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Three Essays on Government Intervention in Financial Markets

By

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To my parents, those I love, and those love me

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Chapter 1

Introduction

Motivation

Since the 1900s, the laissez-faire economic philosophy, famously associated with Adam Smith's concept of the "invisible hand" in his work *The Wealth of Nations* has gained widespread acceptance. This concept posits that markets can naturally reach equilibrium without the need for government intervention or external forces. It asserts that voluntary private markets are inherently more efficient than government-controlled economies.

However, critics argue that this pursuit of equilibrium can lead to undesirable outcomes for society, such as monopolies, excessive market power concentration, environmental degradation, and inequalities. As a result, the role of government intervention in regulating markets has become increasingly evident. Notable financial market regulatory reforms, such as the Dodd-Frank Act in the United States, have aimed to protect investors and enhance stability by introducing new reporting requirements and regulatory bodies. In the European Union, the European Commission has proposed over 50 legislative and non-legislative measures in financial services since the global financial crisis ¹. This ongoing interplay between government intervention and voluntary private markets remains a crucial and necessary topic of discussion.

In this thesis, I examine this issue within the context of the rapidly evolving Chinese financial market. Over the past two decades, this emerging market has experienced remarkable growth, shaped by distinctive reforms and policies. Notably, [Brunnermeier et al. \(2022b\)](#)'s work proposes a theoretical framework for discussing China's economic model, which involves active government intervention in financial markets. This model seeks to strike a balance between stabilizing the market and enhancing stock price efficiency. I specifically focus on two regulatory interventions in the Chinese financial markets: the Random On-Site Inspection Policy in 2016 and the Split Share Reform in

¹<https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-decade-of-financial-regulatory-reform-2009-to-2019.pdf>

2005. Both policies share the common goal of mitigating negative externalities within the financial market, but they employ distinct approaches.

In Chapter 2 and Chapter 3, within the framework of the Random On-Site Inspection Policy, we collectively explore the central question: "What impact do enforcement actions have on listed firms?". Chapter 2 tackles this question by scrutinizing market reactions in light of the heightened probability of detection resulting from the policy. It delves into how the market responds to this increased scrutiny. On the other hand, Chapter 3 delves into how a firm's internal governance adapts in the face of enforcement actions. It delves into the changes in a firm's internal governance structure as a response to enforcement actions. Moving on to Chapter 4, we shift our focus within the context of the Split Share Reform. This chapter aims to demonstrate that, in contrast to the Random Inspection, which is designed as a punitive and deterrent measure, regulators in this case prioritize setting requirements. It grants underperforming firms the opportunity to gradually meet the prerequisites for reform.

Chapter 2 Can markets predict enforcement actions?

In previous studies, endogeneity issues have complicated our understanding of the impact of enforcement actions on firms' violations. There are two primary challenges to consider. First, market reactions to the enforcement action can be challenging to interpret, given that stock prices continually incorporate various market information through trades. It becomes unclear when information related to violating activities is incorporated into stock prices, particularly before regulators reveal their punishments. Second, enforcement actions may be subject to bias due to regulators' limited attention or potential political affiliations with target firms ([Kedia and Rajgopal, 2011](#); [Filip et al., 2020](#); [Calluzzo et al., 2021](#); [Yu and Zheng, 2019](#)). As a result, the future cash flows of firms may be influenced by factors beyond the enforcement actions themselves.

To establish a clear understanding of how enforcement actions affect a firm's future cash flows, I leverage the quasi-random inspection policy implemented in China in 2016. This policy mandated that 36 Chinese jurisdictions randomly select 5% of locally listed firms for investigation, targeting those engaged in violating activities violating securities laws. Through this Random Inspection Policy, I address two empirical challenges. First, it allows us to disentangle information related to violations from other factors influencing a firm's fundamental value. This is possible because the date when the firm has been selected serves as a clear and pivotal time point, marking the initiation of the investigation and the subsequent increase in the likelihood of detection. Moreover, the selection date varies across jurisdictions and years and is unpredictable, adding to the reliability of our event study. Second, enforcement actions' outcomes often carry inherent biases, leading to market reactions influenced by these biases. The randomness inherent in the policy helps mitigate these biases, and it also eliminates endogeneity

issues tied to the concept that pre-existing market signals trigger investigations.

A valid concern revolves around a firm's initial risk exposure just before the selection process. Investors in firms already under regulatory scrutiny prior to the event might not significantly alter their perspective on future detection risks. To address this concern, I categorize firms as either "low-exposed" to regulators if they received no regulatory letters in the year preceding the selection or "high-exposed" if they did. Further differentiating based on their initial exposure level, I classify firms that received regulatory sanction letters after the random inspections as "violating" and those that didn't receive any such letters as "non-violating."

The comparison of market reactions among groups yields surprising findings. Within the "low-exposed" group, violating firms experienced a negative market reaction on the date they were randomly selected. No significant market reactions were observed in non-selected firms or non-violating firms. The same pattern has not been found in the "high-exposed" neither. These results suggest that stock prices respond to the violating behaviors of listed firms when the likelihood of future detection risk increases.

Chapter 3 How firms endure and succeed under detection risks

In this chapter, I collaborate with my colleague, Li Bao, to address the question of how enforcement actions influence a firm's internal governance. Previous studies have indicated that firms often experience reputational damage and job losses after regulatory sanctions (Wu et al., 2020; Blackburne et al., 2021; Qin et al., 2021; Sun and Zhang, 2011; Ji et al., 2023; Billings and Cedergren, 2015). These findings highlight the importance of effective internal governance within violating firms.

However, it's essential to acknowledge that the observed consequences of such punishments may not solely result from the enforcement actions themselves. Factors such as inspection bias and regulators' limited attention can contribute to these outcomes. This complexity makes it challenging to fully comprehend the precise mechanisms through which regulatory interventions impact firms internal governance.

We approach this question in two parts: 1) We first investigate whether blockholders exit due to the heightened intensity of enforcement actions, referred to as "Wall Street Walk" (Dasgupta and Piacentino, 2015). To do this, we begin by examining the turnover among the top 10 largest shareholders. Using a novel proxy that captures shifts in ranking within the top 10 largest shareholders, we find no significant shifts in this group. 2) Moving on to the impact of enforcement actions on management team turnover, we take steps to filter out any turnover attributed to sanctions. This filtering approach excludes members whose tenure began after the selection date and ended after any regulatory sanctions were issued. We find that violating firms, during the post-event period, are

more likely to experience increased turnover compared to non-violating firms. This finding is in line with (Karpoff and Lott, 1993),’s earlier research, which suggested that firms facing litigation risks tend to see increased turnover among managers. Our study extends this insight by demonstrating that violating firms exhibit higher director turnover compared to managers, with no notable turnover changes observed among supervisors. Moreover, we find that in non-violating firms, there’s a decrease in management team turnover.

To solidify the idea that management team turnover responds to the perceived increase in future detection risks, rather than being attributed to regulatory sanctions, we merge turnover data for each management team member with their corresponding transaction records using identification ID numbers. We discover that in the months leading up to the event, resignations among management team members exhibit a significant positive relationship with their share-selling behavior. This provides further evidence supporting the notion that management team turnover is influenced by the perceived increase in future detection risks.

Overall, our study corroborates the findings of previous literature by highlighting the negative impact of regulatory detection on management team turnover. Furthermore, we contribute by presenting new evidence of non-exit strategic behavior among blockholders and the positive effect on non-violating firms.

Chapter 4 A new perspective of the Split Share Reform: the study of market reaction

Chapter 4 discuss the interplay between government intervention and financial market within the context of the Split Share Reform (SSR). The objective is to demonstrate that, unlike the zero-tolerance approach of random inspections, which primarily aims to create a deterrence effect, the regulators, in the case of the SSR, work towards enhancing the performance of poorly performing firms through the implementation of specific reform requirements.

The SSR mandated that all listed firms grant tradability to their previously non-tradable shares (NTS). Additionally, non-tradable shareholders were required to offer compensation to tradable shareholders in exchange for liquidity rights. Notably, the commencement of the reform for each firm depended on a combination of factors, including a recommendation from a sponsoring agent, the firm’s own motivation, and approval from the state. This complex interplay resulted in a unique reform date for each firm.

Due to the endogeneity in the timing of the reform, I divided my sample into two distinct groups based on when firms engaged with the reform: the early-stage and later-

stage groups. I observed that younger firms with higher ROA, fewer tradable shares, greater long-term liabilities, fewer state-owned shares, and better liquidity tended to adopt the reform during the early stage. This finding not only affirms the existence of endogeneity issues in reform timing but also underscores the significance of categorizing firms into these two groups for a more comprehensive study of the SSR's impact.

To assess the reform's impact on firm performance, I performed an event study using each firm's distinct reform date when the compensation plan was initiated. A potential concern was whether there was market learning involved in shaping the expectations of compensation. If this were the case, we would expect to find no significant Cumulative Abnormal Returns (CAR) in the later-stage groups. However, my findings indicate that both early and later-stage groups experienced a significantly positive market reaction. This suggests that the later-stage groups reacted to the firm's specific compensation plan upon its announcement rather than forming expectations beforehand and reacting in advance.

This leads us to the next question: when a firm announces its compensation plan, the observed CAR around the announcement date is expected to encompass both the fundamental impact of the reform and the reaction to the potential compensation anticipated by tradable shareholders. Numerous scholarly articles have examined the substantial impact of this reform (Lu et al., 2012; Beltratti et al., 2016; Firth et al., 2010). They have emphasized a noteworthy positive abnormal return on the announcement date, reflecting investor optimism about the reform. However, there has been limited research exploring market reactions that account for the firm's learning process between the government's announcement and the firm's implementation date, alongside investor expectations regarding compensation levels.

In order to differentiate the effect of the reform from the compensation expectation, I isolated the compensation ratio from the CAR. The results indicate a significant negative abnormal return after removing the compensation component from CAR. I proceeded with further investigation to determine what drives the market reaction after accounting for compensation expectations and how this reaction varies between the early-stage and later-stage groups. I used Free Cash Flow to Equity (FCFE) as a proxy for a firm's financial condition. An increase in FCFE suggest thats the firm has greater opportunities for profitable investments or carries fewer liabilities. Interestingly, I found that firms in the later-stage group exhibited a more substantial increase in the change of FCFE just prior to the reform compared to the early-stage group. Investors responded positively to these financial improvements. In sum, the requirement for compensation encourages firms that initially couldn't meet the criteria to enhance their financial standing. In contrast to prior research on post-privatization effects (Boubakri et al., 2005; Megginson and Netter, 2001; D'Souza et al., 2005; Sheshinski, 2003; Jefferson and Su, 2006), my

study examines how underperforming firms work towards meeting prerequisites before privatization is complete.

In summary, this thesis offers a fresh perspective on the dynamics between government intervention and the financial market, utilizing two significant regulatory policies in the Chinese financial market as its foundation. The context of the random inspection policy offers a quasi-random setting for investigating the trading of concealed information, particularly a firm's violating behaviors influenced by regulatory intervention. In contrast, the Split Share Reform facilitates an event study that accounts for investors' existing expectations already factored into market reactions at the event date.

The thesis reveals several key findings: i) It highlights the presence of hidden negative information that emerges as a response to shifts in the perception of future regulatory conditions. ii) The enforcement action not only penalizes violating firms but also assists the market in recognizing non-violating firms, often leading to decreased management team turnover. iii) The market typically responds positively to improved financial performance in underperforming firms compelled to meet reform targets. In essence, this thesis emphasizes the crucial role played by the government in mitigating negative externalities within the financial market.

Chapter 2

Can Markets Predict Enforcement Actions?

2.1 Introduction

Financial violations have maintained significant attention from regulators and investors for decades. While the methods for detecting financial violations have developed over the years, the techniques for financial manipulation have evolved even more rapidly during the same period (West and Bhattacharya, 2016; Reurink, 2018; Karpoff, 2021). According to information available on the website of the Chinese Securities Regulatory Commission (CSRC), it analyzes financial violations as below ¹

In 2020,...[a] total of 116 cases (15.7% of total financial violation cases) were transferred and reported to the police, a year-on-year growth of 100%, with the following features: 1. the fraud cycle is long, and the amount involved is large; 2. the phenomenon of organized market manipulation is prominent; 3. over 80% of insider trading cases meet criminal prosecution standards.

In this paper, I propose to investigate whether the market possesses information about a firm's violations before regulatory authorities disclose the sanctions they will impose. If this indeed holds true, I will delve into how this information might be reflected in the stock price. Gaining insights into this question could assist regulators in leveraging market information for designing future violation detection strategies.

A substantial body of empirical research examines market reactions to financial violations, particularly how markets respond unfavorably to the disclosure of corporate misconduct (Karpoff et al., 2008a; Gande and Lewis, 2009; Armour et al., 2017; Yu and Zheng, 2019; Ning et al., 2021; Chen et al., 2005; Cheung et al., 2021; Xu and Xu, 2020). This market decline is a result of both the fines imposed and potential future

¹<http://www.csirc.gov.cn/csirc/c100028/c00cf47ad6dcc443ea7a95c24334a463c/content.shtml>

decreases in cash flow for the firm. However, discerning the extent to which this price change aligns with the identified violations proves challenging. Given that stock prices continually incorporate information from market participants' trades, it's plausible that the violation-related information could have already been priced into stock prices during the firms' investigation period. Due to the absence of a clear investigation framework, the empirical studies to date could only explore the ex-post effect of punishing violating firms. Our understanding remains limited regarding pre-regulatory punishment outcomes, underscoring the significance of a specific event that enables differentiation between reactions to violations and other factors influencing the firm's cash flow.

My study is built upon a distinctive inspection policy framework overseen by the CSRC. Launched in 2016, this policy consists of two stages. During the initial stage, local CSRC offices are mandated to randomly choose 5% of locally listed firms for on-site inspections, aimed at identifying potential misconducts that violate securities laws. The selected firms are publicly announced on the respective local authorities' websites. Due to the jurisdiction-based nature of selection, this process occurs at various points throughout the year, without a fixed date for each jurisdiction annually. From 2016 to 2021, regulators selected 853 listed firms across 36 jurisdictions. Moving to the second stage, the selected firms undergo on-site inspections conducted by regulators. These inspections usually take place several months after the initial selection. It is during this phase that any existing violations come to light, leading to the imposition of sanctions on the firms. These sanctions are made public through letters issued by the CSRC or by the exchanges. It's worth noting that even without the element of random selection, firms in violation still have the potential to be exposed (e.g., through routine monitoring or shareholder complaints). Nevertheless, our expectation is that the random selection process will heighten the likelihood of detection for listed firms.

The aim of this study is to gauge the degree to which stock prices assimilate information about existing violations, thereby enabling the anticipation of forthcoming sanctions. To address this question, I conduct an event study focused on the day when the selection results are announced. At this initial stage, the public becomes aware only of the firms chosen for inspection, while the outcome of the subsequent stage, determining whether a firm will face sanctions, remains unknown. I delve into how the market reacts to future sanctions, observing that the market's response is confined to firms that are indeed sanctioned during the second stage, and not to those that do not receive any sanctions. Specifically, I note that the cumulative abnormal return (computed for a window spanning 10 days before and after the event date) falls by 2.3% in reaction to each additional regulatory sanction letter issued within the year following the selection event.

Additionally, I identify this pattern exclusively within "low-exposure" firms. Exposure level serves as a gauge of the degree to which a firm's existing violations are

subject to regulatory scrutiny. As the sanction outcomes are communicated via letters, I split my sample into low-exposure and high-exposure firms, based on whether they had received regulatory letters prior to the selection event. The impact of the random selection event appears to exert a more substantial influence on the likelihood of detection for firms classified as low-exposure, as opposed to those classified as high-exposure. This distinction arises from the fact that firms exposed to regulatory attention inherently possess a higher probability of undergoing investigation, irrespective of whether they are randomly selected. Notably, I discover that among the low-exposure firms, the market's reaction at the selection announcement date diverges significantly contingent upon the diverse outcomes of sanctions during the second stage. I establish a negative correlation between the market's reaction and the number of regulatory letters received within the year subsequent to the selection.

Once I find the existence of the negative relationship between the market reaction and the future punishment, I then move to explain this market predictability. More specifically, is it public information, private information, or both that have been traded on the event date? To answer this question, I refer to the paper of [Gande and Lewis \(2009\)](#) to construct a factor capturing public information-based belief of existing violations: the violation signal. I use the previous two years' public information of listed firms, such as ownership structure, profitability, market size, liquidity, political ties, and M&A activities, to predict letter issuances one year before the selection. I first confirm that the violation signal is significantly positively associated with future letter issuances. I further conduct a two-least-stage-square model to show to what extent the market reaction based on the violation signal is related to the future sanctions. The result is surprising. A 1% increase in the public information-based market reaction is associated with an increase in the future issuance of sanction letters by 1.187. The public information-based market reaction significantly negatively predicts future sanctions of a random inspection, suggesting that the market participants can adjust their belief on the probability of being detected based on the firm's public information. This adjustment is efficiently revealed by stock prices. I further examine market predictability based on private information. Private information is represented as the gap between the actual market reaction at the announcement date and the predicted one based on public information. Interestingly, private information can also significantly predict future sanctions.

To further understand the information, I analyze the content of regulatory letters by conducting textual analysis. I find that private information plays a significant role, especially in predicting future sanctions of violations relating to difficult-to-detect and hidden violations, such as illegal insider trading. To have further evidence on market informational efficiency, I go one step further to dig into the role played by institutional investors. I expect that the change in the stock price will incorporate more accurately the change of firms' fundamental value with the presence of informed traders. The find-

ings confirm this expectation. In firms where institutional investors have a large stake (larger than the sample median), public information predicts future sanctions significantly. However, in firms with smaller institutional ownership, only private information keeps significant predictability.

The random on-site inspection policy setting allows me to study the efficiency of financial markets on firms' violations by addressing the following two difficulties. First, asset prices continuously impound information. It is difficult to distinguish the information of violations from other information affecting the firm's fundamental value if we don't have a specific event that can trigger the trading of this type of information. The very first investigation of a suspected violation may trigger trading by market participants. However, due to the confidentiality of the regulatory investigation, it isn't easy to know the exact time point from which the regulators intervene. In this study, the unique random inspection policy in the Chinese financial markets helped me set a clear investigation time point, which is the day when the regulator announced to the public which firms have been randomly selected to be investigated. Second, the punishment outcomes are often biased for several reasons: the sample of enforcement action usually reflects a small un-random subset of all misconducts. (Kedia and Rajgopal, 2011; Filip et al., 2020; Calluzzo et al., 2021) Due to the limited attention of regulators, the punishment may be concentrated to some specific types of firms. For instance, in the paper of Calluzzo et al. (2021), the authors note that firms closer to the regulators in distance receive more attention and are more likely to be sanctioned, leading some firms that can move to choose to relocate their headquarters. Political ties also show the effect in mitigating the sanctioning impact on the market (Yu and Zheng, 2019) and the propensity to be detected (Mehta and Zhao, 2020). In China, the former Premier pointed out at an executive meeting in 2018 that wayward inspections of some departments have left room for "rent-seeking" market supervision.² Consequently, market reactions to biased enforcement action reflect mixed information: investors' attitudes towards the regulator's intervention and pure information on firms' violations. Therefore, the randomness of the inspection is vital for my research setting. In Section 5, I precisely examine the randomness of this policy. The randomness eliminates the bias of the enforcement action sample. It also removes the endogeneity issues related to the fact that an existing market signal may trigger an investigation (Dyck et al., 2010; Choi et al., 2019). Since the selection covers all the listed firms, no one can predict the selection outcomes. However, some jurisdictions applied a stratified sampling selection process based on regulators' information of firms' violations. Thus, I expect the selection ratio to be lower in low-exposure firms than in high-exposure firms in these jurisdictions. Moreover I confirmed that the selection result is random by regressing on different firm characteristics within each group. Concerns could still rise about the regulator's manipulation of assigning

²Article in State Council: Random inspection method to boost market fairness:
http://english.www.gov.cn/policies/policy_watch/2018/06/12/content_281476181661134.htm

sampling groups due to some other reason that may not be captured by my regression. But I am not suffering from this issue. For instance, if a high-exposure firm is "manipulated" to be "safe" and has been put in a low-selection ratio group, then we could imagine that the selection results would be a stronger shock to this firm compared to other firms.

My paper contributes to two growing literature, including but not limited to: (i) the detection of violations by investors, and (ii) the market efficiency and price formation in financial misconducts.

Discussions on the collection and trading of fundamental firm values for profit by informed traders can be traced back to the model proposed by [Grossman and Stiglitz \(1976\)](#). The information transparency of the firms also decreases the costs for informed traders (short-term) to collect information and further increase the trading volume [Georgakopoulos \(1996\)](#). More recently, a growing body of papers continues to demonstrate the anticipation and predictability of frauds by informed traders ([Cotter and Young, 2007](#); [Karpoff and Lou, 2010](#); [Dai et al., 2021, 2022](#)). For instance, the paper of [Karpoff and Lou \(2010\)](#) finds that short sellers are able to detect the firms that mispresented financial statements, and abnormal short interest builds steadily in these stocks during the 19-month period before the public revelation. A similar conclusion has been drawn by [Dai et al. \(2021\)](#), where firms that are unable to disclose timely financial reports have been predicted by short sellers who trade them with a profit. This isn't only the case for short sellers as [Cotter and Young \(2007\)](#) find that the anticipation of accounting fraud exists in analysts. They observed that firms that commit more extensive fraud are significantly more likely to have analysts drop coverage before the public disclosure of fraud. However, there are two limits concerning this predictability of financial misconducts. First, we only observe that informed investors trade the violating firms to gain profit, which cannot remove the possibility of confounding effect, as other factors affecting the firm's future cash flows differ from violating behaviors. Meanwhile, the endogeneity issue remains as investigation is triggered by the change of informed traders' trading behavior. Second, the previous literature only focuses on the role played by informed traders and discusses little about uninformed trader. As one of the Grossman-Stiglitz investors,³ uninformed traders are also considered to trade with strategy by interpreting the signal of asset value impounded in asset prices. In this sense, my paper shows direct evidence of market predictability of information on violations. I also show the significant role played by uninformed investors in predicting future punishment based on public information on the market. My study also points to a more general conclusion, as I find that market predictability widely exists across markets and is unaffected by the different types of financial frauds.

³Refers to the name used by [Cohen et al. \(2020\)](#) in their paper, who named the investors that are living in a world where Grossman-Stiglitz theory applies perfectly, are compensated for the marginal value of the information they collect, process, and impound into prices.

In attempting to identify the market's role in guiding regulatory institutions, my paper also helps in adding empirical evidence. Some well-known theoretical papers like [Dow et al. \(2017\)](#) and [Goldstein and Guembel \(2008\)](#) discuss how an agent's action affects security's fundamental value. [Bond et al. \(2010\)](#) also discuss the situation where agents learn from the market to correct their intervention decision. Meanwhile, the market also forms their expectation on whether the intervention occurs. As a result, the price becomes less informative. My paper provides empirical evidence that markets adjust their beliefs based on the likelihood of the occurrence of regulatory events. And the results are consistent with theory in showing the complementary relationship between market information and regulatory information. Therefore, market information can be used by regulators to implement efficient detection.

Finally, concerning the question related to undetected frauds ([Ashton et al., 2021](#); [Dyck et al., 2021](#)), my paper also contributes in estimating the pervasiveness of violations. Among the 853 companies that were randomly inspected, 83 companies were further sanctioned by regulators, indicating that about 9.7% of violations were undetected, associated with a market loss of about 126 million US dollars.⁴

2.2 Background

2.2.1 Chinese Securities Regulatory System

Regulators' Rights and Obligations

The CSRC was established in 1992 and based in Beijing. It aims to maintain orderly securities and futures markets and ensure a legal operation of the capital markets. There are 36 securities regulatory bureaus in the jurisdiction as CSRC local offices. In general, the local offices must report all the work to the headquarter. And for some special cases, they need to apply for approval to act from the headquarter.

The CSRC exercises a vertical administration over the domestic securities and futures regulatory institutions. Thus, the securities and futures exchanges have been supervised by the CSRC, whereas their senior managerial personnel by the relevant regulations have been supervised by the CSRC as well. They monitor the behaviors of the listed companies and their shareholders, who should fulfill the pertinent obligations according to the relevant laws and regulations. The regulated subject will be investigated or penalized by the CSRC for conducting any activities violating the relevant securities and futures laws and regulations.

⁴Use the market reaction at the random selection event date multiplies by the average market capitalization of the detected firms, with the exchange rate on the 31st October 2022 between one Chinese Yuan to 0.14 US Dollars.

The local office has the duties and rights to monitor the listed companies as day-to-day supervision and an on-site inspection. The purpose is to collect first-hand documents. The preliminary examination will be made afterward and be reported to the CSRC's main office, which makes the final decision and then delegates the conduct of the decision to the local office. For severe cases, the penalization will be conducted directly to the regulated subject from the CSRC main office. The items to be supervised and inspected includes required disclosures, corporate governance, internal control, operational norms, etc. The local office shall determine the specific inspection items by laws, administrative regulations, and regulations of the CSRC.

There are two stock exchanges in mainland China,⁵ which are the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The securities exchanges are supervised and regulated by the CSRC. Thus, the exchanges must take responsibility to the CSRC in detecting the violation of relevant securities and futures laws and regulations. They check the information disclosures of the listed firms, the trading behaviors of the investors, and the activities of its members.⁶ Before 2015, the exchanges had no right to investigate the listed firms by themselves but only to do daily monitoring. After 2015, the exchanges have been entrusted by the CSRC to investigate some specific cases, increasing the detection efficiency of CSRC, and giving the exchanges the right to collect data from the listed companies.

Regulatory Letters

The listed firms that violate securities laws or any securities regulations are facing enforcement actions from two parts: the CSRC and the exchanges. In general, the investigated firms will receive regulatory letters which describe the facts of violations and the form of punishment.⁷ In this paper, I generalize the regulatory letters into two types depending on its content: sanction letters and question letters. The sanction letters indicate any form of punishment that regulators have decided. They can be issued either from the CSRC or from the exchanges. In comparison, the question letters describe any suspicious facts or cases of missing evidence of violating behaviors and require the investigated firms to give responses. This type of letter can only be found in exchanges.

Since the severe cases need to be reported to the CSRC to make the final punishment

⁵In September 2021, a third stock exchange was established in Beijing. The purpose is to help serve small and medium-sized enterprises in China. I did not exclude this exchange in this study as the study period ends in 2020.

⁶The stock exchange members indicate the qualified domestic securities business institutions established with approval and with legal person status. The foreign securities business institutions could apply for entry as special members. In China, the securities business institutions include the securities company, trust and investment companies, and the consultancy company for investors.

decision, the sanction letters issued by CSRC should be expected to cover severer cases than the ones issued by the exchanges. Meanwhile, the enforcement actions of exchanges focus more on information disclosures and trading behaviors. The enforcement actions of the CSRC concentrate more on the listed firm's corporate governance and any other complicated and hidden cases.

Table 2.1: Summary of Duties and Rights of Chinese Securities Regulatory Institutions

Regulators	Responsibilities	Rights
CSRC and local offices	i. Sanction for any violation of security law	i. On-site inspection; ii. Day-to-day monitoring; iii. Sanction letter
Stock exchanges	i. Be monitored by CSRC; ii. Monitor listed firms	i. Disclosure monitoring; ii. Be entrusted by CSRC to directly investigate and collect info for some specific cases; iii. Question letter, Sanction letter

2.2.2 Random On-site Inspection Policy 2015

In 2015, the State Council of the People's Republic of China established a "Double-Random" on-site inspection policy for the market. The purpose is to enforce the enforcement action and the deterrence effect on market misconduct behaviors. The CSRC, as the primary regulator of the financial market, further conducted a random on-site inspection selection policy for the financial markets at the end of 2015, following the policy guideline of the State Council. More precisely, the CSRC indicates that listed firms should be randomly selected for inspection at least once per year. Each jurisdiction should randomly select at least 5% of the locally listed firms (in number) per year for on-site inspection. And it requires two randomnesses (so-called "Double-Random"): the inspectees - listed firms - should be randomly selected, and the inspectors – inspection officials - should be at least of two persons and be randomly selected from the qualified enforcement inspector's database. The selection process should be recorded and publicly available.⁸

⁸The guideline of the random selection policy of the CSRC precisely defines the firms that should not be included in the random inspection lists. They are: 1. Companies that have undergone a comprehensive on-site inspection by the local office in the past three years, and whose main business and actual controller have not changed; 2. Companies that have been included in various special on-site inspection places; 3. Companies that have been filed for inspection and have not yet closed the case; 4. Companies that have been included in the current year's inspection plan by other departments (such as the issuance department, institutional department, bond department, accounting department, etc.).

On the local office's website, we could find the date of the selection result announcement (usually 1-2 days after the selection has been conducted), the list of firms that have been randomly selected, and the selected inspectors. However, it is unknown for the public as the exact date of the following on-site inspection.⁹

The CSRC local office has a certain level of autonomy in designing the selection based on the local situation. According to the guideline of the State Council:

It's important to ensure the necessary coverage and effort of on-site inspections and prevent excessive inspections and enforcement actions from disturbing people's daily lives. For market entities with many complaints and reports, listed in the list of abnormal business operations, or with records of serious violations of laws and regulations, it is necessary to increase random inspections.

