Organizational Structure, Power Concentration, and Corporate Fraud: A Network Approach *

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Abstract

Organizational structure profoundly impacts strategic objectives. We collect longitudinal data to construct top management team (TMT) membership networks and use network analysis methodology to measure the organizational structure. TMT network structure allows us to investigate the effects of interactions and power distribution among TMT members on strategic decision making. We test a theoretical hypothesis that predicts the relationship between structural centralization and corporate fraud, the former reflecting the power concentration within an organization. Bivariate probit model estimates show that a corporate group has a 9.2% higher likelihood of fraud commission and a 7.8% lower likelihood of fraud detection when its extent of structural centralization increases by one standard deviation. We further test three potential channels: collusion, concealing information, and verbal dominance in decision making.

Keywords: TMT network structure; structural centralization; interaction; power distribution; upper echelons theory

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1 Introduction

Organizational structure profoundly impacts the achievement of organizational aims and strategic objectives. Researchers have devoted great effort to examining their effects on organizational strategy and performance (e.g., Dalton *et al.*, 1980; Hambrick *et al.*, 2015; Kleinbaum *et al.*, 2013; Ma *et al.*, 2022, and references therein). However, the existing research is extremely diverse, and major theoretical gaps persist in the literature (Fredrickson, 1986; Joseph and Gaba, 2020). Many researchers have used case narratives and comparative case studies (e.g., Arora *et al.*, 2014; Csaszar, 2012; Joseph *et al.*, 2016; Rank *et al.*, 2010; Soda and Zaheer, 2012; Soderstrom and Weber, 2020) to analyze the general organizational structure. Moreover, researchers have also centered attention on the top management team (TMT) role structure—the specific roles of TMT members and the relationships among those roles (see, for example, Ma *et al.* (2022) for a recent review). In this paper, we focus on interactions and power distribution among TMT members and develop a novel method for analyzing the effect of organizational structure on corporate fraud.

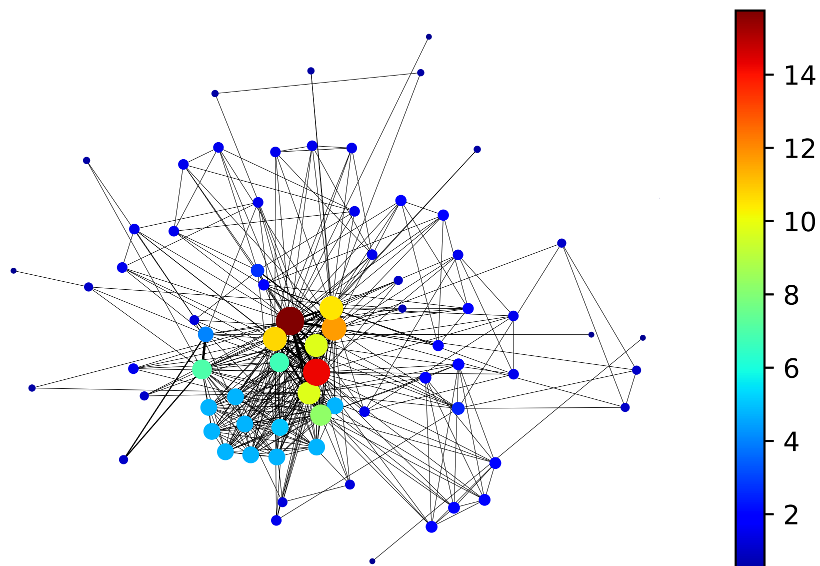
Organizational structure has many definitions (Joseph and Gaba, 2020). We follow Blau (1994, p. 130) and conceptualize organizational structure as "the distribution of their employees among *official positions* [emphasis added] along various lines."[1] If we want to understand why organizations do the things they do or perform the way they do, we must consider their most powerful actors—their TMT members (Hambrick, 2007). Since TMTs play central roles in setting strategy, coordinating activities, and allocating resources across business units, the TMT structure is a reflection of the firm's organizational structure (Beckman and Burton, 2011). However, most of the research in the field of TMT structure has typically focused on the relationship between TMT diversity or the TMT role structure and organizational outcomes (Hambrick *et al.*, 2015; Ma *et al.*, 2022; Vieregger *et al.*, 2017).

One of the main purposes of this paper is to use network analysis methodology to measure

[1] Similarly, Child (1972, p. 2) defines organizational structure as "the formal allocation of work roles and the administrative mechanisms to control and integrate work activities including those which cross formal organizational boundaries."

the organizational structure. The organizational structure in this paper refers to the TMT network structure, which is defined as the structure that emerges from the interactions and relationships among TMT members. In this paper, we identify a corporate group with an organization and use our unique data to construct a TMT membership network within a given corporate group. In its core conception, a corporate group comprises separate legal entities related hierarchically through shareholdings (Witting, 2018, p. 3). The corporate group defined in our paper consists of three types of legal entities: the listed firm itself, its subsidiaries, and the major corporate shareholders of the listed firm. TMT members are personnel who occupy important positions in a legal entity, such as director, supervisor, and senior management. In line with the literature on multiple team memberships (e.g., O'leary *et al.*, 2011), we find that many TMT members hold positions simultaneously in at least two entities of the same corporate group. The colleagueship of TMT members working within one or more entities allows them to form a membership network in a corporate group. A network consists of actors connected by a set of ties, and the pattern of ties yields a particular structure (Borgatti and Halgin, 2011). In this paper, all actors are TMT members in a corporate group, and the ties are the colleagueship of the two incumbent actors working in one or more entities of the same corporate group. Figure 1 shows an example of the membership network. Specifically, we use a standard index in network analysis—network centralization—to measure the extent of the structural centralization in a corporate group.

The second main purpose of this paper is to conduct a quantitative analysis of the effect of structural centralization on corporate fraud. As Granovetter (1985, p. 492) notes, "the extent of disorder resulting from force and fraud depends very much on how the network of social relations is structured." An organization is an instrument made by men in proportion to their power in a given situation (Gouldner, 1954; Ranson *et al.*, 1980). All other things being equal, a TMT member has higher power when holding more positions in a corporate group. The power related to formal organizational positions is also known as structural power, "perhaps the most commonly cited type of power" (Finkelstein, 1992). A centralized organizational structure is a setup in which most rights to make decisions and evaluate activities are concentrated with a few powerful TMT members (Fry and Slocum Jr, 1984; Hall, 1977). Moreover, a high level of centralization is the most obvious way to coordinate organizational decisions (Fredrickson, 1986, p. 282). The greater the extent of structural centralization of a corporate group is, the more opportunities and fewer constraints do the powerful TMT members have to pursue self-interests. Therefore, we expect a positive association between structural centralization and corporate fraud.



Notes. Figure 1 shows an example membership network of the corporate group corresponding to Shanghai Tongjitang Pharmaceutical Co., Ltd.. A color bar on the right side shows the node size, indicating the number of positions held by actors. The edge width is according to the number of ties connecting two actors, reflecting that two actors may work simultaneously in multiple entities within a corporate group.

Figure 1: An Example of the Membership Network

Since not all fraudulent activities are detected, a partial observability problem exists in fraud samples. We employ a bivariate probit model to analyze powerful actors' incentive to commit fraud and their potential to avoid detection conditional on committing fraud (Wang, 2013; Wang *et al.*, 2010). The bivariate probit model estimates confirm our hypothesis. A corporate group has a 9.2% higher likelihood of fraud commission and a 7.8% lower likelihood of detection conditional on committing fraud when the extent of the structural centralization increases by one standard deviation. We also use instrumental variables to alleviate the endogeneity problem. The estimates of the two-stage least square regression are consistent with our hypothesis.

The mechanisms by which structural centralization exacerbates corporate fraud are central to our understanding of collective decision making in organizations. Our data indicate that fraud perpetrators take extremely central positions in a corporate group. In the network literature on power, actors occupying central positions in a network are viewed as potentially powerful (Brass, 1984; Chiu *et al.*, 2017). Power refers to an individual's relative capacity to control, authorize and impact others (Keltner *et al.*, 2003; Thibaut and Kelley, 1959). In "The Spirit of the Laws," Montesquieu warns that "every man invested with power is apt to abuse it, and to carry his authority as far as it will go." Child (1972) recognizes that power is central to strategic choice. Because of its significance to top managerial actions, explicit consideration of the role of power when studying TMTs seems critical (Finkelstein, 1992, p. 507).[2] We consider three channels.

The first channel is that committing fraud requires active coordination or passive acquiescence of multiple members (Albrecht *et al.*, 2015; Free and Murphy, 2015; Granovetter, 1985). Powerful perpetrators often use coercive power to recruit others to participate in fraudulent activities (Albrecht *et al.*, 2015). We find that the increase in the extent of the structural centralization goes hand in hand with more people participating in fraud, suggesting that power concentration makes it easier for active or passive collusion to occur in an organization. Second, perpetrators need to conceal fraudulent information from being leaked to the public or accessed by others. Power concentration helps conceal fraudulent information within the powerful perpetrators' inner circle, or the "dominant coalitions" of

[2]Following Finkelstein (1992), this paper emphasizes that, although most large firms have many officers, only a small subset of TMT members is typically the most responsible for setting policy (Thompson, 1967).

firms, the latter of which is a terminology used by Cyert and March (1963). We find that structural centralization lengthens the time from fraud commission to its detection, implying that it is easier to conceal fraudulent information in a centralized organization than in a decentralized organization. Third, power concentration may produce verbal dominance and make others speechless (Tost *et al.*, 2013) and thus may harm the effectiveness of independent directors' monitoring. Although independent directors, whose main responsibility is to monitor management and detect fraud, may express their dissent through voting behavior (Jiang *et al.*, 2016), we still find that they are less likely to dissent in a more centralized organization.

