# Three Essays in China's Financial Market

by

**Chang Zhang**

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# Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that Chapter 1 of this thesis is a product of joint work with Doctor Chenyu Shan, Professor Dragon Tang, and Doctor Sarah Wang.

# Abstract


This thesis studies several important issues of the fast-developing Chinese financial market. It is comprised of three chapters.

In Chapter 1, we find that China's stock market (the "A share market") has lower correlation with the global market and is less affected by international financial contagions than any other major economies. The inclusion of mainland China stocks into an international portfolio increases its Sharpe Ratio. However, we find that Chinese stocks providing the most diversification benefits also carry the most policy risk for international investors. Holding Chinese stocks listed in Hong Kong does not reap the same diversification benefits. While global market integration and the increase in foreign ownership can diminish diversification benefits, mainland China stocks still provide valuable diversification opportunities for international investors up till most recent time in late 2010s.

Chapter 2 studies the industry contagion effect of financial distress in China. China witnessed a wave of bond defaults in recent years. By exploiting these defaults, I investigates how industry peers of the defaulted firms are affected through industry contagion. I find that while non-SOE peers suffer from decrease in firm value after the defaults, SOE peers' firm value does not change. Consistent with this, SOE peers' debt financing and investment are not affected by the defaults, while non-SOE peers decrease significantly in debt financing (especially bank loans) and investment. The contagion effect is stronger in high competition and high debt-dependent industries. Therefore, I find novel evidence of industry contagion of financial distress and shows that state ownership is an important determinant of industry contagion in China.

A new regulation issued in the end of 2013 as part of the anti-corruption campaign in China leads to a wave of resignation of politically connected independent directors (PCID). In Chapter 3, I find that while firms with PCIDs have negative cumulative abnormal return (CAR) around release of the new regulation, they have even larger positive CAR around announcement of PCID resignations, especially for non-SOEs. This is because firms with PCIDs have higher political risk after release of the regulation, but their political risk decreases after PCIDs resign and they are complied with the regulation. I also show that operating performance does not change after PCID resignations, casting doubt on the "helping hand" theory of political connections.

# Introduction

As the largest emerging country, China's financial market has been developing rapidly in the last few decades. China introduces stock market in 1990 and its economy also grows dramatically since then. China's stock market has been the second largest in the world with over \$10 trillion market capitalization and has increasingly attracted global attention. In the meanwhile, the size of China's bond market has also been ranked second globally with over \$12.5 trillion market value by 2018, surpassed only by the US. As the market grows, both investors and researchers have been showing greater interests to China's financial market, not only because of its greater stake in the international market, but also because of its special institutional features that differentiate it from other markets. Therefore, I investigate several important issues of China's financial market in this thesis.

In the first chapter, we study the value of China's stock market for international diversification and the role of policy risks in affecting the diversification benefits. Using a cross-country sample from 1995 to 2017, we find that China's stock market has the lowest correlation with other markets among all major markets. The dynamic conditional correlation (Engle, 2002) analysis shows that different from other emerging markets, the correlations of China with other markets keep low and stable throughout the sample period. Therefore, adding China to the portfolio of international investors can increase the Sharpe Ratio more than other emerging markets. Moreover, different from other emerging markets, China' stock market does not experience significant negative returns around global index shocks nor show significant increase in the correlation with global market. Last, we find that China is least likely to have market crash at the same time with the global market. These results provide additional evidence that China is less vulnerable to financial contagion and can provide valuable diversification benefits for international investors during global shocks.

Despite the diversification benefits, concerns on policy risks may prevent international investors from accessing China's stock market. However, we find that the correlation with global market for a more policy-sensitive firm is 26.09% lower than that of a less sensitive firm. In addition, policy-sensitive stocks have higher stock return and Sharpe Ratio than other stocks. In this sense, policy-sensitive stock brings both risks and rewards to international investors. Next, using the A-H cross-listed subsample, we find that A share stocks have significant lower correlation with the global market than their H share-listed counterparts despite the same fundamentals. This result suggests that firm fundamentals alone cannot explain the low correlation of the A share market with the global market. Factors related to institutional features in the listing markets that affect firm financing cost and investors' expected rate of return play a greater role. With the liberalization of China's stock market, the increase in foreign ownership may improve the comovement between Chinese stocks and the global market, resulting in decreased diversification benefits. However, we find that although foreign investor-held stocks have greater correlation with the global market than other stocks, it is still much lower than those of other markets. Last, we find that policy sensitivities have larger economic magnitude in explaining the low correlation of China's stocks market with other markets than foreign ownership.

The study in Chapter 1 contributes to three strands of literature. First, different from previous works on international diversifications, this study focuses on the role of China in international portfolio diversification, which has been much less studied thus far. We explore contagions to China through stock markets and document that China's stock markets is relatively resistant to international financial contagion compared with other markets, which is new to the literature. Furthermore, we contribute to the increasing literature on China's stock market. We investigate China's stock market from the perspective of well-diversified global investors. We provide evidence on variations in international diversification benefits around market liberalization efforts in China. Last, we explicitly explore the role of policy risks in affecting the diversification benefits. We find that policy risks can lead to low cross-country correlation and investigate the implications for foreign investors from the perspective of international portfolio diversifications.

The default of "11 Chaori bond" in 2014 was marked as the very first bond default incident in China. Ever since the first default, China has witnessed a wave of bond defaults until now. This provides a good laboratory to study bond defaults in China. In Chapter 2 of this thesis, I investigate how the industry peers, an important group of economically connected firms of the defaulted firms, are affected by the bond defaults. Using a sample of 113 defaulted firms in China from 2014 to 2018, I first perform an event study to test the firm value change of industry peers of defaulted firms. The results show that while SOEs peers do not have negative cumulative abnormal return (CAR) around bond defaults, non-SOE peers suffer from significantly negative CAR. Moreover, the negative effect on non-SOE peers is more prominent in high competition and high debt-dependence industry. These results suggest that SOEs in China may not be vulnerable to industry contagion of financial distress. On the contrary, non-SOEs are vulnerable to industry contagion and the high competition and high dependence on debt financing within industry can amplify the contagion effect.

I further test industry peer's debt financing and investment to explore the underlying mechanism of firm value change. The difference-in-difference analysis shows that the industry peers of defaulted firms overall suffer from 10.37% decrease in debt ratio relative to other firms. However, the subsample analysis shows that debt ratio of SOE peers does not change, while non-SOE peers decrease significantly in debt ratio. I also find that the change is mainly driven by decrease in bank loans, which is the most important source of debt financing of Chinese firms. Next, I show that peers of defaulted firms suffer from 16.8% decrease in investment relative to other firms. Consistent with previous results, SOE peers' investment does not change significantly, but non-SOE peers' investment is reduced significantly. Last, I find that the decrease in peers' debt financing and investment is large and significant in high competition/debt-dependence industries, but not in low competition/debt-dependence industries. In sum, my analysis suggests that firms are vulnerable to industry contagion mainly through reduced bank loans and investment in China. More importantly, while non-SOEs are vulnerable to industry contagion, SOEs can withstand the contagion effect, because SOEs have easy access to debt financing even after their industry peers default. This means beside industry characteristics and default type, ownership structure is an important determinant of the severity of industry contagion in China.

The study in Chapter 2 makes three main contributions. First, it contributes to the emerging literature on China's corporate bond market, especially on bond defaults, which has been overlooked by previous studies. This is the first study looking at how the defaults in China affect other economically connected firms, i.e., industry peers. Second, it contributes to the literature on industry contagion of financial distress. Previous studies have concluded that industry characteristics and the nature of financial distress will affect the severity of contagion. This study further shows that in an emerging market like China, state ownership can be the most important determinant of industry contagion. Third, this study also has important policy implications. The easy access to financing sources of SOEs not only leads to low efficiency as shown in previous studies, it may also crowd out non-SOEs in the credit market after the bond defaults.

A new regulation known as Regulation No.18 was issued in China in 2013 during the anti-corruption campaign. The new regulation prohibits government officials from taking any part-time position in firms and getting any kind of payment from firms. Many government officials had to resign from firms because of the regulation. Independent director is the largest group affected by this regulation given the prevalence of Chinese firms offering these positions to officials. Using this regulation as a shock, I examine the effect of losing political connected independent directors (PCIDs) on Chinese listed firms in Chapter 3. My sample includes 418 treated firms that have PCID resignations and 418 controlled firms matched with the treatment group using propensity score matching. The sample period is from 2011 to 2016.

I find that the treatment group has significantly negative CAR around release of Regulation No.18. However, treated firms have significantly positive CAR around announcement of PCID resignations. This is because firms with PCIDs have higher political risk than other firms before their PCIDs actually leave, leading to higher required rate of return by investors and thus decrease in firm value. After their PCIDs resign, their political risk decreases, leading to increase in firm value. Moreover, the cross-sectional regression on CAR shows that the value effect is only significant for non-SOEs but not for SOEs. Next, I find that firm's operating performance does not change after their PCIDs resign. This suggests that political connections built by PCIDs may not be helpful for firm performance in China and casts doubt on the "helping hand" theory of political connections. On the contrary, political risk decreases significantly after PCIDs resign. The subsample analysis shows that non-SOEs decrease significantly in firm risk but SOEs' firm risk does not change, which is consistent with results from CAR analysis. One possible explanation for the different results is that SOEs have more other political connections than non-SOEs because of their special relationship with the government. Even their PCIDs leave, they still have other connections and thus the same political risk.

Chapter 3 is related to three strands of literature. First, while the literature on political connections is large, most of them focus on connections from blockholders and executives instead of independent directors. My study extends existing literature by testing the effect of independent directors, who may play different roles from the top insiders. I also show that the effect of losing PCIDs is different for SOEs and non-SOEs, suggesting that the effect of political connections is contingent on firm's ownership structure. Second, recent studies have investigated the effect of political risk on asset prices. This study exploits a clean exogenous shock and provide strong support for the existence of priced political risk in China. Third, this study relates to the increasing literature on China's anti-corruption campaign. Different from other studies, I use Regulation No.18, a specific regulation during the campaign, to test the value effect of political connections.

# Chapter 1

# The Diversification Benefits and Policy Risks of Accessing China's Stock Market

## 1.1 Introduction

Theoretical models of portfolio selection suggest that diversification can reduce risk and the degree of risk reduction depends on the return correlations (e.g. Markowitz, 1959). The risk reduction can be facilitated by diversifying portfolios internationally (e.g. Grubel, 1968; Levy and Sarnat, 1970). The 2008 global crisis revealed the complication of international asset allocation. One new element is rising markets which present opportunities for alternative investment. In 1989, China did not have a stock market and its economy was much less significant in the world (ranked #11 after Spain). China introduced stock market in 1990 and its economy also grew dramatically since then. By 2019, China's stock market is the second largest in the world with over $8.7 trillion market capitalization. The stock price in China is as informative about future profits as those in the US market (Carpenter, Lu, and Whitelaw, 2020a). Despite tensions between China and the US, foreign investors show great interests to China A-share market.[1] However, their actual exposure remains small. The recent cancellation of Ant Financial's IPO and the voluntary trading suspensions in July 2015 raise additional concerns of accessing China A shares. In this paper, we conduct a comprehensive analysis of the value of China's stock market for international portfolio diversification and the role of policy risks in affecting the diversification benefits.

Foreign investors can gain exposure to China through passive instruments such as buying emerging market index or China exchanged traded funds (ETF). However, the China exposure through the available emerging market index is limited. For example, J.P. Morgan Asset Management points out that "Global and emerging market equity investment managers are not always a reliable source of China exposure; some actually have zero exposure."[2] With

[1] For example, see https://medium.com/william-blair-investment-management/china-a-too-big-to-ignore-132359bd5f40 and other reports by William Blair (2018).

[2] https://am.jpmorgan.com/us/en/asset-management/institutional/insights/portfolio-insights/equity/understanding-the-opportunity-in-chinese-equities/

the opening up of China's financial market, it is becoming easier for foreign investors to invest directly in China stocks. Before 2003, foreign investors can trade "offshore China" stocks through Chinese firms-listed in the Hong Kong Stock Exchange (H shares) or American Depository Receipts (ADR) traded in the US, whereas B shares offer a way for foreign investors to access China's domestic stock market. However, "offshore China" stocks or B shares are dominated by state-owned enterprises or large stocks.[3] China A shares give greater access to small- and mid-companies from various industries which are important driver for China's economic growth. Since 2003, foreign investors can access A shares through Qualified Foreign Institutional Investors (QFII) program via licence application and quotas. To attract more foreign capital, QFII quotas are removed from June 2020 with simplified process for routine repatriations. Furthermore, the introduction of Stock Connect programs in 2014 and 2016 provides a new mechanism for foreign investors to invest A shares via Hong Kong.[4]

To investigate the attractiveness of China for international portfolio diversification, we first examine correlation benefits from investing in China's stock market and compare such benefits from investing in other developed markets or emerging markets. Using a cross-country sample from January 1995 to December 2017, we find that China's stock market has the lowest correlation with other markets, compared with all other developed markets and emerging markets. To analyze the time-series changes in correlations, we further employ the dynamic conditional correlation model of Engle (2002). We find that while cross-sectional correlations have been increasing, the correlations of emerging markets increase more than developed markets in the last two decades, consistent with the previous literature (e.g. Christoffersen, Errunza, Jacobs, and Langlois, 2012). However, the correlations of China with other markets keep low and stable throughout the sample period. The results suggest that China's stock market may offer valuable diversification benefits for international investors.

We next take the perspective of international investors with a well diversified portfolio, e.g. MSCI global index, as the benchmark portfolio and investigate whether adding China or other emerging market indices to their benchmark portfolio generates incremental performance benefits. We measure the incremental performance benefits as the change in Sharpe Ratio. We find that adding China to the MSCI global index can increase the annual Sharpe Ratio by 0.089. The increase in Sharp Ratio is more than that from other emerging markets. Therefore, we find evidence that China's stock market offer international investors significant diversification benefits.

Diversification benefits are most valuable during economic downturns. Therefore, we further investigate whether China's stock market is less affected by negative global financial shocks. Specifically, we first identify global index shocks and compare the cumulative market returns of emerging markets around global index shocks. We find that, different from other emerging markets, China' stock market does not experience significant negative returns around global index shocks. In addition, we compare dynamic conditional correlation of emerging markets with the global index during the index shock week and that prior to the shock week. We find that while all other emerging markets become more correlated with the global market around

[3] By the end of 2018, only 99 companies have B-shares and the liquidity is much lower than A-shares.

[4] The inclusion of China A shares in the MSCI Emerging Markets Index and MSCI ACWI since June 2018 and the opening up futures trading for foreign investors in November 2020 could boost the A shares access further.

global shocks, China does not show significant increase in the correlation coefficient. Moreover, we follow Bae, Karolyi, and Stulz (2003) to use *coexceedance* to measure financial contagion. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indices. Our results suggest that among all developed and emerging markets, China has the lowest coexceedance with other markets. These results provide additional evidence that China is less vulnerable to financial contagion and can provide valuable diversification benefits for international investors during global shocks.

Despite of the diversification benefits, concerns on policy risks may prevent international investors from accessing China's stock market.[5] On the one hand, governments are likely to provide "insurance" against downside risk. Cieslak and Vissing-Jorgensen (2020) refer this as the "Fed put" in the US where government responds to stock market slumps with a sequence a policy easings. In China, government interventions occur mostly after stock market decline. There is likely more "government put" in China than other countries.[6] On the other hand, frequent interventions can distort market prices and raise concerns on trading freedom (Song and Xiong, 2018). For example, the recent cancellation of Ant Financial's IPO surprised investors and chilled other IPO hopefuls.[7] In July 2015, more than 1,400 companies suspended their Shanghai- and Shenzhen-trading shares raising additional concerns about the ability to exit during market plunge. Additional analysis suggests that while trading suspensions are indeed more frequent before 2009 (see Figure 1), the average numbers of trading suspensions are decreasing in most recent decade. In May 2016, China's two bourses introduced tougher restrictions on voluntary trading suspensions to protect the interests of investors.

While country-specific policy risk can generate comovement among shares trading in the same country, it may reduce shares comovement with international market and contributes to international diversification benefits. If A share stock prices are largely moved by policy changes, then stock prices would be less related to economic fundamental. As a result, return patterns in the A share market would deviate from the global market. Would the policy risk explain the low correlation between the A share market and the global portfolio?

To examine the role of policy risks in diversification benefits, we construct two measures for stocks' policy sensitivity. In the spirit of Baker, Bloom, and Davis (2016) and Liu, Shu, and Wei (2017b), our first measure is based on correlation of inidividual stock returns with China's Economic Policy Uncertainty (EPU) Index. Our second measure is based on the three-day cumulative abnormal return (CAR) of stocks around announcements of new regulatory documents issued by China Securities Regulatory Commission, the main regulatory body of China's stock market. We further construct two firm-level variables, *correlation* and *Global Beta*, to measure the connectedness of stocks with the global market. Then we regress the stock connectedness measures on proxies for stocks' policy sensitivity. The results suggest that the correlation with global market for a more policy-sensitive firms is 0.013 lower than that of a less sensitive firm,

[5]We interpret policy risks as uncertainty in government policies that may affect firm operation or cash flows and relevant institutional features that may affect investors' ability to transfer investment or capital gains.

[6]For example, during the 2015 China's stock market crash, a state-backed "national team" were called on to support the market.

[7]On-going studies including Qian, Ritter, and Shao (2020) posit that heavy-handed regulations have caused inefficient IPO offer prices and high initial returns, resulting in a high cost of going public in the A share market.

or 26.09% relative to the average correlation. In addition, we show that policy-sensitive stocks have higher stock return and Sharpe Ratio than other stocks, suggesting that the potential policy risk is compensated by a higher return. In this sense, China's stock market is attractive for investors looking for portfolio diversification. Policy-sensitive stock brings both risks and rewards to international investors.

To better understand the sources of policy risks and their contributions to diversification benefits, we conduct additional analysis based on A-H cross-listed stocks. From international investors' perspective, policy risks may come from two sources: policy risks that affect firms' operation or cash flows or policy risks that affect investors' expected rate of return. Cross-listed stocks share identical firm fundamentals and thus, provide a good laboratory to separate the above channels. If it is the cash flow channel that explains the low correlation of Chinese stock market with the global market, we would expect similar diversification benefits from A share-listed part and H share-listed part. However, in the sample of 99 cross-listed stocks, we find that A share stocks have significant lower correlation with the global market than their H share-listed counterparts, and A share stocks provide greater diversification benefits than H share stocks. This result suggests that firm fundamentals alone cannot explain the low correlation of the A share market with the global market. Factors related to institutional features in the listing markets that affect firm financing cost and investors' expected rate of return play a greater role in explaining the role of policy risks in explaining the diversification benefits.

With global integration of capital markets, foreign investors may obtain better access to the China's stock market. Silvers (2020) document that regulators' efforts to moderate frictions through regulatory cooperation help integrate equity markets and boost cross-border equity investment. The increase in common foreign ownership after the moderation of frictions may improve the comovement between Chinese stocks and the global market, resulting in decreased diversification benefits. To test the role of market integration in affecting diversification benefits from A share stocks, we identify A share-listed stocks held by QFII, and use QFII indicator as a proxy for foreign ownership. We compare the correlation and coexceedance between QFII and non-QFII A share stocks.[8] We find that, compared with non-QFII stocks, QFII stocks indeed have greater correlation and coexceedance with the global market. However, the correlation and coexceedance of QFII stocks are still much lower than those from other markets. Including both QFII holding and policy sensitivity measures in the regression analysis, we find that policy sensitivities have larger economic magnitude in explaining the low correlation of China's stocks market with other markets than foreign ownership.

This study contributes to three strands of literature. First, there are interrelated literature on international diversifications, stock comovements and contagions (e.g. Bekaert, Hodrick, and Zhang, 2009; Barberis, Shleifer, and Wurgler, 2005a; Christoffersen et al., 2012). Given the more integrated global market, some recent works attempt to search for investments that have relatively lower correlations with the international markets and approaches to obtain these exposure (e.g., Eun, Huang, and Lai, 2008; Eun, Lai, de Roon, and Zhang, 2010; Bae, Elkamhi, and Simutin, 2019). Different from the previous works, this study focuses on the role of China in

[8]Stock Connect programs introduced in 2014 and 2016 are alternative channels for foreign investors accessing A shares.

international portfolio diversification, which has been much less studied thus far. Using various measures of contagion, we explore contagions to China through stock markets and document that China's stock markets is relatively resistant to international financial contagion compared with other markets, which is new to the literature.

Furthemore, we contribute to the increasing literature on China's stock market. Carpenter et al. (2020a) also document the low correlation of China's stock market with international markets. Allen, Qian, Shan, and Zhu (2020) dissect the long-term performance of China's stock market. We investigate China's stock market from the perspective of well-diversified global investors and extend by investigating the dynamics of the correlation overtime and comparing the vulnerability to global contagions across markets. We also explicitly explore the role of policy risks in affecting the diversification benefits. Our results are consistent with Carpenter, Whitelaw, and Zou (2020b) that compared with A share stocks, H shares are not better investment for global investors, although their work focuses on the determinants of the A-H premium. Using Shanghai-Hong Kong Stock Connect Program as a demand shock, Liu, Wang, and Wei (2018a) find evidence of value appreciation, increased turnover and volatility for connected stocks. We instead provide evidence on variations in international diversification benefits around these market liberalization efforts. Lastly, a number of works have documented positive effects of government interventions on corporate financing and default risks (Huang, Miao, and Wang, 2019; Jin, Wang, and Zhang, 2018). Different from these works, we find that policy risks can lead to low cross-country correlation and investigate the implications for foreign investors from the perspective of international portfolio diversifications.

The rest of this paper is organized as follows. Section 2 provides literature review and hypothesis development. Section 3 presents the data and summary statistics. Section 4 examines the diversification benefits from of stocks listed in China A share market for international investors. Section 5 investigates the role of policy risks in explaining the low correlation and diversification benefits of China's stock market. Section 6 concludes.

## 1.2 Literature and Hypothesis Development

International portfolio diversification provides benefits that outweigh various costs. The benefits have relied largely on the low correlations among international assets (Grubel, 1968; Levy and Sarnat, 1970). The low international correlation can be explained by country-specific variations caused by differences in policies, institutional and legal regimes, and regional economic shocks (Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998). In addition, investor demand can explain additional variations in international correlations. Stocks with less common ownership provide more diversification benefits (Barberis and Shleifer, 2003; Barberis, Shleifer, and Wurgler, 2005b).

However, recent studies find that as the international capital markets become more integrated, the correlations of major stock markets increase over time, reducing the international diversification benefits (Longin and Solnik, 1995; Solnik and Roulet, 2000; Christoffersen et al., 2012). Stock markets are even more correlated and subject to contagions in market downturns when the diversification benefits are most needed, particularly for developed markets (e.g., Ang and Bekaert, 2002; Longin and Solnik, 2001; Baur, 2012). As the largest emerging market, China's stock market has been largely ignored by international investors. Allen et al. (2020) posit the disconnection between China's economic growth and its stock market performance. Institutional features including listing and delisting policies, along with corporate governance issues can explain the under-performance of Chinese stock market. The disconnection between economic growth and stock market performance may have resulted in low correlation of the Chinese stock market and other markets in the world. Meanwhile, tight capital control restricts foreign investors from participating in the Chinese stock market, making the A share market a segmented one.[9] The unique features of China's stock market, particularly the role of government policies and low foreign ownership, can potentially make China's stock market even more attractive to international portfolio diversification.

**Hypothesis 1:** China's stock market provides more diversification benefits for international investors than other markets, especially during market downturns.

Government policies can have large impact on China's financial market (Brunnermeier, Sockin, and Xiong, 2020). With the aim of stabilizing financial market, Chinese government tends to intervene when the market is extremely volatile. The active government intervention during economic downturn can also exempt China from crisis "wake-up call" and enable China's stock market to resist financial contagions from other markets.[10] In addition, as part of the reform and open of China's financial markets, Chinese government frequently perform regulatory experiments (Carpenter and Whitelaw, 2017). Markets often react violently to the experiments. While government policies may help stabilize the market in the short run, they may also increase China's idiosyncratic volatility and make it less correlated with global market. Firms that are more sensitive to policy change may see their stock price change more independent of variation of the global market.

**Hypothesis 2:** Stocks with high policy risks in China provide greater diversification benefits to international investors.

While stocks with high policy risks may generate greater diversification benefits, concerns on policy risks can prevent foreign investors from accessing A share market. For international investors, policy risks may come from two sources: 1) government policy related risks that affect firm operation or cash flows; 2) government policy related risks that affect firms' cost of financing, or investors' required rate of returns. This type of risk is related to interest rates and other monetary policies in the listing market, and also related to regulations that affect investors' ability to transfer investment or capital gains.[11] To better understand the sources of policy risks and their contributions to diversification benefits, we conduct additional analysis based on A-H cross-listed shares. Among the 3600 A-share stocks, 99 cross-listed on the Hong Kong Exchange. If it is the firm cash flows or other fundamentals that explain the low correlation of the China A share market with other markets, then we should expect no difference in the correlation coefficients of the A share-listed part and the H share-listed part for A-H cross-listed stocks.

[9] See more detailed discussions in Forbes, Fratzscher, Kostka, and Straub (2016).

[10] "Wake-up call" is one channel of financial contagion documented in the previous literature. Crisis initially restricted to one market can provide new information and wake-up investors to reassess the vulnerability of other markets (Goldstein, 1998).

[11] Cosset and Suret (1995) explore policy risks in a cross-country setting of 36 countries during 1982 to 1991, whereas China is not in the sample due to lack of development in the stock market.

However, if it is the institutional features of the listing markets related to discount rate and investors' investment risks that explain the low correlation of A share market, then we should expect lower correlation coefficients of the A share-listed part than the H share-listed part, and correspondingly larger diversification benefits of the A share-listed than the H share-listed for the cross-listed sample.

**Hypothesis 3:** A share stocks in mainland China provide greater diversification benefits to international investors than H share stocks listed in Hong Kong.

## 1.3 Data and Descriptive Statistics

We start to construct our market-level sample with the G20 countries, which accounts for 85% of global economic output and 80% of global investment.[12] Then we drop the European Union (EU) since the largest four markets of EU (UK, France, Germany, and Italy) are already in the sample. Saudi Arabia is also dropped because the available data period is short and different from all other markets. We add Hong Kong stock market into the sample as it is closely connected with China's A share market and many Chinese firms are listed on Hong Kong Exchange.[13] We collect data of China's market from the China Stock Market and Accounting Research Database (CSMAR). We use MSCI market index collected from DATASTREAM to measure the performance of other markets. At last, we use the MSCI World Index, which includes 23 DMs, to proxy for the performance of the global market. Therefore, our market-level sample includes 9 DMs: US (USA), Japan (JPN), Hong Kong (HKG), UK (GBR), Germany (DEU), France (FRA), Canada (CAN), Italy (ITA), and Australia (AUS); 10 EMs: China (CHN), South Africa (ZAF), South Korea (KOR), India (IND), Indonesia (IDN), Brazil (BRA), Mexico (MEX), Russia (RUS), Turkey (TUR), and Argentina (ARG); and the global market. The 19 stock markets account for more than 90% of global market capitalization according to the World Bank.[14] Our sample period is from January 1995 to December 2017. We also conduct analyses for a more recent sub-period from January 2006 to December 2017 for comparison.

Our firm-level sample includes A share firms listed in Shanghai Stock Exchange and Shenzhen Stock Exchange from 1995 to 2017. Financial firms are excluded because their financial statements are complied under different accounting standards. We construct two stock-level policy sensitivity measures. For the first measure, we collect China's EPU Index at month level during 1995 to 2017 from the EPU Index website.[15] Then we estimate the correlation between individual stock's return and the EPU index as a measure of the stock's policy sensitivity. For the second measure, we hand collect the announcement dates of new regulatory documents issued by the China Securities Regulatory Commission (CSRC) from its official website. The first regulatory document was issued in 2001 and 137 documents are issued during 2001 to 2017.[16]

[12] More information about G20 countries can be found on the official website: `https://www.g20.org/en/g20/what-is-the-g20`.

[13] By the end of 2018, firms that are headquartered in mainland China account for over 60% of the total market capitalization of the Hong Kong stock market.

[14] See `https://data.worldbank.org/indicator/CM.MKT.LCAP.CD`.

[15] `http://www.policyuncertainty.com/`, which is developed by Scott Baker, Nicholas Bloom, and Steven J. Davis based on Baker et al. (2016).

[16] See `http://www.csrc.gov.cn/pub/zjhpublic/index.htm?channel=3300/3311`.

Then we calculate individual firm's stock price reaction to these annoucements as another measure of the stock's policy sensitivity. All other firm-level data and macroeconomic data of China are also obtained from CSMAR.

Panel A of Table 1.1 reports summary statistics of annualized weekly returns in USD for sample markets. In general, emerging markets have much higher return and volatility than developed markets. The mean weekly return of stocks listed in mainland China is 0.151, with standard deviation 0.288. Russia has the highest return and volatility among all markets. In contrast, Japan has the lowest return among all markets, with volatility also among the lowest ones. Although Russia and Turkey have higher return than China, their volatilities are also higher. Emerging markets such as South Africa, India, and Mexico have similar volatility with China but lower returns. Therefore, from the perspective of an international investor, China provides attractive reward-to-volatility compared to other markets.

Panel B reports summary statistics of firm-level variables used in this study. Variable definitions are summarized in Appendix A and all variables are winsorized at 1% to 99% except dummy variables. The average correlation of A share stocks with the MSCI World Index is as low as 0.046. Since our measures of policy sensitivity are normalized ranking which range from 0 to 1, their means are all around 0.5. The average $QFII$ is 0.106, suggesting that only a small part of A share stocks are held by Qualified Foreign Institutional Investors. The mean of $Trade\ suspension$ is 1.602, suggesting that an A share stock's trading is suspended for an average of 1.602 times for reasons other than shareholder meeting and financial report release. The average firm asset size and firm age are 2.4 billion CNY and 11.58 years, respectively. Other firm characteristics are comparable to those in recent studies (e.g. Giannetti, Liao, and Yu, 2015; Liu et al., 2017b), except that our sample includes more SOEs because the sample period starts from 1995 and SOEs account for a larger share of the sample in earlier years of the sample period.

## 1.4 Diversification Benefits for International Investors

### 1.4.1 Correlations

The diversification benefits from international investing is determined by the cross-country correlations (Christoffersen et al., 2012). However, recent studies show that international diversification benefit has been decreasing over time because markets become more correlated in the last few decades and financial contagion makes international investors more vulnerable to global shocks. In this section, we investigate whether China's stock market provides diversification benefits to global investors. We also compare the diversification benefits from China with other markets.

We first report cross-market stock return correlations in Panel A of Table 1.2. All correlations are calculated using weekly USD returns and statistically significant at the 1% level. Consistent with previous studies, correlations between developed markets are generally higher than those between emerging markets. Japan, among all developed markets, has the lowest correlations with other markets. Markets in the EU have high correlations with each other as EU economies are closely connected. Correlations of emerging markets vary a lot across markets. South Africa, Brazil, and Mexico have the highest correlations with other markets, while China has the lowest correlations with both developed markets and emerging markets. For example, the correlation of China with the US is only 0.038. It is worth to note that China has higher correlation with Hong Kong (0.114) than with most other developed markets. We also report the correlations for the period from 2006 to 2017 in Panel A of Table C1 in Appendix C. It shows that correlations of all 19 markets have increased in the last two decades. But the pattern does not change, with China still having the lowest correlations with other markets. The results suggest that compared with other markets, adding China into the global portfolio can potentially generate most diversification benefits for international investors.

The unconditional correlation depicts the long-term connectedness of the sample markets. However, it cannot capture the pattern of connectedness over time. Therefore, we further use a dynamic conditional correlation model of Engle (2002) and Tse and Tsui (2002) to investigate time-varying connectedness. Specifically, we follow Christoffersen, Errunza, Jacobs, and Jin (2014) and fit univariate AR(2)-GARCH(1,1) models to the weekly return of each sample market. The autoregressive model of order two, AR(2), can pick up the potential return dependence of each market. The GARCH(1,1) can pick up the second-moment dependence. The model specification and results of model estimates are summarized in Appendix B.

We first estimate the dynamic conditional correlation model for each pair of sample markets. Then for each market at each week, we calculate three average correlations with other markets: the average correlation with all other 18 markets, the average correlation with all 9 developed markets (or the other 8 developed markets for a developed market), and the average correlation with all 10 emerging markets (or the other 9 emerging markets for an emerging market). We plot the time-series of average dynamic conditional correlation with the other 18 markets for each sample market in Figure 2. Consistent with Christoffersen et al. (2014), most sample markets have an uptrend correlation till the 2008 credit crisis. Moreover, most emerging markets' correlations increase more than developed markets, possibly because of market liberalization in emerging markets. However, we find only marginal increase in China's correlations over the years. Given the increasing connectedness of other markets, China keeps having low correlation with the rest of the world. We then calculate the time-series mean of the three average correlations for each market. The results are reported in Panel B of Table 1.2. The average dynamic conditional correlations with all markets show similar pattern with unconditional correlations in Panel A, suggesting that the dynamic conditional correlation model estimates fit our data well. We again observe the lowest correlation for China with only 0.097. The last two columns show the average correlation of each market with developed markets and emerging markets, respectively. We find that most markets have much higher correlations with developed markets than with emerging markets. However, China has similarly low correlations with developed markets and emerging markets.

### 1.4.2 Sharpe Ratios

In this subsection, we examine diversification benefits of China and other emerging markets to the global portfolio using the Sharpe Ratio. We first calculate annual Sharpe Ratio of the MSCI World Index based on weekly returns in USD. Then we construct portfolios that contain the

World Index and each of the 10 emerging markets, and calculate the Sharpe Ratio of the optimal portfolios. We do not allow short-selling when constructing the portfolio as most emerging markets including China have short-selling constraints. Lastly, we calculate the difference in the Sharpe Ratio between the World Index and the optimal portfolios to test whether investing in an emerging market can increase the Sharpe Ratio for global investors.

The results are presented in Panel A of Table 1.3. We also report the significance level of the difference and the weight of each emerging market in the optimal portfolios. As shown, all emerging markets can provide diversification benefits, as evidenced by the significant increase in the Sharpe Ratio. On average, the 10 emerging markets can increase the Sharpe Ratio of the World Index by 0.059. While the increase is significant for all emerging markets, it is the largest for China, suggesting that the economic magnitude of diversification benefits of China is the largest. Moreover, the weight of China in the optimal portfolio is the lowest among all emerging markets, implying that the optimal portfolio should be more feasible for China. We also perform the test for the more recent period from 2006 to 2017 and report the results in Panel A of Table C2. While most emerging markets provide less diversification in this recent period compared with the full sample period, China increases the Sharpe Ratio of the World Index even more in the recent decade. Therefore, we find novel evidence that China's stock market provides more diversification benefits than other emerging markets to international investors.

Next, since all emerging markets can increase the Sharpe Ratio for international investors, we further explore whether the diversification benefits provided by China can be replicated by investing in other markets. We first calculate the Sharpe Ratio of the optimal portfolio that contain the World Index and all of the 10 emerging markets. Then we exclude each market from the whole portfolio and re-calculate the Sharpe Ratio of new portfolio (which contains the World Index and the other 9 markets). The difference in the Sharpe Ratio between the two portfolios measures the marginal diversification beneifts contributed by each market. The results are reported in Panel B of Table 1.3. As shown, the marginal Sharpe Ratio contributed by most emerging markets are small and less significant, suggesting that the diversification benefits of most emerging markets can be fully replicated by investing in other markets. In contrast, China still contributes the largest marginal increase in Sharpe Ratio to the portfolio by 0.051. Conducting the test for the more recent period from 2006 to 2017, we find similar results (Panel B of Table C2). Therefore, although other emerging markets can provide diversification benefits to the global portfolio, they cannot replicate as large benefits as provided by China. China is an exception among emerging markets in terms of generating diversification to global investors. Underweighting China would bring high opportunity costs to international investors.

### 1.4.3 Financial Contagion

Beside diversification benefits, investigating the low correlation of a market also has important implication for the contagion effect in market downturns. Presumably, a market with low correlation with other markets would also waterproof shocks from other markets. We further examine whether it is the case for China. Testing contagion is difficult because of the spurious relationship between correlation and volatility (Longin and Solnik (2001)). We construct different measures to examine the cross-market financial contagion.

We first examine cumulative returns of the 10 emerging markets around global index shocks. We define a global index shock when the global index return is in the bottom 5% tail during the sample period. Based on the 1150 weekly observations of the global index during 1995-2017, we identify 57 index shock weeks. Then for each emerging market and each index shock, we calculate the cumulative returns during the shock week (0), from one week before to one week after the shock [-1, +1], and from three weeks before to three weeks after the shock week [-3, +3]. Finally, we take average across all the shocks for each emerging market and each window. As Panel A of Table 1.4 shows, all emerging markets, except China, have large and significantly negative cumulative returns around global index shocks. For example, the [-3, +3] cumulative returns of Indonesia and Turkey are -10.213% and -9.995%, respectively. Although the two markets have relatively low correlations with the global market from the previous analysis, they still suffer from large negative returns during global shocks. On the contrary, cumulative returns of China are not significant for all the three windows. Therefore, while most emerging markets are vulnerable to contagion, China can be an exception and stay isolated from global financial market shocks.

An alternative measure for contagion to global market shock is the dynamic conditional correlation. We apply the dynamic conditional correlation measure in the event study setting with the global index shock. Specifically, in the spirit of Chae (2005) and Schiller (2017), we measure contagion using *abnormal dynamic conditional correlation* (ADCC) of emerging markets with the World Index around global shocks. ADCC of market $i$ with the world index at time $t$ is defined as the difference between dynamic conditional correlation in week $t$ and the average dynamic conditional correlation over an estimation window from 30 to 5 weeks prior to week $t$. Then for each index shock, we calculate average ADCC over the weeks during the event window. Lastly, we take average across the 57 event weeks. The results are reported in Panel B of Table 1.4. Similar to cumulaitve returns around global index shocks, all markets, except China, have large and significantly positive ADCC during the event window. For instance, the ADCC of Russia in the event week is 0.052, equivalent to 10% increase of its average dynamic conditional correlation. ADCC of China is insignificant in both the [-1, +1] and the [-3, +3] windows, and becomes negative in the event week. Therefore, unlike other markets, China is not more correlated with the global market during global shocks. Our results from ADCC again suggest that financial contagion from global market shocks is less a concern for China, as the A share market stays less affected by global market downturn.