A stratified sampling selection process is thus recommended based on the severity of the violation risks of the locally listed firms.¹⁰ The CSRC local office is expected to design an accurate selection process according to their information of the local listed firms' violation risks. In this way, random selection ensures the efficiency of the enforcement action: the high-risk firms are more likely to be selected for inspection and to be detected. In contrast, low-risk firms are less likely to be inspected. The selection can cover different violation risks as much as possible to avoid a selection result that may concentrate on just some types of firms. It also indicates that the probability of being randomly selected may vary over listed firms.

It is important to note that the stratified sample selection does not destroy the randomness of the policy but only affects the study of the information-revealing process, as some firms' violations have been highly exposed to regulators and so the market but not others. Therefore, precise information on how the regulators classified the firms would be better to have while setting my research sample. Unfortunately, there is no uniform disclosure for the selection design. This un-precise disclosure of selection design adds difficulty to my research. In Section 5.1, I precisely discuss the measurement to proxy the regulator's information on violation risks and prove the randomness and reliability of this policy.

⁹The firms that have been selected will be informed several days before the on-site inspection to prepare the necessary documents, etc. However, for the public, we have no access to the exact date of this on-site inspection. In general, it may happen several months after the selection results have been announced.

¹⁰The violation risk indicates the historical records and information of violations of securities law or regulations in a listed firm. This information may be discussed between the CSRC local office with different departments of exchanges, such as the department taking charge of the listing, annual report disclosures, capital restructuring activities, etc. We may or may not know the exact classification design on the website. One example of selection design has been given in Appendix 9.5.

2.3 Hypothesis Development

In this section, I set up a probability tree based on traditional asset pricing theory to illustrate my research objective and hypothesis.

Based on asset pricing theory, the stock price of listed firms is the present value of firms' future cash flows. It varies with the change of fundamental value. In my setting, the firm's future cash flows are shocked by the random selection of inspection. Market participants form the price based on their belief with their private information and public information, which reveals the probability that firms' good state and bad state happens. Precisely, in bad states, firms experience punishment related to the violating behaviors imposed by regulators. In good states, firms realize the profit. The random selection event increases the probability of firms' bad states happening. Thus, sophisticated investors with superior information would update firms' expected value, which drives down the stock price on the event date.

2.3.1 The Probability Tree

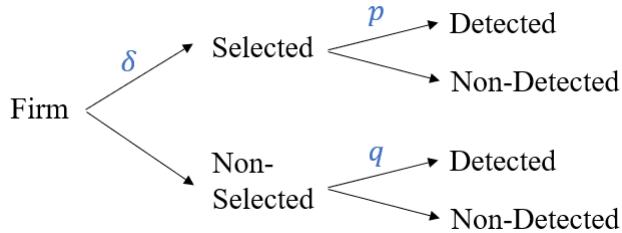


Figure 2.1: Probability tree

Prices Formation and Market Reaction

I use a simple probability tree 2.1 to illustrate my setting. For a listed firm, it has δ as the probability of being selected in this random selection event (at time t). It will further be detected with a probability of p given it has been selected. Otherwise, the probability of being detected is unchanged, which is represented as q . Market participants have information about existing violations form their belief of the firm's probability of being detected as q (at time $(t - 1)$). Meanwhile, they adjust the belief in response to the future probability change from q to p , as the violations might be uncovered once an inspection is (randomly) launched. The firm realizes the profit of π . To simplify, I assume that at bad states where the realization of detection, $\pi(Detected) = 0$. Otherwise, the firm keeps its expected profit as $\pi(NonDetected) > 0$. The price function before the selection happens is given by:

$$Price_{t-1} = [\delta(1-p)\pi + (1-\delta)(1-q)\pi] \quad (2.1)$$

After the selection results has been announced to public, the price is adjusted as follows:

$$Price_t = (1-p)\pi \quad (2.2)$$

where the probability to be selected δ no longer plays a role in forming the expectation.

I am interested in the market reaction at time t when the selection result has been announced, which is the price change before and after the selection:

$$\Delta Price = Price_t - Price_{t-1} = -\pi(1-\delta)(p-q) \quad (2.3)$$

From the equation, $\Delta Price$ is negative. The price drops with the amount of unexpected profit loss $\pi(1-\delta)$ and the increased intensity of enforcement action $(p-q)$.

Hypothesis

Violating firms VS Non-violating firms: Whether the firms have existing violations affect the investor's belief of future probability of being detected. For a good firm with no violations ex-ante, the $(p_{good} - q_{good}) \rightarrow 0$. Therefore, we could expect an insignificant negative price change in non-violating firms. Where else, for the bad firms with violating behaviors, the $(p_{bad} - q_{bad}) > 0$. Thus, I propose the following hypothesis:

Hypothesis 1.1: Market predictability: the market reaction at the selection results announcement date distinguishes the violating firms from the non-violating firms.

Low exposure firms VS High exposure firms: As mentioned in Section 2, the local-level selection event gives some autonomy to CSRC local office to adapt the local situation to the selection process. Firms with sanction records before the selection have been more likely to be selected than those that are not. I thus split the firms into being low exposed and high exposed to the regulators, and I assume that the $\delta_{low-exposure} < \delta_{high-exposure}$. In other words, the random selection is a stronger shock to the probability of being detected for low-exposed firms than for high-exposed firms. I propose the following hypothesis:

Hypothesis 1.2: Market predictability: the market reactions to the selection results is more pronounced in firms with low exposure than in firms that have already been identified as violating firms.

Existing Information of Violations: Investors estimate the probability of being detected given that selection occurs $p = P(\pi(\text{Detection})|\text{Selected})$. This estimation is based on the prior probability of detection q , as $p = f(q)$ where the q indicates the investors' knowledge of existing violations. Therefore, I propose my second hypothesis as follows:

Hypothesis 2: Market predictability can be explained by the information on existing violations held by the investors before the selection.

Role of Sophisticated Investors: In a Grossman-Stiglitz world,¹¹ informed trading mitigate the asymmetric information on the market. The change of firm's fundamental value (future cash flows) incorporate more precisely into prices with the presence of informed traders. Hence, I assume that the additional precision of a signal is added to the estimation of probability p given the existence of informed traders. I propose my last hypothesis as follows:

Hypothesis 3: Market predictability is more pronounced in the firms where the informed traders (e.g. institutional investors) take a large stake.

I further conduct a reliability check of the probability setting, the result can be found in Appendix A5.

2.3.2 Framework

Next, I show some important time point as well as the definition of variables that I will use for the rest of the paper.

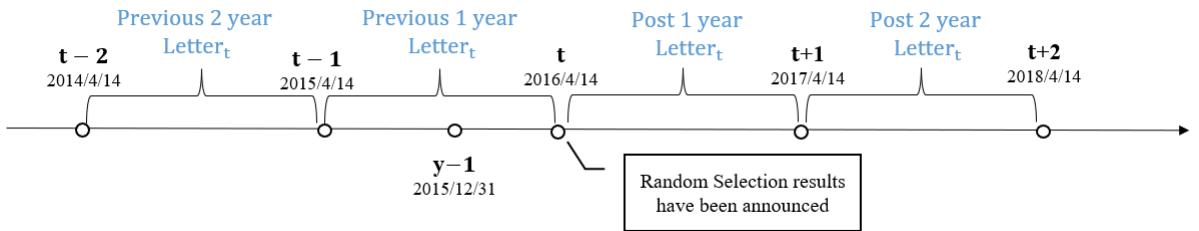


Figure 2.2: Research framework (take the selection result announcement date of Shaanxi on 14th April in 2017 as an example)

I define the t as the random selection results announcement date. Starting from the time t , one year before and after has been noted as $t - 1$ and $t + 1$. The number of

¹¹Refer to the model setting from Grossman and Stiglitz (1976), where there are three types of investors: informed, uninformed and liquidity traders. The investors are compensated for the marginal value of the information they collect, process, and impound into prices.

regulatory letters issued (in the sense of regulators, and otherwise, received, in the sense of listed firms) has been considered given a firm has been selected at time t . Thus, I name the regulatory letters issued refer to the selection date of firms. For example, the number of letters issued in $(t - 2, t - 1)$ has been represented as $Post2yearletter_t$. The “letter” is replaced by either the “question letter” or “sanction letter” depending on which type of letter the firm received. Here, it’s worth to note that the letters represent all types of letters received during an indicated period and are not limited to those related with on-site inspection. The y indicates the end of the firm’s fiscal year. As financial data are represented by the firm’s fiscal year, it is necessary to distinguish the y from t .

2.4 Data and Summary Statistics

2.4.1 Data Resources

Three data resources support my study: the CSMAR (China Stock Market & Accounting Research) database, the two exchanges’ websites, and the CSRC office website. From the CSMAR, I could find all the necessary information needed for Chinese listed firms, which includes the financial statements, the daily stock prices, the shareholder’s ownership structures, the corporate governance, the firms’ capital activities as well as the Fama French five factors for the event study. In the CSMAR database, we could also find information about the enforcement actions, including sanctions letters issued with detailed violation information, letter issuing date, and the regulators. It covers the Chinese listed firms from the year 1994 to the present. To guarantee the data quality, I further double-check the sanction letters on the CSRC’s and the exchanges’ websites. The CSRC’s official website provides access to the 36 CSRC local offices, where I could find the sanction letters issued for all the listed firms in a specific jurisdiction. I downloaded both the sanction letters and the question letters of listed firms from two exchanges’ websites. Due to the data quality, the question letters can only be found starting from the year 2014. The announcement of the random selection result of each year of each jurisdiction has been disclosed to the public. We can find the information on each CSRC jurisdiction website, where the date of the selection result announcement, the listed firms that have been selected, the selected inspectors as well as the witness who were invited for selection process can be found. I collected this information by hand and constructed a selection list containing selected firms, announcement dates, corresponding years, and jurisdictions.

The time frame in this study is from 2010 to 2020. As the starting point of the random-selection policy is in the year 2016, I thus frame my dataset from 5 years before to 5 years later for the use of ex-ante and ex-post selection period information.

2.4.2 Data Cleaning Process

Definition of Selected and Non-Selected Firm

The selected firms represent all the firms selected for a random on-site inspection due to this policy from 2016 to 2021.¹² By hand-collecting the selection-related data, I have 889 selected listed firms in 36 jurisdictions. 853 of them have corresponding selection results announcement date, and 32 firms have been selected twice. In the end, 821 firms have been selected overall.

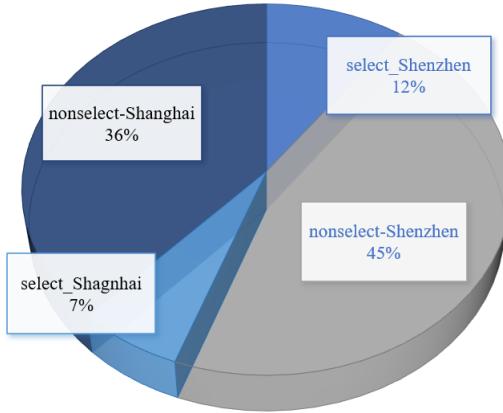


Figure 2.3: Selection distribution in two exchanges

Non-randomly selected firms correspond to the other firms that have not been selected in a specific year in that jurisdiction. From 2010 to 2021, after combing the selected and non-selected firms, I have 35,552 observations. Due to the selection requirement, firms that have been selected will automatically be excluded from the selection lists for the next three years' selection event. Hence, for a firm that has been selected in fiscal year y , I exclude its following three annual observations and reinsert it back into the dataset starting from the $(y + 4)$. In the end, I constructed a panel dataset with 33906 observations.

From 2016 to 2021, there are 18.8% of listed firms (relative to the total number of Chinese listed firms in 2021) that have been randomly selected to do an on-site inspection. The proportion of selection in both exchanges has been shown in Figure 2.3.

Cleaning of Letter Issuance

By collecting the data from the CSMAR database and the exchanges, I have 11,541 question letters from two exchanges with 11,378 letter issuing dates as some letters have

¹²Mainly due to the coronavirus which affected the conduction of on-site inspection of 2021, I have only found random selection information in three jurisdictions with 13 firms have been selected in 2021.

been issued on the same date. I also have 13,287 observations of sanction letters. The dataset is mixed with the announcement of sanction letters received from sanctioned listed companies and other penalties that are not associated with the violation of securities law and regulations. I, firstly, clean the dataset by first eliminating any overlapped letters that have been issued from both regulators and sanctioned listed firms. Secondly, I filter the violating behaviors with keywords indicating the exact enforcement actions. The filters used include warnings, fines, confiscation of illegal gains or confiscation of unlawful property or things of value, ordering for suspension of production or business, temporary suspension or rescission of permit or temporary suspension or rescission of the license, administrative detention. In the end, there are 7,207 qualified sanction letters with 6,491 letter issuing dates, whereby 1,973 of them are issued from CSRC, and the rest are from the two exchanges.

2.4.3 Summary Statistics

Table 2.2 presents the summary statistics of variables related to the firm's specific characters. Before 2016, I summarized the variables in the full sample, as no selection happened. The firms have been further split into selected and non-selected groups since 2016. We find the average size of institutional investors' ownership for 2016 to 2021 is 28.6%, while it was 22% from 2010 to 2015. The firms with pay-to-performance policy in management teams represent 13.3% of the total sample, which increased to 21.8% during the year 2016 to 2022. The same pattern can be found in liquidity and annual report restatement. However, the opposite is the case in state ownership. From the summary statistics it is hard to tell the randomness of the policy as the difference between selected and non-selected groups in different variables have not shown a clear pattern. I will thus further discuss the reliability of the random selection policy in Section 6.

Table 2.3 shows the regulatory letters received at different periods. In Panel A, we can find the number of question and sanction letters issued per selected firm. For example, each firm that was selected in 2017 received on average 0.716 question letters and 0.407 sanction letters in the year following the selection. The question letters in general increase much more than the sanction letters. An increase in the number of both types of letters over the years can also be observed.

This increase in the letters issued can be interpreted as either an increase in enforcement action intensity or an increased pervasiveness of financial misconducts among listed firms. Comparing the selected and non-selected firms can help confirm the first explanation. Compared with the selected firms, the non-selected firms have experienced less letter increases. As for both firms that experienced the selection in the same jurisdiction in 2017, the firms that have yet to be selected received, on average, 0.372 question letters and only 0.195 sanction letters in the following year. This difference

Table 2.2: Summary Statistics

Table 2.2 reports summary statistics for all the variables related to this study. Full sample reports summary statistics for including all the selected and non-selected firms. The selection policy has been launched in 2016, I split the sample into Selected and Non-selected starting from 2016. The Selected sample includes all the firms that have been selected for the random selection of inspection policy from 2016 to 2021. The Non-selected sample includes all the rest of the firms that have not been selected in a specific year in that jurisdiction. See he Appendix Table 4.13 for the variable definitions.

Variable	2010-2015		2016-2021			
	Full Sample		Selected		Non-Selected	
	N	13857	853	19196	Mean	Std
Age listed	9.017	6.583	11.253	7.593	10.160	8.225
Market value	0.287	2.382	0.198	0.270	0.234	0.283
Leverage	1.208	1.462	1.191	1.393	1.057	1.346
Liability	0.435	0.225	0.444	0.200	0.411	0.208
Roa	0.047	0.952	0.010	0.133	0.030	0.398
Roe	0.062	0.138	0.010	0.219	0.054	0.154
Concentration 10	0.173	0.123	0.139	0.107	0.156	0.112
State-owned-shares	0.051	0.143	0.018	0.080	0.027	0.105
State-owned-firms	0.212	0.409	0.129	0.335	0.146	0.353
Institution shares	0.220	0.226	0.279	0.228	0.293	0.241
Management shares	0.100	0.182	0.094	0.158	0.095	0.166
Pay-to-performance shares	0.002	0.007	0.002	0.007	0.002	0.008
Pay-to-performance firms	0.133	0.340	0.226	0.419	0.210	0.408
Tax contribution	0.013	0.049	0.007	0.025	0.009	0.045
Event-Capital restructuring	0.095	0.293	0.125	0.331	0.103	0.303
Modify-Annual report	0.040	0.197	0.208	0.406	0.149	0.356
SUE	-0.070	1.100	0.018	1.209	0.021	1.131
Liquidity-Amihud	0.166	0.775	0.080	0.428	0.267	1.217
Volatility	0.033	0.043	0.029	0.008	0.037	0.058

further shows the increased attention of regulators on selected firms.

Table 2.3: Summary Statistics of Letter Issuing

Table 2.3 reports the summary statistics for the number of letters received per listed firm per year. $Previous1yearQL_t$ corresponds the number of question letters issued by the exchanges during the $(t-1, t)$ where t is the random selection result announcement date. $Previous1yearSL_t$ corresponds the number of sanction letters issued by the CSRC (either headquarter or local bureau) during the $(t-1, t)$. $Post1yearQL_t$, $Post1yearSL_t$ corresponds the number of question letters issued and sanction letters issued during $(t, t+1)$ respectively. $Post2yearQL_t$, $Post2yearSL_t$ corresponds the number of question letters issued and sanction letters issued during $(t+1, t+2)$ respectively.

Panel A: Selected Firms							
Year	Nb.ofFirms	Previous1yearQL _t	Previous1yearSL _t	Post1yearQL _t	Post1yearSL _t	Post2yearQL _t	Post2yearSL _t
2016	118	0.322	0.195	0.517	0.280	0.475	0.322
2017	162	0.451	0.259	0.716	0.407	0.722	0.414
2018	189	0.566	0.212	0.947	0.672	1.000	0.566
2019	183	0.918	0.284	1.022	0.749	0.907	0.683
2020	188	0.941	0.324	1.128	0.745	0.447	0.426
2021 ¹³	13	1.692	0.692	0.923	1.385	/	/

Panel B: Non-Selected Firms							
Year	Nb.ofFirms	Previous1yearQL _t	Previous1yearSL _t	Post1yearQL _t	Post1yearSL _t	Post2yearQL _t	Post2yearSL _t
2016	2767	0.345	0.190702	0.501	0.228	0.388	0.292
2017	2024	0.321	0.142	0.372	0.195	0.507	0.258
2018	2947	0.345	0.191	0.501	0.228	0.539	0.292
2019	2080	0.446	0.216	0.502	0.247	0.546	0.267
2020	3441	0.427	0.207	0.430	0.216	0.201	0.247
2021	3875	0.053	0.024	0.026	0.039	/	/

2.5 Randomness

In this section, I show the reliability of my research based on the randomness of the sample construction. One of the contributions of this paper is the use of the random selection policy to study the market information revealing process. The randomness of the selection rules out the possibility that regulators intervene with their preference and a biased punishment. Hence, the price reaction on the intervention reflects a pure violation information revealing instead of the attitude towards the regulators' interference of non-violating firms' daily operation for rent seeking.

However, the choice of conducting a stratified sampling selection process in some CSRC local offices adds to the difficulty in proving the randomness of this policy. Due to the lack of information on the specific selection process design, I need to reconstruct the latter based on the requirements of the policy. The policy requires an efficient

enforcement action to be conducted as the firms with high violation risks should be efficiently detected. The question is, to whom the regulators considered as high violation risk firms?

One solution is to use the previous regulatory letters issuing situation to proxy the information of regulators. This proxy will be further discussed in Section 7 in showing how it helps in exploring the mechanism. For now, let us just focus on the number of letters issued by regulators before the selection event. I split the sample into two groups: *Low Exposure* group where the letters received of a firm in one year before the selection is zero, and a *High Exposure* group for the opposite. The more letters the listed firm has received, the greater it exposes its violations to the regulators.¹⁴ Thus, the regulators have more information on the firm's misconduct behaviors and considers it as containing high violation risk.

Next, I show that the randomness exists in different samples based on the exposure level. Table 2.4 shows the result of the randomness examination. The dependent variable is a dummy variable that indicates whether the firm has been selected or not in the 2016 to 2021 period. The explanatory variable includes the variables that may affect the regulator's attention while selecting the regulated targets (if under a non-random circumstance). These factors are firm-specific characteristics (*age listed*, *concentration top 10*, *State-Owned-Firms*, *Institution shares*, *Management share*, *Pay-to-Performance Firms*), the firm's financial statement (*ROE*, *Liability*), the firm's market performance (*Market value*, *SUE*, *Illiquidity-Amihud*), the political ties (*Tax contribution*, *Political ties*) as well as the firms other important activities (*Modify-Annual report*, *Event-Capital restructuring*).¹⁵ I use the *Tax contribution* as the ratio of the firm's tax payments relative to the local government's tax income to proxy the influence of firms to local governance. *Political ties* is the number of employees that have been employed in a regulatory institution before, which is expected to capture the political connection between firms and the CSRC local bureau. I also add a dummy variable called *Event-Capital restructuring* to indicate whether the firms have completed any capital restructuring activities, given that the capital restructuring firms have been required to be investigated by the CSRC. The dummy variable *Modify-Annual report* indicates whether the annual report has been modified in a specific year. Given that it is less hidden but more frequent and influential to the market, it may be more likely to attract regulators' attention during the investigation. I also control for industry, firm and year fixed effects.

In Table 2.4, Column (2) shows the results for firms that have been exposed before the selection event, none of our explanatory variables in this column can significantly

¹⁴Due to the severity and complexity of the cases, the sanction letters in general issued with 1 year of delay. Therefore, the total regulatory letters issued during $(t-1, t)$, includes both question and sanction letters issued in $(t-1, t)$ and sanction letters issued in $(t, t+1)$.

¹⁵The detailed definition of each variable can be found in Appendix A1.

predict the selection results. Column (3) shows that for the firms that have been exposed in the year preceding the selection event, the ROE and large shareholder concentration play a role in predicting the selection results. This predictability is mainly seen in the high exposure group. It may be explained by the fact that there are some criteria associated with firms' profitability and ownership structure that has not been fully captured with the proxy of information of regulators, while analyzing the stratified sampling design. In the low exposure group, the results confirm the randomness of the experiment. Thus, this paper focuses on the low exposure group and the difference within these two groups will be discussed.

2.6 Market Predictability of Future Punishment

In this section, I present the main results of my study. I start by conducting an event study at the selection result announcement date to examine the market reaction before proving the hypothesis proposed in Section 3.

2.6.1 Event Study

My primary variable in this study is the market reaction to the outcome of random selection. I define the event date as the day when the random selection results have been published on the website of each CSRC local office. By hand-collecting this information, I have 149 event dates and 853 selected listed firms from the year 2016 to 2021. Figure 2.6 shows the number of selected firms given each event date over time.

I use the Fama-French five-factor model to estimate the abnormal daily return ([Fama and French, 2015](#)),

$$AR_{it} = R_{it} - R_{Ft} = \alpha_i + \beta_i (R_{mt} - R_{Ft}) + s_i SMB_t + h_i HML_O_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (2.4)$$

Where R_{it} is the daily return of stock i , the five factors have been provided directly from the CSMAR dataset. They represent the information related to the market value (SMB), the book-to-market ratio (HML_O), the operating profitability (RMW), the investment pattern (CMA) as well as the market risk premium ($R_{mt} - R_{Ft}$). The estimation window is between 252 days and 30 days before the event. The event window is 10 days before and 10 days after the selection.¹⁶ I first estimate the daily abnormal return and then calculate the cumulative average abnormal return of the event window,

¹⁶I also examine the cumulative abnormal return in differential intervals to verify no information leakage before and the efficiency of price in impounding information. The results have been shown in Appendix A2.

Table 2.4: Randomness Examination

Table 2.4 reports the result of Probit model as randomness check for my research sample. The dependent variable *Selected* is a dummy variable equals to 1 if the firm is selected in a year. The full sample contains all the selected and non-selected firms since the selection policy has been launched in 2016. *High* is a dummy variable equals to 1 if the firms received any regulatory letters (including question type and sanction type) during $(t-1, t)$ where t is the random selection result announcement date. The low exposure group includes the firms with *High* = 0. And high exposure group includes the firms with *High* = 1. See the Appendix Table 4.13 for the variable definitions. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

	Selected		
	(1)	(2)	(3)
	Full Sample	Low Exposure	High Exposure
High Exposure	0.226*** (0.037)		
Age listed	0.011 (0.027)	0.010 (0.036)	0.022 (0.043)
Market value	0.010 (0.023)	-0.007 (0.034)	0.028 (0.035)
State-owned-firms	-0.037 (0.048)	-0.044 (0.065)	-0.029 (0.074)
Concentration top10	0.049 (0.206)	0.224 (0.274)	-0.296 (0.328)
Management shares	-0.125 (0.168)	0.002 (0.240)	-0.084 (0.251)
Institution shares	-0.190 (0.117)	-0.060 (0.176)	-0.211 (0.165)
Liability	0.012 (0.095)	-0.002 (0.146)	0.020 (0.128)
ROE	-0.276** (0.108)	-0.338 (0.266)	-0.188 (0.125)
Tax contribution	-0.270 (0.430)	-0.216 (0.712)	-0.443 (0.537)
Modify-Annual report	0.049 (0.044)	0.024 (0.073)	0.075 (0.056)
Event-Capital Restructuring	0.002 (0.070)	-0.095 (0.227)	0.023 (0.076)
Illiquidity-Amihud	0.007 (0.014)	0.005 (0.016)	-0.007 (0.027)
SUE	-0.014 (0.016)	-0.001 (0.024)	-0.022 (0.021)
Pay-to-performance firms	-0.035 (0.043)	-0.008 (0.063)	-0.064 (0.060)
Political tie	-0.214 (0.130)	-0.177 (0.188)	-0.197 (0.186)
Ind FE	Yes	Yes	Yes
Jurisdiction FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	14852	8612	6140

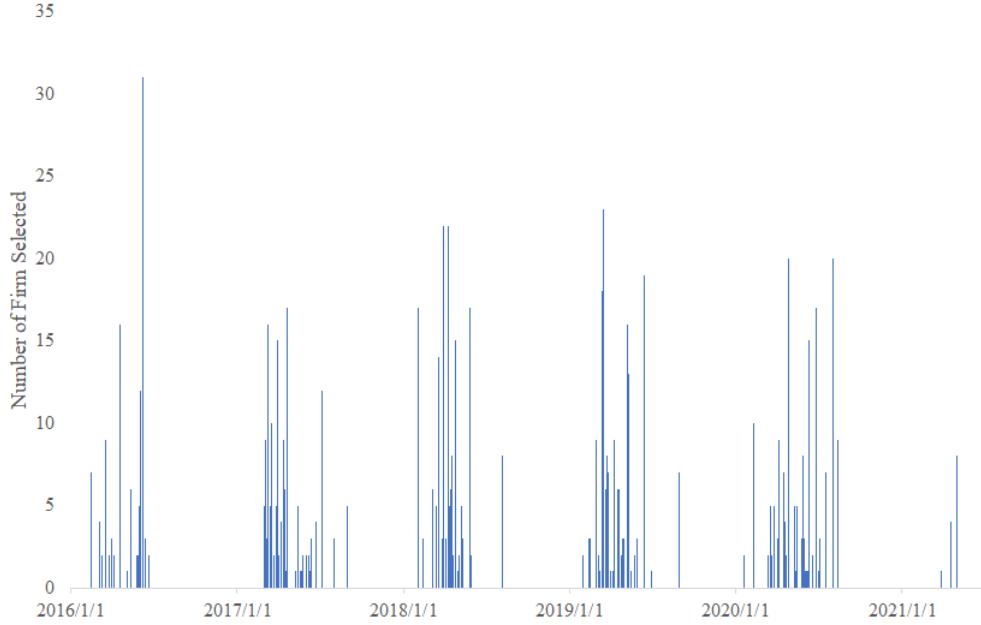


Figure 2.4: Selection distribution in two exchanges

$$CAR_{it}(\tau_1, \tau_2) = \sum_{T=t+\tau_1}^{t_i+\tau_2} AR_{iT} \quad (2.5)$$

Where t_i represents the event date as stock i has been known to be selected or not. The event window is represented by (τ_1, τ_2) .

2.6.2 Test of Hypothesis

To test Hypothesis 1, I show that the cumulative abnormal return $CAR(-10, 10)$ around the event date is significantly negative for violating firms that have been selected but not for non-violating selected firms. Ex-post violation is proxied by the letter receiving situation after the selection. A firm that received any letters is defined as a violating firm and vice versa. However, given the different contents of letters, we may have different interpretations on firms' violations. Firms that have received a question letter can be either a non-violating firm or a violating one. On the contrary, sanction letters contain the firms' committed violation. Therefore, I further split the sample by the letter's type. Next, I run an OLS regression as below to confirm the result by clustering standard errors at the jurisdiction and industry level,¹⁷ and further controlling for firm characteristics and year fixed effect

$$CAR_{i,t} = \alpha + \beta_1 Selected_{i,t} + \beta_2 PostLetter_{i,t} + \beta_3 Selected_{i,t} * PostLetter_{i,t} + Control_{i,y-1} + \epsilon_{i,t} \quad (2.6)$$

¹⁷The cluster-adjusted standard error account for within-cluster correlation or heteroscedasticity refer to paper of Abadie et al. (2017). I also checked the results by controlling for industry and jurisdiction fixed effect, the similar results have been given.

The dependent variable $CAR(-10, 10)_{i,t}$ represents the market reaction at time t for firm i . And the explanatory variables contain the interaction term of $Selected_{i,t} * PostLetter_{i,t}$, where the $Selected_{i,t}$ is a dummy variable that indicates whether firm i has been selected at time t , and $PostLetter_{i,t}$ indicates the number of regulatory letters received in the $(t, t + 1)$ ex-post period. The control variables include all the variables that have been presented in the randomness check in Section 5.. They control for any other explanation of market reaction coming from firm specific characteristics and performance, such as market size, ROE, capital restructuring activities as well as the SUE (Standardized Unexpected Earnings), etc. These variables are recorded in firm's fiscal year. I take the data of the end of last fiscal year ($y - 1$) just before the event. I expect that the coefficient of the interaction term β_3 to be significantly negative.