This paper makes several contributions to the literature. First, we augment the Hambrick and Mason (1984) upper echelons theory by revealing how top members are fundamentally structured (Hambrick *et al.*, 2015). We concentrate on the interactions and relationships built on TMT members' official positions and use the TMT network structure to reflect the general organizational structure. Second, our work provides some new insights into executive leadership research since consideration of power distribution among top managers seems an essential ingredient for research on TMTs (Finkelstein, 1992, p. 505). The TMT network structure in our paper might provide a way to measure power distribution among TMT members, especially the structural power in Finkelstein (1992). Third, we develop a novel network-based measure of the formal organizational structure, which relies on TMTs' observable comemberships in a corporate group. One of the palpable strengths of the structural measure in this paper is that it is replicable and applicable for large sample tests. Fourth, we extend the literature on corporate fraud. To the best of our knowledge, we are the first to empirically investigate how organizational structure affects corporate fraud using the bivariate probit model. Finally, our results contribute to a better understanding of governance, collective decision making, and especially wrongdoing in organizations.

2 Related Literature and Hypothesis Development

2.1 Literature on the Measures of Organizational Structure

The relationship between organizational structure and performance is one of the fundamental questions of strategy research (Rumelt *et al.*, 1994, p. 42) and organization theory (Thompson, 1967). As pointed out by Csaszar (2012), it is unsurprising that it has been addressed extensively from several perspectives—since old, even biblical times (Van Fleet and Bedeian, 1977, p. 357). Rather than summarizing the vast body of literature, this subsection briefly reviews the literature on measures of organizational structure. The quantitative methods to measure organizational structure are extremely diverse. Since firms seldom make structural information publicly available, several studies have used survey experiments or face-to-face interviews to construct organizational structure (e.g., Joseph *et al.*, 2016; Rank *et al.*, 2010; Soda and Zaheer, 2012). Although surveys and interviews are excellent vehicles for measuring a wide variety of unobservable structures, they offer little for making causal inferences between organizational structure and performance.

It is well known that observational, replicable, and large sample data are critical for identifying a causal link between organizational structure and performance. Given data availability challenges, some studies have focused on a specific organizational structure (e.g., Arora *et al.*, 2014; Csaszar, 2012; Soderstrom and Weber, 2020). Csaszar (2012) argues that the large sample of mutual funds in the United States offers a rare window into the implications of organizational design on organizational performance. The mutual fund organizational structure in Csaszar (2012) could be described by two variables representing a committee, i.e., the number of decision makers and the "consensus level," the latter of which is the minimum number of votes for a project to be approved by the committee. Arora *et al.* (2014) develop a new measure of R&D organizational structure for a large sample of American firms that uses the ratio of patents assigned to affiliates versus corporate parents as a proxy for the decentralization of R&D. By studying the structuring of organizational sustainability efforts at a large international medical devices company with headquarters in the United States, Soderstrom and Weber (2020) revisit how new organizational issue domains become structured. Nevertheless, it is still doubtful whether the findings obtained from a specific organizational structure can extend more broadly to the firm structure (Arora *et al.*, 2014).

Research on TMTs has become a central feature of work in strategic leadership and strategic management in general. To better specify the causal mechanisms by which TMTs influence organizational outcomes, recent work calls for TMT scholars to move beyond studies on demography and explore the underresearched area of TMT structure (Beckman and Burton, 2011). Guadalupe *et al.* (2014) argue that, to some extent, the TMT structure reflects the firm's organizational structure, which can be defined as the number of functional and general managers that report directly to the CEO. Vieregger *et al.* (2017) claim that there are two opposing and stylized structures: one in which the TMT is composed entirely of functional corporate executives and the other in which the TMT is dominated by business unit executives or divisional vice presidents. Moreover, Vieregger *et al.* (2017) recognize and empirically demonstrate that most firms fall somewhere between these two stylized TMT structures.

A growing number of studies focus on TMT role structure—particularly in Strategic Management Society journals (see Ma *et al.* (2022) for an excellent review on TMT role structure). TMT role structure is defined as the specific roles of TMT members and the relationships among those roles (Hambrick, 1994, p. 178). Although the TMT role structure has been linked to various outcomes, most existing studies have typically focused on the impact of specific positions in isolation, e.g., chief operating officer (COO), chief strategy officer (CSO), chief marketing officer (CMO), chief financial officer (CMO), chief CSR officer, and chief digital officer (CDO) (Ma *et al.*, 2022). Instead of looking at specific roles, a few studies have explicitly focused on the copresence of other roles and role relationships in TMTs (e.g., Eesley *et al.*, 2014; Guadalupe *et al.*, 2014; Nath and Bharadwaj, 2020; Vieregger *et al.*, 2017). Eesley *et al.* (2014) study founding teams of new ventures, in which TMT roles are coded according to whether they fall into four categories, i.e., technology (chief technology officer (CTO), chief scientist, etc.), finance, sales, marketing, or other. Nath and Bharadwaj (2020) investigate how the relationship between the CMO and firm performance is affected by the copresence of three other functional heads (or CXOs), given various environmental and strategic contingencies.

Although researchers have devoted great effort to examining the attributes of TMTs and their effects on organizational strategy and performance, the findings have been mixed and confusing (Hambrick *et al.*, 2015). Hambrick *et al.* (2015) insightfully point out that structural interdependence is a key moderator in resolving various ambiguities regarding the effects of TMT heterogeneity and composition. However, it is not just TMT interdependence that matters but also the interactions and relationships of all TMT members that influence proximal team processes and more distal organizational outcomes (e.g., Crawford and LePine, 2013; Fombrun, 1984; Soderstrom and Weber, 2020; see Bromiley and Rau (2016) for review).[3] As McEvily *et al.* (2014, pp. 302–303) emphasize, organizational elements generate a web of interactions connecting actors, and these interactions are conduits through which organizational actors coordinate efforts, share goals, exchange information, and access resources that affect an organization's behaviors and performance.

As Beckman and Burton (2011) emphasize, TMT structure is an organization's critical structural choice. Therefore, we believe that an ideal measure of TMT structure needs to be a reflection of at least four major features of an organization, which are categorized by Ma *et al.* (2022) as organizational design, power relationships within the organization, resource dependences of the organization, and institutional pressure in the industry and society. Not to put too fine a point on it, but a substantial gap exists between the measure of TMT structure in the existing empirical research and the organizational structure in the real world. In this paper, we seek to address this gap by collecting observational, replicable, and

[3] Raveendran (2020) highlights that a firm's structure shapes not only the locus of decision-making power but also employees' interaction structure.

large sample data to construct TMT membership networks. Furthermore, we use network analysis methodology to measure organizational structure so that we can investigate the interactions and distribution of power among TMT members.

2.2 Theoretical Hypothesis Development

Organizations are viewed as polities (Gray and Ariss, 1985; March, 1962; Pfeffer, 1981; Selznick, 1948; see Weber and Waeger (2017) for review) and systems of governance in which power and consensus are institutionalized through a process of differentiation and integration (Fombrun, 1984; Galbraith, 1973; Lawrence and Lorsch, 1967). By stressing the process of coalition-building in organizations, several studies have called for an appreciation of power distribution within the organization and an analysis of the patterns of interaction that link those who hold power to one another (e.g., Bacharach and Lawler, 1980; Fombrun, 1984). As Child (1972, p. 13) notes, "The dominant coalition concept opens up a view of organizational structure in relation to the distribution of power and the process of strategic decision making which these reflect." Power is equally central to research on TMTs, and consideration of the power distribution among top managers seems an essential ingredient for research on TMTs (Finkelstein, 1992, p. 505).

However, greater predictive certainty is likely to be achieved only when power can be adequately measured (Child, 1972; Finkelstein, 1992). This paper uses unique data to construct a longitudinal membership network for each corporate group. In the network literature, actors, i.e., TMT members in this paper, occupying central positions in a network are viewed as potentially powerful because of their greater access to and possible control over relevant resources (Brass, 1984). We follow the seminal papers of Bonacich (1987, 2007) and use eigenvector centrality to measure each TMT member's power in a corporate group. One of the primary indices of network structure at the whole network level is centralization, which captures the extent to which the ties of a given network are concentrated on a single actor or a group of actors. Structural centralization reflects the power concentration within an organization (Fombrun, 1984; Hage *et al.*, 1971).

"Power tends to corrupt, and absolute power corrupts absolutely" is one of the most famous and justified maxims of Lord Acton. If the power-holding group dominates the decision process, structural centralization makes it easier for them to pursue self-interest through fraud and to deter fraud detection. Corporate fraud refers to illegal activities undertaken by an individual or a party to obtain private benefits, avoid personal liability, or cause losses to another party. Corporate fraud brings advantages to perpetrators and destructive consequences to victims. A conflict inevitably occurs between the potential victims and the perpetrators. From a polity perspective, conflict is not resolved by consensus or formal rationality but by negotiated compromise or the dominance of some groups over others in an organization (Weber and Waeger, 2017, p. 886). When power is wildly unequal, powerful actors almost always prevail in a conflict; thus, corporate fraud is very likely to arise. In contrast, when power is distributed equally, it is easy for potential victims to prevent corporate fraud. Thus, we hypothesize the following:

Hypothesis (H1). *The extent of structural centralization in a corporate group is positively related to fraud commission and negatively related to fraud detection.*

This baseline hypothesis shows how structural centralization affects fraudulent activities. The mechanisms by which structural centralization exacerbates corporate fraud are central to our understanding of collective decision making in organizations. In "Reflections on Gandhi," George Orwell pointed out with commendably sagacious foresight: "politics, which of their nature are inseparable from coercion and fraud."[4] Coercive power is a leader's ability to force subordinates into complying with his or her demands through threats and punishments. Powerful perpetrators often use coercive power to recruit others to participate in fraudulent activities (Albrecht *et al.*, 2015). Thus:

Hypothesis (H2). *The number of perpetrators involved in fraud is positively associated with the extent of the structural centralization in a corporate group.*

[4] George Orwell was a novelist, journalist, essayist, and critic, best known for his novels *Animal Farm* and *Nineteen Eighty-Four*.