As discussed in Bae et al. (2003), correlations may not be appropriate for an evaluation of the differential impact of large returns. Thus, we use *coexceedance* as the third measure for stock market contagion. Following Bae et al. (2003), we define bottom coexceedance as the ratio of the number of weeks when two market indexes both experience 5% bottom tail returns to the total number of weeks in the 5% bottom tail for each individual index. The bottom coexceedance for each pair of markets have a maximum value of 1. A large coexceedance of a pair of markets suggests that they are very likely to experience market downturns simultaneously and thus, are both vulnerable to financial contagion.

Panel C of Table 1.4 reports cross-market bottom coexceedances. The results show similar pattern with the cross-market correlation coefficients in Table 1.2. Each pair of markets have a bottom coexceedance and each market has a coexceedance of 1 with itself. Developed markets tend to have higher coexceedances than emerging markets. For example, the coexceedance of the US and the UK is 0.544, but that of China and Turkey is only 0.07. However, some emerging markets like South Africa, Brazil, and Mexico have very large coexceedances, with some of them are even greater than developed markets. For instance, while Hong Kong and Canada only have a coexceedance of 0.368, the coexceedance of South Africa and Canada is 0.579. Therefore, although some emerging markets have lower correlations with other markets, they may be even more vulnerable to financial contagion. On the contrary, China seems to be least affected by contagion, as evident by the lowest coexceedances among all markets. The highest coexceedance of China is only 0.175, which is still lower than all other markets. We further plot the average coexceedance with the other 18 sample markets for each market in Figure 1.3. It provides more intuitive results that China's coexceeance is much lower than other markets. In Panel C of Table C1, we also investigate the cross-market bottom coexceedances for the more recent period from 2006 to 2017. It shows that both developed markets and emerging markets are more vulnerable to financial contagion in the last decade. While the coexceedances of China also increase, they are still the lowest among all markets. Collectively, all of our three measures of contagion suggest that China is not or the least vulnerable to global financial contagion and thus it can be a safe haven for international investors when the global market is under shock.

## 1.5 Policy Risks and Diversification Benefits

### 1.5.1 Policy Risks

#### Policy Risks and Diversification Benefits

In this section, we employ firm-level data to investigate explanations for the low correlation of China's stock market. First, as discussed in Section 2, government policy in China may have substantial impact on market performance. Stocks that are more sensitive to local policy/regulation change should be less correlated with markets outside China. We estimate the following regression model to examine whether stocks more sensitive to government policy are less connected with global market:

$$Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{1.1}$$

where $Connectedness_{it}$ is the connectedness of stock $i$ with global market in year $t$, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock $i$'s policy sensitivity in year $t$, and $\omega$ and $\lambda$ are firm and year fixed effect, respectively. Standard errors are two-way clustered by industry and year in all regressions throughout the paper. We construct two measures for stock connectedness with the global market. The first measure is the correlation of stock $i$ with the World Index in year $t$ estimated from weekly USD return (*Correlation*). The second measure is *Global beta*, which is estimated using the following regression model:

$$R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i, \tag{1.2}$$

where $R^u_{i,k}$ is USD return of stock $i$ in week $k$, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the World Index. We estimated the model for each stock in each year.

We construct two measures for policy sensitivity of stocks, too. In the spirit of Baker et al. (2016), our first measure, *Policy sensitivity*1, is based on the correlation of individual stock returns with China's EPU Index, which is reported at monthly frequency. We first use stock $i$'s monthly returns to estimate the correlation of stock $i$ with the EPU Index in year $t$; then we rank all A share-listed stocks based on the absolute values of the correlations in year $t$; lastly we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1).[17] By construction, a larger number represents greater policy sensitivity of a stock. Our second measure, *Policy sensitivity*2, is based on individual stock's reaction to release of regulatory documents by China Securities Regulatory Commission, the regulatory authority of China's stock market. Since the first regulatory document is issued in 2001, the sample period for this measure is from 2001 to 2017. Following Liu et al. (2017b), we first calculate the [-1,+1] three-day cumulative abnormal returns of stock $i$ around announcements of new regulatory documents based on the following market model:

$$R_{i,k} - R_{f,k} = \alpha + \beta_i \times (R_{m,k} - R_{f,k}) + \epsilon_i, \tag{1.3}$$

where $R_{i,k}$ is return of stock $i$ in week $k$, $R_{f,k}$ is China's risk-free rate, and $R_{m,k}$ is China's market return. We estimate annual $\beta_i$ using weekly returns. Second, we rank all A share stocks based on the sum of absolute value of these cumulative abnormal returns in year $t$. Lastly, we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). We report the correlation matrix of the policy sensitivity measure with firm characteristics in Appendix D. It shows that our policy sensitivity measure is positively correlated with firm's volatility, tangibility, and SOE status while negatively correlated with firm age and AH cross-listed status. However, all of the correlation coefficients are economically small, suggesting that our policy sensitivity measure is not driven by some specific firm characteristics.

The regression results are reported in Table 1.5, Panel A. The dependent variable is *Correlation* in column (1) and (2). Column (1) shows that the coefficient on *Policy sensitivity*1 is -0.012, suggesting that *Correlation* of the most policy-sensitive firms is 0.012 lower than the least sensitive firms. The difference is large and equivalent to 26.1% of the average *Correlation* (0.046, Table 1.1, Panel B). Column (2) shows similar results when we use *Policy sensitivity*2 as the main explanatory variable. We use *Global beta* to measure stock's connectedness with global market in column (3) and (4). The coefficients are -0.054 on *Policy sensitivity*1 and -0.062 on *Policy sensitivity*2. They are statistically significant and also economically large compared to the average *Global beta*, 0.135. Coefficients of control variables show that firms with larger size and higher tangibility are more correlated with the global market.

To conclude, Table 1.5, Panel A suggests that stocks that are more sensitive to policy announcements are less correlated with the global market. It implies that government intervention in stock market explains the low connectedness of Chinese stock market with other markets. Policy sensitivities, on one hand, could be associated with more volatile price changes

[17] Note that we also use the raw value of correlation of stock return with EPU Index without ranking to measure firm's policy sensitivity. The results are reported in Table C3 and consistent with the main results.

at policy announcements; on the other hand, may lower the stock's connectedness with foreign markets and thus provide more diversification benefits to international investors.

### Policy Risks and Stock Performance

Do policy sensitive stocks deliver better or worse performance? Pástor and Veronesi (2013) posit that stocks that have higher policy risk may have lower realized returns, as policy uncertainty generates greater stock price volatility. We examine the relation of policy sensitivity and stock performance using regression model (1) with $Performance$ as the dependent variable. We use annual stock returns and the Sharpe Ratio to measure $Performance$. The regression results are reported in Table 1.5, Panel B. Overall, coefficients on *Policy sensitivity* are significantly positive. Particularly, the Sharpe Ratio of A-share stocks increases with policy sensitivity, suggesting that the higher risks of policy-sensitive stocks are compensated by even higher return. This result is consistent with (e.g., Claessens, Feijen, and Laeven, 2008; Fisman, 2001) that policy-sensitive firms may also have more political connections with the government, which provides valuable resources to the firm. Collectively, results in Table 1.5, Panel A and B suggest that policy-sensitive stocks are less connected to foreign markets and thus provide more diversification benefits to international investors. Moreover, they perform better than other A share-listed stocks.

### 1.5.2 Cross-Listed Stocks

Thus far, we document that Chinese stock market has low correlation with other markets and provide diversification benefits to international investors. Policy sensitivities of A share-listed stocks contribute to the diversification benefits. From asset pricing perspective, the effect of policy risks on return correlation may come from two sources: one is related to firm fundamental, i.e., firms' operation and cash flows could be differently affected by policy changes; the other is related to institutional features of listing markets that may affect firms' cost of financing or investment risks for investors. To distinguish these two mechanisms, we examine a special set of firms: firms cross-listed in both the A share market and Hong Kong market. For a A share-HK pair, the two stocks share exactly the same firm fundamentals but are separately traded in two markets with different institutional features. Therefore, firm fundamental is well controlled in this subset of firms.

As of 2017, there are 98 A-H cross-listed stocks. We construct two portfolios using these A-share stocks and their counterpart H-share stocks to compare their connectedness with the global market. The results are reported in Table 1.6, Panel A. A-share stocks have both lower correlation and lower average dynamic conditional correlation than H-share stocks and the differences are significant at 1% significance level. The last column shows that A-share stocks are also less vulnerable to global financial contagion, as evidenced by the significantly lower bottom coexceedance. We also plot time-series dynamic conditional correlation with global market for the two portfolios in Figure 5. It shows that while A-share stocks are increasingly correlated with global market, H-share stocks have always been more correlated with global market than their A share-listed counterparts. The results suggest that the cash flow channel may not be the driving factor to explain the low connectedness of China's stock market. Instead, institutional factors and investor base of A share market have larger explanatory power.

Moreover, dividing these A-H cross-listed stocks into high- and low-groups based on their policy sensitivity measures for the A share-listed part, we find that the A-H correlation difference is larger for the high-sensitivity group (Table 1.6, Panel B). This result further corroborates our interpretation that policy risks explain and contribute to the diversification benefits of the A share market.

### 1.5.3 Global Market Integration and Foreign Ownership

Besides policy risks, do other factors help explain the low correlation of the China's stock market? "Common ownership" can generate extra comovement among stocks because of investors' trading pattern (e.g., Brealey, Cooper, and Kaplanis, 2010; Barberis et al., 2005a). Previous literature documents that "common ownership" is an important channel of financial contagion (e.g., Elliott, Golub, and Jackson, 2014). When some investors fire sell assets because of exogenous shocks, other investors' portfolio value will also decrease if they have common holdings. Compared with other major economies, China A shares are less accessed by foreign investors. The relatively low foreign ownership might explain the low correlation of China's stock market with the global market. However, with the opening up of China's capital market to global investors, the increase in foreign ownership can increase the correlation and decrease the diversification benefits from China A shares. In this section, we consider two important programs via which foreign investors access China's stock market, QFII and the Stock Connect Program, to examine whether and how foreign ownership explains the low correlation of China' stock market.

#### Foreign Ownership through QFII

Before 2002, foreign investors could only access China's stock market by trading B shares in mainland China, which represent a tiny fraction of the total market capitalization. As one step in openning the financial market, Chinese government introduced the QFII program in 2002 and Renminbi Qualified Foreign Institutional Investors (RQFII) program in 2011 that allows foreign institutional investors to trade A shares directly. However, QFII and RQFII are not ideal for most international investors due to licensing requirement, quotas, and repatriation restrictions (Carpenter and Whitelaw, 2017). Therefore, Chinese government has been relaxing regulation on QFII and RQFII in recent years, including increasing quotas and expanding investor eligibility. As of January 2019, the total quota of QFII is \$300 billion with \$101 billion already granted, and the total quota of RQFII is around \$277 billion with \$93 billion already granted.[18] The quotas are never fully fulfilled, suggesting potential concerns of international investors in investing in China.

We extract QFII holding data in CSMAR and identify stocks that are held by QFII. We define $QFII_{it}$ as a dummy variable to represent stock i that has QFII holdings in year t. We estimate the below model to examine the effect of foreign holdings on stock return

[18] See the official document of CSRC on `http://www.csrc.gov.cn/pub/newsite/zjhxwfb/xwdd/201901/t20190131_350598.html`.

connectedness:

$$Connectedness_{it} = \beta_0 + \beta_1 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{1.4}$$

The regression results are reported in Table 1.7. Column (1) shows that QFII held stocks have 0.006 higher *Correlation* than others not held by QFII, which is equivalent to 13.04% of the average correlation. Coefficient on $QFII$ is also significantly positive in column (3) when we use *Global beta* as the dependent variable, although is has lower significance level. In general, stocks held by QFII are more connected with global market.

To mitigate the selection issue, we estimate the following difference-in-difference (DID) regression model to explore whether stock's connectedness with the global market increases after they have QFII holdings:

$$Connectedness_{it} = \beta_0 + \beta_1 \times In\ QFII_i \times Post_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}, \tag{1.5}$$

where $In\ QFII_i$ is a dummy variable which is equal to 1 if stock $i$ ever has QFII holdings during the sample period and 0 otherwise, $Post_{it}$ is a dummy variable which is equal to 1 if the stock-year observation is after stock $i$ starts to have QFII holdings for the first time, and 0 otherwise. Other control variables are the same. The regression results are reported in Column (2) and (4) of Table 1.7. Consistent with previous results, the coefficients on $In\ QFII \times Post$ are significantly positive at 1% level in both column (2) and (4). Stocks have 0.01 higher *Correlation* and 0.039 higher *Global beta* after they have QFII holdings. Therefore, we conclude from Table 1.7 that stocks with foreign ownership are more connected with the global market. However, only 10.6% A-share stocks ever have QFII holding as shown in Table 1.1, and the holdings are usually small because of capital control. This can partly explain the low connectedness of the whole A share market with global market. As a result, international investors that invest in A share stocks continue to enjoy diversification benefits, and such benefit will be larger for stocks with less foreign ownership.

#### Stock Connect Program

Because of the restrictions on QFII and RQFII, only large institutional investors have access to these programs. Thus, most global investors interested in China have been investing in Chinese firms traded in external markets, mainly Hong Kong and US, to obtain exposure to China. As discussed in Carpenter and Whitelaw (2017), both the largest and oldest ETF traded in US hold equities traded outside of China. The first ETF tracking broad A-share index was introduced in 2010 and has not gained significant traction. To further open the stock market, Chinese government launched the Shanghai-Hong Kong Stock Connect Program in November 2014 and Shenzhen-Hong Kong Stock Connect Program in December 2016. The programs allow international and local investors in mainland China to trade securities in each other's markets through the trading and clearing facilities of their home exchange.[19] The SH-HK Connect includes constituent stocks in the SSE 180 Index and SSE 380 Index and all A-H cross-listed

[19] For more information about the stock connect, see the official website of Hong Kong Exchange: `https://www.hkex.com.hk/Mutual-Market/Stock-Connect`.

stocks. The SZ-HK Connect includes constituent stocks with market capitalization greater than 6 billion CNY in the Shenzhen Stock Exchange Component Index, constituent stocks in the Shenzhen Stock Exchange Small/Mid Cap Innovation Index, and all A-H cross-listed stocks. The main differences between the programs and QFII are that the Connect Programs allow retail investors to trade A-share directly and has much higher quota.

As the stocks in both programs are adjusted every few months, we keep only stocks that are in the programs throughout the sample period. This leaves us 546 stocks in the SH-HK Connect and 833 stocks in the SZ-HK Connect. To investigate the effect of the Stock Connect on stocks' correlation with global market, We estimate the following DID regression:

$$Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post_t + Controls_{it} + \omega + \lambda + \epsilon_{it}, \qquad (1.6)$$

where $HK\ connected_i$ is a dummy variable which is equal to 1 if stock $i$ is in the SH-HK Connect or SZ-HK Connect and 0 otherwise, $Post_t$ is a dummy variable which is equal to 1 after the start of each program and 0 otherwise. The regression results are reported in Panel B of Table 1.7. The sample includes all A-share stocks in Shanghai Stock Exchange from three years before to three years after the introduction of SH-HK Connect (2012-2017) and stocks in Shenzhen Stock Exchange from one year before to one year after the introduction of SZ-HK Connect (2016-2017). Column (1) and (3) show results for the full sample. Coefficients on $HKconnected \times Post$ are small and insignificant, suggesting that connected stocks are not more correlated with global market after the introduction of the programs. We also perform the sub-sample analysis for SH-HK Connect. The results are reported in column (2) and (4) and similar to the full sample results. We also compare alternative measures, including the dynamic conditional correlation adn bottom coexceedance of stocks in/out of the Connect Program, we do not find evidence that connected stocks are significantly more correlated with the global market.

Although China has been opening its stock market to international investors in recent decades, it is still partially segmented from the global market and not as easily accessed as developed markets. Therefore, international investors may be concerned about the transaction costs that may wipe out the benefits of investing in China. First, international investors used to have very limited access to China's stock market. For example, to invest in A shares, QFIIs need to go through a lengthy approval process, which increases the overall transaction costs. However, the Stock Connect Program allows all international investors (including retail investors) to trade China A share through Hong Kong Exchange. The daily quota on buy-order of the Stock Connect Program is 104 billion CNY, which is more than 10% of the daily trading volume of the whole A share market. This suggests that costs associated with market access is minimal now. Second, the explicit transaction cost of the Stock Connect Program is also small. The overall clearing and settlement fee is normally 0.11% and the brokerage fee is 0.2%.[20] Third, previous studies suggest that the implicit transaction cost can be higher and more difficult to measure. Based on the estimation of Zhang (2018), the implicit trading cost of A share market is around 1%. However, recent studies also show that Chinese investors pay up for liquidity (Carpenter et al., 2020a) and illiquidity risk is priced in A share market (Li, Zhang,

[20] See `https://www.sc.com/hk/invest/shanghai-hongkong-stock-connect-fees-levis.html`

and Li, 2019). Moreover, as discussed earlier, trading freedom has been increasing, evident by the decreasing number of trading suspensions. The daily price limit of the Growth Enterprise Market (NASDAQ of China) has also increased to 20% in 2020. Last, for international investors, another transaction cost is from difficulty of withdrawing, especially during market downturns. With the Stock Connect Program, this risk is also mitigated, as the Program only has quota restriction on buy-order but not on sell-order.

With the stable increase of the Stock Connect Program, MSCI finally agreed to add China A share to its flagship emerging market index in June 2017. FTSE Russell also decided to add A share to its key emerging market index in September 2018. In the meanwhile, US traded ETF on A share increase dramatically, with the largest ETF has a $1.2 billion asset under management as of January 2019.[21] However, since global investors still have various concerns of investing in China, particularly policy risk, foreign investment represents a small fraction of China's stock market until now.

**Joint Test of Policy Risk and Foreign Ownership**

As the last set of test, we compare which factor, policy risk or foreign ownership, is more important in explaining the low correlation of A share market with other markets. We include both policy sensitivity measures and QFII indicator in the specification, with the same control variables as we used in the previous tests. The results are shown in Table 1.8. Column 1 shows that, a one standard deviation increase in *Policy Sensitivity*1 (0.289) is associated with a 0.0035 (or 7.5% relative to mean *Correlation*) decline in the stock's correlation with the global market, while a one standard deviation increase in the likelihood to be included in the QFII program (0.308) is associated with a 0.0022 (or 4.7% relative to mean *Correlation*) increase in the stock's correlation with the global market. Therefore, the economic magnitude of the policy sensitivity on stock correlation is roughly 1.5 times that of foreign ownership. Columns (3) and (4) report results for the alternative connectedness measure, *Global Beta*. Column 3 shows that, the effect of policy sensitivity measures is significant at the 5% or 1% level, while the effect of QFII is marginally significant. In terms of economic magnitude, the effect of policy sensitivity is around 2.4 times that of foreign ownership.

Collectively, the above results show that policy sensitivity, or stocks' prompt reaction to government intervention, explains the low correlation of A share stocks with the global market. Other factors, including low foreign ownership, may also explain, but to a less extent. Stocks that are accessed by foreign investors via QFII and Stock Connect Program still account for a small percent of the A share market. Given the low foreign ownership of A share-listed stocks, international investors may potentially reap substantial diversification benefits from investing in the A share market.

[21] See `https://etfdb.com/etfs/country/china/#etfs&sort_name=assets_under_management&sort_order=desc&page=1` for the list of China ETF.

## 1.6 Conclusions

This paper investigates the value of China's stock market for international diversification and the role of policy risks in affecting the diversification benefits. We find that China stocks have lower correlation with the global market compared with all other major markets. From the perspective of international investors, adding China stocks into a well-diversified portfolio can further increase its Sharpe Ratio. In addition, China stocks are less affected by global financial contagion when diversification benefits are most valuable. We further find that mainland China stocks with high policy sensitivity provide greater diversification benefits. However, concerns on policy risks can prevent international investors from accessing mainland China stock market. While holding Hong Kong listed Chinese stocks is less affected by friction-related policy risks such as capital control, it cannot reap the same diversification benefits with that from mainland China stocks. The global market integration can mitigate concerns on policy risks and boost foreign investor holdings, but also diminish diversification benefits. The market capitalization of stocks that are included in QFII and Stock Connect Program is small relative to the total market size. We find that the effect of foreign ownership in increasing the correlation of China's stock market with the global market is still limited. China's stock market still provides valuable diversification opportunity for international investors up till most recent time in late 2010s.

Our findings have important implications for international investors and policy makers. In recent years, China's government has made significant efforts in opening up China's capital market to foreign investors.[22] Foreign portfolio managers also expressed great interests to China, whereas the value of diversifying into China's stock market has largely not been explored. The China exposure through passive instruments such as emerging market index and China EFT is not always reliable and limited to large firms in particular sectors. Foreign portfolio managers' actual exposures to mainland China stocks are small and some even have zero exposure. Concerns on policy risks help explain why foreign investors forgo the benefits of diversification into Chinese stocks. However, our results suggest that those exact mainland China stocks carry the most policy risk provide the most diversification benefits for international investors. Hong Kong-listed mainland China stocks are not perfect substitute for capturing these diversification benefits. Policy makers may consider the interactions among market integration, policy risks, foreign investor holdings, and investor objectives when making relevant policies. The recent inclusion of A shares into the MSCI index, QFII quota removal and deepening of the Stock Connect Programs provide a new laboratory to study these interactions.

[22] See for example "China boosts foreign access to huge onshore capital markets", Financial Times, November 1, 2020.

## 1.7 Appendix A: Variable Definitions

**Table A1: Variable Definitions**

| Variable | Definition |
|---|---|
| ADCC | Abnormal dynamic conditional correlation, which is defined as the difference between dynamic conditional correlation (DCC) of a sample market with the MSCI World Index in the global index shock week and the average DCC over an estimation window from 30 to 5 weeks prior to the shock week. |
| Bottom coexceedance | The ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. |
| Correlation | The correlation of weekly USD return of the stock with MSCI World Index. |
| Global beta | The loading of weekly excess return of the stock on excess return of MSCI World Index. It is estimated using the regression model: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock $i$ in week $k$, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. |
| Policy sensitivity1 | The ranking of the absolute value of the correlation of the stock's monthly return with China's Economic Policy Uncertainty (EPU) index. We first calculate the correlation of the stock's monthly return with EPU index; then we rank all A-share firms based on the absolute value of the correlations in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). |
| Policy sensitivity2 | The ranking of the absolute cumulative abnormal returns (CAR) over the three-day window around announcements of the new regulatory documents issued by China Securities Regulatory Commission. We first calculate the three-day CAR of the stock around announcements of new regulatory documents issued by CSRC using market model; then we rank all A-share firms based on the sum of absolute value of these CAR in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). |
| QFII | A dummy variable which is equal to 1 if the stock has Qualified Foreign Institutional Investor (QFII) holdings and 0 otherwise. |
| In QFII | A dummy variable which is equal to 1 if the stock ever has Qualified Foreign Institutional Investor (QFII) holdings during the sample period and 0 otherwise. |
| HK connected | A dummy variable which is equal to 1 if the stock is in the Shanghai-Hong Kong or Shenzhen-Hong Kong Stock Connect Program and 0 otherwise. |

Table A1 Continued

| Variable | Definition |
|---|---|
| Trade suspension | The number of times of trading suspension excluding suspensions because of shareholders meeting and release of financial reports. |
| Firm size | The natural logarithm of total assets. |
| Volatility | The standard deviation of weekly return of the stock. |
| ROE | Return on equity is defined as the ratio of net profit to book value of equity. |
| Leverage | The ratio of total liabilities to total assets. |
| B/M | The ratio of book value of equity to market value of equity. |
| Tangibility | The ratio of tangible assets to total assets. |
| Firm age | The natural logarithm of firm age from firm foundation. |
| AH cross-listed | A dummy variable which is equal to 1 if the stock is cross-listed in A- and H-share market and 0 otherwise. |
| SOE | A dummy variable which is equal to 1 if the firm is a state owned enterprise and 0 otherwise. |

## 1.8 Appendix B: Model Specification and Estimates

We first estimate the following AR(2) model for each market $i$ at time $t$:

$$R_{i,t} = \mu + \phi_{1i} R_{i,t-1} + \phi_{2i} R_{i,t-2} + \epsilon_{i,t}, \tag{1.7}$$

where $\epsilon_{i,t}$ is assumed to be uncorrelated with $R_{i,s}$ for $s < t$. Then we fit the GARCH(1,1) model to the AR filtered residual $\epsilon_{i,t}$:

$$\begin{aligned} \epsilon_{i,t} &= \sigma_{i,t} z_{i,t} \\ \sigma^2_{i,t} &= \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \end{aligned} \tag{1.8}$$

where $\alpha_i > 0$, $\beta_i > 0$ and $\alpha_i + \beta_i < 1$. Because of the inability of normal return to match skewness and kurtosis in residuals, the i.i.d. return residuals $z_{i,t}$ are assumed to follow $t$-distribution. Because the covariance is given by the product of correlation and standard deviations, we can write

$$\Sigma_t = D_t \Gamma_t D_t, \tag{1.9}$$

where $D_t$ has the standard deviations $\sigma_{i,t}$ on the diagonal and zeros elsewhere, and $\Gamma_t$ has ones on the diagonal and conditional correlations off the diagonal. The correlation dynamics are driven by the cross-product of the return shocks $z_{i,t}$ in equation (9):

$$\tilde{\Gamma}_t = (1 - \lambda_1 - \lambda_2)\tilde{\Gamma} + \lambda_1 (z_{t-1} z'_{t-1}) + \lambda_2 \tilde{\Gamma}_{t-1}, \tag{1.10}$$

where $\lambda_1$ and $\lambda_2$ are set to be non-negative scalar parameters satisfying $\lambda_1 + \lambda_2 < 1$. Lastly, we normalize the conditional correlation between market $i$ and $j$ by

$$\Gamma_{ij,t} = \tilde{\Gamma}_{ij,t} / \sqrt{\tilde{\Gamma}_{ii,t} \tilde{\Gamma}_{jj,t}}, \tag{1.11}$$

which ensures that all correlations are between -1 and 1. We use $1/T \sum_{t=1}^{T} z_t z'_t$ to estimate $\tilde{\Gamma}$ so that only two correlation parameters, $\lambda_1$ and $\lambda_2$ need to be estimated simultaneously using numerical optimization. Following Christoffersen et al. (2014), we reply on composite likelihood estimation using

$$CL(\lambda_1, \lambda_2) = \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j>i} \ln f(\lambda_1, \lambda_2; z_{it}, z_{jt}) \tag{1.12}$$

for each pair of sample markets $i$ and $j$. $f(\lambda_1, \lambda_2; z_{it}, z_{jt})$ denotes the bivariate normal distribution of return residuals of $i$ and $j$ and covariance targeting is imposed.

Table B1 reports results from the estimation of the AR(2)-GARCH(1,1) models on sample markets. The results are fairly standard. The volatility updating parameter, $\alpha$, is around 0.1. And the autoregressive variance parameter, $\beta$, is mostly between 0.8 and 0.9. Therefore, consistent with previous literature, we find a high degree of volatility persistence. The p-values of Ljung-Box (LB) test on model residuals show that AR(2) models are able to pick up the potential return predictability of sample markets. Moreover, p-values of LB test on absolute residuals suggest that GARCH models are able to pick up the potential predictability in absolute returns. Therefore, we conclude from Table B1 that the AR(2)-GARCH(1,1) models are successfully in delivering the white-noise residuals required to obtain unbiased estimates of the dynamic correlations. Table B2 reports estimation results of the dynamic conditional correlation model. Consistent with prior literature (e.g., Christoffersen et al., 2014), the correlation persistence defined as $(\lambda_1 + \lambda_2)$ is very close to 1, implying very slow mean-reversion in correlations. We also report the special case of no dynamics in the last row.

**Table B1: AR(2)-GARCH(1,1) Model Parameter Estimates**

This table reports parameter estimates and residual diagnostics of the AR(2)-GARCH(1,1) models fitted to weekly returns of the 19 sample markets. The sample period is from Janaury 1995 to December 2017. The coefficients from the AR models are not shown. Data source: CSMAR and DATASTREAM.

| Market | $\alpha$ | $\beta$ | LB(20) P-Value on Residuals | LB(20) P-Value on Absolute Residuals | Residual Mean | Residual Skewness | Residual Excess Kurtosis |
|---|---|---|---|---|---|---|---|
| China | 0.152 | 0.819 | 0.657 | 0.906 | 0.001 | 0.954 | 16.653 |
| US | 0.122 | 0.867 | 0.421 | 0.282 | -0.001 | -0.710 | 5.818 |
| Japan | 0.056 | 0.938 | 0.877 | 0.597 | -0.001 | 0.124 | 1.751 |
| Hong Kong | 0.077 | 0.915 | 0.203 | 0.444 | -0.001 | -0.235 | 3.149 |
| UK | 0.104 | 0.864 | 0.335 | 0.170 | -0.002 | -0.938 | 10.031 |
| Germany | 0.092 | 0.899 | 0.841 | 0.477 | -0.002 | -0.566 | 4.626 |
| France | 0.071 | 0.916 | 0.437 | 0.332 | -0.001 | -0.637 | 5.145 |
| Canada | 0.117 | 0.870 | 0.727 | 0.073 | -0.001 | -0.680 | 6.730 |
| Italy | 0.081 | 0.900 | 0.417 | 0.946 | -0.001 | -0.433 | 4.797 |
| Australia | 0.104 | 0.861 | 0.497 | 0.238 | -0.001 | -0.960 | 9.305 |
| South Africa | 0.115 | 0.866 | 0.596 | 0.195 | -0.001 | 0.172 | 5.519 |
| South Korea | 0.124 | 0.860 | 0.551 | 0.473 | -0.001 | -0.211 | 8.621 |
| India | 0.081 | 0.897 | 0.975 | 0.468 | -0.001 | -0.026 | 2.500 |
| Indonesia | 0.152 | 0.850 | 0.225 | 0.667 | -0.002 | 0.126 | 12.707 |
| Brazil | 0.102 | 0.864 | 0.922 | 0.620 | -0.002 | -0.107 | 3.610 |
| Mexico | 0.104 | 0.868 | 0.771 | 0.942 | -0.001 | -0.050 | 4.799 |
| Russia | 0.132 | 0.856 | 0.217 | 0.753 | 0.000 | 0.902 | 10.091 |
| Turkey | 0.082 | 0.892 | 0.854 | 0.111 | -0.001 | 0.193 | 8.499 |
| Argentina | 0.103 | 0.839 | 0.991 | 0.203 | -0.001 | -0.032 | 4.297 |
| World | 0.090 | 0.904 | 0.503 | 0.211 | -0.001 | -0.906 | 8.164 |

**Table B2: Dynamic Conditional Correlation Model Parameter Estimates**

This table reports parameter estimates of the dynamic conditional correlation models fitted to weekly returns of the 19 sample markets. The sample period is from January 1995 to December 2017. We also report the special case of no dynamics. Data source: CSMAR and DATASTREAM.

| Market | $\lambda_1$ | $\lambda_2$ | Log Likelihood |
|---|---|---|---|
| China | 0.022 | 0.812 | 4444.311 |
| US | 0.033 | 0.943 | 5302.217 |
| Japan | 0.026 | 0.945 | 4922.675 |
| Hong Kong | 0.040 | 0.908 | 4926.350 |
| UK | 0.038 | 0.903 | 5242.330 |
| Germany | 0.046 | 0.883 | 5014.976 |
| France | 0.042 | 0.896 | 5065.420 |
| Canada | 0.039 | 0.885 | 5066.029 |
| Italy | 0.036 | 0.940 | 4896.195 |
| Australia | 0.035 | 0.932 | 5007.404 |
| South Africa | 0.033 | 0.948 | 4712.220 |
| South Korea | 0.037 | 0.943 | 4529.017 |
| India | 0.029 | 0.943 | 4651.815 |
| Indonesia | 0.024 | 0.959 | 4354.062 |
| Brazil | 0.030 | 0.956 | 4406.130 |
| Mexico | 0.035 | 0.924 | 4664.868 |
| Russia | 0.040 | 0.932 | 4162.212 |
| Turkey | 0.038 | 0.937 | 4064.726 |
| Argentina | 0.035 | 0.892 | 4265.520 |
| Average | 0.035 | 0.920 | 4720.972 |
| No Dynamics | 0.000 | 0.000 | 4361.075 |

## 1.9 Appendix C: Robustness Tests

**Table C1: Correlations and Financial Contagion of Stock Markets from 2006 to 2017**

This table reports correlations and bottom coexceedances of the 19 sample markets for the period from January 2006 to December 2017 based on weekly USD returns. Panel A reports cross-market unconditional correlations. All correlations are significant at 1% significance level. Panel B reports average dynamic conditional correlations (DCC). We report three average DCC for each market: average DCC with all the other 18 markets; average DCC with 9 developed markets (DMs) (or the other 8 DMs for a DM), average DCC with 10 emerging markets (EMs) (or the other 9 EMs for a EM). Panel C reports bottom coexceedances of each pair of the 19 sample markets. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. Data source: CSMAR and DATASTREAM.

