How Do CEO Political Connections Influence Corporate Fraud Commission and Enforcement? Evidence from China

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ABSTRACT

We examine how CEO political connections influence fraud commission and enforcement using their unique measurability in China. We find that firms with politically connected CEOs exhibit both more frauds and longer fraud detection times. Further evidence indicates that CEO political connections are associated with smaller fraud penalties, lower CEO turnover, and more positive investor responses to an anti-corruption campaign intervention. Overall, our findings provide evidence that CEO political connections relate both to the commission of fraud and to related enforcement actions in China, with related implications for prior research and other enforcement contexts.

Keywords: Chief executive officer; Political connections; Fraud commission; Enforcement

JEL Classifications: G30, G34, M41, M42.

Data Availability: Data are available from the public sources cited in the text.

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1. Introduction

Combating corporate fraud is a priority for financial market regulators globally given its consequences for market efficiency, resource allocation and shareholder wealth.[1] CEO accountability is a primary focus.[2] The rationale for CEO accountability is straightforward—to deter fraud by holding the ultimate decision-makers liable for inappropriate actions by their firms. However, prior evidence indicates that enforcement is influenced by political contributions and lobbying activities (Correia, 2014; Kedia and Rajgopal, 2011; Yu and Yu, 2011). Less clear is how CEO political connections relate to the incidence of corporate fraud and regulatory responses. This study provides evidence that CEO political connections relate positively to fraud incidence and fraud detection times, and negatively to penalties and CEO turnover in the consequential context of China that is conducive to their measurement as we explain and that provides the quasi-experimental intervention of an anti-corruption campaign.

Prior studies indicate that CEO characteristics are associated with corporate fraud, including past work experience (Benmelech and Frydman, 2015), managerial ability (Wang, Chen, Chin and Zheng, 2017), compensation design (Burns and Kedia, 2006), personality (Dikolli et al., 2020; Van Scotter and Roglio, 2020) and other personal traits (Davidson et al., 2015; Du, 2019; Jia et al., 2014; Schrand and Zechman, 2012) with recent evidence that CEOs who are more connected with their directors are more likely to commit fraud (Khanna et al., 2015). Prior research further identifies CEO political connections as a determinant of various aspects of firm performance (Faccio, 2006; Faccio et al., 2006; Fan et al., 2007) including enhancing firm value (Faccio, 2006; Fisman, 2001) despite lower

[1] For example, The US Department of Justice (2015) confirmed that "[f]ighting corporate fraud and other misconduct is a top priority."
[2] US Securities and Exchange Commission (SEC) Chairman, Jay Clayton (2017) "firmly believe[s] that individual accountability drives behavior more than corporate accountability." The Hong Kong Securities and Futures Commission implemented a Manager-in-Charge Regime in 2017; Australia's Bank Executive Accountability Regime became effective in mid-2018; the Central Bank of Malaysia, Central Bank of Ireland and Monetary Authority of Singapore issued Discussion Papers on the merits of adopting a regime that strengthens senior management accountability.

managerial monitoring (Cao et al., 2017; Chaney et al., 2011). In particular, Wang et al. (2017) find that political connections weaken the mitigating effect of managerial ability on financial fraud in China, especially for non-state-owned-enterprises (non-SOEs). Wu et al. (2016) find political connections to mitigate regulatory responses, also especially for non-SOEs, whereas institutional ownership dominates for SOEs. However, as observed by Wu et al. (2016), it is possible that committed fraud is only partially observed if managers use political connections to influence enforcement actions by which committed fraud is revealed (Khanna et al., 2015; Wang, 2013; Wang et al., 2010). This partial observability of committed fraud makes less clear whether an association between CEO political connections and regulatory *enforcement* relates to firms' fraud-committing behaviors, regulator responses, or both, where policy implications and corporate practices could differ depending on source.[3]

We address this partial observability condition intrinsic in fraud samples (Khanna et al., 2015; Wang, 2013; Wang et al., 2010) in two ways. First, we adopt a bivariate probit model to test associations between CEO political connections and fraud commission and fraud enforcement, respectively, to better enable the separate identification of these distinct latent effects examined in prior studies. Second, we extend prior research by examining the added triangulating effect of CEO political connections on elapsed time between (versus presence of) fraud commission and enforcement.

Prior evidence is mixed regarding whether politically connected CEOs are more or less likely to commit fraud. On the one hand, CEO political connections have been found to convey "soft influence" advantages (Khanna et al., 2015) including access to cheap credit (Boubakri, Guedhami, Mishra and Saffar, 2012; Li, Meng, Wang and Zhou, 2008), regulatory favors in the IPO market (Francis, Hasan and Sun, 2009; Liu, Tang and Tian, 2013), government financial assistance (Faccio, 2006; Faccio et al., 2006), and tax advantages (Wu, Wu, Zhou and Wu, 2012) that reduce motivations to commit fraud. On the other hand, politically connected CEOs are associated with lower-quality accounting information characteristic of fraudulent behavior (Demerjian, Lev, Lewis and McVay, 2013) and they tend to be less experienced professionals that can result in unintentional fraud (Fan et al., 2007). In addition, with the expectation that their political connections can protect them from severe

[3] We refer to enforcement rather than detection since a regulator, perhaps influenced by CEO political connections, could choose to not puruse enforcement and thereby preclude fraud observability.

consequences (Correia, 2014; Wu et al., 2016; Yu and Yu, 2011), politically connected CEOs may be more prone to commit intentional fraud. Given the prevalence of politically connected CEOs in China, we posit a positive relation between CEO political connections and fraud commission.

Regarding the association between CEO political connections and fraud detection, prior evidence indicates that current or previous work experience in government or political institutions equips CEOs with knowledge of processes and policies and access to key decision-makers in government and regulatory agencies (Hillman, Cannella and Paetzold, 2000). This “inside” knowledge may help connected CEOs to avoid fraud being detected. Connected CEOs may seek help from connected government officials or politicians to influence regulatory enforcement decisions (Correia, 2014; Wu et al., 2016; Yu and Yu, 2011), thus lowering by partial observability the likelihood of revealed fraud detection. Reflecting these findings, we predict a negative association between CEO political connections and fraud detection.

We also predict a negative relation between CEO political connections and elapsed time between fraud commission and fraud enforcement reflecting. Our reasoning reflects that CEOs with political connections will use their inside knowledge of governmental and/or regulatory process and personal connections to reduce the personal consequences of fraud detected by related officials that can include their delay. Examining time between fraud commission and enforcement thus abstracts from the partial observability inherent in relations between CEO political connections and fraud commission that is dependent on fraud enforcement, and it augments the relation between CEO political connections and fraud enforcement by isolating the choice of enforcement timing. In later empirical tests we also examine enforcement penalties, CEO turnover, and investor responses to enforcement actions.

Our sample is comprised of non-SOEs listed on Chinese financial markets between 2008 and 2017. China provides an ideal setting for this study for three reasons. First, China offers unique data regarding non-SOE CEO political connections arising from the large-scale privatization of state-controlled firms over the past three decades. During the privatization period, many government officials who previously had lower compensation compared with private counterparts resigned from government positions to start their own businesses or join private firms, a migration colloquially called “plunging into the sea” (Cao et al., 2017). Resulting political connections apply to 23.5% of non-SOE CEOs in

China during our sample period.[4] Second, as Chen, Firth, Gao and Rui (2006) detail, nearly a quarter of Chinese listed firms engaged in fraudulent behaviors. This large sample allows for more meaningful variations in CEO political connections and fraud for testing study relations. Third, the Chinese setting provides a superior context for distinguishing CEO-level political connections from firm-level political connections arising from the State-owned Assets Supervision and Administration Commission (SASAC) authority to directly appoint officials from political institutions as CEOs of SOEs (Naughton, 2008) among other benefits compared with non-SOEs(Cao, Pan, Qian and Tian, 2017; Gu, Tang and Wu, 2020).

We find that firms with politically connected CEOs are more likely to exhibit fraud as predicted. Also as predicted, we find that frauds by politically connected CEOS are less likely to be detected. To corroborate this latter finding, we exploit the negative exogenous shock to CEO political connections of the high-profile anti-corruption campaign of 2013, when more than 1.3 million government officials received disciplinary actions and 170 ministers were sacked or jailed by 2017 (BBC, 2017). Consistent with this effect, we find a weaker subsequent negative relation between CEO political connections and fraud detection and higher valuations for firms with politically connected CEOs. Using settings of semi-naturally unforced CEO turnovers in a difference-in-difference design, we further find that replacing a more politically connected CEO with a less politically connected CEO is followed by a higher likelihood of fraud detection. Following prior studies, we also estimate two-stage least squared (2SLS) regressions with consistent findings. In addition, we find longer times between fraud commission and detection for more politically connected CEOs. The consistent results across three identification approaches lend support to a causal effect. In additional corroborative tests, we find for politically connected CEOs committing frauds lower likelihoods of being dismissed and smaller penalties. We further find that detection reduction is most prominent for CEOs who hold current high-ranking

[4] Our data on CEO political connection is retrieved from the "Serving Institution" from the Listed Firm's Figure Characteristic (LFFC) database provided by CSMAR. However, we realized that the data is no longer available on CSMAR since 2021. We contacted CSMAR and they responded that data on political connection will no longer be updated and has been taken down from their datasets due to related political sensitivity. Our data on CEO political connection is thus also now unique for Chinese setting.

politically related positions, participate directly in making policies, and have long-term political experience.

We contribute to several streams of research. First, we extend evidence that CEO political connections relate positively to both corporate fraud commission and enforcement, respectively, using a bivariate probit model to separate their associations, triangulating tests of time between fraud commission and enforcement, and unique China data well-suited to their identifications. Our findings indicate that CEO political connections influence both firm fraud-committing behavior and regulatory enforcement decisions, including enforcement timing and penalties, with additional evidence provided regarding other determinants and effects (Basu, Bhattacharya and Mishra, 1992; Chan, 1999; Chander and Wilde, 1992; Huther and Shah, 2000; Rose-Ackerman, 1975).

Second, we extend a growing literature on the influence of top executives' personal traits (Benmelech and Frydman, 2015; Boubakri et al., 2012; Chaney et al., 2011; Davidson et al., 2015; Dikolli et al., 2020; Du, 2019; Faccio, 2006; Faccio et al., 2006; Francis et al., 2009; Jia et al., 2014; Khanna et al., 2015; Schrand and Zechman, 2012; Van Scotter and Roglio, 2020; Wu et al., 2012) to include CEO versus firm political connections as a risk indicator for fraud with implications for shareholder wealth creation and related regulation.

Third, we shed new light on CEO and regulator incentives. Whereas prior research has shown that regulators take geographical distance, scarce enforcement resources, political contributions, and lobbying into consideration when deciding whether to investigate (Correia, 2014; Kedia and Rajgopal, 2011; Yu and Yu, 2011), we provide evidence that CEO political connections are an additional factor in influencing regulator decision-making regarding fraud enforcement. We provide corresponding evidence that CEO political connections, which by nature include knowledge, experience and connections with regulators, in turn influence CEO decision-making regarding fraud commission. These findings thus extend prior evidence regarding the increasingly prevalent "revolving door" phenomenon of government officers migrating into firm leadership roles, and *vice versa*, that the influence of which on regulations or corporate decisions has been inconclusive to date (DeHaan, Kedia, Koh and Rajgopal, 2015; Shive and Forster, 2017).

Finally, our study has practical implications for regulators and investors by providing timely evidence regarding effects of anti-corruption efforts by the Chinese government since 2013. In particular, our findings regarding both fraud commission by firms and fraud detection by regulators highlight that ineffective public monitoring is partly caused by political connection interference in regulatory process, and that a high-profile anti-corruption campaign can disrupt political connections. This finding also confirms this element of the World Bank’s anti-corruption recommendations (Huther and Shah, 2000).

The remainder of the study is organized as follows. Section 2 reviews the relevant literature and develops hypotheses. Section 3 describes empirical methods, sample selection, and variable measurements. Section 4 reports main findings, while Section 5 addresses endogeneity concerns. Sections 6 and 7 present additional tests and cross-sectional analyses, respectively, and Section 8 investigates the economic consequences. Section 9 concludes.

2. Literature review and hypothesis development

2.1. Literature review

Policies, regulations, and laws are political designs, whereas their effectiveness is naturally dependent on the political agents' incentives (e.g., government officers) (Becker, 1968; Stigler, 1970). This nature provides firms and individuals with a motivation to build connections with political agents. CEOs' political connections ex-ante to joining the firms are thus a crucial personal trait for shareholders to consider because it makes ex-post rent-seeking effectiveness predictable.[5] An extensive body of literature has documented that CEOs' personal political connections bring firms preferential treatments from the government in the form of more bailouts (Faccio et al., 2006) and lower costs of financing activities (Boubakri et al., 2012; Claessens et al., 2008). Using the Chinese setting, Francis et al. (2009) and Li et al. (2008) find that CEOs' personal political connections are associated with a higher price and lower fixed costs in the initial public offerings (IPO) and they are more likely to get access to bank loans. Wu et al. (2012) find that CEOs' personal political connections are associated with lower taxation and more tax rebates.