Corporate fraud rarely occurs without perpetrators' subsequent acts to hide fraudulent behavior. When fraud is being committed but is not yet detected, i.e., during the fraud-committing period, perpetrators need to conceal the fraudulent information from being leaked to the public or accessed by nonperpetrators. Powerful perpetrators can exert their authority to control the flow of fraudulent information more easily throughout the organization with a greater extent of structural centralization. In fact, most fraudulent activities are not detected immediately, and detection takes time—from the beginning to the detection date. We expect a longer detection duration if perpetrators conceal fraudulent information more easily and rigorously. Thus:

Hypothesis (H3). *On average, the detection duration is positively associated with the extent of structural centralization in a corporate group.*

Fraudulent activities bring personal benefits for perpetrators but hurt the interest of other stakeholders and destroy the organization's value. The responsibility to monitor management and detect fraud mainly falls on independent directors, and career-conscious directors are more likely to dissent through voting behavior (Jiang *et al.*, 2016). However, power may make others speechless (Tost *et al.*, 2013). If powerful members intend to commit fraud, they may deter independent directors' dissension for implementing fraudulent activities. Thus:

Hypothesis (H4). *Independent directors' dissension is negatively associated with the extent of structural centralization in a corporate group.*

3 Data and Sample

3.1 Network Construction

We focus on individuals' membership network in a corporate group. The corporate group consists of three types of legal entities: the listed firm itself, its subsidiaries, and the corporate entities among the top 10 shareholders of the listed firm (hereafter, top 10 corporate shareholders). Each corporate group corresponds to a unique listed firm in China. TMT members in the abovementioned legal entities occupy important positions, such as director, supervisor, and senior management. The colleagueship of two incumbent TMT members working within the same entity allows them to forge a strong relationship, serving as a bond that aligns and coordinates actors' actions, enabling groups of nodes to act as a single node with greater capabilities (Borgatti and Halgin, 2011). We construct a membership network for all TMT members in the corresponding corporate group for each firm-year observation. Our network sample covers 30,615 firm-year observations for 2,957 unique listed firms in the Main Board Market in China from 2004 through 2021.

The information on TMT members' positions comes from the Market Entity Registration Database created and maintained by the State Administration for Market Regulation (SAMR). A top member may take multiple positions in many legal entities of a corporate group. Specifically, the sum of all positions in the three types of legal entities is 3,545,894, which is occupied by 2,311,165 individual TMT members.[5] Thus, a membership network has an average of 75 (=2,311,165/30615) TMT members. In the online appendix, we offer a detailed description of network construction. The total number of TMT members in a corporate group—2,311,165—is much less than the total of all positions—3,545,894—in our sample, indicating that a TMT member typically has multiple team memberships in the organization (O'leary *et al.*, 2011).

3.2 Structural Variables

The membership network demonstrates the complex interactions and relationships among top members and reflects the general organizational structure. Network analysis enables us to develop several standardized structural variables, which can be used to compare different organizations with each other. This paper focuses on structural centralization, measured by network centralization. Network centralization refers to the extent to which ties are organized around particular focal nodes (see Park *et al.* (2020) for a recent review on network analysis

[5] We identify a position in a year as a position-year observation. The sum of all position-year observations in the three types of legal entities is 3,545,894. Similarly, the sum of all member-year observations is 2,311,165.

in work teams). Centrality refers to the extent to which a focal node is positioned in a central position in the network (Park *et al.*, 2020). Several studies have found that network centrality is associated with individual power (Brass, 1984; Chiu *et al.*, 2017), and the power related to official organizational positions is also known as structural power (Finkelstein, 1992). Among the several ways to calculate centrality, eigenvector centrality has advantages in measuring individual power because it calculates a node's influence while considering the importance of its neighbors (Bonacich, 1987, 2007).

We calculate structural centralization using the Gini coefficient of eigenvector centrality (Jacobs and Watts, 2021). When TMT members have an unequal power distribution, a higher Gini coefficient of eigenvector centrality indicates that fewer members exercise more disproportionate control over many others. In other words, a greater extent of structural centralization in a corporate group results in more power being concentrated in those retaining more positions. In addition to structural centralization, our network also offers a variable of structural connectivity calculated by network density. Network density characterizes the extent of TMT members' connectivity in an organization, a typical control variable in studies investigating network centralization (e.g., Balkundi and Harrison, 2006; Park *et al.*, 2020).

3.3 Corporate Fraud

Our source of fraud data is the China Stock Market and Accounting Research (CSMAR) database, which collects every financial fraud event officially released by the Shanghai Stock Exchange, Shenzhen Stock Exchange, and China Securities Regulatory Commission (CSRC). The CSMAR database records sixteen types of fraud: fictitious profit, fictitious assets, misleading statements, false statements, major omissions in reports, accounting mishandling, fraudulent listings, insider dealing, illegal stock trading, stock price manipulations, illegal capital contributions, unauthorized change in use of funds, occupation of company assets, illegal guarantees, postponing disclosure, and others. In the online appendix, we report the case distribution of the sixteen types of fraud. These illegal activities are mostly undertaken by an individual or a party to obtain personal benefits or avoid personal liability.[6] Our data include 8,189 cases of fraud. As some corporate groups might commit more than one fraud case in a year, our sample has 6,851 corporate group-year observations with discovered fraud cases. In the online appendix, we report the sample distribution by year.

Fraudulent activities often involve the collusion of the listed firm with its subsidiaries or shareholders. For all 8,189 cases, 54.2% were committed solely by listed firms as legal entities, 19.8% were committed by listed firms and their subsidiaries or shareholders, and other individuals or legal entities committed the remaining 26.0%. More importantly, our sample shows that fraudulent activities are undertaken by very powerful members. Using eigenvector centrality as a measure of TMT members' power Bonacich (1987, 2007), we find that in cases involving at least one named perpetrator, on average, perpetrators rank 9th, and nonperpetrators rank 66th, in power. The results validate that those who commit fraud have relatively significant power in their corporate groups.

4 Method and Variables

4.1 Empirical Methodology

There is a partial observability problem in the fraud sample. The detected fraud events that we observe consist of a subset of the population of fraudulent events. In other words, the observed fraud depends on two processes: fraud commission and fraud detection. Following Wang *et al.* (2010) and Wang (2013), we employ a bivariate probit model to decompose the likelihoods of these two processes.[7]

For corporate group i, we denote by $Fraud^*_{it}$ and $Detect^*_{it}$ the latent variables indicating

[6] In the sixteen types of fraud, postponing disclosure and others may be irrelevant to misconduct for self-interest. Thus, we conduct a robustness test where postponing disclosure and others are not recognized as corporate fraud, and the results still hold.

[7] The bivariate probit model was proposed by Poirier (1980) and has become a standard tool to estimate the likelihood of fraud commission and fraud detection (e.g., Khanna *et al.*, 2015; Kuang and Lee, 2017; Shi *et al.*, 2017; Yiu *et al.*, 2019).

group i's likelihood of committing fraud in year t and the possibility of detecting it. We suppose

$$Fraud^*_{it} = X_{F,it}\delta + \mu_{it}, \quad Detect^*_{it} = X_{D,it}\eta + v_{it},$$

where $X_{F,it}$ contains variables explaining group i's likelihood of committing fraud in year t, $X_{D,it}$ contains variables explaining group i's possibility of being detected, and (μ_{it}, ν_{it}) has a bivariate normal distribution with zero-mean, unity-variance, and correlation ρ. Define

$$Fraud_{it} = \begin{cases} 1, & \text{if } Fraud^*_{it} > 0 \\ 0, & \text{otherwise} \end{cases} \quad \text{and} \quad Detect_{it} = \begin{cases} 1, \text{ if } Detect^*_{it} > 0 \\ 0, \text{ otherwise} \end{cases}.$$

The partial observability problem arises because we cannot directly observe the realizations of $Fraud_{it}$ and $Detect_{it}$ but only $Observe_{it} = Fraud_{it} \cdot Detect_{it}$ instead. $Observe_{it} = 1$ if and only if group i committed at least one fraud in year t and was detected subsequently. Then, the empirical model for $Observe_{it}$ is

$$P\left(Observe_{it} = 1\right) = P\left(Fraud_{it} \cdot Detect_{it} = 1\right) = \Phi\left(X_{F,it}\delta, X_{D,it}\eta, \rho\right),$$
$$P\left(Observe_{it} = 0\right) = P\left(Fraud_{it} \cdot Detect_{it} = 0\right) = 1 - \Phi\left(X_{F,it}\delta, X_{D,it}\eta, \rho\right),$$

where Φ is the bivariate standard normal cumulative distribution function.

Thus, the log-likelihood function for the model is

$$L(\delta, \eta, \rho) = \sum \log\left(Observe_{it} = 1\right) + \sum \log\left(Observe_{it} = 0\right),$$

which can be estimated by using maximum likelihood. In the baseline model, we use lagged structural variables in the regression to alleviate the endogeneity problem.