Panel A: cross-market unconditional correlation

| | CNH | USA | JPN | HKG | GBR | DEU | FRA | CAN | ITA | AUS | ZAF | KOR | IND | IDN | BRA | MEX | RUS | TUR | ARG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CNH | 1 | | | | | | | | | | | | | | | | | | |
| USA | 0.120 | 1 | | | | | | | | | | | | | | | | | |
| JPN | 0.206 | 0.522 | 1 | | | | | | | | | | | | | | | | |
| HKG | 0.267 | 0.577 | 0.593 | 1 | | | | | | | | | | | | | | | |
| GBR | 0.138 | 0.832 | 0.564 | 0.649 | 1 | | | | | | | | | | | | | | |
| DEU | 0.149 | 0.810 | 0.553 | 0.604 | 0.883 | 1 | | | | | | | | | | | | | |
| FRA | 0.148 | 0.807 | 0.574 | 0.624 | 0.897 | 0.951 | 1 | | | | | | | | | | | | |
| CAN | 0.131 | 0.799 | 0.513 | 0.647 | 0.858 | 0.784 | 0.810 | 1 | | | | | | | | | | | |
| ITA | 0.145 | 0.725 | 0.534 | 0.560 | 0.812 | 0.872 | 0.919 | 0.731 | 1 | | | | | | | | | | |
| AUS | 0.218 | 0.732 | 0.624 | 0.724 | 0.824 | 0.754 | 0.780 | 0.818 | 0.709 | 1 | | | | | | | | | |
| ZAF | 0.158 | 0.637 | 0.459 | 0.600 | 0.759 | 0.713 | 0.705 | 0.737 | 0.587 | 0.722 | 1 | | | | | | | | |
| KOR | 0.224 | 0.615 | 0.548 | 0.683 | 0.674 | 0.673 | 0.644 | 0.643 | 0.577 | 0.713 | 0.684 | 1 | | | | | | | |
| IND | 0.177 | 0.552 | 0.452 | 0.661 | 0.603 | 0.619 | 0.606 | 0.588 | 0.571 | 0.614 | 0.598 | 0.645 | 1 | | | | | | |
| IDN | 0.180 | 0.421 | 0.417 | 0.559 | 0.496 | 0.473 | 0.478 | 0.538 | 0.418 | 0.577 | 0.485 | 0.521 | 0.552 | 1 | | | | | |
| BRA | 0.160 | 0.673 | 0.452 | 0.610 | 0.770 | 0.720 | 0.726 | 0.789 | 0.629 | 0.729 | 0.753 | 0.667 | 0.585 | 0.518 | 1 | | | | |
| MEX | 0.130 | 0.786 | 0.476 | 0.589 | 0.783 | 0.768 | 0.754 | 0.762 | 0.664 | 0.721 | 0.750 | 0.667 | 0.583 | 0.509 | 0.782 | 1 | | | |
| RUS | 0.111 | 0.594 | 0.387 | 0.543 | 0.686 | 0.664 | 0.627 | 0.693 | 0.553 | 0.638 | 0.706 | 0.645 | 0.563 | 0.440 | 0.704 | 0.675 | 1 | | |
| TUR | 0.141 | 0.569 | 0.423 | 0.535 | 0.618 | 0.622 | 0.610 | 0.576 | 0.546 | 0.586 | 0.682 | 0.581 | 0.528 | 0.471 | 0.654 | 0.651 | 0.600 | 1 | |
| ARG | 0.157 | 0.534 | 0.393 | 0.455 | 0.583 | 0.588 | 0.584 | 0.579 | 0.534 | 0.542 | 0.488 | 0.474 | 0.413 | 0.427 | 0.559 | 0.549 | 0.488 | 0.438 | 1 |

Table C1 Continued

| Panel B: average dynamic conditional correlation | | | |
|---|---|---|---|
| Market | All Markets | DMs | EMs |
| China | 0.119 | 0.121 | 0.118 |
| US | 0.551 | 0.660 | 0.463 |
| Japan | 0.421 | 0.480 | 0.369 |
| Hong Kong | 0.504 | 0.535 | 0.477 |
| UK | 0.615 | 0.728 | 0.524 |
| Germany | 0.625 | 0.713 | 0.546 |
| France | 0.607 | 0.733 | 0.507 |
| Canada | 0.583 | 0.662 | 0.520 |
| Italy | 0.578 | 0.663 | 0.503 |
| Australia | 0.584 | 0.656 | 0.526 |
| South Africa | 0.565 | 0.596 | 0.540 |
| South Korea | 0.508 | 0.541 | 0.481 |
| India | 0.461 | 0.492 | 0.437 |
| Indonesia | 0.376 | 0.368 | 0.384 |
| Brazil | 0.594 | 0.595 | 0.594 |
| Mexico | 0.566 | 0.612 | 0.529 |
| Russia | 0.485 | 0.519 | 0.458 |
| Turkey | 0.437 | 0.452 | 0.425 |
| Argentina | 0.421 | 0.462 | 0.392 |

Table C1 Continued

Panel C: cross-market bottom coexceedance

| | CNH | USA | JPN | HKG | GBR | DEU | FRA | CAN | ITA | AUS | ZAF | KOR | IND | IDN | BRA | MEX | RUS | TUR | ARG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CNH | 1 | | | | | | | | | | | | | | | | | | |
| USA | 0.167 | 1 | | | | | | | | | | | | | | | | | |
| JPN | 0.200 | 0.267 | 1 | | | | | | | | | | | | | | | | |
| HKG | 0.167 | 0.467 | 0.400 | 1 | | | | | | | | | | | | | | | |
| GBR | 0.133 | 0.633 | 0.433 | 0.567 | 1 | | | | | | | | | | | | | | |
| DEU | 0.200 | 0.567 | 0.433 | 0.433 | 0.633 | 1 | | | | | | | | | | | | | |
| FRA | 0.133 | 0.567 | 0.400 | 0.467 | 0.700 | 0.767 | 1 | | | | | | | | | | | | |
| CAN | 0.200 | 0.667 | 0.333 | 0.567 | 0.733 | 0.633 | 0.633 | 1 | | | | | | | | | | | |
| ITA | 0.100 | 0.500 | 0.333 | 0.400 | 0.600 | 0.633 | 0.767 | 0.500 | 1 | | | | | | | | | | |
| AUS | 0.167 | 0.600 | 0.467 | 0.600 | 0.767 | 0.600 | 0.633 | 0.733 | 0.567 | 1 | | | | | | | | | |
| ZAF | 0.200 | 0.500 | 0.400 | 0.500 | 0.600 | 0.533 | 0.533 | 0.600 | 0.433 | 0.633 | 1 | | | | | | | | |
| KOR | 0.267 | 0.367 | 0.333 | 0.533 | 0.533 | 0.467 | 0.433 | 0.500 | 0.400 | 0.600 | 0.500 | 1 | | | | | | | |
| IND | 0.100 | 0.400 | 0.300 | 0.467 | 0.500 | 0.433 | 0.467 | 0.533 | 0.333 | 0.567 | 0.500 | 0.500 | 1 | | | | | | |
| IDN | 0.167 | 0.333 | 0.200 | 0.367 | 0.400 | 0.333 | 0.300 | 0.433 | 0.233 | 0.433 | 0.367 | 0.500 | 0.467 | 1 | | | | | |
| BRA | 0.133 | 0.467 | 0.267 | 0.500 | 0.700 | 0.533 | 0.500 | 0.633 | 0.433 | 0.633 | 0.600 | 0.533 | 0.433 | 0.400 | 1 | | | | |
| MEX | 0.167 | 0.633 | 0.333 | 0.467 | 0.700 | 0.633 | 0.567 | 0.733 | 0.500 | 0.633 | 0.600 | 0.467 | 0.433 | 0.367 | 0.667 | 1 | | | |
| RUS | 0.200 | 0.433 | 0.300 | 0.433 | 0.567 | 0.533 | 0.500 | 0.633 | 0.433 | 0.533 | 0.533 | 0.600 | 0.533 | 0.400 | 0.500 | 0.567 | 1 | | |
| TUR | 0.067 | 0.367 | 0.267 | 0.367 | 0.400 | 0.333 | 0.400 | 0.367 | 0.333 | 0.433 | 0.467 | 0.433 | 0.467 | 0.367 | 0.467 | 0.400 | 0.433 | 1 | |
| ARG | 0.133 | 0.300 | 0.267 | 0.300 | 0.400 | 0.400 | 0.333 | 0.400 | 0.333 | 0.367 | 0.267 | 0.433 | 0.267 | 0.333 | 0.400 | 0.367 | 0.400 | 0.267 | 1 |

## Table C2: Diversification Benefits: Sharpe Ratio from 2006 to 2017

This table reports diversification benefits of the 10 emerging markets (EMs) measured by Sharpe ratio (SR) based on weekly USD return over from 2006 to December 2017. In Panel A, we first calculate SR of the MSCI World Index each year. Then we calculate SR of the optimal portfolios constructed by the World Index and each of the 10 EMs. Last we calculate the difference of SR between the World Index and the optimal portfolios to test whether adding each EM to the World Index increase the SR. We report the increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. In Panel B, for each EM, we first calculate SR of the optimal portfolio constructed by the World Index and the other 9 EMs every year. Then we calculate SR of the optimal portfolio constructed by the World Index and all of the 10 EMs. Last we calculate the difference of SR between the two portfolios to test whether adding each EM to the portfolio can further increase SR. We report increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. $^{***}$, $^{**}$, $^{*}$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| | Panel A: global index with one EM | | Panel B: global index with all EMs | |
|---|---|---|---|---|
| Market | Increase in SR | Weight | Increase in SR | Weight |
| China | 0.114** | 0.386 | 0.063** | 0.273 |
| South Africa | 0.026** | 0.514 | 0.000 | 0.000 |
| South Korea | 0.030** | 0.430 | 0.000 | 0.005 |
| India | 0.051** | 0.442 | 0.004 | 0.055 |
| Indonesia | 0.067*** | 0.525 | 0.012 | 0.152 |
| Brazil | 0.046* | 0.346 | 0.001 | 0.032 |
| Mexico | 0.026** | 0.479 | 0.002 | 0.084 |
| Russia | 0.037** | 0.545 | 0.006 | 0.079 |
| Turkey | 0.046** | 0.449 | 0.010 | 0.092 |
| Argentina | 0.054** | 0.434 | 0.016* | 0.108 |

## Table C3: Regression Results of Robustness Tests

This table reports the effect of government intervention on A-share stocks' connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock $i$ with the global market in year $t$, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock $i$'s policy sensitivity in year $t$, and $\omega$ and $\lambda$ are firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock $i$ with MSCI World Index in year $t$ based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* is measured using global beta of stock $i$ in year $t$ (*Global beta*), which is defined as the loading of weekly excess return of stock $i$ on excess return of the World Index: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta1_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock $i$ in week $k$, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the World Index. *Policy sensitivity*1 is the absolute value of the correlation of stock $i$'s monthly return with China's Economic Policy Uncertainty Index in year $t$. The sample includes all non-financial A-share firms from 1995 to 2017. *Policy sensitivity*2 is the sum of absolute value of three-day cumulative abnormal return of stock $i$ around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year $t$. The sample includes all non-financial A-share firms from 2001 to 2017. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| | Dep. Var: *Correlation* | | Dep. Var: *Global beta* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Policy sensitivity*1 | -0.020*** | | -0.086*** | |
| | (0.005) | | (0.024) | |
| *Policy sensitivity*2 | | -0.123* | | -0.524 |
| | | (0.066) | | (0.364) |
| Firm size | 0.004*** | 0.004** | 0.018** | 0.019** |
| | (0.002) | (0.002) | (0.008) | (0.009) |
| Volatility | -0.239*** | -0.237*** | 0.985** | 1.599*** |
| | (0.055) | (0.063) | (0.410) | (0.464) |
| ROE | -0.006 | -0.002 | 0.008 | 0.014 |
| | (0.005) | (0.005) | (0.025) | (0.027) |
| Leverage | -0.000 | -0.002 | -0.019 | -0.035 |
| | (0.006) | (0.006) | (0.029) | (0.032) |
| B/M | 0.002 | -0.001 | -0.050* | -0.059* |
| | (0.006) | (0.007) | (0.029) | (0.032) |
| Tangibility | 0.038*** | 0.027* | 0.135* | 0.115 |
| | (0.015) | (0.015) | (0.075) | (0.081) |
| Firm age | 0.010* | 0.011 | 0.024 | 0.028 |
| | (0.005) | (0.007) | (0.022) | (0.030) |
| AH cross-listed | 0.002 | -0.013 | -0.059 | -0.090 |
| | (0.027) | (0.026) | (0.079) | (0.078) |
| SOE | 0.002 | -0.001 | 0.005 | -0.002 |
| | (0.003) | (0.004) | (0.015) | (0.017) |
| Constant | -0.281*** | -0.041 | -1.783*** | -0.480** |
| | (0.036) | (0.043) | (0.172) | (0.208) |
| N | 33,615 | 30,051 | 33,615 | 30,051 |
| Adj. $R^2$ | 0.470 | 0.473 | 0.438 | 0.416 |

## 1.10 Appendix D: Correlation Matrix

**Table D1: Correlation Matrix of Policy Sensitivity Measure with Firm Characteristics**

This table reports correlation matrix of our policy sensitivity measure with other firm characteristics. The sample includes all non-financial A-share firms from 1995 to 2017. All variables are defined in Appendix A. All variables are winsorized at 1% to 99% except dummy variables. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| | Volatility | B/M | Tangibility | Leverage | Firm age | AH cross-listed | ROE | Size | SOE | QFII | *Policy sensitivity*1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Volatility | 1 | | | | | | | | | | |
| B/M | -0.153*** | 1 | | | | | | | | | |
| Tangibility | -0.026*** | 0.089*** | 1 | | | | | | | | |
| Leverage | 0.004 | -0.008 | 0.007 | 1 | | | | | | | |
| Firm age | 0.014*** | 0.112*** | -0.170*** | 0.017*** | 1 | | | | | | |
| AH cross-listed | -0.023*** | 0.115*** | -0.045*** | 0 | 0.011** | 1 | | | | | |
| ROE | 0.002 | -0.001 | -0.001 | -0.006 | 0 | -0.003 | 1 | | | | |
| Size | -0.065*** | 0.522*** | -0.047*** | -0.061*** | 0.273*** | 0.295*** | -0.003 | 1 | | | |
| SOE | -0.089*** | 0.212*** | 0.150*** | -0.002 | -0.142*** | 0.102*** | -0.009 | 0.099*** | 1 | | |
| QFII | -0.003 | 0.040*** | -0.018*** | -0.005 | 0.105*** | 0.080*** | 0 | 0.217*** | 0.025*** | 1 | |
| *Policy sensitivity*1 | 0.037** | 0.002 | 0.022*** | 0.007 | -0.023*** | -0.010* | 0.002 | -0.003 | 0.013** | 0 | 1 |

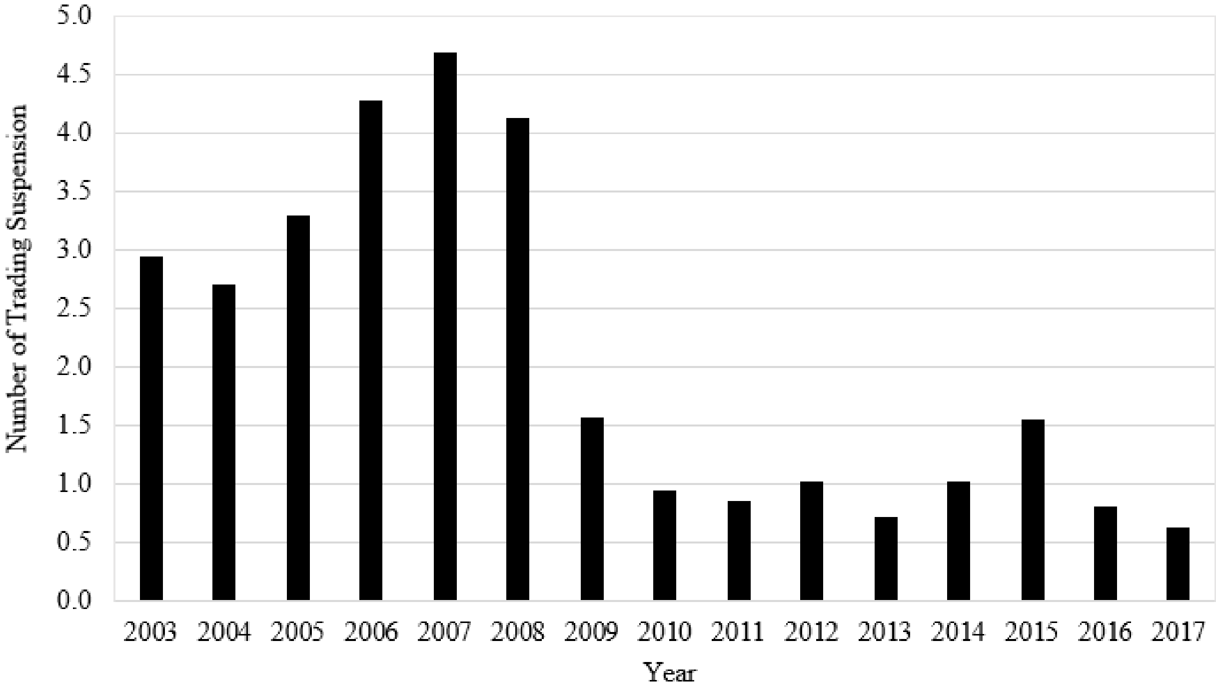
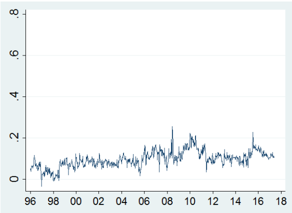
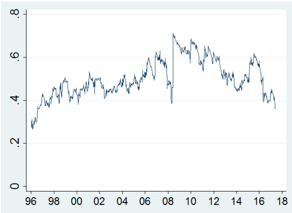



Figure 1.1: Trading Suspension of A-share Market

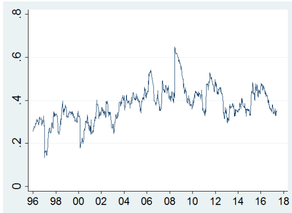
This figure plots the average number of times of trading suspension excluding suspension because of shareholder meeting and financial report release of A-share stocks from 2003 to 2017. Data source: CSMAR.



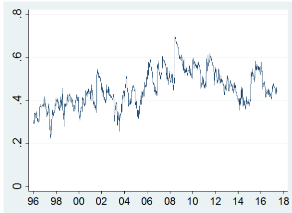

(a) China




(b) US

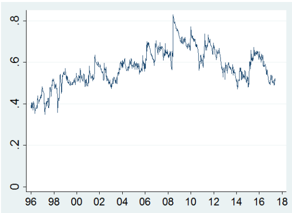



(c) Japan

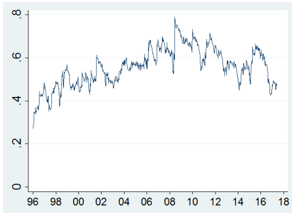



(d) Hong Kong


(e) UK

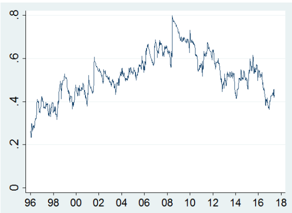



(f) Germany

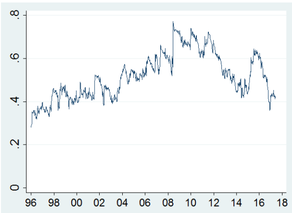



(g) Frane

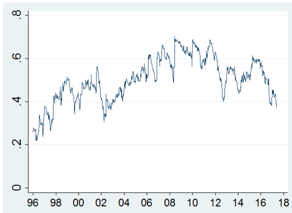

(h) Canada



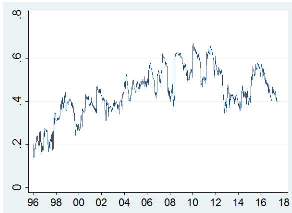

(i) Italy



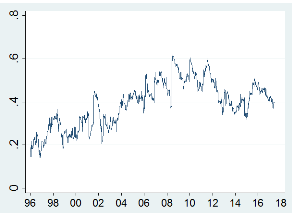

(j) Australia



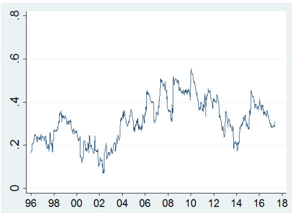

(k) South Africa



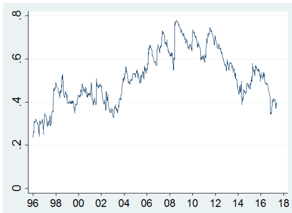

(l) South Korea



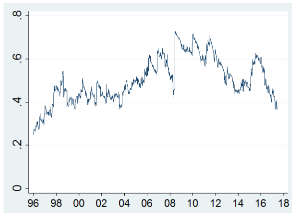

(m) India



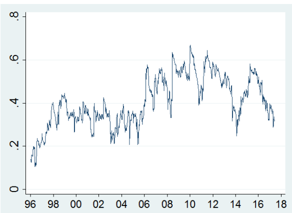

(n) Indonesia



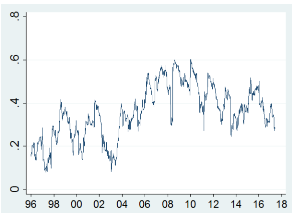

(o) Brazil



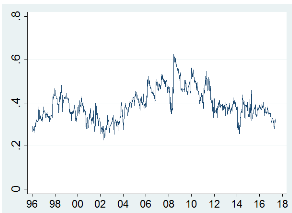

(p) Mexico




(q) Russia




(r) Turkey




(s) Argentina

Figure 1.2: Dynamic Conditional Correlations of Stock Markets

This figure plots average dynamic conditional correlations of each sample market with the other 18 sample markets based on weekly USD returns from January 1996 to December 2017. Data source: CSMAR and DATASTREAM.

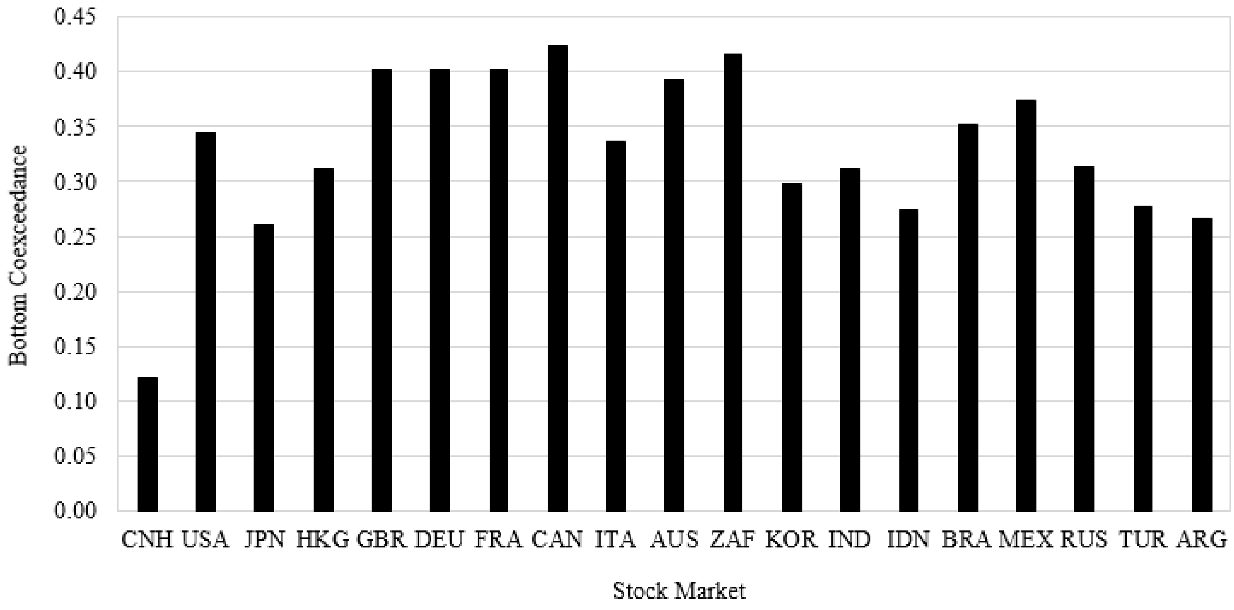
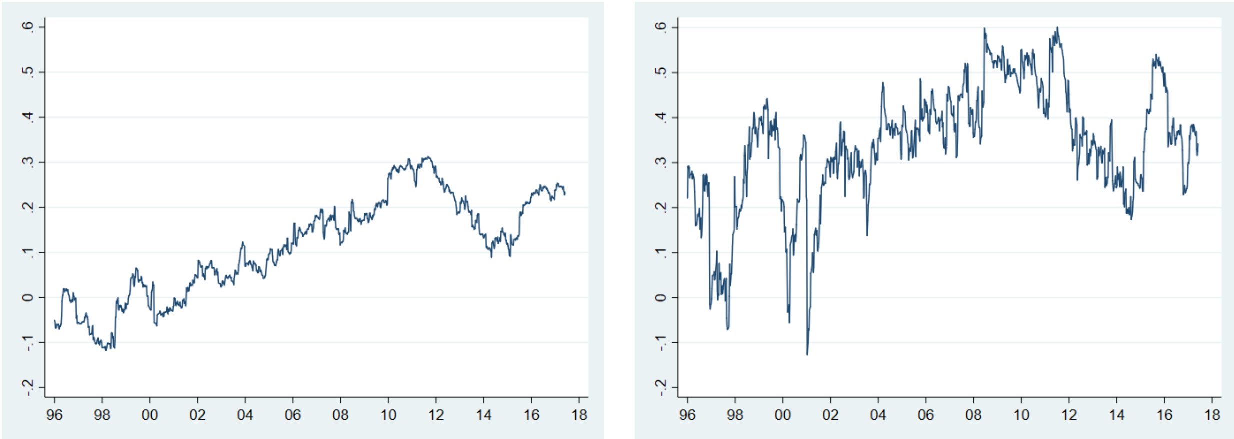



Figure 1.3: Bottom Coexceedances of Stock Markets

This figure plots the bottom coexceedances of the 19 sample markets for the period from January 1995 to December 2017. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. For each market, we report its average bottom coexceedance with the other 18 sample markets. Data source: CSMAR and DATASTREAM.




(a) A-share Stocks (b) H-share Stocks

Figure 1.4: Dynamic Conditional Correlations of A-H Cross-listed Stocks with Global Market

This figure compares dynamic conditional correlations with MSCI World Index of A-H cross-listed A-share stocks to the their counterpart H-share stocks based on weekly return. Data source: CSMAR and DATASTREAM.

**Table 1.1: Summary Statistics**

Panel A reports summary statistics of annualized weekly USD returns of the 19 sample markets and MSCI World Index over the period from January 1995 to December 2017. Panel B reports summary statistics of firm-level variables used in the study for all non-financial listed A-share firms from 1995 to 2017. All returns and volatilities in Panel A are in %. All variables in Panel B are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Data source: CSMAR and DATASTREAM.

Panel A: market return in USD

| Market | N | Mean | S.D. | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| China | 1150 | 15.132 | 28.768 | -91.237 | 14.940 | 119.408 |
| US | 1150 | 9.462 | 16.908 | -54.184 | 13.836 | 74.816 |
| Japan | 1150 | 3.335 | 19.917 | -85.794 | -0.680 | 81.823 |
| Hong Kong | 1150 | 6.909 | 22.637 | -85.413 | 12.974 | 97.335 |
| UK | 1150 | 4.220 | 19.094 | -63.610 | 12.139 | 78.628 |
| Germany | 1150 | 7.966 | 23.737 | -80.398 | 20.813 | 98.423 |
| France | 1150 | 7.292 | 22.099 | -76.535 | 17.557 | 96.271 |
| Canada | 1150 | 9.752 | 21.689 | -62.058 | 19.290 | 91.410 |
| Italy | 1150 | 3.860 | 24.969 | -93.495 | 9.849 | 106.726 |
| Australia | 1150 | 7.128 | 22.277 | -73.988 | 19.090 | 97.558 |
| South Africa | 1150 | 7.160 | 28.229 | -99.345 | 13.415 | 116.836 |
| South Korea | 1150 | 11.947 | 35.571 | -117.330 | 15.500 | 135.104 |
| India | 1150 | 8.762 | 26.504 | -106.997 | 14.340 | 123.801 |
| Indonesia | 1150 | 8.364 | 42.442 | -118.339 | 10.125 | 128.946 |
| Brazil | 1150 | 11.499 | 37.342 | -125.765 | 21.518 | 157.558 |
| Mexico | 1150 | 11.646 | 29.993 | -101.271 | 17.695 | 130.125 |
| Russia | 1150 | 20.768 | 49.431 | -136.294 | 19.635 | 179.611 |
| Turkey | 1150 | 17.994 | 47.386 | -159.495 | 22.684 | 190.797 |
| Argentina | 1150 | 15.367 | 37.890 | -132.523 | 14.460 | 164.225 |
| MSCI World Index | 1150 | 6.785 | 16.106 | -54.038 | 14.545 | 66.636 |

Table 1.1 Continued

| Panel B: firm-level variables | | | | | | |
|---|---|---|---|---|---|---|
| Variable | N | Mean | S.D. | p25 | p50 | p75 |
| Correlation | 37,227 | 0.046 | 0.181 | -0.076 | 0.041 | 0.161 |
| Global beta | 37,227 | 0.135 | 0.861 | -0.234 | 0.109 | 0.530 |
| Policy sensitivity1 | 36,817 | 0.500 | 0.289 | 0.250 | 0.501 | 0.750 |
| Policy sensitivity2 | 32,772 | 0.508 | 0.158 | 0.402 | 0.504 | 0.609 |
| QFII | 30,797 | 0.131 | 0.337 | 0 | 0 | 0 |
| In QFII | 37,967 | 0.586 | 0.492 | 0 | 1 | 1 |
| Trade suspension | 31,992 | 1.602 | 2.355 | 0 | 1 | 2 |
| Firm size | 37,316 | 21.598 | 1.270 | 20.709 | 21.444 | 22.308 |
| Volatility | 37,227 | 0.068 | 0.032 | 0.047 | 0.060 | 0.080 |
| Return | 34,305 | 0.241 | 0.736 | -0.240 | 0.015 | 0.497 |
| ROE | 34,499 | 0.060 | 0.169 | 0.026 | 0.071 | 0.122 |
| Leverage | 37,316 | 0.455 | 0.221 | 0.289 | 0.448 | 0.607 |
| B/M | 36,437 | 0.505 | 0.245 | 0.309 | 0.475 | 0.680 |
| Tangibility | 37,316 | 0.944 | 0.076 | 0.933 | 0.968 | 0.988 |
| Firm age | 37,314 | 2.449 | 0.598 | 2.197 | 2.565 | 2.890 |
| AH cross-listed | 37,318 | 0.025 | 0.157 | 0 | 0 | 0 |
| SOE | 37,318 | 0.651 | 0.477 | 0 | 1 | 1 |

**Table 1.2: Correlations of Stock Markets**

This table reports correlations of the 19 sample markets for the period from January 1995 to December 2017 based on weekly USD returns. Panel A reports cross-market unconditional correlations. All correlations are significant at 1% significance level. Panel B reports average dynamic conditional correlations (DCC). We report three average DCC for each market: average DCC with all the other 18 markets; average DCC with 9 developed markets (DMs) (or the other 8 DMs for a DM), average DCC with 10 emerging markets (EMs) (or the other 9 EMs for a EM). Data source: CSMAR and DATASTREAM.

Panel A: cross-market unconditional correlation

| | CNH | USA | JPN | HKG | GBR | DEU | FRA | CAN | ITA | AUS | ZAF | KOR | IND | IDN | BRA | MEX | RUS | TUR | ARG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CNH | 1 | | | | | | | | | | | | | | | | | | |
| USA | 0.038 | 1 | | | | | | | | | | | | | | | | | |
| JPN | 0.115 | 0.362 | 1 | | | | | | | | | | | | | | | | |
| HKG | 0.114 | 0.474 | 0.439 | 1 | | | | | | | | | | | | | | | |
| GBR | 0.073 | 0.743 | 0.426 | 0.539 | 1 | | | | | | | | | | | | | | |
| DEU | 0.104 | 0.736 | 0.426 | 0.514 | 0.817 | 1 | | | | | | | | | | | | | |
| FRA | 0.083 | 0.737 | 0.449 | 0.512 | 0.846 | 0.900 | 1 | | | | | | | | | | | | |
| CAN | 0.076 | 0.752 | 0.398 | 0.498 | 0.734 | 0.693 | 0.730 | 1 | | | | | | | | | | | |
| ITA | 0.097 | 0.641 | 0.370 | 0.417 | 0.742 | 0.795 | 0.842 | 0.628 | 1 | | | | | | | | | | |
| AUS | 0.117 | 0.610 | 0.493 | 0.585 | 0.736 | 0.655 | 0.679 | 0.708 | 0.628 | 1 | | | | | | | | | |
| ZAF | 0.103 | 0.541 | 0.373 | 0.485 | 0.659 | 0.638 | 0.634 | 0.660 | 0.524 | 0.656 | 1 | | | | | | | | |
| KOR | 0.106 | 0.441 | 0.438 | 0.507 | 0.477 | 0.470 | 0.449 | 0.471 | 0.401 | 0.536 | 0.486 | 1 | | | | | | | |
| IND | 0.117 | 0.395 | 0.294 | 0.446 | 0.451 | 0.474 | 0.471 | 0.450 | 0.445 | 0.488 | 0.485 | 0.449 | 1 | | | | | | |
| IDN | 0.078 | 0.254 | 0.293 | 0.436 | 0.301 | 0.299 | 0.302 | 0.326 | 0.250 | 0.376 | 0.355 | 0.406 | 0.309 | 1 | | | | | |
| BRA | 0.086 | 0.556 | 0.325 | 0.434 | 0.601 | 0.576 | 0.584 | 0.613 | 0.505 | 0.587 | 0.602 | 0.446 | 0.408 | 0.327 | 1 | | | | |
| MEX | 0.052 | 0.658 | 0.354 | 0.445 | 0.619 | 0.606 | 0.607 | 0.612 | 0.544 | 0.575 | 0.601 | 0.447 | 0.405 | 0.308 | 0.679 | 1 | | | |
| RUS | 0.066 | 0.414 | 0.287 | 0.380 | 0.484 | 0.474 | 0.454 | 0.490 | 0.408 | 0.425 | 0.516 | 0.409 | 0.321 | 0.334 | 0.477 | 0.455 | 1 | | |
| TUR | 0.075 | 0.343 | 0.253 | 0.303 | 0.407 | 0.429 | 0.418 | 0.368 | 0.382 | 0.400 | 0.468 | 0.345 | 0.308 | 0.183 | 0.440 | 0.422 | 0.379 | 1 | |
| ARG | 0.089 | 0.437 | 0.265 | 0.353 | 0.478 | 0.460 | 0.487 | 0.456 | 0.437 | 0.438 | 0.420 | 0.335 | 0.299 | 0.266 | 0.535 | 0.537 | 0.355 | 0.285 | 1 |

Table 1.2 Continued

| Panel B: average dynamic conditional correlation | | | |
|---|---|---|---|
| Market | All Markets | DMs | EMs |
| China | 0.097 | 0.101 | 0.094 |
| US | 0.502 | 0.621 | 0.407 |
| Japan | 0.378 | 0.433 | 0.329 |
| Hong Kong | 0.453 | 0.501 | 0.410 |
| UK | 0.552 | 0.680 | 0.449 |
| Germany | 0.575 | 0.675 | 0.486 |
| France | 0.557 | 0.694 | 0.447 |
| Canada | 0.530 | 0.623 | 0.456 |
| Italy | 0.524 | 0.613 | 0.446 |
| Australia | 0.519 | 0.598 | 0.456 |
| South Africa | 0.502 | 0.545 | 0.466 |
| South Korea | 0.442 | 0.480 | 0.411 |
| India | 0.391 | 0.422 | 0.366 |
| Indonesia | 0.314 | 0.316 | 0.313 |
| Brazil | 0.515 | 0.518 | 0.513 |
| Mexico | 0.502 | 0.555 | 0.459 |
| Russia | 0.408 | 0.434 | 0.387 |
| Turkey | 0.356 | 0.368 | 0.347 |
| Argentina | 0.390 | 0.433 | 0.360 |

## Table 1.3: Diversification Benefits: Sharpe Ratio

This table reports diversification benefits of the 10 emerging markets (EMs) measured by Sharpe ratio (SR) based on weekly USD return from January 1995 to December 2017. In Panel A, we first calculate SR of the MSCI World Index each year. Then we calculate SR of the optimal portfolios constructed by the World Index and each of the 10 EMs. Last we calculate the difference of SR between the World Index and the optimal portfolios to test whether adding each EM to the World Index increase the SR. We report the increase in SR and the significance level from t-tests. We also report weight of each EM in the optimal portfolios. In Panel B, for each EM, we first calculate SR of the optimal portfolio constructed by the World Index and the other 9 EMs every year. Then we calculate SR of the optimal portfolio constructed by the World Index and all of the 10 EMs. Last we calculate the difference of SR between the two portfolios to test whether adding each EM to the portfolio can further increase SR. We also report weight of each EM in the optimal portfolios. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| | Panel A: global index with one EM | | Panel B: global index with all EMs | |
|---|---|---|---|---|
| Market | Increase in SR | Weight | Increase in SR | Weight |
| China | 0.089*** | 0.335 | 0.051*** | 0.227 |
| South Africa | 0.035** | 0.417 | 0.001 | 0.030 |
| South Korea | 0.054*** | 0.412 | 0.005 | 0.068 |
| India | 0.056*** | 0.413 | 0.006** | 0.064 |
| Indonesia | 0.062*** | 0.421 | 0.009** | 0.110 |
| Brazil | 0.050*** | 0.435 | 0.002* | 0.032 |
| Mexico | 0.056*** | 0.549 | 0.006* | 0.104 |
| Russia | 0.078*** | 0.540 | 0.012** | 0.102 |
| Turkey | 0.067*** | 0.421 | 0.012* | 0.072 |
| Argentina | 0.052*** | 0.422 | 0.012** | 0.074 |

## Table 1.4: Financial Contagion of Stock Markets

This table reports financial contagion of the 19 sample markets using different measures for the period from January 1995 to December 2017 based on weekly USD return. Panel A reports cumulative market returns of the 10 emerging markets (EMs) around index shocks of MSCI World Index and their significance levels from t-tests. We define the World Index is under shock when it has 5% bottom tail returns during the sample period. And we calculate the average cumulative market returns across all global index shock weeks for each EM. Panel B reports average abnormal dynamic conditional correlation (ADCC) of the 10 EMs with the World Index around 5% shocks of the World Index for different windows and their significance levels from t-tests. ADCC of week $t$ is the difference between the dynamic conditional correlation in week $t$ and the average dynamic conditional correlation over an estimation window from 30 to 5 weeks prior to week $t$. Then we calculated the mean of ADCC over the weeks in every event window. Last we take average across all global index shocks for each event window to calculate average ADCC. Panel C reports bottom coexceedances of each pair of the 19 sample markets. We define bottom coexceedance as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Panel A: cumulative market return

| Market | 0 | [-1,1] | [-3,3] |
|---|---|---|---|
| China | -0.885 | -0.547 | 0.066 |
| South Africa | -6.274*** | -4.929*** | -5.623*** |
| South Korea | -5.460*** | -4.854*** | -6.710*** |
| India | -4.562*** | -6.255*** | -9.172*** |
| Indonesia | -5.875*** | -3.960** | -10.213*** |
| Brazil | -7.805*** | -6.900*** | -7.445*** |
| Mexico | -7.116*** | -5.362*** | -5.721*** |
| Russia | -7.349*** | -6.311*** | -5.979** |
| Turkey | -6.624*** | -6.233*** | -9.995*** |
| Argentina | -6.937*** | -5.556*** | -7.540*** |

Panel B: average ADCC

| Market | 0 | [-1,1] | [-3,3] |
|---|---|---|---|
| China | -0.016* | 0.006 | -0.003 |
| South Africa | 0.004 | 0.015* | 0.017* |
| South Korea | 0.034** | 0.044*** | 0.042*** |
| India | 0.033** | 0.042*** | 0.040*** |
| Indonesia | 0.023** | 0.029*** | 0.028*** |
| Brazil | 0.021*** | 0.027*** | 0.027*** |
| Mexico | 0.012* | 0.018*** | 0.019*** |
| Russia | 0.052*** | 0.064*** | 0.061*** |
| Turkey | 0.033* | 0.040** | 0.037** |
| Argentina | 0.033** | 0.042*** | 0.042*** |

Table 1.4 Continued

Panel C: cross-market bottom coexceedances

| | CNH | USA | JPN | HKG | GBR | DEU | FRA | CAN | ITA | AUS | ZAF | KOR | IND | IDN | BRA | MEX | RUS | TUR | ARG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CNH | 1 | | | | | | | | | | | | | | | | | | |
| USA | 0.105 | 1 | | | | | | | | | | | | | | | | | |
| JPN | 0.105 | 0.193 | 1 | | | | | | | | | | | | | | | | |
| HKG | 0.105 | 0.316 | 0.316 | 1 | | | | | | | | | | | | | | | |
| GBR | 0.140 | 0.544 | 0.281 | 0.316 | 1 | | | | | | | | | | | | | | |
| DEU | 0.140 | 0.526 | 0.298 | 0.316 | 0.632 | 1 | | | | | | | | | | | | | |
| FRA | 0.123 | 0.491 | 0.298 | 0.316 | 0.614 | 0.667 | 1 | | | | | | | | | | | | |
| CAN | 0.175 | 0.579 | 0.281 | 0.368 | 0.596 | 0.491 | 0.526 | 1 | | | | | | | | | | | |
| ITA | 0.088 | 0.368 | 0.281 | 0.263 | 0.439 | 0.544 | 0.649 | 0.404 | 1 | | | | | | | | | | |
| AUS | 0.105 | 0.421 | 0.386 | 0.386 | 0.544 | 0.491 | 0.526 | 0.561 | 0.421 | 1 | | | | | | | | | |
| ZAF | 0.140 | 0.421 | 0.386 | 0.368 | 0.526 | 0.456 | 0.456 | 0.579 | 0.404 | 0.526 | 1 | | | | | | | | |
| KOR | 0.140 | 0.193 | 0.263 | 0.404 | 0.281 | 0.281 | 0.281 | 0.351 | 0.246 | 0.298 | 0.368 | 1 | | | | | | | |
| IND | 0.105 | 0.316 | 0.246 | 0.386 | 0.333 | 0.351 | 0.351 | 0.404 | 0.246 | 0.421 | 0.368 | 0.316 | 1 | | | | | | |
| IDN | 0.123 | 0.246 | 0.193 | 0.404 | 0.228 | 0.228 | 0.228 | 0.333 | 0.193 | 0.298 | 0.316 | 0.404 | 0.333 | 1 | | | | | |
| BRA | 0.070 | 0.333 | 0.246 | 0.316 | 0.404 | 0.404 | 0.351 | 0.439 | 0.316 | 0.404 | 0.509 | 0.368 | 0.281 | 0.316 | 1 | | | | |
| MEX | 0.140 | 0.421 | 0.263 | 0.368 | 0.491 | 0.474 | 0.439 | 0.491 | 0.421 | 0.404 | 0.474 | 0.281 | 0.298 | 0.246 | 0.509 | 1 | | | |
| RUS | 0.175 | 0.263 | 0.211 | 0.246 | 0.298 | 0.316 | 0.333 | 0.421 | 0.281 | 0.281 | 0.439 | 0.368 | 0.333 | 0.386 | 0.351 | 0.333 | 1 | | |
| TUR | 0.070 | 0.246 | 0.246 | 0.193 | 0.298 | 0.333 | 0.298 | 0.316 | 0.228 | 0.333 | 0.439 | 0.263 | 0.298 | 0.228 | 0.333 | 0.333 | 0.298 | 1 | |
| ARG | 0.140 | 0.211 | 0.193 | 0.228 | 0.281 | 0.281 | 0.281 | 0.316 | 0.263 | 0.263 | 0.316 | 0.263 | 0.211 | 0.246 | 0.404 | 0.351 | 0.298 | 0.246 | 1 |