Khanna et al. (2015) argue that, in addition to their explicit legal authority, CEOs have a substantial "soft" influence, to direct corporate behavior. They investigate whether CEOs' connections with executives and board members affect corporate fraudulent behavior and find that such internal connections increase the risk of corporate fraud. Similarly, CEOs' external political connections may also have a significant influence on corporate fraudulent behavior. An emerging stream of studies on corporate fraud investigates whether factors such as personality (Dikolli et al., 2020; Van Scotter and Roglio, 2020), surname sharing with auditors (Du, 2019), equity-based compensation (Burns and Kedia, 2006; Hass et al., 2016; Peng and Röell, 2008), military experiences (Benmelech and Frydman, 2015), outside legal infractions (Davidson et al., 2015), physical traits (Jia et al., 2014), behavioral style (Schrand and Zechman, 2012), and managerial ability (Wang et al., 2017) have a significant influence

[5] Reasonably, politically connected CEOs' preference of rent seeking objects are often their existing connections in government.

on corporate fraud. However, the crucial personal factor—CEO political connections—has been understudied.

Limited prior studies show mixed findings on how political connections influence corporate fraud. Wu et al. (2016) provide some evidence that political connections bring firms privileges in regulatory enforcement. Wang et al. (2017) find that political connections vitiate the positive effects of a CEO's managerial ability on reducing fraud-committing behaviors. Such mixed findings may be due to the limitation of the methodologies that have been employed in these studies. One inherent nature of regulatory enforcement actions is that, detected fraud is subject to partial observability problems since observed fraud depends on two distinct but latent processes—the commission of fraud and the detection of fraud (Kedia and Rajgopal, 2011; Khanna et al., 2015; Wang, 2013; Wang et al., 2010). Without differentiating the two processes, inferences on this question will be limited. To enhance our understanding of how political connections influence corporate fraud, we explicitly address whether CEO's personal political connections have any effect on a firm's fraud commission, and whether and how this political power promotes subsequent favorable regulatory treatment once fraud has been detected.

2.2. Hypothesis development

Faccio (2006) indicates that political connections are less common in the presence of more stringent regulation of political conflicts of interest; however, they are particularly common in countries that have greater restrictions on foreign investment and less transparent systems. While the Chinese economy has experienced significant market-oriented reforms over the past decades, the government still plays a dominant role in resource allocation through regulation, financing access, licensing, subsidies, or tax benefits. Given the lack of property right protection, resource allocation is at the discretion of government officials. This motivates disadvantaged participants and private firms to build political connections to obtain favorable treatment (Chen et al., 2011). On one hand, the financial value generated from CEO's political connections (i.e., preferential access to financing, government financial assistance, or tax exemptions) may help them achieve better performance and outweigh any loss to effectively mitigate their poor performance in the absence of any fraud enforcement risk. Consequently, CEOs with political connections have fewer job security pressures, which makes it unnecessary for them to commit fraud. On the other hand, politically connected CEOs may have motivations to commit fraud. First, anticipating the potential protection due to their political connections, whenever CEOs seek better performance (e.g., meeting performance criteria, raising funds, or pleasing local government), they may be tempted to commit corporate fraud to achieve such goals. Second, politically connected CEOs may have less business experience and opportunities to improve their business managerial abilities and financial expertise, given their previous political career. This leads to the higher possibility of "unintentional mistakes" in their new role as CEO because they may have not gained enough experience to oversee and monitor the behaviors of other staff members (e.g., the CFO) in preparing disclosures (Demerjian et al., 2013). Moreover, the lack of managerial professionalism (Faccio, 2010; Fan et al., 2007) or the exploitation of shareholders to benefit politicians' personal interests (Bertrand et al., 2018) means that politically connected CEOs are likely to underperform. In such cases, facing reduced regulatory pressure, CEOs may resort to commit corporate fraud to cover up financial problems (Chaney et al., 2011).

***H1: Ceteris paribus*, political connections of CEOs are positively associated with the likelihood of fraud commission.**

However, the political connections of CEOs may have a directional influence on the likelihood of fraud being detected. Prior research has shown substantial evidence of the value of CEOs' personal political connections to shareholders. Part of this value is in terms of preferential treatment from the government, such as bailouts (Faccio et al., 2006), tax favors (Wu et al., 2012), and privileged access to financing (Boubakri et al., 2012; Claessens et al., 2008; Francis et al., 2009; Li et al., 2008). The value of preferential treatment is well received by investors (Faccio, 2006; Liu et al., 2013). In the context of corporate fraud, protection from fraud detection is a potential outcome of preferential treatment, whereby CEOs involved in fraud can seek protection from their political allies to interfere in the decisions and actions of regulators (Chaney et al., 2011; Wu et al., 2016). Referencing the criminal model of Becker (1968), which states that regulatory deterrence preventing contravention relies on both penalties and the likelihood of detection, corporate fraud regulations would be ineffective in deterring CEOs from committing fraud.In addition, another advantage of political connections is having unique knowledge and information about “the rules of the game.” Experience gained from working in political institutions provides CEOs with intimate knowledge about detection procedures and legitimacy. This means that the CEOs know how to evade detection and enforcement (Hillman et al., 2000). Thus, we expect that the political connections of CEOs will reduce the probability of fraud being investigated by regulators.

***H2: Ceteris paribus*, the political connections of CEOs are negatively associated with the likelihood of fraud detection.**

3. Data

3.1. Sample selection

We construct our sample from all Chinese non-SOEs listed on either the Shanghai Stock Exchange or the Shenzhen Stock Exchange from 2008 to 2017. We start our sample construction from 2008 because CEO political connection data on the Chinese Stock and Market Accounting Research (CSMAR) database only became available from that year[6]. We only focus on non-SOEs because this allows us to clearly differentiate between CEO political connections and firm political connections. In contrast, SOEs are controlled by the government; therefore, and are naturally connected to the political system. We define SOE firm-year observations as the firm-year observations when the controlling block holder is state-owned (Firth et al., 2006a). All the data in this study are from the CSMAR database, which is widely used in research in China, such as Cao et al. (2019) and Fan et al. (2007), and we summarize the detailed data sources of each variable in the Appendix. In addition, we follow prior studies to exclude firms in the finance industry because of their significant differences in financial regulations and accounting standards (Cao et al., 2017; Wu et al., 2016).

[6] Data on political connections is no longer available on CSMAR due to the concern over political sensitivity since 2021. Please refer to footnote 4 for details.

Initially, we obtain 25,061 firm-year observations for our sample period from CSMAR. Then, we exclude 10,302 SOE firm-year observations, 70 firm-year observations listed on B-share market, and 169 firm-year observations from financial industries. After excluding 1,138 observations without complete data on CEO political connections, other CEO characteristics, and firm financial characteristics, our final sample consists of 13,382 firm-year observations from 2,342 unique firms. Our sample includes 1,155 detected fraud observations, in which a firm receives at least one CSRC enforcement recorded in CSRC's Enforcement Actions (CSRCEA) database in CSMAR in a specific year. This sample size is comparable with (Wang et al., 2017; Wu et al., 2016; Zhang, 2018).

Table 1 reports summary statistics for all key variables. Panel A reports the summary statistics for the full sample. First, we focus on fraud-related variables. The mean of the enforcement indicator (*Enforce*) of 0.086 suggests that 8.6% of all firm-year observations involve some type of fraud, as alleged by CSRC. On average, CSRC spent 2.074 years detecting the occurrence of fraud since it was committed (*Fraud_Duration*) and the average penalty size was RMB 1.397 million (*Fraud_Penalty*). Then, we discuss the variables related to CEO political connections. The mean of 0.235 for *CEO_PC* suggests that the CEOs of 23.5% of the sampled firm-years have political connections. Of these politically connected CEOs, 27% have prior or current experience in government or the military (the mean of *PC_Gov* = 0.064).

Panel B reports the summary statistics separately for the fraud and non-fraud subsamples. Most of the values for variables related to CEO political connections (and their alternative proxies used in robustness tests) are similar for the two subsamples, while CEO turnover was more frequent in enforced firms. Panel B also reveals that the firms involved in the fraud were on average larger in size, less profitable, and from more litigious industries. Compared with the firms with no fraud detected, fraud firms also used higher leverage, demonstrating a history of higher sales growth, valued lower by the market (Tobin's Q), and lower analyst following. They were also more likely to use one of the Top 10 auditing firms for their financial reports. Their share returns were lower but share turnovers were higher. Fraud firms tended to have lower state ownership and higher institutional ownership. Their board was typically larger and more independent, but less politically connected. Their board held board meetings more frequently, had a larger audit committee, and had more non-independent directors sitting on their audit committee. On average, the CEOs in the fraud sample were less likely to have founded the firm and chaired the board. They were on average younger, had longer tenure, and fewer internal connections.

[Insert Table 1 here]

3.2. Bivariate probit model: Addressing the partial observability problem

The partial observability problem, if not addressed, may lead to profoundly different policy conclusions. If corporate fraud is predominantly driven by firm-level incentives to commit fraud, increasing the maximum penalty size would be an appropriate policy response for deterrence (Becker, 1968; Stigler, 1970). However, if regulators are showing favors to selected regulatees—suggestive of a corrupt environment—increasing the maximum penalty could in fact be counter-productive (Basu et al., 1992; Chander and Wilde, 1992; Rose-Ackerman, 1975).[7] In such an environment, anti-corruption efforts other than increasing penalty size would be more effective (Chan, 1999; Huther and Shah, 2000).[8]

The traditional univariate probit model on partially observable outcomes tends to generate biased results and unreliable inferences (Poirier, 1980). We follow prior studies on solving the partial observability issues (Khanna et al., 2015; Wang, 2013; Wang et al., 2010) and employ a bivariate probit model. In our partial observability bivariate probit model, the effects of political connections on corporate fraud are divided into two distinct but latent processes: committing fraud and detecting fraud. For each firm i, we define two latent variables as the likelihood of committing fraud and the likelihood of the fraud being detected, respectively:

$$F^{*} = X_{F,it}\alpha + \varepsilon_{i,t},$$

[7] Rose-Ackerman (1975, p. 188), the pioneer of "the economics of corruption," argues that "an effective law must do more than impose heavy penalties upon the participants to the illicit bargain; so far as firms are concerned, even a heavy fine whose amount is a function of the bribe paid may fail to deter corrupt activity." Basu et al. (1992) arrive at a similar conclusion in the context of auditors or the police. Chander and Wilde (1992) concur, using the game-theoretic model in the context of tax administration.

[8] The World Bank's 1999 report entitled *Anti-Corruption Policies and Programs* provides non-penalty related recommendations against corruption activities. These include establishing the rule of law, strengthening institutions of participation and accountability, limiting government interventions to focus on core mandates, implementing explicit anti-corruption programs, raising public and officials' awareness, no bribery pledges, "frying big fish," among others (Huther and Shah, 2000, p. 12). Chan (1999) features China in his analysis.

$$D^* = X_{D,it}\beta + \mu_{i,t}.$$

Then, we follow the previous studies (Khanna et al., 2015; Wang, 2013; Wang et al., 2010) to create F_{it} as an indicator that equals 1 when F^* is positive, and 0 otherwise. D_{it} is an indicator that equals 1 if D^* is positive, and 0 otherwise. $X_{F,it}$ is a row vector that contains the variables explaining the propensity of firm *i* to commit fraud in year *t*. $X_{D,it}$ is the row vector including the variables that determine the likelihood of the firm *i*'s fraud being detected in year *t*. $X_{F,it}$ and $X_{D,it}$ should not include the same variables. Instead, at least one variable should affect only one of fraud commission and detection but not the other (Poirier, 1980). Through such variables, namely, exogenous identifying variables, the partial observability probit model can separate the effect of CEO political connections on fraud commission and fraud detection. ε_{it} and μ_{it} are the zero-mean disturbance terms with a bivariate normal distribution, and ρ decides their correlation.

Because undetected fraud is inherently unobservable, the dependent variable, $Enforce_{it}$, is the observable outcome of the fraud commission and fraud detection. $Enforce_{it}$ equals 1 if fraud committed by firm *i* is detected in year *t*, and 0 if no fraud is committed, or if the potentially committed fraud was not detected in that year. As D^* is conditional on $Fraud^* = 1$, the model assumes no type I error (Wang et al., 2010). This means that no detected firms are innocent, and thus, $P(F_{it} = 0 \cap D_{it} = 1) = 0$. Φ denotes the bivariate standard normal cumulative distribution function:

$$\begin{aligned}\Pr(Enforce_{i,t} = 1) &= \Pr(F_{i,t} \times D_{i,t} = 1)\\ &= \Pr(F_{i,t} = 1 \cap D_{i,t} = 1)\\ &= \Phi(X_{F,it}\alpha, X_{D,it}\beta, \rho)\end{aligned} \tag{1}$$

$$\begin{aligned}\Pr(Enforce_{i,t} = 0) &= \Pr(F_{i,t} \times D_{i,t} = 0)\\ &= \Pr(F_{i,t} = 0 \cap D_{i,t} = 0) + \Pr(F_{i,t} = 1 \cap D_{i,t} = 0)\\ &= 1 - \Phi(X_{F,it}\alpha, X_{D,it}\beta, \rho)\end{aligned} \tag{2}$$

This model is estimated with the maximum likelihood method. Hence, the logarithm likelihood function of this model is:

$$L(\alpha,\beta,\rho) = \sum_{Enforce_{it}=1} \log[P(Enforce_{it} = 1)] + \sum_{Enforce_{it}=0} \log[P(Enforce_{it} = 0)]$$

$$= \sum log\Phi(X_{F,it}\alpha, X_{D,it}\beta, \rho) + \sum \log \Phi[\, 1 - \Phi\,(X_{F,it}\alpha, X_{D,it}\beta, \rho)\,]$$

(3)

In addition, because the variables in the partial observability bivariate probit model need to exhibit substantial variation in the sample, including too many indicator variables will lead to estimation failure (Wang 2013). Therefore, following Khanna et al. (2015) and Wang et al. (2010), we do not include industry or year indicators in the model but cluster standard errors by industry to mitigate the influence of heteroscedasticity in the estimation. We classify the industries based on the CSRC's two-digit industry classification codes.[9]

3.3. Variable definition

3.3.1. Fraud enforcement

The dependent variable we observe is fraud enforcement from CSRC or the stock exchanges. We define that an indicator variable, *Enforce,* equals 1 if in that year the CSRC or the stock exchanges declared enforcement to allege the firm committed fraud, and 0 otherwise. We exclude cases with "N" in the variable of "Is Violated" in the CSRCEA database, which represents firms that do not violate financial market regulations.