In two equations, the bivariate probit model simultaneously estimates the likelihood of fraud commission and the probability of fraud detection. The model requires two sets of control variables, $X_{F,it}$ for the fraud commission equation and $X_{D,it}$ for the fraud detection equation. Full identification of the model parameters requires that $X_{F,it}$ and $X_{D,it}$ do not contain exactly the same variables. Therefore, we selected each unique variable for the fraud commission equation and the fraud detection equation. In the baseline model, except for these two unique variables, all of the remaining controls are added in both the fraud commission and detection equations.

4.2 Common Control Variables

We first introduce the common controls in both equations. To address possible omitted variable bias, we include all necessary controls in line with the literature on corporate fraud (Khanna *et al.*, 2015; Kuang and Lee, 2017; Shi *et al.*, 2017; Yiu *et al.*, 2019). We categorize the common controls into the three levels of internal and external governance, firm characteristics, and industry idiosyncrasies to justify their validity in detail based on prior research. The sources of control variables include the CSMAR database, the RESSET database, and the structural data calculated from the Market Entity Registration database.

Governance variables. Internal and external governance play an important role in fraud commission and detection. According to Gillan (2006), we focus on three categories of internal governance: (1) the board of directors, (2) managerial incentives, and (3) shareholder ownership.

Internal governance starts with the board of directors. We include three control variables related to the board. First, we include the number of directors on the board, $BoardSize$. Prior studies have found that larger boards are less likely to function effectively because of the extra effort needed to reach a consensus (Cheng, 2008). Second, we include the share of independent directors, $\%\_IndepDirectors$. Jiang *et al.* (2016) indicate that career-conscious independent directors are more likely to dissent, which improves the corporate governance of listed firms in China. Third, we include the number of board meetings, $BoardMeetings$. Vafeas (1999) suggests that frequent board meetings are one way for a board to respond to poor performance and remedy limited director interaction time.

Managerial incentives play a crucial role in aligning the interests of managers and corporate performance. We include managerial equity share, $ManagerialOwnership$, as a control variable. Furthermore, our controls include whether the CEO chairs the board, $Duality\_ChairCEO$. In China, the chairman often actively runs the firm (Jiang and Kim, 2020). We also include the turnover of the chairperson or CEO, $Turnover\_ChairCEO$.

Related to shareholder ownership, controlling shareholders are prevalent in Chinese public firms. Johnson *et al.* (2000) point out that a controlling shareholder (typically also a top manager) can transfer resources from the firm for private benefit through self-dealing transactions, known as tunneling. Thus, our controls include $Top5OwnerShare$, the percentage shareholdings of the top five owners. As state-owned enterprises have their own features (Jiang and Kim, 2020), we also control whether the listed firm is state-owned, SOE.

Following the categories in Gillan (2006) for external governance, we include three variables as common controls. First, we include institutional ownership $InstitutionalShare$. Second, we include analyst coverage, $Log(analyst)$, which is the log of the number of analysts following the listed firm plus one. Third, we use $Big4AccountingFirm$ to measure audit quality (Chen *et al.*, 2006). The variable $Big4AccountingFirm$ equals one if the listed firm's auditor is a joint venture with one of the international Big Four accounting firms and zero otherwise.

Firm characteristics. We control for several variables related to firm characteristics, including firm age, size, growth, and performance. We measure firm age as the log of the years since the firm was listed, $Log(Age)$, firm size as the log of the total assets, $Log(TotalAssets)$, and firm growth as the total assets growth rate, $TotalAssetsGrowth$. Prior studies have found that misconduct is more prevalent in firms with relatively low profits and performance pressures (Greve *et al.*, 2010). The performance variables include return on assets, ROA, and stock returns, $StockReturns$. We also include stock turnover and stock return volatility in performance variables. $StockTurnover$ is the trading volume divided by outstanding shares. Stock return volatility, $StockVolatility$, is the standard deviation of daily stock returns over a given year. Wang *et al.* (2010) suggest that stock turnover and stock return volatility are related to a firm's litigation risk. In addition, we add $Log(\#\_LegalEntities)$, the log value of the number of legal entities in the corporate group, to control for the organization's size.

Industry idiosyncrasies. Wang *et al.* (2010) suggest that industry business conditions are associated with firms' incentive to commit fraud and the likelihood of being detected. We include three industry variables in both the fraud commission and detection equations. The first industry variable is $IndustryQ$, the log value of the median Tobin's Q in an industry. Prior studies have provided evidence of a hump-shaped relation between fraud and $IndustryQ$ (Vafeas, 1999; Wang *et al.*, 2010), so we also add $(IndustryQ)^2$. The second is $IndustryHHI$, the Herfindahl-Hirschman Index (HHI), which measures the market concentration of that industry. A lower IndustryHHI indicates greater competition. The third is $IndustryLitigation$, the median number of lawsuits against listed firms in an industry. Litigation intensity can be correlated among firms within an industry.

4.3 The Unique Variable for the Fraud Commission Equation

The unique variable that we include in the fraud commission equation is firm leverage, $Leverage$, measured as the sum of short- and long-term debt divided by total assets. Leverage is a typical measure of financial distress (Purnanandam, 2008). The pressure stemming from financial distress may induce misbehavior to fulfill the performance goal, known as "pressure-driven fraud" (Schnatterly *et al.*, 2018).

The bivariate probit model requires that the unique variable in the fraud commission equation does not affect fraud detection. Some researchers add firm leverage to the fraud detection equation in the bivariate probit model, but the estimates show no significant effects of firm leverage on the likelihood of detection (Chen *et al.*, 2006; Khanna *et al.*, 2015; Kuang and Lee, 2017). As a typical strategy of using the bivariate probit model to estimate fraud, several studies have added firm leverage to only the fraud commission equation but not the detection equation (Shi *et al.*, 2017; Yiu *et al.*, 2019). Given the above, we use firm leverage as the unique variable for the fraud commission equation.

4.4 Unique Variable for the Fraud Detection Equation

At the core of all fraud—even fraud by large corporate entities—are decisions and actions by individuals.[8] Our sample shows that fraud is undertaken by very powerful members of the organization. From the outset, almost all perpetrators do their utmost to cover up fraud. It is not easy for perpetrators to carry out concealment activities when they are sidelined; thus, fraud is more likely to come to light when they no longer hold central positions. Fraud detection does not occur instantaneously after the fraud commission but over time. On average, the regulator detects the initial fraudulent activity after approximately two years. Therefore, we calculate the proportion of the ten most central actors remaining the ten most central actors after three years, $\%\_Top10RemainAfter3Years$. We add this variable only to the fraud detection equation following the hypothesis that it decreases the likelihood of fraud detection but is unlikely to be related to fraud commission.

The variable $\%\_Top10RemainAfter3Years$ ideally satisfies two requirements for being a unique control only in the fraud detection equation for two reasons. First, the variable $\%\_Top10RemainAfter3Years$ cannot affect the fraud commission of the current year because it is calculated according to the power structure after three years. When considering whether to commit fraud, participants in the current year could not anticipate who will hold the most central positions after three years. Thus, we could omit the variable $\%\_Top10RemainAfter3Years$ from the fraud commission equation. Second, $\%\_Top10RemainAfter3Years$ indeed affects the likelihood of detection. For example, given powerful perpetrators commit fraud in year t, if more perpetrators lose their top 10 positions in year $t+3$, the fraud in year t is more likely to be detected afterward. When fraudulent activities in year t are detected, there is a fraud record in the year t observation. Thus, we should include the variable $\%\_Top10RemainAfter3Years$ in the fraud detection equation.

[8] https://www.sec.gov/news/speech/2008/spch090908lar.htm, speech by the former director of the SEC's Office of Compliance Inspections and Examinations (OCIE), Lori Richards: "Why Does Fraud Occur and What Can Deter or Prevent it?"

4.5 Summary Statistics

Table 1 contains summary statistics for all of the variables. Variable definitions and sources are provided in the online appendix.

Table 1: Summary Statistics

	Number (1)	Mean (2)	Median (3)	Std (4)	Min (5)	Max (6)
Fraud Variables						
Fraud	30615	0.224	0.000	0.417	0.000	1.000
Structural Variables						
StructuralCentralization	30615	0.531	0.551	0.169	0.003	0.989
StructuralConnectivity	30615	0.262	0.215	0.184	0.006	1.000
Governance Variables						
BoardSize	30615	8.947	9.000	1.933	5.000	19.000
%_IndepDirectors	30615	0.370	0.333	0.054	0.111	0.800
BoardMeetings	30615	9.562	9.000	4.117	1.000	58.000
Big4AccountingFirm	30615	0.074	0.000	0.262	0.000	1.000
Log(Analyst)	30615	1.313	1.099	1.200	0.000	4.382
InstitutionalShare	30615	0.487	0.510	0.228	0.004	0.921
Top5OwnerShare	30615	0.530	0.531	0.158	0.190	0.896
SOE	30615	0.466	0.000	0.499	0.000	1.000
ManagementOwnership	30615	0.078	0.000	0.161	0.000	0.900
Turnover_ChairCEO	30615	0.121	0.000	0.326	0.000	1.000
Duality_ChairCEO	29229	0.225	0.000	0.418	0.000	1.000
Firm Characteristics						
Log(Age)	30615	2.241	2.398	0.734	0.000	3.466
Log(TotalAssets)	30615	22.227	22.034	1.441	19.249	27.414
TotalAssetsGrowth	30615	0.128	0.084	0.242	-0.388	1.291
ROA	30615	0.030	0.032	0.072	-0.351	0.200
StockReturns	30615	0.115	-0.046	0.645	-0.757	2.810
StockTurnover	30608	3.126	2.376	2.605	0.168	12.371
StockVolatility	30613	0.029	0.028	0.009	0.012	0.055
#_LegalEntities	30615	2.627	2.565	0.816	0.693	4.934
Industry Idiosyncrasies						
IndustryQ	30615	1.632	1.529	0.489	0.984	3.222
IndustryHHI	30323	0.108	0.066	0.138	0.016	1.000
IndustryLitigation	30615	0.170	0.000	3.618	0.000	224.000
Unique Commission Variable						
Leverage	30615	0.482	0.480	0.215	0.068	1.069
Unique Detection Variable						
%_Top10RemainAfter3Years	22907	0.454	0.421	0.253	0.000	1.000
Instrumental Variables for Structural Variables						