## Table 1.5: Policy Risks, Correlations, and Returns

Panel A reports the effect of policy risks on A-share stock's connectedness with the global market using the following model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock $i$ with the global market in year $t$, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock $i$'s policy sensitivity in year $t$, and $\omega$ and $\lambda$ are firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock $i$ with the MSCI World Index in year $t$ based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* is measured using global beta of stock $i$ in year $t$ (*Global beta*), which is defined as the loading of weekly excess return of stock $i$ on excess return of the World Index: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock $i$ in week $k$, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the Index. *Policy sensitivity*1 is constructed as follows: we first calculate the correlation of stock $i$'s monthly return with the Economic Policy Uncertainty Index in year $t$; then we rank all A-share firms based on the absolute values of the correlations in year $t$; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The sample includes all non-financial A-share firms from 1995 to 2017. *Policy sensitivity*2 is constructed as follows: we first calculate the three-day cumulative abnormal return (CAR) of stock $i$ around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year $t$; then we rank all A-share firms based on the sum of absolute value of these CARs in year $t$; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Panel B reports the relation of policy sensitivity and A-share stock's performance using the following regression: $Performance_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Performance_{it}$ is a variable used to measure performance of stock $i$ in year $t$ We use stock return in column (1) and (2) and Sharpe ratio (SR) in column (3) and (4) to measure *Performance*. The sample includes all non-financial A-share firms from 2001 to 2017. All variables are defined in Appendix A. All variables are winsorized at 1% to 99% except dummy variables. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| Panel A: policy risks and correlations | Dep. Var: *Correlation* | | Dep. Var: *Global beta* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Policy sensitivity*1 | -0.012*** | | -0.054*** | |
| | (0.003) | | (0.012) | |
| *Policy sensitivity*2 | | -0.014** | | -0.062** |
| | | (0.006) | | (0.030) |
| Firm size | 0.004*** | 0.004** | 0.018** | 0.019** |
| | (0.002) | (0.002) | (0.008) | (0.009) |
| Volatility | -0.242*** | -0.242*** | 0.974** | 1.591*** |
| | (0.055) | (0.062) | (0.410) | (0.464) |
| ROE | -0.006 | -0.002 | 0.008 | 0.015 |
| | (0.005) | (0.005) | (0.025) | (0.027) |
| Leverage | -0.000 | -0.001 | -0.019 | -0.034 |
| | (0.006) | (0.006) | (0.029) | (0.032) |
| B/M | 0.002 | -0.002 | -0.050* | -0.061* |
| | (0.006) | (0.007) | (0.029) | (0.032) |
| Tangibility | 0.038*** | 0.027* | 0.135* | 0.114 |
| | (0.015) | (0.015) | (0.075) | (0.081) |
| Firm age | 0.010* | 0.012* | 0.024 | 0.031 |
| | (0.005) | (0.007) | (0.022) | (0.030) |
| AH cross-listed | 0.002 | -0.013 | -0.060 | -0.092 |
| | (0.027) | (0.026) | (0.079) | (0.077) |
| SOE | 0.002 | -0.001 | 0.005 | -0.002 |
| | (0.003) | (0.004) | (0.015) | (0.017) |
| Constant | -0.279*** | -0.039 | -1.772*** | -0.470** |
| | (0.036) | (0.043) | (0.172) | (0.209) |
| N | 33,615 | 30,051 | 33,615 | 30,051 |
| Adj. $R^2$ | 0.470 | 0.473 | 0.438 | 0.416 |

Table 1.5 Continued

| Panel B: policy risks and stock performance | | | | |
|---|---|---|---|---|
| | Dep. Var: Return | | Dep. Var: SR | |
| | (1) | (2) | (3) | (4) |
| *Policy sensitivity*1 | 0.024*** | | 0.004** | |
| | (0.009) | | (0.002) | |
| *Policy sensitivity*2 | | 0.121*** | | 0.047*** |
| | | (0.020) | | (0.005) |
| Firm size | 0.130*** | 0.117*** | 0.033*** | 0.032*** |
| | (0.006) | (0.007) | (0.002) | (0.002) |
| Volatility | 9.110*** | 8.573*** | 1.231*** | 1.064*** |
| | (0.236) | (0.262) | (0.042) | (0.045) |
| ROE | 0.272*** | 0.245*** | 0.064*** | 0.059*** |
| | (0.021) | (0.022) | (0.005) | (0.005) |
| Leverage | 0.039 | 0.042 | 0.005 | 0.006 |
| | (0.024) | (0.026) | (0.006) | (0.006) |
| B/M | -1.141*** | -1.150*** | -0.294*** | -0.303*** |
| | (0.023) | (0.026) | (0.006) | (0.006) |
| Tangibility | 0.140*** | 0.109* | 0.064*** | 0.061*** |
| | (0.054) | (0.057) | (0.011) | (0.012) |
| Firm age | 0.080*** | -0.000 | 0.019*** | 0.002 |
| | (0.016) | (0.024) | (0.004) | (0.006) |
| AH cross-listed | 0.075 | 0.084 | 0.039** | 0.038** |
| | (0.070) | (0.074) | (0.018) | (0.019) |
| SOE | 0.014 | 0.005 | 0.004 | -0.000 |
| | (0.011) | (0.012) | (0.003) | (0.003) |
| Constant | -3.051*** | -2.802*** | -0.698*** | -0.805*** |
| | (0.140) | (0.170) | (0.032) | (0.040) |
| N | 33,068 | 29,511 | 33,615 | 30,051 |
| Adj. $R^2$ | 0.707 | 0.726 | 0.683 | 0.694 |

**Table 1.6: Diversification Benefits and Policy Risks: Cross-Listed Stocks**

Panel A compares connectedness with the global market of A-H cross-listed A-share stocks and their counterpart H-share stocks. We first calculate the weekly market-weighted USD return of the A-share stocks and H-share stocks as the portfolio return. We compare correlation and average dynamic conditional correlation (DCC) of the two portfolios with the MSCI World Index, and average bottom coexceedances of the two portfolios with the other 18 sample markets. Average DCC is the time series average of the weekly DCC of the portfolio with the World Index. Bottom coexceedance is defined as the ratio of the number of weeks when two market indexes both have 5% bottom tail returns to the total number of observations in the 5% bottom tail return of the indexes. We also report significance levels of the differences between the two portfolios from t-tests. Panel B first compares policy sensitivity of A-H cross-listed A-share stocks and their counterpart H-share stocks. To measure policy sensitivity, we first calculate the correlation of stock's monthly return with the Economic Policy Uncertainty Index in the year; then we rank all stocks based on the absolute values of the correlations in the year; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). Then Panel B reports A-H correlation difference by policy sensitivity. We divide the cross-listed stocks into high and low policy sensitivity groups by their A-share stocks' policy sensitivity. For each group, we calculate the correlation with the World Index using weekly USD return for A-share stocks and H-share stocks, respectively. Then we take difference of their correlations as A-H correlation difference. Last, we compare the A-H correlation difference between high and low policy sensitivity groups. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| Panel A: correlation of A-H cross-listed stocks | Correlation | Average DCC | Bottom coexceedance |
|---|---|---|---|
| H-share | 0.350 | 0.333 | 0.266 |
| A-share | 0.118 | 0.110 | 0.166 |
| Difference | 0.232*** | 0.224*** | 0.099*** |

| Panel B: policy sensitivity of A-H cross-listed stocks | A-share | H-share | Difference |
|---|---|---|---|
| Policy sensitivity | 0.476 | 0.467 | 0.010*** |

| | High Policy sensitivity | Low Policy sensitivity | Difference |
|---|---|---|---|
| A-H Correlation Difference | 0.126 | 0.110 | 0.016*** |

## Table 1.7: Foreign Ownership and Correlations

This table reports the effect of foreign ownership on A-share stock's connectedness with the global market. Panel A reports results for qualified foreign institutional investor (QFII) held stocks. Column (1) and (3) report results using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock $i$ with the global market in year $t$, $QFII_it$ is a dummy variable which is equal to 1 if stock $i$ has QFII holdings in year $t$ and 0 otherwise, and $\omega$ and $\lambda$ are firm and year fixed effect. Column (2) and (4) report results using the following difference-in-difference regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times In\ QFII_i \times Post_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $In\ QFII_i$ is a dummy variable which is equal to 1 if stock $i$ ever has QFII holdings during the sample period and 0 otherwise, and $Post$ is a dummy variable which is equal to 1 after stock $i$ first has QFII holdings and 0 otherwise. In column (1) and (2), $Connectedness$ is measured using the correlation of stock $i$ with the MSCI World Index in year $t$ based on weekly USD return ($Correlation$). In column (3) and (4), $Connectedness$ is measured using global beta of stock $i$ in year $t$ ($Global\ beta$), which is defined as the loading of weekly excess return of stock $i$ on excess return of the World Index: $R^u_{i,k} - R^u_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R^u_{f,k}) + \epsilon_i$, where $R^u_{i,k}$ is USD return of stock $i$ in week $k$, $R^u_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the World Index. The sample includes all non-financial A-share firms from 1995 to 2017. Panel B report change of connectedness with the global market of A-share stocks in the Shanghai-Hong Kong Connect Program (SH-HK Connect) and Shenzhen-Hong Hong Stock Connect Program (SZ-HK Connect) using the following difference-in-difference regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times HK\ connected_i \times Post_t + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $HK\ connected_i$ is a dummy variable which is equal to 1 if stock $i$ is in the Programs and 0 otherwise, $Post_t$ is a dummy variable which is equal to 1 after the start of each Program and 0 otherwise, and $\omega$ and $\lambda$ are firm and year fixed effect. The full sample includes stocks in the Shanghai Stock Exchange from three years before to three years after the introduction of SH-HK Connect (2012-2017) and stocks in the Shenzhen Stock Exchange from one year before to one year after the introduction of SZ-HK Connect (2016-2017). We also report separate results for stocks in the Shanghai Stock Exchange (SSE). All variables are winsorized at 1% to 99% except dummy variables. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

Table 1.7 Continued

| Panel A: QFII held stocks | Dep. Var: *Correlation* | | Dep. Var: *Global beta* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $QFII$ | 0.006** | | 0.021* | |
| | (0.003) | | (0.012) | |
| $In\ QFII \times Post$ | | 0.010*** | | 0.039*** |
| | | (0.003) | | (0.012) |
| Firm size | 0.004** | 0.004** | 0.018** | 0.017** |
| | (0.002) | (0.002) | (0.008) | (0.008) |
| Volatility | -0.256*** | -0.252*** | 0.873** | 0.889** |
| | (0.055) | (0.056) | (0.415) | (0.415) |
| ROE | -0.007 | -0.007 | 0.002 | 0.003 |
| | (0.005) | (0.005) | (0.025) | (0.025) |
| Leverage | 0.000 | 0.001 | -0.019 | -0.016 |
| | (0.006) | (0.006) | (0.029) | (0.029) |
| B/M | 0.002 | 0.002 | -0.052* | -0.051* |
| | (0.006) | (0.006) | (0.029) | (0.029) |
| Tangibility | 0.036** | 0.037** | 0.129* | 0.131* |
| | (0.015) | (0.015) | (0.075) | (0.075) |
| Firm age | 0.010* | 0.009* | 0.024 | 0.021 |
| | (0.005) | (0.005) | (0.022) | (0.022) |
| AH cross-listed | 0.003 | 0.002 | -0.056 | -0.058 |
| | (0.027) | (0.027) | (0.081) | (0.080) |
| SOE | 0.002 | 0.001 | 0.006 | 0.004 |
| | (0.003) | (0.003) | (0.015) | (0.015) |
| Constant | -0.281*** | -0.272*** | -1.785*** | -1.743*** |
| | (0.036) | (0.036) | (0.174) | (0.175) |
| N | 33,621 | 33,621 | 33,621 | 33,621 |
| Adj. $R^2$ | 0.469 | 0.469 | 0.437 | 0.437 |

Table 1.7 Continued

| Panel B: connected stocks | Dep. Var: *Correlation* | | Dep. Var: *Global beta* | |
|---|---|---|---|---|
| | Full Sample | SSE stocks | Full Sample | SSE stocks |
| | (1) | (2) | (3) | (4) |
| *HK connected* × *Post* | 0.000 | 0.012 | -0.042 | -0.018 |
| | (0.007) | (0.009) | (0.037) | (0.049) |
| Firm size | -0.018** | -0.020** | -0.053 | -0.048 |
| | (0.008) | (0.009) | (0.055) | (0.055) |
| Volatility | -0.690*** | -0.516*** | 0.418 | 0.597 |
| | (0.156) | (0.167) | (1.297) | (1.363) |
| ROE | 0.023 | 0.010 | 0.179 | 0.074 |
| | (0.017) | (0.015) | (0.115) | (0.096) |
| Leverage | 0.067*** | 0.036 | 0.343** | 0.150 |
| | (0.024) | (0.026) | (0.156) | (0.157) |
| B/M | -0.041* | -0.039 | -0.243* | -0.150 |
| | (0.024) | (0.026) | (0.135) | (0.138) |
| Tangibility | -0.033 | -0.053 | -0.277 | -0.345 |
| | (0.054) | (0.067) | (0.322) | (0.377) |
| Firm age | -0.137** | -0.163*** | -0.774*** | -0.717*** |
| | (0.056) | (0.060) | (0.274) | (0.273) |
| AH cross-listed | 0.049*** | 0.046*** | -0.120 | -0.132 |
| | (0.014) | (0.016) | (0.213) | (0.219) |
| SOE | -0.009 | -0.014 | -0.054 | -0.074 |
| | (0.019) | (0.020) | (0.108) | (0.116) |
| Constant | 0.832*** | 1.016*** | 3.495** | 3.470** |
| | (0.244) | (0.271) | (1.475) | (1.521) |
| N | 7,724 | 4,777 | 7,724 | 4,777 |
| Adj. $R^2$ | 0.633 | 0.580 | 0.514 | 0.489 |

### Table 1.8: Determinants of Low Correlation of A-share Stocks with Global Market

This table reports the effect of policy sensitivity and foreign ownership on A-share stock's connectedness with the global market using the following regression model: $Connectedness_{it} = \beta_0 + \beta_1 \times Policy\ sensitivity_{it} + \beta_2 \times QFII_{it} + Controls_{it} + \omega + \lambda + \epsilon_{it}$, where $Connectedness_{it}$ is the connectedness of stock $i$ with the global market in year $t$, $Policy\ sensitivity_{it}$ is a variable constructed to measure stock $i$'s policy sensitivity in year $t$, $QFII_{it}$ is a dummy variable which is equal to 1 if stock $i$ has qualified foreign institutional investor (QFII) holdings in year $t$ and 0 otherwise, and $\omega$ and $\lambda$ are firm and year fixed effect. In column (1) and (2), *Connectedness* is measured using the correlation of stock $i$ with MSCI World Index in year $t$ based on weekly USD return (*Correlation*). In column (3) and (4), *Connectedness* is measured using global beta of stock $i$ in year $t$ (*Global beta*), which is defined as the loading of weekly excess return of stock $i$ on excess return of the World Index: $R_{i,k} - R_{f,k} = \alpha + Global\ beta_i \times (R_{gm,k} - R_{f,k}) + \epsilon_i$, where $R_{i,k}$ is USD return of stock $i$ in week $k$, $R_{f,k}$ is USD risk free rate, and $R_{gm,k}$ is return of the World Index. *Policy sensitivity*1 is constructed as follows: we first calculate the correlation of stock $i$'s monthly return with China's Economic Policy Uncertainty Index in year $t$; then we rank all A-share firms based on the absolute values of the correlations in year $t$; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). *Policy sensitivity*2 is constructed as follows: we first calculate the three-day cumulative abnormal return (CAR) of stock $i$ around announcements of new regulatory documents issued by China Securities Regulatory Commission based on market model in year $t$; then we rank all A-share firms based on the sum of absolute value of these CARs in year $t$; last we convert the rank into a number between zero and one using the formula: rank/(number of firms + 1). The sample includes all non-financial A-share firms from 1995 to 2017. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. The standard errors are two-way clustered by industry and year and reported in parentheses. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and DATASTREAM.

| | Dep. Var: *Correlation* | | Dep. Var: *Global beta* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Policy sensitivity*1 | -0.012*** | | -0.054*** | |
| | (0.003) | | (0.012) | |
| *Policy sensitivity*2 | | -0.014** | | -0.062** |
| | | (0.006) | | (0.030) |
| *QFII* | 0.007** | 0.006** | 0.021* | 0.021* |
| | (0.003) | (0.003) | (0.012) | (0.012) |
| Firm size | 0.004** | 0.003* | 0.017** | 0.018** |
| | (0.002) | (0.002) | (0.008) | (0.009) |
| Volatility | -0.240*** | -0.240*** | 0.980** | 1.596*** |
| | (0.055) | (0.062) | (0.410) | (0.464) |
| ROE | -0.006 | -0.002 | 0.007 | 0.014 |
| | (0.005) | (0.005) | (0.025) | (0.027) |
| Leverage | 0.000 | -0.001 | -0.018 | -0.033 |
| | (0.006) | (0.006) | (0.029) | (0.032) |
| B/M | 0.003 | -0.001 | -0.047 | -0.058* |
| | (0.006) | (0.007) | (0.029) | (0.032) |
| Tangibility | 0.037** | 0.026* | 0.134* | 0.112 |
| | (0.015) | (0.015) | (0.075) | (0.081) |
| Firm age | 0.010* | 0.012* | 0.023 | 0.030 |
| | (0.005) | (0.007) | (0.022) | (0.030) |
| AH cross-listed | 0.002 | -0.013 | -0.060 | -0.091 |
| | (0.027) | (0.026) | (0.080) | (0.078) |
| SOE | 0.001 | -0.001 | 0.004 | -0.003 |
| | (0.003) | (0.004) | (0.015) | (0.017) |
| Constant | -0.273*** | -0.033 | -1.752*** | -0.450** |
| | (0.036) | (0.043) | (0.173) | (0.209) |
| N | 33,615 | 30,051 | 33,615 | 30,051 |
| Adj. $R^2$ | 0.470 | 0.473 | 0.439 | 0.416 |

# Chapter 2

# Industry Contagion of Financial Distress: Evidence from Bond Defaults in China

## 2.1 Introduction

China's bond market has been growing rapidly in recent years. By the end of 2018, the size of China's bond market has been ranked second globally with a market cap of RMB 85.7 trillion (USD 12.5 trillion), surpassed only by the US. In the meanwhile, as part of the internationalization of RMB, the Chinese government has been trying to push forward the liberalization of the bond market. However, research on China's bond market has been very limited, especially on bond defaults. This is mainly because the history of China's bond market is very short and there was no bond default in China before 2014. The default of "11 Chaori bond" in 2014 was marked as the very first bond default incident in China. Ever since the first default, China has witnessed a wave of bond defaults until now. This provides a good laboratory to study bond defaults in China. In this study, I try to investigate the wide impact of bond defaults on the corporate world in China. Specifically, I test how the industry peers, an important group of economically connected firms of the defaulted firms, are affected by the bond defaults.

The nature, extent, and consequences of industry contagion have received considerable scrutiny in the literature. Studies have identified two opposite effects of financial distress on industry peers: contagion effect and competitive effect. On the one hand, financial distress increases cost of debt financing of peers and decrease peers' investment (e.g., Benmelech and Bergman, 2011). Therefore, industry peers of bankrupt firms suffer from loss in firm value (Lang and Stulz, 1992). On the other hand, some studies argue that non-distressed competitors in some industries will gain more market share and become more profitable after a firm's bankruptcy as the industry will have less competition, especially in highly concentrated industries (e.g., Hertzel, Li, Officer, and Rodgers, 2008). Therefore, the effect of financial distress on industry peers can be different depending on industry characteristics. One feature of China's market is the existence of large number of SOEs. Studies have concluded that SOEs in China have more access to debt financing sources like bank loans and bond issuance (e.g. Cong, Gao, Ponticelli, and Yang, 2019). Debt financing of SOEs should be less affected by the bond defaults. Moreover, some studies also find that state ownership is very important in distress resolution in China (e.g. Li and Ponticelli, 2019). Therefore, the contagion effect should be stronger for non-SOE peers than SOE peers in China. Last, the default of SOEs is even more surprised to the market (Jin et al., 2018), as they are owned and guaranteed by the government. Thus, the contagion effect should be stronger if the defaulted firm is a SOE.

To test my hypothesis, I collect the bond default data from 2014 to 2018 from WIND. 113 Chinese firms defaulted on their bonds during this period, in which 18 firms are SOEs and 95 are non-SOEs. Both the number of defaulted firm each year and the average default value have been increasing. Moreover, although most defaulted firms are non-listed, the number of defaulted listed firms is increasing dramatically. The defaulted firms may be listed or non-listed, but I only examine their listed industry peers since the firm-level data of non-listed peers are not available. I first perform an event study to test the firm value change of industry peers of defaulted firms around the default announcements. The results suggest that peers overall do not have negative cumulative abnormal return (CAR) around bond defaults. However, SOE and non-SOE peers show different reactions. While the CAR of SOE peers are not significant, those of non-SOE peers are significantly negative.

Then I perform sub-sample analysis by testing bond defaults in high/low competition industries and high/low debt-dependence industries. Consistent with previous studies, firms in high competition and high debt-dependence industries suffer from more contagion effect than those in low competition and low debt-dependence industries, suggesting that the effect of bond default on industry peers is contingent on industry structure. More importantly, for both sub-samples, SOE peers do not have significant CAR, but the CAR of non-SOE peers are significantly negative in high competition and high debt-dependence industries and the magnitude are even larger than those in the full sample. The negative CAR of non-SOE peers diminish in low competition and low debt-dependence industries. In sum, the CAR analysis shows that SOEs in China are not be vulnerable to industry contagion of financial distress. On the contrary, non-SOEs are vulnerable to industry contagion and the high competition and high dependence on debt financing within industry can amplify the contagion effect. Last, I perform the sub-sample analysis using only SOE defaults. Instead of having stronger contagion, SOE defaults do not have any effect on industry peers. The possible reason is that non-SOE defaults may contain more industry-specific information about the increase in financing cost, which leads to industry contagion, while SOE defaults contain more information about government's willingness to guarantee for SOEs.

I further test industry peer's debt financing and investment to explore the underlying mechanism of firm value change. To build the causal relation, I perform the difference-in-difference (DID) analysis using industry peers of defaulted firms as the treatment group and firms in the non-defaulted industries as control group. The results show that the treated firms suffer from a 10.37% decrease in debt ratio relative to controlled firms. However, the subsample analysis shows that debt ratio of SOE peers does not change, while non-SOE peers decrease significantly in debt ratio. Next, I examine peers' debt financing in more detail by testing the change of their bond issuance and bank loans. While the change in bond issuance is not significant, the decease in bank loans of peers is large and significant, as most debt financing of Chinese firms is still from banks. Further analysis shows that SOEs peers even have slightly more bond issuance after the default, possibly as a precautionary measure after defaults in the industry. Similar to debt ratio, SOE peers do not change in bank loans, while non-SOE peers decrease significantly in bank loans.

Next, I investigate the change of industry peer's investment using the same DID regressions. The results suggest that the treatment group suffer from 16.8% decrease in investment relative to the control group. Consistent with previous results, although SOE peers tend to decrease in investment, the change is not significant. In contrast, non-SOE peers' investment is reduced significantly. Last, I find that that the decrease in peers' debt financing and investment is large and significant in high competition/debt-dependence industries, but not in low competition/debt-dependence industries. This suggests that industry contagion is also dependent on industry characteristics in China. In sum, my analysis suggests that firms are vulnerable to industry contagion mainly through reduced bank loans and investment in China. More importantly, while non-SOEs are vulnerable to industry contagion, SOEs can withstand the contagion effect, because SOEs still have easy access to debt financing even after their industry peers default. This means beside industry characteristics and default type, ownership structure is an important determinant of the severity of industry contagion in China.

The study makes three main contributions. First, it contributes to the emerging literature on China's corporate bond market, especially on bond defaults, which has been overlooked by previous studies. Although some recent studies such as (Jin et al., 2018) also investigate the recent bond defaults in China, this is the first study looking at how the defaults in China affect other economically connected firms, i.e., industry peers. It provides the comprehensive evidence on the nature and economic consequences of bond defaults in China. Second, it contributes to the literature on industry contagion of financial distress. Previous studies have concluded that industry characteristics and the nature of financial distress will affect the severity of contagion. This study further shows that in an emerging market like China, state ownership can be the most important determinant of industry contagion. Evidence that there are contagion effects for non-SOEs peers, but not SOE peers, has important implications not only for borrowers, but also for lenders concerned with managing credit risk. Third, this study also has important policy implications. The easy access to financing sources of SOEs not only leads to low efficiency as shown in previous studies, it may also crowd out non-SOEs in the credit market after the bond defaults. Therefore, the industry contagion on non-SOEs can amplify the discrimination against non-SOEs in credit market in China. This suggests that the Chinese government should further eliminate the discrimination against non-SOEs in the effort to liberalize the financial market.

The rest of this paper is organized as follows. Section 2 provides institutional background of China's bond market and bond defaults in China. Section 3 reviews related literature and constructs hypothesis. Section 4 presents the sample and empirical design. The empirical results are reported in sections 5. Section 6 concludes.

## 2.2 Institutional Background

### 2.2.1 China's Bond Market

China's bond market has been growing rapidly in recent years. By 2018, the size of China's bond market has been ranked second globally, surpassed only by the US. Figure 1 shows that both the amount of bond outstanding and the market capitalization scaled by GDP have been increasing in the past decade. In 2018, the total bond market value reached RMB 85.7 trillion (USD 12.5 trillion), about 95.2% of China's GDP. The bond market has been an important component in China's financial market and the main channel of direct financing for corporates [1]. China's bond market is shaped by several key features. First, the market is comprised of two segmented markets: the interbank bond market (OTC market) and the exchange market. The interbank market is the dominating market for bond issuance and trading in China. As a wholesale market, the participants are restricted to qualified institutional investors (Amstad and He, 2018). The exchange market consists of the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). Although smaller in size, the exchange market is more liquid than the interbank market (Jin et al., 2018). In the context of market fragmentation of the two markets, regulators have taken measures to promote market connectivity in recent years.

Second, the fixed-income securities in China can be classified into three broad categories: government bonds, financial bonds, and corporate bonds (Amstad and He, 2018). Table 2.1 presents the composition of outstanding bonds in China. The focus of this study, corporate bond, covers all fixed-income securities issued by non-financial firms in China. Non-financial firms can issue several different types of bonds: enterprise bond are mostly issued by SOEs and government-related entities; exchange-traded corporate bonds are corporate bonds that are issued in the exchange market; medium-term notes are mainly used by large SOEs and prominent private enterprises and are traded in the interbank market; commercial papers and super commercial paper are similar to medium-term notes except that they have shorter maturity.

Third, the distribution of the bond ratings in China is well-known to be skewed to the upside (Poon and Chan, 2008). Over 90% of the outstanding non-financial credit bonds are covered in only three rating categories. In the meanwhile, the issuance of non-investment grade bonds is scarce in China. Fourth, foreign investment in China's bond market is very small until now. In 2018, the amount held by foreign investors account for 2.3% of the total bond market value. However, as part of the internationalization of RMB, Chinese government has been trying to attract more international investors. Given China's strong intention to push forward the liberalization of the bond market, we can expect a more and more relaxed regulatory environment for foreign investors to participate.

### 2.2.2 Bond Defaults in China

The default of "11 Chaori bond" in March 2014 was marked as the very first bond default incident in China. Ever since the first default, China has witnessed a wave of credit events and the number of bond defaults has increased gradually with an increasing average defaulted value. Table 2.2 shows the number of bond default every year from 2014 to 2018. At the end

[1] See `https://www.acra-ratings.com/research/1116`

of 2018, the total number of defaulted issuers and defaulted bonds has reached 113 and 322, respectively. The two peaks of default are in 2016 and 2018, when the number of newly defaulted firms increase dramatically. However, the main defaulting triggers are different. In 2016, the main cause of defaults was the low-sentiment and over-capacity of some industries, while in 2018 the main cause was the increased difficulties in refinancing faced by corporates due to tightened liquidity and deepening financial deleveraging campaign. Another feature of the defaults is that most defaulted firms are non-SOEs. Table 2.2 shows that among the 113 defaulted firms, only 18 are SOEs and the others are non-SOEs. There are two possible reasons. First, as shown in many previous studies (e.g., Ru, 2018), private enterprises are at a disadvantage compared to SOEs in terms of financing channels and financing costs. When the financing environment deteriorates, the ability of private enterprises to obtain financing will be the first thing affected. Second, as the risk appetite of investors decreases and their demand for high risk bonds declines, they tend to invest in safer government-backed bonds.

On the one hand, although a series of defaults have occurred since 2014, the overall credit risk of China's bond market is still low compared to other countries. Considering the large size of China's bond market, the total number of bonds that are materially defaulted is small. By the end of 2018, the default rate in terms of value in China's bond market was only 0.61%. On the other hand, the series of defaults, especially the SOE defaults starting from 2015, marked the beginning of the elimination of implicit government guarantee, which accounts for at least 1.75% of corporate bond market value as shown in Jin et al. (2018). Despite the low default rate, the jitters aroused by the default shocks have expanded far beyond the bond market, even to the entire Chinese financial system and the macro economy.

Resolving bond defaults can be different in China as the judicial system is weak and the government often takes active role in this process (see e.g., Li and Ponticelli, 2019). China introduced the Enterprise Bankruptcy Law in 1986, though it is the 2006 reform that led China on a path towards convergence with international practice. There are three types of bankruptcy proceedings in China now: liquidation, settlement, and reorganization. Despite these positive changes, many concerns about implementation of the bankruptcy code remain nowadays due to lack of legal infrastructure, a disparate court system, and potentially moral hazard issues related to SOEs. In general, "government-led/coordinated solutions," especially by local governments, are one of the most prominent Chinese characteristics when dealing with defaulted bonds. Chinese local governments often rescue failing firms by either issuing relevant guidance documents, or pushing other healthy local SOEs or financial institutions to inject capital. However, local governments do not have limitless resources. The wave of breaking "implicit guarantees" should help local authorities to escape from the notion of unconditionally rescuing the zombie firms, and alleviate the notorious soft budget constraint problem that still looms in China's financial reform today Amstad and He (2018).

## 2.3 Literature Review and Hypothesis Development

The nature and consequences of financial contagion have received considerable scrutiny in academic literature. One line of research examines the effect of firm's financial distress on its industry peers, which is an important group of economically connected firms of the distressed firm. Studies have identified two opposite effects of financial distress on industry peers: the contagion effect and the competitive effect. On the one hand, the early study of Lang and Stulz (1992) and Ferris, Jayaraman, and Makhija (1997) find that overall industry peers of the bankrupt firm experience negative abnormal return after the announcement of Chapter 11 bankruptcy. The negative effect is stronger if the industry is more levered and if the bankrupt firm is larger in size. Consistent with these findings, Benmelech and Bergman (2011) show that a firm's bankruptcy reduces the collateral value of other industry participants, thereby increasing their cost of debt financing. Hertzel and Officer (2012) also find that spreads on new and renegotiated corporate loans are significantly higher when the loan originates (or is renegotiated) in the two years surrounding bankruptcy filings by industry rivals. Further, Garcia-Appendini (2018) shows that firms in distress impose indirect costs to non-distressed competitors by increasing costs of credit in the industry and hence restricting credit access and investment. In sum, previous studies conclude that firms are vulnerable to industry contagion of financial distress through reduced debt financing and restricted investment. Therefore, I postulate the following:

**Hypothesis 1:** Industry peers of defaulted firms decrease in firm value as a result of reduced debt financing and investment after the bond defaults in China.

On the other hand, since levered firms lose substantial market share to their more conservatively financed competitors in industry downturns (Opler and Titman, 1994), the competitive effect may dominate, where non-distressed competitors will gain more market share and become more profitable after a firm's bankruptcy as the industry will have less competition. Consistent with this argument, Lang and Stulz (1992) find that in highly concentrated industries, peers of the bankrupt firm have positive abnormal return after the announcement of bankruptcy, as it is easier for the surviving peers to take market share of the bankrupt firm in concentrated industries. Hertzel et al. (2008) also show that the increase in loan spreads surrounding bankruptcy of industry rivals is mitigated in concentrated industries. Although Garcia-Appendini (2018) finds contagion effect on industry peer's investment after the bankruptcy, the effect is mitigated for firms with stronger balance sheets or in concentrated markets. Further, using CDS data, Jorion and Zhang (2007) find strong evidence of contagion effects for Chapter 11 bankruptcies and competitive effects for Chapter 7 bankruptcies, as under Chapter 11, the bankrupt firm might reemerge with lower costs, as a result of debt forgiveness or concessions from unions, for example, which is unfavorable to competitors and lead to less competitive effect. In another study, they test the market reaction to bond rating downgrades and find that for investment-grade (speculative-grade) firms, industry abnormal equity returns are negative (positive), which implies a predominant contagion (competition) effect (Jorion and Zhang, 2010). In sum, existing studies conclude that the effect of financial distress on industry peers can be different, depending on industry characteristics, firm characteristics, and types of distress. Therefore, I postulate the following:

**Hypothesis 2:** The contagion effect of bond defaults on industry peers is stronger in more competitive industries and more debt-dependent industries in China.

Another related stream of research is China's credit market. Since China is a developing country with underdeveloped financial market, bank loan is still the major source of financing for Chinese firms (Allen, Qian, and Qian, 2005). Therefore, most previous studies on China's credit market focus on bank loans. Some studies investigate the bank loan or credit allocation in China. For example, Cong et al. (2019) use loan-level data from the 19 largest Chinese banks and document that the stimulus-driven credit expansion after global financial crisis disproportionately favored SOEs. Ru (2018) finds that industrial loans of China Development Bank to SOEs crowd out private firms in the same industry. In general, most studies in this area conclude that SOEs and politically connected firms have more access to bank loans in China. Another line of research focus on bank loan defaults and financial distress in China. Ai, Bailey, Gao, Yang, and Zhao (2017) show that politically connected borrowers perform poorly on several dimensions of the lending process and borrowers owned by the state default more frequently on bank loans. Consistent with this, Fan, Huang, and Zhu (2013) find that distressed companies facing stronger institutional discipline and with greater private ownership have relatively better operating performance and are more likely to recover. Last, the most recent study of Li and Ponticelli (2019) exploit the staggered introduction of courts specialized in bankruptcy across Chinese cities as a shock to political influence on judicial decisions. They conclude that the introduction of specialized courts leads to higher liquidation of local SOEs, lower share of zombie firms, and higher capital productivity of local firms. In sum, previous studies have addressed the importance of state ownership and connection with the government in credit allocation and distress resolution in China.

Because of the massive credit boom after the global financial crisis, debt problem of China has been the most studied topic in recent years. Some studies focus on the shadow banking problem, which has been a major threat to China's financial system in the last few years (e.g., Allen, Qian, Tu, and Yu, 2019; Chen, He, and Liu, 2020; Chen, Ren, and Zha, 2018). Another stream of research focuses on local government debt, mainly the Chengtou bond (e.g., Liu, Lyu, and Yu, 2017a; Bai and Zhou, 2018; Huang, Pagano, and Panizza, 2016). However, the study on corporate bond is still limited, especially on bond default, because bond has not been largely used by Chinese firms until recent years and there was no bond default in China until 2014. Similar to bank loans, studies in this area also emphasis the importance of the government in firm's access to corporate bond market. Pessarossi and Weill (2013) find evidence in favor of the influence of central government ownership on the financing choices of firms because central SOEs are more likely to issue bonds and to borrow uniquely on the bond market. Similarly, Schweizer, Walker, and Zhang (2017) show that politically-connected non-SOEs are more likely to issue corporate bonds as a debt-financing instrument than their non-connected counterparts, and that they achieve lower coupon rates. In sum, previous studies conclude that it is much easier for SOEs to access the credit market than non-SOE. Therefore, I postulate the following:

**Hypothesis 3:** The contagion effect of bond defaults on industry peers is stronger for non-SOE peers than SOE peers in China.

With the wave of corporate bond defaults starting in 2014, academic researchers have also turned to this issue in recent years. Jin et al. (2018) exploit the first bond default of SOEs in China and they find that bond price of SOEs decrease relative to non-SOEs and SOEs reduce their investments by 3% of book assets relative to propensity-score matched non-SOEs after the first SOE default. The effect is particularly large as the default of SOEs is even more unexpected by investors. Therefore, I postulate the following:

**Hypothesis 4:** The contagion effect of bond defaults on industry peers is stronger if the defaulted firm is a SOE.

## 2.4 Sample and Empirical Design

### 2.4.1 Data Sources and Variables

I collect firm-level and return data of Chinese A-share listed firms for the period of 2009 to 2018 from CSMAR. The bond and default data from 2014 to 2018 are collected from WIND database. The default information includes name of the defaulted bond and firm, date and value of the default, as well as firm characteristics. Next, I match the default data from WIND with firm-level data from CSMAR. Based on the default information, I can identify which industries have bond defaults every year. The defaulted firms may be listed or non-listed firms, but I only examine their listed industry peers since the firm-level data of non-listed peers are not available. My sample for empirical analysis also excludes financial firms as their financial statements are complied under different standards.

I use debt ratio to examine the change of firm's debt financing after industry peer's bond defaults. I also further look at firm's bond issuance and bank loan to investigate the impact on different sources of firm's debt financing. Next, I use capital expenditure to measure firm's investment. The Herfindahl-Hirschman Index (HHI) is used to measure the competition of an industry. It is equal to the sum of the squared market share of each firm in the industry, where market share is calculated as the sales of a firm to total sales of all firms in the industry. A high HHI index means the market is dominated by a few firms and is not competitive. Last, I use the median leverage ratio of an industry to measure its debt dependence. Definition of other variables are summarized in Appendix A.