3.3.2. Fraud commission

We define fraud as noncompliance with regulations enforced by the CSRC. We create an indicator variable for committing fraud (*F*), which equals 1 if the firm-year observation indicates alleged fraudulent behavior, and 0 otherwise. When we measure the duration of fraud, the year when the fraud was committed is measured as the year when a firm started to commit fraud, which is retrieved as the earliest year alleged in the "Violation Year" from the CSRCEA database of CSMAR.

[9] We follow prior studies (Khanna et al., 2015; Wang et al., 2010) to cluster standard errors by industry. However, our main findings remain unchanged when we cluster standard errors by firm level.

3.3.3. Fraud detection

We define fraud detection as corporate fraud being investigated in a firm by the CSRC and the CSRC announcing fraud enforcement in that firm. We use an indicator variable for fraud detection (*D*), which equals 1 if the firm-year observation shows an announcement for enforcement action made by the CSRC, and 0 otherwise. When we measure fraud duration, we define the fraud detection date as the end of the fraud duration. Following Khanna et al. (2015), we measure the fraud detection date as the earlier of the following two dates: (1) the date of the first enforcement action proceeding, or (2) the date of the first public announcement made to investors revealing that the firm will face enforcement action by regulators. Date 1 is retrieved from the "Disposal Date" and Date 2 is obtained from the "Declare Date" in the CSRCEA database of CSMAR.

3.3.4 Political connections

We follow previous studies conducted under the China setting in defining CEO political connections. A CEO is considered to have political connections if they have current or prior work experience in (1) central government, (2) local government, (3) the military, (4) Chinese People's Political Consultative Conference (CPPCC) or (5) a National People's Congress (NPC) (Cao et al., 2017; Fan et al., 2007; Wu et al., 2016). Thus, we define *CEO_PC* as an indicator variable, which equals 1 if the firm employs a CEO who has political connections in the financial year, and 0 otherwise. The political connection data are retrieved from the "Serving Institution" from the Listed Firm's Figure Characteristic (LFFC) database from CSMAR.

3.3.5 Control variables

There are four sets of control variables included in both models in this study. Our first set of control variables includes the proxies for firm financial characteristics, which have been used in research on the fraud bivariate probit model (Khanna et al., 2015; Wang, 2013; Wang et al., 2010). These include firm size, leverage, sales growth, and profitability. Taking into consideration financial incentives and career concerns, fraud in larger firms tends to attract more attention from whistle-blowers, investors, and regulators (Dyck et al., 2010). Firms with high leverage have a higher likelihood of committing fraud to manipulate the reported numbers to avoid violating debt covenants (Stanley and Sharma, 2011), which will attract greater scrutiny from creditors. The firms' manipulations can also be motived by management's desire to disguise moderate growth performance (Crutchley et al., 2007); however, firms suffering losses are more likely to commit fraud (Alexander and Cohen, 1999). We measure firm size, *Ln(Asset)*, as the natural logarithm of the firm total assets; financial leverage, *Leverage*, as the ratio of total liability to total assets; sales growth, *Growth*, as the average growth rate of operating income over the past five years; and profitability, *EBITDA/TA*, as earnings before interest, taxes, depreciation, and amortization, divided by the book value of total assets. We also control for Tobin's Q and industry median Tobin's Q and its square term. Tobin's Q reflects the growth opportunities optimism of shareholders, which may motivate managers to commit fraud to meet market expectations in case of stock price reduction. The expectations of shareholders toward the whole industry have similar effects on managers' propensity to commit fraud, and this relation is inverted-U-shaped (Wang et al., 2010). We measure Tobin's Q, *TobinQ*, as the sum of book value of total liability and market value of common equity divided by total assets. Industry median Tobin's Q, *Ind_ TobinQ*, is measured as the median of Tobin's Q among the industry, and its square equals $(Ind\_TobinQ)^2$.

The second set of control variables is related to internal and external governance mechanisms. First, we control for the effects of political influence other than CEO political connections. These include the proportion of state ownership, *State_Ownership*, because it can reduce the incidence of enforcement (Hou and Moore, 2010), and board political connections, *Board_PC*, measured as the proportion of politically connected directors on the whole board. Although compared with CEOs, directors may not be directly involved in the decision-making around the commission of fraud, their political connections are still likely to influence fraud commission or detection. Controlling for board political connections can eliminate the effect of the political connections of directors.

Second, we include eight control variables to control corporate governance quality because of their monitoring effects on the likelihood of fraud prevention. Larger boards are related to weaker monitoring, whereas independent boards can improve monitoring (Chen et al., 2006). Large shareholders are found to have more incentives and be more effective in monitoring the firm's behavior (Wu et al., 2016). Therefore, we control for board size, *Ln(Board)*, measured as the natural logarithm of the total number of directors on the board; board independence, *Board_Indep%*, measured as the proportion of independent directors on the board; and institutional shareholder ownership, *Institutional_Ownership*, measured as the total equity proportion of institutional shareholders. The frequency of board meetings is related to effective internal monitoring (Jia et al., 2009). Audit committees have the direct responsibility of internal control over corporate fraud; their size and independence are found to be positively related to the effectiveness of monitoring (Wilbanks et al., 2017). We then follow (Fauver et al., 2017) to include the natural log of the number of board meetings, *Ln(Board_Meeting)*, the natural log of audit committee size, *Ln(Audit_Committee)*, and the proportion of non-independent directors on the whole audit committee, *AuditCom_NonIndep%*, to control for those internal monitoring mechanisms.

Since high-quality auditing ensures stronger monitoring, which in turn, reveals firm fraud (Defond and Zhang, 2014), and since analysts are also effective external monitors who reduce earning manipulation activities (Yu 2008), we indicate whether the auditors are from one of the top 10 auditing firms as ranked by the Chinese Institute of Certified Public Accountants (CICPA). This is specified as *Big10,* while the natural logarithm of the number of analysts tracking the firm, *Ln(Analyst)*, controls for these external monitoring mechanisms.

Following Khanna et al. (2015), we include our third set of control variables consisting of the proxies for the personal characteristics of CEOs. The upper echelons theory suggests that the personal characteristics of executives have a significant influence on firms' strategic decision-making (Hambrick and Mason, 1984). Our control variables for CEO personal characteristics contain the log of CEO age, *Ln(CEO_Age)*; the length of CEO tenure, *CEO_Tenure*; CEO ownership, *CEO_Ownership*, and its square term, $(CEO\_Ownership)^2$; whether the CEO is also the chairman of the board, *CEO_Duality*; and whether the CEO is the founder of the firm, *CEO_Founder*. Previous studies indicate that the age of the CEO is related to corporate fraud. On the one hand, age is negatively related to the CEOs' risk tolerance when they are making decisions; consequently, younger CEOs are more likely to commit fraud (Troy et al., 2011). On the other hand, older CEOs have more experience, which allows them to better evade fraud detection (Khanna et al., 2015). Greater ownership is related to greater voting rights in the decision-making around fraud commission. This relationship is also hump-shaped (Khanna et al., 2015). CEOs with longer tenure, CEOs who are chairs, and CEOs who are founders are all believed to have more influence and power to commit fraud and cover it up. Moreover, we also control for the variable of interest in Khanna et al. (2015), which is, the internal connections of CEOs, *CEO_InterConnect*, measured as the percentage of directors appointed to the board during a CEO's tenure.

Following Wang et al. (2010), the last set of control variables in our study are the proxies for litigation risk. This set of control variables consists of security litigation variables and stock performance variables. First, we control for stock returns, turnover, and price volatility. Johnson et al. (2006) state that litigation risk is associated with stock turnover and the volatility of stock prices. Poor performance in terms of stock price will lead to a significant loss of investors. As a result, the plaintiff investors make particular efforts to monitor the misconduct of those firms, thereby increasing the likelihood of fraud detection. However, good stock performance reduces CEO incentives to manipulate the stock price upward to increase personal wealth. For these reasons, we expect that stock return will have a negative effect on both the likelihood of fraud being committed and the likelihood of the fraud being detected. In particular, when turnover is high, more plaintiff investors will suffer from the loss, and the underperforming firms will face greater scrutiny (Wang et al., 2010). In addition, a less concentrated industry implies more intense competition, which suggests a greater propensity to commit fraud (Khanna et al., 2015). Wang et al. (2010) claim that more violations in an industry imply higher industrial litigation intensity, which makes it harder to evade fraud. However, firms committing fraud can bring their whole industry into disrepute, which may raise regulators' attention and thus increases fraud detection risk. We measure stock return as the annual stock return with cash dividends reinvested, *Stock_Return*, stock turnover as the annual stock trade volume divided by the number of shares outstanding, *Stock_Turnover*, and stock price volatility as the standard deviation of share return per day, *Stock_Volatility*. Following Khanna et al. (2015), we measure the industry concentration ratio, *Ind_Concentration*, as the sum of the market share of the four largest firms in terms of sales among the pool sample in each industry, while industry litigation, *Litigation_Risk*, is measured as the natural logarithm of total market value of fraudulent firms in an industry in a specific year.

Because the likelihood of fraud detection is partially perceived as the risk of committing fraud by CEOs, some variables included in the fraud detection model should also be included in the fraud commission model (Khanna et al., 2015). We include most of the control variables in both the Fraud and Detection models. We follow Khanna et al. (2015) to include *CEO_Option* only in the fraud commission model. This is because stock options motivate CEOs to commit fraud for personal gain from stock price growth. However, this is not related to either their voting rights or their efforts to prevent themselves from being dismissed once the fraud is detected or their influence on being detected by regulators.

4. Main results

Table 2 reports the partial observability bivariate probit estimation results for CEO political connections. Columns (1) and (2) report the associations between political connections and the likelihood of fraud commission and fraud detection, respectively. The coefficient of *CEO_PC* in Column (1) is significant and positive, suggesting that CEOs with political connections are associated with a higher likelihood of committing fraud. In contrast, the coefficient of *CEO_PC* in Column (2) is significant and negative, indicating that connected CEOs are associated with a lower likelihood of detection. These results are consistent with H1 and H2, which posits that fraud committed by politically connected CEOs is less likely to be detected by the regulators.[10]

The majority of the control variables also show significant coefficients and are mostly consistent with previous studies (Khanna et al., 2015; Wang et al., 2010). In particular, large firms are

[10] One may argue that board chair may play the role of "CEO" in Chinese business environment. However, since 2002, China has implemented a series of reforms in Company Law and SOE administration. Many firms adopt modern governance design to ensure CEO's dominating detailed daily decision-making power, as required by Company Law (Schipani and Liu, 2017). In SOE reforms, Chinese government calls for the introduction of professional managers in SOEs, where the number of actual "CEOs" increases (Pei et al., 2019). A recent study has shown evidence that CEOs have stronger effects than board chairs in Chinese firms' operation performance (Krause et al., 2019). Nevertheless, we further conduct two tests to address this concern. First, we measure *CEO_PC* as an indicator variable equal to one when either the chairman of board or the CEO has political connections, and zero otherwise. Second, we measure *CEO_PC* based on whether the chairman of board is a founder of the firm. If the chairman of board is a founder of the firm, *CEO_PC* equal to one when she has political connections, and zero otherwise; if the chairman of board is not a founder of the firm, *CEO_PC* equal to one only when the CEO has political connections, and zero otherwise. The untabulated results for the two tests are consistent with our main findings.

more likely to be detected because of more intense public scrutiny (Dyck et al., 2010). Past sales growth is positively associated with the propensity to commit fraud, possibly because firms demonstrating a continuing growth track record feel the pressure to continue delivering, potentially via fraud (Khanna et al., 2015). State ownership, serving as an alternative form of political connections, reduces the likelihood of fraud detection.

Boards appear to be effective monitors of firms in general. Firms with a large board are more likely to be investigated. Board independence increases the likelihood of detection. The frequency of board meetings is positively associated with the likelihood of detection. CEO–chair duality is significantly and positively related to fraud commission, consistent with Khanna et al. (2015).

External parties such as analysts and external auditors also serve as monitors. Higher institutional ownership is associated with a greater probability of detection. Higher analyst following reduces the likelihood of fraud occurring.

Consistent with Wang et al. (2010), stock performance and industrial litigation risks are related to fraud commission. Regulators are more likely to investigate firms with higher stock turnover, while higher stock returns are associated with less fraud. In addition, the relationship between industrial Tobin's Q and fraud commission propensity tends to be inverted-U-shaped. Firms in more concentrated, litigation-riskier industries are more likely to be investigated.