Continued on next page

Table 1 – continued from previous page

	Number (1)	Mean (2)	Median (3)	Std (4)	Min (5)	Max (6)
#_DeathHealth	30615	0.019	0.000	0.182	0.000	5.000
#_Retirement	30615	0.050	0.000	0.323	0.000	7.000
Δ*_LegalEntities*	26846	1.979	1.000	5.978	-13.000	36.000
Dependent Variables for Mechanism Analysis						
#_Charged	8189	1.363	0.000	3.011	0.000	17.000
DetectDuration	8189	1.578	1.000	1.948	0.000	16.000
#_Dissension	30615	0.056	0.000	0.514	0.000	16.000

Notes. All continuous variables are winsorized at the 1% and 99% levels. Variable definitions and sources are provided in the online appendix.

5 Results

5.1 Baseline Results

Table 2 reports the bivariate probit estimation results for structural centralization. The dependent variable in column (1) is *Fraud*, an indicator variable equal to one if the corporate group commits fraud and zero otherwise. The dependent variable in column (2) is $Detect|Fraud$, an indicator variable equal to one if the corporate group's fraudulent activities are detected and zero otherwise. The independent variable *StructuralCentralization*, measured as the Gini coefficient of eigenvector centrality, captures the intent of the power concentration in the corporate group.

Table 2: Bivariate Probit Estimation Results for Structural Centralization

	Fraud (1)	Detect|Fraud (2)
Structural Variables		
StructuralCentralization	1.799	-1.453
	(0.002)	(0.045)
StructuralConnectivity	1.531	-1.257
	(0.018)	(0.060)
Governance Variables		
BoardSize	0.059	-0.050
	(0.005)	(0.044)

Continued on next page

Table 2 – continued from previous page

	Fraud (1)	Detect|Fraud (2)
%_IndepDirectors	-0.344	-0.088
	(0.419)	(0.863)
BoardMeetings	0.007	0.041
	(0.298)	(0.000)
Big4AccountingFirm	-0.171	-0.179
	(0.103)	(0.383)
Log(Analyst)	-0.053	-0.079
	(0.068)	(0.028)
InstitutionalShare	-0.192	-0.472
	(0.641)	(0.044)
Top5OwnerShare	-0.006	0.000
	(0.189)	(0.917)
SOE	-0.290	-0.181
	(0.000)	(0.128)
ManagementOwnership	0.221	-0.306
	(0.590)	(0.223)
Turnover_ChairCEO	0.065	0.051
	(0.214)	(0.442)
Duality_ChairCEO	0.250	-0.088
	(0.012)	(0.186)
Firm Characteristics		
Log(Age)	-0.216	0.172
	(0.002)	(0.028)
Log(TotalAssets)	-0.148	0.100
	(0.002)	(0.008)
TotalAssetsGrowth	0.165	0.077
	(0.031)	(0.283)
ROA	-1.337	-2.989
	(0.004)	(0.000)
StockReturns	-0.083	-0.020
	(0.054)	(0.629)
StockTurnover	-0.015	-0.032
	(0.239)	(0.010)
StockVolatility	18.136	18.107
	(0.000)	(0.000)
#_LegalEntities	-0.049	0.125
	(0.517)	(0.253)
Industry Idiosyncrasies		
IndustryQ	0.837	-0.016
	(0.019)	(0.961)
$(IndustryQ)^2$	-0.166	-0.003
	(0.053)	(0.964)
IndustryHHI	0.341	-0.142

Continued on next page

Table 2 – continued from previous page

	Fraud (1)	Detect|Fraud (2)
	(0.154)	(0.456)
IndustryLitigation	0.297	-0.004
	(0.621)	(0.206)
Unique Commission Variable		
Leverage	0.612	
	(0.001)	
Unique Detection Variable		
$\%\_Top10RemainAfter3Years$		-0.339
		(0.001)
Constant	-0.362	-2.094
	(0.756)	(0.080)
Year Dummies	Y	Y
Observations	21,426	21,426
Prob >Chi^2	0.000	0.000
Log likelihood	-10570.15	-10570.15

Notes. Table 2 reports bivariate probit model estimation results. Column (1) reports the estimated relations between structural centralization and the incidence of fraud. Column (2) reports the estimated relations between structural centralization and the likelihood of detection given fraud. The sample covers the 2004 to 2018 period. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

The coefficients for $StructuralCentralization$ are statistically significant in both columns, showing that power concentration is associated with a higher incidence of fraud and a lower likelihood of detection. The estimated coefficients for $StructuralCentralization$ suggest that a corporate group has a 9.2% higher incidence of fraud and a 7.8% lower likelihood of detection given fraud when $StructuralCentralization$ increases by one standard deviation.

The key to decomposing fraud commission and fraud detection is to choose a different set of controls in each equation. The unique variables we use to decompose the two processes show significant coefficients consistent with our conjectures. First, we add $Leverage$ only to the fraud commission equation, hypothesizing that firm leverage increases the incidence of fraud. The coefficient of $Leverage$ is significantly positive in column (1). Second, we add $\%\_Top10RemainAfter3Years$ only in the fraud detection equation, hypothesizing that it decreases the likelihood of fraud detection. In column (2), the coefficient of

$\%\_Top10RemainAfter3Years$ is significantly negative.

Many common controls in the two equations also show significant coefficients consistent with the literature. We include three control variables related to the board. The variable $BoardSize$ shows significant coefficients consistent with prior studies, suggesting that larger boards are less likely to function effectively (Cheng, 2008). The number of board meetings, $BoardMeetings$, is positively associated with the likelihood of fraud detection, suggesting that frequent board meetings can remedy the limited time during which directors interact (Vafeas, 1999). SOE has a significantly negative coefficient in the fraud commission equation, indicating that state-owned firms are less likely to commit fraud. We also find that CEO duality, $Duality\_ChairCEO$, significantly increases the incidence of fraud and decreases the likelihood of detection.

The coefficients of firm characteristics are also consistent with the literature. Prior studies have found that misconduct is more prevalent in firms with relatively low profits and performance pressures (Greve *et al.*, 2010). We find that ROA and $StockReturns$ have significantly negative coefficients of fraud commission. Some studies have also found that a firm's growth aspirations may induce corporate fraud (Schnatterly *et al.*, 2018). Our estimation also shows that firm growth increases the incidences of fraud. Stock return volatility, $StockVolatility$, has a significant positive effect on fraud commission and detection, indicating that $StockVolatility$ can increase the incidence of fraud but can also draw attention from the regulator.

Finally, the coefficients of industry idiosyncrasies are also consistent with the literature. We find that the incidence of fraud is related to $IndustryQ$ in a hump-shaped fashion, which is consistent with the results of Wang *et al.* (2010) and Khanna *et al.* (2015).

5.2 Endogeneity Issues

The structural variables $StructuralCentralization$ and $StucturalConnectivity$ may be endogenous. We construct instrumental variables (IVs) and estimate two-stage least square regressions to address endogeneity concerns. We construct three IVs. The first IV is the number of top members in the listed firm left due to death or a health reason, $\#\_DeathHealth$. The second IV is the number of top members in the listed firm that regularly retired, $\#\_Retirement$. The third IV is the annual change in the number of legal entities in a corporate group, $\Delta\_LegalEntities$. These variables satisfy the requirements of instrumental variables because they change the organizational structure due to exogenous reasons unlikely to be related to corporate fraud.

Table 3: First–Stage Instrumental Variable Regression Results

	First Stage			
	$StructuralCentralization$		$StructuralConnectivity$	
	(1)	(2)	(3)	(4)
Instrumental Variables				
$\#\_DeathHealth$	-0.005	-0.005	0.003	0.003
	(0.356)	(0.335)	(0.641)	(0.622)
$\#\_Retirement$	0.009	0.008	-0.008	-0.008
	(0.012)	(0.016)	(0.006)	(0.007)
$\Delta\_LegalEntities$	0.007	0.007	-0.006	-0.006
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Y (Commit)	Y (Detect)	Y (Commit)	Y (Detect)
Year Dummies	Y	Y	Y	Y
R-squared	0.342	0.343	0.337	0.337
Observations	18,634	18,634	18,634	18,634
F-statistics (IVs)	66.27	66.34	60.42	60.52
Prob $>F$ (IVs)	0.000	0.000	0.000	0.000

Notes. Table 3 reports the first–stage instrumental variable regression estimation results. An F *test* of the joint significance of instrumental variables is reported in the first-stage regressions. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

The first-stage estimation results are reported in Table 3. We have two first-stage regressions for both $StructuralCentralization$ and $StructuralConnectivity$ because the fraud commission and detection regressions have different control variables. The F-statistics of all IVs are well above 10, indicating that the IVs are not weak instruments.

The second-stage estimation results for the bivariate probit model are reported in Table 4.