### 2.4.2 Summary Statistics

Table 2.2 presents summary statistics of bond defaults from 2014 to 2018 in China. Panel A shows that the number of newly defaulted firms has been increasing except in 2017. Among the 113 defaulted firms during this period, 18 of them are SOEs and 95 are non-SOEs. Although most defaulted firms are non-listed firms, the number of defaulted listed firms increase dramatically, especially in 2018. This suggests that the wave of defaults may start from small non-listed firms and has spread to large listed firms later. Panel B shows that the sum of defaulted firms each year is 136, which means some firms defaulted in multiple years during this period. In Panel C, both the number of defaulted bond and the value of default increase dramatically, especially in 2018. Moreover, combined with Panel B, it can be seen that the average number of defaulted bond for each firm also increases. Panel D shows that almost all industries have bond defaults during this period[2]. The industry distribution of defaulted firms is also similar

[2]The industry classification here is based on level one industry classification of China Securities Regulatory Commission (CSRC). In the empirical analysis, I use level two industry classification, which is more a detailed classification than level one.

to that of the overall A-share market with a few exceptions, suggesting that only testing listed peers will not lead to bias on the industry distribution of my sample.

Table 2.3 presents summary statistics for variable used in this study. All variables are winsorized at 1% on both tails throughout the paper. Panel A shows that A-share firms typically have a debt ratio of 16.4%. Among all debt borrowed, bond only takes a very small fraction and the main debt financing resource is still bank loan. Capital expenditure is 38.1% of property, plant, and equipment (PPE) every year. Next, the mean of *Size* is 21.971, which is equivalent to RMB 3.5 billion of total assets. The high tangibility (95.3%) suggests that A-share market is still dominated by manufacturing industry. The large standard deviation of growth in sales suggests that the growth of A-share firms is very unbalanced, with more than a quarter firms have negative growth. The summary statistics in general are similar to those from recent studies. Panel B further compares the characteristics of SOEs and non-SOEs in China. In general, SOEs are significantly different from non-SOEs in all variables except cash flow. Consistent with previous studies that find SOEs have more access to credit, SOEs have higher debt ratio, more bond issuance and more bank loan than non-SOEs. However, non-SOEs have more investment than SOEs, possibly because of the smaller size and higher growth rate. Non-SOEs also have higher ROE and Z score than SOEs, suggesting that they are more profitable and financially solvent despite they have less access to credit. Therefore, non-SOEs are also valued higher by investors as reflected by the higher Tobin's q. The higher HHI of SOEs means that they tend to operate in more dominate industries than non-SOEs.

### 2.4.3 Empirical Method

To investigate how firm value of industry peers change after the defaults, I perform an event study to test the stock price reaction to the defaults. Specifically, I analyze the CAR of industry peers around the bond defaults. If an industry has more than one bond defaults on the same day, I count the default day only once. To obtain CAR, I first calculate the value-weighted industry portfolio return using the daily stock return from 2013 to 2018. Then I estimate the following regression for each industry $j$ and for each bond default:

$$R_{j,t} = \beta_{1,j} MRP_t + \beta_{2,j} SMB_t + \beta_{3,j} HML_t + \epsilon_{j,t} \tag{2.1}$$

where $R_{j,t}$ is the excess return of industry $j$ on day $t$, $MRP_t$, $SMB_t$, and $HML_t$ are market risk premium, size premium, and value premium, respectively. The estimation window is from 250 days to 50 days before each bond default. The estimated coefficients $\hat{\beta}_{1,j}$, $\hat{\beta}_{2,j}$, and $\hat{\beta}_{3,j}$ are used to construct the abnormal return as $AR_{j,\tau} = R_{j,\tau} - (\hat{\beta}_{1,j} MRP_\tau + \hat{\beta}_{2,j} SMB_\tau + \hat{\beta}_{3,j} HML_\tau)$, where $\tau$ is equal to 0 on the event day or the bond default day. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{j,\tau}$, where $T$ is equal to 1, 3, 5, 7, 10, and 15 for different windows. Since many Chinese listed firms have a large fraction of non-tradable shares, I use float value weighted return when calculating CAR. I also use total value weighted market return for robustness tests.

Then I perform a DID analysis to explore the effect of bond default on industry peer's debt financing and investment. DID methodology is ideally suited for establishing casual claims in a quasi-experimental setting. It eliminates the bias that comes from changes other than the default that could have affected the treatment group (Vig, 2013). The regression model is specified as follows:

$$y_{i,t} = \alpha + \beta_1 Industry\ peer_i + \beta_2 Post_{i,t} + \beta_3 Industry\ peer_i \times Post_{i,t} + Controls_{i,t-1} + \omega + \gamma + \lambda + \epsilon_{i,t}, \tag{2.2}$$

where $y_{i,t}$ is the variable used to measure firm $i$'s s debt financing or investment in year $t$, $Industry\ peer_i$ is defined as a dummy variable which is equal to 1 if firm $i$'s industry peers have bond default and 0 otherwise, $Post_{i,t}$ is a dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise, and $\omega$, $\gamma$, and $\lambda$ are industry, year, and area fixed effect, respectively. I also control for firm characteristics in the regression. The interaction dummy variable, $Industry\ peer_i \times Post_{i,t}$ is the main interest variable that reflects the change of treated firms after the event compared to controlled firms. In order to avoid correlations in the error term due to unobserved heterogeneity, I adjust standard errors by clustering observations at industry level throughout the paper.

## 2.5 Empirical Results

### 2.5.1 Firm Value of Peers After Bond Defaults

I first perform abnormal return analysis to investigate the firm value change of industry peers of defaulted firms. Table 2.4 reports CAR of industry peers around bond defaults from 2014 to 2018. The sample in Panel A includes all bond defaults during this period. First, it shows that in general, industry peers of the defaulted firms do not have significant change in firm value around bond defaults, as the CAR are not significant in all event windows. To further compare SOE and non-SOE peers, I calculate the daily return of SOE industry portfolio and non-SOE industry portfolio, respectively. Then I obtain the CAR of the two portfolios for each industry using the same method introduced in Section 2.4. The results are shown in the next two columns. While CAR of SOE peers are not significant, those of non-SOE peers are significantly negative, especially in the longer windows. Specifically, CAR of non-SOE peers is -0.128% in the five-day window. It further increases to -0.232% and -0.421% in the seven-day and nine-day window, after which it decreases to -0.358% in the twelve-day window. Moreover, the difference of CAR of SOE peers and non-SOE peers are significant in general. I also use different event windows as robustness tests and the results are reported in Appendix B. In general, the results are consistent with the main results. Therefore, consistent with expectation, non-SOEs are more vulnerable to industry contagion of bond defaults than SOEs. The insignificant results of SOE peers suggest that the bond defaults may not affect SOE peers' future debt financing. I will further explore this in the next subsection. Last, the insignificant results for the full sample may be explained by the two opposite effects of bond defaults on industry peers as discussed in Section 3. Therefore, I perform some sub-sample analysis to examine the two effects in more detail.

Panel B provides sub-sample analysis for bond defaults in high and low competition industries. Specifically, I calculate the HHI of all industries every year. Industry whose HHI is below the median HHI of that year is defined as high competition industry. Inconsistent with my hypothesis, the results are not significant as shown in the first column, suggesting that even in high competition industry where the contagion effect should be stronger, firm value of industry peers overall still does not change after the bond defaults. However, the next two columns show that peers in low competition industries tend to have positive CAR and the difference between high and low competition industries tend to be significant. This suggests that similar to other markets, the effect of bond default on industry peers is related to industry structure and competition effect may dominate in low competition industries in China. Next, I conduct the same analysis for SOE peers and non-SOE peers and still have different results. Similar to the full sample results, the CAR of SOE peers are mostly insignificant, although the difference between high and low competition industries is still significant in some event windows. On the contrary, the CAR of non-SOE peers in high competition industries are significantly negative and even larger in magnitude than those in the full sample. For example, the CAR in the longest window is -1.307%, while it is only -0.407% in the full sample. Moreover, the contagion effect on non-SOE peers also diminish in low competition industries and and difference between high and low competition industries is significant.

Next, I perform the sub-sample analysis using defaults in high and low debt-dependent industries. To identify high and low debt-dependent industries, I first use the median leverage ratio of the industry to measure its debt dependence. Then I divide all industries into high and low debt-dependence every year by comparing their debt dependence. The results in Panel C suggests that firm value of industry peers overall does not change significantly after bond defaults in high debt-dependent industries, while their firm value increase marginally in low debt-dependent industries. Similar to previous results, SOE and non-SOE peers have different reactions. While SOE peers do not have significant CAR, non-SOEs peers have significantly negative CAR in high debt-dependence industries and the CAR are larger in magnitude than the full sample. However, the negative CAR diminish in low debt-dependence industries. The results in Panel B and C suggest that similar to other markets, the effect of bond default on industry peers is contingent on industry structure in China. More importantly, while SOEs in China are not vulnerable to industry contagion, non-SOEs are vulnerable to industry contagion and the high competition and high debt-dependence within industry can amplify the contagion effect. These findings suggest that instead of industry competition and debt dependence, government ownership is the dominate factor in explaining industry contagion of financial distress in China, which is different from the developed markets as shown in previous studies.

The sub-sample in Panel D only includes SOE defaults. The results suggest that instead of having stronger contagion effect, SOE defaults do not have any effect on either SOE or non-SOE industry peers. As shown in Jin et al. (2018), the first SOE bond default can be perceived as an explicit reduction of implicit government guarantee on SOEs. Therefore, SOEs overall suffer from decrease in bond value and investment after the first SOE default. However, industry peers are vulnerable to industry contagion mainly because the defaults reveal industry-specific information like the decreased collateral value or increased financing costs. In this sense, non-SOE defaults may contain more industry-specific information about the change of financing cost, while SOE defaults contain more information about government's willingness to guarantee for SOEs. Since the implicit guarantee has already been broken in the first SOE default, the other SOE defaults do not necessarily affect stock price anymore.

### 2.5.2 Debt Financing and Investment of Peers After Bond Defaults

#### Contagion Effect on Debt Financing

I estimate DID regression model (2) to build the causal relation between bond defaults and change in industry peers' debt ratio. The results are reported in Table 2.5. The sample includes all A-share firms in China from 2009 to 2018. I first use debt ratio to measure firm's overall debt financing in Panel A. For the full sample, the coefficient on the main interest variable, $Industry\ peer \times Post$, is -0.016 and is significant at 1% level. Given the average debt ratio of A-share firms during the sample period is 0.164, it means that peers of defaulted firms decrease 10% in debt ratio relative to those in non-defaulted industries because of the bond defaults, suggesting that industry peers are vulnerable to contagion effect through reduced debt financing. The coefficients on control variables are also consistent with previous studies. Large firms have more access to debt financing and thus higher debt ratio. Firms with more cash flow and higher ROE have less need of external financing, leading to lower debt ratio. Firms with high growth rate and young firms have more investment opportunities that result in more external financing needs. Last, firms with high Z score are those who have less dependence on debt financing and thus are more solvent.

While the evidence of decreasing debt ratio is consistent with previous studies of other markets, China's market provides an unique setting to investigate whether firm's ownership structure or state ownership plays a role in industry contagion effect. Therefore, I perform the sub-sample analysis for SOEs and non-SOEs using regression (2). The regression results are reported in column (2) and (3). Column (2) shows that the coefficient on $Industry\ peer \times Post$ is small and not significant in the SOE sub-sample, suggesting that compared to SOEs in other industries, SOE peers of defaulted firms do not decrease in debt ratio because of the defaults. On the contrary, the coefficient for non-SOE sub-sample in column (3) is significantly negative and it is even larger in magnitude than that in the full sample. To be specific, given the average debt ratio of non-SOEs is 0.142, the coefficient of -0.027 suggests that non-SOE peers decrease 19% in debt ratio compared to non-SOEs in other industries, which is much larger than the 10% decrease in full sample. To further compare the different effects on SOE and non-SOE peers, I perform a t-test on the coefficients of the main interest variable, $Industry\ peer \times Post$, for SOE and non-SOE sub-sample regressions. The result is reported in Appendix C and it shows that the coefficients for SOE and non-SOE peers are significantly different. As shown in previous studies, SOEs have more access to debt financing for several reasons. First, since the major banks in China are owned by the government, they have preference to SOEs when granting credit. Second, SOEs also have more access to the bond market because of their special relationship with the government. More importantly, SOEs are owned by the government and are thought to be guaranteed by the government. Therefore, they have low credit risk and are preferred by most creditors. Even their industry peers default, creditors still believe SOEs are relatively safe and the government will bill them out eventually. As a result, SOE peers do not suffer from loss of debt financing.

In Panel B and C, I examine industry peers' debt financing in more detail by testing the two major sources of debt financing: bond and bank loans. Panel B shows results for bond issuance. For the full sample, the coefficient on *Industry peer* × *Post* is not significant, suggesting that peers of defaulted firms do not change in bond issuance because of the defaults. However, the summary statistics in Table 2.3 shows that only less than 10% of debt financing of A-share firms is from bond. Previous studies also conclude that bank loan is the main financing resource for Chinese firms (e.g., Cong et al., 2019; Ru, 2018). Therefore, as a supplement to bank loan, bond issuance of most firms is not affected much. The next two columns show that although bond issuance of non-SOE peers does not change, SOE peers actually have more bond issuance after the defaults. Since SOEs have easier access to the bond market (Pessarossi and Weill, 2013), they may issue more bond as a precautionary measure after they see defaults in the industry. However, since bond still takes small fraction of debt financing, the overall debt ratio of SOE peers does not change significantly.

In Panel C, I test the change of bank loans of peers. Column (1) shows that the coefficient on the main interaction variable is -0.010 in the full sample and it is significant at 5% level, suggesting that peers of defaulted firms decrease significantly in bank loans because of the bond defaults. Similar to the results in Panel A, SOE peers do not change in loans, while non-SOE peers decrease significantly in bank loans and the magnitude of decrease is also larger than the full sample. The coefficients on the main interest variable are still significantly different for SOE and non-SOE peers as shown in Appendix C. The coefficients on *Industry peer* × *Post* in Panel C are close to those in Panel A, which again suggests that bank loan is the main source of debt financing for A-share firms. After the announcement of bond defaults in a particular industry, banks become more cautions when granting credit to firms in the same industries, as the industry may have poor performance in the future and its collateral value is reduced. In sum, peers are vulnerable to industry contagion mainly through reduced bank loans in China.

**Contagion Effect on Investment**

I further investigate how peers' investment is affected by bond defaults in this subsection. To build the causal relation between bond defaults and change in peers' investment, I estimate the DID regression model (2) using investment as the dependent variable. The results are reported in Table 2.6. First, the coefficient on *Industry peer* × *Post* is -0.060 and is significant at 5% level in the full sample. Given the average investment of A-share firms during the sample period is 0.381, it suggests that peers of defaulted firms decrease 17% in investment relative to those in non-defaulted industries because of the bond defaults, which is even larger than the decrease in debt ratio. Therefore, the peers are vulnerable to industry contagion through decreased investment. The next two columns show results for the SOE and non-SOE subsamples. Although SOE peers tend to decrease in investment, the change is not significant. In contrast, non-SOE peers decrease significantly in investment. Specifically, the coefficient of -0.111 on *Industry peer* × *Post* suggests that non-SOE peers decrease 24% in investment compared to other non-SOEs because of the defaults. The difference of the coefficients of the main interest variable for SOE and non-SOE peers is significant as shown in Appendix C. The coefficients on control variables are also consistent with previous studies. Large and mature firms have less growth opportunities and thus less investment. Firms with more tangible assets tend to be in manufacturing industries that grow slowly and have less investment opportunities. More cash flows and higher profitability both lead to more investment. Last, as an indicator of investment opportunities, Tobin's q is positively associated with investment.

In sum, results in Table 2.5 and 2.6 provide novel evidence that Chinese firms are vulnerable to industry contagion of bond default through reduced debt financing and investment. However, while non-SOEs are vulnerable to industry contagion, SOEs can withstand the contagion effect. This suggests that beside industry characteristics and default type shown in previous studies, ownership structure is an important determinant of the severity of industry contagion in an emerging market like China. It has important implications not only for borrowers, but also for lenders concerned with managing credit risk. Last, industry contagion on non-SOEs but not on SOEs can further crowd out non-SOEs in credit market in China, suggesting that the Chinese government should further eliminate the discrimination against non-SOEs in the effort to liberalize the financial market.

**Contagion Effect in Different Industries**

As shown in previous studies, the contagion effect of financial distress on industry peers can be dependent on industry characteristics. In this subsection, I investigate how peers are affected by the bond defaults in different industries. I estimate regression model (2) using different subsamples and the results are reported in Table 2.7. In Panel A, the sample firms are divided into high/low competition groups every year by comparing their industry HHI to the median HHI of all industries. I again examine the change in peers' debt ratio, bond issuance, bank loan, and investment. Column (1) and (2) show that consistent with Hypothesis 2, peers in competitive industries suffer from decrease in debt financing, while peers in concentrated industries do not change in debt ratio, as the competitive effect may dominate the contagion effect in concentrated industries (e.g., Lang and Stulz, 1992). The next two columns show results for bond issuance. Consistent with the full sample results, the coefficient on $Industry\ peer \times Post$ is not significant in either the high or low competition sub-samples, suggesting that peers of defaulted firms do not change in bond issuance because of the defaults, even in high competition industries. Column (5) and (6) show that bank loan of peers decrease dramatically in high competition industries after the default but not in low competition industries. Last, peers in high competition industries have much larger and more significant decrease in investment. I also test the difference of the coefficients of the main interest variable between high and low competition industries and the results are significant as shown in Panel B of Table C1.

In Panel B, the sample firms are divided into high/low debt-dependence sub-samples by comparing industry leverage ratio to the median leverage ratio of all industries every year. The results are still consistent with my hypothesis. Specifically, peers in high debt-dependence industries suffer from decrease in debt financing and investment, but peers in low debt-dependence industries are not affected. The difference of the coefficients of the main interest variable is significant as shown in Panel C of Table C1. This is because firms in the high debt-dependence industries rely more on debt for financing and thus their debt level is more sensitive to the change of debt financing circumstances, which is worsen after bond default in the industry. In sum, results in Table 2.7 suggest that consistent with previous studies, industry characteristic is an important determinant of industry contagion in China. The contagion effect is much stronger in high competition/debt-dependence industries.

### 2.5.3 Robustness Tests

#### Firm Value of Peers around Distress Date

Measures of contagion based solely on announcement of bond default could underestimate the overall contagion effect of financial distress, as financial distress is typically widely known in advance of the announcement of default, suggesting that contagion effects for industry peers could also be evident before the announcement (Hertzel et al., 2008). Therefore, in the spirit of Hertzel et al. (2008), beside default day, I also use the distress day of the defaulted firm as an alternative event day in the robustness test. Specifically, I look for pre-default contagion effects around the day that has the most significant abnormal drop in market value of the defaulted firm during two years leading up to the default announcement. The approach is motivated, in part, by the fact that long-run CAR leading up to default contain too much noise to serve as useful measures of pre-default contagion effects. To implement this approach, I calculate the abnormal return of the defaulted firm using Fama-French three factor model over two years prior to the default date and identify the day on which the firm has the most negative abnormal return. This day is referred to as the distress date. Last, I estimate the CAR of industry peers around the distress date using the same method as in Section 4. The sample only includes bond defaults of A-share listed firms as the distress date of non-listed firms cannot be identified based on stock return.

The results are reported in Table 2.8. Similar to CAR around default date in Table 2.4, CAR of industry peers around distress date tend to be negative but not significant. However, SOE peers and non-SOE peers show different reactions. Consistent with previous results, although SOE peers do not have significant CAR, non-SOE peers suffer from significantly negative CAR and the difference between SOE and non-SOE peers is significant. While the significance level of the CAR is low mainly because of the small number of observations, the magnitude of the CAR is even larger than those in Table 2.4. This suggests that peers are already vulnerable to industry contagion before the default announcement when the defaulted firm starts to suffer from distress. Then the contagion effect is fully priced into stock price of industry peers when the default is announced, evident by the fact that peers further suffer from negative CAR around the defaults. This raises another concern of whether it is appropriate to use default year as the event year in the DID analysis, as peers may already suffer from contagion before the official announcement. However, in untabulated results, I find that the distress date is only around 105 days before the default date on average. Since I use annual data in the DID analysis, the three and half months lag should not be a major concern.

#### Contagion Effect Excluding Industry Downturn

An alternative explanation to the findings is that instead of industry contagion, peers suffer from decrease in debt financing and investment because of industry-wide shock and thus the whole industry is in downturn. Another similar argument is that firms decrease in debt ratio because they borrow less as a result of less investment opportunities during industry downturn, rather than banks are less willing to lend to them because of industry contagion. To mitigate this concern, I perform another sub-sample analysis excluding industries that are in downturn in any year during 2009 to 2018. Specifically, in the spirit of Opler and Titman (1994), an industry is in downturn when its median sales growth is negative in the year and it experiences median stock returns below 0. The negative stock return criteria are needed in order to eliminate downturns that are not considered either long-term or serious by participants in financial markets. The negative change in sales is required to eliminate those otherwise healthy industries that experience negative stock returns because prior expectations were unduly optimistic. The regression results are reported in Table 2.9. In general, the coefficients on $Industry\ peer \times Post$ are significantly negative except for bond issuance, which is consistent with the full-sample result. Therefore, firms still suffer from large decrease in debt financing and investment after excluding industry downturns, suggesting that my results are not driven by industry-wide shock or industry downturn.

## 2.6 Conclusions

The default of "11 Chaori bond" in 2014 was marked as the very first bond default incident in China. Ever since the first default, China has witnessed a wave of bond defaults until now. This study exploits these bond defaults to investigate the industry contagion effect of financial distress in China. I have four main findings. First, the abnormal return analysis shows that while SOE peers of defaulted firms overall do not have significant decrease in firm value, non-SOE peers suffer from significant drop in firm value, especially in high competition and high debt-dependent industries. Second, debt financing of industry peer decreases because of the bond defaults, especially bank loans, which is the main debt financing source for Chinese firms. Beside debt financing, industry peers also suffer from drop in investment. Third, using the unique setting of China's market where almost half of the listed firms are SOEs, I further show that the contagion effect on peers' debt financing and investment only affects non-SOE peers but not SOE peers. This is because SOEs in China have superior access to debt financing through both bond issuance and bank loans. This also explains the finding that SOE peers do not have significant CAR around bond defaults, while non-SOE peers have significant decrease in firm value after the defaults. Last, I show that consistent with previous studies, the industry contagion effect in China is stronger in high competition and high debt-dependent industries.

## 2.7 Appendix A: Variable Definitions

**Table A1: Variable Definitions**

| Variable | Definition |
|---|---|
| Debt ratio | The sum of long- and short-term debt scaled by total assets. |
| Bond issuance | Bonds issued scaled by total assets. |
| Bank loan | Bank loans borrowed scaled by total assets. |
| Investment | Capital expenditures scaled by lagged property, plant, and equipment (PPE). |
| Industry peer | A dummy variable which is equal to 1 if the firm is the industry peer of a defaulted firm and 0 otherwise. |
| Post | A dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise. |
| SOE | A dummy variable which is equal to 1 if the firm is a state owned enterprise and 0 otherwise. |
| Size | The natural logarithm of total assets. |
| Tangibility | Tangible assets scaled by total assets. |
| Cash flow | Total cash flows scaled by lagged total assets. |
| ROE | Return on equity, which is equal to the ratio of net profit to lagged book value of equity. |
| Growth | The one-year lagged growth rate of net sales. |
| Age | The natural logarithm of firm age from foundation. |
| Z score | Distance to default, which is equal to 3.3*(EBIT/total assets) + (sales/total assets) + 1.4*(retained earnings/total assets) + 1.2*(working capital/total assets) + 0.6*(market value of equity/total liabilities). |
| Tobin's q | The ratio of market value of equity plus total liabilities to total assets. |
| HHI | The Herfindahl-Hirschman Index, which is equal to the sum of the squared market share of each firm in the industry, where market share is calculated as the sales of a firm to total sales of all firms in the industry. |
| Industry Leverage | The median leverage ratio of a industry. |

## 2.8 Appendix B: Robustness Tests with Different Event Windows

### Table B1: CAR of Industry Peers around Bond Defaults

This table reports cumulative abnormal return (CAR) of industry peers of defaulted firms around the announcement day of bond defaults. To obtain CAR, I first calculate the float value-weighted industry portfolio return using the daily stock return from 2013 to 2018. Then I estimate the following regression for each industry $j$ and for each bond default: $R_{j,t} = \beta_{1,j}MRP_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \epsilon_{j,t}$, where $R_{j,t}$ is the excess return of industry $j$ on day $t$, $MRP_t$, $SMB_t$, and $HML_t$ are market risk premium, size premium, and value premium, respectively. The estimation window is 250 days to 50 days before each bond default. If a industry has more than one bond defaults on the same day, I count the default day only once. The estimated coefficients $\hat{\beta}_{1,j}$, $\hat{\beta}_{2,j}$, and $\hat{\beta}_{3,j}$ are used to construct the abnormal return as $AR_{j,\tau} = R_{j,\tau} - (\hat{\beta}_{1,j}MRP_\tau + \hat{\beta}_{2,j}SMB_\tau + \hat{\beta}_{3,j}HML_\tau)$, where $\tau$ is equal to 0 on the bond default day. CAR is calculated as $\sum_{\tau=-T}^{T} AR_{j,\tau}$, where $T$ is equal to 3, 5, 7, 10, and 15 for different windows. I also calculate the daily return of SOE industry portfolio and non-SOE industry portfolio separately. Then I obtain the CAR of the two portfolios for each industry using the same method. I report the differences of CAR of SOE peers and non-SOEs and the statistical significance of the differences from t-tests. The sample includes all bond defaults from 2014 to 2018. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and WIND.

| | Industry Peers | SOE peers | non-SOE peers | Difference |
|---|---|---|---|---|
| (-3, +3) | 0.093 | 0.202 | -0.082 | 0.284* |
| | (0.109) | (0.134) | (0.148) | (0.148) |
| (-5, +5) | 0.123 | 0.248 | -0.107* | 0.355** |
| | (0.132) | (0.162) | (0.058) | (0.167) |
| (-7, +7) | 0.029 | 0.177 | -0.296* | 0.473** |
| | (0.154) | (0.176) | (0.152) | (0.209) |
| (-10, +10) | -0.057 | 0.082 | -0.342* | 0.424* |
| | (0.183) | (0.199) | (0.194) | (0.232) |
| (-15, +15) | 0.084 | 0.219 | -0.491** | 0.710* |
| | (0.215) | (0.237) | (0.225) | (0.310) |

## 2.9 Appendix C: Statistics Tests for Differences of Key Coefficients

**Table C1: Statistics Tests for Differences of Key Coefficients**

The table reports the statistic tests for differences of the key coefficient, *Industry peer* $\times$ *Post*, in different sub-samples in Table 2.5, Table 2.6, and Table 2.7. Panel A reports the coefficients on *Industry peer* $\times$ *Post* in the regression on debt ratio, bond issuance, bank loan, and investment for SOE sub-samples and non-SOE sub-samples (from Table 2.5 and Table 2.6). Then it reports the difference of coefficients for SOE and non-SOE sub-samples and the statistical significance of the difference from t-test. Panel B reports the same coefficient for high and low competition industries (from Panel A of Table 2.7) and compare the difference in coefficients. Panel C reports the same coefficient for high and low debt-dependence industries (from Panel B of Table 2.7) and compare the difference in coefficients. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. Data source: CSMAR and WIND.

| Panel A: full sample | Debt ratio | Bond issuance | Bank loan | Investment |
|---|---|---|---|---|
| SOEs | -0.008 | 0.005 | 0.005 | -0.026 |
| Non-SOEs | -0.027 | 0.002 | -0.024 | -0.111 |
| Difference | 0.019*** | 0.003*** | 0.029*** | 0.085*** |
| $t$-statistics | 17.693 | 11.175 | 17.942 | 16.007 |

| Panel B: high and low competition industries | Debt ratio | Bond issuance | Bank loan | Investment |
|---|---|---|---|---|
| High | -0.014 | -0.002 | -0.015 | -0.079 |
| Low | -0.021 | 0.007 | 0.011 | -0.012 |
| Difference | 0.007 | -0.009*** | -0.026*** | -0.067*** |
| $t$-statistics | 1.565 | -17.608 | -13.119 | -10.799 |

| Panel C: high and low debt-dependence industries | Debt ratio | Bond issuance | Bank loan | Investment |
|---|---|---|---|---|
| High | -0.019 | 0.003 | -0.014 | -0.083 |
| Low | -0.011 | -0.002 | -0.006 | 0.008 |
| Difference | -0.008*** | 0.005 | -0.008*** | -0.091*** |
| $t$-statistics | -7.450 | 1.179 | -5.709 | -15.561 |

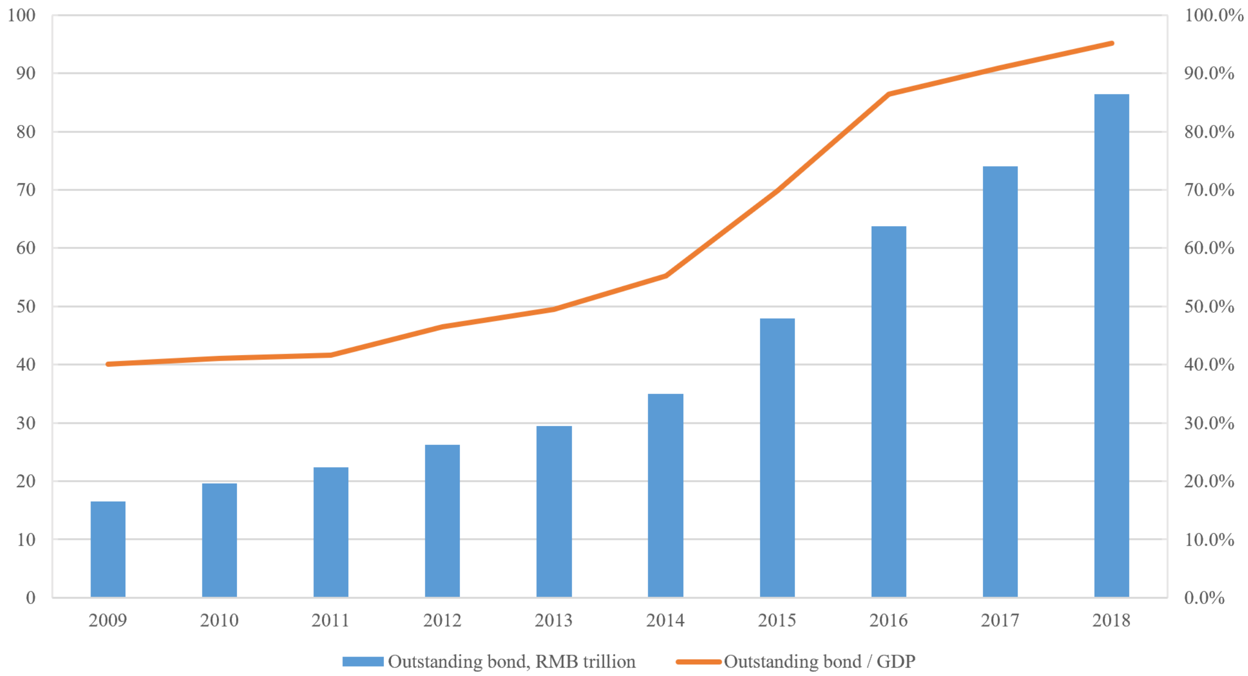



Figure 2.1: Outstanding Bonds and Bond Value to GDP of China

This figure plots the value of bond outstanding in China and the ratio of bond outstanding to GDP of China from 2009 to 2018. Data source: WIND.

**Table 2.1: Composition of Outstanding Bonds in China**

This table presents the composition of outstanding bonds in China. Data source: WIND.

| Bond Type | | Shares |
|---|---|---|
| Government bonds | Treasury bonds | 17.4% |
| | Local government bonds | 21.1% |
| | Government-backed agency bonds | 1.9% |
| Financial bonds | Policy bank bonds | 16.8% |
| | Financial bonds excluding policy bank bonds | 6.9% |
| Corporate bonds | Enterprise bonds | 3.0% |
| | Exchange-traded corporate bonds | 6.8% |
| | Medium-term notes | 6.6% |
| | Commercial paper and super commercial paper | 2.3% |
| | ABS | 3.1% |
| | Private placements | 2.3% |
| Interbank negotiable certificates of deposits | Interbank negotiable certificates of deposits | 11.5% |
| Others | Others | 0.5% |

### Table 2.2: Bond Default in China

This table presents statistics of bond default in China from 2014 to 2018. Panel A reports the number of firm defaulted for the first time every year. Panel B reports the number of defaulted firm each year. Panel C reports the number and value of defaulted bond (billion CNY) each year. Panel D reports the industry distribution of defaulted firms. Data source: CSMAR and WIND.

| Panel A: number of newly defaulted firm | Total | SOE | Non-SOE | Listed | Non-listed |
|---|---|---|---|---|---|
| 2014 | 5 | 0 | 5 | 1 | 4 |
| 2015 | 24 | 4 | 20 | 3 | 21 |
| 2016 | 29 | 8 | 21 | 3 | 26 |
| 2017 | 10 | 0 | 10 | 3 | 7 |
| 2018 | 45 | 6 | 39 | 16 | 29 |
| Total | 113 | 18 | 95 | 26 | 87 |

| Panel B: number of defaulted firm | Total | SOE | Non-SOE | Listed | Non-listed |
|---|---|---|---|---|---|
| 2014 | 5 | 0 | 5 | 1 | 4 |
| 2015 | 24 | 4 | 20 | 3 | 21 |
| 2016 | 34 | 9 | 25 | 4 | 30 |
| 2017 | 19 | 2 | 17 | 5 | 14 |
| 2018 | 54 | 7 | 47 | 17 | 37 |
| Total | 136 | 22 | 114 | 30 | 106 |

| Panel C: number of defaulted bond | Total | SOE | Non-SOE | Listed | Non-listed | Defaulted Value |
|---|---|---|---|---|---|---|
| 2014 | 6 | 0 | 6 | 1 | 5 | 0.20 |
| 2015 | 28 | 5 | 23 | 3 | 25 | 6.21 |
| 2016 | 79 | 27 | 52 | 6 | 73 | 27.04 |
| 2017 | 45 | 6 | 39 | 7 | 38 | 19.59 |
| 2018 | 164 | 19 | 145 | 59 | 105 | 83.03 |
| Total | 322 | 57 | 265 | 76 | 246 | 136.07 |

Table 2.2 Continued

| Panel D: industry distribution of defaulted firm | | | |
|---|---|---|---|
| Industry | Number | Percentage | Fraction of A-Share Market |
| Agriculture | 3 | 2.65% | 1.56% |
| Mining | 7 | 6.19% | 2.42% |
| Manufacturing | 59 | 52.21% | 63.11% |
| Utility | 4 | 3.54% | 3.22% |
| Construction | 4 | 3.54% | 2.57% |
| Wholesale and Retail | 6 | 5.31% | 5.29% |
| Transport and Storage | 6 | 5.31% | 3.16% |
| Hotel and Restaurant | 1 | 0.88% | 0.40% |
| IT | 2 | 1.77% | 5.87% |
| Finance | 6 | 5.31% | 1.96% |
| Real Estate | 4 | 3.54% | 4.78% |
| Business Leasing and Service | 2 | 1.77% | 1.17% |
| Research Service | 0 | 0.00% | 0.78% |
| Environment | 1 | 0.88% | 0.98% |
| Residential Service | 0 | 0.00% | 0.11% |
| Education | 0 | 0.00% | 0.05% |
| Healthcare and Social Work | 0 | 0.00% | 0.17% |
| Cultural Industry | 0 | 0.00% | 1.16% |
| Comprehensive | 8 | 7.08% | 1.24% |
| Total | 113 | 100% | 100% |

## Table 2.3: Summary Statistics

Panel A reports summary statistics of variables used in this study. The sample includes all A-share firms in China from 2009 to 2018. Panel B compares the variable means of SOEs and non-SOEs in the sample. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Data source: CSMAR and WIND.