[Insert Table 2 here]

5. Identification tests

5.1. Exogenous shock: The 2013 anti-corruption campaign

We conduct a series of tests to address endogeneity concerns and reinforce causality. First, we employ the high-profile 2013 anti-corruption campaign of the Chinese government as a plausible exogenous shock weakening the effect of political connections. This far-reaching campaign against corruption, carried out under the administration of President Xi Jinping, was the largest of its kind in the history of the People's Republic of China. According to official data, up to late 2017, as many as 1.34 million corrupt officials at all levels (known as "tigers and flies") faced disciplinary charges. More than 170 ministers and deputy ministers were sacked and some were even jailed (BBC, 2017). With a record number of turnovers of government and political officials, CEO political connections were likely to have been disrupted and reshuffled, and therefore, significantly weakened. For example, Xingtian Ma, the former CEO of Kangmei, inflated the sales of his firm by RMB 30 billion (USD five billion) since 2005. As a member of the standing committee of the local CPPCC, his connections protected the fraud from being detected for 15 years. Until 2020, Xingtian Ma got involved in an investigation by the Central Commission for Discipline Inspection (CCDI), the fraud was then revealed and Xingtian Ma was finally sentenced to twelve years in prison. Consequently, after this shock, we expect the protective effect of CEO political connections against fraud detection to be significantly reduced. Because the anti-corruption campaign was launched in 2013, we exclude all observations in 2013 to keep the sample clean. We define *Post-Anti-Corruption* as a period indicator that equals 1 if the year of observation is after 2013.

Table 3 reports the results of this test. In Column (1), the coefficient of *CEO_PC* is positive and significant, while the coefficient of *CEO_PC×Post-Anti-Corruption* is negative and significant. This implies that the anti-corruption campaign deterred politically connected CEOs from committing fraud. In Column (2), the coefficient of *CEO_PC* is negative and significant, while the coefficient of *CEO_PC×Post-Anti-Corruption* is positive and significant, showing the difference in the effect of CEO political connections on fraud detection between the pre-event and post-event periods. Therefore, the results suggest that the protective shield of connected CEOs against detection almost vanished following the anti-corruption campaign. We also note similar findings on the effect of board political connections on fraud detection.

These results clearly reflect the effects of the high-profile anti-corruption campaign: following the reshuffle of officials in power, politically connected CEOs were no longer able to influence the detection preferences of the CSRC and were thereby deterred from committing fraud. The post-anti-corruption results provide supporting evidence on the directional influence of CEOs' political connections on fraud detection. These results support our primary findings.

[Insert Table 3 here]

5.2. *Difference-in-difference: Changes in CEO political connections*

While the exogenous shock effects are at the market level, we employ a firm-level difference-in-difference (DID) analysis on the appointment of CEOs with political connections to reinforce causal inferences. To be specific, we gauge the change in the likelihood of fraud detection in firms replacing politically connected CEOs with non-politically connected CEOs. We further require the outgoing CEOs to be replaced for "normal" reasons to preclude the possibility that the outgoing CEO is sacked because of fraud being uncovered. We identify "normal" or unforced turnover in two ways. In Panel A of Table 4, we follow Firth et al. (2006b) to identify CEO unforced turnover as occurring due to (2) retirement, (3) expiration of term of office, (5) resignation, or (7) health-related reasons. The data on CEO turnover reasons is obtained from the Corporate Governance (CG) database of CSMAR[11]. In Panel B, we follow Chen et al. (2017) to define departure at age 60 or above as unforced turnover (i.e., retirement).[12]

We employ a DID design for these tests. Given that the average time gap between fraud commission and fraud detection is more than two years (2.074), we only include firm-year observations three years before and three years after the CEO appointment to keep a clean and balanced sample, but exclude the year of appointment (Chen et al., 2017). This design provides some degree of confidence that all the fraud during three years after the CEO appointment could be detected. To be included in the treatment group, a firm must appoint one non-politically connected CEO to replace a departing connected CEO in the turnover year, which in other words means that the firm loses CEO political connections. The DID model closely resembles that of Chen et al. (2017), who examine the relationship

[11] In CSMAR, the turnover reasons are classified into (1) occupation mobility, (2) retirement, (3) expiration of term of office, (4) change in control right, (5) resignation, (6) dismissal, (7) health-related reasons, (8) personal reasons, (9) corporate governance improvement, (10) litigation, (11) end of acting position, and (12) other.
[12] We acknowledge that neither of the two ways necessarily precludes *all* "unnatural" turnovers but hope these two tests provide complementary reassurance for the robustness of our main findings. CEO sudden deaths (for example, deaths due to heart attacks) may be a more exogeneous identification strategy for changes in CEO unforced turnover. However, the extremely small sample does not allow us to do further tests. During our sample period, 11 CEOs are deceased. Three of the 11 CEOs have political connections, but two deceased CEOs with political connections only held the CEO positions for approximately two months and seven months, respectively. For another one deceased CEO with political connections, during his tenure of one year and two months, no fraud was detected by CSRC. Half a year after his death, a financial misstatement during his tenure was detected by CSRC.

between female independent directors and dividend payouts. Based on the baseline models, we add two variables, *Post_Turnover* and *NPCAppoint*, and their interaction term, *NPC_Appoint×Post_Turnover*. *Post_Turnover* is an indicator variable that equals 1 if the year is within three years after the unforced departure of a politically connected CEO, and 0 otherwise. *NPC_Appoint* is an indicator variable that equals 1 if the newly appointed CEO does not have political connections, and 0 otherwise. Our variable of interest is the interaction term, *NPC_Appoint×Post_Turnover*, which reports the difference in detection likelihood changes between treatment group and the control group before and after the appointment.

Table 4 reports the results of the DID tests. In Columns (1) and (3), the results of *NPC_Appoint×Post_Turnover* are significant and positive, suggesting that losing CEO political connections is negatively related to the likelihood of committing fraud. In Columns (2) and (4), the results of *NPC_Appoint×Post_Turnover* indicate that losing CEO political connections increases fraud detection likelihood compared with retaining CEO political connections. The results of the DID tests reinforce the causality in our primary findings.

[Insert Table 4 here]

5.3. Instrument variable: Province-level political connections of CEOs and oversea birthplace of CEOs

We also follow Khanna et al. (2015) to adopt the instrumental variable (IV) two-stage least squares (2SLS) approach as an alternative approach to address endogeneity. The IV is expected to only affect the dependent variable through its effect on the original independent variable (i.e., *CEO_PC*). The IV we use is the proportion of the firms with politically connected CEOs in the total firms in the same province, *Location_PC*, as our IV for CEO political connections. This choice is motivated by Ferris et al. (2016), who use total political contribution at the industry level as the IV when examining political contributions and corporate merger activity. To cover the eventuality of some industries having potential systematic patterns related to fraud (e.g., some industries have high litigation risks), we focus our measurement of the IV at the province level. The mean of CEO political connections at the province level is highly correlated with each firm’s decision to appoint a CEO with political connections;

however, its association with a specific firm's propensity to commit fraud and the CSRC's detection attitudes toward a specific firm are not obvious.

Consistent with prior studies (e.g., (Khanna et al., 2015)), we estimate the first-stage models using the fraud commission model and the detection model, respectively. In other words, we estimate two first-stage regressions with difference sets of control variables. We then impute the predicted values from each first-stage model into the second-stage partial observability bivariate probit model as the independent variable.

Table 5 reports the results of the analysis with province-level average political connections as the IV. In the first stage, *Location_PC* is significantly and positively related to the dependent variable, *CEO_PC*, in Column (1) and Column (2), respectively. In the second stage, in Columns (3) and (4), the predicted values of the first-stage estimation are significantly and positively related to fraud commission, and significantly and negatively related to fraud detection. Overall, the results of analyses with IVs are consistent with our primary results. providing additional support that our results are robust to endogeneity.

[Insert Table 5 here]

6. Mechanisms of political protection

We explore three potential channels through which CEO political connections translate into the higher likelihood of fraud commission. Specifically, we examine whether the greater likelihood of committing fraud can arise from CEO personal protection, the long survival period of existing fraud; and in case of fraud being detected, penalty reduction.

6.1 Personal protection: Likelihood of CEO turnover post fraud detection

The dismissal of the CEO often follows the discovery of fraud (Khanna 1995). However, Cao et al. (2017) argue that the potential benefits of CEO political connections offer these CEOs higher bargaining power, and they are more likely to retain their jobs. Hence, if shareholders perceive that the potential benefits of CEO political connections outweigh the negative outcomes of the fraud, politically connected CEOs are less likely to be fired when fraud is detected. To test whether such protective effects exist, we follow Khanna et al. (2015) to investigate whether politically connected CEOs are less likely to be sacked after fraud is detected.

We obtain CEO turnover data from the CG database of CSMAR. The indicator variable, *CEO_Turnover*, equals 1 if there was a CEO dismissal in that year, and 0 otherwise. Following Khanna et al. (2015), we determine whether fraud was committed within the preceding three years. This allowed us to identify fraud that was committed by the prior CEO and not the present CEO. Hence, we create another indicator variable, $Recent\_Fraud_{(t-3,\ t)}$, which equals 1 if the detected fraud was committed within three years prior to the detection year, and 0 otherwise.

Panel A in Table 6 reports the results of the test for fraud-related CEO turnover. The coefficient of $Recent\_Fraud_{(t-3,\ t)}$ is positive and significant, indicating that involvement in recent fraud increases the likelihood of dismissal, while the coefficient of $CEO\_PC \times Recent\_Fraud_{(t-3,\ t)}$ is negative and significant, suggesting that political connections mitigate the CEO's risk of dismissal because of fraud. These results support our primary findings, that political connections reduce the costs of committing fraud.

6.2 Risk of detection: Cox proportional hazards model

We conduct a survival analysis to infer fraud detection. For the subsample with the required data, we conduct the Cox proportional hazards test with the duration of fraud (i.e., the time gap between the "Violation Year" and the year of "Declare Date") as inputs. In this model, in addition to the usual set of control variables, we also control for fraud-type fixed effects because some types of fraud are easier to investigate than others.

Panel B in Table 6 reports the results of the Cox proportional hazards test. In Column (1), we find the hazards ratio (exponential of coefficient) of *CEO_PC* is significant. The estimated hazards ratio of 0.898 indicates that CEO political connections reduce the risks of detection by 10.2%.[13] The hazard ratios of some control variables are noteworthy. Consistent with Khanna et al. (2015), strong internal connections reduce fraud detection risk, and higher state ownership relates to lower risk.

[13] Interpreting the hazards ratio of an indicator: 1 – exp(coef.). A hazard ratio of less than 1.00 implies a reduction of risk.

6.3 Penalty size: Difference-in-difference with propensity score matching

We test the effects of CEO political connections on the penalty size of fraud by assuming that a lower penalty may be a reflection of political connections. We conduct two tests for this investigation. First, we conduct an OLS regression with year, industry, and fraud-type fixed effects, as shown in Panel C (1) of Table 6. In Column (1), the coefficient of *CEO_PC* is significant and negative, which suggests that CEOs with political connections receive a lower penalty for detected fraud. The penalty reduction is both statistically significant and economically meaningful. On average, for fraud detected by the CSRC, penalties issued to firms with politically connected CEOs were RMB 1.247 million (USD 0.184 million) less than comparable firms with non-politically connected CEOs. Given that the mean penalty is RMB 1.397 million (USD 0.207 million), the penalties that firms receive are, on average, 89.26% lower if their CEOs are politically connected.

We then adopt the propensity score matching (PSM) method to mitigate potential self-selection bias because fraud penalties might be endogenously determined, for example, more severe fraud may lead to higher penalties. Our PSM matching is based on a range of variables including *Ln(Assets)*, *EBITDA/TA*, *Fraud_Type* indicators, *Year* indicators, and *Industry* indicators. We match each firm-year observation with a politically connected CEO with another firm-year observation with a non-politically connected CEO. First, we run a logit regression with *CEO_PC* as the dependent variable and the five control variables mentioned above as independent variables. Then, we derive the propensity score of each firm and match the treatment group (*CEO_PC* = 1) and control group (*CEO_PC* = 0) with the propensity score with 1:1 nearest neighbor method with replacement. Finally, based on the matched sample, we test the average treatment effect on the treated firms (ATT). Panel C (2) in Table 6 reports the results of ATT based on the PSM method. Column (2) shows that in the matching sample, the average enforcement penalty that treated firms (*CEO_PC* = 1) receive is RMB 1.940 million (USD 0.287 million) less than that of control firms (*CEO_PC* = 0). Overall, consistent with our primary findings, the results suggest that CEOs with political connections obtain preferential treatment from regulators.

[Insert Table 6 here]

7. Variation across characteristics of CEO political connections

7.1 Governmental political connections

In the main test, we define a CEO as politically connected without differentiating their current or past experience in working for the government, the military, or as a representative of the CPPCC or NPC. In this section, we investigate the potential differences between the effects of different types of CEO political connections on the likelihood of committing fraud and fraud detection. To be specific, we divide CEO political connections into two groups: (1) political connections obtained as government officials and (2) political connections obtained as congress representatives. We define *PC_Gov* as an indicator variable that equals 1 if a CEO has current or past work experience in central government, local government, or the military, and 0 otherwise. Then, we use an interaction term, *CEO_PC×PC_Gov*, to investigate whether the effects of the more direct connections with the government on fraud tend to be more pronounced.

Panel A of Table 7 reports the results of these additional tests. In Column (2), the coefficient of *CEO_PC×PC_Gov* is significant and negative, which suggests that government political connections have a more pronounced influence on reducing the likelihood of detection by regulators.

7.2 Political rank of politically connected CEOs

Next, we investigate whether higher-ranked political connections of CEOs show even stronger effects on fraud commission and fraud detection than those found in the main test. To this end, we obtain the political position of CEOs from the LFFC database of CSMAR. The database classifies political positions into 20 ranks. We exclude observations classified as “98”, which is “Unknown”. In the database, for CEOs with more than one political connection, the political position rank records the highest level of political positions that each CEO has obtained. We define *PC_High* as an indicator variable that equals 1 if the position of a CEO is higher than its industrial mean, and 0 otherwise.