2.6.3 Market Reaction

The results have been discussed depending on the firms' violation information in regulators (ex-ante exposure to the regulators): *Low Exposure* group and *High Exposure* group. As discussed in Section 5, the firms with low exposure experienced an exogenous shock of the upcoming investigation, which triggered the market reaction in revealing the information of violations. On the contrary, for the highly exposed firms, regulators' investigation is less relevant to this random selection, the market reaction is expected to be biased with the attitude towards the selection outcomes. The investors with exposed violation information will also form an expectation of firms which mitigate the shock effect.

I categorize the firms into five scenarios based on the ex-post letters receiving. For firms receiving any question letters in the following year, I categorize in $Post1yearQuestionLetter_t > 0$. Otherwise, if the firm did not receive any question letters in the following year, it is categorized as $Post1yearQuestionLetter_t = 0$. The $PostLetter_t$ is the sum of number of question letter received in the year following the selection($Post1yearQuestionLetter_t$) and the number of sanction letter received in the second year following the selection ($Post2yearSanctionLetter_t$). The cumulative abnormal returns are reported in Table 2.5.

Panel A of Table 2.5 presents the low exposed firms' market reaction. Panel A shows that firms that receive regulatory letters ex-post (at the second stage, after the investigation) experience a CAR of -1.6% ex-ante (at the first stage, before the investigation). This market drop is explained by the significant negative reaction towards sanction letters. The firms that receive any sanction letters in two years following the event experiences a -2.73% cumulative abnormal returns. No significant abnormal returns are associated with firms that received sanction letters one year later. This result confirms that the sanction letters deliver in delay. The sanction letters issued within

Table 2.5: Market Reaction on Event Date

Table 2.5 reports the t-test result of cumulative abnormal return of 10 days before and after the event date. The event date is the day when the random selection results have announced to public in that year in that jurisdiction. $Post1yearQL_t > 0$ and $Post1yearSL_t > 0$ corresponds to the firms that received at least one question or sanction letters during the $(t, t + 1)$ respectively. Where t is the random selection result announcement date. $Post2yearQL_t > 0$ and $Post2yearSL_t > 0$ corresponds to the firms that received at least one question or sanction letters during the $(t + 1, t + 2)$ respectively. $PostLetter_t > 0$ includes firms that received any regulatory letters in the year following the selection. $PostLetter_t = 0$ thus represents the firms that have not received any regulatory letters after the selection. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Panel A: Low Exposure						
	$Post1yearQL_t > 0$	$Post2yearQL_t > 0$	$Post1yearSL_t > 0$	$Post2yearSL_t > 0$	$PostLetter_t > 0$	$PostLetter_t = 0$
Selected	-1.570% (-1.57)	0.143% (0.14)	-0.422% (-0.37)	-2.730% *** (-3.11)	-1.580% ** (-2.05)	-0.157% (-0.26)
Non-Selected	0.332% (1.02)	0.003% (0.01)	0.029% (0.07)	0.283% (0.82)	0.346% (1.38)	0.173% (1.34)
Difference	-1.902% (-1.55)	0.140% (0.13)	-0.451% (-0.35)	-3.013% *** (-3.19)	-0.362% ** (-2)	-0.330% (-0.54)

Panel B: High Exposure						
	$Post1yearQL_t > 0$	$Post2yearQL_t > 0$	$Post1yearSL_t > 0$	$Post2yearSL_t > 0$	$PostLetter_t > 0$	$PostLetter_t = 0$
Selected	-0.034% (-0.03)	-0.578% (-0.58)	-1.250% (-1.24)	-1.780% (-1.47)	-0.381% (-0.42)	1.370% (1.4)
Non-Selected	-0.603% (-1.76)	-1.000% *** (-3.04)	-1.380% *** (-3.1)	-1.190% *** (-2.76)	-0.543% * (-1.84)	0.079% (0.32)
Difference	0.569% (0.53)	0.422% (0.39)	0.130% (0.11)	-0.590% (-0.47)	0.162% (0.17)	1.291% (1.13)

one year after the event is expected to contain the violations that have already been discovered ex-ante. The question letters, on the other hand, have not shared the same pattern. It can be explained by the fact that the question letters are issued to both types of firms (violating and non-violating). Its purpose is to question the potential violation risks rather than punishing the committed violations. In this case, the market signal in revealing violations is mixed.

Unsurprisingly, non-violating firms with no letters received ex-post, experience an insignificant market drop. The same pattern is not shown in non-selected firms. The gap in the market drop between selected and non-selected firms given that both are violating firms is around/approximately 3%. The market predictability of future punishments can be found: the ex-ante market reaction distinguishes the violating firms from the non-violating firms. This market reaction has been triggered by the random selection.

Panel B of Table 2.5 presents the market reaction for firms that have been exposed to regulators in the year before the event, because they received at least one regulatory letter. As expected, no significant market reaction has been found when the firm has been selected. Surprisingly, we can see that the market reactions are significant and negative given that a violating firm was not selected. This is different from the hypothesis that the market reaction is triggered by the selection event. One possible explanation can be that the selection results disappointed the investors given that the firm has already been exposed. Although the market reaction is significant and unexpected, the difference between selected and non-selected firms are insignificant as expected. These results also prove the validity of using low exposure groups in the further exploration of mechanism.

Table 2.6 shows the results of the OLS regression. Each coefficient of the interaction term is significantly negative in the low exposure group, implying that the firms that received any regulatory letters ex-post, experience a decrease in the market reaction on the day of being selected. The market contains information that has significant predictability on the ex-post punishment. This result continues to hold after including a variety of additional controls. Moreover, market predictability becomes significant for question letter issuances after clustering and this predictability continues to hold when add more controls. In term of magnitude, the coefficient on *Selected* and the interaction term *Selected*Post2yearSanctionLetter_t* in column (6) ($=-0.008, -0.015$), implies that given a firm has been selected, the market decreases ex-ante by 2.3% for each additional sanction letters issued ex-post. In general, one regulatory letter issued in the future is associated with a market drop of 7%.

Table 2.6: OLS Regression: Ex-Post Letter Issuing Associated with Market Reaction

Table 2.6 reports the results of OLS regression of letter issuance in the year following the selection in selected firms on the random selection result announcement date. I split the sample into low exposure and high exposure group regarding to the number of regulatory letters received before the selection. *Selected* is a dummy variable equals to 1 if the firm is selected in a year. *PostLetter* is the sum of *Post1yearQL_t* and *Post2yearSL_t*. *Post1yearQL_t* corresponds the number of question letters issued during $(t, t + 1)$, and *Post2yearSL_t* corresponds the number of sanction letters issued during $(t + 1, t + 2)$. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

CAR(-10,10)												
	Low Exposure						High Exposure					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Selected	-0.005 (0.006)	-0.006 (0.004)	-0.007 (0.006)	-0.008** (0.004)	-0.006 (0.006)	-0.008* (0.004)	0.006 (0.008)	0.007 (0.007)	0.002 (0.008)	0.003 (0.007)	0.007 (0.007)	0.009*** (0.003)
<i>Selected * PostLetter_t</i>	-0.009* (0.005)	-0.009*** (0.003)					-0.000 (0.003)	0.000 (0.004)				
<i>Selected * Post1yearQL_t</i>			-0.009 (0.007)	-0.009*** (0.004)					0.002 (0.004)	0.002 (0.004)		
<i>Selected * Post1yearSL_t</i>					-0.015* (0.008)	-0.015*** (0.003)					-0.004 (0.005)	-0.004 (0.005)
<i>PostLetter_t</i>	0.001 (0.002)	0.001 (0.002)					-0.004*** (0.001)	-0.003*** (0.001)				
<i>Post1yearQL_t</i>			0.003 (0.002)	0.003 (0.002)					-0.005*** (0.001)	-0.003* (0.002)		
<i>Post2yearSL_t</i>					-0.000 (0.003)	-0.001 (0.002)					-0.008*** (0.002)	-0.007*** (0.002)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	7774	7774	7774	7774	7774	7774	5445	5445	5445	5445	5445	5445
adj. R-sq	0.000	0.007	0.000	0.007	0.000	0.008	0.004	0.015	0.002	0.014	0.004	0.016

2.7 Mechanism

In this section, to test my second hypothesis, I explore the channel through which the market reacts to the selection outcomes in a negative way in selected firms. From the hypothesis development setting, I have shown that firms with violations will experience a price drop. This price drop should be explained by the investors' adjustment of beliefs based on not only the probability of future punishment occurring, but also the signal of violations investors trade on the market. Uninformed traders can only observe the true signal of violations via public information but not private information.

Therefore, the channels through which violations impact the price takes place through 3 steps. Section 7.1, you can find the measure that I construct to proxy the signal of violations based on public information. Next, I show how the market predicts ex-post punishment based on the ex-ante signal of violations. In Section 7.2, I discuss how private information is involved in explaining the predictability of the market. Finally, in Section 7.3, I dig into the information content of the ex-post regulatory letters by using the textual analysis. It helps us further explore the predictability of public and private information ex-ante.

2.7.1 Predictability of Public Information

Measuring Ex-ante Violations Signal

The selection event triggers the trading of uninformed investors who uses the public information to form their belief before the punishment takes place. This belief represents part of the signal of violations on the market. Thus, I estimate the signal of violations based on public information. Specifically, I refer to the method of [Gande and Lewis \(2009\)](#), where the authors used the probit model to estimate the propensity to be sued. I use a similar approach to estimate of likelihood of being detected from the following probit model to proxy the signal of violations:

$$\begin{aligned} \text{Previous Letter}_{i,t} = & \alpha + \beta_1 \text{Firm Specific Char.}_{i,y-2} + \beta_2 \text{Firm Financial Stat.}_{i,y-2} \\ & + \beta_3 \text{Market Performance}_{i,y-2} + \beta_4 \text{Political Tie}_{i,y-2} \\ & + \beta_5 \text{Activities}_{i,y-2} + \epsilon_{i,t} \end{aligned} \quad (2.7)$$

where the dependent variable Previous Letter is a dummy variable which indicates whether a firm has received any regulatory letter within one year prior to the event ($t - 1$) from the securities regulators.¹⁸ The explanatory variables are the factors that reflect public information, which would correlate with the firm's violation risks.¹⁹ These

¹⁸I also add the sanction letter issued one year after the event ($t+1$). Due to the severity of the cases, the investigation process of the sanctions often takes 2 years to complete. Thus, it would be more reasonable to take the letters that have been issued one year after.

¹⁹The violation risks correspond to any potential suspicious evidence that correlates with the firm's violations. The regulatory letters include question letters issued from the exchanges, which may question any potential violation risks in firms. Therefore, I used the violation risks instead of the violations to

factors are firm-specific characteristics (*age listed, concentration top 10, State-Owned Firms, Institution shares, Management share, Pay-to-Performance Firms*), the firm's financial statement (*ROE, Liability*), the firm's market performance (*Market value, SUE, Illiquidity-Amihud*), the political ties (*Tax contribution, Political tie*) as well as the important activities (*Modify-Annual report, Event-Capital restructuring*).²⁰ A firm's listed age and profitability would affect the motivation for manipulation. One would expect that the firms that just gone through an IPO may attract more attention from regulators. A firm with bad operating performance is more likely to manipulate their financial statement. The ownership structure, the tax contribution to the province, or the political relationship could affect the facility of concealing misconducts. I also include the situation associated with the capital restructuring activities and the modification of the annual report behavior to identify the necessity of being inspected. As required by the security law, the firm with capital restructuring activities in progress should be inspected. The delay or change of the annual report release time may also attract the attention of regulators. I thus predict a positive relationship between the likelihood of receiving a letter and the number of both activities. The liquidity and the market value have been included to proxy the potential damages. Higher levels of both factors increase the size of impact due to misconduct behaviors, which leads to a higher likelihood of being detected (Simmons et al., 1993). Here, I didn't add the explanatory variables related to the previous regulatory environment or punishment. This information is supposed to be known and used by regulators as well. The objective of the regression setting is to explain the uninformed traders' belief adjustment based on the market information beyond the knowledge of regulators.

Table 2.7 shows that except the tax contribution and political ties, listing age and management ownership, all the other factors can significantly predict the second-year punishment. More specifically, firms that have fewer listing years, with less profitability and more liability are more likely to receive regulatory letters. The state-owned firms are less likely to be punished. The ownership of institutional investors also helps to decrease the likelihood of being punished. Firms that provide investors with a positive earnings surprise are less likely to be punished. And, as predicted, the firms that have modified their annual reports announcement date or have capital restructuring activities in progress are more likely to misbehave. They're, therefore, more likely to receive regulatory letters. I also find that firms with higher liquidity and a larger size are more likely to receive letters, which correspond to the findings in literature.

In the second column, I show the marginal effect which is calculated at the means of independent variables. For example, the marginal effect for ROE indicates that there's a 48.9% increase in the likelihood of being detected for violation risks if a firm's ROE

proxy the information.

²⁰The detailed definition of each variable can be found in Appendix A1.

Table 2.7: Probit Model of Measuring Violation Signal

Table 2.7 reports the result of Probit model 2.8 estimating the violation signal in the market just before the selection event. The dependent variable is equal to 1 if a firm received any letters during $(t - 1, t)$, and 0 otherwise. The independent variables are defined in the Appendix Table 4.13. Coefficient estimates and standard errors are reported. Column (2) measures the marginal effect of changes in the levels of the independent variables. The sample contains both selected and non-selected firms from 2016 to 2021. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

	<i>Previous Letter_t</i>	
	(1)	(2)
	Full Sample	Marginal Effect
Age_listed	0.001 (0.018)	0.000 (0.007)
Market value	-0.087*** (0.015)	-0.032*** (0.006)
State-owned-firms	-0.127*** (0.030)	-0.047*** (0.011)
Concentration_top10	-1.162*** (0.118)	-0.431*** (0.044)
Mgt_shares	-0.141 (0.092)	-0.052 (0.034)
Institution_shares	-0.154** (0.062)	-0.057** (0.023)
Liability	0.400*** (0.060)	0.148*** (0.022)
ROE	-1.319*** (0.090)	-0.489*** (0.034)
Modify_Annual report	0.284*** (0.030)	0.105*** (0.011)
Event_Capital Restructuring	0.313*** (0.048)	0.116*** (0.018)
Illiquidity_Amihud	-0.020** (0.009)	-0.007** (0.003)
SUE	-0.024** (0.010)	-0.009** (0.004)
Pay-to-performance-firms	0.048* (0.028)	0.018* (0.010)
Tax shares	-0.187 (0.280)	-0.069 (0.104)
Political tie	0.033 (0.086)	0.012 (0.032)
Year FE	Yes	Yes
Ind FE	Yes	Yes
Jurisdiction FE	Yes	Yes
N	15,231	15,231

decreased by 1% ex-ante. Firms that modify their annual report announcement are 10.5% more likely to be punished. Moreover, the firms that pay managers high bonuses are more likely to be punished, with a marginal effect of 1.8%.

Does Ex-post Punishment Correspond to Ex-ante Violation Signal ?

To examine whether the ex-post detected violations correspond to the ex-ante violation signal, I next regress the ex-post regulatory letters received on the ex-ante signal of violations estimated from the previous Probit model. This regression allows me to infer to what extent the ex-post punishment corresponds to ex-ante violations signal estimated by public information.

$$Post\ Letter_{i,t} = \alpha + \beta Violation\ Signal_{i,t-1} + Control_{i,y-1} + \epsilon_{i,t} \quad (2.8)$$

The dependent variable $Post\ Letter_{i,t}$ is the total number of regulatory letters received for firm i in the year following the selection event.²¹ I further replace it by the number of question letters in $(t, t + 1)$ and number of sanction letters in $(t + 1, t + 2)$. Here, because of the delay in receiving sanction letters, I consider the sanction letters issued two years after rather than one year after. The main explanatory variable is the estimated propensity to be detected from Probit model 2.7, which proxies for the ex-ante violation signal on the market. Control variables include all the explanatory variables that are shown in Probit model 2.7 but in firm fiscal year $y - 1$. I further controlled for year fixed effects and clustered the standard error at industries and jurisdictions level.

Table 2.8 provides the results. The exposure states are proxied by the number of regulatory letters received in the $(t, t - 1)$, which play a role in affecting the punishment predictability. I split the sample into two groups depending on the previous exposure states. The coefficient of the main explanatory variable *Violation Signal* in Column (1) and Column (4) shows that, the propensity to be detected – violation signal - one year prior to the event has significant positive correlation with the regulatory letters receiving in the year following the event. The coefficient of 2.031 suggests that a 1% increase in the violation signal increases the number of regulatory letters issuance by 2.031 in the future. Specifically, a 1% increase in public information-based violation signal is associated with an increase of 1.103 sanction letters. However, this significant correlation is not shown in the question letter issuance. This result shows the extent to which public information-based violation signals play a role in predicting future punishment.

²¹The total regulatory letters include the question letters and sanction letters. Due to the severity and complexity of the cases, the sanction letters are generally issued with a delay of one year. Therefore, the total regulatory letters issued during $(t, t + 1)$, includes the question letters issued in $(t, t + 1)$ and the sanction letters issued in $(t + 1, t + 2)$.

Table 2.8: Ex-ante Violation Signal Associated with Ex-post Punishment

Table 2.8 reports the result of regression 2.9 in selected firms. I further split the sample into low exposure and high exposure regarding to the number of regulatory letters received before the selection. The dependent variable is the number of letters. In column (1) and (4), dependent variable $PostLetter_t$ represents the total regulatory letter received in a firm during $(t, t + 1)$. The dependent variable in column (2) and (5) $Post1yearQL_t$ corresponds the number of question letters issued during $(t, t + 1)$. The dependent variable in column (2) and (5) $Post2yearSL_t$ corresponds the number of sanction letters issued during $(t + 1, t + 2)$. The independent variable are defined in the Appendix Table 4.13. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

	Selected Sample					
	Low Exposure			High Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
	$PostLetter_t$	$Post1yearQL_t$	$Post2yearSL_t$	$PostLetter_t$	$Post1yearQL_t$	$Post2yearSL_t$
$Violation Risks_{t-1}$	2.031** (0.978)	0.928 (0.565)	1.103* (0.618)	3.385*** (0.473)	2.261*** (0.514)	1.125*** (0.383)
Age_listed	-0.020 (0.147)	0.037 (0.088)	-0.057 (0.084)	-0.149* (0.088)	-0.011 (0.084)	-0.138** (0.060)
Market value	0.049 (0.093)	0.029 (0.039)	0.020 (0.055)	0.467*** (0.115)	0.279*** (0.105)	0.188** (0.090)
State-owned-firms	-0.268* (0.138)	-0.168 (0.106)	-0.100 (0.085)	-0.396 (0.295)	-0.279 (0.204)	-0.117 (0.188)
Concentration top10	-0.152 (0.833)	-0.504 (0.431)	0.352 (0.464)	-1.807** (0.724)	-1.015 (0.774)	-0.791*** (0.298)
Institution_shares	-0.284 (0.190)	-0.138 (0.191)	-0.146 (0.117)	-0.367 (0.681)	-0.140 (0.413)	-0.227 (0.290)
Liability	0.224 (0.344)	0.264 (0.267)	-0.040 (0.128)	0.831 (0.563)	0.346 (0.383)	0.485 (0.349)
Modify_Annual report	0.208 (0.306)	0.138 (0.191)	0.071 (0.126)	0.061 (0.160)	0.087 (0.167)	-0.026 (0.088)
Event_Capital Restructuring	-0.175 (0.309)	0.057 (0.330)	-0.232** (0.106)	0.060 (0.325)	-0.113 (0.257)	0.174 (0.150)
Illiquidity_Amihud	-0.679 (0.567)	-0.281 (0.440)	-0.398* (0.214)	-0.779*** (0.266)	-0.404* (0.225)	-0.375** (0.184)
SUE	-0.117 (0.082)	-0.085 (0.062)	-0.032 (0.031)	-0.345*** (0.091)	-0.191*** (0.062)	-0.154*** (0.038)
Pay-to-performance-firms	0.508 (0.341)	0.463* (0.267)	0.045 (0.092)	-0.339** (0.161)	-0.265* (0.155)	-0.075 (0.074)
Political tie	-0.315** (0.147)	-0.190 (0.120)	-0.125* (0.071)	-0.949*** (0.190)	-0.735*** (0.254)	-0.214 (0.165)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	335	335	335	452	452	452
adj. R-sq	0.062	0.069	0.006	0.112	0.078	0.059

Given that the violation information has been more exposed on the market in the high exposure group, I find that the estimated violation signal does show a more significant correlation with future letter issuance. For instance, a 1% increase in violation risks is significantly associated with an additional 3.385 regulatory letters issued in the future.

The findings indicate the predictability of ex-ante violation signal estimated by the public information of listed firms. The previous signal of violations is highly correlated with the punishment outcomes afterwards. The punishment of regulators is continuous and predictable, as the firms that are more likely to be detected in the previous year are also more likely to be detected in the following year. This finding leads us to the next question, which is how much of this predictable violation signal has been revealed by the market on the day the firm has been selected?

Market Predictability of Future Punishment

To further complete the exploration of the mechanism, I next examine how efficiently the market reflects the predictable violation signal at the selection event date. Once the firm is selected at the event date, the market reaction is affected by the extent to which the firm's violation signal has been revealed by the investors. The investors adjust their beliefs of punishment outcomes based on the information they hold. To uninformed traders, their belief has been adjusted by the public information. While informed traders adjust their trading based on private information. In this subsection, I first show the efficiency of market predictability based on the violation signal estimated by public information. I conduct a two least stage square model(2SLS). In the first stage, I regress the market reaction on the ex-ante violation signal:

$$CAR(-10, 10)_{i,t} = \alpha + \beta Violation\ Signal_{i,t-1} + Controls_{i,y-1} + \epsilon_{i,t} \quad (2.9)$$

in the second stage, the predicted CAR (-10,10) is taken to regress the ex-post regulatory letters received:

$$Post\ Letters_{i,t} = \alpha + \beta \widehat{CAR}(-10, 10)_{i,t}^{public} + Controls_{i,y-1} + \epsilon_{i,t} \quad (2.10)$$

Where the first stage predicted cumulative abnormal return under the form of $CAR(-10, 10)_{i,t}$ has been used as an explanatory variable in the second stage. The control variables are the same as in regression 2.8. The results are presented in Table 2.9. In panel A, we can find the result of low exposure firms. The result of the first stage shows that the ex-ante violation signal is significantly negatively correlated with the market reaction. A 1% increase in the likelihood of detection in the year before the selection drives down the stock price by 6.9 basis points. This estimated market reaction is significantly associated with the number of regulatory letters issued ex-post. More precisely, this predictability of the market is mainly due to the predictability in

sanction letters issuance. It indicates that a 1% increase in public information-based market reaction results in the future increases the sanction letters issued by the regulators by approximately 13.082. The same pattern has not been found in predicting the question letters and in high exposure firms.

2.7.2 Predictability of Private Information

The previous results suggest that public information-based market reactions can predict ex-post sanction letters issuance. I next dig further, to show how private information plays a role in revealing predictable information of violations. I use the same method by conducting a two least stage square model. The first stage stays unchanged as follow:

$$CAR(-10, 10)_{i,t} = \alpha + \beta * Violation\ Signal_{i,t-1} + Controls_{i,y-1} + \epsilon_{i,t} \quad (2.11)$$

In the second stage, to proxy the private information, I use the gap between the realized market reaction and the predicted market reaction by public information in regression 2.11:

$$Post\ Letters_{i,t} = \alpha + \beta \left[CAR(-10, 10)_{i,t} - \widehat{CAR}(-10, 10)_{i,t}^{public} \right] + Controls_{i,y-1} + \epsilon_{i,t} \quad (2.12)$$

I rename the gap of $\left[CAR(-10, 10)_{i,t} - \widehat{CAR}(-10, 10)_{i,t}^{public} \right]$ as $\widehat{CAR}(-10, 10)_{i,t}^{private}$. Table 2.10 reports evidence on which the informed investors deliver information on the market in helping to predict the regulatory letters issuance. The result of the second stage shows that the ex-ante violation signal estimated by private information is significantly negatively correlated with the ex-post punishment. A one basis point decrease in market reaction at the event date is associated with an additional 1.566 regulatory letters issued in the following year. More specifically, a one basis point decrease in market reaction at the event date is associated with an additional 0.743 (0.823) question (sanction) letters issued in the following year. These results suggest that private information also plays an important role in predicting the ex-post punishment. More importantly, although the magnitude is small, it complements the predictability of markets for question letters issuance.

2.7.3 Textual Analysis of Regulatory Letters

To explore the mechanism further, I dig deeper into the content of the regulatory letters. The predictability of markets to the specific information that is contained in ex-post regulatory letters allows me to infer the type of ex-ante violation information revealed on the market. To do so, I exploit the text in the ex-post regulatory letters issued and focus on the low exposure group. I analyze the information depending on the complexity and

Table 2.9: Mechanism: Public Information-Based Market Predictability

Table 2.17 reports the result of two least stage square model in selected firms. The Panel A shows the result of low exposure groups, where the firms did not receive any regulatory letters before the selection. The Panel B shows the result of high exposure groups, where the firms received regulatory letters before the selection. In the first stage, the dependent variable is $CAR(-10, 10)$. $ViolationSignal_{t-1}$ is the main explanatory variable estimated by the Probit model 2.8. In the second stage, the dependent variable is the number of letters' issuance after the selection. $Post1yearQL_t$ corresponds the number of question letters issued during $(t, t+1)$. $Post2yearSL_t$ corresponds the number of sanction letters issued during $(t+1, t+2)$. And the main explanatory variable is the estimated $CAR(-10, 10)$ from the first stage. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Panel A: Low Exposure_Selected Sample

	First stage		Second stage		
	CAR (-10,10)		<i>Post Letter_t</i>	<i>Post1yearQL_t</i>	<i>Post1yearSL_t</i>
<i>Violation Signal_{t-1}</i>	-0.069** (0.033)				
$CAR(-10, 10)^{public}$			-29.233* (15.258)	-16.152 (10.717)	-13.082** (6.408)
Controls	Yes				Yes
Year FE	Yes				Yes
N	327				327

Panel B: High Exposure_Selected Sample

	First stage		Second stage		
	CAR (-10,10)		<i>Post Letter_t</i>	<i>Post1yearQL_t</i>	<i>Post1yearSL_t</i>
<i>Violation Signal_{t-1}</i>	-0.028 (0.064)				
$CAR(-10, 10)^{public}$			-120.846 (248.540)	-74.202 (147.652)	-46.644 (102.018)
Controls	Yes				Yes
Year FE	Yes				Yes
N	421				421

Table 2.10: Mechanism: Private Information-Based Market Predictability

Table 2.18 reports the result of two least stage square model in selected firms. The Panel A shows the result of low exposure groups, where the firms did not receive any regulatory letters before the selection. The Panel B shows the result of high exposure groups, where the firms received regulatory letters before the selection. In the first stage, the dependent variable is $CAR(-10, 10)$. $Violation Signal_{t-1}$ is the main explanatory variable estimated by the Probit model 2.8. In the second stage, the dependent variable is the number of letters' issuance after the selection. $Post1yearQL_t$ corresponds the number of question letters issued during $(t, t+1)$. $Post2yearSL_t$ corresponds the number of sanction letters issued during $(t+1, t+2)$. And the main explanatory variable is the estimated $CAR(-10, 10)$ from the first stage. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Panel A: Low Exposure_Selected Sample

	First stage		Second stage		
	CAR (-10,10)		<i>Post Letter_t</i>	<i>Post1yearQL_t</i>	<i>Post1yearSL_t</i>
<i>Violation Signal_{t-1}</i>	-0.069** (0.033)				
$CAR(-10, 10)^{private}$			-1.566*** (0.180)	-0.743*** (0.103)	-0.823*** (0.205)
Controls	Yes			Yes	
Year FE	Yes			Yes	
N	327			327	

Panel B: High Exposure_Selected Sample

	First stage		Second stage		
	CAR (-10,10)		<i>Post Letter_t</i>	<i>Post1yearQL_t</i>	<i>Post1yearSL_t</i>
<i>Violation Signal_{t-1}</i>	-0.028 (0.064)				
$CAR(-10, 10)^{private}$			-0.705 (1.015)	0.059 (0.518)	-0.764* (0.394)
Controls	Yes			Yes	
Year FE	Yes			Yes	
N	421			421	

concealment of the misconducts in the following steps.

Analysis of Information Content

Firstly, with the *pdfplumber* package from Python to download all the files as regulatory letters on the two exchanges and the CSRC. The new database has been constructed with the downloads of letter files. Next, with the use of *Regular Expression* coding method, I extract texts from question letters and sanction letters separately, which are in a pdf format. Depending on the focus of different regulators, the complexity and concealment, I categorize the violations (or suspicious misconducts) mentioned in these letters into three categories: assets manipulation, profit manipulation, and illegal stock trading. Before that, I design a dictionary that contains all the keywords in the above three categories.²² Asset manipulation is supposed to capture the complex misconducts focused by the CSRC the amount involved is usually large and has large impact on firm value. Profit manipulation is considered as pervasive misconducts and less hidden. On the contrary, illegal stock trading should be more complex and hidden given that it represents the trading behavior of insiders.

By exploring the information content, it also allows us to remove any letters that have endogeneity suspicions. For instance, any ex-post question letters questioning the previous abnormal stock price movements have been removed. In addition, I exclude any sanction letters that sanction violation activities that happened after the selection event (in other words, no delay of these sanction letters issuance). In the end, I exclude 1,442 letters from the total sample of the ex-post letters.