Panel A: full sample

| Variable | N | Mean | S.D. | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Debt ratio | 21300 | 0.164 | 0.142 | 0.038 | 0.143 | 0.255 |
| Bond issuance | 26131 | 0.015 | 0.038 | 0.000 | 0.000 | 0.000 |
| Bank loan | 14735 | 0.181 | 0.141 | 0.064 | 0.156 | 0.267 |
| Investment | 24099 | 0.381 | 0.664 | 0.085 | 0.191 | 0.394 |
| SOE | 26133 | 0.430 | 0.495 | 0.000 | 0.000 | 1.000 |
| Size | 26131 | 21.971 | 1.319 | 21.025 | 21.811 | 22.731 |
| Tangibility | 26070 | 0.953 | 0.053 | 0.942 | 0.967 | 0.984 |
| Cash flow | 24102 | 0.017 | 0.131 | -0.037 | 0.003 | 0.047 |
| ROE | 23899 | 0.064 | 0.140 | 0.028 | 0.071 | 0.122 |
| Growth | 24093 | 0.213 | 0.572 | -0.022 | 0.116 | 0.287 |
| Age | 26116 | 2.661 | 0.440 | 2.398 | 2.773 | 2.944 |
| Z score | 24929 | 6.138 | 6.636 | 2.533 | 4.018 | 6.915 |
| Tobin's q | 24947 | 2.584 | 1.491 | 1.772 | 2.110 | 2.807 |
| HHI | 26021 | 0.098 | 0.093 | 0.043 | 0.068 | 0.123 |
| Industry leverage | 25900 | 0.455 | 0.139 | 0.374 | 0.422 | 0.510 |

Panel B: SOEs vs. non-SOEs

| Variable | SOEs | non-SOEs | Difference |
|---|---|---|---|
| Debt ratio | 0.191 | 0.142 | 0.049*** |
| Bond issuance | 0.019 | 0.011 | 0.008*** |
| Bank loan | 0.209 | 0.161 | 0.048*** |
| Investment | 0.287 | 0.460 | -0.173*** |
| Size | 22.477 | 21.590 | 0.888*** |
| Tangibility | 0.951 | 0.955 | -0.004*** |
| Cash flow | 0.018 | 0.016 | 0.002 |
| ROE | 0.060 | 0.068 | -0.008*** |
| Growth | 0.174 | 0.246 | -0.072*** |
| Age | 2.765 | 2.584 | 0.182*** |
| Z score | 4.766 | 7.201 | -2.435*** |
| Tobin's q | 2.488 | 2.658 | -0.170*** |
| HHI | 0.108 | 0.090 | 0.019*** |
| Industry leverage | 0.486 | 0.431 | 0.055*** |

### Table 2.4: CAR of Industry Peers around Bond Defaults

This table reports cumulative abnormal return (CAR) of industry peers of defaulted firms around the announcement day of bond defaults. To obtain CAR, I first calculate the float value-weighted industry portfolio return using the daily stock return from 2013 to 2018. Then I estimate the following regression for each industry $j$ and for each bond default: $R_{j,t} = \beta_{1,j}MRP_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \epsilon_{j,t}$, where $R_{j,t}$ is the excess return of industry $j$ on day $t$, $MRP_t$, $SMB_t$, and $HML_t$ are market risk premium, size premium, and value premium, respectively. The estimation window is 250 days to 50 days before each bond default. If a industry has more than one bond defaults on the same day, I count the default day only once. The estimated coefficients $\hat{\beta}_{1,j}$, $\hat{\beta}_{2,j}$, and $\hat{\beta}_{3,j}$ are used to construct the abnormal return as $AR_{j,\tau} = R_{j,\tau} - (\hat{\beta}_{1,j}MRP_\tau + \hat{\beta}_{2,j}SMB_\tau + \hat{\beta}_{3,j}HML_\tau)$, where $\tau$ is equal to 0 on the bond default day. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{j,\tau}$, where $T$ is equal to 1, 3, 5, 7, 10, and 15 for different windows. I also calculate the daily return of SOE industry portfolio and non-SOE industry portfolio separately. Then I obtain the CAR of the two portfolios for each industry using the same method. I report the differences of CAR of SOE peers and non-SOEs and the statistical significance of the differences from t-tests. The sample in Panel A includes all bond defaults from 2014 to 2018. In Panel B, I divide all industries into high and low competition groups every year based on Herfindahl-Hirschman Index (HHI), which is equal to the sum of the squared market share of each firm in the industry, where market share is calculated as the sales of a firm to total sales of all firms in the industry. The industry is in high competition group if its HHI is lower than the median HHI of all industries. In Panel C, I divide all industries into high and low debt-dependent groups every year based on the industry leverage ratio, which is equal to the median leverage ratio of the industry. The industry is in high debt-dependent group if its leverage ratio is higher than the median leverage ratio of all industries. I report the differences of CAR of industry peers in high and low competition/debt-dependence and the statistical significance of the differences from t-tests. The sample in Panel D includes only SOE defaults. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and WIND.

| Panel A: full sample of all defaults | Industry Peers | SOE peers | non-SOE peers | Difference |
|---|---|---|---|---|
| 0 | 0.014 | 0.104 | -0.041 | 0.145 |
| | (0.059) | (0.065) | (0.085) | (0.107) |
| (-1, +1) | 0.015 | 0.017 | 0.004 | 0.013 |
| | (0.085) | (0.087) | (0.129) | (0.144) |
| (-1, +3) | -0.009 | 0.015 | -0.128$^{*}$ | 0.143$^{*}$ |
| | (0.095) | (0.099) | (0.073) | (0.081) |
| (-1, +5) | -0.035 | -0.003 | -0.232$^{**}$ | 0.230$^{**}$ |
| | (0.105) | (0.136) | (0.116) | (0.109) |
| (-1, +7) | -0.063 | 0.014 | -0.421$^{***}$ | 0.435$^{**}$ |
| | (0.126) | (0.139) | (0.161) | (0.212) |
| (-1, +10) | -0.106 | -0.010 | -0.358$^{**}$ | 0.348$^{*}$ |
| | (0.133) | (0.152) | (0.180) | (0.188) |
| (-1, +15) | 0.039 | 0.112 | -0.407$^{*}$ | 0.519$^{*}$ |
| | (0.182) | (0.206) | (0.232) | (0.310) |
| N | 319 | 317 | 309 | |

Table 2.4 Continued

Panel B: sub-sample of defaults in high and low competition industries

| | Industry peers | | | SOE peers | | | Non-SOE peers | | |
|---|---|---|---|---|---|---|---|---|---|
| | High | Low | Difference | High | Low | Difference | High | Low | Difference |
| 0 | -0.032 | 0.038 | -0.070 | 0.222 | 0.037 | 0.185 | -0.167 | 0.018 | -0.185 |
| | (0.148) | (0.047) | (0.128) | (0.153) | (0.059) | (0.139) | (0.212) | (0.066) | (0.177) |
| (-1, +1) | 0.069 | -0.014 | 0.083 | 0.151 | -0.068 | 0.219 | -0.002 | 0.020 | -0.022 |
| | (0.208) | (0.071) | (0.182) | (0.207) | (0.082) | (0.188) | (0.333) | (0.097) | (0.257) |
| (-1, +3) | -0.048 | 0.034 | -0.082 | 0.111 | -0.009 | 0.120 | -0.394* | 0.012 | -0.406* |
| | (0.234) | (0.080) | (0.203) | (0.271) | (0.093) | (0.235) | (0.227) | (0.122) | (0.222) |
| (-1, +5) | -0.164 | 0.088* | -0.252* | -0.050 | 0.051 | -0.101 | -0.620* | -0.012 | -0.608** |
| | (0.265) | (0.052) | (0.142) | (0.270) | (0.120) | (0.257) | (0.330) | (0.148) | (0.286) |
| (-1, +7) | -0.232 | 0.015 | -0.247* | 0.039 | 0.005 | 0.034 | -0.928*** | -0.181 | -0.746** |
| | (0.301) | (0.120) | (0.131) | (0.302) | (0.147) | (0.298) | (0.351) | (0.163) | (0.338) |
| (-1, +10) | -0.408 | 0.041 | -0.449** | -0.181 | 0.067 | -0.248* | -0.892** | -0.096 | -0.796** |
| | (0.296) | (0.130) | (0.211) | (0.310) | (0.166) | (0.140) | (0.399) | (0.176) | (0.375) |
| (-1, +15) | -0.640 | 0.361** | -1.002*** | -0.514 | 0.416** | -0.930** | -1.307** | 0.039 | -1.346*** |
| | (0.411) | (0.143) | (0.343) | (0.429) | (0.195) | (0.431) | (0.518) | (0.228) | (0.487) |
| N | 207 | 112 | | 207 | 110 | | 207 | 102 | |

Panel C: sub-sample of defaults in high and low debt-dependence industries

| | Industry peers | | | SOE peers | | | Non-SOE peers | | |
|---|---|---|---|---|---|---|---|---|---|
| | High | Low | Difference | High | Low | Difference | High | Low | Difference |
| 0 | 0.025 | 0.133 | -0.107 | 0.057 | 0.272* | -0.214* | -0.062 | 0.033 | -0.095 |
| | (0.117) | (0.109) | (0.165) | (0.115) | (0.156) | (0.116) | (0.150) | (0.143) | (0.211) |
| (-1, +1) | 0.026 | 0.087 | -0.061 | 0.034 | 0.070 | -0.036 | -0.127 | 0.012 | -0.147* |
| | (0.163) | (0.133) | (0.221) | (0.149) | (0.142) | (0.212) | (0.202) | (0.207) | (0.084) |
| (-1, +3) | 0.066 | 0.048 | 0.018 | 0.168 | 0.015 | 0.154 | -0.270* | -0.158 | -0.112 |
| | (0.182) | (0.164) | (0.251) | (0.180) | (0.202) | (0.272) | (0.150) | (0.215) | (0.334) |
| (-1, +5) | 0.065 | 0.128** | -0.063 | 0.193 | -0.096 | 0.289 | -0.432** | 0.034 | -0.466** |
| | (0.231) | (0.060) | (0.307) | (0.229) | (0.226) | (0.329) | (0.176) | (0.231) | (0.235) |
| (-1, +7) | -0.010 | 0.133* | -0.143* | 0.266 | -0.078 | 0.344 | -0.820*** | 0.015 | -0.835** |
| | (0.256) | (0.072) | (0.080) | (0.261) | (0.278) | (0.384) | (0.296) | (0.297) | (0.369) |
| (-1, +10) | -0.008 | 0.104 | -0.111 | 0.246 | 0.016 | 0.229 | -0.558* | -0.071 | -0.487* |
| | (0.258) | (0.252) | (0.362) | (0.267) | (0.329) | (0.419) | (0.289) | (0.319) | (0.284) |
| (-1, +15) | 0.337 | -0.006 | 0.343 | 0.203 | -0.157 | 0.360 | -0.514* | -0.134 | -0.380 |
| | (0.321) | (0.316) | (0.459) | (0.701) | (0.393) | (0.551) | (0.296) | (0.382) | (0.579) |
| N | 120 | 97 | | 120 | 90 | | 115 | 90 | |

Table 2.4 Continued

| Panel D: sub-sample of SOE defaults | Industry Peers | SOE peers | non-SOE peers | Difference |
|---|---|---|---|---|
| 0 | -0.156 | -0.096 | -0.150 | 0.177 |
| | (0.168) | (0.192) | (0.247) | (0.308) |
| (-1, +1) | -0.095 | -0.111 | 0.133 | -0.532 |
| | (0.217) | (0.250) | (0.399) | (0.460) |
| (-1, +3) | 0.130 | 0.133 | 0.651 | -0.795 |
| | (0.241) | (0.317) | (0.595) | (0.652) |
| (-1, +5) | 0.010 | -0.036 | 0.613 | -0.901 |
| | (0.270) | (0.324) | (0.675) | (0.721) |
| (-1, +7) | 0.125 | 0.179 | 0.122 | 0.072 |
| | (0.392) | (0.449) | (0.678) | (0.795) |
| (-1, +10) | 0.120 | 0.117 | 0.419 | -0.354 |
| | (0.412) | (0.481) | (0.726) | (0.853) |
| (-1, +15) | 0.586 | 0.628 | 0.506 | 0.101 |
| | (0.584) | (0.688) | (1.028) | (1.211) |
| N | 48 | 48 | 42 | |

### Table 2.5: Contagion Effect on Industry Peer's Debt Financing

This table reports the contagion effect of bond defaults on industry peers' debt financing using the following regression: $y_{i,t} = \alpha + \beta_1 Industry\ peer_i + \beta_2 Post_{i,t} + \beta_3 Industry\ peer_i \times Post_{i,t} + Controls_{i,t-1} + \omega + \gamma + \lambda + \epsilon_{it}$, where $y_{i,t}$ is the variable used to measure firm $i$'s s debt financing in year $t$, $Industry\ peer_i$ is defined as a dummy variable which is equal to 1 if firm $i$'s industry peers have bond default and 0 otherwise, $Post_{i,t}$ is a dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise, and $\omega$, $\gamma$, and $\lambda$ are industry, year, and area fixed effect. The full sample includes all A-share firms from 2009 to 2018. In Panel A, the debt financing is measured using debt ratio, which is defined as the sum of long- and short-term debt scaled by total assets. Beside the full sample, it also reports the sub-sample regression results of SOEs and non-SOEs. In Panel B, the debt financing is measured using bond issuance, which is defined as the bond issued scaled by total assets. In Panel C, the debt financing is measured using bank loans, which is defined as bank loans borrowed scaled by total assets. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and WIND.

| Panel A: debt ratio | Full sample<br>(1) | SOE sub-sample<br>(2) | Non-SOE sub-sample<br>(3) |
|---|---|---|---|
| *Industry peer* | 0.018 | 0.025 | 0.039 |
| | (0.016) | (0.021) | (0.024) |
| *Post* | 0.016*** | 0.010 | 0.025*** |
| | (0.006) | (0.008) | (0.008) |
| *Industry peer* × *Post* | -0.016*** | -0.008 | -0.027*** |
| | (0.006) | (0.008) | (0.008) |
| Size | 0.017*** | 0.013*** | 0.020*** |
| | (0.001) | (0.001) | (0.001) |
| Tangibility | -0.043** | -0.017 | -0.094*** |
| | (0.019) | (0.024) | (0.028) |
| Cash flow | -0.020*** | -0.052*** | -0.017** |
| | (0.007) | (0.014) | (0.007) |
| ROE | -0.158*** | -0.135*** | -0.136*** |
| | (0.008) | (0.010) | (0.012) |
| Growth | 0.008*** | 0.008*** | 0.006*** |
| | (0.002) | (0.003) | (0.002) |
| Age | 0.017*** | 0.022*** | 0.019*** |
| | (0.003) | (0.005) | (0.003) |
| Z score | -0.007*** | -0.012*** | -0.005*** |
| | (0.000) | (0.000) | (0.000) |
| Constant | -0.157*** | -0.055 | -0.216*** |
| | (0.030) | (0.043) | (0.046) |
| N | 16,193 | 8,004 | 8,189 |
| Adj. $R^2$ | 0.336 | 0.398 | 0.298 |

Table 2.5 Continued

| Panel B: bond issuance | Full sample<br>(1) | SOE sub-sample<br>(2) | Non-SOE sub-sample<br>(3) |
|---|---|---|---|
| *Industry peer* | 0.004 | -0.008 | -0.000 |
| | (0.005) | (0.005) | (0.006) |
| *Post* | -0.006*** | -0.007*** | -0.005** |
| | (0.002) | (0.002) | (0.002) |
| *Industry peer* × *Post* | 0.001 | 0.005** | 0.002 |
| | (0.002) | (0.002) | (0.002) |
| Size | 0.011*** | 0.006*** | 0.008*** |
| | (0.000) | (0.000) | (0.000) |
| Tangibility | -0.011* | -0.002 | -0.005 |
| | (0.006) | (0.006) | (0.007) |
| Cash flow | 0.003* | -0.014*** | -0.002 |
| | (0.002) | (0.004) | (0.002) |
| ROE | -0.005* | 0.008*** | 0.009*** |
| | (0.002) | (0.003) | (0.003) |
| Growth | -0.003*** | -0.001 | -0.001*** |
| | (0.000) | (0.001) | (0.000) |
| Age | -0.002** | 0.003** | -0.000 |
| | (0.001) | (0.001) | (0.001) |
| Z score | -0.000*** | -0.000 | -0.000** |
| | (0.000) | (0.000) | (0.000) |
| Constant | -0.213*** | -0.127*** | -0.149*** |
| | (0.009) | (0.011) | (0.011) |
| N | 19,634 | 9,221 | 10,413 |
| Adj. $R^2$ | 0.179 | 0.117 | 0.095 |

Table 2.5 Continued

| Panel C: bank loan | Full sample (1) | SOE sub-sample (2) | Non-SOE sub-sample (3) |
|---|---|---|---|
| *Industry peer* | 0.040* | 0.046* | 0.058* |
| | (0.021) | (0.027) | (0.034) |
| *Post* | 0.012 | 0.000 | 0.026* |
| | (0.009) | (0.013) | (0.013) |
| *Industry peer* × *Post* | -0.010** | 0.005 | -0.024** |
| | (0.004) | (0.013) | (0.011) |
| Size | 0.017*** | 0.012*** | 0.019*** |
| | (0.001) | (0.002) | (0.002) |
| Tangibility | -0.047** | -0.035 | -0.063* |
| | (0.023) | (0.030) | (0.033) |
| Cash flow | -0.025*** | -0.058*** | -0.018** |
| | (0.009) | (0.019) | (0.009) |
| ROE | -0.188*** | -0.185*** | -0.144*** |
| | (0.009) | (0.013) | (0.014) |
| Growth | 0.010*** | 0.010*** | 0.008*** |
| | (0.002) | (0.003) | (0.002) |
| Age | 0.014*** | 0.011* | 0.018*** |
| | (0.003) | (0.007) | (0.004) |
| Z score | -0.007*** | -0.012*** | -0.006*** |
| | (0.000) | (0.001) | (0.000) |
| Constant | -0.120*** | 0.007 | -0.197*** |
| | (0.037) | (0.054) | (0.055) |
| N | 12,546 | 5,678 | 6,868 |
| Adj. $R^2$ | 0.318 | 0.396 | 0.248 |

## Table 2.6: Contagion Effect on Industry Peer's Investment

This table reports the contagion effect of bond defaults on industry peers' investment using the following regression: $y_{i,t} = \alpha + \beta_1 Industry\ peer_i + \beta_2 Post_{i,t} + \beta_3 Industry\ peer_i \times Post_{i,t} + Controls_{i,t-1} + \omega + \gamma + \lambda + \epsilon_{it}$, where $y_{i,t}$ is the variable used to measure firm $i$'s s investment in year $t$, $Industry\ peer_i$ is defined as a dummy variable which is equal to 1 if firm $i$'s industry peers have bond default and 0 otherwise, $Post_{i,t}$ is a dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise, and $\omega$, $\gamma$, and $\lambda$ are industry, year, and area fixed effect. The full sample includes all A-share firms from 2009 to 2018. Investment is measured using firm's capital expenditures scaled by lagged property, plant, and equipment (PPE). Beside the full sample, it also reports the sub-sample regression results of SOEs and non-SOEs. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and WIND.

| | Full sample<br>(1) | SOE sub-sample<br>(2) | Non-SOE sub-sample<br>(3) |
|---|---|---|---|
| *Industry peer* | 0.197*** | 0.083 | 0.358** |
| | (0.073) | (0.070) | (0.143) |
| *Post* | -0.001 | 0.015 | 0.007 |
| | (0.028) | (0.028) | (0.051) |
| *Industry peer* × *Post* | -0.060** | -0.026 | -0.111** |
| | (0.027) | (0.027) | (0.049) |
| Size | -0.020*** | 0.001 | -0.032*** |
| | (0.004) | (0.004) | (0.009) |
| Tangibility | -0.437*** | -0.614*** | -0.219 |
| | (0.087) | (0.082) | (0.171) |
| Cash flow | 0.328*** | 0.321*** | 0.349*** |
| | (0.031) | (0.047) | (0.041) |
| ROE | 0.438*** | 0.280*** | 0.638*** |
| | (0.036) | (0.033) | (0.071) |
| Growth | 0.016** | 0.002 | 0.008 |
| | (0.007) | (0.009) | (0.011) |
| Age | -0.095*** | -0.089*** | -0.067*** |
| | (0.012) | (0.016) | (0.019) |
| Tobin's q | 0.022*** | 0.020*** | 0.032*** |
| | (0.003) | (0.004) | (0.005) |
| Constant | 1.205*** | 0.899*** | 1.201*** |
| | (0.142) | (0.147) | (0.277) |
| N | 19,620 | 9,217 | 10,403 |
| Adj. $R^2$ | 0.090 | 0.112 | 0.087 |

## Table 2.7: Contagion Effect in Different Industries

This table compares the contagion effect of bond defaults on industry peers' debt financing and investment in different industries using the following regression model: $y_{i,t} = \alpha + \beta_1 Industry\ peer_i + \beta_2 Post_{i,t} + \beta_3 Industry\ peer_i \times Post_{i,t} + Controls_{i,t-1} + \omega + \gamma + \lambda + \epsilon_{it}$, where $y_{i,t}$ is the variable used to measure firm $i$'s s debt financing or investment in year $t$, $Industry\ peer_i$ is defined as a dummy variable which is equal to 1 if firm $i$'s industry peers have bond default and 0 otherwise, $Post_{i,t}$ is a dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise, and $\omega$, $\gamma$, and $\lambda$ are industry, year, and area fixed effect. The sample includes all A-share firms from 2009 to 2018. Panel A compares high competition industries and low competition industries by dividing the sample into high and low industry competition sub-samples. Specifically, I divide all industries into high and low competition groups every year based on Herfindahl-Hirschman Index (HHI), which is equal to the sum of the squared market share of each firm in the industry, where market share is calculated as the sales of a firm to total sales of all firms in the industry. The industry is in high competition group if its HHI is lower than the median HHI of all industries. Debt financing is measured using three different variables. The first one is debt ratio, which is defined as the sum of long- and short-term debt scaled by total assets. The second one is bond issuance, which is defined as the bond issued scaled by total assets. The third one is bank loans, which is defined as bank loans borrowed scaled by total assets. Investment is measured using firm's capital expenditures scaled by lagged property, plant, and equipment (PPE). Panel B compares high debt-dependent industries and low debt-dependent industries by dividing the sample into high and low industry debt-dependence sub-samples. Specifically, I divide all industries into high and low debt-dependent groups every year based on the industry leverage ratio, which is equal to the median leverage ratio of the industry. The industry is in high debt-dependent group if its leverage ratio is higher than the median leverage ratio of all industries. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and WIND.

Table 2.7 Continued

| Panel A: high and low competition industries | Debt ratio | | Bond issuance | | Bank loan | | Investment | |
|---|---|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Industry peer* | -0.041 | 0.047* | 0.005 | -0.005 | 0.004 | 0.053* | 0.375** | 0.528*** |
| | (0.042) | (0.024) | (0.010) | (0.007) | (0.039) | (0.029) | (0.161) | (0.101) |
| *Post* | 0.017** | 0.013 | -0.004* | -0.006 | 0.020* | -0.019 | 0.009 | -0.042 |
| | (0.007) | (0.012) | (0.002) | (0.004) | (0.011) | (0.021) | (0.033) | (0.059) |
| *Industry peer* $\times$ *Post* | -0.014** | -0.021 | -0.002 | 0.007 | -0.015** | 0.011 | -0.079** | -0.012 |
| | (0.006) | (0.015) | (0.002) | (0.005) | (0.006) | (0.020) | (0.032) | (0.057) |
| Size | 0.019*** | 0.011*** | 0.011*** | 0.009*** | 0.020*** | 0.005** | -0.015*** | -0.035*** |
| | (0.001) | (0.002) | (0.000) | (0.001) | (0.001) | (0.003) | (0.005) | (0.010) |
| Tangibility | -0.052** | 0.009 | -0.007 | -0.028* | -0.059** | 0.006 | -0.617*** | 0.276 |
| | (0.021) | (0.046) | (0.006) | (0.015) | (0.025) | (0.056) | (0.096) | (0.209) |
| Cash flow | -0.021*** | -0.015 | 0.004** | -0.002 | -0.022** | -0.045** | 0.353*** | 0.195** |
| | (0.008) | (0.017) | (0.002) | (0.005) | (0.009) | (0.022) | (0.034) | (0.077) |
| ROE | -0.162*** | -0.128*** | -0.005* | -0.000 | -0.194*** | -0.151*** | 0.423*** | 0.475*** |
| | (0.009) | (0.019) | (0.003) | (0.006) | (0.010) | (0.023) | (0.040) | (0.084) |
| Growth | 0.008*** | 0.008** | -0.003*** | -0.002* | 0.010*** | 0.010** | 0.021** | -0.002 |
| | (0.002) | (0.004) | (0.001) | (0.001) | (0.002) | (0.004) | (0.008) | (0.016) |
| Age | 0.016*** | 0.021*** | -0.003*** | 0.002 | 0.013*** | 0.013 | -0.117*** | -0.001 |
| | (0.003) | (0.007) | (0.001) | (0.002) | (0.004) | (0.008) | (0.013) | (0.031) |
| Z score | -0.007*** | -0.007*** | -0.000*** | -0.000** | -0.007*** | -0.007*** | 0.023*** | 0.022*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.004) | (0.008) |
| Constant | -0.124** | -0.101 | -0.220*** | -0.168*** | -0.127** | 0.080 | 1.175*** | 0.590* |
| | (0.051) | (0.071) | (0.013) | (0.023) | (0.051) | (0.087) | (0.209) | (0.329) |
| N | 13,416 | 2,777 | 16,346 | 3,288 | 10,419 | 2,127 | 16,332 | 3,288 |
| Adj. $R^2$ | 0.348 | 0.295 | 0.177 | 0.215 | 0.331 | 0.273 | 0.093 | 0.106 |

Table 2.7 Continued

| Panel B: high and low debt-dependence industries | Debt ratio | | Bond issuance | | Bank loan | | Investment | |
|---|---|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Industry peer* | -0.078*** | -0.034* | 0.012 | -0.001 | -0.134*** | 0.006 | 0.138 | 0.485*** |
| | (0.027) | (0.020) | (0.009) | (0.006) | (0.036) | (0.028) | (0.129) | (0.100) |
| *Post* | 0.022** | 0.006 | -0.011*** | 0.001 | 0.024 | 0.004 | -0.052 | 0.061 |
| | (0.010) | (0.008) | (0.003) | (0.002) | (0.016) | (0.013) | (0.048) | (0.040) |
| *Industry peer* × *Post* | -0.019** | -0.011 | 0.003 | -0.002 | -0.014* | -0.006 | -0.083** | 0.008 |
| | (0.008) | (0.008) | (0.004) | (0.002) | (0.007) | (0.013) | (0.036) | (0.050) |
| Size | 0.018*** | 0.015*** | 0.011*** | 0.011*** | 0.017*** | 0.015*** | -0.002 | -0.031*** |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.002) | (0.001) | (0.006) | (0.006) |
| Tangibility | -0.047* | -0.025 | 0.002 | -0.027*** | -0.049 | -0.023 | -0.351*** | -0.479*** |
| | (0.026) | (0.027) | (0.009) | (0.008) | (0.032) | (0.032) | (0.120) | (0.130) |
| Cash flow | -0.026** | -0.018** | 0.002 | 0.004* | -0.042*** | -0.014 | 0.235*** | 0.379*** |
| | (0.012) | (0.008) | (0.004) | (0.002) | (0.015) | (0.010) | (0.053) | (0.038) |
| ROE | -0.164*** | -0.153*** | -0.004 | -0.006* | -0.170*** | -0.199*** | 0.426*** | 0.463*** |
| | (0.012) | (0.011) | (0.004) | (0.003) | (0.014) | (0.012) | (0.052) | (0.050) |
| Growth | 0.009*** | 0.006*** | -0.003*** | -0.002*** | 0.011*** | 0.008*** | 0.015 | 0.022** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.003) | (0.003) | (0.010) | (0.011) |
| Age | 0.022*** | 0.014*** | -0.003** | -0.000 | 0.023*** | 0.009** | -0.080*** | -0.109*** |
| | (0.004) | (0.003) | (0.001) | (0.001) | (0.005) | (0.004) | (0.019) | (0.016) |
| Z score | -0.008*** | -0.006*** | -0.000* | -0.000*** | -0.010*** | -0.006*** | 0.042*** | 0.012*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.006) | (0.004) |
| Constant | -0.078* | -0.124*** | -0.236*** | -0.197*** | 0.055 | -0.079* | 0.714*** | 1.580*** |
| | (0.047) | (0.040) | (0.016) | (0.011) | (0.061) | (0.048) | (0.226) | (0.192) |
| N | 7,948 | 8,186 | 9,016 | 10,557 | 5,777 | 6,747 | 9,009 | 10,550 |
| Adj. $R^2$ | 0.318 | 0.297 | 0.191 | 0.137 | 0.297 | 0.251 | 0.071 | 0.114 |

### Table 2.8: CAR of Industry Peers around Distress Date

This table reports cumulative abnormal return (CAR) of industry peers of defaulted firms around the distress date. In the spirit of Hertzel et al. (2008), I use the date when the defaulted firm has the most significant Fama-French three factor adjusted drop in stock price during the two years leading up to the default announcement as the distress date. To obtain CAR, I first calculate the float value-weighted industry portfolio return using the daily stock return from 2013 to 2018. Then I estimate the following regression for each industry $j$ and for each distress date: $R_{j,t} = \beta_{1,j}MRP_t + \beta_{2,j}SMB_t + \beta_{3,j}HML_t + \epsilon_{j,t}$, where $R_{j,t}$ is the excess return of industry $j$ on day $t$, $MRP_t$, $SMB_t$, and $HML_t$ are market risk premium, size premium, and value premium, respectively. The estimation window is 250 days to 50 days before each distress date. The estimated coefficients $\hat{\beta}_{1,j}$, $\hat{\beta}_{2,j}$, and $\hat{\beta}_{3,j}$ are used to construct the abnormal return as $AR_{j,\tau} = R_{j,\tau} - (\hat{\beta}_{1,j}MRP_\tau + \hat{\beta}_{2,j}SMB_\tau + \hat{\beta}_{3,j}HML_\tau)$, where $\tau$ is equal to 0 on the distress day. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{j,\tau}$, where $T$ is equal to 1, 3, 5, 7, 10, and 15 for different windows. I also calculate the daily return of SOE industry portfolio and non-SOE industry portfolio separately. Then I obtain the CAR of the two portfolios for each industry using the same method. I report the differences of CAR of SOE peers and non-SOEs and the statistical significance of the differences from t-tests. The sample includes all bond defaults of A-share listed firms from 2014 to 2018. It does not include defaults of non-listed firms as the distress date of non-listed firms cannot be identified based on stock market return. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and WIND.

| | Industry Peers | SOE peers | Non-SOE peers | Difference |
|---|---|---|---|---|
| 0 | -0.532 | -0.237 | -1.433* | 1.196* |
| | (0.358) | (0.230) | (0.806) | (0.678) |
| (-1, +1) | -0.084 | 0.401 | -2.427* | 2.828* |
| | (0.426) | (0.398) | (1.395) | (1.610) |
| (-1, +3) | -0.571 | 0.053 | -2.454 | 2.507 |
| | (0.586) | (0.372) | (1.472) | (1.533) |
| (-1, +5) | -0.806 | -0.031 | -2.995** | 2.964* |
| | (0.773) | (0.473) | (1.351) | (1.523) |
| (-1, +7) | -0.451 | 0.374 | -2.974* | 3.348** |
| | (0.825) | (0.657) | (1.556) | (1.555) |
| (-1, +10) | 0.058 | 1.326 | -2.843** | 4.169** |
| | (0.534) | (0.823) | (1.246) | (1.700) |
| (-1, +15) | -0.346 | 1.263 | -3.833* | 5.096** |
| | (0.627) | (0.930) | (2.102) | (2.298) |
| N | 20 | 20 | 20 | |

## Table 2.9: Contagion Effect Excluding Industry Downturn

This table reports the contagion effect of bond defaults on industry peers' debt financing and investment using the following regression: $y_{i,t} = \alpha + \beta_1 Industry\ peer_i + \beta_2 Post_{i,t} + \beta_3 Industry\ peer_i \times Post_{i,t} + Controls_{i,t-1} + \omega + \gamma + \lambda + \epsilon_{it}$, where $y_{i,t}$ is the variable used to measure firm $i$'s s debt financing or investment in year $t$, $Industry\ peer_i$ is defined as a dummy variable which is equal to 1 if firm $i$'s industry peers have bond default and 0 otherwise, $Post_{i,t}$ is a dummy variable which is equal to 1 after the first bond default in the industry and 0 otherwise, and $\omega$, $\gamma$, and $\lambda$ are industry, year, and area fixed effect. The sample includes all A-share firms from 2009 to 2018 excluding industries that have industry downturn during this period. In the spirit of Opler and Titman (1994), an industry is in downturn when its median sales growth is negative in the year and it experiences median stock returns below 0. Debt financing is measured using three different variables. The first one is debt ratio, which is defined as the sum of long- and short-term debt scaled by total assets. The second one is bond issuance, which is defined as the bond issued scaled by total assets. The third one is bank loans, which is defined as bank loans borrowed scaled by total assets. Investment is measured using firm's capital expenditures scaled by lagged property, plant, and equipment (PPE). All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and WIND.

| | Debt ratio (1) | Bond issuance (2) | Bank loan (3) | Investment (4) |
|---|---|---|---|---|
| *Industry peer* | 0.138*** | -0.004 | 0.109*** | -0.341*** |
| | (0.026) | (0.008) | (0.031) | (0.120) |
| *Post* | 0.024*** | -0.005** | 0.025** | -0.023 |
| | (0.007) | (0.002) | (0.012) | (0.035) |
| *Industry peer* × *Post* | -0.024*** | -0.000 | -0.024** | -0.033** |
| | (0.007) | (0.002) | (0.011) | (0.015) |
| Size | 0.019*** | 0.011*** | 0.018*** | -0.016*** |
| | (0.001) | (0.000) | (0.001) | (0.005) |
| Tangibility | -0.034 | -0.010 | -0.034 | -0.532*** |
| | (0.021) | (0.006) | (0.025) | (0.098) |
| Cash flow | -0.019** | 0.003 | -0.023** | 0.323*** |
| | (0.007) | (0.002) | (0.009) | (0.034) |
| ROE | -0.163*** | -0.003 | -0.194*** | 0.481*** |
| | (0.009) | (0.003) | (0.011) | (0.041) |
| Growth | 0.008*** | -0.003*** | 0.011*** | 0.011 |
| | (0.002) | (0.001) | (0.002) | (0.008) |
| Age | 0.016*** | -0.002** | 0.014*** | -0.102*** |
| | (0.003) | (0.001) | (0.004) | (0.013) |
| Z score | -0.007*** | -0.000*** | -0.007*** | |
| | (0.000) | (0.000) | (0.000) | |
| Tobin's q | | | | 0.024*** |
| | | | | (0.004) |
| Constant | -0.246*** | -0.223*** | -0.188*** | 1.622*** |
| | (0.037) | (0.011) | (0.046) | (0.176) |
| N | 13,571 | 16,460 | 10,593 | 16,449 |
| Adj. $R^2$ | 0.336 | 0.178 | 0.320 | 0.088 |

# Chapter 3

# Value of Politically Connected Independent Directors: Evidence from the Anti-Corruption Campaign in China

## 3.1 Introduction

Political connections are widely considered as valuable resources to firms, especially in emerging markets. For example, politically connected firms can have more access to financing, preferential regulatory treatment, and lower tax rate that increase firm value. However, political connections may also destroy firm value because connected firms can have worse corporate governance and lower operating efficiency. Moreover, they may also have higher political risk and thus higher required rate of return from investors. Therefore, studies have shown evidence supporting both the "helping hand theory" and "grabbing hand theory" of political connections. Although the literature is large, most previous studies focus on connections from blockholders and executives instead of independent directors. However, it was prevalent for Chinese firms to appoint politicians as independent directors to build political connections. Appointing politically connected independent director (PCID) may help firms to build connections and thus increase firm value, but it can also distort the original role that independent directors should play and thus destroy firm value. Therefore, this study tries to extend existing research by focusing on PCIDs and shed more light on the overall effect of political connections.

In early 2013, the Chinese government started a massive anti-corruption campaign after President Xi Jinping came to power. During this campaign, a new regulation known as Regulation No.18 was issued by the Organization Department of the Communist Party of China (CPC) Central Committee on October 19, 2013. The new regulation prohibits all levels of government officials, who are currently in an official position or retried within 3 years, from taking any part-time position in firms and getting any kind of payment from firms. Many government officials had to resign from firms because of the regulation. Independent director is the largest group affected by this regulation given the prevalence of Chinese firms offering these positions to officials. Since officials are not required to resign immediately, we witnessed a wave of resignation of PCIDs in the following two years. Using this regulation as a shock, I examine the effect of losing PCIDs on Chinese listed firms in this study.

One may expect firms with PCIDs decrease in firm value after the release of Regulation No.18, because they may lose various benefits from political connections, which leads to worse operating performance or less future cash flows (cash flow explanation). However, since PCIDs do not necessarily resign right after the release of the regulation, firms with PCIDs may have higher political risk than other firms before their PCIDs actually leave, leading to higher required rate of return by investors and thus decrease in firm value (political risk explanation). To explore these two explanations, I test the value effect when firms announce the actual resignation of their PCIDs. If the cash flow explanation holds, firm value should not change around announcement of PCID resignation as the loss of benefits from political connection is already expected when Regulation No.18 is released. Moreover, firms should have worse operating performance after losing PCIDs. On the contrary, if the political risk explanation holds, firms should gain in firm value around PCID resignation because of lower political risk after announcing the actual leave of PCIDs.

In order to identify PCIDs, I first collect the resignation reports of all resigning independent directors during the period of January 2013 to May 2017. Then I use the most popular definition of political official in the literature to identify PCID: directors who are current or former (1) government officials, (2) leaders of the People's Congress, or (3) leaders of the People's Consultative Conference. My sample includes 418 treated firms that have PCID resignations and 418 controlled firms matched with the treatment group using propensity score matching. The sample period is from 2011 to 2016. I have three event dates (year) during the period. The first one is the issuance date of Regulation No.18. The second one is the announcement date of PCID resignation, which is different across firms. Since the resignation of an independent director cannot take effect if the fraction of independent directors is less than one third until the firm appoints a new director, the third one is the actual leaving date of the resigning PCID.

This study has three main findings. First, the treatment group has significantly negative cumulative abnormal return (CAR) around release of Regulation No.18, especially in the longer event windows. This is consistent with the hypothesis that firms with PCIDs decrease in firm value because of the new regulation. Second, treated firms have large and significantly positive CAR around announcement of PCID resignations, providing support to the political risk explanation. However, the cross-sectional regression on CAR shows that the value effect is only significant for non-SOEs but not for SOEs. Third, using a difference-in-difference (DID) regression model, I find that firm's operating performance does not change after their PCIDs resign. This suggests that political connections built by PCIDs may not be helpful for firm performance in China and casts doubt on the "helping hand" theory of political connections. On the contrary, political risk decreases significantly after PCIDs resign, providing further support to the political risk explanation. The subsample analysis shows that while non-SOEs decrease significantly in firm risk, SOEs' firm risk does not change. This is consistent with results from CAR analysis. One possible explanation for the different results is that SOEs have more other political connections than non-SOEs because of their special relationship with the government. Even their PCIDs leave, they still have other connections and thus the same political risk.

This study is related to three strands of literature. First, previous studies have investigated the effect of political connections on firms. On the one hand, some studies find that political connected firms have easier access to debt financing (Khwaja and Mian, 2005; Sapienza, 2004) and equity financing (Claessens et al., 2008), preferential regulatory treatment (Faccio, 2006; Johnson and Mitton, 2003), and lower tax rates (Faccio, 2010). Therefore, political connections improve firm performance and firm value (Fisman, 2001; Goldman, Rocholl, and So, 2008). On the other hand, some studies also show that connected firms are associated with worse corporate governance (Cao, Pan, Qian, and Tian, 2017; Fan, Wong, and Zhang, 2007; Wang, 2015). The recent study of Akcigit, Baslandze, and Lotti (2018) find that although politically connected firms have a higher rate of survival, as well as growth in employment and revenue, they are much less likely to innovate and have lower productivity. Several studies also find that while political connections are valuable to firms, the rent-seeking behavior distorts the allocation of economic resources and therefore brings about costs to the society overall (Claessens et al., 2008; Khwaja and Mian, 2005). In general, evidence on the overall effect of political connections is still mixing. While the literature is large, most of them focus on connections from blockholders and executives instead of independent directors. My study extends existing literature by testing the effect of independent directors, who may play different roles from the top insiders. By exploiting an exogenous shock, my study provides more comprehensive evidence on the effect of political connections and cast doubt on the "helping hand" theory. I also show that the effect of losing PCIDs is different for SOEs and non-SOEs, suggesting that the effect of political connections is contingent on firm's ownership structure.