Panel B of Table 7 reports the results of the political position tests. In Column (2), the coefficient of *CEO_PC×PC_High* is negative and significant. The results suggest that a higher political position tends to have an incremental effect on the influence of CEO political connections on reducing the likelihood of fraud detection.

7.3 Tenure in political position

Next, we compare the effects of connected CEOs who hold longer versus shorter political tenure. We define *PC_Tenure* as the number of years the CEO has served in political institutions. Panel C of Table 7 reports the results. In Column (1), the coefficient of *PC_Tenure* on fraud commission is positive and significant, while in Column (2), the coefficient of fraud detection is negative and significant. The results suggest that CEOs who possess longer political tenure are more likely to commit fraud and less likely to be investigated. Political tenure is an alternative measurement of whether political connections are strong or weak. The findings document that the stronger the political connections, the greater their effect on fraud, which supports our primary findings.

7.4 Power of the current political position

We then investigate the differences in political power depending on whether the position is “current”. Since 1986, government officials have been prohibited from participating in corporate management by the Civil Servant Law. Therefore, current officials can no longer simultaneously serve as CEOs of firms (Cao et al., 2017). However, current congress representatives (CPPCC or NPC) can still serve as CEOs. In particular, for CEOs who are former government officials but current NPC or CPPCC representatives, their government connections can still be seen as active, namely, “current”.

Considering the differences between the effects of government official connections and representative connections, we thus define a ranking variable *PC_Current*, which equals 2 if the CEO is a current CPPCC or NPC representative with past experience in government; 1 if the CEO is a current CPPCC or NPC representative without past experience in government; and 0 if the political position of the CEO is not current.

Panel D of Table 7 reports the results. In Column (2), the coefficient of fraud detection is negative and significant. The results indicate that holding a current political position has an incremental effect on the negative association between CEO political connections and fraud detection. These results support our primary findings.

7.5 Revolving-door CEOs

The phenomenon that prior officers of financial market regulators (e.g., CSRC or SEC) joined firms as top officers (e.g., CEOs) is termed as revolving doors. Because revolving-door CEOs have expertise in regulatory activities and direct connections with regulators, such CEOs may have more pronounced relationships with corporate fraud. Nevertheless, Shive and Forster (2017) find no relationship between revolving doors and SEC enforcement and fines. As CSRC is an institution directly under the state council of China, CEOs' prior working experiences in CSRC have been considered as political connections in our setting. Therefore, we examine whether our primary findings are more pronounced for revolving-door CEOs.

We define *PC_CSRC* as an indicator variable that equals 1 if the CEO previously served in CSRC, and 0 otherwise. The variable of our interest is its interaction term with *CEO_PC*, which is, *CEO_PC×PC_CSRC*. Panel E of Table 7 reports the results. In Column (1), the coefficient on *CEO_PC×PC_CSRC* is not significant. The results suggest that compared with personal political connections to other political institutions, the direct connections to CSRC do not lead to a more pronounced positive relationship between CEO political connections and their likelihood of committing fraud. The finding implies that among politically connected CEOs, revolving-door CEOs are not different in committing fraud. The revolving-door CEOs neither developed greater integrity from the previous role of enforcing regulations nor exploit their expertise related to CSRC to commit more fraud. In Column (2), the coefficient on *CEO_PC×PC_CSRC* is significantly negative. The results suggest that the negative relationship between CEO political connections and their likelihood of committing fraud is more pronounced when the CEOs are connected to CSRC. The finding implies that with the most direct connections to regulators, revolving-door CEOs can intervene in fraud detection more effectively than other politically connected CEOs.

[Insert Table 7 here]

8. Economic consequences: Firm valuation

Further, we examine the economic benefits of weakened political connections by using an interaction term between political connections and corporate fraud. Firm value experiences a significant drop subsequent to an announcement about corporate fraud (Eisenhofer et al., 2004). In this sense, CEO political connections tend to benefit shareholders by protecting the firms (if they are fraudulent) from fraud detection. However, such benefits, together with other preferential treatment from the government due to political connections, were largely affected by the 2013 anti-corruption campaign. Wang et al. (2018) provide evidence that there was an approximate 2% drop in the valuation of non-SOEs with politically connected CEOs after 2013. Meanwhile, regulation deterrence should be stronger in the improved political environment. For these reasons, we expect investors to reward such improvement of the firms that committed fraud during the pre-2013 era in the form of increased valuation.

In our analysis of firm valuation, our dependent variable is the industry-adjusted Tobin's Q in year *t*+1, IA_TobinQ_{t+1}. We define an indicator for treated firms, which received at least one fraud enforcement prior to 2013, *PreFraud*. We then create interaction variables for *CEO_PC* with *PreFraud* and *Post-Anti-Corruption*, respectively, and an interaction term of the three variables. In addition, we control the impacts of enforcement in the current year, *Enforce.*

Table 8 reports the results of our analysis of firm valuation. Consistent with prior literature (Faccio, 2006; Liu et al., 2013), the coefficient of *CEO_PC* is significant and positive, which implies that before the anti-corruption campaign, the financial markets reacted positively to CEO political connections because of preferential treatment from the government. However, the coefficient of *CEO_PC×PreFraud* is significant and negative, showing that this positive reaction tends to be mitigated by corporate fraud detection (Eisenhofer et al., 2004). The significant and negative coefficient of *CEO_PC×Post-Anti-Corruption* supports the findings of Wang et al. (2018), who assert that the anti-corruption campaign terminated political benefits and that private firms with politically connected CEOs experienced a drop in firm value. Finally, the coefficient of *CEO_PC×Post-Anti-Corruption×PreFraud* is positive and significant. This supports our expectation that when protection against fraud detection is withdrawn, investors react positively to the potentially improved disclosure quality of politically connected firms that had committed fraud in the past.

[Insert Table 8 here]

9. Conclusion

Corporate fraud raises significant concerns for financial markets because it weakens minority investor protection, reduces market efficiency, undermines market confidence, and disrupts resource allocations (Ball, 2009; Free and Murphy, 2015). We examine how CEO political connections affect the propensity of firms to commit fraud and the likelihood of such fraud being detected by regulators. Our results suggest that firms with politically connected CEOs are more likely to commit fraud, but this fraud is less likely to be detected. We apply three identification approaches to address endogeneity concerns, and our findings suggest these relationships are causal. Further investigation of the mechanisms through which CEO political connections influence corporate fraud shows that it takes the regulators significantly longer to detect fraud committed by firms led by politically connected CEOs. Moreover, the penalties applied are smaller and CEOs personally benefit insofar as they are less likely to be dismissed. Consistent with our conjecture, we find that CEOs with current, higher-level political positions and government political connections (i.e., government or military) create a greater protective effect than their non-politically connected counterparts. Further analysis shows that investors react positively to the potential improvement in disclosure quality of politically connected firms that committed fraud in the past after the anti-corruption campaign.

Our study contributes to the literature on corporate fraud, CEO personal traits, and regulators' preferential treatment. It also yields significant implications for investors and regulators. It reveals the additional fraud risks of appointing CEOs with current or prior working experience in political institutions, which does not align with the best interests of shareholders. For regulators, our findings provide supportive evidence that the regulators of key financial markets have been endeavoring their efforts in the right direction in increasing the accountability of individuals who committed fraud (Yates Memo, 2015). Our additional evidence on penalty size and anti-corruption effects also provides valuable insights to guide future policy formulation and regulatory efforts.

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Appendix: Variable definition

Variable	Definition	Source#
Enforce	Indicator for fraud enforcement. Equals 1 if the CSRC or stock exchanges accused a firm of committing fraud in that year, and 0 otherwise. As classified by CRSCEA, the types of fraud are: (1) fictitious profit, (2) fictitious assets, (3) misleading statements, (4) delayed disclosure, (5) material omission, (6) other false information disclosure, (7) fraudulent listings, (8) false capital contributions, (9) unauthorized changes in capital usage, (10) occupancy of company assets, (11) insider trading, (12) illegal stock trading, (13) stock price manipulation, (14) illegal guarantees, (15) misleading general accounting, (16) Others	CSRCEA
F	Indicator for fraud commission. Equals 1 if a firm in a specific year is deemed to have committed fraud as estimated by the bivariate probit model.	
D	Indicator for fraud detection. Equals 1 if a firm in a specific year is deemed to have fraud detected by the CSRC, as estimated by the bivariate probit model.	
CEO_PC	Indicator for politically connected CEO. Equals 1 if a firm's CEO is currently serving or has previously served one or more roles in: (1) central government, (2) local government, (3) military service, (4) or as a CPPCC representative, or (5) an NPC representative, and 0 otherwise.	LFFC
giLn(Assets)	The natural logarithm of total assets, adjusted for inflation index based in 1978.	FS
Growth	The average growth rate of operating income over the past five years.	FS
Leverage	Total liability over total assets.	FS
EBITDA/TA	Earnings before interest, taxes, depreciation and amortization, scaled by total assets.	FS
TobinQ	The sum of total liability and market value of common equity divided by total assets.	FS & ST
Ind_TobinQ	The median of Tobin's Q of the industry to which the firm belongs.	FS & ST
Ind_TobinQ^2	The square term of *Ind_TobinQ*.	FS & ST
State_Ownership	The percentage ownership of the firm by state government.	CG
Board_PC	The proportion of politically connected directors in the board of a firm	CG
Ln(Board_Size)	The natural logarithm of the number of directors on the board of a firm.	CG
Board_Indep%	The proportion of independent directors on the board of a firm.	CG
Institutional_Ownership	Total percentage shareholdings of institutional shareholders.	II
Ln(Board_Meeting)	The natural logarithm of a firm's number of board meetings in a year.	CG
Audit_Committee	The number of audit committee members of a firm.	CG
AuditCom_NonIndep%	The proportion of non-independent directors on the whole audit committee.	CG
Ln(Analyst)	The natural logarithm of 1 plus the numbers of analysts following a firm.	AFA
Big10	Indicator for the top 10 auditing firms. Equals 1 if the auditor of a firm is one of the top 10 auditors as ranked by the CICPA, and 0 otherwise.	AO
Ln(CEO_Age)	The natural logarithm of the age of a firm's CEO.	LFFC
CEO_Tenure	The continued service as a firm's CEO up to that year, measured in number of years.	LFFC

CEO_Ownership	The percentage ownership of CEO in a firm.	LFFC
CEO_Ownership²	The square term of *CEO_Ownership*.	LFFC
CEO_Founder	Indicator for founding CEO. Equals 1 if a firm's current CEO joined for at least five years before the firm listed.	EN
CEO_Duality	Indicator for CEO duality. Equals 1 if a firm's CEO also sits as the chair of the board of directors.	LFFC
CEO_InterConnect	The proportion of directors on a board appointed during CEO's tenure at the firm.	LFFC
CEO_Option	The stock option holding of a firm's CEO, measured as a percentage of shares outstanding.	CG
Stock_Return	The annual buy-and-hold stock return of a firm.	ST
Stock_Turnover	The annual turnover rate of stock of a firm, measured as the annual trading volume in stock divided by the number of shares outstanding.	ST
Stock_Volatility	Annual average standard deviation of daily stock returns for a firm.	ST
Ind_Concentration	The sum of the market share of the four largest firms in terms of sales among the pool sample in each industry.	CSRCEA
Litigation_Risk	The natural logarithm of total market value of fraudulent firms in an industry in a specific year.	CSRCEA&ST
PC_Gov	Indicator for politically connected CEO with government background. Equals 1 if a firm's CEO is currently serving or has previously served one or more roles in: (1) central government, (2) local government or (3) military service, and 0 otherwise.	LFFC
PC_High	Indicator variable for CEO with high-rank political position(s). Equals 1 if the position level of a CEO is higher than its industrial mean, and 0 otherwise.	LFFC
PC_Tenure	The number of years that a CEO has served in political institutions.	LFFC
PC_Current	Ranking variable. Equals 2 if a politically connected CEO is a current representative of NPC or CPPCC with past working experience in government; 1 if a politically connected CEO is a current representative of NPC or CPPCC but without working experience in government, and 0 if the political position of CEO is not current.	LFFC
PC_Military	Indicator for politically connected CEO with military background. Equals 1 if a firm's CEO served in military, and 0 otherwise.	LFFC
Post-Anti-Corruption	Indicator for the high-profile 2013 anti-corruption campaign in China. Equals 1 if the year of observation is after 2013, and 0 otherwise.	
Post_Turnover	Indicator variable. Equals 1 for the years after the unforced departure of a politically connected CEO, and 0 otherwise. Unforced turnover is defined in two ways: in Panel A, we follow Firth et al. (2006b) to identify CEO unforced turnover as the turnover due to retirement, expiration of term of office, resignation or health-related reasons. The CEO turnover reason data are from the CG database in CSMAR, classified into (1) occupation mobility, (2) retirement, (3) expiration of term of office, (4) change in control rights, (5) resignation, (6) dismissal, (7) health-related reasons, (8) personal reasons, (9) corporate governance improvement, (10) litigation involved, (11) end of acting position, (12) other. In Panel B, we follow Chen et al. (2017) to identify CEO unforced turnover as the departure of the CEO who is older than 60 years old.	CG
NPC_Appoint	Indicator variable. Equals 1 if the newly appointed CEO has no political connections, and 0 otherwise.	LFFC
Location_PC	The percentage of the firms with CEO political connection in the total firms of a same province in a year.	LFFC
CEO_Turnover	Indicator variable for CEO turnover. Equals 1 if there is a CEO dismissal, and 0 otherwise.	LFFC
Recent_Fraud$_{(t-3,\ t)}$	Indicator for recent fraud. Equals 1 if the detected fraud was committed within three years prior to the detection year, and 0 otherwise.	CSRCEA
Fraud_Duration	The number of years since a firm has committed fraud until it was detected by the CSRC or stock exchanges, as announced by the CSRC or stock exchanges. The year of fraud is measured as the year when a fraud was committed, retrieved as the earliest year alleged in the "Violation Year" under CSRCEA. The detection date is the earlier of the following	CSRCEA

	two dates: (1) the date of the first enforcement action proceeding, or (2) the date of the first public announcement made to reveal to investors that the firm will face an enforcement action by regulators in the future. Date (1) is retrieved from the "Disposal Date" and Date (2) is obtained from the "Declare Date" in the CSRCEA database of the CSMAR database.	
Fraud_Penalty	The size of the penalty applied by the CSRC in relation to the fraud, measured in RMB millions. No penalties but with other types of punishment is considered 0.	CSRCEA
IA_TobinQ_{t+1}	The gap between Tobin's Q and its industrial median in year t+1.	FS&ST
PreFraud	Indicator variable for treated firms equals 1 if the firm received at least one fraud enforcement prior to 2013.	CSRCEA