Market Predictability of Specific Information

Next, I conduct the same two least stage square model in Section 7.1.3 and 7.2 to examine the predictability of both public and private information in predicting the specific type of information. The first stage remains unchanged, where the signal of violation estimated is based on the public information. In the second stage, I estimate public information-based predictability and private information-based predictability separately as follow:

$$\text{Post Letters}_{i,t}^j = \alpha + \beta \widehat{\text{CAR}}(-10, 10)_{i,t}^{\text{public}} + \text{Controls}_{i,y-1} + \epsilon_{i,t} \quad (2.13)$$

$$\text{Post Letters}_{i,t}^j = \alpha + \widehat{\text{CAR}}(-10, 10)_{i,t}^{\text{private}} + \text{Controls}_{i,y-1} + \epsilon_{i,t} \quad (2.14)$$

²²The dictionary can be found in Appendix A3.

The j represents one of the categories from the three categories above. For each regulatory letter, it may contain key words in one or all of the categories. The dependent variable $Post\ Letters_{i,t}^j$ represents the sum of $Post1yearQuestionLetters_{i,t}^j$ and $Post1yearSanctionLetters_{i,t}^j$ of regulatory letters in category j for firm i . Table 2.11 shows the results.

We can find the predictability of market reaction on specific types of violations exists in the data. The second stage of Panel A, consists of results that have been shown in Section 7.2: public information-based violation signals increase the market predictability in sanction letters issuance. For instance, it reveals more information associated with the asset manipulation related violations. With the magnitude as an 1% increase of violation signal significantly predict 0.005 additional asset-oriented sanction letters issued in the future. Market predictability based on public information is up to three times more predictive for asset-based sanction letter issuance than for trading-oriented sanction letter issuance. However, this predictability is not shown for question letter issuance, which is also consistent with the result in Section 7.1.3. It suggests that public information can only predict the clear violations that are contained in the sanction letters, and cannot predict any suspicious and unclear violations in question letters.

In Panel B of Table 2.11, the same pattern keeps showing in private information-based market predictability to sanction but not question letters issuance. The coefficient on $\underline{CAR}(-10, 10)_{i,t}^{private}$ in predicting trade-oriented question letters issuance is significant and negative, indicating that a 1% drop in private information-based market price is associated with 0.157 additional trading-oriented question letters issuance. These results can be viewed as providing suggestive evidence that the private information is more contributive in predicting future punishment when the punishment is somewhat associated with violations that are hidden. Moreover, private information is consistent in predicting sanction letters. A more significant coefficient in asset-oriented violations indicates that private information is especially related with the information of asset manipulation.

By isolating the violation types, I find that the predictability of markets is driven by the specific contents of regulated activities. For violations that are easy to detect and have a great impact, public information can exert sufficient and significant predictability. While for violations that are hidden and difficult to detect, private information plays a greater role in predicting than for other violations.

2.7.4 Robustness check

Role of Institutional Investors

In the last set of analyses, I further dig into the information content, and examine the role played by institutional investors. Given that institutional investors are informed, I

Table 2.11: Mechanism: Predictability in Specific Misconduct Information

Table 2.11 reports the result of two least stage square model in selected and low exposed firms. The Panel A shows the result of public information based predictability of punishment. The Panel B shows the result of private information based predictability of punishment. In the first stage, the dependent variable is $CAR(-10, 10)$. $Violation Signal_{t-1}$ is the main explanatory variable estimated by the Probit model 2.8. In the second stage, the dependent variable is the number of letters' issuance after the selection. $Question Letter$ corresponds the number of question letters issued during $(t, t+1)$. $Sanction Letter$ corresponds the number of sanction letters issued during $(t+1, t+2)$. And the main explanatory variable is the estimated $CAR(-10, 10)$ from the first stage. The $Asset$, $Profit$ and $Trade$ correspond to the number of regulatory letters with asset, profit and trade-oriented information contents, respectively. The keywords of each category are defined in the Appendix Table 2.16. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Panel A: Public information predicted $CAR(-10,10)$							
	First stage			Second stage			
				Question Letter		Sanction Letter	
	CAR (-10,10)	Asset	Proft	Trade	Asset	Proft	Trade
$Violation Signal_{t-1}$	-0.069** (0.033)						
$CAR(-\widehat{10}, 10)^{public}$		-10.711 (7.683)	-7.990 (6.796)	-5.732 (3.686)	-7.381* (4.066)	-4.580* (2.485)	-2.200* (1.259)
Controls	Yes			Yes			Yes
Year FE	Yes			Yes			Yes
N	327			327			327

Panel B: Private information predicted $CAR(-10,10)$							
	First stage			Second stage			
				Question Letter		Sanction Letter	
	CAR (-10,10)	Asset	Proft	Trade	Asset	Proft	Trade
$Violation Signal_{t-1}$	-0.069** (0.033)						
$CAR(-\widehat{10}, 10)^{private}$		-0.188 (0.143)	-0.108 (0.085)	-0.157*** (0.059)	-0.427*** (0.154)	-0.308** (0.137)	-0.227** (0.091)
Controls	Yes			Yes			Yes
Year FE	Yes			Yes			Yes
N	327			327			327

would expect that their ownership to play a crucial role in decreasing the asymmetric information. To confirm this hypothesis, I further split my sample based on the size of institutional ownership.

The results in Table 2.12 confirm the expectation. We can find that in firms where the institutional investors' ownership is larger than the median of the sample, public information keeps significant predictability of ex-post regulatory letter issuance. Surprisingly, public information can significantly predict the question letter issuance. However, public information loses its predictability of punishment when institutions take a relatively lower proportion of shares.

On the other side, in Panel B, we can see that private information keeps predicting the issuance of regulatory letters. In firms where the institutional investors' ownership is smaller than the median of the sample, private information still significantly predicts trading-oriented violations. This result further shows evidence of the price informativeness given the information asymmetry of the market. The predictability of public information to the future regulatory letters' issuance can only be found when institutional ownership is below a certain threshold.

2.8 Conclusion

In this paper, I show the existence of one of the most mysterious information - financial violations – in the market even before the violations have been detected and revealed by the regulators. In particular, this information contains the significant predictability to the future regulatory punishment. Although past literature shows the predictability of short sellers to financial misstatement, and the anticipation of analyst to firms' accounting frauds, my study points out to a more general conclusion. I find that this predictability widely exist in the whole market which is not affected by the type of financial frauds but only by the type of investors who trade different information on the market.

The endogeneity issue has been eliminated with using a random selection policy in conducting the investigation. Therefore, I exclude the possibility that a firm has been selected by regulators because of any market signal sent by investors. I find that firms that are randomly selected to be investigated experience a significant market drop, which is associated with future punishment situations. Specifically, the market drops by 2.73% in the firms that receive sanction letters ex-post, but no significant reaction has been found in firms that didn't receive any letters ex-post. In addition, this predictability of market is further explained by investors' trading of information on ex-ante violation risks. Uninformed investors form their beliefs on public information and informed in-

Table 2.12: Mechanism: Role of Institutional Ownership

Table 2.11 reports the result of the second stage in two least stage square model in selected and low exposed firms. The firms have been split into two groups regarding to the size of institutional ownership. The Panel A shows the result of public information based predictability of punishment. The Panel B shows the result of private information based predictability of punishment. In the first stage, the dependent variable is $CAR(-10, 10)$. $ViolationSignal_{t-1}$ is the main explanatory variable estimated by the Probit model 2.8. In the second stage, the dependent variable is the number of letters' issuance after the selection. *Question Letter* corresponds the number of question letters issued during $(t, t+1)$. *Sanction Letter* corresponds the number of sanction letters issued during $(t+1, t+2)$. And the main explanatory variable is the estimated $CAR(-10, 10)$ from the first stage. The *Asset*, *Profit* and *Trade* correspond to the number of regulatory letters with asset, profit and trade-oriented information contents, respectively. The key-words of each category are defined in the Appendix Table 2.16. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

vestors trade their private information. As a result, public information-based market reaction is more efficient in predicting the easy-to-discover and high impact violations, while private information plays a complementary role in predicting the more hidden violations.

Moreover, this study proves the fact that the information of violations has started to be impounded into price as soon as the regulatory investigation is involved. It also completes the interpretation of the market reaction on the day when the firm's penalty is publicized, as the market had already started to react long before the results of the penalties were announced.

Financial misconducts have continuously attracted attention by regulators because of the huge impact and consequences it has on in the finance industry, government, corporate sectors, and other stakeholders. The difficulty and complexity of frauds and violations have increased dramatically, which leads to the question: how to efficiently detect the financial misconducts? The discussion of this question has been widely shown in literature and particularly in the computer science field. This paper sheds light on the detection in policy design under the context of strong-form market efficiency, where regulators can benefit from market information to conduct efficient detection. It is also worth to discuss how the market-based corrective action plays an important role in this detection methodology, where regulators make decisions based on market reactions. The previous paper of [Bond et al. \(2010\)](#) shows that a decrease of price informativeness can be found theoretically as agents correct their actions based on market expectations of the action takes place. However, one thing that helps to mitigate this concern is that in this paper, I show a circumstance under which regulators already make the decision of inspection, instead of making a market-based inspection. The conclusion of this paper gives clear evidence that markets do have information related to violations that regulators don't, which could benefit their efficiency in the detection process.

2.9 Appendix

2.9.1 Definition of Variables

Table 2.13: Variable Definitions

Age listed	Natural logarithm of the firm's year of listing in the exchange
Market value	Natural logarithm of equity market capitalization of firm (in millions of RMB)
State_Owned_Firms	A dummy variable indicates whether the firms have state-owned shares
State_Owned_Firms shares	The state-owned shares standardized by the total shares outstanding
Institution shares	The shares of institutional investors standardized by the total shares outstanding
Management shares	The shares of management team standardized by the total shares outstanding
Concentration top 10	The square of ownership of the top 10 largest shareholders
Pay_to_Performance_Firms	A dummy variable indicates whether the firms incentivize management teams with additional bonus. The bonus includes stock options, restricted stocks, stock appreciation rights.
Pay_to_Performance shares	The incentive paid by stocks standardized by total shares outstanding
ROE	Net income/total equity
ROA	Net income/total asset
Liability	Total liability
Illiquidity_Amihud	The annual illiquidity calculated by Amihud (Amihud, Y., 2002)
Volatility	Estimated as daily standard deviation of the rate of return in one year
SUE	Standardized unexpected earnings constructed by Wu,2003. The gap between the EPS of stock in current year and one year before, which is standardized by the standard deviation of the EPS during the previous 2 years.
Tax contribution	The tax payments of firm relative to the total tax receiving of the local government where it is located.
Modify_Annual report	A dummy variable indicates whether the firm in current year conduct any restatement of annual report.
Event_Captial restructuring	The number of major capital restructuring projects completed/in process in current year.

2.9.2 Market Reaction on Different Interval

Table 2.14: Market Reaction on Event Date

CAR (-10,2)						
Panel A: Low Exposure						
	$Post1yearQL_t > 0$	$Post2yearQL_t > 0$	$Post1yearSL_t > 0$	$Post2yearSL_t > 0$	$PostLetter_t > 0$	$PostLetter_t = 0$
Selected	-0.648% (-1.05)	0.122% (0.24)	-0.144% (-0.14)	0.088% (0.16)	-0.300% (-0.23)	-0.530% (-1.15)
Non-Selected	0.245% (1.18)	-0.310% (-1.71)	0.129% (0.54)	0.031% (0.13)	0.157% (0.96)	-0.056% (-0.67)
Difference	-0.893% (-1.38)	0.432% (0.81)	-0.273% (-0.25)	0.058% (0.1)	-0.457% (-0.73)	-0.474% (-1.19)
Panel B: High Exposure						
	$Post1yearQL_t > 0$	$Post2yearQL_t > 0$	$Post1yearSL_t > 0$	$Post2yearSL_t > 0$	$PostLetter_t > 0$	$PostLetter_t = 0$
Selected	0.286% (0.46)	-0.422% (-0.66)	0.421% (0.59)	-0.362% (-0.51)	0.055% (0.1)	0.679% (1.02)
Non-Selected	-0.262% (-1.17)	-0.739%*** (-3.38)	-0.487%** (-1.65)	-0.593%* (-2.19)	-0.296% (-1.56)	-0.080% (-0.48)
Difference	0.548% (0.8)	0.317% (0.45)	0.908% (1.14)	0.231% (0.29)	0.351% (0.59)	0.759% (0.99)

2.9.3 Dictionary of Textual Analysis

Table 2.16 shows the dictionary I designed for the textual analysis of regulatory letters.

2.9.4 Reliability of Probability Setting

In this section, I explore the validity of my probability tree setting in Section 3. Recall the setting, the p presents the probability of being detected after being selected at the random selection event. The q represents the probability to be detected without being selected. I assume that the p is greater than q as there is an increase of intensity in enforcement actions. I begin with the estimation of propensity of being detected in selected firms and in non-selected firms (p, q) . I use the Probit model 2.15 with the dependent variable being equal to 1 for firms that have received any regulatory letters in the year following the selection, and 0 otherwise. The sample has been split into selected and non-selected groups given a fiscal year y . Table 2.17 shows the summary statistics of (p, q) .

$$Post\ Letter_{i,t} = \alpha + \beta_i Firm\ Characteristics_{i,y-1} + \beta_j Previous\ Letter_{i,t} + Controls_{i,y-1} + \epsilon_{i,y-1} \quad (2.15)$$

The explanatory variables include the number of regulatory letters received during $(t-1, t)$ before the selection and the controls are the factors that are related to firm

Table 2.15: Market Reaction on Event Date

CAR (-5,5)					
Panel A: Low Exposure					
	<i>Post1yearQL_t > 0</i>	<i>Post2yearQL_t > 0</i>	<i>Post1yearSL_t > 0</i>	<i>Post2yearSL_t > 0</i>	<i>PostLetter_t > 0</i>
Selected	-0.877% (-1.14)	0.276% (0.35)	-0.449% (-0.59)	-1.810% ** (-2.34)	-0.901% (-1.44)
Non-Selected	0.305% (1.22)	0.152% (0.69)	0.173% (0.57)	0.479% * (1.83)	0.419% ** (2.18)
Difference	-1.182% (-1.25)	0.124% (0.15)	-0.622% (-0.64)	-2.289% (-2.39)	-1.320% (-1.78)
Panel B: High Exposure					
	<i>Post1yearQL_t > 0</i>	<i>Post2yearQL_t > 0</i>	<i>Post1yearSL_t > 0</i>	<i>Post2yearSL_t > 0</i>	<i>PostLetter_t > 0</i>
Selected	-0.291% (-0.37)	-0.368% (-0.48)	-1.360% * (-1.8)	-1.720% ** (-2.15)	-0.652% (-0.96)
Non-Selected	-0.258% (-1.08)	-0.240% (-1.01)	-0.498% (-1.62)	-0.877% *** (-2.93)	-0.279% (-1.36)
Difference	-0.033% (-0.04)	-0.128% (-0.16)	-0.862% (-1.05)	-0.843% (-0.97)	-0.373% (-0.57)

Table 2.16: Regulatory Letters Analysis Dictionary

Category	Keywords
Asset manipulation	<i>Capital restructuring, M&A, Occupancy of assets, Related party transaction, Supply chain, Top5 customer, Illegal guarantee, Liability, Receivables, Cash, Asset impairment</i>
Profit manipulation	<i>Profit, Earnings, Net profit, Cash flows, Inventory, Provision for uncollectible accounts</i>
Illegal stock trading	<i>Illegal buying/selling, Insider trading, Short-term trading</i>

characteristics that have been used in the OLS regression (3) in Section 6.3. The table shows a clear increase in the intensity of detection over the years. Moreover, as expected, the non-selected firms experience less attention from regulators than the selected firms.

Table 2.17: Propensity of Detection in Probability Tree

Year	Non-Selected (q)		Selected (p)		Difference	
	Mean	Std	Mean	Std	Mean	p-value
2016	0.377	0.156	0.491	0.269	0.114	< .0001
2017	0.408	0.153	0.519	0.277	0.111	< .0001
2018	0.398	0.148	0.555	0.285	0.157	< .0001
2019	0.396	0.176	0.582	0.278	0.186	< .0001
2020	0.366	0.177	0.617	0.272	0.251	< .0001

I further separate the firms into a low exposure group and a high exposure group to explore this difference. Table 2.18 shows the magnitude and significance of $(p_E, p_{NE}, q_E, q_{NE})$. For a high-exposed firm, the likelihood to of being detected on average is much larger than the low-exposed firm. Within the group, same pattern can be found as selected firms experience a greater detection force than non-selected firms. In addition, the magnitude of the gap between p_E and q_E on average is similar to the gap between p_{NE} and q_{NE} . Indeed, for both types of firms, they should experience the same increase of intensity in enforcement action due to the selection policy which is applied to the whole financial market.

2.9.5 Shenzhen CSRC Local Office Random Selection Design

Table 2.18: Propensity of Detection in Probability Tree - Exposure Level

Panel A: High Exposure						
Year	Non-Selected (q_E)		Selected (p_E)		Difference	
	Mean	Std	Mean	Std	Mean	p-value
2016	0.418	0.159	0.53	0.289	0.112	0
2017	0.437	0.161	0.528	0.282	0.091	0.001
2018	0.439	0.156	0.628	0.269	0.19	< .0001
2019	0.451	0.187	0.653	0.27	0.201	< .0001
2020	0.432	0.187	0.685	0.268	0.253	< .0001

Panel B: Low Exposure						
Year	Non-Selected (q_{NE})		Selected (p_{NE})		Difference	
	Mean	Std	Mean	Std	Mean	p-value
2016	0.337	0.141	0.457	0.245	0.12	< .0001
2017	0.379	0.139	0.511	0.274	0.133	< .0001
2018	0.358	0.129	0.492	0.285	0.134	< .0001
2019	0.342	0.144	0.523	0.272	0.181	< .0001
2020	0.299	0.136	0.557	0.263	0.258	< .0001

The screenshot shows the official website of the Shenzhen Supervision Bureau, a branch of the China Securities Regulatory Commission (CSRC). The header includes the logo of the CSRC, the text '中国证券监督管理委员会' (China Securities Regulatory Commission), 'Shenzhen Supervision Bureau', and links for 'front page', 'Introduction of Jurisdiction', 'Government', 'Office service', 'Jurisdiction', 'Regulation', 'Information', and 'Special Column'. A banner at the top right says 'Respect the market, the rule of law'. The main content area displays a document titled 'Notice on the arrangement of on-site inspection of listed companies in 2018'. The document details include: The index number is bm56000001/2021-00303582; The publisher is Shenzhen Bureau; The name is Notice on the arrangement of on-site inspection of listed companies in 2018; The document number is Shenzhen Securities Bureau Company Zi [2018] No. 9; The classification is Listed company supervision; notice announcement; The date of publication is May 25, 2018; and the subject word is listed company supervision. Below the document, a link to 'Notice on the arrangement of on-site inspection of listed companies in 2018' is provided.

Figure 2.5: Random selection policy design - Shenzhen CSRC office (website screen shoot)

According to the risk level of listed companies, past regulatory inspection records, etc., Shenzhen Securities Regulatory Bureau has set up four random inspection groups based on regulatory priorities. Different random inspection groups correspond to different random inspection ratios, and each company is only classified into one random inspection group. The sampling groups and the number of sampling households are as follows:

Restructuring and listing group: According to the requirements of the Listing Department, companies that have been reorganized and listed in the past three years should carry out on-site inspections one by one, and a special group has been set up for this purpose. **In 2017, the restructuring and listing group selected 1 company.**

Annual report risk company group: After reviewing the 2016 annual reports of listed companies in the jurisdiction, and discussing with the exchange, the annual report risk company group was determined. **In 2017, seven companies were selected from the annual report risk company group.**

Non-inspected group: For companies that have not undergone on-site inspection by our bureau since their listing, a special group is set up. **In 2017, the uninspected group selected 3 companies.**

Ordinary group: All companies other than those that meet the above conditions are classified into the common group. **In 2017, one general group was selected.**

Figure 2.6: Random selection policy design details - Shenzhen CSRC office

Chapter 3

How Firms Endure and Succeed under Detection Risks

Joint with Li Bao (TSM)

3.1 Introduction

Government investigations play a pivotal role in upholding the integrity of financial markets (Brunnermeier et al., 2022a). Experienced investors also factor in government enforcement actions when making investment choices (Brazel et al., 2015). Extensive research has looked at how regulatory investigations and enforcement actions affect both companies and individuals. Companies being investigated often see their value drop and a higher chance of changes in their management. However, the exact impact of regulatory intervention isn't always clear, as it usually starts with companies revealing potential problems (Karpoff et al., 2008b,a; Blackburne et al., 2020). Distinguishing the reactions of non-violating firms from those of violating firms towards regulatory intervention presents an intriguing avenue for exploration. How do these two distinct categories respond differently to such intervention? Delving into this question can help us gain a better grasp of how regulatory intervention works.

The impact of regulatory investigations on firms is a complex interplay of two distinct yet interconnected components. First, there is the direct impact of government intervention, which includes the actions and measures taken by regulatory authorities when investigating potential violations. This component examines how firms react to the investigative process itself - the inquiries, audits, and scrutiny that come with regulatory attention (Impact I). Secondly, we have the aspect of potential effects, which extends beyond the investigation phase. This facet focuses on the perceived detection or penalties that may arise due to detected violations. Such effects can vary widely, from fines and sanctions to reputational damage and legal consequences (Impact II).

The key challenge complicates the examination of the regulatory intervention effect is the endogeneity arising from the interplay between firms' decisions to reveal information and the subsequent investigations. The prevalent analysis typically concentrates on firms with a high likelihood of violating laws in the past. The investigation effect can be overestimated (Impact II be overestimated). Firms with severe problems are more likely to hide information, and the negative effects of regulatory investigations may be underestimated because some cases of non-disclosure are not accounted for (Dyck et al., 2010). Conversely, firms with more significant issues can attract more attention and are consequently more likely to be detected, the observed investigation effect could be overestimated due to the increased visibility of violations (Impact II be underestimated)(Blackburne and Quinn, 2023; Rogers and Van Buskirk, 2009; Ji et al., 2023; Lowry, 2009).

Our empirical approach addresses these challenges. Beginning in 2016, the China Securities Regulatory Commission (CSRC) initiated a random selection program aimed at investigating potential violations of securities laws. This policy mandates each CSRC local bureau to randomly select a minimum of 5% of locally listed firms for in-depth investigation. We note that firms with no prior indications of law violations can also be included in the program, as can those with previous law violations, irrespective of any prior signals. This unique event provides us with a quasi-natural experiment, offering insight into how firms respond to government investigation pressure. Consequently, we analyze a dataset comprising 853 Chinese-listed firms, randomly selected from 36 jurisdictions during the period 2016 to 2021.

Firms' reaction to the pressure from government investigation is determined by the choices of their shareholders. On the one hand, shareholders may choose to sell their shares if they know that their firms violate laws. This strategic move could be triggered by the anticipation of a decline in share value, which could, in turn, create an opportunity for potential shareholders to acquire a greater stake in the company. Conversely, shareholders who choose to maintain their position within the firm signal a commitment to its governance enhancement. This decision could reflect an intention to actively address and rectify any existing issues, thus contributing to the long-term stability and reputation of the organization.

To test the hypothesis, we start by examining the impact of government investigation on the turnover of the top 10 largest shareholders. This analysis serves as a foundational step in our exploration. Subsequently, we delve into the potential effects on the management team, shedding light on how their positions may be influenced in the wake of such regulatory scrutiny. We initiate the analysis by refining our sample to include only those firms that remained untouched by regulatory letters in the year leading up to their selection. This step ensures that no exceptional regulatory scrutiny had been

directed toward these firms prior to our study. Subsequently, we split our sample into two categories: firms flagged as violating and those with no such indications, as revealed by future detection outcomes. We first examine the quarterly turnover observed within the ranks of the top 10 largest shareholders subsequent to a firm's random selection. To quantify this phenomenon, we introduce a novel proxy that captures the extent of alteration in ranking among the top 10 largest shareholders. Our finding shows that in violating firms, no significant shifts have been found in the rankings of the top 10 largest shareholders. Remarkably, the stability among the top 10 largest shareholders is even more pronounced with a significant decrease in turnover.

Next, we explore the response of the management team by delving into the turnover patterns of its members on a daily basis. We implement a stringent filtering approach, excluding members whose tenure commenced before the selection date and ended before any regulatory sanctions were issued. For other cases, our observation window expands to cover the 2 years following the random selection event. To assess the relationship between detection outcomes and management team turnover, we employ an OLS regression model. The results indicate that violating firms, during the post-event phase, exhibit a higher likelihood of experiencing increased turnover compared to the non-violating ones. Specifically, there is an additional count of 0.04 members resigning, constituting 40% of the mean resignation rate. The observed increase in turnover aligns with the notion that the perceived risk of detection prompts strategic changes within these firms, potentially necessitating managerial reshuffling.

Conversely, non-violating firms display a different pattern: prior to selection, non-violating firms exhibited a higher turnover rate in comparison to violating firms, resulting in an additional 0.02 members resigning. However, following their inclusion in future random investigations, these non-violating firms experienced a significant reduction in turnover. The subsequent decrease in turnover suggests that regulatory scrutiny acts as a catalyst for improving stability within the management team. This could be attributed to a heightened focus on governance and compliance in response to the anticipation of regulatory review.

Past research has also indicated a connection between trading behavior and litigation risks. In a study by [Blackburne et al. \(2021\)](#), it's shown that insider selling is present during undisclosed investigations and seems quite opportunistic. This type of trading also happened among blockholders, as observed by [Ji et al. \(2023\)](#). The paper shows that larger shareholders foresee potential bad news about corporate misconduct, and proactively initiate their sales even up to eight quarters beforehand. Building upon this existing literature, we expand our investigation into the relationship between trading behaviors and management team turnover under the context of regulatory investigation. Our findings reveal that in detected firms, members who engage in share selling during

the first six months following the firm's selection event are 71.6% more likely to leave compared to cases where the firm remains undetected.

Our paper has several contributions. It contributes to the literature on the impact of government investigation on internal governance. Previous papers find that government investigation can decrease firm value while increasing manager turnover (Karpoff et al., 2008a,b; Blackburne and Quinn, 2023; Blackburne et al., 2021, 2020; Gao et al., 2017). However, the secrecy surrounding regulatory investigations poses challenges in determining the specific timeframe when shareholders alter their perception of detection risks and when firms adjust their governance practices accordingly. Our study addresses this challenge by providing a clear investigation timeframe, enabling us to examine when firms begin to respond and the extent of their reactions. Our findings are closely aligned with Karpoff's observations (Karpoff et al., 2008b), where he highlights the efficacy of a firm's internal governance in removing managers involved in financial misconduct, particularly in cases of detected firms. Unlike his study whose research emphasizes effective internal governance within violating firms, our study explores the impact of regulatory investigations. In other words, our study sheds light on whether firms not subjected to regulatory attention bias would exhibit similar reactions, and also contributes to the understanding of the impact of government investigation on non-violating firms.

Furthermore, our research extends the scope of the broader literature on litigation risk. While existing studies primarily focus on the negative impact of litigation risks, such as increased capital costs, our study highlights a positive aspect (Wu et al., 2020; Blackburne et al., 2021; Qin et al., 2021; Sun and Zhang, 2011; Ji et al., 2023; ?). Regulatory investigations, as we reveal, contribute to enhancing stability within the management team of non-violating firms and send positive signals to the market. In contrast to earlier findings, we also uncover the proactive stance of blockholders in violating firms, who choose to remain and actively enhance internal governance rather than exiting. This perspective adds depth to the understanding of how firms respond to litigation risks.

3.2 Hypothesis development

Firms' reaction to the pressure from government investigation is determined by the choices of their shareholders. On the one hand, shareholders may choose to sell their shares if they know that their firms violate laws. This strategic move (Wall Street Walk) could be triggered by the anticipation of a decline in share value, which could, in turn, create an opportunity for potential shareholders to acquire a greater stake in the company. Conversely, shareholders who choose to maintain their position within the firm signal a commitment to its governance enhancement. This decision could reflect

an intention to actively address and rectify any existing issues, thus contributing to the long-term stability and reputation of the organization. Hence, we develop the two hypotheses as follows:

H1 Wall street walk: There is an exit among the top 10 largest shareholder exits. We observe the ranking of the original top 10 before the firm has been selected decreases.

H2 Internal governance improvement: The ranking of the original top 10 does not change, we should observe the turnover in the management team.

Previous literature shows that firms under enforcement action are more likely to fire the responsible parties. The directors that are aware of financial fraud depart before the sanctions. The findings of the previous studies suggest that firms that have conducted any violating behaviors perceive higher detection probability in the near future, thus are more likely to resign the management team members. In light of this, we put forth the following sub-hypothesis:

H2.1: violating firms experience an increase in turnover subsequent to their random selection for future investigation, whereas non-violating firms will not experience such an increase.

3.3 Data and main variables

3.3.1 Data sources

Our sample encompasses all 853 Chinese-listed firms randomly selected from 36 jurisdictions between 2016 and 2021. The data used in this study is organized into five distinct datasets. The initial dataset includes regulatory detection information, including variables linked to random selection events and regulatory letters. The event dates, selected firms per year, and per jurisdiction were sourced from local CSRC offices' websites. Regulatory letters, which include query letters from stock exchanges and sanction letters issued by both stock exchanges and the CSRC, were manually collected from the respective stock exchanges and local CSRC offices' websites. Ultimately, among the selected firms, our dataset comprises 1,757 sanction letters and 3,632 question letters from the year 2015 to 2022.

