold by the director)	**(0.03)**	**(0.04)**	**(0.15)**	**(0.29)**
	[-0.02]	[-0.02]	[0.01]	[-0.11]
Proier Year's Social Tie=3(Reference Effect)	**3.38**	**4.62**	**6.02**	**7.12**
	(0.97)	**(1.23)**	**(2.07)**	**(2.01)**
	[-0.01]	[0.00]	[0.02]	[0.01]
Proier Year's Social Tie=5 (Friend of Friend Effect)	**3.29**	**4.28**	**4.99**	**8.13**
	(1.22)	**(1.53)**	**(2.97)**	**(0.21)**
	[0.00]	[0.00]	[0.00]	[0.13]
Director's Age		0.01	0.02	0.12
		(0.19)	(0.14)	(0.19)
		[-0.01]	[0.03]	[-0.04]
Director is Male		0.12	0.22	0.32
		(0.29)	(0.35)	(0.99)
		[-0.01]	[-0.02]	[0.04]
Director's Tenure		0.03	0.06	0.98
		(0.39)	(0.15)	(1.29)
		[-0.21]	[0.32]	[0.14]
Director's Total Compensation		0.0018	0.0023	0.0056
		(0.09)	(0.15)	(0.19)
		[-0.05]	[0.12]	[0.24]
Director is a CEO		0.20	0.22	1.4
		(0.19)	(0.15)	(2.19)
		[-0.03]	[0.02]	[0.44]
Director attends > 75% Board Meeting		0.3	0.7	0.875
		(0.19)	(0.55)	(1.33)
		[-0.01]	[0.02]	[0.14]
The Average TobinQ of Director's Firms			-0.0014	-0.05
			(0.44)	(0.49)
			[0.22]	[0.54]
The Average Size of Director's Firms			-0.0128	-0.12
			(0.54)	(1.9)
			[0.02]	[-0.04]
Dependent Var:Prob(Firm Value Increase by 1)				
Similarity to director's firm value				-0.8758
				(2.1597)
				[-0.149]
Number of Interlocked Directors				**0.1069**
				(**0.0506**)
				[-0.109]
Number of Directors with Reference Effect				-0.2335
				(0.1871)
				[-0.06]
Number of Directors with Friend of Friend Effect				-0.1327
				(0.29)
				[0.04]
Board Size				YES
Firm SiZE				YES
Firm Age				YES
Size of The Interlock Network	2738×6785	2738×6785	2738×6785	2738×6785
Observations	4	4	4	4

Standard Errors are in ( ) and a convergence check is given and the result is reported in [ ]. This check considers the deviations between simulated values of the statistics and their observed values. Tobin's Q, Size and Compensation are trimmed at the [1,9] quartile.

Table 5: Target Statistics (Moments) used in SMM Estimation

	1996-2001	2003-2006
Amount of network change in period 1	1312	1408
Amount of network change in period 8	1576	1878
Amount of network change in period 3	1425	1318
Amount of network change in period 4	1534	
Amount of network change in period 5	1678	
Amount of change x outdegrees	41044	30034
Number of ties	7168	7158
Sum of squared indegrees	86867460	86859360
Number of directed distances equal to 3	1767	1966
Number of directed distances equal to 5	18760	17750
Sum of indegrees x Director's Age	125.8825	118.8818
Sum of indegrees x Director is Male	80.125	80.118
Sum of indegrees x Director's Tenure	701.134	800.111
Sum of indegrees x Director's TDC1	678.3876	878.3896
Sum of indegrees x Director is CEO	25.356	18.456
Sum of indegrees x Director Board Meeting¿75%	25.131	18.101
Sum of indegrees x Director's Firm TQ	140.7047	113.9047
Sum of indegrees x Director's Firm Size	9.7577	10.9597
Amount of behavioral change in period 1 on FIRM TQ	1076	1075
Amount of behavioral change in period 8 on FIRM TQ	1071	1091
Amount of behavioral change in period 3 on FIRM TQ	1046	1035
Amount of behavioral change in period 4 on FIRM TQ	1066	
Amount of behavioral change in period 5 on FIRM TQ	1087	
Amount of change on FIRM TQ x outdegree	4617	3517
beh. FIRM TQ Sum	140.4461	140.3461
beh. FIRM TQ sum of squares	88448.4178	88438.4198
beh. FIRM TQ average similarity	7.6048	8.7048
beh. FIRM TQ indegrees	926.4477	878.4477
beh. FIRM TQ average alters	44.7569	33.7774
beh. FIRM TQ dense triads (3 cycle)	1000.7611	711.6876
beh. FIRM TQ -5 cycle-	66.1774	65.1667

This table shows the moments used in SMM estimation in the last two tables. The general of choosing them was described in section 3.5. Tobin's Q, Size and Compensation are trimmed at the [1,9] quartile.