 # Abbreviations for databases used:

- AFA: Analyst Forecasts database, under CSMAR
- AO: Audit Opinion database, under CSMAR
- CG: Corporate Governance database, under CSMAR
- CSMAR: Chinese Stock and Market Accounting Research database
- CSRCEA: CSRC's Enforcement Actions database, under CSMAR
- EN: Equity Nature, under CSMAR
- FS: Financial Statements database, under CSMAR
- II: Institutional Investor, under CSMAR
- LFFC: Listed Firm's Figure Characteristic database, under CSMAR
- ST: Stock Trading

Table 1

Descriptive statistics

This table presents the descriptive statistics. Panel A describes the full sample, which contains 13,382 firm-year observations from 2008 to 2017. Panel B describes the subsamples where fraud was detected for a firm in that year (*Enforce* = 1) versus where no fraud detected for a firm in that year (*Enforce* = 0) *Fraud* is an indicator that equals 1 if fraud was detected for a firm in that year, and 0 otherwise. *CEO_PC* is an indicator that equals 1 if the incumbent CEO is deemed to have political connections. Detailed variable definitions can be found in the Appendix.

Panel A: Descriptive statistics of the full sample						
	N	Mean	S.D.	Min	Median	Max
Enforce	13,382	0.086	0.281	0.000	0.000	1.000
CEO_PC	13,382	0.235	0.424	0.000	0.000	1.000
Ln(Assets)	13,382	7.721	1.094	5.217	7.607	13.145
Leverage	13,382	0.380	0.215	0.047	0.356	1.067
Growth	13,382	0.285	0.864	–0.242	0.104	6.594
EBITDA/TA	13,382	0.077	0.063	–0.176	0.074	0.281
TobinQ	13,382	3.357	2.426	0.874	2.597	13.894
Ind_TobinQ	13,382	2.503	0.941	1.019	2.296	5.889
Ind_TobinQ2	13,382	7.152	5.900	1.037	5.270	34.675
State_Ownership	13,382	0.006	0.030	0.000	0.000	0.648
Board_PC	13,382	0.241	0.185	0.000	0.222	0.857
Ln(Board_Size)	13,382	2.218	0.168	1.792	2.303	2.773
Board_Indep%	13,382	0.375	0.053	0.308	0.333	0.571
Institutional_Ownership	13,382	0.041	0.046	0.000	0.026	0.221
Ln(Board_Meeting)	13,382	2.325	0.337	1.609	2.303	3.178
Ln(Audit_Committee)	13,382	1.718	0.803	0.000	1.946	2.996
AuditCom_NonIndep%	13,382	0.163	0.128	0.000	0.143	0.667
Ln(Analysts)	13,382	1.590	1.110	0.000	1.609	3.714
Big10	13,382	0.554	0.497	0.000	1.000	1.000
Ln(CEO_Age)	13,382	3.870	0.141	3.497	3.871	4.174
CEO_Tenure	13,382	4.878	3.050	1.000	4.000	14.000
CEO_Ownership	13,382	0.078	0.134	0.000	0.002	0.515
CEO_Ownership2	13,382	0.024	0.056	0.000	0.000	0.265
CEO_Founder	13,382	0.338	0.473	0.000	0.000	1.000
CEO_Duality	13,382	0.371	0.483	0.000	0.000	1.000
CEO_InterConnect	13,382	0.763	0.251	0.000	0.857	1.200
CEO_Option	13,382	0.490	2.864	0.000	0.000	20.370
Stock_Return	13,382	0.154	0.762	–0.779	–0.053	3.226
Stock_Turnover	13,382	3.638	2.479	0.257	3.035	12.721
Stock_Volatility	13,382	0.030	0.009	0.013	0.028	0.055
Ind_Concentration	13,382	0.441	0.196	0.169	0.420	1.000
Litigation_Risk	13,382	0.003	0.004	0.001	0.002	0.026
PC_Gov	13,382	0.064	0.245	0.000	0.000	1.000
PC_High	13,284	0.866	0.341	0.000	1.000	1.000
PC_Tenure	424	6.068	4.270	0.000	5.000	19.000
PC_Current	13,382	0.105	0.329	0.000	0.000	2.000
PC_Military	13,382	0.005	0.071	0.000	0.000	1.000
Post-Anti-Corruption	12,012	0.608	0.488	0.000	1.000	1.000
$Post\_Turnover_{Panel\ A}$	1,230	0.791	0.407	0.000	0.000	1.000
$NPC\_Appoint_{Panel\ A}$	1,230	0.444	0.497	0.000	1.000	1.000
$Post\_Turnover_{Panel\ B}$	184	0.435	0.497	0.000	0.000	1.000
$NPC\_Appoint_{Panel\ B}$	184	0.804	0.398	0.000	1.000	1.000
Location_PC	13,382	0.202	0.056	0.029	0.203	0.344
CEO_Turnover	13,382	0.254	0.435	0.000	0.000	1.000
$Recent\_Fraud_{(t-3,\ t)}$	13,382	0.064	0.244	0.000	0.000	1.000
Fraud_Duration	1,083	2.074	2.074	0.000	1.000	11.000
Fraud_Penalty	107	1.397	1.517	0.005	0.900	9.430

IA_TobinQ$_{t+1}$	13,382	0.630	2.524	–2.981	0.000	14.553
PreFraud	13,382	0.312	0.463	0.000	0.000	1.000

Panel B: Descriptive statistics of the fraud and non-fraud subsamples

	Enforce = 1				*Enforce* = 0			
	N	Mean	S.D.	Median	*N*	Mean	S.D.	Median
CEO_PC	1,155	0.234	0.423	0.000	12,227	0.235	0.424	0.000
Ln(Assets)	1,155	7.770	1.168	7.733	12,227	7.716	1.086	7.595
Leverage	1,155	0.460	0.233	0.455	12,227	0.372	0.212	0.348
Growth	1,155	0.423	1.208	0.121	12,227	0.272	0.824	0.103
EBITDA/TA	1,155	0.048	0.077	0.052	12,227	0.079	0.061	0.076
TobinQ	1,155	3.307	2.542	2.392	12,227	3.362	2.414	2.612
Ind_TobinQ	1,155	2.438	0.903	2.264	12,227	2.509	0.944	2.296
Ind_TobinQ2	1,155	6.759	5.596	5.124	12,227	7.189	5.927	5.270
State_Ownership	1,155	0.005	0.027	0.000	12,227	0.006	0.030	0.000
Board_PC	1,155	0.228	0.168	0.222	12,227	0.242	0.186	0.222
Ln(Board_Size)	1,155	2.208	0.167	2.303	12,227	2.219	0.168	2.303
Board_Indep%	1,155	0.378	0.054	0.364	12,227	0.375	0.053	0.333
Institutional_Ownership	1,155	0.042	0.048	0.024	12,227	0.041	0.046	0.026
Ln(Board_Meeting)	1,155	2.445	0.340	2.485	12,227	2.314	0.334	2.303
Ln(Audit_Committee)	1,155	1.863	0.636	1.946	12,227	1.704	0.816	1.946
AuditCom_NonIndep%	1,155	0.179	0.130	0.167	12,227	0.161	0.127	0.143
Ln(Analysts)	1,155	1.221	1.129	1.099	12,227	1.625	1.102	1.792
Big10	1,155	0.525	0.500	1.000	12,227	0.556	0.497	1.000
Ln(CEO_Age)	1,155	3.869	0.147	3.892	12,227	3.870	0.141	3.871
CEO_Tenure	1,155	4.985	3.285	4.000	12,227	4.868	3.027	4.000
CEO_Ownership	1,155	0.057	0.118	0.000	12,227	0.080	0.135	0.002
CEO_Ownership2	1,155	0.017	0.048	0.000	12,227	0.025	0.057	0.000
CEO_Founder	1,155	0.246	0.431	0.000	12,227	0.347	0.476	0.000
CEO_Duality	1,155	0.366	0.482	0.000	12,227	0.371	0.483	0.000
CEO_InterConnect	1,155	0.739	0.267	0.857	12,227	0.766	0.249	0.875
CEO_Option	1,155	0.385	2.564	0.000	12,227	0.500	2.890	0.000
Stock_Return	1,155	0.086	0.612	–0.052	12,227	0.160	0.774	–0.054
Stock_Turnover	1,155	4.107	2.719	3.471	12,227	3.593	2.451	2.996
Stock_Volatility	1,155	0.029	0.009	0.027	12,227	0.030	0.009	0.028
Ind_Concentration	1,155	0.441	0.197	0.420	12,227	0.441	0.196	0.420
Litigation_Risk	1,155	0.004	0.004	0.002	12,227	0.003	0.004	0.002
PC_Gov	1,155	0.070	0.255	0.000	12,227	0.064	0.245	0.000
PC_High	1,145	0.862	0.345	1.000	12,139	0.866	0.341	1.000
PC_Tenure	46	6.370	5.127	5.000	424	5.709	4.221	5.000
PC_Current	1,155	0.087	0.305	0.000	12,227	0.106	0.331	0.000
PC_Military	1,155	0.006	0.078	0.000	12,227	0.005	0.070	0.000
Post-Anti-Corruption	997	0.715	0.452	1.000	11,015	0.599	0.490	1.000
Post_Turnover$_{Panel\ A}$	106	0.811	0.393	1.000	730	0.788	0.409	0.000
NPC_Appoint$_{Panel\ A}$	106	0.509	0.502	1.000	730	0.434	0.496	1.000
Post_Turnover$_{Panel\ B}$	32	0.438	0.504	0.000	198	0.434	0.497	0.000
NPC_Appoint$_{Panel\ B}$	32	0.938	0.246	1.000	198	0.783	0.413	1.000
Location_PC	1,155	0.202	0.055	0.207	12,227	0.202	0.056	0.203
CEO_Turnover	1,155	0.375	0.484	0.000	12,227	0.242	0.429	0.000
IA_TobinQ$_{t+1}$	1,155	0.688	2.956	–0.071	12,227	0.625	2.479	0.000
PreFraud	1,155	0.660	0.474	1.000	12,227	0.279	0.448	0.000

Table 2

Effect of CEO political connections on the likelihood of fraud commission and fraud detection: Bivariate probit model

This table reports the results of the bivariate probit model estimation for the main models. The sample consists of 13,382 firm-year observations from 2008 to 2017. Column (1) reports model (1) to estimate the association between CEO political connections and the likelihood of committing fraud. Column (2) reports model (2) to estimate the association between CEO political connections and the likelihood of fraud being detected. Detailed variable definitions can be found in the Appendix. Robust standard errors clustered at the industry level are reported in parentheses. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Pr(F) (1)	*Pr(D|F)* (2)
CEO_PC	0.092***	–0.226***
	(0.036)	(0.047)
Ln(Assets)	–0.011	0.072**
	(0.028)	(0.031)
Leverage	0.308***	1.129***
	(0.085)	(0.142)
Growth	0.044*	0.319***
	(0.023)	(0.041)
EBITDA/TA	–1.890***	–2.556***
	(0.276)	(0.318)
TobinQ	0.021**	0.024***
	(0.008)	(0.008)
Ind_TobinQ	0.314***	–2.309***
	(0.117)	(0.257)
Ind_TobinQ^2	–0.047***	0.309***
	(0.018)	(0.038)
State_Ownership	–0.175	–2.185***
	(0.618)	(0.622)
Board_PC	0.077	–1.249***
	(0.102)	(0.151)
Ln(Board_Size)	–0.195	1.618***
	(0.153)	(0.232)
Board_Indep%	–0.089	2.366***
	(0.324)	(0.455)
Institutional_Ownership	0.686**	2.153***
	(0.333)	(0.465)
Ln(Board_Meeting)	0.528***	0.746***
	(0.060)	(0.073)
Ln(Audit_Committee)	0.051**	0.000
	(0.022)	(0.028)
AuditCom_NonIndep%	0.021	–0.473***
	(0.130)	(0.141)
Ln(Analysts)	–0.109***	–0.228***
	(0.020)	(0.021)
Big10	–0.023	–0.105**
	(0.041)	(0.053)
Ln(CEO_Age)	–0.117	0.498***
	(0.106)	(0.132)
CEO_Tenure	0.005	0.061***
	(0.006)	(0.012)
CEO_Ownership	0.768	–6.097***
	(0.554)	(0.877)
CEO_Ownership^2	–0.438	9.799***