Datasets two through five are derived from the data vendor CSMAR (China Stock Market & Accounting Research Database). The second dataset includes firm characteristics, including attributes such as firm age, market capitalization, state ownership, management team ownership, and return on equity (ROE). The first two datasets align with those utilized in the second paper.¹

¹The second paper is titled 'Can Markets Predict Enforcement Action of Securities Regulators.'

The third dataset concerns the ownership of the top 10 largest shareholders and is a quarterly dataset. It features details like the ranking, ownership percentage, and share nature of each shareholder per year. Examples of share nature include state, foreign, individual, and funds, among others.².

The fourth dataset represents the turnover of management team members. This provides details on their positions, service status, and whether they stayed or left in a specific fiscal year. It additionally provides precise commencement and cessation dates for their positions, along with the reasons behind any departures occurring during that period. Notably, we exclude any resignation reason as retirement. We further segment these positions into three broad categories: managers, directors, and supervisors. Positions such as honorary chairman, honorary chairman of the supervisory board, independent director, and independent supervisor are excluded, as these individuals are deemed not to be directly affected if the firm comes under regulatory scrutiny. Our sample consists of 18,848 management team departures from 2015 to 2022. After position-related constraints, there are 14,825 observations, further reduced to 14,390 by excluding retirements.

The final dataset records daily transactions by management team members. It includes reported transactions in percentage³ to the regulatory authority, along with the transaction methods used. These methods comprise block trade, auction, secondary market trading, dividend distribution, conversion from capital reserve, share placement with old shareholders during seasoned new issues, new share subscriptions, equity incentive implementation, and others. For this study, we focus on management-initiated methods like block trades, auctions, and secondary market trading. In the following sections, we will detail how variables used in this paper are constructed from each dataset.

3.3.2 Variable measurement

We begin by categorizing the 853 randomly selected firms into two groups based on their previous regulatory exposure. We define low-exposed firms as those without any regulatory letters in the year preceding the event. These firms could either be non-violating or violating but undetected. This approach helps us narrow our focus to firms with minimal prior exposure to the regulators. As a result, we address potential endogeneity concerns stemming from previous detection outcomes while isolating the influence of random detection pressure from the event on managerial strategy.

²For a comprehensive breakdown of shareholder types, refer to the Appendix

³Article 86 of the Securities Law of the People's Republic of China (2014) requires investors to report to the regulatory authority and the exchange if they hold or jointly hold five percent or more of a listed company's shares. They must also notify the company and make a public announcement. Subsequent changes of five percent or more in their shareholding also require reporting and a two-day trading restriction.

In the first part, we examine the impact of regulatory detection on the top 10 largest shareholders. We construct a measure to capture the change of ownership among the top 10 largest shareholders. For each top 10 largest shareholders in firm i at time t , we assign a score based on their rank. The j^{th} largest shareholder gets a score of $11 - j$. Then we track the existence of the top 10 largest shareholders at time $t + n$ and update their score based on their new rank. Finally, we have the measure $Ownerchange_{t+n}$ by summing the new score and standardizing by 55.

$$Top10_j = \alpha + \beta_1 Detect_j + \beta_2 Detect_j * Post_j + \beta_3 Post_j + \beta_4 Firm Specific Char_{i,y-1} + \epsilon_i \quad (3.1)$$

where the $Top10$ represents the change of ownership among the top 10 largest shareholders. We also examine the top 5 largest shareholder turnover.

The dummy $Detect$ indicates the future detection status of firm j . Precisely, $Detect = 1$: for any firms that have $PostLetter_t > 0$. $Detect = 0$: for any firms that have $PostLetter_t = 0$. The $PostLetter_t$ is the sum of the number of question letters received in the first year following the selection event($QuestionLetter_{t+1}$) and the number of sanction letters received in the second year following the selection ($SanctionLetter_{t+2}$).

The variable $Post$ is a dummy. It is set to 0 if the observation corresponds to the two quarters prior to the event, and it is set to 1 if it corresponds to the first or second quarter after the event. The post period varies individually for each firm due to their distinct event dates.

We control the firm characteristics in the previous fiscal year ($y - 1$) of the event represented as $Firm Specific Char$, including firm age, market capitalization, state ownership, ownership of the management team, and the return on equity (ROE). We also controlled the industry and year-fixed effect.

In the second part, we explore the impact of regulatory detection on the management team. Our exploration entails assessing the effect of detection on management team turnover:

$$Nb. left_{k,j,g} = \alpha + \beta_1 Detect_j + \beta_2 Detect_j * Post_j + \beta_3 Post_j + \beta_4 Firm Specific Char_{i,y-1} + \epsilon_i \quad (3.2)$$

In equation 4.10, the dependent variable $Nb. Left$ counts the number of members in a specific position k in firm j who departed in g period. We define the g as the gap in years between the date of resignation of the member and the firm's random selection event date. We classify the gap into 1 (2) if the gap in days is smaller than 365 (730) days. If the gap in days is larger than -365 (-730) days, then it will be classified as a gap equal to -1 (-2). We can see a clear decline in management team members after the

event in general.

Additionally, to standardize the turnover, we divide the number of members who left a position in the firm by the total number of management team members of the firm. Specifically, for the post period, which is the two years following the selection event, we keep the turnover that takes place before the receipt of the first sanction letters in the second year following the event or the second year following the event if the firm doesn't receive any sanction letter. On the one hand, firms can utilize the opportunity of the investigation to improve their governance by changing their top management team. On the other hand, sanction letters can potentially lead the company to dismiss its management team or disclose violating individuals to the public. To concentrate on exploring the company's independent strategies, we eliminate any turnover that takes place after the receipt of the first sanction letters in the second year following the event.⁴

In this regression, *Post* is a dummy that is set to 0 if the member's service status corresponds to the two years prior to the event, and is set to 1 if it corresponds to the first or second year after the event. The post period varies individually for each firm due to their distinct event dates.

To delve into the influence of regulatory detection on the management team, we investigate how management team member turnover outcomes relate to their trading behavior after the event. We structure the data frame as follows: Firstly, we match the turnover of a member with his or her net transaction percentage within a specific time frame. Next, we analyze the connection between transactions and turnover using a Probit model 3.3, detailed as follows:

$$\begin{aligned} Left_i = & \alpha + \beta_1 Sell_{i,(t+n)} + \beta_2 Sell_{i,(t+n)} * Detect_j \\ & + \alpha + \beta_3 Buy_{i,(t+n)} + \beta_4 Buy_{i,(t+n)} * Detect_j + \beta_5 Detect_j \\ & + \beta_6 Firm Specific Char_{i,y-1} + \epsilon_i \end{aligned} \quad (3.3)$$

where the dependent variable *Left* is a dummy that indicates whether a specific member *i* is resigned during the observation period.

To observe the transactions made by the management team, we divided the time period into 12 intervals: 6 months before and 6 months after the event. For each additional month, we calculated the accumulated net transaction for specific members. This gives us the net transaction within the first 30 days following the event (*t* + 1), the first 60 days (*t* + 2), the first 90 days (*t* + 3), and so on, until the first 6 months (*t* + 6). The same calculation for the period before the event (from *t* - 6 to *t* - 1). Using the daily transaction records, we associated each transaction made by a member of a firm

⁴Within the two years following the selection, the gap between the first date of sanction letter issuance following the selection (if any) and the event date is around 302.495 days.

with a specific month (*gap_letter_month*) based on the selection event date of that firm. For example, if the event occurred on April 4, 2014, and there was a transaction on June 3, 2014, it would be assigned to *gap_letter_month* = 2. Then, we calculated the total transaction amount per member for each *gap_letter_month* and year⁵ and further classified them into selling and buying transactions based on the transaction value. The summary statistics have been shown in Table 3.2. The dummy *Sell* and *Buy* therefore, indicate the net transaction value during the period $(t, t + n)$, whether it's negative or positive.

3.3.3 Summary statistics

Ownership structure overview

As a starting point to look into firms' reactions to investigations, we conduct an overview of firms' ownership structure. Figure 3.1 presents the distribution of the Top 10 largest shareholder and the non-top 10 shareholders. (only keep the selected firms)

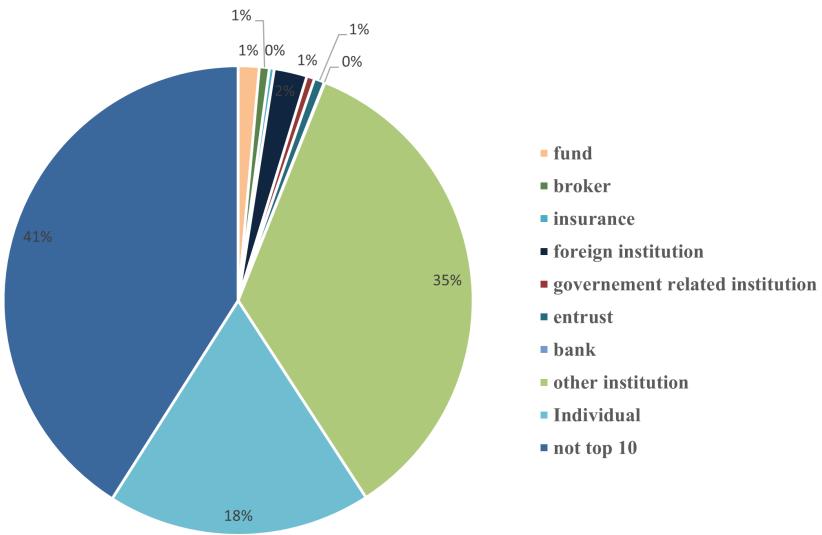


Figure 3.1: Shareholder distribution

Tables 3.1 through 3.11 present summary statistics for detected and undetected firms. Among the sample, 114 firms were detected, while 267 were not. Table 3.1 shows that, on average, management teams consist of 16 members. Notably, the position of managers exhibits the highest turnover, nearing 1, within a qualified 2-year window after the selection event. In detected (undetected) firms, 2.6% (7.9%) had state ownership

⁵There are 32 firms that have been selected twice, they have two event dates in two different years. In this case, we assign all the transactions for each event date separately.

exceeding 20% before the event. Detected firms display lower ROE compared to undetected firms.

Table 3.1: Turnover in Management Team

Table 3.1 provides summary statistics of turnover within distinct management team positions, including directors, managers, and supervisors. The sample has been split into two groups: violating firms ($detect = 1$) and non-violating firms ($detect = 0$). The table also reports the firm characteristics from the year prior to the selection event.

Nb.firms	Detect=1				Detect=0			
	114				267			
variables	Nb.obs	Mean	Std	Median	Nb.obs	Mean	Std	Median
Nb.director left	456	0.792	1.339	0.000	1068	0.799	1.375	0.000
Nb.manager left	456	0.987	1.503	0.000	1068	0.883	1.468	0.000
Nb.supervisor left	456	0.570	0.996	0.000	1068	0.633	1.170	0.000
Total member	456	15.803	11.977	20.000	1068	15.505	12.750	20.000
State ownership	456	0.012	0.063	0.000	1068	0.043	0.133	0.000
Management ownership	456	0.120	0.176	0.012	1068	0.120	0.197	0.000
State-owned firm	456	0.026	0.160	0.000	1068	0.079	0.269	0.000
Con10	456	0.149	0.098	0.118	1068	0.185	0.117	0.155
ROE	456	0.054	0.098	0.068	1068	0.079	0.092	0.080
Age	456	3.085	0.276	3.091	1068	3.068	0.255	3.091
Market value	456	15.689	0.792	15.609	1068	15.893	0.990	15.773

Figure 3.2 further shows the turnover in management teams in different time frames. Figures 3.3 and 3.4 show turnover among detected and undetected firms, illustrating turnover disparities within different positions—ranging from directors and managers to supervisors. A noticeable decline in management team is evident after the event, as depicted in the general trend. Figures 3.3 and 3.4 provide insights that detected firms experience higher turnover than undetected firms, particularly following the event.

Table 3.2 describes the individual daily transactions with summary statistics. Notably, both detected and undetected firms exhibit a substantial reduction in transactions around the selection event, spanning one month before and after. Detected firms feature a higher frequency of transactions with more negative net positions compared to undetected firms. Over the ensuing six months post-event, management team members in detected firms, on average, sold 0.197% of their shares, while this figure is 0.106% for undetected firms.

Table 3.3 describes the ownership and turnover of top 10 shareholders. For both detected and undetected firms, largest shareholder has more than 30% of shares, while top 5 shareholders have more than 50% of shares. In terms of turnover, the closer to 1,

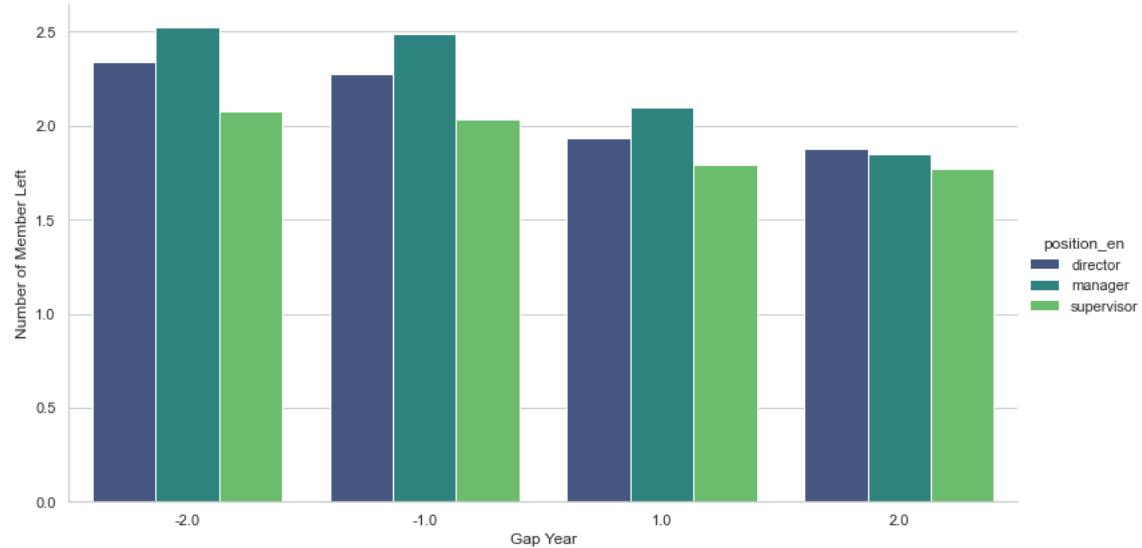


Figure 3.2: Turnover in management team

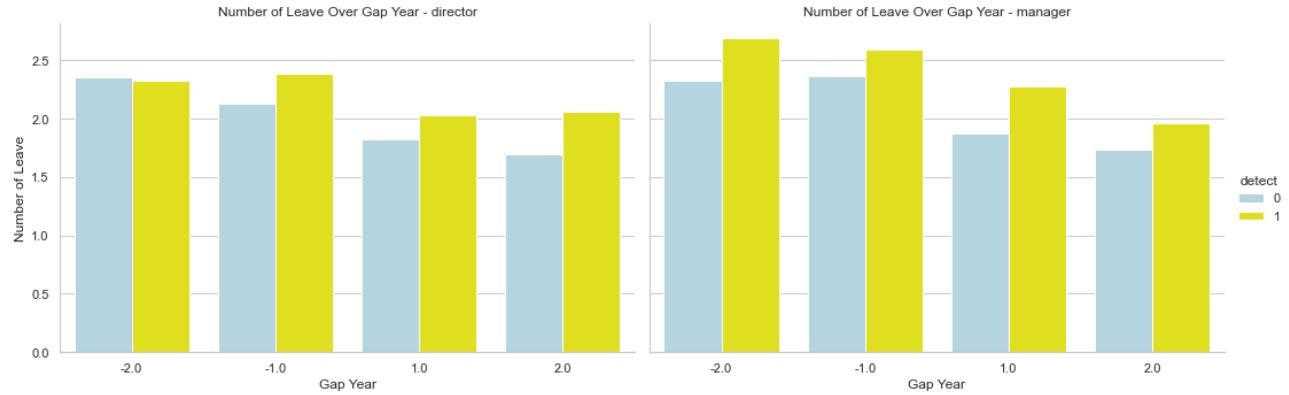


Figure 3.3: Turnover in management team: director and manager

the lower the shareholder turnover is. Both detected and undetected firms depicts a low shareholder turnover, top 5 shareholders have lower slightly lower turnover than top 10 shareholders.

3.4 Empirical results

3.4.1 Impact on top 10 shareholders

As the random investigation conducted by CSRC creates pressure on firms, shareholders can follow a wall street walk to exit the firm, which is our hypothesis H1. We start our analysis by testing this hypothesis.

Table 3.4 shows the regression analysis of the impact on the top 10 shareholder turnover. Column 1 - 2 analyze the turnover of top 10 and top 5 shareholders. Column

Table 3.2: Transaction in Management Team

Table 3.2 presents summary statistics of transactions within the management team in different time frames. t represents the date when a random selection event of a firm occurred. $t + n$ and $t - n$ represent the n^{th} month following and before the event, respectively.

	(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)	(t,t+1)	(t,t+2)	(t,t+4)	(t,t+6)	(t,t+8)
Detect=1									
Nb.obs	253	204	110	59	55	126	238	331	413
Mean	-0.154	-0.137	-0.151	-0.160	-0.203	-0.190	-0.208	-0.197	-0.236
Std	0.507	0.412	0.418	0.375	0.474	0.464	0.574	0.568	0.753
Median	0.000	0.000	0.000	-0.002	-0.012	-0.003	-0.003	-0.002	-0.002
Detect=0									
Nb.obs	167	149	98	48	36	82	164	235	285
Mean	-0.030	-0.022	-0.041	-0.053	-0.045	-0.055	-0.123	-0.106	-0.100
Std	0.399	0.329	0.368	0.332	0.136	0.210	0.387	0.392	0.401
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 3.3: Ownership turnover

Table 3.3 presents summary statistics of the ownership of the top 10 largest shareholders in different time frames. *Before* is the quarter end before the random selection, *After* represents the quarter end after the random selection.

Detect=1						
	Before			After		
	Mean	Std	Nb.obs	Mean	Std	Nb.obs
Top 10 turnover	0.913	0.109	114	0.911	0.124	119
Top 5 turnover	0.933	0.113	114	0.934	0.105	118
Top 10 ownership	58.884	12.913	114	59.078	12.889	119
Top 5 ownership	52.292	13.168	114	52.473	13.418	119
Largest ownership	32.392	13.862	114	32.729	14.320	119
Detect=0						
	Before			After		
	Mean	Std	Nb.obs	Mean	Std	Nb.obs
Top 10 turnover	0.891	0.129	238	0.891	0.122	256
Top 5 turnover	0.917	0.136	238	0.926	0.113	256
Top 10 ownership	62.779	14.280	238	62.208	14.378	256
Top 5 ownership	57.638	14.660	238	57.173	14.625	256
Largest ownership	37.490	14.981	238	37.463	14.673	256

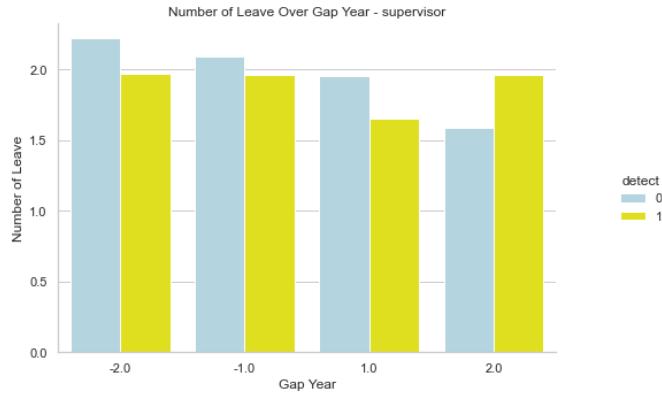


Figure 3.4: Turnover in management team: supervisor

3 - 5 analyze the ownership change of top 10, top 5 and largest shareholder. Detect captures the fact that before the random selection, there is no difference between detected firms and undetected firms in terms of top 10 shareholder turnover and their ownership. Post captures the fact that after the random selection, the change for undetected firms. The results show that only top 10 ownership is slightly negatively significant with a coefficient of -1.8096, while for others are insignificant. Post*Dectect captures the difference between detected firms and after detected firms. The results suggest that there are no significantly difference between detected and undetected firms after the random selection. Overall, the results suggest that there is no significant difference between detected and undetected firms for their top 10 shareholder turnover and their ownership. Also, top 10 shareholders have not run away from the firms. Our results do not support the wall street walk, thus rejecting our hypothesis H1.

3.4.2 Impact on management teams

Turnover of management teams

Table 3.5 presents the OLS regression of the impact of detection on turnover in the management team. The equation model 4.10 is defined in Section 4.2. In the first column, the results encompass the entire management team, utilizing total member departures as the dependent variable. Columns (2) through (4) delve into specific positions: directors, managers, and supervisors. The coefficient of the interaction term *Detect * Post* in Column (1) signifies the detection impact on total management team turnover. Consequently, detected firms in the post-event phase are more prone to experiencing elevated turnover compared to undetected firms, resulting in a higher count of 0.04 additional members resigning. Notably, directors display higher turnover than managers, while no significant change has been found in supervisors' turnover. Furthermore, the consistently significant negative coefficient in *Post* across all columns suggests that undetected firms are more likely to undergo a significant decrease in management team turnover.

This finding aligns with Karpoff's earlier research, which concluded that firms facing

Table 3.4: Regression analysis of top 10 turnover

Table 3.4 provides the regression analysis of top 10 shareholder turnover. Column 1 - 2 analyze the turnover of top 10 and top 5 shareholders. Column 3 - 5 analyze the ownership change of top 10, top 5 and largest shareholder. Detect is a dummy variable with a value of one if the firm has been detected by regulatory authorities within one year after the random selection event, and zero otherwise. Post is the dummy captures the effect before and after the random event. The regression controls the firm's characteristics including firm's state-owned ownership, the ownership concentration ratio of top 10 shareholders, Return on Equity (ROE), the firm's age, its market value, and its liquidity, all measured in the fiscal year preceding the event. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

	(1)	(2)	(3)	(4)	(5)
	Top 10 Turnover	Top 5 Turnover	Top 10 ownership	Top 5 ownership	Largest ownership
Detect	0.0200	0.0176	0.4936	-0.5400	-0.5400
	0.0140	0.0140	1.0710	0.9550	0.9550
Post	-0.018	-0.0094	-1.8096*	-1.2443	-1.2443
	0.0140	0.0140	1.074	0.9570	0.9570
Post*Detect	-0.0020	-0.0087	0.3947	0.2061	0.2061
	0.0190	0.0190	1.4620	1.3030	1.3030
State-owned firm	-0.0024	0.0067	2.9179*	2.8113**	2.8113**
	0.0200	0.0200	1.5540	1.3860	1.3860
Con_top10	-0.1814***	-0.0872**	77.2083***	92.0948***	92.0948***
	0.0430	0.0420	3.2820	2.9260	2.9260
ROE	0.0440	0.0299	8.5610**	4.9998	4.9998
	0.0520	0.0520	4.0180	3.5830	3.5830
Market value	0.0640	0.1158	56.2340***	44.3150***	44.3150***
	0.1810	0.1780	13.8410	12.3400	12.3400
Age	-0.0446**	-0.0531***	-8.4643***	-6.8795***	-6.8795***
	0.0190	0.0180	1.4210	1.2670	1.2670
Amihud	0.0030	0.0043*	1.09***	0.7746***	0.7746***
	0.0030	0.0030	0.1960	0.1740	0.1740
Quarter FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Nb.obs	727	726	727	727	727
R2-adjusted	0.0490	0.0230	0.5840	0.6760	0.9010

litigation risks tend to witness increased turnover among managers. Our study extends this insight by demonstrating that violating firms exhibit heightened director turnover compared to managers, while supervisors display no noteworthy turnover alteration. In addition, we contribute fresh insights by examining non-violating firms. Prior to selection events, these firms experienced higher turnover compared to violating ones. However, turnover decreased significantly after being chosen for future random investigations.

Table 3.5: Turnover in Management Team

Table 3.5 presents the outcomes of the OLS regression model for the management team turnover with 1524 observations. The dependent variable, denoted as *Detect*, is a dummy variable with a value of one if the firm has been detected by regulatory authorities within one year after the random selection event, and zero otherwise. The dummy variable *Post* distinguishes whether the turnover occurred before or after the event. The regression controls the firm's characteristics including the firm's state-owned ownership, the ownership held by the management team, Return on Equity (ROE), the firm's age, and its market value, all measured in the fiscal year preceding the event. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

	(1)	(2)	(3)	(4)
Dependent:	Total	Director	Manager	Supervisor
Detect	-0.0206*	-0.0099**	-0.0055	-0.0051
	0.010	0.005	0.005	0.004
Detect*Post	0.0407***	0.0182***	0.0161**	0.0064
	0.015	0.006	0.007	0.005
Post	-0.0371***	-0.0144***	-0.0169***	-0.0058**
	0.008	0.003	0.004	0.003
State-owned-firm	0.0156	0.0034	0.0080	0.0042
	0.015	0.006	0.007	0.005
Management ownership	-0.0532***	-0.0266***	-0.0146	-0.0121*
	0.019	0.008	0.009	0.007
ROE	-0.1010***	-0.0237	-0.0569***	-0.0204
	0.038	0.017	0.018	0.014
Age	0.0397***	0.0182***	0.0094	0.0120**
	0.014	0.006	0.007	0.005
Market value	0.0061	0.0011	0.0042**	0.0007
	0.004	0.002	0.002	0.001
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R2-adjusted	0.0467	0.0457	0.0325	0.0145

Turnover and management trading behavior

In the next section, our objective is to establish that the observed management team turnover is linked to strategic responses employed by firms in light of perceived detection

risks, rather than being attributed to regulatory enforcement actions. We investigate the response of resigned members subsequent to the firm's selection. We demonstrate that these members possessed an awareness of violating behavior and a recognition of potential litigation risks, leading to a shift in their trading strategy upon being selected.

We integrate the turnover data of each management team member with their corresponding transaction records using identification ID numbers. This process guarantees that we possess a comprehensive record of an individual's transactions across various time frames following the selection event, along with their departure or retention status within the qualified 2-year period. Summary statistics of individual-level turnover are presented in Tables 3.6 and 3.7. Table 3.6 presents member counts, while Table 3.7 displays ratios. These ratios are derived by dividing member counts by the total number of departed and retained members, respectively. t represents the date when a random selection event of a firm occurred. $t + n$ and $t - n$ represent the n^{th} month post-event and n^{th} month prior to the event, respectively. *Left Member* represents the number of members who departed, while *Stay Member* represents those who remained. Transactions have been categorized as *Net Buy* or *Net Sell* based on whether the net transaction value of a member during the corresponding period is positive or negative.

We can see from Table 3.7 that detected firms experience an increase of member who sells in ratios starting from the fourth month following the selection event. In Panel A, for instance, there were 12 management team members who departed after participating in share selling within the initial 4 months following the event. This accounts for 1.94% of the total departed members, and steadily climbs to 4.03% within the ensuing 12 months (Table 3.7). This upward trend, however, is not as prominent in either undetected firms or share buying behaviors. These findings suggest that, in the case of detected firms, members who departed initiated share selling once the firm was selected for scrutiny. To delve deeper into these outcomes, next, we conduct the Probit model 3.3 for further examination.

Table 3.13 presents the outcomes of Probit model 3.3, encompassing a dataset of 8219 observations. Columns (1) through (4) detail findings preceding the event, while Columns (5) through (9) report the post-event period. We observe that in the months leading up to the event (Columns (1) and (2)), member resignations exhibit a significant positive correlation with selling behavior. This aligns with our hypothesis that individuals are more likely to sell before their departure.

However, during the post-event phase, this phenomenon finds a comprehensive explanation in detection risks. Particularly, the coefficient of the interaction term *Sell*Detect* is both significant and positive, indicating an intertwined connection between selling behavior and perceived detection risks. This pattern becomes evident from the fourth

month following the event. In Columns (8), the positive and significant coefficient of *Sell * Detect* (0.9225 units in log odds) reveals that within detected firms (*Detect*=1), members who engaged in share selling during the initial six months following the firm's selection event are 71.6% more likely to depart compared to when firm has not been detected (*Detect*=0).

Table 3.6: Summary of Turnover in Management Team

Table 3.6 reports the number of members who left and stayed in the management team in the low-exposed group with the corresponding transaction behavior. t represents the date when a random selection event of a firm occurred. $t + n$ and $t - n$ represent the n^{th} month following and before the event, respectively. *Left Member* denotes the number of members who departed within the two years following the event, while *Stay Member* represents those who remained with the firm during the same period. Transactions have been categorized as *Net Buy* or *Net Sell* based on whether the net transaction value of a member during the corresponding period is positive or negative.