Second, recent studies have investigated the effect of political risk on asset prices. The theoretical work of Pástor and Veronesi (2013) predicts that political uncertainty commands a risk premium whose magnitude is larger in weaker economic conditions. The recent empirical studies also find evidence consistent with this prediction. For example, using the Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2016), Brogaard and Detzel (2015) find that EPU positively forecasts log excess market returns. However, as argued in Liu et al. (2017b), most existing studies are unable to rule out the issue of endogeneity and isolate political uncertainty from economic uncertainty. To address this issue, Liu et al. (2017b) use the Bo scandal in China as an exogenous shock and finds that firms connected with Bo suffer decrease in firm value after the scandal. This study also exploits a clean exogenous shock and provide strong support for the existence of priced political risk in China. Consistent with Liu et al. (2017b), I find that firm value decreases around release of the regulation when political risk increases. Moreover, I also show that stock price increases when political risk decreases around the actual resignation of PCIDs.

Third, this study relates to the increasing literature on China's anti-corruption campaign.

For example, Ding, Fang, Lin, and Shi (2017) use the inspection of provincial government as the event to examine the consequences of corruption on firms. Lin, Morck, Yeung, and Zhao (2016) and Griffin, Liu, and Shu (2018) also examine consequences of the anti-corruption campaign on firms. Different from them, I use Regulation No.18, a specific regulation during the campaign, to test the value effect of political connections. Although Liu, Lin, and Wu (2018b) also use Regulation No.18 to test the value effect of political connections, they only focus on the value effect around release of the regulation and do not explore the potential mechanisms. Instead, they take it for granted that firms with PCIDs decrease in firm value after the release of Regulation No.18 because they are expected to lose benefits from political connections. Therefore, they conclude political connections add value to Chinese firms. However, my results suggest that the negative CAR is because of higher political risk instead of loss of benefits, casting doubt on the value of PCIDs in China. The recent work of Hu, Karim, Lin, and Tan (2019) also investigate the effect of PCID resignations using Regulation No.18, but they only provide very limited analysis on the value effect and their sample size is much smaller. Moreover, while they mainly focus on the change of debt financing, government subsidy, and corporate governance after the loss of PCIDs, they do not consider the change of political risk, which is the focus of this study.

The rest of this paper is organized as follows. Section 2 introduces Chinese institutional background and develops my hypotheses. Section 3 describes the data and variables. Section 4 presents empirical results and Section 5 concludes.

## 3.2 Institutional Background and Hypotheses

First introduced in 1990 with only eight firms listed, China's stock market has become the second largest in the world by 2012. 3052 companies are listed in Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) with market capitalization of about 50 trillion CNY (7.4 trillion USD) as of 2016.[1] However, corporate governance in Chinese listed firms has always been a looming issue because of the weak institute and underdeveloped legal system. In order to improve corporate governance, on August 16, 2001, China Securities Regulatory Commission (CSRC) issued the *Guideline for the Establishment of the Independent Director System in Listed Firms* (Guideline). The Guideline requires that all firms listed on Chinese stock exchanges should have at least one third of board members as independent directors by June 30, 2003. As in Clarke (2006), the independent director system in China was meant to be a "legal transplant" from the U.S. corporate governance law and practice, but the definition of "independence" is even stricter. A director affiliated with or representing a non-insider block holder who holds more than 1% of shares outstanding is not considered independent in China, while the common ownership threshold for insider classification is 10% in the United States (Jiang, Wan, and Zhao, 2015).

Although the definition of independence is stricter, monitoring from independent directors can be weak in China. One of the reasons is that many of them are government officials instead of industry experts. Studies have shown that although appointing PCID may bring

[1]Source: The Annual Report of the CSRC.

valuable political resources to firms, it may also distort the original role that independent directors should play in firm's governance. Some Chinese SOEs appoint politicians as independent directors in order to occupy more board seats and achieve political and social objectives (Wang, 2015). For non-SOEs, building good relationship with the government is even more important as the government has large control over resources and Chinese culture values interpersonal connections in business (or *Guanxi* in Chinese). Appointing PCIDs is an easy way to build such a relationship with the government. As a result, appointing PCID was prevalent in Chinese listed firms.

However, this situation has changed from 2013. In early 2013, the Chinese government started a massive anti-corruption campaign after President Xi Jinping came to power. During this campaign, the Organization Department of the CPC Central Committee issued a new regulation known as Regulation No.18 on October 19, 2013.[2] This regulation prohibits all levels of government officials, who are currently in an official position or retried within 3 years, from taking any part-time position in firms and getting any kind of payment from firms. One feature of the new regulation is that it applies to all officials: officials of local and central government, leaders of the CPC, leaders of People's Congress or People's Consultative Conference, leaders of main SOEs, and leaders of main public universities and hospitals. Independent director is the largest group affected by this regulation. Most PCIDs resigned after the release of this regulation. However, since this regulation gives some time for government officials to resign in order to maintain the normal operation of boards, we witnessed a wave of independent director resignations over the next two years. According to the Guideline of CSRC, all listed firms must have at least one third board members as independent. Therefore, the resignation of an independent director cannot take effect if the fraction of independent directors is less than one third until the firm appoints a new director in a shareholder meeting. Some PCID stayed in the board after announcing resignation until they are replaced by a new independent director.

Regulation No.18 is an exogenous shock to the market because it is difficult to anticipate the release of such a regulation. Even though firms could anticipate that their political connections could be affected by the anti-corruption campaign, it is unlikely for them to know to what extent officials would be regulated or the exact time of a new regulation. Moreover, this regulation applies to officials who resigned or retired from the government within 3 years, which means officials could not choose to leave the government and stay in firms. Therefore, some firms unexpectedly lost political connections, especially some privately controlled firms.

One would expect firms with PCIDs decrease in value after release of Regulation No.18 for two different reasons. First, previous studies find that political connections can bring various benefits, especially in China where government has large control over resources. After the release of the new regulation, some firms are expected to lose such valuable connections and thus benefits when PCIDs resign (cash flow explanation). Second, since government officials do not necessarily resign immediately, firms may have higher political risk before the actual leave of PCIDs, especially during the anti-corruption campaign when connected firms are more likely

[2] See Organization Department of the CPC Central Committee, *Guanyu jinyibu guifan dangzheng lingdao ganbu zai qiye jianzhi (renzhi) wenti de yijian (Guidance on the Regulation of Party and Government Leaders Taking Office in Companies)*, issued on October 19, 2013. The original document is available on http://hdtz.buct.edu.cn/docs/20141103161920781696.pdf.

to be investigated by the government (Griffin et al., 2018), which leads to decrease in firm value (political risk explanation). Therefore, I postulate the following:

**Hypothesis 1**: Firms with PCIDs decrease in firm value following the release of Regulation No.18.

To further explore the two explanations, I test the value effect when firms announce the actual resignation of their PCIDs. If the cash flow explanation holds, firm value should not change around announcement of PCID resignation since the loss of PCID is already expected when Regulation No.18 is released. Moreover, firms should have worse operating performance as a result of losing political connections. Therefore, according to the cash flow explanation, I postulate the following:

**Hypothesis 2a**: Firm value does not change around the announcement of PCID resignation.

**Hypothesis 2b**: Firms have worse operating performance after replacing PCIDs.

However, if the political risk explanation holds, firm value should increase around announcement of PCID resignation, because firms have lower political risk after announcing the actual leave of PCIDs and complying with the regulation. Therefore, according to the political risk explanation, I postulate the following:

**Hypothesis 3a**: Firms value increases around the announcement of PCID resignation.

**Hypothesis 3b**: Firms have lower risk after replacing PCIDs.

## 3.3 Data and Variables

### 3.3.1 Data Sources and Identification Strategy

CSRC requires listed firms to make public announcements for all firm-related major issues, including independent director resignations. In order to identify resigning PCIDs, I first collect the resignation reports of all resigning independent directors during the period of January 2013 to May 2017 from the official website of SSE (www.sse.com.cn) and SZSE (www.szse.cn). A resignation report normally states which director resigns, why the director resigns and when the resignation is effective. Based on the resignation reports, I identify 2342 independent directors resigning from 1477 firms, in which 2217 independent directors from 1433 firms resign after the release of Regulation No.18. Then I use the most popular definition of political official in the literature to identify PCID: directors who are current or former (1) government officials, (2) leaders of the People's Congress, or (3) leaders of the People's Consultative Conference (Chen, Li, Su, and Sun, 2011; Fan et al., 2007; Li, Meng, Wang, and Zhou, 2008). I do not include leaders of main SOEs, public universities and hospitals although they are also affected by the new regulation, as their political connections can be limited and firms appoint them mainly for their industry or academic expertise. Using this method, I identify 741 PCIDs resigning from 562 firms. Then I exclude financial firms as their financial statements are complied under different standards. Since I use 2010 as the matching year for propensity score matching, I also exclude firms listed after 2010. Finally, I am left with 418 firms that comprise my treatment group. The sample period is from 2011 to 2016 for the empirical analysis. The firm-level data are from CSMAR database maintained by GTA Information Technology Company Ltd. The background information of independent directors are collected from firm's annual reports. Last, I collect release dates of 55 regulatory documents of CSRC issued during 2011 to 2016 from the official website (www.csrc.gov.cn) to construct the policy risk measure.

Figure 1 plots the number of independent director resignations during January 2013 to May 2017. The solid line shows that the total number of independent director resignations increase dramatically after the release of Regulation No.18 and goes back to normal level from the beginning of 2016. At the end of 2014 and 2015, there are two peaks when more than 200 independent directors resign within a month. This is probably because they tend to resign in the end of the financial year in order to take full compensation. The dashed line shows that the first resignation of PCID takes place in January 2014 and the last one in June 2016. The distribution of PCID resignations shows the same pattern as that of independent director resignation. Figure 2 plots the actual leaving dates of the resigning PCIDs following the release of Regulation No.18. The first effective resignation takes place in January 2014. Since many Chinese listed firms hold their annual shareholder meetings in April and May, we witness three peaks of effective PCID resignation around May 2014, 2015, and 2016.

To perform the event study, I have three event dates (year) during the sample period. The first one is the release date of Regulation No.18. Since the regulation is issued on Saturday, I use the following Monday (October 21, 2013) as the event date. The second one is the announcement date of PCID resignation, which is different across firms. I use this event date to examine the value effect of PCID resignation. Third, since some of the resignations cannot take effect if the fraction of independent director is less than one third until a new director is appointed in a shareholder meeting, I use the effective date of the resignation as the actual leaving date of the PCID. Since listed firms are also required to make public announcements after each shareholder meeting, it is possible to identify the appointing date of the new director or the actual leaving date of the resigning director. I use this event date to test the change of operating performance and firm risk. For firms that have more than one independent director resignation, I use the date when the firm loses its first PCID as the event date.

### 3.3.2 Variables

I calculate CAR around the event dates to measure the value effect of Regulation No.18 and PCID resignation. Following the literature, I use return on equity (ROE) and cash flow from operation (CFO) to measure firm's operating performance. I also use operating profit to total assets (OPOA) and total cash flow (CF) in the robustness tests. As shown in previous studies, it is difficult to measure firm's political risk and isolate political risk from firm's overall risk. Therefore, following Liu et al. (2017b), I use stock return volatility to measure firm risk. If firm's political risk change, the overall risk measured by volatility should also change. Volatility is defined as the annual standard deviation of daily stock return multiplied by 100. I also construct a political sensitivity measure is the spirit of Liu et al. (2017b). Specifically, I calculate the firm's CAR from market model over the three-day window around announcements of the new regulatory documents issued by CSRC each year. Then I sum the absolute value of these CAR in the year and use it to proxy firm's political sensitivity. A full list of variable definitions can be found in Appendix A.

### 3.3.3 Propensity Score Matching

In order to use DID regression in the empirical analysis, firms in the treatment and control groups need to be comparable before release of the new regulation. Therefore, I implement propensity score matching as a resampling technique. Since the regression analysis uses data from 2011 to 2016, I use 2010 as the matching year to make the treatment and control groups comparable throughout the pre-event period. I first estimate the following cross-sectional logit regression in 2010 for all non-financial listed firms in China to estimate an ex-ante probability of being treated, i.e., the propensity score:

$$\begin{aligned} PCID_i = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 B/M_i + \beta_4 Growth_i \\ + \beta_5 Top1_i + \beta_6 Independence_i + \beta_7 Board\ size_i + \epsilon_i, \end{aligned} \tag{3.1}$$

where $PCID_i$ is a dummy variable which is equal to 1 if firm $i$ is in the treatment group and 0 otherwise. The regression results are reported in Table B1 of Appendix B. Then for each treated firm, I use one-to-one matching without replacement to identify a controlled firm with the closest propensity score as well as the same industry and ownership structure (SOE or non-SOE). The propensity score density of the treatment and control groups is plotted in Figure B1 of Appendix B. It shows that the two groups have similar propensity score distributions, suggesting that they have similar ex-ante probability of being treated. Table B2 reports summary statistics of firm characteristics for the matched sample, which includes 418 treated firms and 418 controlled firms. I compare firm characteristics of the two groups in all three pre-event years. It shows that the treatment and control groups are not significantly different in most firm characteristics, suggesting the propensity score matching succeeds in finding comparable controlled firms.

## 3.4 Empirical Results

### 3.4.1 Summary Statistics

Table 3.1 reports summary statistics of variables used in this study. In Panel A, the sample includes all non-financial listed firms in China from 2011 to 2016. All variables are winsorized at 1%-99% except dummy variables. $PCID$ has a mean of 0.204, which means that 20.4% A-share firms have PCIDs resignation after the release of Regulation No.18. *Policy sensitivity* has a mean of 4.95%, suggesting that policy and regulation of CSRC has a large impact on market performance. The average board independence is 0.374, which is consistent with the regulation in China that at least one third board members should be independent. The statistics of other variables are comparable with other recent studies (e.g., Liu et al., 2017b). Panel B shows the summary statistics of the matched sample used in the empirical analysis. Firm characteristics of the matched sample are similar to those of the full sample except the matched sample has more SOEs.

### 3.4.2 Value Effect

**Market Reaction to Release of Regulation No.18**

To investigate the value effect of Regulation No.18, I perform an event study to test the stock price reaction to the release of the regulation. To obtain CAR, I first estimate the following regression for stock $i$:

$$R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t} \tag{3.2}$$

where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized returns of stock $i$ and market return on day $\tau$. $\tau$ is equal to 0 on the event day (October 21, 2013). CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different windows. Since many Chinese listed firms have a large fraction of non-tradable shares, I use float value weighted market return when calculating CAR. I also use total value weighted market return for robustness tests.

Table 3.2 reports CAR of treated firms around release of Regulation No.18. It first shows the results of full sample. Generally, treated firms have negative CAR in all five windows, although they are not significant in the short event windows. The CAR is -0.04% in the 3-day window and -0.543% in the 7-day window without significance. In the 12-day window, the negative CAR is very large in magnitude (-2.006%) and significant at 1% level. While it decreases to -1.729% and -0.933% in the 11-day and 22-day window, it is still significant. The insignificant CAR in short event windows is possibly because of inefficient information transmission. As in Liu et al. (2018b), the new regulation was initially sent to certain government agencies and institutions concerned through the internal administrative system, which may have caused a delay in the dissemination of the message across the market. The next two columns show results for the SOEs and non-SOEs subsamples. Non-SOEs seems to be more affected by the new regulation than SOEs as evident by the slightly larger CAR. The CAR estimated using total value weighted market return are reported in Panel A of Table C1 of Appendix C and are similar with the main results. I also use different event windows as robustness tests in Panel B and the results are consistent.

Next, to further build the causal effect of Regulation No.18 on firm value, I estimate the following cross-sectional regression:

$$CAR_i = \alpha + \beta_1 PCID_i + Controls + \omega_j + \epsilon_i, \tag{3.3}$$

where $CAR_i$ is the CAR of firm $i$, and $PCID_i$ is a dummy variable which is equal to 1 if the firm $i$ is in the treatment group and 0 otherwise. I control for firm size, leverage ratio, book-to-market ratio, growth rate, ROE, ownership of the largest shareholder, idiosyncratic risk, and SOE status in the regression. I also include $\omega_j$ to control for industry fixed effect. Moreover, in order to avoid correlations in the error term due to unobserved heterogeneity, I adjust standard errors by clustering observations at industry level throughout the paper. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group.

The regression results are reported in Table 3.3. It shows that coefficients on the main interest variable, $PCID$, are all significantly negative. The coefficient is -0.342% in the 3-day window. It further decreases to -1.047%, -1.267%, and -1.437% in the 7-day, 12-day, and 17-day window, respectively. Although the coefficient is smaller in magnitude in the longest window, it is still significant at 1% level. The results suggest that the treated firms have significant lower CAR than controlled firms and thus the release of Regulation of No.18 has negative effect on firm value of treated firms. Regression results of CAR estimated using total value weighted market return and different event windows are reported in Table C2. The results show similar pattern as those in Table 3.3. In sum, the abnormal return analysis provides strong evidence supporting Hypothesis 1.

### Market Reaction to PCID Resignation

Although treated firms decrease in firm value around the release of Regulation No.18, the underlying mechanism is not straightforward. To test Hypothesis 2a and 3a, I calculate CAR of treated firms around the announcement of PCID resignation. I use the same method to estimate CAR as in previous subsection, except that the event date is the announcement date of PCID resignation, which is different across treated firms. Table 3.4 shows that firms have large and significantly positive CAR around the announcements of PCID resignations. Overall, the treatment group has a 1.3% CAR in the 3-day window and the CAR further increases to 2.782% in the 7-day window and 3.681% in the 12-day window, after which it decreases to 3.579% in the 17-day window and 3.025% in the 22-day window. The next two columns show that both SOEs and non-SOEs have positive CAR, but their magnitudes are different. Non-SOEs have significantly larger CAR than SOEs in most windows, especially in the longer windows, suggesting that non-SOEs may be more affected by PCID resignation. The results are similar if I use total value weighted market return and different event windows as shown in Table C3. I also use market-adjusted return and Fama-French three factor model to estimate CAR for robustness tests. The results are consistent with the main results.

Next, to further address the causal effect of PCID resignation on firm value, I run regression model (3) on CAR around PCID resignation. The results are reported in Panel A of Table 3.5. The coefficient on $PCID$ is 0.519 in the 3-day window and further increases to 1.086 and 2.413 in the 7-day and 12-day window. Although the coefficients decrease in longer windows, they are still significant and economically large. This suggests that treated firms have higher CAR around announcements of PCID resignations than controlled firms after controlling for other firm characteristics. The results using different methods to calculate CAR and different event windows are reported in Table C4 and are almost identical with those in Table 3.5. To conclude, Table 3.4 and 3.5 suggest that treated firms increase in firm value when their PCIDs resign, providing support for Hypothesis 3a or the political risk explanation. The results are also consistent with those in Ding et al. (2017). However, they mainly investigate the overall market reaction to the anti-corruption campaign, while I focus on the lose of political connections from

PCIDs in this study.

As shown in Table 3.4, CAR of SOEs and non-SOEs are different in magnitude. To further explore whether the value effect is contingent on ownership structure, I estimate the cross-sectional regression for SOEs and non-SOEs subsamples. The results are reported in Panel B and C of Table 3.5. Panel B shows that although SOEs still have positive coefficients on $PCID$, they are not significant. On the contrary, the coefficients in non-SOEs subsample are significant and even larger in magnitude than those in the full sample. I also test the difference between the coefficients of the main interest variable, $PCID$, for SOE and non-SOE subsamples. The results in Table D1 of Appendix D shows that their coefficients are significantly different. Therefore, the positive value effect around PCID resignations are mainly driven by non-SOEs. The results are consistent with Liu et al. (2018b) who find that market reaction to the release of Regulation No.18 is significant for non-SOEs but not significant for SOEs. One possible explanation is that non-SOEs decrease more in political risk than SOEs after their PCIDs resign. I will further explore this issue in the next subsection. Results of the robustness tests using total value weighted market return are shown in Table C5 and are consistent with the main results.

### 3.4.3 Change of Operating Performance and Firm Risk

To further explore the cash flow and political risk explanations, I perform a DID analysis on firm's operating performance and firm risk. DID methodology is ideally suited for establishing casual claims in a quasi-experimental setting. It eliminates the bias that comes from changes other than the regulation that could have affected the treatment group (Vig, 2013). The regression model is specified as follows:

$$y_{it} = \alpha + \beta_1 PCID_i + \beta_2 PCID_i \times Post_t + Controls_{t-1} + \omega_j + \gamma_t + \epsilon_{it}, \tag{3.4}$$

where $PCID_i$ is defined as above and $Post_t$ is a dummy variable which is equal to 1 after the PCID physically leaves the board, and $\omega_j$ and $\gamma_t$ are industry and year fixed effect. The regression model does not have the dummy variable $Post$ like a typical DID regression model since it has year fixed effect that overlaps with $Post$. The interaction dummy variable, $PCID_i \times Post_t$ is the main interest variable that reflects the change of treated firms after the event compared to controlled firms. Before performing the regression analysis, I test the parallel assumption of DID by comparing the pre-event trend of firm's operating performance and risk for the treatment group and control group. The results in Figure 3.3 show that the two groups have similar trend before the event year, suggesting that my treatment group and control group are comparable before the event.

Table 3.6 reports regression results of operating performance. In Panel A, I use ROE to measure operating performance. The first column shows that ROE of the treatment group does not change significantly after losing PCIDs compared to controlled firms. The next two columns further show that operating performance of either SOEs or non-SOEs is not affected by PCID resignation. In Panel B, I use CFO to measure operating performance. Similar to results in Panel A, the coefficients on $PCID \times Post$ are not significant in all three columns. I also use OPOA and CF as alternative measures of operating performance. The results are reported in Table C6 and are consistent with the main results. Therefore, firms do not have worse operating performance after losing political connections from PCID, providing consistent evidence with the CAR analysis that the cash flow explanation does not hold. Therefore, the results suggest that political connections built by PCIDs may not be so valuable for firm performance in China and cast doubt on the "helping hand" theory of political connections.

The regression results of firm risk is reported in Table 3.7. I use stock price volatility to measure firm risk in Panel A. It shows that the coefficient of $PCID \times Post$ in the full sample is negative but not significant. However, the next two columns show different results for SOEs and non-SOEs. While the coefficient is not significant for SOEs, it is significantly negative for non-SOEs, suggesting that stock return volatility of non-SOEs in the treatment group decrease significantly after losing PCIDs. I also compare the difference of coefficients on $PCID \times Post$ for SOEs and non-SOEs. The results shown in Panel B of Table D1 suggest that the coefficients for SOEs and non-SOEs are significantly different. In Panel B, the results are similar when using political sensitivity as the dependent variable. Non-SOEs decrease significantly in political sensitivity while SOEs' political sensitivity does not change. One possible explanation is that SOEs have more other sources of political connections than non-SOEs because of their special relation with the government. Even their PCIDs leave, they still have other connections and thus similar political risk. On the contrary, PCIDs may be a main source of political connection for some non-SOEs. Therefore, their political risk decreases significantly after losing this connection. The results are also consistent with the CAR around PCID resignation where I find the non-SOEs have more significant CAR than SOEs. Since non-SOEs have lower firm risk after losing PCIDs, they gain in firm value when their PCIDs resign. Therefore, Table 3.7 provides supporting evidence for Hypothesis 3b and suggests that political risk explanation dominates the cash flow explanation. Although political connections may bring various benefits to firms in China as shown in previous studies, they also increase firm's political risk, especially during the anti-corruption campaign, casting doubt on the "helping hand" theory. Moreover, the results also provide novel evidence that political risk is priced by investors in China. To conclude, the previous two subsections suggest that while treated firms lose in firm value after the release of Regulation No.18 because of higher political risk, they gain in firm value when their PCIDs resign and their political risk decrease.

## 3.5 Conclusions

On October 19, 2013, the CPC Central Committee issued a new regulation known as Regulation No.18, which leads to a wave of PCID resignation in the following two years. Using this regulation as a quasi-natural experiment, I investigate the effects of losing PCIDs on Chinese listed firms. There are three main findings in this study. First, firms with PCIDs have significantly negative CAR around the release of the new regulation. Further analysis suggests that the decrease in firm value is probably because of increase in political risk. Second, firms have large and significantly positive CAR around resignation announcement of PCIDs, because their political risk decreases after replacing PCIDs and complying with the new regulation. The positive CAR is more prominent for non-SOEs than SOEs as SOEs may have more other connections with the government and thus their political risk does not change significantly. Third, using DID methodology, I show that firms' operating performance does not change after replacing PCIDs. Consistent with the CAR analysis, political risk of non-SOEs decreases significantly, while SOEs' political risk does not change. The findings cast doubt on the "helping hand" theory of political connections. Although connections may bring benefits to firms and increase firm value, it can also increase firm risk and thus decrease firm value, especially during the anti-corruption campaign.

## 3.6 Appendix A: Variable Definitions

**Table A1: Variable Definitions**

| Variable | Definition |
|---|---|
| PCID | A dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise. The firm is in the treatment group if it has politically connected independent directors (PCID) resignation to comply with Regulation No.18 and 0 otherwise. |
| Post | A dummy variable which is equal to 1 after the resignation of politically connected independent director takes effect and 0 otherwise. |
| ROE | The ratio of net profit to book value of equity. |
| CFO | The ratio of cash flows from operation to total assets. |
| OPOA | The ratio of operating profit to total assets. |
| CF | The ratio of total cash flows to total assets. |
| Volatility (%) | Stock price volatility, which is calculated as the standard deviation of daily stock return, multiplied by 100. |
| Political sensitivity (%) | The sum of absolute cumulative abnormal return over the three-day window around announcements of the new regulatory documents issued by China Securities Regulatory Commission (CSRC) estimated using market model each year. |
| Size | The natural logarithm of total assets. |
| Leverage | The ratio of total liabilities to total assets. |
| Tangibility | The ratio of tangible assets to total assets. |
| ROA | The ratio of net profit to total assets. |
| B/M | The ratio of book value of equity to market value of equity. |
| Growth | The one-year lagged growth rate of net sales. |
| Top1 | The ratio of shares held by the largest shareholder to total shares outstanding. |
| Age | The natural logarithm of firm age. |
| Independence | Board independence, which is defined as the ratio of the number of independent director to the total number of board member. |
| Board size | The natural logarithm of number of board members. |
| Beta | The beta obtained from market model. |
| Ivol (%) | Idiosyncratic volatility, which is defined as the standard deviation of daily stock return residuals from market model, multiplied by 100. |
| SOE | A dummy variable which is equal to 1 if the firm is a state owned enterprise and 0 otherwise. |

## 3.7 Appendix B: Propensity Score Matching

**Table B1: Logit Regression Results**

This table reports regression results of propensity score matching using the following logit regression model: $PCID_i = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 B/M_i + \beta_4 Growth_i + \beta_5 Top1_i + \beta_6 Independence_i + \beta_7 Board\ size_i + \epsilon_i$, where $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise. The firm is in the treatment group if it has politically connected independent directors resignation to comply with Regulation No.18. The matching year is 2010. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | |
|---|---|
| Size | 0.137** |
| | (0.054) |
| Leverage | -0.174 |
| | (0.197) |
| B/M | -0.207 |
| | (0.204) |
| Growth | 0.002 |
| | (0.002) |
| Top1 | 0.002 |
| | (0.004) |
| Independence | 2.222** |
| | (0.993) |
| Board size | 0.115*** |
| | (0.033) |
| Constant | -5.407*** |
| | (1.236) |
| Observations | 1920 |
| Pseudo $R^2$ | 0.012 |

**Table B2: Summary Statistics after Matching**

This table reports summary statistics of variables used in this study for the matched sample during the pre-event period. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. For each treated firm, I use one-to-one propensity score matching without replacement to find a controlled firm in the same industry and with the same SOE status in 2010. I report summary statistics for 2011, 2012, and 2013 separately. I also report difference between the treatment and control group and perform t-test on the difference. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. ***, **, and * represent statistical significance at the 1%, 5%, and 10%, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | 2011 | | |
|---|---|---|---|
| | Treatment | Control | Difference |
| ROE | 0.087 | 0.073 | 0.015** |
| CFO | 0.033 | 0.033 | 0.000 |
| OPOA | 0.051 | 0.041 | 0.009** |
| CF | 0.625 | 0.604 | 0.020 |
| Volatility (%) | 2.480 | 2.497 | -0.017 |
| Political sensitivity (%) | 5.238 | 5.269 | -0.031 |
| Size | 22.005 | 21.801 | 0.204 |
| Leverage | 0.463 | 0.458 | 0.005 |
| Tangibility | 0.952 | 0.954 | -0.002 |
| ROA | 0.047 | 0.041 | 0.006 |
| B/M | 0.485 | 0.482 | 0.003 |
| Growth | 0.420 | 0.261 | 0.160** |
| Top1 | 0.372 | 0.373 | -0.001 |
| Age | 2.490 | 2.479 | 0.011 |
| Independence | 0.373 | 0.369 | 0.003 |
| Board size | 2.204 | 2.197 | 0.007 |
| Beta | 1.187 | 1.185 | 0.003 |
| Ivol (%) | 1.957 | 1.982 | -0.026 |
| SOE | 0.555 | 0.560 | -0.005 |

| | 2012 | | |
|---|---|---|---|
| | Treatment | Control | Difference |
| ROE | 0.066 | 0.046 | 0.020** |
| CFO | 0.047 | 0.045 | 0.003 |
| OPOA | 0.038 | 0.031 | 0.007* |
| CF | 0.594 | 0.599 | -0.004 |
| Volatility (%) | 2.439 | 2.482 | -0.043 |
| Political sensitivity (%) | 3.787 | 3.901 | -0.114 |
| Size | 22.159 | 21.919 | 0.239*** |
| Leverage | 0.471 | 0.458 | 0.013 |
| Tangibility | 0.947 | 0.950 | -0.003 |
| ROA | 0.037 | 0.034 | 0.003 |
| B/M | 0.537 | 0.528 | 0.009 |
| Growth | 0.165 | 0.176 | -0.011 |
| Top1 | 0.371 | 0.376 | -0.005 |
| Age | 2.580 | 2.570 | 0.010 |
| Independence | 0.372 | 0.371 | 0.001 |
| Board size | 2.207 | 2.198 | 0.009 |
| Beta | 1.241 | 1.241 | 0.000 |
| Ivol (%) | 1.876 | 1.935 | -0.059 |
| SOE | 0.565 | 0.560 | 0.005 |

Table B2 Continued

| | 2013 | | |
|---|---|---|---|
| | Treatment | Control | Difference |
| ROE | 0.048 | 0.034 | 0.014 |
| CFO | 0.040 | 0.037 | 0.003 |
| OPOA | 0.034 | 0.026 | 0.008 |
| CF | 0.580 | 0.584 | -0.004 |
| Volatility (%) | 2.558 | 2.628 | 0.070* |
| Political sensitivity (%) | 4.510 | 4.571 | -0.061 |
| Size | 22.285 | 22.042 | 0.243*** |
| Leverage | 0.474 | 0.471 | 0.003 |
| Tangibility | 0.947 | 0.948 | -0.001 |
| ROA | 0.032 | 0.027 | 0.005 |
| B/M | 0.541 | 0.529 | 0.012 |
| Growth | 0.149 | 0.162 | -0.013 |
| Top1 | 0.368 | 0.368 | 0.000 |
| Age | 2.661 | 2.651 | 0.009 |
| Independence | 0.372 | 0.374 | -0.002 |
| Board size | 2.204 | 2.191 | 0.013 |
| Beta | 1.087 | 1.088 | -0.001 |
| Ivol (%) | 2.156 | 2.231 | -0.075* |
| SOE | 0.567 | 0.562 | 0.005 |
| N | 418 | 418 | |

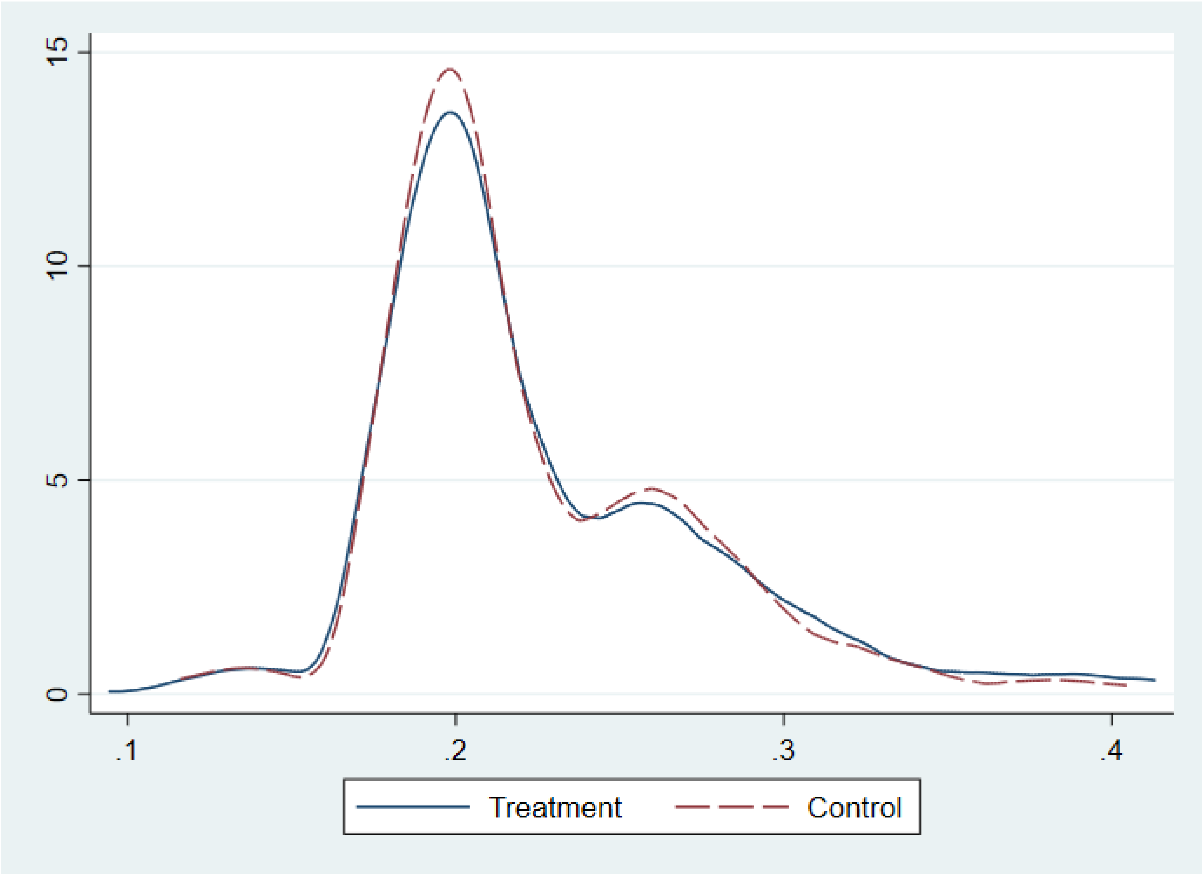



Figure B1: Propensity Score Density

This figure plots the density of propensity scores from the propensity score matching for the treatment and control group. The solid line plots propensity score density of the treatment group and the dashed line plots propensity score density of the control group. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. For each treated firm, I use one-to-one propensity score matching without replacement to find a controlled firm in the same industry and with the same SOE status in 2010. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

## 3.8 Appendix C: Robustness Tests

### Table C1: Robustness test of CAR around Release of Regulation No.18

This table reports cumulative abnormal return (CAR) of treated firms around the release of Regulation No.18 on October 19, 2013. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. In Panel A, I use total value weighted market return when estimating CAR. In Panel B, I use different event windows when estimating CAR. I also report the difference between SOEs and non-SOEs and the statistical significance of the difference from t-test. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: market model with total value weighted market return | | | | |
|---|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
| (-1, +1) | -0.195 | -0.475** | 0.169 | -0.644 |
| | (0.173) | (0.214) | (0.282) | (0.429) |
| (-1, +5) | -0.587* | -0.206 | -0.879** | 0.673 |
| | (0.331) | (0.582) | (0.377) | (0.489) |
| (-1, +10) | -1.893*** | -1.553*** | -2.335*** | 0.782* |
| | (0.438) | (0.494) | (0.777) | (0.422) |
| (-1, +15) | -1.546*** | -1.285** | -1.885** | 0.600* |
| | (0.474) | (0.574) | (0.797) | (0.337) |
| (-1, +20) | -0.870* | -0.878 | -0.859 | -0.019 |
| | (0.495) | (0.608) | (0.821) | (0.791) |
| N | 418 | 230 | 188 | |

| Panel B: robustness tests using different event windows | | | | |
|---|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
| (-5, +5) | -0.762** | -0.580 | -0.903** | 0.323 |
| | (0.334) | (0.534) | (0.426) | (0.482) |
| (-10, +10) | -1.717*** | -1.574*** | -1.902** | 0.328 |
| | (0.510) | (0.591) | (0.889) | (0.749) |
| (-15, +15) | -0.520** | -0.084 | -1.086*** | 1.002** |
| | (0.258) | (0.625) | (0.404) | (0.460) |
| (-20, +20) | 0.579 | 0.466 | 0.724 | -0.258 |
| | (0.600) | (0.739) | (0.994) | (0.772) |
| N | 418 | 230 | 188 | |

## Table C2: Robustness test of Cross-sectional Regression of CAR around Release of Regulation No.18

This table reports results of the cross-sectional regression of cumulative abnormal returns (CAR) around release of Regulation No.18 using the following model: $CAR_i = \alpha + \beta_1 PCID_i + Controls + \omega_j + \epsilon_i$, where $CAR_i$ is the CAR of firm $i$, $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, and $\omega_j$ is industry fixed effect. The firm is in the treatment group if it has politically connected independent directors (PCID) resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and total value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = Ret_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. I use different event windows as robustness test in Panel B. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: market model with total value weighted market return | | | | | |
|---|---|---|---|---|---|
| | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
| $PCID$ | -0.420 | -1.043** | -1.262* | -1.444** | -1.000*** |
| | (0.243) | (0.442) | (0.661) | (0.553) | (0.305) |
| Size | -0.120 | -0.241 | -0.021 | 0.042 | 0.053 |
| | (0.107) | (0.283) | (0.267) | (0.367) | (0.472) |
| Leverage | -0.243 | -1.263 | -0.375 | -2.906 | -5.537*** |
| | (0.746) | (1.445) | (1.627) | (1.963) | (1.434) |
| B/M | 0.268 | -0.030 | -0.417 | -1.817* | -4.082*** |
| | (0.225) | (0.694) | (0.669) | (0.866) | (1.272) |
| Growth | -0.286 | -0.287 | -0.232 | 0.029 | -0.050 |
| | (0.172) | (0.392) | (0.706) | (0.547) | (0.426) |
| ROE | -0.203 | 1.894 | 1.266 | 1.468 | 3.060 |
| | (1.236) | (1.087) | (3.522) | (4.574) | (3.490) |
| Top1 | 0.136 | 0.835 | 3.244** | 1.944 | 3.190* |
| | (0.710) | (1.295) | (1.311) | (1.203) | (1.801) |
| Ivol | 1.645*** | -0.569 | -0.192 | 0.415 | 3.628*** |
| | (0.193) | (0.455) | (0.832) | (0.777) | (0.610) |
| SOE | -0.472 | -0.600 | 0.376 | -0.273 | -0.021 |
| | (0.398) | (0.359) | (0.478) | (0.893) | (0.777) |
| Constant | -0.319 | 10.150 | 4.084 | 6.519 | -0.793 |
| | (2.105) | (6.090) | (5.546) | (7.807) | (9.815) |
| N | 836 | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.083 | 0.050 | 0.041 | 0.038 | 0.116 |