	(1.240)	(1.550)
CEO_Founder	–0.054	–0.378***
	(0.054)	(0.078)
CEO_Duality	0.088*	0.069
	(0.050)	(0.067)
CEO_InterConnect	–0.192***	0.249***
	(0.069)	(0.077)
CEO_Option	–0.010**	
	(0.005)	
Stock_Return	–0.089***	0.009
	(0.025)	(0.033)
Stock_Turnover	0.021**	0.214***
	(0.009)	(0.015)
Stock_Volatility	–7.827***	–10.180***
	(2.404)	(2.875)
Ind_Concentration	–0.359***	0.685***
	(0.114)	(0.123)
Litigation_Risk	15.437***	21.480**
	(4.427)	(10.510)
Constant	–1.708***	–6.196***
	(0.646)	(0.868)
Cluster S.E. by industry	Yes	
Observations	13,382	
Log likelihood	–3576.239	

Table 3

CEO political connections and the likelihood of fraud commission and fraud detection: 2013 anti-corruption campaign

This table reports the results of the bivariate probit model estimation for the anti-corruption effect on the relationship between corporate fraud and CEO political connection. To yield a cleaner test, we exclude observations in 2013 when the high-profile anti-corruption campaign started. The sample consists of 12,012 firm-year observations. Column (1) reports the anti-corruption effect on the relation between CEO political connections and the likelihood of committing fraud. Column (2) reports the anti-corruption effect on the relation between CEOs' political connections and the likelihood of fraud being detected. *Post-Anti-Corruption* is a period indicator variable that equals 1 after 2013, and 0 otherwise. Detailed variable definitions can be found in the Appendix. Robust standard errors clustered at the industry level are reported in parentheses. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Pr(F) (1)	*Pr(D|F)* (2)
CEO_PC	0.117*	–0.187**
	(0.065)	(0.095)
Post-Anti-Corruption	1.335***	–2.245***
	(0.137)	(0.259)
CEO_PC×Post-Anti-Corruption	–0.579***	0.340***
	(0.116)	(0.119)
Ln(Assets)	–0.147***	–0.015
	(0.041)	(0.036)
Leverage	0.200*	0.915***
	(0.122)	(0.124)
Growth	–0.048**	0.115***
	(0.024)	(0.019)
EBITDA/TA	–1.037***	–1.993***
	(0.363)	(0.325)
TobinQ	–0.031*	0.0240**
	(0.016)	(0.012)
Ind_TobinQ	–0.392***	0.295**
	(0.145)	(0.143)
Ind_TobinQ^2	0.041**	–0.042*
	(0.021)	(0.023)
State_Ownership	0.126	2.963***
	(0.846)	(1.030)
State_Ownership×Post-Anti-Corruption	–1.947	–1.874
	(1.290)	(1.306)
Board_PC	–0.300*	–3.376***
	(0.166)	(0.378)
Board_PC×Post-Anti-Corruption	1.642***	3.323***
	(0.298)	(0.413)
Ln(Board_Size)	–0.043	0.133
	(0.193)	(0.165)
Board_Indep%	1.460***	–0.295
	(0.445)	(0.422)
Institutional_Ownership	–0.010	1.375***
	(0.610)	(0.395)
Ln(Board_Meeting)	0.546***	0.408***
	(0.075)	(0.067)
Ln(Audit_Committee)	0.013	0.124***
	(0.027)	(0.033)
AuditCom_NonIndep%	–0.047	0.127
	(0.161)	(0.168)
Ln(Analysts)	–0.123***	–0.091***

	(0.027)	(0.025)
Big10	–0.053	–0.144***
	(0.053)	(0.042)
Ln(CEO_Age)	0.114	–0.258
	(0.166)	(0.162)
CEO_Tenure	–0.027***	0.005
	(0.010)	(0.007)
CEO_Ownership	0.596	–1.508**
	(0.719)	(0.602)
CEO_Ownership^2	0.404	1.444
	(1.628)	(1.536)
CEO_Founder	0.089	–0.278***
	(0.064)	(0.072)
CEO_Duality	–0.226***	0.319***
	(0.054)	(0.067)
CEO_InterConnect	–0.205**	0.049
	(0.093)	(0.077)
CEO_Option	0.012	
	(0.009)	
Stock_Return	0.053*	–0.149***
	(0.029)	(0.029)
Stock_Turnover	0.021**	0.046***
	(0.010)	(0.011)
Stock_Volatility	–24.47***	–1.338
	(2.541)	(3.523)
Ind_Concentration	–0.040	–0.191
	(0.160)	(0.127)
Litigation_Risk	15.211**	15.653***
	(6.455)	(5.559)
Constant	–0.815	–0.149
	(0.784)	(0.833)
Cluster S.E. by industry	Yes	
Observations	12,012	
Log likelihood	–3043.839	

Table 4

Changes in CEO political connections and the likelihood of fraud commission and fraud detection

This table reports the results of the bivariate probit model for appointing a non-politically connected CEO following the unforced turnover of a politically connected CEO. In Panel A, we follow Firth et al. (2006b) to identify CEO unforced turnover, which includes turnover due to retirement, expiration of term of office, resignation or health-related reasons. The CEO turnover reason data are from the CG database under CSMAR, which is classified into (1) occupation mobility, (2) retirement, (3) expiration of term of office, (4) change in control rights, (5) resignation, (6) dismissal, (7) health-related reasons, (8) personal reasons, (9) corporate governance improvement, (10) litigation involved, (11) end of acting position, (12) other. The sample for model 1 consists of 836 firm-year observations, which includes three years before the unforced departure of a politically connected CEO and three years after. In Panel B, we follow Chen et al. (2017) to identify CEO unforced turnover as the departure of the CEO who is older than 60 years old. The sample consists of 230 firm-year observations, and includes three years before the departure of a politically connected CEO aged 60 years old or over and three years after. The treatment group includes observations where a non-politically connected CEO was appointed to replace the departing politically connected CEO. The control group is the rest of the observations where both the departing and incoming CEOs are politically connected. Columns (1) and (3) report the results of estimating the association between losing CEO political connections and the likelihood of committing fraud, Columns (2) and (4) report the results of estimating the association between losing CEO political connections and the likelihood of fraud being detected. *Post_Turnover* is an indicator variable that equals 1 for the years after the unforced departure of a politically connected CEO, and 0 otherwise. *NPC_Appoint* is an indicator variable that quals 1 if the newly appointed CEO has no political connections, and 0 otherwise. Accordingly, the interaction term, *Post*NPC_Appoint*, tests the difference of appointing a non-politically connected CEO in the year after departure versus appointing a politically connected CEO. Definitions of all control variables are provided in the Appendix. Robust standard errors clustered at the industry level are reported in parentheses. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Panel A		Panel B	
	Pr(F)	*Pr(D|F)*	*Pr(F)*	*Pr(D|F)*
	(1)	(2)	(3)	(4)
NPC_Appoint	1.243***	–0.720**	71.414***	–17.625***
	(0.325)	(0.335)	(0.647)	(1.508)
Post_Turnover	1.155***	–0.630	26.008***	–5.194*
	(0.443)	(0.407)	(0.698)	(2.54)
NPC_Appoint×Post_Turnover	–2.285***	1.090**	–31.666***	14.192***
	(0.588)	(0.485)	(0.786)	(2.651)
Ln(Assets)	0.214	0.152	–7.161***	11.324***
	(0.157)	(0.106)	(0.249)	(0.191)
Leverage	–0.399	0.787	15.816***	–5.859***
	(0.454)	(0.510)	(0.306)	(1.366)
Growth	0.818***	–0.087*	9.108***	–5.966***
	(0.275)	(0.045)	(0.064)	(0.245)
EBITDA/TA	–3.904***	–1.112	4.617***	–41.988***
	(1.060)	(1.134)	(0.953)	(1.184)
TobinQ	–0.192***	0.14**	–5.455***	3.823***
	(0.071)	(0.064)	(0.081)	(0.275)
Ind_TobinQ	–0.422	–0.331	–43.24***	–11.72***
	(0.276)	(0.456)	(0.714)	(0.666)
Ind_TobinQ^2	0.075*	0.045	11.185***	1.088***
	(0.043)	(0.081)	(0.119)	(0.075)
State_Ownership	–1.291	4.176**	–296.91***	401.481***
	(2.813)	(2.114)	(4.196)	(9.191)
Board_PC	1.181*	–0.903***	–55.43***	35.995***
	(0.664)	(0.321)	(0.501)	(0.579)
Ln(Board_Size)	1.406*	–2.494***	41.767***	10.515***
	(0.758)	(0.482)	(0.526)	(2.892)
Board_Indep%	–1.595	–6.316***	172.648***	22.798***
	(2.304)	(1.407)	(2.014)	(5.073)

Institutional_Ownership	–0.063	–0.192	–194.103***	43.908***
	(1.939)	(1.703)	(1.039)	(2.199)
Ln(Board_Meeting)	1.246***	0.237	13.502***	3.579***
	(0.351)	(0.190)	(0.482)	(0.312)
Ln(Audit_Committee)	–0.008	0.127	9.995***	–12.88***
	(0.131)	(0.127)	(0.19)	(0.21)
AuditCom_NonIndep%	0.123	1.908***	46.373***	43.891***
	(0.585)	(0.609)	(0.927)	(0.939)
Ln(Analysts)	–0.365***	0.059	5.987***	–10.479***
	(0.135)	(0.105)	(0.278)	(0.324)
Big10	0.036	–0.342**	21.561***	–1.629***
	(0.129)	(0.160)	(0.303)	(0.422)
Ln(CEO_Age)	–0.670	1.152**	–20.382***	–0.71**
	(0.686)	(0.562)	(0.314)	(0.311)
CEO_Tenure	–0.17***	0.071*	2.08***	–2.771***
	(0.055)	(0.037)	(0.101)	(0.11)
CEO_Ownership	–0.162	–1.540	–39.471***	–50.967***
	(2.367)	(3.537)	(2.234)	(2.768)
CEO_Ownership^2	–1.813	1.495	295.379***	115.367***
	(5.746)	(8.246)	(5.452)	(3.18)
CEO_Founder	–1.583***	1.205***	–3.511***	–12.786***
	(0.362)	(0.415)	(0.461)	(0.457)
CEO_Duality	0.217	0.689***	–38.813***	16.656***
	(0.215)	(0.162)	(0.553)	(0.431)
CEO_InterConnect	1.604***	–0.877**	49.698***	3.206***
	(0.450)	(0.397)	(0.293)	(0.39)
CEO_Option	0.007		–3.604***	
	(0.039)		(0.168)	
Stock_Return	–0.210	–0.110	–2.686***	–3.537***
	(0.136)	(0.080)	(0.204)	(0.449)
Stock_Turnover	0.034	0.066**	12.485***	–4.234***
	(0.030)	(0.033)	(0.072)	(0.05)
Stock_Volatility	–0.719	–0.361	–64.067***	133.336***
	(11.255)	(8.424)	(9.819)	(2.964)
Ind_Concentration	–0.460	0.514	–32.154***	24.147***
	(0.419)	(0.553)	(0.549)	(1.577)
Litigation_Risk	10.273	11.359	–848.981***	–120.547***
	(17.689)	(18.738)	(2.653)	(1.267)
Constant	–4.066	0.438	–136.709***	–64.333***
	(3.446)	(3.093)	(1.93)	(6.899)
Cluster S.E. by industry	Yes		Yes	
Observations	836		230	
Log likelihood	–255.913		–0.000	

Table 5

CEO political connections on the likelihood of fraud commission and fraud detection: An IV approach

This table reports the results from probit model of CEO political connections proportion in the province as an IV. The sample consists of 13,382 firm-year observations from 2008 to 2017. Panel A reports the 2SLS analysis with province-level average political connections as an instrument. At the first stage, we examine OLS models for the IV and CEO political connections. At the second stage, we examine partial observability bivariate probit model for corporate fraud and estimated values of the first stage OLS model. Column (1) reports the fraud equation, while Column (2) reports the detection equation. The IV is *Location_PC*, which is measured as the proportion of the firms with politically connected CEOs in the same province. Definitions of all control variables are provided in the Appendix. Robust standard errors clustered at the industry level are reported in parentheses. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	First stage: Logit Using province-level average political connections as instrument		*Second stage:* Partial observability bivariate probit model	
	Dep. var. = *CEO_PC*			
	Pr(F) (1)	*Pr(D|F)* (2)	*Pr(F)* (3)	*Pr(D|F)* (4)
Dependent variable: *CEO_PC*				
*CEO_PC^* (from model (1))			0.522**	
			(0.215)	
*CEO_PC^* (from model (2))				–1.967***
				(0.378)
Location_PC	6.433***	6.388***		
	(0.917)	(0.911)		
CEO_Oversea				
Ln(Assets)	0.147**	0.143**	–0.022	0.158***
	(0.060)	(0.060)	(0.027)	(0.029)
Leverage	–0.035	–0.038	0.330***	0.839***
	(0.252)	(0.254)	(0.089)	(0.117)
Growth	–0.017	–0.014	0.045**	0.340***
	(0.065)	(0.065)	(0.022)	(0.038)
EBITDA/TA	0.681	0.662	–1.913***	–2.357***
	(0.552)	(0.550)	(0.271)	(0.280)
TobinQ	–0.032	–0.031	0.022**	0.017
	(0.023)	(0.023)	(0.009)	(0.014)
Ind_TobinQ	–0.241	–0.232	0.341***	–2.769***
	(0.160)	(0.159)	(0.116)	(0.318)
Ind_TobinQ^2	0.017	0.016	–0.051***	0.386***
	(0.027)	(0.027)	(0.018)	(0.045)
State_Ownership	–0.144	–0.124	–0.030	–2.917***
	(1.026)	(1.026)	(0.643)	(0.747)
Board_PC	1.865***	1.862***	–0.082	–0.472***
	(0.225)	(0.225)	(0.109)	(0.130)
Ln(Board_Size)	0.076	0.071	–0.187	1.541***
	(0.347)	(0.347)	(0.158)	(0.237)
Board_Indep%	1.033	1.032	–0.321	3.657***
	(1.026)	(1.025)	(0.349)	(0.582)
Institutional_Ownership	0.823	0.787	0.592*	2.826***
	(0.677)	(0.675)	(0.349)	(0.413)
Ln(Board_Meeting)	–0.175	–0.192	0.532***	0.731***
	(0.132)	(0.132)	(0.060)	(0.073)