Detected firm	(t-6, t)	(t-4, t)	(t-2, t)	(t-1, t)	(t, t+1)	(t, t+2)	(t, t+4)	(t, t+6)	(t, t+8)	(t, t+10)	(t, t+12)
Left Members	620	620	620	620	620	620	620	620	620	620	620
- with transactions	13	12	6	4	6	8	16	25	33	34	34
- Net buy	7	6	2	2	4	3	4	5	9	9	9
- Net sell	6	6	4	2	2	5	12	20	24	25	25
- without transaction	607	608	614	616	614	612	604	595	587	586	586
Stay Members	1945	1945	1945	1945	1945	1945	1946	1946	1947	1947	1947
- with transactions	21	19	11	6	8	15	19	31	42	48	49
- Net buy	16	14	7	3	4	5	7	12	13	13	13
- Net sell	5	5	4	3	4	10	12	19	29	35	36
- without transaction	1924	1926	1934	1939	1937	1930	1927	1915	1905	1899	1898
Undetected firm											
Left Members	1152	1152	1152	1152	1152	1152	1152	1152	1152	1152	1152
- with transactions	19	16	7	1	6	9	13	15	18	19	19
- Net buy	5	4	3	1	2	2	3	4	4	4	4
- Net sell	14	12	4	0	4	7	10	11	14	15	15
- without transaction	1133	1136	1145	1151	1146	1143	1139	1137	1134	1133	1133
Stay Members	4502	4502	4502	4502	4502	4502	4502	4502	4502	4502	4502
- with transactions	30	28	20	11	15	25	49	75	81	86	88
- Net buy	14	12	11	7	7	10	12	17	20	21	21
- Net sell	16	16	9	4	8	15	37	58	61	65	67
- without transaction	4472	4474	4482	4491	4487	4477	4453	4427	4421	4416	4414

Table 3.7: Summary of Turnover in Management Team (ratios)

Table 3.7 presents the ratios of members who left and stayed within the management team of the low-exposed group, along with their corresponding transaction behaviors. These ratios are calculated by dividing the number of members by the total number of left members and staying members, respectively. t represents the date when a random selection event of a firm occurred. $t + n$ and $t - n$ represent the n th month following and before the event, respectively. *Left Member* denotes the number of members who departed within the two years following the event, while *Stay Member* represents those who remained with the firm during the same period. Transactions have been categorized as *Net Buy* or *Net Sell* based on whether the net transaction value of a member during the corresponding period is positive or negative.

Detected firm	(t-6, 0)	(t-4, 0)	(t-2, 0)	(t-1, 0)	(0, t+1)	(0, t+2)	(0, t+4)	(0, t+6)	(0, t+8)	(0, t+10)	(0, t+12)
<i>Left Members</i>											
<i>- with transactions</i>											
- with transactions	2.10%	1.94%	0.97%	0.65%	0.97%	1.29%	2.58%	4.03%	5.32%	5.48%	5.48%
- Net buy	1.13%	0.97%	0.32%	0.32%	0.65%	0.48%	0.65%	0.81%	1.45%	1.45%	1.45%
- Net sell	0.97%	0.97%	0.65%	0.32%	0.32%	0.81%	1.94%	3.23%	3.87%	4.03%	4.03%
- without transaction	97.90%	98.06%	99.03%	99.35%	99.03%	98.71%	97.42%	95.97%	94.68%	94.52%	94.52%
<i>Stay Members</i>											
<i>- with transactions</i>											
- with transactions	1.08%	0.98%	0.57%	0.31%	0.41%	0.77%	0.98%	1.59%	2.16%	2.47%	2.52%
- Net buy	0.82%	0.72%	0.36%	0.15%	0.21%	0.26%	0.36%	0.62%	0.67%	0.67%	0.67%
- Net sell	0.26%	0.26%	0.21%	0.15%	0.21%	0.51%	0.62%	0.98%	1.49%	1.80%	1.85%
- without transaction	98.92%	99.02%	99.43%	99.69%	99.59%	99.23%	99.02%	98.41%	97.84%	97.53%	97.48%
<i>Undetected firm</i>											
<i>Left Members</i>											
<i>- with transactions</i>											
- with transactions	1.65%	1.39%	0.61%	0.09%	0.52%	0.78%	1.13%	1.30%	1.56%	1.65%	1.65%
- Net buy	0.43%	0.35%	0.26%	0.09%	0.17%	0.17%	0.26%	0.35%	0.35%	0.35%	0.35%
- Net sell	1.22%	1.04%	0.35%	0.00%	0.35%	0.61%	0.87%	0.95%	1.22%	1.30%	1.30%
- without transaction	98.35%	98.61%	99.39%	99.91%	99.48%	99.22%	98.87%	98.70%	98.44%	98.35%	98.35%
<i>Stay Members</i>											
<i>- with transactions</i>											
- with transactions	0.67%	0.62%	0.44%	0.24%	0.33%	0.56%	1.09%	1.67%	1.80%	1.91%	1.95%
- Net buy	0.31%	0.27%	0.24%	0.16%	0.16%	0.22%	0.27%	0.38%	0.44%	0.47%	0.47%
- Net sell	0.36%	0.36%	0.20%	0.09%	0.18%	0.33%	0.82%	1.29%	1.35%	1.44%	1.49%
- without transaction	99.33%	99.38%	99.56%	99.76%	99.67%	99.44%	98.91%	98.33%	98.20%	98.09%	98.05%

Table 3.8: Probit Regression on Individual Turnover

Table 3.13 presents the results of Probit regression analysis that examines the relationship between members' service status and their corresponding transaction behavior across different time periods. The dependent variable indicates whether the individual's service status is 'left' (1) or not (0). *Sell* and *Buy* are dummies indicating negative and positive net transactions, respectively. *Detect* has a value of one if the firm has been identified by regulatory authorities within one year after the random selection event; otherwise, it is zero. The model controls for firm characteristics, including state-owned ownership, management team ownership, Return on Equity (ROE), firm age, and market value, all measured in the fiscal year preceding the event. Statistical significance is marked by ***, **, and *, denoting 1%, 5%, and 10% levels, respectively.

Dependent:	Turnover in individual level								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)	(t,t+1)	(t,t+2)	(t,t+4)	(t,t+6)	(t,t+8)
Sell	0.6937*** 0.232	0.5951** 0.241	0.3297 0.368	-6.3994 1.29e+05	0.4220 0.376	0.3710 0.281	0.0332 0.208	-0.1413 0.184	-0.0276 0.170
Buy	0.1977 0.311	0.1741 0.342	0.0422 0.378	-0.3125 0.575	0.0709 0.468	-0.1345 0.433	0.0076 0.372	-0.0319 0.317	-0.1227 0.306
Sell*Detect	0.1189 0.444	0.2164 0.449	0.4076 0.577	6.9136 1.29e+05	-0.0923 0.652	-0.0621 0.439	0.7188** 0.331	0.9225*** 0.274	0.6594*** 0.244
Buy*Detect	0.0300 0.417	0.0438 0.453	-0.0406 0.598	0.8788 0.807	0.6782 0.645	0.5717 0.627	0.3851 0.537	0.2434 0.453	0.6558 0.410
Detect	0.1355*** 0.034	0.1348*** 0.034	0.1356*** 0.034	0.1338*** 0.034	0.1349*** 0.034	0.1351*** 0.034	0.1274*** 0.034	0.1197*** 0.034	0.1156*** 0.034
State-owned firm	0.0381 0.062	0.0395 0.062	0.0509 0.062	0.0518 0.062	0.0524 0.062	0.0516 0.062	0.0522 0.062	0.0520 0.062	0.0515 0.062
Management ownership	-0.1892** 0.096	-0.1877* 0.096	-0.1820* 0.096	-0.1764* 0.096	-0.1813* 0.096	-0.1843* 0.096	-0.1907** 0.096	-0.1995** 0.096	-0.2031** 0.096
ROE	-0.2662 0.172	-0.2711 0.172	-0.2849* 0.172	-0.3017* 0.172	-0.2919* 0.172	-0.2952* 0.172	-0.2884* 0.172	-0.2971* 0.172	-0.2948* 0.172
Age	-0.0287 -0.450	-0.0301 -0.472	-0.0281 -0.442	-0.0327 -0.514	-0.0305 -0.479	-0.0304 -0.477	-0.0299 -0.469	-0.0300 -0.470	-0.0312 -0.490
Market value	0.0004 0.025	0.0003 0.016	8.284e-05 0.005	0.0001 0.007	7.309e-05 0.004	0.0002 0.009	-0.0006 -0.031	-0.0013 -0.073	-0.0014 -0.078
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2-adjusted	0.0070	0.0067	0.0058	0.0058	0.0058	0.0058	0.0065	0.0072	0.0073

Sanction letter and management team turnover

So far, we have demonstrated that the perceived detection risks affect the turnover of the management team. The detected firm experiences an increase in turnover, while undetected firms experience the opposite trend. Furthermore, our findings extend to the management team members' trading behavior, revealing a significant association with management team turnover against the backdrop of detection risks. This association becomes especially pronounced when compared to non-violating firms that are not subject to these detection risks.

In this section, we delve into the perceived detection risks, investigating the sanctions associated with regulatory detection, whether targeted at firms or individuals. Gaining insight into the content of regulatory sanction letters serves to deepen our understanding of post-event individual trading behaviors. We modify the Probit model 3.3 to a new Probit model (equation 3.4), which examines the relationship between the transaction and the turnover in the context of sanction targets:

$$\begin{aligned} Left_i = & \alpha + \beta_1 Sell_{i,(t+n)} + \beta_2 Sell_{i,(t+n)} * Individual\ Sanction_j \\ & + \alpha + \beta_3 Buy_{i,(t+n)} + \beta_4 Buy_{i,(t+n)} * Individual\ Sanction_j \\ & + \beta_5 Individual\ Sanction_j + \beta_6 Firm\ Specific\ Char_{i,y-1} + \epsilon_i \end{aligned} \quad (3.4)$$

where the dependent variable indicates whether the individual's service status is 'left' (1) or not (0) consistent with the model 3.3. *Sell* and *Buy* are dummies indicating negative and positive net transactions, respectively. *Individual, sanction* has a value of one if the firm has received any sanction letters issued by the CSRC after the random selection event, which targets individual violating behaviors; otherwise, it is zero.

We begin by presenting a distribution of the number of resigned members in the management team who trade, along with the corresponding count of firms that have been detected due to individual violating behaviors. It is important to note that in our sample, sanction letters specifically target either firms or individuals, with no overlap between the two categories. Table 3.9 illustrates that the sample size notably shrinks in the 2 months preceding and following the selection event. It implies an extreme decline, with transactions even dwindling to zero due to the event's influence. Consequently, we focus our analysis on time frames commencing from the fourth month preceding and following the selection event. We can see from Panel A that there are 8 management team members across 5 firms who sold shares within the initial 6 months after the event and subsequently departed. Notably, these 5 firms were recipients of sanction letters directed at individual violating behaviors.

Table 3.10 presents the outcomes of the Probit model 3.4. The results in Column (1) demonstrate a significant positive association between the share selling and buying behaviors of management team members and their turnover. However, it's important

Table 3.9: Resigned Members with The Respective Firms

Table 3.9 presents a summary of management team resignation and the associated number of firms. Panel A shows the distribution within low-exposed and detected firms, while Panel B reports the low-exposed but undetected firms. The sample is further divided based on individual net transactions during the specified period. *Net Buy* includes members with net transactions exceeding zero, while *Net Sell* comprises those with transactions less than zero.

Panel A: Low and Detected									
	(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)	(t,t+1)	(t,t+2)	(t,t+4)	(t,t+6)	(t,t+8)
Net Buy	3	2	0	0	3	2	3	3	5
- Nb.Firms	2	1	0	0	1	1	2	2	4
Net Sell	3	3	2	2	2	3	8	9	12
- Nb.Firms	3	3	2	2	2	2	5	5	6

Panel B: Low and Undetected									
	(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)	(t,t+1)	(t,t+2)	(t,t+4)	(t,t+6)	(t,t+8)
Net Buy	9	8	5	3	3	3	4	6	8
- Nb.Firms	9	8	5	3	3	3	4	6	8
Net Sell	17	15	6	0	4	9	14	22	26
- Nb.Firms	12	11	6	0	3	7	9	13	16

to note that these associations find comprehensive explanations through the context of the firm's individual detection. Specifically, the coefficient of the interaction term *Sell * Individual Sanction* highlights a pertinent insight. For a firm that has received any sanction linked to the detection of individual violations, the relationship between its management team members' share selling behaviors and their turnover becomes 66.2% (as indicated by the coefficient of *Sell * Individual Sanction* of 0.6739 in Column (3)) more pronounced compared to the relationship observed in undetected firms.

Extending the timeline from 4 months to 6 and 8 months after the event reveals a consistent and significant positive association between share selling and turnover (Columns (4) and (5)), while no similar association is observed with share buying. This observation reinforces the notion that management team members, in response to individual detection risks, opted to proactively sell their shares prior to any resignations. This discovery highlights the pivotal role of individual detection in influencing the observed relationships between management turnover and shares trading.

Table 3.10: Probit Regression on Individual Turnover with Individual Sanctions

Table 3.10 presents the results of Probit regression analysis that examines the relationship between members' service status and their corresponding transaction behavior across different time periods. The dependent variable indicates whether the individual's service status is 'left' (1) or not (0). *Sell* and *Buy* are dummies indicating negative and positive net transactions, respectively. *Individual_sanction* has a value of one if the firm has received any individual sanction letters issued by the CSRC within one year after the random selection event; otherwise, it is zero. The model controls for firm characteristics, including state-owned ownership, management team ownership, Return on Equity (ROE), firm age, and market value, all measured in the fiscal year preceding the event. Statistical significance is marked by ***, **, and *, denoting 1%, 5%, and 10% levels, respectively.

Dependent:	Turnover in individual level				
	(1)	(2)	(3)	(4)	(5)
Variable	(t-6,t)	(t-4,t)	(t,t+4)	(t,t+6)	(t,t+8)
Sell	0.6486*** 0.209	0.5698*** 0.215	0.1238 0.183	0.1263 0.146	0.1564 0.136
Buy	0.2375*** 0.219	0.2390 0.235	-0.0961 0.313	0.1115 0.241	0.1585 0.219
Sell*Individual_sanction	0.8289 0.718	0.9062 0.719	0.6739** 0.333	0.6219** 0.297	0.5148** 0.244
Buy*Individual_sanction	0.0113 0.311	-0.0539 0.343	1.5897** 0.753	-0.0499 0.248	0.1623 0.177
Individual_sanction	0.0342 0.030	0.0346 0.030	0.0254 0.030	0.0285 0.030	0.0199 0.030
State-owned-firm	0.0127 0.062	0.0139 0.062	0.0261 0.061	0.0266 0.061	0.0277 0.061
Management ownership	-0.1914 0.096	-0.1898** 0.096	-0.1955** 0.097	-0.2014** 0.097	-0.2049** 0.097
ROE	-0.3247 0.171	-0.3296* 0.171	-0.3385** 0.171	-0.3396** 0.171	-0.3377** 0.171
Age	-0.0288 -0.450	-0.0303 -0.474	-0.0314 -0.491	-0.0302 -0.472	-0.0280 -0.438
Market value	-0.0026 -0.145	-0.0028 -0.153	-0.0040 -0.223	-0.0039 -0.214	-0.0042 -0.232
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R2-adjusted	0.0055	0.0051	0.0052	0.0046	0.0051

3.5 Conclusion

In this study, we've explored the question of how government intervention in response to misconduct affects a firm's internal governance. Prior research has tackled this issue in two main ways: some studies have looked at the aftermath of detection, highlighting how managers often face job loss and reputational damage. On the other hand, research like that by [Karpoff et al. \(2008a\)](#) has delved into a firm's internal governance effectiveness before the misconduct becomes public. Yet, the secretive nature of regulatory scrutiny and the limited attention of regulators create a blend of intervention impact and perceived punishment outcomes. This impact's estimation can also be distorted based on a firm's disclosure practices.

To address these challenges, we take advantage of a quasi-random government investigation policy implemented in China since 2016. The policy's randomness ensures that future detection is not driven by firm-initiated signals or other trigger events. Instead, firms respond solely to perceived detection risks arising from random regulatory investigations. Our clear investigation timeline allowed us to establish distinct observation periods and turnover benchmarks. We found that firms perceiving higher detection risks are more likely to experience management team turnover rather than blockholder exits. This conclusion is supported by shifts in trading behavior among departed team members right after the selection event.

Our contribution lies in identifying when and to what degree firms react to regulatory intervention. We've extended our examination to non-violating firms—those uninvolved in prior misconduct detections, yet still significantly influenced by regulatory intervention. The remarkable reduction in turnover within non-violating firms after the selection event suggests that regulatory scrutiny acts as a catalyst for enhancing management team stability. This new perspective enriches our comprehension of how firms navigate regulatory attention, emphasizing the multi-faceted impacts that extend beyond punitive measures.

In our final analysis, we've also linked the share-selling behavior of departed management team members to individual detection risks. This further confirms that turnover is influenced by the impact of regulatory investigation stemming from the selection event. Overall, our study provides new insights into the complex interplay between regulatory intervention, firm behavior, and governance dynamics, shedding light on the broader landscape of corporate responses to government intervention.

3.6 Appendix

3.6.1 Robustness check

Table 3.11 provides the change of ownership among the top 10 largest shareholders.

Table 3.11: Ownership Change in Top 10

Table 3.11 provides summary statistics of the top 10 largest shareholders' ownership. q represents the quarter when a random selection event of a firm occurred. $q+1$ represents the quarter after the event.

Add new measurement summary stat.

	Individual	Other	Government-related institution	Entrust	Foreign institution
$(q-1, q)$	0.06%	-0.09%	-0.02%	-0.04%	0.06%
$(q, q+1)$	-0.21%	-0.23%	-0.01%	-0.01%	0.01%
	Bank	Broker	Fund	Insurance	Non top 10
$(q-1, q)$	0.00%	0.00%	-0.04%	-0.01%	0.06%
$(q, q+1)$	0.00%	0.02%	-0.01%	-0.01%	0.44%

The robustness check reports the results in the high-exposed group.

Table 3.12: Turnover in Management Team: High-exposed group

Table 3.12 presents the outcomes of the OLS regression model for the management team turnover in high-exposed gorup. The dependent variable, denoted as *Detect*, is a dummy variable with a value of one if the firm has been detected by regulatory authorities within one year after the random selection event, and zero otherwise. The dummy variable *Post* distinguishes whether the turnover occurred before or after the event. The regression controls the firm's characteristics including the firm's state-owned ownership, the ownership held by the management team, Return on Equity (ROE), the firm's age, and its market value, all measured in the fiscal year preceding the event. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent:	(1)	(2)	(3)	(4)
Dependent:	Total	Director	Manager	Supervisor
Detect	0.0297*** 0.011	0.0096** 0.005	0.0196*** 0.005	0.0006 0.004
Detect*Post	-0.0180 0.015	-0.0039 0.006	-0.0151** 0.007	0.0011 0.005
Post	-0.0480*** 0.012	-0.0166*** 0.005	-0.0178*** 0.006	-0.0136*** 0.004
State-owned-firm	0.0128 0.024	0.0073 0.010	0.0012 0.012	0.0042 0.008
Management ownership	-0.0790*** 0.024	-0.0444*** 0.010	-0.0119 0.012	-0.0228*** 0.008
ROE	-0.0325* 0.017	-0.0139** 0.007	-0.0126 0.008	-0.0059 0.006
Age	-0.0016 0.015	0.0048 0.006	-0.0053 0.008	-0.0011 0.005
Market value	-0.0056 0.005	-0.0046** 0.002	0.0007 0.003	-0.0017 0.002
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R2-adjusted	0.0605	0.0520	0.0520	0.0187

Table 3.13: Turnover in Management Team: High-exposed group

Table 3.13 presents the results of Probit regression analysis that examines the relationship between members' service status and their corresponding transaction behavior across different time periods. The dependent variable indicates whether the individual's service status is 'left' (1) or not (0). *Sell* and *Buy* are dummies indicating negative and positive net transactions, respectively. *Detect* has a value of one if the firm has been identified by regulatory authorities within one year after the random selection event; otherwise, it is zero. The model controls for firm characteristics, including state-owned ownership, management team ownership, Return on Equity (ROE), firm age, and market value, all measured in the fiscal year preceding the event. Statistical significance is marked by ***, **, and *, denoting 1%, 5%, and 10% levels, respectively.

Dependent:		Turnover in individual level								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable		(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)	(t,t+1)	(t,t+2)	(t,t+4)	(t,t+6)	(t,t+8)
Sell	0.8056***	0.8061***	0.8744**	1.1335***	0.2021	0.6190*	0.3193	0.2591	0.1955	
	0.306	0.306	0.363	0.403	0.685	0.347	0.263	0.229	0.204	
Buy	0.4118	0.3609	0.1005	0.0703	-6.3002	-8.9312	-0.0516	-0.0949	-0.2697	
	0.284	0.301	0.385	0.466	7.76e+04	3.07e+07	0.363	0.308	0.289	
Sell*Detect	-0.4549	-0.3766	-0.3520	-0.9170*	-0.1167	-0.5747	-0.1050	0.0334	0.0037	
	0.339	0.346	0.412	0.475	0.731	0.389	0.291	0.253	0.227	
Buy*Detect	-0.2532	0.0036	0.1626	0.2961	6.3550	8.8532	-0.2021	0.0786	0.2073	
	0.355	0.379	0.506	0.707	7.76e+04	3.07e+07	0.453	0.372	0.340	
Detect	0.0724**	0.0706**	0.0688**	0.072088	0.0667**	0.0692**	0.0690**	0.0633*	0.0615*	
	0.033	0.033	0.032	0.032	0.032	0.032	0.033	0.033	0.033	
State-owned firm	0.1609**	0.1596**	0.1571**	0.1580**	0.1533*	0.1562**	0.1613**	0.1563**	0.1558**	
	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	
Management ownership	-0.1701*	-0.1757*	-0.1699*	-0.1616	-0.1516	-0.1558	-0.1658	-0.1722*	-0.1531	
	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	
ROE	-0.1502**	-0.1515**	-0.15058*	-0.1507**	-0.1499**	-0.1495**	-0.1509**	-0.15258*	-0.1511**	
	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	
Age	0.0015	0.0014	-0.0025	-0.0008	-0.0026	-0.0017	-0.0041	-0.0007	-0.0020	
	0.024	0.023	-0.041	-0.013	-0.043	-0.027	-0.066	-0.011	-0.032	
Market value	-0.0040	-0.0039	-0.0038	-0.0036	-0.0040	-0.0040	-0.0036	-0.0037	-0.0036	
	-0.192	-0.186	-0.183	-0.172	-0.195	-0.193	-0.171	-0.179	-0.172	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
R2-adjusted	0.0088	0.0090	0.0086	0.0082	0.0076	0.0081	0.0078	0.0081	0.0078	

3.6.2 Definition of Variables

Table 3.14: Variable Definitions

Age listed	Natural logarithm of the firm's year of listing in the exchange
Market value	Natural logarithm of equity market capitalization of the firm (in millions of RMB)
State_Owned_Firms	A dummy variable indicates whether the firms' ownership of state-owned shares is larger than 20%.
State_Owned_Firms shares	The state-owned shares standardized by the total shares outstanding.
Con10	The sum squares of the shareholding ratios of the top 10 major shareholders of the company.
Management shares	The shares of the management team are standardized by the total shares outstanding.
ROE	Net income/total equity.
Nb.director left	The total count of directors who left within a 2-year qualified period.
Nb.manager left	The total count of managers who left within a 2-year qualified period.
Nb.supervisor left	The total count of supervisors who left within a 2-year qualified period.
Detect	A dummy that equals 1 if the firm is violating, zero otherwise.
Post	A dummy, 1 if observations are within two years after the random selection event, 0 if it's two years before.
Net Sell	The total number of management team members with negative net transaction values.
Net Buy	The total number of management team members with positive net transaction values.
Sell	A dummy that is set to 1 if the net sell value is greater than 0, and 0 if the net sell is 0.
Buy	A dummy that is set to 1 if the net buy value is greater than 0, and 0 if the net buy is 0.
Individual sanction	A dummy, 1 if the firm receives a sanction letter punishing the individual, 0 if no such letter is received.

Table 3.15: Turnover in Management Team

Table 3.15 presents the results of the OLS regression model for the management team turnover. The dependent variable, denoted as *Detect*, is a dummy variable with a value of one if the firm has been detected by regulatory authorities within one year after the random selection event, and zero otherwise. The dummy variable *Post* distinguishes whether the turnover occurred before or after the event. The regression controls the firm characteristics including state-owned ownership, the ownership held by the management team, Return on Equity (ROE), the firm's age, and its market value, all measured in the fiscal year preceding the event. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent: Turnover in individual level		(t-6,t)	(t-4,t)	(t-2,t)	(t-1,t)
Variable					
sell	0.6937*** 0.232	0.5951** 0.241	0.3297 0.368	-6.3994 1.29e+05	
buy	0.1977 0.311	0.1741 0.342	0.0422 0.378	-0.3125 0.575	
sell_detect	0.1189 0.444	0.2164 0.449	0.4076 0.577	6.9136 1.29e+05	
buy_detect	0.0300 0.417	0.0438 0.453	-0.0406 0.598	0.8788 0.807	
detect	0.1355*** 0.034	0.1348*** 0.034	0.1356*** 0.034	0.1338*** 0.034	
sof2	0.0381 0.062	0.0395 0.062	0.0509 0.062	0.0518 0.062	
mgt_ratio	-0.1892** 0.096	-0.1877* 0.096	-0.1820* 0.096	-0.1764* 0.096	
roe	-0.2662 0.172	-0.2711 0.172	-0.2849* 0.172	-0.3017* 0.172	
log_age	-0.0287 -0.450	-0.0301 -0.472	-0.0281 -0.442	-0.0327 -0.514	
log_mv	0.0004 0.025	0.0003 0.016	8.284e-05 0.005	0.0001 0.007	
Year FE	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	
R2-adjusted	0.0070	0.0067	0.0058	0.0058	

Chapter 4

A New Perspective of the Split Share Reform: The Study of Market Reaction

4.1 Introduction

On April 29th, 2005, the Chinese government introduced the Split Share Reform (SSR), a policy mandating that all listed firms grant tradability to their previously non-tradable shares (NTS). Simultaneously, non-tradable shareholders were required to provide compensation to tradable shareholders in exchange for liquidity rights. Subsequent to this announcement, the reform was gradually implemented across various firms. Every firm initiates the reform process by initially introducing a compensation plan. Numerous scholarly articles have investigated the substantial impact of this reform on both companies and the stock market in recent years. Many of these studies have focused on short-term effects through event analyses. Noteworthy research by [Lu et al. \(2012\)](#); [Beltratti et al. \(2016\)](#), and [Firth et al. \(2010\)](#) highlighted a significant positive abnormal return on the announcement date, indicative of investor optimism toward the reform. However, there has been little exploration of market reactions considering the firm's learning process between the government's announcement and the firm implementation date, along with the investor's anticipation of compensation levels.

In this study, I conducted an event analysis to delve into the market's response, aiming to gain deeper insights into the impact of the reform. This inquiry has encountered two significant challenges. Firstly, the issue of endogeneity in reform timing arises. The commencement of reform by a firm is contingent upon three factors: recommendations from a sponsoring agent, the firm's intrinsic motivations, and the state's approval. The role of the sponsoring agent is pivotal, as they facilitate the formulation and execution of SSR schemes for listed companies, overseeing the fulfillment of commitments and obligations by all relevant parties. Consequently, each firm establishes its unique re-

form initiation date (firm announcement date), linked to the firm's specific attributes. The second challenge revolves around the execution of compensation. A requirement of the reform is the transfer of compensation from non-tradable shareholders to tradable shareholders. In practice, this compensation is calibrated to ensure that the shareholding value of tradable and non-tradable shareholders remains constant before and after the reform (Li et al., 2011). Theoretically, guided by the non-arbitrage opportunity theory, while the overall firm value remains unchanged, there is a redistribution of share ownership. As a result, the abnormal return observed on the firm's announcement date is anticipated to encapsulate both the response to the fundamental impact of the reform and the reaction to the potential compensation expected by tradable shareholders.

To solve the first challenge, diverging from prior research, I split the sample into two groups based on the timing of a firm's engagement with the reform. This categorization facilitated a more nuanced exploration of the various drivers behind market reactions within these different groups. The early stage contains 267 listed firms, and the later stage contains 978 listed firms. Through this classification, I observe that younger firms with higher ROA, fewer tradable shares, greater long-term liability, fewer state-owned shares, and better liquidity tend to adopt the reform in the early stage. Furthermore, in the early stage, a significantly positive correlation emerged between compensation and market abnormal returns on the day when firms announced their engagement with the reform. Specifically, with each incremental unit increase in compensation, the cumulative abnormal return (CAR(-5,5)) exhibited an increase of 0.430%. Conversely, in the later stage, this coefficient was estimated at 0.181%.

The next question is to explain the impact of the reform by excluding the expectation of compensation from the market abnormal return. I discovered a significant negative value of -0.240% in the early stage and -0.133% in the later stage. This implies that when we remove the compensation effect, a noticeable negative market response is evident throughout the reform timeline. Digging deeper, I uncover the fundamental drivers behind the adjusted CAR. I suggested that in the later stage, firms have had more time to adjust to the reform's requirements by enhancing their financial standing. My findings revealed that in the later stage, a one-unit increase in the change of free cash flows to equity between the government's reform announcement and just prior to the firm's reform engagement corresponds to a 0.179% increase in the adjusted CAR. On the contrary, this connection isn't apparent in the early stage, as evidenced by the lack of meaningful statistical significance.