The predicted value of the structural variables *StructuralCentralization_Hat* is positively related to the likelihood of fraud commission and negatively related to detection given fraud commission. The estimations of the two-stage least square regressions are consistent with our baseline analysis.

Table 4: Second–Stage Instrumental Variable Regression Results

	Second Stage	
	Fraud	Detect|Fraud
	(1)	(2)
Structural Variables		
StructuralCentralization_Hat	110.883	-146.994
	(0.053)	(0.010)
StructuralConnectivity_Hat	111.047	-147.910
	(0.053)	(0.010)
Controls	Y (Commit)	Y (Detect)
Year Dummies	Y	Y
Observations	18,634	18,634
Prob >Chi^2	0.000	0.000
Log likelihood	-9283.806	-9283.806

Notes. Table 4 reports the second–stage instrumental variable regression estimation results. The endogenous variables are *StructuralCentralization* and *StructuralConnectivity*. The endogenous variables' predicted values are *StructuralCentralization_Hat* and *StructuralConnectivity_Hat*. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

6 Mechanism Analysis

The mechanisms by which structural centralization increases the incidence of committing fraud and decreases the likelihood of fraud detection are central to understanding interactions and relationships among TMT members and the collective decision making in an organization. This section tests three potential mechanisms through which structural centralization increases the incidence of fraud commission and decreases the likelihood of fraud detection.

6.1 Number of Perpetrators Involved

Fraud committing requires multiple members' active coordination or passive acquiescence (Albrecht *et al.*, 2015; Free and Murphy, 2015; Granovetter, 1985). Powerful perpetrators often use coercive power to recruit others to participate in fraudulent activities (Albrecht *et al.*, 2015). Coercive power is a leader's ability to force subordinates into complying with his or her demands through threats and punishment. Structural centralization makes it easier for active or passive collusion in an organization. Thus, hypothesis (H2) predicts a positive association between structural centralization and the number of perpetrators involved.

Table 5: Number of Perpetrators Charged and Structural Centralization

	$\#\_Charged$	
	OLS	Poisson
	(1)	(2)
$StructuralCentralization$	1.253	0.992
	(0.059)	(0.055)
$StructuralConnectivity$	0.499	0.441
	(0.478)	(0.419)
Industry Dummies	Y	Y
Observations	7,878	7,870
(Pseudo) R-squared	0.044	0.058

Notes. Table 5 reports how the average structural centralization during the fraud period affects the number of perpetrators charged. The dependent variable is the number of perpetrators charged with detection. The sample covers the 2004 to 2021 period. Structural variables and controls are their average values over the fraud period. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

Table 5 reports how structural centralization affects the number of perpetrators involved. In line with the literature, the estimation is based on cross-sectional data for each fraud case (Khanna *et al.*, 2015; Kuang and Lee, 2017). Column (1) employs an OLS regression, and column (2) employs a Poisson regression. Cohn *et al.* (2022) point out that the fixed-effects Poisson model produces consistent and reasonably efficient estimates for count-based outcome variables, in contrast to the common practice of taking the log of 1 plus the outcome as the dependent variable. Structural and control variables are their average values over the fraud period. The coefficients of *StructuralCentralization* are significantly positive, indicating that power concentration makes more people participate in fraudulent activities. The results provide evidence for hypothesis (H2).

6.2 Detection Duration

Perpetrators need to conceal fraudulent information from being leaked to the public or accessed by others. Powerful perpetrators can exert their authority to control the flow of fraudulent information throughout the organization. Thus, hypothesis (H3) predicts a longer detection duration with a higher level of structural centralization.

Table 6: Fraud Detection Duration and Structural Centralization

	DetectDuration	
	OLS	Poisson
	(1)	(2)
StructuralCentralization	0.977	0.577
	(0.027)	(0.048)
StructuralConnectivity	-0.143	-0.156
	(0.759)	(0.631)
Industry Dummies	Y	Y
Observations	7,878	7,876
(Pseudo) R-squared	0.061	0.035

Notes. Table 6 reports how average structural centralization during the fraud period affects the detection duration. The dependent variable is the number of years from the beginning of the fraudulent activity to its detection date. The sample covers the 2004 to 2021 period. Structural variables and controls are their average values over the fraud period. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

Table 6 reports how structural centralization affects detection duration. We use cross-sectional data for each fraud case, in line with the literature (Khanna *et al.*, 2015; Kuang and Lee, 2017). Structural and control variables are their average values over the fraud period. The coefficients of *StructuralCentralization* are significantly positive, indicating that power concentration lengthens the time from the commission of a fraud to its detection. The results also confirm the channel of information concealing.

6.3 Dissension of Independent Directors

Structural centralization may harm the effectiveness of independent directors' monitoring because power concentration produces verbal dominance and makes others speechless (Tost *et al.*, 2013). Independent directors monitor management and detect fraud by expressing dissension through voting behavior (Jiang *et al.*, 2016). Thus, hypothesis (H4) predicts that independent directors are less likely to dissent in a more centralized organization.

Table 7: Independent Director Dissension and Structural Centralization

	$\#\_Dissension$	
	OLS	Poisson
	(1)	(2)
$StructuralCentralization$	-0.081	-1.790
	(0.088)	(0.047)
$StructuralConnectivity$	-0.085	-1.909
	(0.078)	(0.053)
$Fraud$	0.030	0.499
	(0.001)	(0.000)
Industry FE	Y	Y
Year FE	Y	Y
Observations	28,977	28,641
(Pseudo) R-squared	0.027	0.180

Notes. Table 7 reports the relations between independent director dissension and network centralization. The dependent variable is the number of independent director dissension, $\#\_Dissension$. The sample covers the 2004 to 2021 period. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

Table 7 reports how structural centralization affects the dissension of independent directors. The dependent variable, $\#Dissension$, is the number of independent directors' dissension in the listed firm. Column (1) employs an OLS regression, and column (2) employs a Poisson regression. The coefficients of $StructuralCentralization$ are significantly negative in both columns, indicating that power concentration deters independent directors from dissenting. The results verify hypothesis (H4).

7 Robustness Tests

This section tests the robustness of the bivariate probit model. In the baseline model, the sample period is from 2004 to 2018. The baseline sample begins in 2004 because it is the initial year of our network construction. We retest the bivariate probit model in two alternative sample periods: 2008–2018 and 2012–2018. In addition, corporate fraud in the baseline model includes all sixteen types of fraud. Among these sixteen types, postponing disclosure and others may be irrelevant to misconduct for self-interest purposes. Thus, we also conduct a robustness test where postponing disclosure and others are not recognized as corporate fraud. Table 8 shows that all results are consistent with the estimations of our baseline model.

Table 8: Bivariate Probit Estimation Results by Alternative Periods

Panel A: Alternative Periods				
	2008–2018		2012–2018	
	Fraud (1)	Detect|Fraud (2)	Fraud (3)	Detect|Fraud (4)
Structural Variables				
$StructuralCentralization$	1.757	-2.292	2.682	-1.772
	(0.051)	(0.083)	(0.000)	(0.037)
$StructuralConnectivity$	1.467	-1.927	1.631	-1.306
	(0.044)	(0.104)	(0.055)	(0.092)
Unique Commission Variable				
$Leverage$	0.467		0.548	
	(0.086)		(0.052)	
Unique Detection Variable				
$\%\_Top10RemainAfter3Years$		-0.395		-0.299
		(0.002)		(0.001)
Common Controls	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
Observations	18,365	18,365	13,288	13,288
Prob >Chi^2	0.000	0.000	0.000	0.000

Log likelihood	-9607.88	-9607.88	-7213.62	-7213.62

Panel B: Alternative Fraud Types

	Except postponing disclosure		Except other types	
	Fraud (1)	Detect|Fraud (2)	Fraud (3)	Detect|Fraud (4)
Structural Variables				
StructuralCentralization	1.815	-1.313	2.042	-2.006
	(0.018)	(0.056)	(0.004)	(0.014)
StructuralConnectivity	1.432	-1.259	1.851	-1.543
	(0.048)	(0.060)	(0.010)	(0.020)
Unique Commission Variable				
Leverage	0.542		0.586	
	(0.012)		(0.003)	
Unique Detection Variable				
%_Top10RemainAfter3Years		-0.348		-0.241
		(0.008)		(0.039)
Common Controls	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
Observations	21,426	21,426	21,426	21,426
Prob >Chi^2	0.000	0.000	0.000	0.000
Log likelihood	-10223.42	-10223.42	-9868.24	-9868.24

Notes. Table 8 reports robustness tests of bivariate probit model estimation results. Columns (1) and (2) in Panel A covers the 2008-2018 period; Columns (3) and (4) in Panel A covers the 2012-2018 period. Columns (1) and (2) in Panel B examine fraud except the type of postponing disclosure; Columns (3) and (4) in Panel B examine fraud except other types. Robust standard errors are clustered at the industry level. Industries are classified by the China Securities Regulatory Commission (2012) 90-industry groupings. Robust p-values in parentheses.

8 Conclusion

Focusing on TMT members' interactions and power distribution, we develop a novel method for analyzing the effect of organizational structure on corporate fraud. Specifically, we construct a membership network for all top members in a corporate group and use it to measure the organizational structure. Based on the membership network, we use a standardized index—network centralization—to measure the level of structural centralization in a corporate group. The level of structural centralization measures the extent of power concentration in the corporate group. We find that a corporate group has a 9.2% higher likelihood of fraud commission and a 7.8% lower likelihood of detection conditional on committing fraud when the extent of the structural centralization increases by one standard deviation. In addition, our data show that fraud perpetrators take extremely central positions and hold large power in a corporate group.