Ln(Audit_Committee)	–0.025	–0.026	0.042*	0.035
	(0.025)	(0.025)	(0.023)	(0.025)
AuditCom_NonIndep%	–0.131	–0.128	0.040	–0.589***
	(0.279)	(0.281)	(0.141)	(0.181)
Ln(Analysts)	0.004	–0.001	–0.112***	–0.238***
	(0.046)	(0.045)	(0.020)	(0.022)
Big10	–0.091	–0.090	–0.020	–0.127***
	(0.079)	(0.078)	(0.041)	(0.040)
Ln(CEO_Age)	1.315***	1.322***	–0.209*	1.004***
	(0.302)	(0.302)	(0.113)	(0.192)
CEO_Tenure	0.045***	0.044***	0.003	0.058***
	(0.017)	(0.017)	(0.007)	(0.011)
CEO_Ownership	1.702	1.786	0.477	–4.853***
	(1.419)	(1.408)	(0.545)	(0.799)
CEO_Ownership^2	–4.725*	–4.858*	0.678	6.661***
	(2.828)	(2.809)	(1.279)	(1.464)
CEO_Founder	0.439***	0.444***	–0.099*	–0.213***
	(0.151)	(0.152)	(0.055)	(0.061)
CEO_Duality	0.937***	0.938***	0.041	0.216***
	(0.108)	(0.109)	(0.056)	(0.083)
CEO_InterConnect	0.225	0.227	–0.209***	0.331***
	(0.181)	(0.183)	(0.069)	(0.113)
CEO_Option	–0.031**		–0.008	
	(0.015)		(0.005)	
Stock_Return	–0.063**	–0.064**	–0.076***	–0.061**
	(0.029)	(0.029)	(0.025)	(0.030)
Stock_Turnover	0.021	0.021	0.020**	0.220***
	(0.017)	(0.017)	(0.008)	(0.023)
Stock_Volatility	2.544	2.525	–7.432***	–12.860***
	(2.741)	(2.751)	(2.211)	(3.047)
Ind_Concentration	–0.224	–0.217	–0.373***	0.827***
	(0.361)	(0.358)	(0.117)	(0.143)
Litigation_Risk	40.430***	40.855***	14.638***	19.683***
	(14.746)	(14.759)	(4.857)	(5.963)
Constant	–9.941***	–9.893***	–1.251*	–8.345***
	(1.809)	(1.808)	(0.670)	(0.953)
Cluster S.E. by industry	Yes		Yes	
Observations	13,382	13,382	13,382	
Log likelihood	–6445.135	–6451.232	–3573.952	
Pseudo R-squared	11.7%	11.7%	-	

Table 6

Mechanisms of political protection

This table reports the results for mechanisms of political protection. Panel A reports the OLS results for CEO political connections and turnover after fraud detection. The sample consists of 13,382 firm-year observations with politically connected CEOs from 2008 to 2017. Column (1) reports the coefficient. The dependent variable is *CEO_Turnover*, which is an indicator variable that equals 1 if there was a CEO dismissal, and 0 otherwise. $Fraud_{t\text{-}3\text{-}t}$ is an indicator variable that equals 1 if the fraud was committed within 3 years prior to fraud detection year, and 0 otherwise. Robust standard errors clustered at industry level are reported in Column (2). Panel B reports the analysis results of the relationships between CEO political connections and risk of detection. The sample consists of 1,083 firm-year observations and covers the 2008 to 2017 period. Column (1) reports the ratios of the Cox proportional hazards model. Column (2) reports the robust standard errors clustered at industry level. The dependent variable is *Fraud_Duration*, measured as the period between the year when fraud was committed and year of declaring enforcement. This is retrieved from "Violation Year" and "Declare Date" in "CSRC's Enforcement Action" of CSMAR. The model controls fraud type fixed effects. *Fraud_Type* is retrieved from CSMAR and categorized into 16 types: (Fictitious Profit = 1, Fictitious Asset = 2, Misleading Statement = 3, Delayed Disclosure = 4, Material Omission = 5, Other False Information Disclosure = 6, Fraudulent Listing = 7, False Capital Contribution = 8, Unauthorized Changes in Capital Usage = 9, Occupancy of Company's Assets = 10, Insider Trading = 11, Illegal Stock Trading = 12, Stock Price Manipulation = 13, Illegal Guarantee = 14, Misleading of General Accounting = 15, Other = 16. Panel C reports the results for CEO political connections and enforcement penalty. Panel C (1) reports the OLS results for enforcement penalty and CEO political connections based on the non-SOE sample with available data of enforcement penalty. The sample consists of 107 firm-year observations from 2008 to 2017. Column (1) reports the coefficient. Robust standard errors clustered at firm level are reported in Column (2). The dependent variable is *Fraud_Penalty*, which is the penalty amount in RMB millions retrieved from the CSRC's Enforcement Action database under CSMAR. Panel C (2) reports average treatment effect on the treated (ATT) for the sample matched with 1:1 nearest neighbor propensity score method without replacement based on *Ln(Assets)*, *EBITDA/TA*, *Fraud_Type* indicators, year indicators and industry indicators. Detailed variable definitions can be found in the Appendix. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: CEO political connection and CEO turnover following fraud detection		
Dependent variable: *CEO_Turnover*		
	Coef (1)	*S.E.* (2)
CEO_PC	–0.067	0.045
$Recent\_Fraud_{(t\text{-}3,\,t)}$	0.626***	0.086
$CEO\_PC\times Recent\_Fraud_{(t\text{-}3,\,t)}$	–0.347**	0.165
Controls	Yes	
Cluster S.E. by industry	Yes	
Observations	13,382	
R-squared	3.8%	
Log likelihood	–7296.958	

Panel B: CEO political connections and detection risk		
Dependent variable: *Fraud_Duration*		
	Hazards Ratio: Exp(Coef) (1)	*S.E.* (2)
CEO_PC	0.898***	0.013
Controls	Yes	
Fraud type fixed effect	Yes	
Cluster S.E. by industry	Yes	
Observations	1,083	

Concordance	0.645 (S.E. = 0.002)
R-squared	99.8%
Likelihood ratio test	6,831 (D.o.F. = 41)
Wald test	6,431 (D.o.F. = 39)
Score (logrank) test	6,661 (D.o.F. = 39)

Panel C: CEO political connections and detection penalty		
Panel C (1): Regression results of non-SOE sample		
Dependent variable:	*Fraud_Penalty* (RMB mil)	
	Coef. (1)	S.E. (2)
CEO_PC	–1.247*	0.749
Controls	Yes	
Year fixed effect	Yes	
Industry fixed effect	Yes	
Fraud type fixed effect	Yes	
Cluster S.E. by firm	Yes	
Observations	107	
R-squared	73.1%	
Log likelihood	–6.688	

Panel C (2): ATT results on propensity-score matched sample				
Dependent variable:	*Fraud_Penalty* (RMB mil)			
	Treated (3)	Control (4)	Difference (5)	S.E. (6)
ATT	1.352	3.293	–1.940**	0.918

Table 7

Different characteristics of CEO political connections and the likelihoods of fraud commission and fraud detection

This table reports the results of the bivariate probit model estimation for characteristics of political connections and corporate fraud. The sample covers the period from 2008 to 2017. Panel A reports the analysis of the effects of governmental political connections. *PC_Gov* is an indicator variable that equals 1 if a CEO has current or past experience of working in central government, local government, or the military, and 0 otherwise. Panel B reports the analysis of the effects of political positions. *PC_High* is an indicator variable that equals 1 if the CEO political position is higher than its industrial mean. CEO political position data are retrieved from the CSMAR database, which ranks the position level of political connections of CEOs (Chiefs at state level = 18, Deputies at state level = 17, Chiefs at the provincial and ministerial level = 16, Deputies at the provincial and ministerial level = 15, Chiefs at the department and bureau level = 14, Deputies at the department and bureau level = 13, Chiefs at the county and section level = 12, Deputies at the county and section level = 11, Chiefs at the township and sub-division level = 10, Deputies at the township and sub-division level = 9, Counsel = 8, Associate counsel = 7, Consultant = 6, Associate consultant = 5, Principal staff member = 4, Senior staff member = 3, Staff member = 2, Clerk = 1, Others = 0). Panel C reports the analysis of the effects of political tenure length. *PC_Tenure* is the number of years that a CEO has served in a political institution. Panel D reports the analysis of the effects of current political position. *PC_Current* is a ranking variable that equals 2 if a politically connected CEO is a current NPC or CPPCC representative with past working experience in government, 1 if a politically connected CEO is a current NPC or CPPCC representative but without working experience in government, and 0 if the political position of CEO is not current. Panel E reports the analysis of the effects of military connections. *PC_Military* is an indicator variable that equals 1 if a CEO served in the military in the past, and 0 otherwise. Column (1) of each panel reports the effects of the political connection characteristic on the likelihood of committing fraud. Column (2) of each panel reports the effects of the political connection characteristic on the likelihood of fraud being detected. Detailed variable definitions can be found in the Appendix. Robust standard errors clustered at the industry level are reported in parentheses. Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Panel A		Panel B		Panel C		Panel D		Panel E	
	Experience in central or local government, or the military		Political position ranking above industrial mean		Political tenure length		Power of current political connections		Revolving-door CEOs	
	Pr(F) (1)	*Pr(D|F)* (2)	*Pr(F)* (1)	*Pr(D|F)* (2)	*Pr(F)* (1)	*Pr(D|F)* (2)	*Pr(F)* (1)	*Pr(D|F)* (2)	*Pr(F)* (1)	*Pr(D|F)* (2)
CEO_PC	0.050	–0.008	0.075	–0.332***			0.110***	–0.132***	0.089*	-0.109**
	(0.049)	(0.104)	(0.058)	(0.063)			(0.042)	(0.044)	(0.048)	(0.047)
CEO_PC×PC_Gov	0.086	–1.541***								
	(0.097)	(0.513)								
CEO_PC×PC_High			–0.049	–0.176**						
			(0.077)	(0.084)						
PC_Tenure					0.139***	–0.658***				
					(0.033)	(0.216)				
CEO_PC×PC_Current							–0.044	–0.125*		
							(0.074)	(0.072)		
CEO_PC×PC_CSRC									0.533	-2.414***
									(0.342)	(0.637)

Controls	Yes	Yes	Yes	Yes	Yes
Cluster S.E. by industry	Yes	Yes	Yes	Yes	Yes
Observations	13,382	13,382	424	13,382	13,382
Log likelihood	–3565.747	–3545.269	–64.362	–3576.459	-3577.489

Table 8

CEO political connections, past fraud, and firm valuation

This table reports the OLS results for CEO political connections, past fraud, and firm valuation. The sample consists of 13,382 firm-year observations from 2008 to 2017. Column (1) reports the coefficient. The dependent variable is industry-adjusted Tobin's Q in year t+1, $IA\_TobinQ_{t+1,}$ which is measured as the gap between Tobin's Q and its industrial median in year t+1. *PreFraud* is an indicator variable for treated firms which received at least one fraud enforcement prior to 2013. Detailed variable definitions can be found in the Appendix. Standard errors are reported in Column (2). Classification of industries is based on the 2012 CSRC Industry Codes. Coefficients marked with *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Dependent variable: IA_TobinQ_{t+1}	Coef. (1)	S.E. (2)
CEO_PC	0.143**	0.064
CEO_PC×PreFraud	–0.228**	0.098
CEO_PC×Post-Anti-Corruption	–0.129**	0.056
CEO_PC×PreFraud×Post-Anti-Corruption	0.251***	0.090
Enforce	–0.021	0.035
Ln(Assets)	–0.09***	0.029
Leverage	0.771***	0.091
Growth	–0.008	0.016
EBITDA/TA	0.086	0.210
TobinQ	0.988***	0.008
Ind_TobinQ	–0.749***	0.081
Ind_TobinQ2	–0.026**	0.010
State_Ownership	–0.659*	0.379
Board_PC	0.106	0.080
Ln(Board_Size)	0.205	0.127
Board_Indep%	–0.003	0.345
Institutional_Ownership	0.65**	0.268
Ln(Board_Meeting)	–0.001	0.039
Ln(Audit_Committee)	–0.02	0.015
AuditCom_NonIndep%	–0.073	0.095
Ln(Analysts)	0.067***	0.015
Big10	0.049	0.033
Ln(CEO_Age)	–0.077	0.116
CEO_Tenure	0.012*	0.006
CEO_Ownership	0.386	0.496
CEO_Ownership2	0.769	1.089
CEO_Founder	–0.01	0.063
CEO_Duality	–0.002	0.040
CEO_InterConnect	–0.208***	0.054
Stock_Return	0.001	0.004
Stock_Turnover	0.06***	0.018
Stock_Volatility	0.005	0.006
Constant	–1.838	2.108
Year fixed effect	Yes	
Firm fixed effect	Yes	
Observations	13,382	
R-squared	84.6%	
Log likelihood	–17563.88	