My study contributes to the literature in the following ways: the paper explored how the reform effect may differ among firms engaged in the reform at different times. The separation of firms by reform timing also helps to solve the endogeneity problems. Second, unlike the previous studies, I found a negative market reaction after adjusting

the expectation of the compensation proposal. The new determinants of this negative market reaction have been found. More specifically, I identified two distinct pathways through which the reform influences early-stage and later-stage firms. Due to limited negotiation time, early-stage firms exhibit a higher compensation rate (31.3%) and less positive market response, focusing primarily on compensation levels. Conversely, later-stage firms have more time to adapt to reform requirements, thereby needing less compensation (24.7%) and garnering investor attention for financial improvements just before the reform initiation. Price movements further differentiate the two groups: early-stage firms experience declines in firm value post-reform, while later-stage firms witness substantial value growth. Third, the paper contributes to the discourse on the implications of compensation. Prior research has predominantly indicated that compensation is mandated to address disparities in the cost of capital and the substantial discounting of illiquid stocks (Wei et al., 2005; Chen and Xiong, 2005). In contrast, my findings suggest that the compensation stipulation within the reform serves as a catalyst for weaker-performing firms to enhance their corporate governance and financial performance. Lastly, the research contributes fresh evidence concerning the impact of financial market reform. The aim of the SSR is to clean the path for future privatization. Previous research has shown significant improvements in the firm's post-privatized performance (Boubakri et al., 2005; Megginson and Netter, 2001; D'Souza et al., 2005; Sheshinski, 2003; Jefferson and Su, 2006). my research delves into the initiatives taken by underperforming firms to meet the prerequisites even before the privatization process is finalized.

The remainder of the paper is structured as follows: Section 2 provides background on the SSR. Section 3 outlines the data and main variables. Section 4 presents the empirical findings, followed by a robustness check in Section 6. The paper concludes in Section 7.

4.2 Background and Literature review

The dual share structure has long been prevalent among Chinese firms. This structure primarily exists due to the government's incentive to maintain control over State-Owned Enterprises (SOEs). After the establishment of the Shanghai Stock Exchange market and the Shenzhen Stock Exchange market, the Chinese government encouraged SOEs to go public and offer shares. However, concerns emerged regarding the potential loss of state assets and control over firm governance. In response, a solution was devised wherein all listed firms were mandated to retain the original founders' shares as non-tradable shares. Only newly issued shares were permitted for trading on the market. This arrangement divided ownership of the listed firms into non-tradable shares (encompassing state shares, legal person shares, and other shares issued before IPOs) and

tradable shares (A shares and B shares). While differing in tradability, non-tradable shares (NTS) and tradable shares (TS) hold identical voting rights and cash flow attributes.

It's worth noting that despite being nontradable on the market, nontradable shares (NTS) retained the potential for trading outside of the market. In the early 2000s, the China Securities Regulatory Commission (CSRC) introduced policy measures that indicated the feasibility of trading NTS through agreement transfers or auctions. Transactions involving NTS typically occurred with the transfer of substantial share quantities. Notably, the prices and information disclosed in these transactions differed from those observed in the public market. Within the public market, the price of freely traded shares could be driven higher due to limited supply, allowing informed investors to manipulate the price more easily. Conversely, the illiquid and substantial nature of NTS made their transfer at a fair price more challenging. A previous study by [Chen and Xiong \(2005\)](#) revealed that the average discount for illiquid Chinese shares can be as substantial as 80%.

Due to the substantial discount associated with illiquid stocks and the significant abnormal premium linked to liquidity rights, transferring state-owned shares to the private sector posed considerable challenges. Despite multiple unsuccessful attempts ([Leung et al., 2002](#)), it became evident that the dual share structure stood as a significant obstacle to the privatization effort. Recognizing this barrier, the government proposed the dissolution of the existing dual share structure in 2005. On April 29th, 2005, the CSRC issued a comprehensive announcement introducing the Split Share Reform (SSR). This marked the onset of a significant reform effort aimed at dismantling the dual share structure.

The implementation of the SSR can be categorized into four distinct stages: the initiation stage, full implementation stage, transition stage, and finalization stage. These stages are characterized by varying criteria for firm selection and focus areas within the reform process. In the initial stage, due to the absence of prior experience, the government selected representative pilot firms from diverse sectors to kickstart the reform. These pilot groups, comprising 46 firms across various ownership types and sizes, effectively encompassed the spectrum of Chinese firms. On August 23rd, 2005, the second stage commenced following positive feedback. Encouraged by the pilot results, the Chinese government extended the SSR to the entire market. By mid-February 2006, the first ten batches totaling 203 firms had successfully completed the reform. The third stage targeted firms facing challenges in implementation. This included firms with substantial market values requiring more time for reform, those grappling with internal governance and financial issues, and firms encountering difficulties during compensation negotiations between nontradable and tradable shareholders. Consequently, these firms confronted more complex reform processes that extended over time. By the end of April

2003, thirty batches of firms had initiated reform plans. The last stage aimed to assist firms unable to complete the reform before May 2006 due to implementation issues. By November 2006, approximately 90% of Chinese listed firms had concluded the reform.¹ Figure 4.2 illustrates the number of firms involved in each batch.

The commencement of reform for each firm was contingent upon the recommendation from a sponsoring agent, the firm's own motivation, and approval from the state. This interplay determined the unique reform date for each firm. There are two suspension periods: the first from when the firm becomes eligible to reform until it announces the reform plan, and the second from the voting day (a few days after the announcement) until the compensation plan is enacted. On the firm announcement date, the board of directors presents the initial compensation plan for approval by shareholders. The plan requires approval by at least 2/3 of the shareholders present. Additionally, for the firm to proceed with the compensation, it requires the approval of at least 2/3 of the tradable shareholders. In the event that the initial reform plan fails to garner approval, nontradable shareholders have the option to request a reorganization of the board meeting three months later.

In the literature, compensation is mandated to be transferred from NTS to TS for several reasons. First, from the perspective of NTS, this compensation primarily covers trading privileges. For tradable shareholders, the compensation acknowledges their forfeiture of the liquidity premium. In this context, the liquidity premium signifies the disparity between the tradable share price and the price if all shares were tradable. Second, compensation is stipulated due to the breach of the original contract at the IPO stage resulting from the newfound tradability of NTS. Third, the compensation is intended to address the unequal capital costs between NTS and TS during the IPO stage, where NTS holders possess lower capital costs than TS holders. To fulfill compensation obligations, various methods have been employed during the reform. Some firms issue new shares, provide dividends, or offer options. Subsequently, NTS holders employ these compensation components to remunerate TS holders. In other cases, NTS holders directly allocate a portion of their wealth (either in cash or shares) as compensation and transfer it to TS holders.

Prior studies have examined the factors influencing compensation and yielded noteworthy findings. Ownership structure and corporate governance have emerged as pivotal

¹Upon the successful transfer of compensation from NTS to TS, the firm finalizes the reform process and resumes trading on the stock market. With the exception of the shares distributed as compensation, all NTS are subject to trading restrictions following the reform plan implementation. This lockup period extends for 12 months. Once this initial 12-month period concludes, the original NTS gain the privilege to trade and sell their shares on the market. They are allowed to trade up to 5% of the firm's total shares outstanding within the subsequent 12 months, and up to 10% within the following 12 months (a total of 24 months).

determinants affecting compensation outcomes (L Liao and HB Shen, 2008). It has been observed that higher ownership concentration corresponds to lower applied compensation (Chaopeng et al., 2006). Additionally, Li et al. (2011) developed a model to explore compensation dynamics, revealing a positive correlation between compensation size and both enhanced risk-sharing gains and the price effect of stock liquidity stemming from the reform. Jin and Yuan (2008) uncovered a linkage between improved corporate governance and decreased compensation ratios.

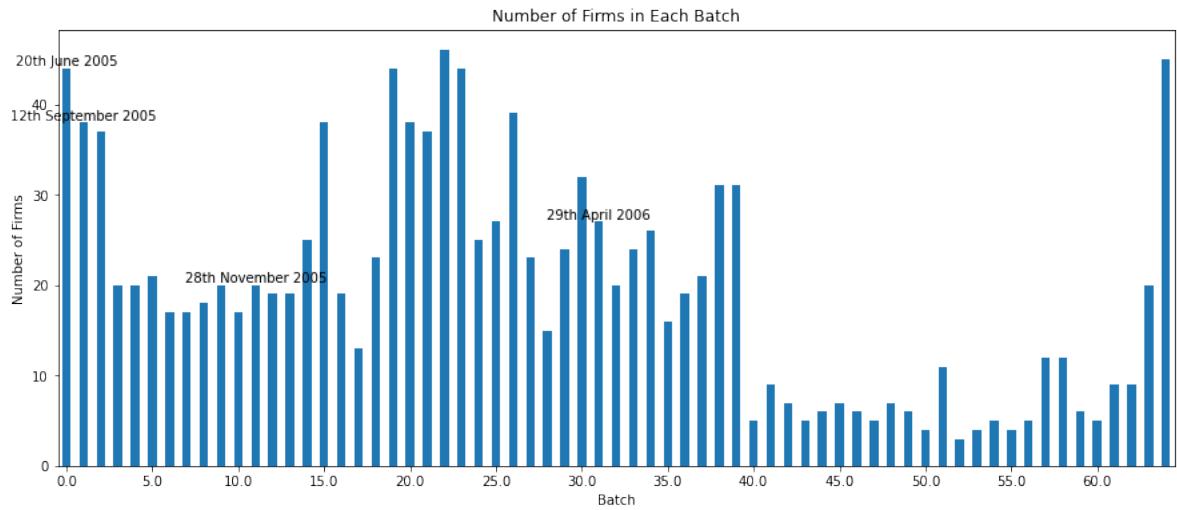


Figure 4.1: Turnover in management team

4.3 Data and Main variables

4.3.1 Data source and Sample selection

The data I utilized is sourced from the CSMAR dataset (Chinese Stock Market & Accounting Research), which provides comprehensive data relating to the Chinese financial market. Additionally, I cross-referenced the information using the Thomson Reuters Eikon database for stock prices. This database includes the adjusted closing prices for each stock ². The original dataset includes 1331 Chinese-listed firms. I excluded the ST stocks ³, resulting in a remaining count of 1245 firms that underwent reform before 2007. I also excluded non-financial firms from the analysis.

Based on the implementation of the SSR levels, the SSR process can be divided into four stages: the initial stage, the full implementation stage, the turbulent stage, and the

²The adjusted closing price has considered the capital action such as the dividends and share splits.

³“ST” is an abbreviation for “special treatment.” To safeguard the interests of investors, the “Shenzhen Stock Exchange Listing Rules” and “Shanghai Stock Exchange Listing Rules” were introduced on January 1, 1998. Under these regulations, companies experiencing abnormal circumstances are designated as ST stocks, subject to specific monitoring and regulations.

complementary stage. In order to investigate the gap between the CAR (Cumulative Abnormal Return) and the proposed compensation, I further categorized the firms into two groups: the first two stages, denoted as the Early stage (first stage and second stage), consisting of 267 firms; and the subsequent two stages, categorized as the Later stage (third stage and fourth stage), consisting of 978 firms.

4.3.2 Main variables

The initial step involves estimating the abnormal return in the market at the announcement date of the firm's reform. To accomplish this, I download the Fama-French three-factor dataset for analysis. The event date is defined as the first trading day following the conclusion of the initial suspension period. To make comparisons, I have chosen to assess the 3-day Cumulative Abnormal Return (CAR), the 5-day CAR, and the 10-day CAR. It's worth noting that typically, the firm's sponsor requires approximately one week to gather the necessary information and provide a list of eligible firms for the reform process. As a result, I consider this one-week period as indicative of potential information leakage before the event date, and I monitor the 5-day CAR during this interval.

For the estimation of abnormal return, I utilize the Fama-French three-factor model. The process unfolds as follows: Initially, I conduct regression analyses to estimate the theoretical daily return for each individual firm, using historical daily stock daily returns as the basis. Subsequently, I calculate the abnormal return as the gap between the actual daily return and the estimated daily return.

$$AR_{it} = R_{it} - R_{Ft} = \alpha_i + \beta_i (R_{mt} - R_{Ft}) + s_i SMB_t + h_i HML_t \quad (4.1)$$

Further, daily abnormal returns (ARs) have been averaged over N companies for each day t and are calculated as follows.

$$AAR_{it} = \frac{1}{n} \sum_{i=1}^n AR_{it} \quad (4.2)$$

Where R_{it} is the daily return of stock i , the three factors have been provided directly from the CSMAR dataset. They represent the information related to the market value (SMB), the book-to-market ratio (HML), as well as the market risk premium ($R_{mt} - R_{Ft}$). The estimation window is between 252 days and 30 days before the event.

$$CAR_{it} (\tau_1, \tau_2) = \sum_{T=t+\tau_1}^{t_i+\tau_2} AR_{iT} \quad (4.3)$$

Where t_i represents the event date as stock i has been known to be selected or not. The event window is represented by (τ_1, τ_2)

Next, I examine the relationship between market abnormal return at the firm announcement date and the firm proposed compensation by the following OLS regress:

$$\begin{aligned} CAR_{i,t_1} = & \alpha + \beta_1 Compensation_i + \beta_2 Reform\ factor_i \\ & + \beta_3 Firm\ Specific\ Char._{i,t_0} \\ & + Industry\ FE_i + \epsilon_i \end{aligned} \quad (4.4)$$

Where i represents the firm undergoing the reform, t_0 denotes the government announcement date, and $t - 1$ corresponds to the date when firm i announced the reform. The variable CAR signifies the cumulative abnormal return at the date of the firm's reform announcement. The $Compensation$ has been adjusted based on the original compensation ratio.

Inspired by the paper by [Jin and Yuan \(2008\)](#), I construct a new measurement of compensation relative to the tradable shareholders' original ownership, noted as $Compensation$. This proxy of compensation represents the change of TS ownership before and after the compensation, given that the total firm value is not changed. This proposed compensation is measured as follows:

$$Adjusted\ Comp\ ratio = TS * k * Price + TS * c \quad (4.5)$$

$$Compensation_{i,t} = \frac{Ownership_{i,t} - Ownership_{i,t-1}}{Ownership_{i,t}} \quad (4.6)$$

$$Onwership_{i,t} = \frac{TShares_{i,t-1} + Adjusted\ Comp\ ratio_{i,t}}{Common\ shares\ outstanding_{i,t}} \quad (4.7)$$

$$Onwership_{i,t-1} = \frac{TShares_{i,t-1}}{Common\ shares\ outstanding_{i,t}} \quad (4.8)$$

Where i represents the firm and t denotes the fiscal year when the firm announced the reform. The variable $TShares$ corresponds to the total shareholdings of tradable shareholders, and k represents the initial compensation ratio specified in the firm's reform announcement report. This ratio indicates the number of shares that NTS (Non-Tradable Share) holders can receive as compensation per share held by TS (Tradable Share) holders. $Price$ signifies the closing stock price on the day when the compensation is implemented, while c signifies the cash amount granted as compensation to TS holders per share. The variable $CommonSharesOutstanding$ pertains to the overall count of shares issued by the firm.

In this regression analysis (see Equation 4.4), I have incorporated control variables to account for various factors. These include elements associated with the reform, including the batch of firms, the gap in days between the firm's announcement date and the

first trading date (event date), the count of firms reformed within the same batch, and a binary indicator signifying whether any alterations were made to the compensation plan.

Furthermore, I have introduced control variables to account for specific characteristics of the firms. These factors relate to financial attributes before the government announcement date, which is April 29th, 2005. To achieve this, I have retained the firm's semi-annual reports for the year 2005. These attributes include variables such as Return on Equity (ROE), leverage ratio, ownership of tradable shareholders, and state-owned shares. Additionally, I have included controls for firm size and the duration since the firm's initial listing. Moreover, I have integrated industry-specific indicators aimed at capturing the effects particular to each industry.

4.3.3 Summary statistics

Table 4.1 and Table 4.2 present the summary statistics for firms in the initial two stages and firms in the subsequent two stages, respectively. An examination of Table 4.1 reveals that just before the government's reform announcement, the firms in the first stage exhibit more favorable performance metrics in terms of Return on Assets (ROA) and Return on Equity (ROE). They also possess a higher quantity of non-tradable shares, greater liquidity, and lower volatility.

Furthermore, upon comparing the third stage group with the fourth stage group, it becomes evident from the data in Table 4.2 that the fourth stage group demonstrates poorer performance. This is evidenced by its comparatively lower market value, lower ROA and ROE value. Additionally, this group holds a larger share of short-term debt, possesses less cash, and exhibits higher levels of illiquidity. It is worth noting that the largest shareholder of the fourth-stage group has a lower shareholding ratio, and the concentration of the top ten shareholders is also smaller. The outcomes of the analysis validate the hypothesis suggesting the presence of a firm bias in engaging reform. It indicates that firms, on the whole, with stronger performance, improved profitability, and influential presence among major shareholders are more inclined to initiate the reform process. These trends have emerged for the year 2004, as illustrated in the robustness check.

Table 4.1: Summary statistics of early stage

Table 4.1 provides a summary of statistics across the first stage and the second stage. These observations belong to the quarter immediately preceding the quarter in which the government announcement occurred. A detailed definition of each variable is provided in Appendix A1 4.13. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Nb.Obs	First stage					Second stage					Diff_Mean
	43					212					
variable	Mean	Std	P25	Median	P75	Mean	Std	P25	Median	P75	
Gap	14.395	6.645	9.500	14.000	17.000	12.439	6.304	10.000	10.000	11.000	1.957*
Period	49.070	10.826	52.000	52.000	52.000	167.500	23.984	143.000	171.000	192.000	-118.43***
Change_plan	0.000	0.000	0.000	0.000	0.000	0.033	0.180	0.000	0.000	0.000	-0.033
ROA	0.016	0.011	0.008	0.015	0.019	0.011	0.011	0.004	0.010	0.017	0.005**
ROE	0.030	0.019	0.017	0.026	0.040	0.023	0.024	0.009	0.018	0.032	0.008*
Leverage	1.942	2.167	0.748	1.200	1.902	1.619	1.612	0.635	1.088	1.823	0.323
Short term liab	0.150	0.105	0.058	0.173	0.222	0.161	0.110	0.069	0.138	0.263	-0.011
long term liab	0.065	0.081	0.000	0.029	0.108	0.067	0.080	0.000	0.031	0.112	-0.002
Cash	0.186	0.108	0.092	0.179	0.248	0.173	0.120	0.083	0.141	0.227	0.013
FCFE	-0.038	0.068	-0.087	-0.031	0.010	-0.045	0.082	-0.085	-0.029	0.004	0.006
Net CF_invest	-0.209	0.340	-0.254	-0.092	-0.026	-0.201	0.326	-0.245	-0.097	-0.030	-0.008
SOE	22.480	24.292	0.000	7.425	52.510	28.384	23.194	0.000	37.282	52.510	-5.904
Largest	44.892	14.980	30.347	45.480	60.563	44.078	14.853	31.426	45.691	58.547	0.815
Con_top10	0.245	0.119	0.133	0.237	0.372	0.237	0.115	0.136	0.227	0.348	0.008
Tradable share	31.954	10.368	25.110	28.571	37.795	34.229	11.432	26.920	34.727	40.000	-2.274
Nontradable share	68.046	10.368	62.205	71.429	74.890	62.871	10.601	57.662	64.076	70.060	5.175***
Illiquidity_Amihud	0.213	0.129	0.094	0.214	0.358	0.265	0.114	0.173	0.349	0.358	-0.052***
Volatility	0.242	0.079	0.189	0.231	0.284	0.295	0.152	0.219	0.265	0.332	-0.053**
Market value	21.857	1.041	20.924	21.713	22.325	21.584	0.795	20.883	21.263	22.025	0.273*
Age_list	1.108	0.854	0.095	0.937	1.922	1.498	0.848	0.742	1.719	2.208	-0.404

Table 4.2: Summary statistics of later stage

Table 4.2 provides a summary of statistics across the third stage and the fourth stage. These observations belong to the quarter immediately preceding the quarter in which the government announcement occurred. A detailed definition of each variable is provided in Appendix A1 4.13. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Nb.Obs	Third stage					Fourth stage					Diff_Mean
	Mean	Std	P25	Median	P75	Mean	Std	P25	Median	P75	
Gap	18.980	14.640	10.000	14.000	21.000	30.937	79.837	10.000	14.000	21.000	-11.957
Period	291.420	43.239	255.000	297.000	325.000	554.119	452.143	402.000	430.000	563.000	-262.699***
Change_plan	0.148	0.355	0.000	0.000	0.000	0.412	0.493	0.000	0.000	1.000	-0.265
ROA	0.008	0.012	0.002	0.006	0.012	0.003	0.012	-0.001	0.002	0.007	0.005***
ROE	0.015	0.022	0.004	0.011	0.024	0.008	0.032	0.000	0.006	0.015	0.007***
Leverage	1.657	1.753	0.673	1.062	1.827	1.382	1.696	0.503	0.845	1.465	0.275**
Short term liab	0.159	0.109	0.066	0.157	0.252	0.195	0.109	0.105	0.197	0.318	-0.036***
long term liab	0.053	0.067	0.000	0.022	0.083	0.049	0.070	0.000	0.013	0.072	0.004
Cash	0.147	0.099	0.075	0.122	0.197	0.121	0.102	0.041	0.090	0.160	0.026***
FCFE	-0.041	0.071	-0.074	-0.026	0.003	-0.039	0.069	-0.073	-0.021	0.003	-0.001
Net CF_invest	-0.188	0.342	-0.217	-0.070	-0.016	-0.155	0.340	-0.172	-0.058	-0.007	-0.033
SOE	34.425	21.006	14.077	44.914	52.510	29.930	20.783	7.060	34.519	52.510	4.495
Largest	43.133	15.105	29.420	44.034	58.465	37.967	14.461	27.500	34.547	50.979	5.166***
Con_top10	0.231	0.118	0.127	0.216	0.348	0.191	0.112	0.103	0.158	0.277	0.04***
Tradable share	36.309	12.134	28.960	36.166	43.257	38.328	12.569	30.254	37.500	45.822	-2.019
Nontradable share	60.708	10.941	54.789	62.310	68.353	59.053	11.331	52.447	60.893	67.677	1.655
Illiquidity_Amihud	0.285	0.109	0.202	0.358	0.358	0.318	0.080	0.339	0.358	0.358	-0.033***
Volatility	0.351	0.412	0.236	0.300	0.372	0.410	0.370	0.297	0.361	0.429	-0.058
Market value	21.600	0.744	20.903	21.435	21.999	21.332	0.656	20.883	21.012	21.567	0.268***
Age_list	1.829	0.617	1.629	1.960	2.208	1.931	0.560	1.629	2.092	2.208	-0.104

I further conduct the Probit model to confirm the firm bias in engagement timing of the SSR reform:

$$\begin{aligned} Early\ stage_i = \alpha + \beta_1 Firm\ Specific\ Char_{i,t_0} + \beta_2 Reform\ factor_i + \\ + Industry\ FE_i + \epsilon_i \end{aligned} \quad (4.9)$$

where the *Early stage*, is represented as a dummy with a value of 1 denoting firms reformed in the first or second stage, and 0 otherwise. The predictors employed in the analysis include a range of variables related to firm-specific characteristics, including *ROE* (Return on Equity), *FCFE* (Free Cash Flow to Equity), and *Long term liab* (Long-Term Liability). Additionally, the analysis integrates supplementary control variables such as the proportion of nontradable shares, ownership of state-owned shares, firm age (*Age_{1st}*), and firm size (*Marketvalue*). The assessment of illiquidity is conducted using the Amihud illiquidity method. The outcomes of the Probit regression 4.3 offer insights into how these various factors influence the likelihood of reform timing. Consistent with the summary statistics, I've found that younger firms with higher ROA, fewer tradable shares, greater long-term liability, fewer state-owned shares, and better liquidity tend to adopt the reform in the early stages. This discovery further emphasizes the importance of categorizing firms into two separate groups: the early-stage and later-stage groups to study the impact of SSR.

4.4 Empirical results

4.4.1 Market reaction

To initiate the analysis, I begin by presenting the market's abnormal return observed on the first trading day following the initial suspension period of a firm. This assessment is showcased in Table 4.4, where the abnormal return is estimated using Equation 4.2 for each day in relation to the event date. Here, Day 0 corresponds to the actual event date. The table also provides the standard deviation and the corresponding p-value.

The results are categorized into Panel A, B, C, and D, each representing a distinct stage of the reform process. Starting with the initial stage group (the pilots), we note that the daily abnormal return on the event date reaches up to 0.035%. Despite a reduction in the market reaction in the subsequent stage, a consistent pattern of significant positive market abnormal returns is evident across all four stages, with 0.038% and 0.03% in the third and fourth stages, respectively. An intriguing observation coming from these results is that there is a significant decline in market reaction in the firms of the second stage. However, investors continue to exhibit abnormal reactions to the proposed compensation of their firm in the later stage. This suggests no obvious market learning process seems to have transpired based on previous reformed firms, particularly when comparing the later stage with the early stage.

Table 4.3: Probit regression of firm characteristics on engagement timing

Table 2, labeled as Table 4.3, presents the outcomes of the Probit regression analysis concerning firm characteristics and their influence on the likelihood of reform timing. The dependent variable, *Early dummy*, is represented as a dummy with a value of 1 denoting firms reformed in the first or second stage, and 0 otherwise. The variables used for prediction include factors: *ROE* (Return on Equity), *FCFE* (Free Cash Flow to Equity), and *Long term liab* (Long-Term Liability). Additional controls incorporated in the analysis comprise the proportion of nontradable shares, state-owned share ownership, firm age (*Age_list*), and firm size (*Marketvalue*). The level of illiquidity is estimated through the Amihud illiquidity method. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent: Early dummy			
variable	(1)	(2)	(3)
ROA	16.6734*** 3.461	15.9003*** 3.593	16.6175*** 3.777
FCFE	-0.5257 0.555	-0.4325 0.585	-0.3854 0.597
Long term liab	1.5232*** 0.568	1.5825*** 0.605	1.6963*** 0.628
Nontradable share	0.0177*** 0.004	0.0084** 0.004	0.0094** 0.004
State-owned firm	-0.4338*** 0.097	-0.3875*** 0.101	-0.3578*** 0.104
Illiquidity_Amihud	-1.2170*** 0.422	-1.0015* 0.538	-1.2143** 0.560
Age_list		-0.4321*** 0.062	-0.4388*** 0.064
Market value		0.0265 0.076	0.0050 0.079
Industry FE	No	No	Yes
Nb.obs	1293	1289	1289
R2-adjusted	0.09	0.122	0.138

Table 4.4: Abnormal return from the event study

Table 4.4 presents the results of the average daily abnormal returns (AR) at the first trading day following the firm's first suspension period. Day 0 indicates the event date. Panel A to Panel D reports the results in each stage group.

Day	-10	-5	-1	0	1	5	10
Panel A: First stage (pilot)							
Average AR	-0.0021	-0.0032	0.0148	0.0350	0.0074	0.0023	0.0071
Std	0.0186	0.0163	0.0273	0.0615	0.0335	0.0180	0.0224
P-value	0.4559	0.1915	0.0007	0.0004	0.1453	0.3885	0.0389
Panel B: Second stage (1st-10th)							
Average AR	-0.0011	-0.0028	0.0079	0.0083	0.0021	0.0054	0.0016
Std	0.0168	0.0166	0.0217	0.0544	0.0256	0.0349	0.0256
P-value	0.3396	0.0126	0.0000	0.0214	0.2100	0.0200	0.3580
Panel C: Third stage (11th-30th)							
Average AR	-0.0012	0.0006	0.0087	0.0379	0.0119	0.0196	0.0018
Std	0.0158	0.0164	0.0229	0.0534	0.0365	0.0524	0.0269
P-value	0.0561	0.3366	0.0000	0.0000	0.0000	0.0000	0.1155
Panel D: Fourth stage (30th-64th)							
Average AR	0.0018	-0.0003	0.0114	0.0298	0.0117	0.0098	-0.0006
Std	0.0225	0.0240	0.0277	0.0577	0.0421	0.0534	0.0277
P-value	0.0950	0.8075	0.0000	0.0000	0.0000	0.0001	0.6418

Table 4.5 presents the Cumulative Abnormal Return (CAR) calculated for various estimation windows, spanning from (-10,10) to (1,2). Within the first stage group, a notable 0.11% CAR is observed over 5 days before and after the event. Although the second stage exhibits a slightly lower CAR, it remains significant and positive at 0.036%. Transitioning to the third stage, the CAR surges to 0.13%, and further stabilizes at 0.12% in the fourth stage. This prompts the question: What is driving these reactions?

Theoretically, in line with the no-arbitrage opportunity theory, the stock price should have increased by an amount equivalent to the proposed compensation mentioned on the firm's announcement date. This increment should have been factored into the cumulative abnormal return around that specific date. In light of this, my further analysis delves into the relationship between the proposed compensation and the observed market reaction on the event date through a multivariate OLS regression, as denoted in Equation 4.4.

The results of this analysis are presented in Table 4.6. Columns (1) and (2) showcase the findings for the early stage, encompassing firms from pilots to batch 10. In both cases, with or without controlling for the industry fixed effect, the coefficient of *Compensation* exhibits significant positive associations. This significance is observed at the 1% level. Specifically, for each unit increase in compensation, the CAR(-5,5) surges by 0.40% without industry fixed effect control and by 0.43% when industry fixed effect is accounted for. In contrast, a diminished effect becomes apparent in the later stage, as presented in columns (3) and (4). The positive relationship between compensation and market reaction weakens. A unit increment in compensation leads to a 0.18% rise in the market reaction.

Furthermore, the coefficient of the *State – ownedfirm* dummy variable displays a significant correlation with market reaction in early stage. Firms with state ownership exceeding 20% experience a clear lower market reaction compared to firms with lower state ownership. Notably, this trend is not observed in later-stage firms. This aligns with expectations, wherein investors seem to harbor negative sentiments regarding the implications of Share-Split Reform (SSR) when state-owned shares are divested to private investors.