There are three channels through which structural centralization exacerbates corporate fraud. First, we find that structural centralization makes active or passive collusion easier in an organization. Second, structural centralization helps conceal fraudulent information within the powerful perpetrators' inner circle or the dominant coalition of firms. Third, structural centralization may harm the effectiveness of independent directors' monitoring by producing verbal dominance. These results suggest that organizational structure profoundly impacts decision-making processes and governance effectiveness. Although our paper focuses on the dark side of structural centralization in corporate governance, we do not intend to claim that power concentration necessarily has a stifling effect on team outcomes. What should be opposed is power abuse rather than power concentration. We believe that further investigations into organizational structure and power distribution are promising for advancing the understanding of corporate governance.

References

Albrecht, C., Holland, D., Malagueño, R., Dolan, S., and Tzafrir, S. 2015. The role of power in financial statement fraud schemes. *Journal of Business Ethics*, 131(4):803–813.

Arora, A., Belenzon, S., and Rios, L. A. 2014. Make, buy, organize: The interplay between research, external knowledge, and firm structure. *Strategic Management Journal*, 35(3):317–337.

Bacharach, S. B. and Lawler, E. J. 1980. *Power and Politics in Organizations*. Jossey-Bass, San Francisco.

Balkundi, P. and Harrison, D. A. 2006. Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *Academy of Management Journal*, 49(1):49–68.

Beckman, C. M. and Burton, M. D. 2011. *Bringing organizational demography back in: Time, change, and structure in top management team research*. Edward Elgar Publishing.

Blau, P. M. 1994. *Structural contexts of opportunities*. University of Chicago Press.

Bonacich, P. 1987. Power and centrality: A family of measures. *American Journal of Sociology*, 92(5):1170–1182.

Bonacich, P. 2007. Some unique properties of eigenvector centrality. *Social Networks*, 29(4):555–564.

Borgatti, S. P. and Halgin, D. S. 2011. On network theory. *Organization Science*, 22(5):1168–1181.

Brass, D. J. 1984. Being in the right place: A structural analysis of individual influence in an organization. *Administrative Science Quarterly*, pages 518–539.

Bromiley, P. and Rau, D. 2016. Social, behavioral, and cognitive influences on upper echelons during strategy process: A literature review. *Journal of Management*, 42(1):174–202.

Chen, G., Firth, M., Gao, D. N., and Rui, O. M. 2006. Ownership structure, corporate governance, and fraud: Evidence from china. *Journal of Corporate Finance*, 12(3):424–448.

Cheng, S. 2008. Board size and the variability of corporate performance. *Journal of Financial Economics*, 87(1):157–176.

Child, J. 1972. Organizational structure, environment and performance: The role of strategic choice. *Sociology*, 6(1):1–22.

Chiu, C.-Y. C., Balkundi, P., and Weinberg, F. J. 2017. When managers become leaders: The role of manager network centralities, social power, and followers' perception of leadership. *The Leadership Quarterly*, 28(2):334–348.

Cohn, J. B., Liu, Z., and Wardlaw, M. I. 2022. Count (and count-like) data in finance. *Journal of Financial Economics*, 146(2):529–551.

Crawford, E. R. and LePine, J. A. 2013. A configural theory of team processes: Accounting for the structure of taskwork and teamwork. *Academy of Management Review*, 38(1):32–48.

Csaszar, F. A. 2012. Organizational structure as a determinant of performance: Evidence from mutual funds. *Strategic Management Journal*, 33(6):611–632.

Cyert, R. M. and March, J. G. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall, Englewood Cliffs N.J.

Dalton, D. R., Todor, W. D., Spendolini, M. J., Fielding, G. J., and Porter, L. W. 1980.

Organization structure and performance: A critical review. *Academy of Management Review*, 5(1):49–64.
Eesley, C. E., Hsu, D. H., and Roberts, E. B. 2014. The contingent effects of top management teams on venture performance: Aligning founding team composition with innovation strategy and commercialization environment. *Strategic Management Journal*, 35(12):1798–1817.
Finkelstein, S. 1992. Power in top management teams: Dimensions, measurement, and validation. *Academy of Management journal*, 35(3):505–538.
Fombrun, C. J. 1984. Structures of organizational governance. *Human Relations*, 37(3):207–223.
Fredrickson, J. W. 1986. The strategic decision process and organizational structure. *Academy of Management Review*, 11(2):280–297.
Free, C. and Murphy, P. R. 2015. The ties that bind: The decision to co-offend in fraud. *Contemporary Accounting Research*, 32(1):18–54.
Fry, L. W. and Slocum Jr, J. W. 1984. Technology, structure, and workgroup effectiveness: A test of a contingency model. *Academy of Management Journal*, 27(2):221–246.
Galbraith, J. R. 1973. *Designing Complex Organizations*. Addison-Wesley, Boston.
Gillan, S. L. 2006. Recent developments in corporate governance: An overview. *Journal of Corporate Finance*, 12(3):381–402.
Gouldner, A. W. 1954. *Patterns of Industrial Bureaucracy*. Patterns of industrial bureaucracy. Free Press, New York, NY, US.
Granovetter, M. 1985. Economic action and social structure: the problem of embededness. *American Journal of Sociology*, 91(3).
Gray, B. and Ariss, S. S. 1985. Politics and strategic change across organizational life cycles. *Academy of Management Review*, 10(4):707–723.
Greve, H. R., Palmer, D., and Pozner, J. 2010. Organizations gone wild: The causes, processes, and consequences of organizational misconduct. *Academy of Management Annals*, 4(1):53–107.
Guadalupe, M., Li, H., and Wulf, J. 2014. Who lives in the c-suite? organizational structure and the division of labor in top management. *Management Science*, 60(4):824–844.
Hage, J., Aiken, M., and Marrett, C. B. 1971. Organization structure and communications. *American Sociological Review*, 36(5):860–871.
Hall, R. H. 1977. *Organizations: Structure and Process*. Prentice-Hall.
Hambrick, D. C. 1994. Top management groups: A conceptual integration and reconsideration of the" team" label. *Research in Organizational Behavior*, 16:171–213.
Hambrick, D. C. 2007. Upper echelons theory: An update. *Academy of Management Review*, 32(2):334–343.
Hambrick, D. C., Humphrey, S. E., and Gupta, A. 2015. Structural interdependence within top management teams: A key moderator of upper echelons predictions. *Strategic Management Journal*, 36(3):449–461.
Hambrick, D. C. and Mason, P. A. 1984. Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, 9(2):193–206.
Jacobs, A. Z. and Watts, D. J. 2021. A large-scale comparative study of informal social networks in firms. *Management Science*, 67(9):5489–5509.
Jiang, F. and Kim, K. A. 2020. Corporate governance in china: A survey. *Review of Finance*,

24(4):733–772.

Jiang, W., Wan, H., and Zhao, S. 2016. Reputation concerns of independent directors: Evidence from individual director voting. *The Review of Financial Studies*, 29(3):655–696.

Johnson, S., La Porta, R., Lopez-de Silanes, F., and Shleifer, A. 2000. Tunneling. *American Economic Review*, 90(2):22–27.

Joseph, J. and Gaba, V. 2020. Organizational structure, information processing, and decision-making: A retrospective and road map for research. *Academy of Management Annals*, 14(1):267–302.

Joseph, J., Klingebiel, R., and Wilson, A. J. 2016. Organizational structure and performance feedback: Centralization, aspirations, and termination decisions. *Organization Science*, 27(5):1065–1083.

Keltner, D., Gruenfeld, D. H., and Anderson, C. 2003. Power, approach, and inhibition. *Psychological Review*, 110(2):265.

Khanna, V., Kim, E. H., and Lu, Y. 2015. Ceo connectedness and corporate fraud. *The Journal of Finance*, 70(3):1203–1252.

Kleinbaum, A. M., Stuart, T. E., and Tushman, M. L. 2013. Discretion within constraint: Homophily and structure in a formal organization. *Organization Science*, 24(5):1316–1336.

Kuang, Y. F. and Lee, G. 2017. Corporate fraud and external social connectedness of independent directors. *Journal of Corporate Finance*, 45:401–427.

Lawrence, P. R. and Lorsch, J. W. 1967. *Organization and Environment: Managing Differentiation and Integration*. Harvard Business School, Boston.

Ma, S., Kor, Y. Y., and Seidl, D. 2022. Top management team role structure: A vantage point for advancing upper echelons research. *Strategic Management Journal*, 43(8):O1–O28.

March, J. G. 1962. The business firm as a political coalition. *The Journal of politics*, 24(4):662–678.

McEvily, B., Soda, G., and Tortoriello, M. 2014. More formally: Rediscovering the missing link between formal organization and informal social structure. *Academy of Management Annals*, 8(1):299–345.

Nath, P. and Bharadwaj, N. 2020. Chief marketing officer presence and firm performance: assessing conditions under which the presence of other c-level functional executives matters. *Journal of the Academy of Marketing Science*, 48(4):670–694.

O'leary, M. B., Mortensen, M., and Woolley, A. W. 2011. Multiple team membership: A theoretical model of its effects on productivity and learning for individuals and teams. *Academy of Management Review*, 36(3):461–478.

Park, S., Grosser, T. J., Roebuck, A. A., and Mathieu, J. E. 2020. Understanding work teams from a network perspective: A review and future research directions. *Journal of Management*, 46(6):1002–1028.

Pfeffer, J. 1981. *Power in Organizations*. Pitman Pub, Marshfield Mass.

Poirier, D. J. 1980. Partial observability in bivariate probit models. *Journal of Econometrics*, 12(2):209–217.