Among later-stage firms, those that modified their initial compensation plans witnessed heightened market reactions. This finding reinforces the notion that, in later stage firms, investor responses are not solely attributed to the initially proposed compensation. Instead, additional factors are at play in influencing market reactions.

Table 4.5: CAR around the firm announcement date

Table 4.5 presents the results of the cumulative abnormal returns (CAR) at the firm reform announcement date in each reform stage.

Period	(-10, 10)	(-5, 5)	(-3, 3)	(-1, 1)	(1, 2)
Panel A: First stage (pilot)					
Average CAR	0.1649	0.1120	0.1003	0.0540	0.0111
Std	0.1130	0.0948	0.0942	0.0839	0.0389
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: Second stage (1st-10th)					
Average CAR	0.0620	0.0357	0.0339	0.0197	0.0030
Std	0.1349	0.0978	0.0870	0.0725	0.0355
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: Third stage (11th-30th)					
Average CAR	0.1787	0.1277	0.0895	0.0588	0.0202
Std	0.1975	0.1515	0.1140	0.0789	0.0548
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Panel D: Fourth stage (30th-64th)					
Average CAR	0.1784	0.1142	0.0862	0.0551	0.0181
Std	0.2553	0.1742	0.1280	0.0858	0.0623
P-value	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.6: OLS regression on CAR around the firm announcement date

Table 4.6 presents the OLS regression results of the cumulative abnormal returns (CAR) at the firm reform announcement on the Compensation. The early stage encompasses firms that underwent reform as pilots, and also the firms from the 1st to the 10th batches. The later stage includes firms engaged in reform from the 11th to the 64th batches. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent: Average CAR (-5,5)				
variable	Early stage		Later stage	
	(1)	(2)	(3)	(4)
Gap	0.0036*** 0.001	0.0033** 0.001	0.0008*** 0.000	0.0008*** 0.000
Batch	0.0004 0.004	0.0018 0.004	0.0001 0.000	0.0001 0.000
Compensation	0.4006*** 0.112	0.4299*** 0.114	0.1810** 0.073	0.1830** 0.074
State_owned firm	-0.0306** 0.015	-0.0292* 0.016	0.0007 0.015	-0.0002 0.015
ROE	0.0383 0.329	0.2486 0.349	0.0792 0.220	0.0593 0.222
Leverage	0.0020 0.004	0.0013 0.005	0.0007 0.003	0.0020 0.003
Market value	0.0080 0.010	0.0088 0.011	0.0056 0.009	0.0086 0.009
Age_list	0.0079 0.009	0.0044 0.009	-0.0094 0.009	-0.0130 0.009
Nb.firm	0.0010 0.001	0.0018 0.001	0.0006 0.001	0.0007 0.001
Change_plan	0.0657 0.040	0.0951** 0.044	0.0561*** 0.013	0.0591*** 0.014
Nb.obs	212	212	782	782
Industry FE	No	Yes	No	Yes
R2-adjusted	0.0847	0.0839	0.0801	0.0786

4.4.2 Adjusted market reaction

To conduct a deeper exploration into the factors influencing market reactions, I exclude the compensation component from the market reaction. This approach is in line with the no-arbitrage theory and builds upon the insights gained from previous analyses. The results are presented in Table 4.7, which shows the summary statistics of the proposed compensation according to different stages, along with the adjusted CAR after removing the compensation component.

In the first stage, the average compensation amounts to 0.33, implying that tradable shareholders receive approximately 3.3 additional shares for every 10 shares they originally held. The adjusted market reaction is then derived as the difference between the CAR(-5,5) and this compensation value. We note that the adjusted CAR exhibits significant negative values across all four stages. This suggests that after discounting the compensation effect, a pronounced negative market reaction has been found throughout the reform process.

Table 4.7: Summary Statistics

Table 4.7 presents the summary statistics of the proposed compensation and the adjusted cumulative abnormal returns (Adjusted CAR) after extracting the compensation level from the CAR at the firm reform announcement date. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Panel A: Proposed Compensation								
	Nb.obs	Mean	Std	Min	P25	P50	P75	Max
First stage	34	0.3329	0.0858	0.1000	0.3000	0.3250	0.4000	0.5000
Second stage	194	0.2897	0.0611	0.1000	0.2503	0.3000	0.3000	0.6560
Third stage	472	0.2617	0.0653	0.0300	0.2400	0.2700	0.3000	0.5788
Fourth stage	337	0.2317	0.0887	0.0243	0.1800	0.2500	0.2998	0.5533

Panel B: Adjusted CAR								
	Nb.obs	Mean	Std	Min	P25	P50	P75	Max
First stage	34	-0.2173	0.0898	-0.3864	-0.2822	-0.2115	-0.1472	-0.0781
Second stage	194	-0.2618	0.1081	-0.5039	-0.3422	-0.2680	-0.1980	0.0427
Third stage	472	-0.1351	0.1646	-0.5289	-0.2551	-0.1617	-0.0376	0.3790
Fourth stage	337	-0.1304	0.1797	-0.5262	-0.2654	-0.1668	-0.0239	0.4090

Next, I delve into uncovering the key factors driving the adjusted CAR. I start by analyzing the changes in firm performance and governance surrounding the government announcement date and the firm announcement date. Table 4.8 presents the summary statistics of the changes occurring between the two aforementioned dates. The quarterly report for 2005 serves as a representation of the firm's initial state, while the quarterly

report immediately preceding the date of the firm's reform announcement characterizes the latter state. I proceed to compare the attributes of firms in the early stage with those in the later stage. The differences in means are also presented.

Early-stage firms tend to exhibit higher ROA, possess greater long-term liability, maintain higher concentration among the top largest shareholders, and hold a higher market value at the government announcement date. Additionally, a significant increase in leverage difference is shown between the two stages at the firm announcement date. This is accompanied by later stage experiencing lower leverage and a smaller gap in ROA in comparison to early-stage firms.

Table 4.8: Change between government and firm announcement date

Table 4.8 presents the summary statistic between the Early group and Later group at the governance announcement date and at the firm reform announcement. The quarterly report for 2005 serves as a representation of the firm's initial state, while the quarterly report immediately preceding the date of the firm's reform announcement characterizes the latter state. The early stage encompasses firms that underwent reform as pilots, and also the firms from the 1st to the 10th batches. The later stage includes firms engaged in reform from the 11th to the 64th batches. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

variable	Governance announcement				Firm announcement			
	Early	Later	Difference	T-Value	Early	Later	Difference	T-Value
ROA	0.012	0.006	0.006***	7.687	0.027	0.015	0.012***	6.271
Leverage	1.674	1.540	0.133	1.094	1.684	1.383	0.301**	2.669
Short term liab	0.159	0.174	-0.015	-1.908	0.159	0.171	-0.012	-1.533
long term liab	0.067	0.051	0.015**	3.093	0.067	0.050	0.018***	3.606
FCFE	-0.044	-0.040	-0.004	-0.753	-0.106	-0.099	-0.008	-0.684
Net CF_invest	-0.202	-0.174	-0.028	-1.166	-0.422	-0.387	-0.034	-0.850
SOE	27.388	32.519	-5.13	-3.383	27.484	31.797	-4.313	-2.895
Largest	44.415	40.963	3.453**	3.261	44.229	40.495	3.734***	3.643
Con_top10	0.239	0.214	0.025**	3.074	0.238	0.211	0.028***	3.474
Tradable share	33.845	37.165	-3.32	-3.886	33.682	37.272	-3.589	-4.301
Nontradable share	63.743	60.007	3.737***	4.805	64.032	59.779	4.252***	5.578
Illiquidity_Amihud	0.503	0.969	-0.466	-2.286	0.376	0.452	-0.076	-1.263
Volatility	0.286	0.376	-0.09	-3.578	0.276	0.326	-0.05	-6.182
Market value	21.630	21.486	0.144**	2.728	21.616	21.520	0.096*	1.837
Age_list	1.397	1.853	-0.456	-9.476	1.404	1.945	-0.541	-11.870

To conduct a more detailed exploration of these determinants, I move forward with regression analyses. The primary explanatory variable in these analyses revolves around the financial statements of the firms:

$$\begin{aligned} \text{Adjusted } CAR_i = & \alpha + \beta_1 \Delta FCFE_i + \beta_2 \Delta FCFE_i * \text{ROA low}_{i,t_0} + \beta_3 \text{ROA low}_{i,t_0} \\ & + \beta_4 \Delta \text{Illiquidity_Amihud}_i + \beta_5 \text{Age}_i + \beta_6 \text{Market value}_i \\ & + \text{Industry FE}_i + \epsilon_i \end{aligned} \quad (4.10)$$

where the dependent variable *Adjusted CAR* represents the adjusted Cumulative Abnormal Return (CAR) achieved by subtracting the proposed compensation from the CAR(-5,5). This adjustment isolates the market reaction effect beyond the compensation factor. The variable $\Delta FCFE$ represents the change in Free Cash Flow to Equity between the periods (t_0, t_1) standardized by firm total assets. I employ Free Cash Flow to Equity as a proxy for the firm's financial statement. An increase in FCFE might indicate that the firm has more opportunities for profitable investments or less liability. Additionally, I extend this analysis by substituting $\Delta FCFE$ with the variable representing the change in net cash flows generated from investment as *CF_invest* to confirm the hypothesis.

The dummy *ROA low* equals 1 if the firm i exhibits a lower ROA just prior to the government announcement date (t_0) in comparison to the median value of the sample. Conversely, it takes a value of 0 otherwise. $\Delta \text{Illiquidity_Amihud}$ signifies the change in the level of illiquidity as measured by the Amihud illiquidity method during the time span (t_0, t_1) . The regression results have been reported in Table 4.9.

The outcomes in columns (1) and (5) focus on the primary explanatory variable: the change in Free Cash Flow to Equity ($\Delta FCFE$) in both the early and later stages. I ensure control over factors like liquidity alteration, firm age, and size. Notably, a significant pattern emerges specifically within the later stage. In the later stage, column (5) reveals a meaningful and positive coefficient of 0.1788 for $\Delta FCFE$. This coefficient signifies that a one-unit increase in $\Delta FCFE$ results in a corresponding 0.1788% increase in the adjusted CAR. Interestingly, this relationship is not evident within the early stage, as indicated by the absence of statistical significance.

Moreover, the significant positive coefficients of the interaction term $\Delta FCFE * \text{ROA low}$ (Columns (2) and (7)) and $\Delta FCFE Ltlab low$ (Columns (3) and (8)) lend further credence to the hypothesis. These coefficients suggest that firms in the later stage experience an increase in $\Delta FCFE$ just before the reform, as compared to their early-stage counterparts. Investors respond positively to these enhancements, with this trend being consistently significant for firms with lower ROA and lower long-term debt.

Column(1) and (5) shows the results with the main explanatory variable as the

change of FCFE in the early and later stage, respectively. I control the liquidity change, the firm age, and size. We can see that only in the later stage, there is a significant positive coefficient of the $\Delta FCFE$ of 0.1788, suggesting that a 1 unit of FCFE increased, the adjusted CAR increased by 0.179%. However, no significant relationship has been found in the early stage. Moreover, the significant positive coefficient of the interaction term $\Delta FCFE * ROA_{low}$ and the $\Delta FCFE * Ltlab_{low}$ further confirm the hypothesis. They suggest that firms in the later stage have experienced an increase in FCFE during the period just before the reform compared to the early stage, and investors show positive reactions towards these improvements. This result is more pronounced in firms with lower ROA and lower long-term debt.

Furthermore, I replace $\Delta FCFE$ with ΔCF_{invest} , and the results remain consistent. Later-stage firms display an increase in cash flows to investment shortly before the reform, and this change aligns with a positive adjusted market reaction. Lastly, I employ the change in the concentration of the top 10 largest shareholders (ΔCon_{top10}) as a proxy for improvements in corporate governance. However, I observe no statistically significant results in both the early and later stages. In essence, these results highlight the role of financial performance improvements, specifically in the context of Free Cash Flow to Equity and cash flows to investment, in shaping investor reactions. This relationship is particularly pronounced in the later stage of the reform process but not in the early stage.

Table 4.9: Determinants of Adjusted Market Reaction

Table 4.9 presents the regression of adjusted CAR on the change of firm performance. $\Delta FCFE$ represents the change in Free Cash Flow to Equity between the periods (t_0, t_1) standardized by firm total assets. $\Delta FCFE$ represents the change in net cash flows from investment between the periods (t_0, t_1) standardized by firm total assets. $\Delta Illiquidity_Amihud$ represents the change in illiquidity between the periods (t_0, t_1) . Dummy ROA_low equals 1 if the firm has a lower ROA than the median, 0 otherwise. Dummy $Ltliab_low$ equals 1 if the firm has a lower long-term liability than the median, 0 otherwise. The early stage encompasses firms that underwent reform as pilots, and also the firms from the 1st to the 10th batches. The later stage includes firms engaged in reform from the 11th to the 64th batches. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent: Adjusted CAR										
variable	Early stage					Later stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta FCFE$	0.0749	0.0236	0.0778			0.1788***	0.0860	0.0526		
	0.072	0.117	0.094			0.045	0.064	0.062		
ROA_low		0.0055					0.0042*			
		0.017					0.014			
$Ltliab_low$			-0.0012					0.0373***		
			0.017					0.014		
$\Delta FCFE * ROA_low$	0.0869					0.1805**				
	0.150					0.090				
$\Delta FCFE * Ltliab_low$		-0.0062					0.2532***			
		0.141					0.089			
ΔCF_invest			0.0084					0.0310**		
			0.022					0.012		
Con_top10				0.2257					0.0963	
				0.158					0.109	
$\Delta Illiquidity_Amihud$	0.1612	0.1614*		0.1667*	0.1793*	-0.1439*	-0.1396*		-0.1423*	-0.1457*
	0.103	0.103		0.103	0.102	0.075	0.075		0.076	0.075
Market value	0.0176	0.0192*		0.0181	0.0158	0.0027	0.0026		0.0023	-0.0007
	0.011	0.012		0.011	0.011	0.009	0.009		0.009	0.009
Age	-0.0004	-0.0008		-0.0035	-0.0002	0.0054	0.0052		0.0006	0.0008
	0.010	0.010		0.010	0.010	0.010	0.010		0.010	0.010
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb.obs	212	212	212	212	212	782	782	782	782	782
R2-adjusted	0.0189	0.0105	0.0087	0.0160	0.0237	0.0191	0.0222	0.0306	0.0078	-0.0003

4.5 Robustness check

4.5.1 Summary statistic in 2004

Table 4.10 and 4.11 offer a comprehensive summary of statistics covering the four stages. These observations belong to the final quarter of 2004. We can see that these results align with the observations made in the quarter preceding the government's reform announcement date in 2005 in Table 4.1 and 4.2. The consistent findings suggest that no significant changes occurred in firm characteristics before the Chinese government unveiled the reform. This observation further implies that firms displaying stronger performance, heightened profitability, and a substantial presence among major shareholders were more likely to initiate the reform process.

Table 4.12 examines the robustness of the results by dissecting the regression 4.4 into four distinct stages. Given the heterogeneous nature of firms' characteristics and the diverse reform processes they undertake, I customize the regression by introducing specific factors tailored to each reform stage.

To illustrate, I incorporate state ownership as an explanatory variable in Columns (1) and (2) for the early stage. Given that the early stage exhibits higher levels of state ownership, it's plausible that this ownership structure could elucidate abnormal returns. Conversely, I drop the state ownership while introducing the batch, number of firms, and a dummy variable indicating compensation plan changes in the later stage (Columns (3) and (4)). This adjustment accommodates the broader spectrum of batches and the varying number of firms engaged within each batch. Additionally, more firms within the later stage modify their compensation proposals, potentially influencing market reactions. By tailoring the variables to each specific case, I ensure a more focused analysis. Remarkably, even after such specific control adjustments, the findings consistently hold. This robustness reinforces the validity and stability of the observed relationships.

Table 4.10: Summary Statistics

Table 4.10 provides a summary of statistics across the first stage and the second stage. These observations belong to the quarter immediately preceding the quarter in which the government announcement occurred. A detailed definition of each variable is provided in Appendix A1.

Nb.Obs	First stage					Second stage					Diff_Mean
	43					212					
variable	Mean	Std	P25	Median	P75	Mean	Std	P25	Median	P75	Diff_Mean
Gap	14.636	6.759	9.750	14.000	18.000	12.300	5.753	10.000	10.000	11.000	2.336**
Period	49.136	10.709	52.000	52.000	52.000	167.812	23.897	143.000	171.000	192.000	-118.676***
Change_plan	0.000	0.000	0.000	0.000	0.000	0.033	0.179	0.000	0.000	0.000	-0.033
ROA	0.062	0.025	0.038	0.062	0.087	0.048	0.027	0.028	0.048	0.066	0.015***
ROE	0.113	0.037	0.091	0.105	0.142	0.091	0.046	0.060	0.090	0.129	0.022***
Leverage	1.903	1.930	0.779	1.206	1.909	1.670	1.599	0.628	1.141	1.964	0.233
Short term liab	0.138	0.102	0.048	0.135	0.215	0.156	0.111	0.056	0.141	0.259	-0.018
long term liab	0.067	0.080	0.000	0.040	0.114	0.064	0.078	0.000	0.029	0.108	0.003
Cash	0.208	0.126	0.097	0.210	0.315	0.186	0.126	0.090	0.145	0.259	0.022
FCFE	-0.273	0.260	-0.599	-0.234	-0.084	-0.255	0.241	-0.483	-0.228	-0.049	-0.019
Net CF_invest	-0.840	0.625	-1.406	-0.656	-0.339	-0.677	0.679	-1.238	-0.416	-0.140	-0.163
SOE	23.163	24.431	0.000	7.608	52.510	28.463	23.106	0.000	37.320	52.510	-5.301
Largest	45.294	15.042	30.520	46.407	62.409	44.158	14.707	32.563	45.643	58.507	1.136
Con_top10	0.248	0.120	0.134	0.241	0.399	0.237	0.114	0.139	0.228	0.347	0.011
Tradable share	31.839	10.290	25.096	28.708	37.647	34.293	11.340	27.273	34.774	40.000	-2.454
Nontradable share	68.161	10.290	62.353	71.292	74.904	62.819	10.490	57.143	64.032	70.012	5.342***
Illiquidity_Amihud	0.255	0.130	0.148	0.355	0.358	0.297	0.099	0.247	0.358	0.358	-0.042**
Volatility	0.265	0.085	0.223	0.260	0.308	0.317	0.131	0.233	0.283	0.369	-0.052**
Market value	21.841	1.009	20.931	21.611	22.232	21.578	0.788	20.883	21.252	22.018	0.263*
Age_list	1.227	0.859	0.173	1.386	1.946	1.594	0.723	1.314	1.792	2.079	-0.366

Table 4.11: Summary Statistics (continuous)

Table 4.11 provides a summary of statistics across the third stage and the fourth stage. These observations belong to the quarter immediately preceding the quarter in which the government announcement occurred. A detailed definition of each variable is provided in Appendix A1.

Nb.Obs	Third stage					Fourth stage					Diff_Mean
	557					411					
variable	Mean	Std	P25	Median	P75	Mean	Std	P25	Median	P75	Diff_Mean
Gap	19.084	14.782	10.000	14.000	21.000	30.617	78.573	10.000	14.000	21.000	-11.532
Period	290.975	43.264	255.000	297.000	325.000	558.239	460.564	402.000	437.000	563.000	-267.264***
Change_plan	0.151	0.358	0.000	0.000	0.000	0.411	0.493	0.000	0.000	1.000	-0.26
ROA	0.033	0.032	0.012	0.029	0.051	0.015	0.032	0.000	0.012	0.033	0.018***
ROE	0.063	0.058	0.025	0.059	0.098	0.035	0.064	0.005	0.032	0.068	0.028***
Leverage	1.645	1.726	0.675	1.047	1.841	1.358	1.637	0.499	0.858	1.484	0.287***
Short term liab	0.159	0.110	0.056	0.158	0.253	0.196	0.109	0.116	0.202	0.308	-0.037***
long term liab	0.052	0.067	0.000	0.021	0.083	0.046	0.067	0.000	0.011	0.067	0.006
Cash	0.163	0.104	0.084	0.142	0.216	0.135	0.106	0.056	0.103	0.181	0.028***
FCFE	-0.187	0.212	-0.330	-0.170	-0.006	-0.186	0.209	-0.325	-0.163	-0.023	0
Net CF_invest	-0.589	0.655	-1.010	-0.365	-0.084	-0.520	0.669	-0.908	-0.274	-0.043	-0.069
SOE	34.157	21.160	12.877	44.820	52.510	29.727	20.791	7.060	33.824	52.510	4.43***
Largest	43.020	15.127	29.367	43.911	58.344	37.807	14.587	27.314	34.515	50.980	5.213***
Con_top10	0.230	0.118	0.125	0.215	0.347	0.189	0.113	0.103	0.152	0.277	0.041***
Tradable share	36.079	12.120	28.571	36.040	42.977	38.389	12.568	30.254	37.280	46.008	-2.31***
Nontradable share	60.888	10.818	55.000	62.368	68.421	58.896	11.480	52.036	60.782	67.727	1.992***
Illiquidity_Amihud	0.302	0.097	0.271	0.358	0.358	0.324	0.075	0.358	0.358	0.358	-0.022***
Volatility	0.366	0.390	0.256	0.308	0.379	0.415	0.408	0.288	0.356	0.432	-0.048
Market value	21.600	0.735	20.919	21.413	22.000	21.333	0.630	20.883	21.032	21.578	0.267***
Age_list	1.722	0.608	1.386	1.946	2.079	1.821	0.556	1.609	1.946	2.197	-0.099

Table 4.12: Determinants of Market Reaction

Table 4.12 presents the summary statistic between the Early group and Later group at the governance announcement date and at the firm reform announcement. Statistical significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively.

Dependent: Average CAR				
variable	First stage	Second stage	Third stage	Fourth stage
	(1)	(2)	(3)	(4)
Gap	-0.0013 0.003	0.0056*** 0.002	0.0026*** 0.000	0.0005*** 0.000
Compensation	0.4549** 0.172	0.2354* 0.131	0.2039*** 0.099	0.2058*** 0.097
State-owned firm	-0.0697* 0.036	-0.0151 0.017		
ROA	0.1593 1.699	0.1345 0.761	1.3695** 0.612	-0.3588 0.806
Leverage	-0.0182** 0.008	-0.0009 0.006	-0.0014 0.004	0.0072 0.005
Market value	-0.0165 0.025	0.0090 0.009	0.0003 0.010	0.0226 0.015
Age_list	-0.0174 0.019	0.0002 0.014	-0.0077 0.010	-0.0171 0.015
Batch			0.0088*** 0.001	0.0027*** 0.001
Nb.firm			-0.0039*** 0.001	0.0031*** 0.001
New_compensation			0.0822*** 0.019	0.0402** 0.018
Year FE	Yes	Yes	Yes	Yes
Nb.obs	33	179	461	321
R2-adjusted	0.6240	0.0355	0.2328	0.1842

4.5.2 Price movements

Figure 4.2 visually depicts the stock price dynamics throughout the reform process. The markers *Gov – A* and *F – A* correspond to the dates of the government's and firm's announcements of the reform, respectively. The timeline is divided into distinct segments, each symbolizing a significant phase of the reform process. The initial segment delineates the stock prices over the ten days preceding the government's preliminary announcement. Subsequently, the second segment illustrates stock prices over the ten days prior to the firm's reform announcement date. The third segment captures the fluctuations in prices subsequent to the conclusion of the first suspension period. Lastly,

the fourth segment showcases the price changes following the implementation of the compensation plan.

The figure highlights noticeable dissimilarities in price movement patterns between early-stage and later-stage firms. Specifically, early-stage firms encounter a substantial decline subsequent to the reform, leading to stock prices even lower than those prior to the reform. Conversely, later-stage firms witness a remarkable surge in stock price post-reform. This disparity in price trends underscores the divergence in market reactions between these two distinct categories of firms.

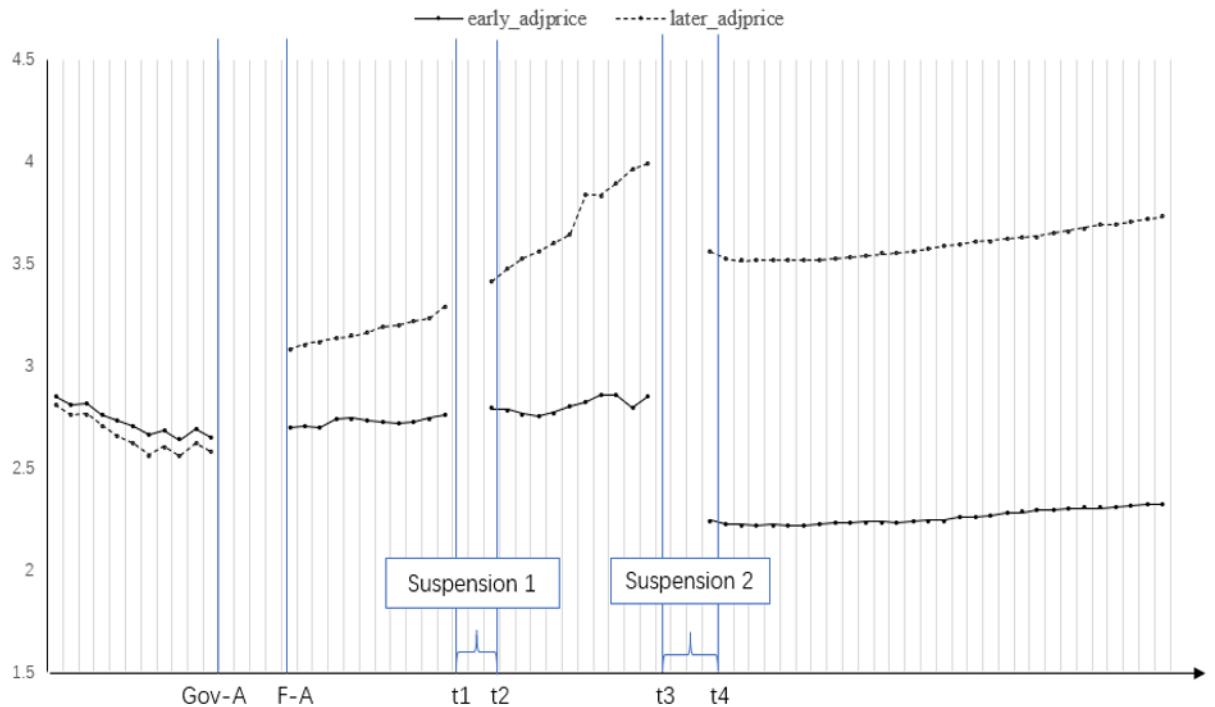


Figure 4.2: Stock price movements during the reform

4.6 Conclusion

The Chinese government's introduction of the Split Share Reform is aimed at dismantling the dual share structure and fostering future privatization. While many studies assess the reform's impact on firms' future performance through abnormal returns on the reform date, there's a scarcity of research addressing the endogeneity concerns tied to firm reform timing and the market's anticipation of compensation proposals.

In this study, I split the sample based on the reform timing of the firm's reform engagement. This classification allowed for a more detailed investigation into the distinct factors influencing market responses among different groups. I find that in the early stage, younger firms with higher ROA, fewer tradable shares, larger long-term liabilities, fewer state-owned shares, and improved liquidity demonstrated a propensity

for early adoption of the reform. Additionally, for firms in the early stage, a significant positive relationship surfaced between compensation and market abnormal returns on the day firms disclosed their participation in the reform.

Through an event study conducted on the firm announcement date, I adjust the market reaction by accounting for the market's learning capacity regarding compensation realization. I find that both early-stage and later-stage reformed firms encountered a significantly negative abnormal return. Nonetheless, early-stage firms experienced a reduction in firm value post-reform, whereas later-stage firms witnessed a rise in firm value. Finally, upon delving into the factors influencing the actual market reaction, I find that for early-stage firms, the reform's impact was less influenced by financial statement improvements. Rather, the compensation level had a greater influence. In contrast, for later-stage firms that have had more time to adjust and enhance their strategies, investors exhibit a more positive response to improvements in the firm's financial performance, particularly concerning free cash flows to equity and the net cash flows generated by the investment. These findings offer a new perspective for comprehending the Split Share Reform in terms of market reactions and the timing of the reform.

4.7 Appendix

Table 4.13: Variable Definitions

Age listed	Natural logarithm of the firm's year of listing in the exchange
Market value	Natural logarithm of equity market capitalization of the firm (in millions of RMB)
State_Owned_Firms	A dummy variable indicates whether the firms' ownership of state-owned shares is larger than 20%.
State_Owned_Firms shares	The state-owned shares standardized by the total shares outstanding.
Con_top10	The sum squares of the shareholding ratios of the top 10 major shareholders of the company.
ROE	Net income/total equity.
ROA	Net income/total asset.
Gap	Nb. of days between the firm announced the reform and the first trading day following the suspension.
Period	Nb. of days for the firm to complete the reform.
Changed_plan	Dummy that equals 1 if the firm changed the compensation proposal, otherwise 0.
Leverage	Debt/Equity.
Largest	The ownership of the largest shareholder of the firm.
Illiquidity_Amihud	The liquidity level estimated by the Amihud method.
Volatility	$2 \times \text{Absolute Value of (Trading Price} - \text{Midpoint Price between Buying Price and Selling Price}) / \text{Midpoint Price between Buying Price and Selling Price.}$

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