Purnanandam, A. 2008. Financial distress and corporate risk management: Theory and evidence. *Journal of Financial Economics*, 87(3):706–739.

Rank, O. N., Robins, G. L., and Pattison, P. E. 2010. Structural logic of intraorganizational networks. *Organization Science*, 21(3):745–764.

Ranson, S., Hinings, B., and Greenwood, R. 1980. The structuring of organizational structures. *Administrative Science Quarterly*, 25(1):1–17.

Raveendran, M. 2020. Seeds of change: How current structure shapes the type and timing of reorganizations. *Strategic Management Journal*, 41(1):27–54.

Rumelt, R. P., Schendel, D., and Teece, D. J. 1994. *Fundamental Issues in Strategy: A Research Agenda*. Harvard Business School Press.

Schnatterly, K., Gangloff, K. A., and Tuschke, A. 2018. Ceo wrongdoing: A review of pressure, opportunity, and rationalization. *Journal of Management*, 44(6):2405–2432.

Selznick, P. 1948. Foundations of the theory of organization. *American Sociological Review*, 13(1):25–35.

Shi, W., Connelly, B. L., and Hoskisson, R. E. 2017. External corporate governance and financial fraud: Cognitive evaluation theory insights on agency theory prescriptions. *Strategic Management Journal*, 38(6):1268–1286.

Soda, G. and Zaheer, A. 2012. A network perspective on organizational architecture: performance effects of the interplay of formal and informal organization. *Strategic Management Journal*, 33(6):751–771.

Soderstrom, S. B. and Weber, K. 2020. Organizational structure from interaction: Evidence from corporate sustainability efforts. *Administrative Science Quarterly*, 65(1):226–271.

Thibaut, J. W. and Kelley, H. H. 1959. *The Social Psychology of Groups*. John Wiley & Sons, Inc., New York.

Thompson, J. D. 1967. *Organizations in Action: Social Science Bases of Administrative Theory*. McGraw-Hill, New York.

Tost, L. P., Gino, F., and Larrick, R. P. 2013. When power makes others speechless: The negative impact of leader power on team performance. *Academy of Management Journal*, 56(5):1465–1486.

Vafeas, N. 1999. Board meeting frequency and firm performance. *Journal of Financial Economics*, 53(1):113–142.

Van Fleet, D. D. and Bedeian, A. G. 1977. A history of the span of management. *Academy of Management Review*, 2(3):356–372.

Vieregger, C., Larson, E. C., and Anderson, P. C. 2017. Top management team structure and resource reallocation within the multibusiness firm. *Journal of Management*, 43(8):2497–2525.

Wang, T. Y. 2013. Corporate securities fraud: Insights from a new empirical framework. *The Journal of Law, Economics, & Organization*, 29(3):535–568.

Wang, T. Y., Winton, A., and Yu, X. 2010. Corporate fraud and business conditions: Evidence from ipos. *The Journal of Finance*, 65(6):2255–2292.

Weber, K. and Waeger, D. 2017. Organizations as polities: An open systems perspective. *Academy of Management Annals*, 11(2):886–918.

Witting, C. A. 2018. *Liability of Corporate Groups and Networks*. International Corporate Law and Financial Market Regulation. Cambridge University Press, Cambridge.

Yiu, D. W., Wan, W. P., and Xu, Y. 2019. Alternative governance and corporate financial fraud in transition economies: Evidence from china. *Journal of Management*, 45(7):2685–2720.

Online Appendix for "Organizational Structure, Power Concentration, and Corporate Fraud: A Network Approach"

February 26, 2023

Table A1: Variable Definitions and Data Sources

Variables	Definitions	Sources
	Panel A: Fraud Variables	
Fraud	Indicator equal to one if a firm-year observation shows a detected fraud and zero otherwise.	CSMAR
	Panel B: Structural Variables	
StructuralCentralization	Measure of the extent to which ties are organized around particular focal nodes, calculated by the Gini coefficient of eigenvector centrality.	Calculated from the network database
StructuralConnectivity	Measure of the connectivity of a network, defined as the ratio of observed edges to the number of possible edges for a given network.	
	Panel C: Governance Variables	
BoardSize	Number of directors on the board.	CSMAR
%_IndepDirectors	Proportion of independent directors.	
BoardMeetings	Number of board meetings held during a given year.	
Big4AccountingFirm	Indicator equal to one if the listed firm's auditor is a joint venture with one of the international Big 4 accounting firms, including Deloitte, PwC, EY, and KPMG, and zero otherwise.	
Log(Analyst)	Log of the number of analysts following the listed firm plus one.	
InstitutionalShare	Share of institutional investors.	
Top5OwnerShare	Share of top 5 largest shareholders.	
SOE	Indicator equal to one if the listed firm is a state-owned enterprise, and zero otherwise.	
ManagementOwnership	Share of management ownership.	
Change_ChairCEO	Indicator equal to one if there is turnover of the chairperson or CEO in that year, and zero otherwise.	
Duality_ChairCEO	Indicator equal to one when a CEO also chairs the board, and zero otherwise.	
	Panel D: Firm characteristics	
Log(Age)	Logged value of the age of the listed firm since listing.	CSMAR
Log(TotalAssets)	Logged value of the book value of total assets.	

Table A1 – continued from previous page

Variables	Definitions	Sources
$TotalAssetsGrowth$	Annual total assets growth rate.	
ROA	Return on assets of the listed firm.	
$StockReturns$	Annual buy-and-hold stock returns.	
$StockTurnover$	(Number of shares traded in a year)/(Number of shares outstanding).	
$StockVolatility$	Standard deviation of daily stock returns over a given year.	RESSET
$\#\_LegalEntities$	Number of legal entities in a corporate group, including the listed firm, its subsidiaries, and its top 10 corporate shareholders.	CSMAR
	Panel E: Industry Idiosyncrasies	
$IndustryQ$	Log value of the median Tobin's Q in an industry.	
$IndustryHHI$	Herfindahl-Hirschman Index (HHI) measuring the market concentration of that industry using total assets as market share.	CSMAR
$IndustryLitigation$	Median number of lawsuits against listed firms in an industry.	
	Panel F: Unique Commission Variable	
$Leverage$	Sum of total debt divided by the book value of total assets.	CSMAR
	Panel G: Unique Detection Variable	
$\%\_Top10RemainAfter3Years$	Percentage of how many top 10 most powerful incumbents are still the top 10 most powerful incumbents in the next 3 years.	Calculated from the network database
	Panel H: Instrumental Variables for Structural Variables	
$\#\_DeathHealth$	Number of people leaving the listed firm due to death and for health reasons.	
$\#\_Retirement$	Number of people leaving the listed firm due to retirement.	RESSET
$\Delta\_LegalEntities$	Annual change in the number of legal entities in a corporate group.	CSMAR
	Panel I: Dependent Variables for Mechanism Analysis	
$\#\_Charged$	Number of people charged in litigation or enforcement action.	
		CSMAR

Table A1 – continued from previous page

Variables	Definitions	Sources
DetectDuration	Number of years from the beginning of fraudulent activity to the fraud detection date.	
#_*Dissension*	Number of dissent voting by independent directors.	

Table A2: Description of Network Construction

Panel A: Sample Distribution by Three Types of Legal Entities

	Entity-Year Obs.	Position-Year Obs.
	(1)	(2)
Listed firm	30,615	619,009
Subsidiary	542,347	2,494,067
Top 10 Corporate Shareholder	71,212	432,818
Total	644,174	3,545,894

Panel B: Sample Distribution by Corporate Group

Group-Year Obs.	Actor-Year Obs.	Avg Corporate Group Size
30,615	2,311,165	75=2,311,165/30,615

Notes. Table A2 describes the network construction. A corporate group consists of three types of legal entities. Each legal entity has many formal positions taken by actors—director, supervisor, and senior management. Column (1) in Panel A reports the number of entity-year observations for the three types of legal entities. Column (2) in Panel A reports the number of position-entity-year observations corresponding to three types of legal entities. The first column in Panel B provides the number of corporate group-year observations. The second column in Panel B provides the number of actor-year observations. The third column in Panel B provides the average number of actors in one corporate group, i.e., the average number of actors in one network.

Table A3: Sample Distribution of Cases by Fraud Type

Two Categories	Sixteen Types	Number of Cases
Accounting Fraud	Fictitious profit	449
	Fictitious assets	80
	Misrepresentation (misleading statement)	2,152
	Postponing disclosure	3,198
	Major omission in reports	2,626
	False statement	461
	General accounting mishandling	1,136
Nonaccounting Fraud	Fraudulent listing	3
	Insider dealing	199
	Illegal stock trading	1,519
	Stock price manipulation	21
	Illegal capital contribution	0
	Unauthorized change in use of funds	181
	Occupation of company assets	699
	Illegal guarantee	481
	Others	4,506

Table A4: Sample Distribution of Observations by Year

Year (1)	#_Corporate Groups (2)	#_Groups with Fraud (3)	#_Accounting Fraud (4)	#_Nonaccounting Fraud (5)
2004	957	119	115	82
2005	1,033	101	89	72
2006	1,031	114	98	74
2007	1,077	162	124	124
2008	1,222	218	167	190
2009	1,285	254	183	214
2010	1,347	245	171	201
2011	1,448	326	242	271
2012	1,704	408	298	340
2013	1,778	439	320	352
2014	1,753	407	288	316
2015	1,778	509	373	413
2016	1,942	626	472	497
2017	2,103	650	488	539
2018	2,449	702	542	607
2019	2,505	639	489	568
2020	2,550	526	409	463
2021	2,653	406	303	364
Total	30,615	6,851	5,171	5,687