Table C2 Continued

| Panel B: robustness tests using different event windows | | | | |
| --- | --- | --- | --- | --- |
| | (-5, +5) | (-10, +10) | (-15, +15) | (-20, +20) |
| *PCID* | -0.830* | -1.586** | -1.453* | -1.100* |
| | (0.433) | (0.589) | (0.740) | (0.524) |
| Size | -0.394 | -0.349 | -0.201 | -0.066 |
| | (0.311) | (0.359) | (0.369) | (0.422) |
| Leverage | -0.171 | -1.449 | -0.577 | -3.669** |
| | (1.642) | (1.736) | (1.869) | (1.658) |
| B/M | 0.309 | 0.221 | -0.227 | -1.744** |
| | (0.551) | (0.612) | (0.612) | (0.803) |
| Growth | -0.065*** | -0.059*** | -0.033*** | 0.017*** |
| | (0.010) | (0.009) | (0.007) | (0.005) |
| ROE | -0.021 | -0.025 | -0.021 | -0.011 |
| | (0.020) | (0.051) | (0.072) | (0.072) |
| Top1 | 0.583 | 1.144 | 3.143** | 2.169 |
| | (1.217) | (1.490) | (1.413) | (1.293) |
| Ivol | 0.104 | -0.487 | -0.285 | -0.167 |
| | (0.495) | (0.512) | (0.703) | (0.702) |
| SOE | -0.631 | -0.682* | 0.305 | -0.451 |
| | (0.411) | (0.358) | (0.482) | (0.907) |
| Constant | 5.072 | 12.136 | 8.197 | 10.730 |
| | (6.689) | (7.640) | (7.255) | (8.326) |
| N | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.071 | 0.045 | 0.038 | 0.037 |

## Table C3: Robustness test of CAR around PCID Resignation

This table reports cumulative abnormal return (CAR) of treated firms around the announcement of politically connected independent director (PCID) resignation using different models to estimate abnormal return. A firm is treated if it has PCID resignation to comply with Regulation No.18. In Panel A, I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and total value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. In Panel B and C, the abnormal return is estimated using market-adjusted return: $AR_{i,\tau} = R_{i,\tau} - R_{m,\tau}$. In Panel B, I use different event windows as robustness tests. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: market model with total value weighted market return | | | | |
|---|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
| (-1, +1) | 1.325*** | 1.187*** | 1.494** | -0.307 |
| | (0.338) | (0.390) | (0.581) | (0.652) |
| (-1, +5) | 2.783*** | 1.991*** | 3.752*** | -1.761* |
| | (0.644) | (0.719) | (1.129) | (1.036) |
| (-1, +10) | 3.668*** | 2.254*** | 5.397*** | -3.143** |
| | (0.851) | (0.824) | (1.596) | (1.574) |
| (-1, +15) | 3.581*** | 2.127** | 5.36*** | -3.233** |
| | (0.974) | (0.876) | (1.877) | (1.409) |
| (-1, +20) | 3.094*** | 1.944* | 4.502** | -2.558* |
| | (1.055) | (0.992) | (2.006) | (1.394) |
| N | 418 | 230 | 188 | |

| Panel B: robustness tests using different event windows | | | | |
|---|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
| (-5, +5) | 2.429*** | 1.276 | 3.840*** | -2.564** |
| | (0.713) | (0.799) | (1.242) | (1.159) |
| (-10, +10) | 3.380*** | 1.668* | 5.475*** | -3.807** |
| | (0.957) | (0.998) | (1.734) | (1.763) |
| (-15, +15) | 3.999*** | 1.807* | 6.708*** | -4.901** |
| | (1.128) | (1.050) | (2.150) | (2.091) |
| (-20, +20) | 3.533*** | 1.689 | 5.810** | -4.121* |
| | (1.244) | (1.194) | (2.352) | (2.334) |
| N | 418 | 230 | 188 | |

**Table C4: Robustness test of Cross-sectional Regression of CAR around PCID Resignation**

This table reports results of the cross-sectional regression of cumulative abnormal returns (CAR) around announcement of politically connected independent directors (PCID) resignation estimated from different models using the following model: $CAR_i = \alpha + \beta_1 PCID_i i + Controls + \omega_j + \epsilon_i$, where $CAR_i$ is the CAR of firm $i$, $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, and $\omega_j$ is industry fixed effect. The firm is in the treatment group if it has PCID resignation to comply with Regulation No.18. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. In Panel A, I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and total value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = Ret_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. In Panel B, I use different event windows as robustness tests. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: market model with total value weighted market return | | | | | |
|---|---|---|---|---|---|
| | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
| $PCID$ | 0.515* | 1.047* | 2.371*** | 1.971*** | 1.330** |
| | (0.265) | (0.562) | (0.456) | (0.463) | (0.488) |
| Size | -0.196 | -0.439 | -0.629 | -0.394 | 0.211 |
| | (0.347) | (0.532) | (0.527) | (0.533) | (0.637) |
| Leverage | -0.238 | 0.652 | 2.067 | 1.595 | 0.802 |
| | (0.791) | (1.590) | (1.805) | (2.212) | (2.461) |
| B/M | -1.912* | -1.858 | -1.135 | -2.926* | -3.676* |
| | (1.041) | (1.451) | (1.765) | (1.585) | (1.799) |
| Growth | 0.301 | 0.083 | 0.155 | -0.321 | -0.523 |
| | (0.203) | (0.344) | (0.485) | (0.533) | (0.688) |
| ROE | 0.127 | 0.469** | 0.739*** | 0.876*** | 0.841*** |
| | (0.077) | (0.164) | (0.207) | (0.189) | (0.248) |
| Top1 | 1.200 | 2.359 | 0.727 | 2.221 | 0.516 |
| | (2.410) | (5.352) | (5.589) | (5.683) | (6.545) |
| Ivol | -0.014*** | -0.036*** | -0.069*** | -0.105*** | -0.063*** |
| | (0.004) | (0.010) | (0.015) | (0.014) | (0.015) |
| SOE | 0.344 | -0.754 | -1.150 | -1.302 | -1.551 |
| | (0.487) | (0.842) | (1.066) | (1.361) | (1.390) |
| Constant | 4.201 | 10.008 | 12.891 | 7.573 | -4.855 |
| | (6.784) | (9.757) | (9.517) | (9.765) | (11.697) |
| N | 836 | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.025 | 0.029 | 0.033 | 0.034 | 0.027 |

Table C4 Continued

| Panel B: robustness tests using different event windows | (-5, +5) | (-10, +10) | (-15, +15) | (-20, +20) |
|---|---|---|---|---|
| $PCID$ | 0.519* | 2.528*** | 2.111** | 1.342 |
| | (0.262) | (0.666) | (0.788) | (0.962) |
| Size | -0.195 | -1.476*** | -1.138** | -0.805 |
| | (0.351) | (0.487) | (0.501) | (0.934) |
| Leverage | -0.190 | 4.266** | 4.235 | 6.396** |
| | (0.806) | (1.796) | (2.552) | (2.987) |
| B/M | -2.032* | -3.205* | -6.814*** | -7.352*** |
| | (1.065) | (1.645) | (1.799) | (2.299) |
| Growth | 0.293 | -0.123 | -0.823*** | -1.174** |
| | (0.220) | (0.306) | (0.249) | (0.487) |
| ROE | 0.135* | 1.014*** | 1.295*** | 1.347*** |
| | (0.076) | (0.186) | (0.191) | (0.256) |
| Top1 | 1.366 | 5.181 | 6.645 | 7.792 |
| | (2.446) | (5.997) | (6.015) | (8.054) |
| Ivol | -0.014*** | -0.109*** | -0.164*** | -0.111*** |
| | (0.004) | (0.013) | (0.021) | (0.018) |
| SOE | 0.352 | -1.767 | -2.602* | -3.458** |
| | (0.504) | (1.129) | (1.362) | (1.610) |
| Constant | 4.305 | 26.629*** | 20.200** | 12.071 |
| | (6.839) | (8.844) | (9.467) | (18.078) |
| N | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.026 | 0.049 | 0.057 | 0.051 |

## Table C5: Robustness Test of Cross-sectional Regression of CAR around PCID Resignation by Ownership Structure

This table reports results of the cross-sectional regression of cumulative abnormal returns (CAR) around announcement of politically connected independent directors resignation by ownership structure using the following model: $CAR_i = \alpha + \beta_1 PCID_i + Controls + \omega_j + \epsilon_i$, where $CAR_i$ is the CAR of firm $i$, $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, and $\omega_j$ is industry fixed effect. The firm is in the treatment group if it has PCID resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and total value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. The SOEs sample includes 230 treated firms and 230 controlled firms matched with the treatment group. The non-SOEs sample includes 188 treated firms and 188 controlled firms. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | SOEs | | | | |
|---|---|---|---|---|---|
| | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
| *PCID* | 0.432 | 0.683 | 1.120 | 0.832 | 0.840 |
| | (0.592) | (1.315) | (1.096) | (1.025) | (0.907) |
| Size | -0.365 | -0.394 | -0.566 | -0.514 | 0.145 |
| | (0.399) | (0.537) | (0.736) | (0.515) | (0.627) |
| Leverage | -0.701 | -1.439 | -0.853 | -1.510 | -2.011 |
| | (0.888) | (1.848) | (2.061) | (2.052) | (2.431) |
| B/M | -0.585 | 0.099 | 1.002 | 0.679 | 0.586 |
| | (1.170) | (1.674) | (1.957) | (2.028) | (2.341) |
| Growth | 0.242 | -0.524 | 0.279 | -0.530 | -1.630* |
| | (0.160) | (0.563) | (0.860) | (0.754) | (0.782) |
| ROE | 0.705 | 3.350 | 7.578 | 6.188 | 4.391 |
| | (2.013) | (5.168) | (8.495) | (7.877) | (7.089) |
| Top1 | 1.528 | 1.739 | 0.891 | 6.376* | 4.379 |
| | (1.528) | (3.186) | (2.962) | (3.094) | (3.158) |
| Ivol | 0.649*** | 1.599*** | 1.708* | 2.156*** | 2.526*** |
| | (0.170) | (0.413) | (0.786) | (0.664) | (0.689) |
| Constant | 6.651 | 6.032 | 8.336 | 3.222 | -13.566 |
| | (8.368) | (10.959) | (14.330) | (10.136) | (12.388) |
| N | 460 | 460 | 460 | 460 | 460 |
| Adj. $R^2$ | 0.050 | 0.057 | 0.072 | 0.065 | 0.058 |

Table C5 Continued

| | non-SOEs | | | | |
|---|---|---|---|---|---|
| | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
| $PCID$ | 0.716* | 2.023** | 4.541*** | 4.038*** | 2.561* |
| | (0.376) | (0.763) | (0.986) | (1.045) | (1.394) |
| Size | -0.118 | -1.040 | -1.747 | -1.286 | -0.935 |
| | (0.764) | (1.279) | (1.018) | (0.764) | (0.769) |
| Leverage | 0.523 | 3.626 | 6.188** | 6.694*** | 4.991 |
| | (2.036) | (2.775) | (2.509) | (2.152) | (3.505) |
| B/M | -2.811 | -2.613 | -0.480 | -3.922 | -5.102 |
| | (1.687) | (2.347) | (2.752) | (3.142) | (3.967) |
| Growth | 0.342 | 0.194 | 0.034 | -0.296 | -0.065 |
| | (0.269) | (0.385) | (0.648) | (0.742) | (0.746) |
| ROE | 0.120 | 0.506* | 0.765*** | 0.936*** | 0.921*** |
| | (0.131) | (0.254) | (0.191) | (0.096) | (0.126) |
| Top1 | 2.001 | 6.217 | 6.268 | 3.128 | 2.636 |
| | (3.512) | (6.732) | (5.937) | (7.833) | (10.195) |
| Ivol | -0.023*** | -0.054*** | -0.084*** | -0.132*** | -0.090*** |
| | (0.005) | (0.008) | (0.010) | (0.012) | (0.010) |
| Constant | 1.961 | 19.744 | 31.996 | 24.100 | 19.256 |
| | (14.871) | (24.380) | (19.009) | (14.713) | (14.619) |
| N | 376 | 376 | 376 | 376 | 376 |
| Adj. $R^2$ | 0.044 | 0.051 | 0.065 | 0.074 | 0.070 |

## Table C6: Robustness test of Operating Performance

This table reports change of firm's operating performance after politically connected independent director (PCID) resignation using the following regression model: $y_{it} = \alpha + \beta_1 PCID_i + \beta_2 PCID_i \times Post_t + Controls_{t-1} + \omega_j + \gamma_t + \epsilon_{it}$, where $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, $Post_t$ is a dummy variable which is equal to 1 after the PCID resignation takes effect and 0 otherwise, $\omega_j$ and $\gamma_t$ are industry and year fixed effect. The firm is in the treatment group if it has PCIDs resignation to comply with Regulation No.18. Operating performance is measured using operating profits (OPOA) in Panel A and total cash flow (CF) in Panel B. OPOA is defined as the ratio of operating profit to total assets and CF is defined as the ratio of total cash flows to total assets. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. I report results for the full sample, SOEs subsample, and non-SOEs subsample. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: operating profits (OPOA) | Full sample | SOEs subsample | Non-SOEs subsample |
|---|---|---|---|
| $PCID$ | 0.005 | 0.010** | -0.003 |
| | (0.004) | (0.004) | (0.004) |
| $PCID \times Post$ | -0.001 | -0.002 | 0.001 |
| | (0.002) | (0.003) | (0.003) |
| Size | 0.020*** | 0.019*** | 0.024*** |
| | (0.003) | (0.003) | (0.002) |
| Tangibility | -0.151*** | -0.159*** | -0.147*** |
| | (0.009) | (0.013) | (0.007) |
| Leverage | 0.006 | -0.019 | 0.043 |
| | (0.015) | (0.016) | (0.028) |
| B/M | -0.061*** | -0.049*** | -0.095*** |
| | (0.008) | (0.008) | (0.006) |
| Growth | 0.010*** | 0.013** | 0.006** |
| | (0.003) | (0.005) | (0.002) |
| Top1 | 0.015*** | -0.003 | 0.044*** |
| | (0.005) | (0.011) | (0.009) |
| Age | 0.005* | 0.008* | 0.002 |
| | (0.003) | (0.004) | (0.003) |
| Independence | 0.005 | -0.005 | 0.024 |
| | (0.026) | (0.027) | (0.028) |
| Board size | 0.007 | 0.000 | 0.026*** |
| | (0.005) | (0.009) | (0.008) |
| SOE | -0.013*** | | |
| | (0.003) | | |
| Constant | -0.380*** | -0.339*** | -0.528*** |
| | (0.049) | (0.047) | (0.034) |
| N | 4,871 | 2,747 | 2,124 |
| Adj. $R^2$ | 0.259 | 0.272 | 0.272 |

Table C6 Continued

| Panel B: total cash flow (CF) | Full sample | SOEs subsample | Non-SOEs subsample |
|---|---|---|---|
| $PCID$ | -0.015 | -0.022 | -0.009 |
| | (0.015) | (0.028) | (0.025) |
| $PCID \times Post$ | 0.020 | 0.003 | 0.032 |
| | (0.018) | (0.024) | (0.022) |
| Size | 0.026 | 0.052** | 0.013 |
| | (0.017) | (0.024) | (0.018) |
| Tangibility | 0.386*** | 0.251** | 0.482*** |
| | (0.054) | (0.094) | (0.069) |
| ROA | 0.405*** | 0.398*** | 0.157 |
| | (0.085) | (0.129) | (0.130) |
| Leverage | 1.001*** | 1.004*** | 0.806** |
| | (0.216) | (0.219) | (0.374) |
| B/M | -0.155*** | -0.180*** | -0.136 |
| | (0.043) | (0.031) | (0.127) |
| Growth | 0.024 | 0.052 | 0.007 |
| | (0.016) | (0.035) | (0.005) |
| Top1 | 0.254 | 0.174 | 0.416*** |
| | (0.170) | (0.194) | (0.129) |
| Age | 0.021 | 0.049 | -0.017 |
| | (0.040) | (0.091) | (0.028) |
| Independence | -0.210 | -0.154 | -0.375** |
| | (0.238) | (0.330) | (0.138) |
| Board size | -0.071 | -0.051 | -0.105*** |
| | (0.048) | (0.071) | (0.019) |
| SOE | 0.078*** | | |
| | (0.016) | | |
| Constant | -0.517 | -0.985* | 0.080 |
| | (0.368) | (0.513) | (0.428) |
| N | 4,871 | 2,747 | 2,124 |
| Adj. $R^2$ | 0.241 | 0.256 | 0.226 |

## 3.9 Appendix D: Statistics Tests for Differences of Key Coefficients

**Table D1: Statistics Tests for Differences of Key Coefficients**

The table reports the statistic tests for differences of the key coefficient in Table 3.5 and Table 3.7. Panel A reports the coefficients on $PCID$ for SOE subsample and non-SOE subsample (from Panel B and C of Table 3.5). Then it reports the difference of coefficients for SOE and non-SOE subsamples and the statistical significance of the difference from t-test. Panel B reports the coefficients on $PCID \times Post$ for SOE subsample and non-SOE subsample (from Panel B of Table 3.7) and compare the difference in coefficients. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. Data source: CSMAR and WIND.

| Panel A: cross-sectional regression of CAR around PCID resignation | | | | | |
|---|---|---|---|---|---|
| | (-1, +1) | (-1, +5) | (-1, +10) | (-1, +15) | (-1, +20) |
| SOEs | 0.445 | 0.750 | 1.186 | 0.929 | 0.912 |
| Non-SOEs | 0.707 | 2.025 | 4.554 | 4.009 | 2.529 |
| Difference | -0.262** | -1.275*** | -3.368*** | -3.080*** | -1.617*** |
| t-statistics | -2.088 | -4.667 | -12.724 | -11.696 | -5.384 |

| Panel B: Loss of PCID and firm risk | | |
|---|---|---|
| | Stock price volatility | Political sensitivity |
| SOEs | -0.010 | -0.058 |
| Non-SOEs | -0.054 | -0.190 |
| Difference | 0.044*** | 0.132*** |
| t-statistics | 9.863 | 5.509 |

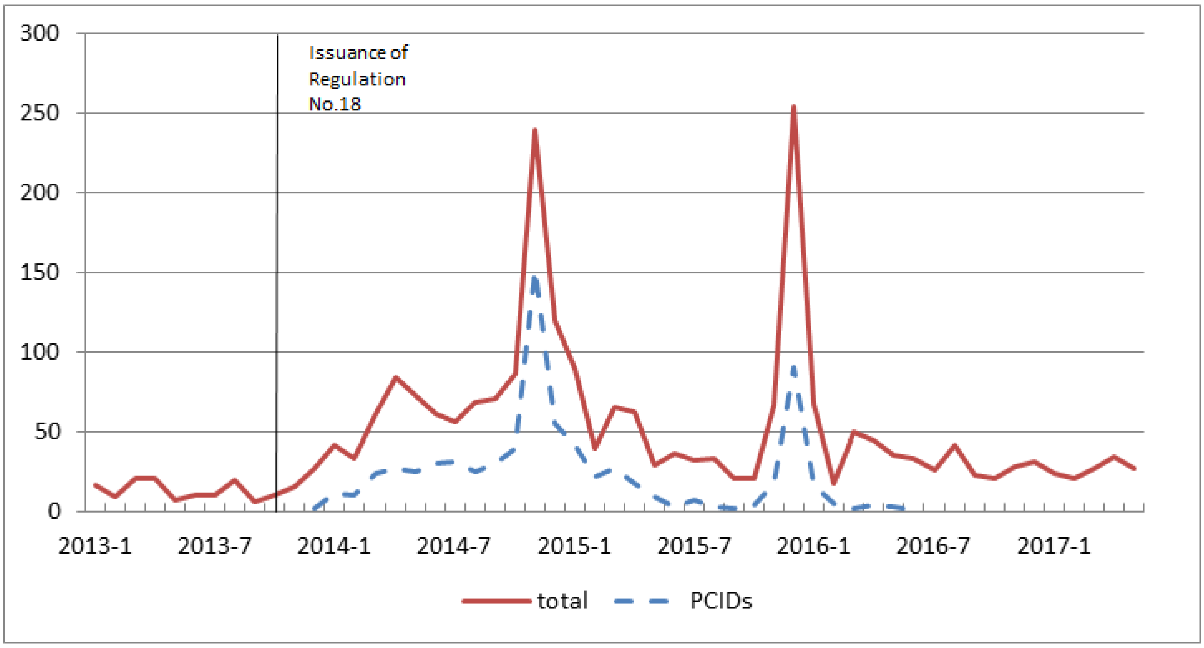



Figure 3.1: Resigning Dates of Independent Directors and PCIDs

This figure plots the number of independent director resignation and politically connected independent director (PCID) resignation every month during January 2013 to May 2017. The solid line plots the total number of independent director resignation and the dashed line plots the number of PCIDs resignation. Data source: website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

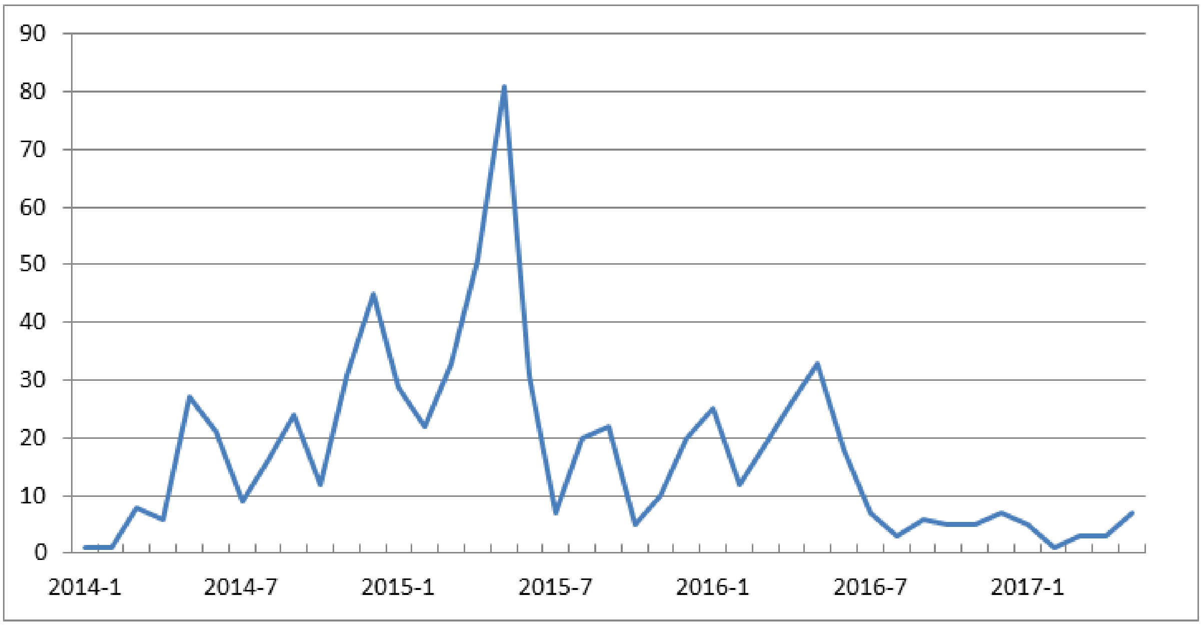
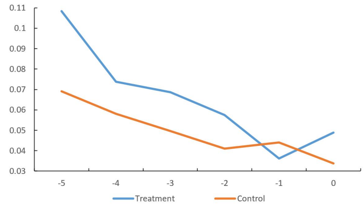
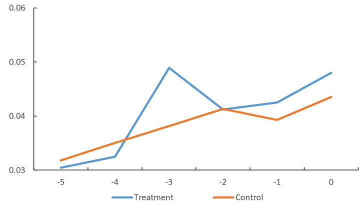



Figure 3.2: Leaving Dates of Resigning PCIDs

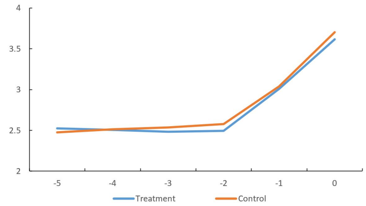
This figure plots the actual leaving dates of resigning politically connected independent directors (PCIDs) after the release of Regulation No.18. Data source: website of Shanghai Stock Exchange and Shenzhen Stock Exchange.



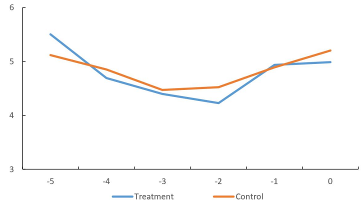

(a) ROE of Full Sample



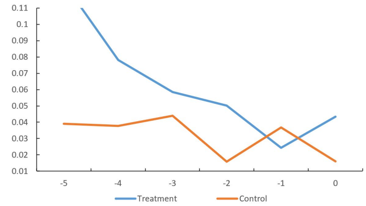

(b) CFO of Full Sample



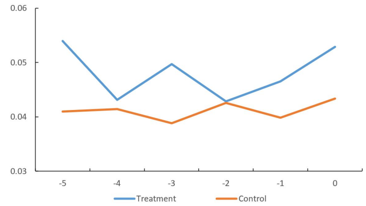

(c) Firm Risk of Full Sample



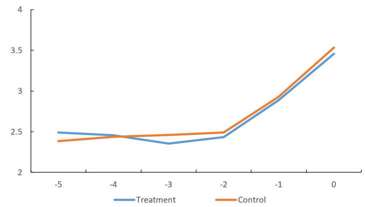

(d) Political Risk of Full Sample



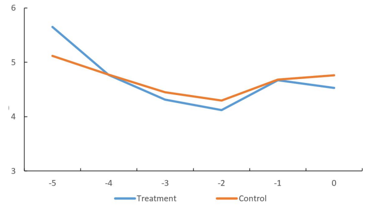

(e) ROE of SOEs



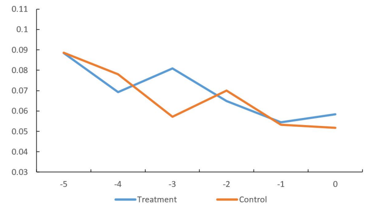

(f) CFO of SOEs



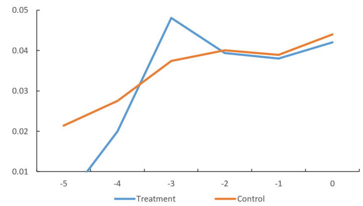

(g) Firm Risk of SOEs



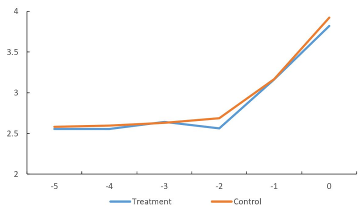

(h) Political Risk of SOEs



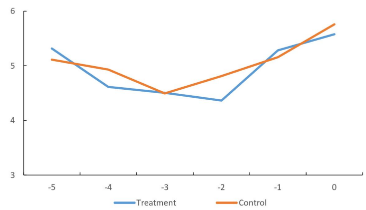

(i) ROE of Non-SOEs




(j) CFO of Non-SOEs




(k) Firm Risk of Non-SOEs




(l) Political Risk of Non-SOEs

Figure 3.3: Parallel Test of DID Analysis

This figure compares the trend of firm's ROE, CFO, firm risk, and political risk before politically connected independent directors (PCIDs) leave the firm between the treatment group and control group. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. Controlled firms are matched with the treatment group using propensity matching. Data source: CSMAR and DATASTREAM.

## Table 3.1: Summary Statistics

This table reports summary statistics of variables used in this study. The sample in Panel A includes all non-financial A-share firms in China from 2011 to 2016. The sample in Panel B is a matched sample including treated firms and controlled firms. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. For each treated firm, I use one-to-one propensity score matching without replacement to find a controlled firm in the same industry and with the same SOE status in 2010. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

Panel A: all listed firms

| Variable | Mean | S.D. | p25 | p50 | p75 |
|---|---|---|---|---|---|
| PCID | 0.204 | 0.403 | 0.000 | 0.000 | 0.000 |
| ROE | 0.063 | 0.121 | 0.028 | 0.068 | 0.112 |
| CFO | 0.039 | 0.074 | 0.000 | 0.040 | 0.083 |
| OPOA | 0.040 | 0.063 | 0.011 | 0.038 | 0.072 |
| CF | 0.555 | 0.471 | 0.253 | 0.429 | 0.695 |
| Volatility (%) | 3.241 | 1.318 | 2.375 | 2.848 | 3.697 |
| Political sensitivity (%) | 4.946 | 2.018 | 3.652 | 4.579 | 5.740 |
| Size | 21.957 | 1.295 | 21.027 | 21.795 | 22.695 |
| Leverage | 0.431 | 0.222 | 0.250 | 0.418 | 0.600 |
| Tangibility | 0.953 | 0.052 | 0.941 | 0.966 | 0.984 |
| ROA | 0.039 | 0.055 | 0.013 | 0.036 | 0.066 |
| B/M | 0.394 | 0.270 | 0.199 | 0.336 | 0.515 |
| Growth | 0.204 | 0.608 | -0.040 | 0.098 | 0.263 |
| Top1 | 0.354 | 0.1525 | 0.233 | 0.3344 | 0.4576 |
| Age | 2.642 | 0.431 | 2.398 | 2.708 | 2.944 |
| Independence | 0.374 | 0.053 | 0.333 | 0.333 | 0.429 |
| Board size | 2.143 | 0.198 | 1.946 | 2.197 | 2.197 |
| Beta | 0.975 | 0.589 | 0.631 | 1.063 | 1.367 |
| Ivol (%) | 2.579 | 1.217 | 1.840 | 2.289 | 2.947 |
| SOE | 0.433 | 0.496 | 0.000 | 0.000 | 1.000 |
| N | 15530 | | | | |

Panel B: matched sample

| Variable | Mean | S.D. | p25 | p50 | p75 |
|---|---|---|---|---|---|
| PCID | 0.500 | 0.500 | 0.000 | 0.500 | 1.000 |
| ROE | 0.051 | 0.145 | 0.022 | 0.062 | 0.108 |
| CFO | 0.042 | 0.072 | 0.003 | 0.041 | 0.085 |
| OPOA | 0.033 | 0.064 | 0.006 | 0.031 | 0.065 |
| CF | 0.560 | 0.479 | 0.248 | 0.434 | 0.698 |
| Volatility (%) | 2.949 | 0.963 | 2.285 | 2.702 | 3.338 |
| Political sensitivity (%) | 4.681 | 1.587 | 3.566 | 4.474 | 5.539 |
| Size | 22.233 | 1.331 | 21.313 | 22.073 | 22.994 |
| Leverage | 0.464 | 0.218 | 0.287 | 0.469 | 0.632 |
| Tangibility | 0.950 | 0.059 | 0.939 | 0.966 | 0.984 |
| ROA | 0.032 | 0.057 | 0.009 | 0.030 | 0.059 |
| B/M | 0.442 | 0.300 | 0.232 | 0.370 | 0.573 |
| Growth | 0.185 | 0.607 | -0.054 | 0.080 | 0.243 |
| Top1 | 0.359 | 0.153 | 0.239 | 0.333 | 0.471 |
| Age | 2.684 | 0.408 | 2.485 | 2.773 | 2.996 |
| Independence | 0.373 | 0.054 | 0.333 | 0.355 | 0.400 |
| Board size | 2.182 | 0.205 | 2.079 | 2.197 | 2.197 |

Table 3.1 Continued

| Variable | Mean | S.D. | p25 | p50 | p75 |
|---|---|---|---|---|---|
| Beta | 1.147 | 0.237 | 0.989 | 1.165 | 1.312 |
| Ivol (%) | 2.287 | 0.749 | 1.758 | 2.163 | 2.706 |
| SOE | 0.554 | 0.497 | 0.000 | 1.000 | 1.000 |
| N | 5016 | | | | |

## Table 3.2: Market Reaction to Release of Regulation No.18

This table reports cumulative abnormal return (CAR) of treated firms around the release of Regulation No.18 on October 19, 2013. A firm is treated if it has politically connected independent directors resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. I use float value weighted market return when estimating CAR. I also report the difference between SOEs and non-SOEs and the statistical significance of the difference from t-test. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
|---|---|---|---|---|
| (-1, +1) | -0.040 | -0.235 | 0.397 | -0.632 |
| | (0.172) | (0.213) | (0.282) | (0.472) |
| (-1, +5) | -0.543 | -0.167 | -0.832$^{**}$ | 0.665 |
| | (0.331) | (0.582) | (0.377) | (0.421) |
| (-1, +10) | -2.006$^{***}$ | -1.898$^{***}$ | -2.674$^{***}$ | 0.776$^{*}$ |
| | (0.371) | (0.493) | (0.778) | (0.397) |
| (-1, +15) | -1.729$^{***}$ | -1.605$^{***}$ | -2.199$^{***}$ | 0.594$^{*}$ |
| | (0.414) | (0.573) | (0.798) | (0.311) |
| (-1, +20) | -0.933$^{*}$ | -0.944 | -0.920 | -0.024 |
| | (0.495) | (0.607) | (0.821) | (0.738) |
| N | 418 | 230 | 188 | |

### Table 3.3: Cross-sectional Regression of CAR around Release of Regulation No.18

This table reports results of the cross-sectional regression of cumulative abnormal returns (CAR) around release of Regulation No.18 using the following model: $CAR_i = \alpha + \beta_1 PCID_i + Controls + \omega_j + \epsilon_i$, where $CAR_i$ is the CAR of firm $i$, $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, and $\omega_j$ is industry fixed effect. The firm is in the treatment group if it has politically connected independent directors resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and float value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = Ret_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
|---|---|---|---|---|---|
| $PCID$ | -0.342** | -1.047** | -1.267* | -1.437** | -0.989*** |
| | (0.140) | (0.442) | (0.660) | (0.551) | (0.306) |
| Size | 0.143*** | -0.238 | -0.026 | 0.045 | 0.067 |
| | (0.046) | (0.283) | (0.268) | (0.366) | (0.470) |
| Leverage | -0.568 | -1.207 | -0.359 | -2.870 | -5.636*** |
| | (0.353) | (1.449) | (1.637) | (1.960) | (1.434) |
| B/M | -0.290 | -0.007 | -0.423 | -1.780* | -4.007*** |
| | (0.181) | (0.692) | (0.673) | (0.862) | (1.248) |
| Growth | -0.099 | -0.298 | -0.245 | 0.018 | -0.049 |
| | (0.108) | (0.396) | (0.711) | (0.548) | (0.421) |
| ROE | 0.764 | 1.842 | 1.184 | 1.382 | 2.933 |
| | (0.757) | (1.084) | (3.531) | (4.569) | (3.468) |
| Top1 | -0.386 | 0.857 | 3.250** | 1.943 | 3.152 |
| | (0.821) | (1.294) | (1.324) | (1.204) | (1.841) |
| Ivol | 1.236*** | -0.638 | -0.193 | 0.384 | 3.663*** |
| | (0.187) | (0.450) | (0.838) | (0.777) | (0.606) |
| SOE | -0.347 | -0.571 | 0.384 | -0.246 | -0.009 |
| | (0.201) | (0.357) | (0.479) | (0.888) | (0.770) |
| Constant | -5.150*** | 10.122 | 4.011 | 6.556 | -0.615 |
| | (1.202) | (6.071) | (5.562) | (7.794) | (9.782) |
| N | 836 | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.139 | 0.050 | 0.041 | 0.037 | 0.115 |

### Table 3.4: Market Reaction to PCID Resignations

This table reports cumulative abnormal return (CAR) of treated firms around the announcement of politically connected independent directors (PCID) resignation. A firm is treated if it has PCID resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = R_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. I use float value weighted market return when estimating CAR. I also report the difference between SOEs and non-SOEs and the statistical significance of the difference from t-test. Standard errors are reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1%, 5%, and 10%, respectively. All returns and standard errors are in %. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| | Full sample | SOEs subsample | Non-SOEs subsample | Difference |
|---|---|---|---|---|
| (-1, +1) | 1.300*** | 1.168*** | 1.462** | -0.294 |
| | (0.341) | (0.394) | (0.586) | (0.657) |
| (-1, +5) | 2.782*** | 1.979*** | 3.764*** | -1.785** |
| | (0.650) | (0.725) | (1.140) | (0.746) |
| (-1, +10) | 3.681*** | 2.240*** | 5.445*** | -3.205** |
| | (0.860) | (0.832) | (1.612) | (1.589) |
| (-1, +15) | 3.579*** | 2.095** | 5.394*** | -3.299* |
| | (0.983) | (0.888) | (1.892) | (1.831) |
| (-1, +20) | 3.025*** | 1.800* | 4.524** | -2.724** |
| | (1.071) | (1.009) | (2.035) | (1.226) |
| N | 418 | 230 | 188 | |

## Table 3.5: Cross-sectional Regression of CAR around PCID Resignation

This table reports results of the cross-sectional regression of cumulative abnormal returns (CAR) around announcement of politically connected independent director (PCID) resignation using the following model: $CAR_i = \alpha + \beta_1 PCID_i + Controls + \omega_j + \epsilon_i$, where $CAR_i$ is the CAR of firm $i$, $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, and $\omega_j$ is industry fixed effect. The firm is in the treatment group if it has PCID resignation to comply with Regulation No.18. I use market model to obtain abnormal return: $R_{i,t} = \beta_i R_{m,t} + \epsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the excess return of stock $i$ and float value weighted market excess return on day $t$. The estimation window is 280 days to 90 days before the release of Regulation No.18. The estimated coefficients $\hat{\beta}_i$ is used to construct the abnormal return as $AR_{i,\tau} = Ret_{i,\tau} - \hat{\beta}_i R_{m,\tau}$, where $R_{i,\tau}$ and $R_{m,\tau}$ are realized excess returns of stock $i$ and market on day $\tau$. CAR is calculated as $\sum_{\tau=-1}^{T} AR_{i,\tau}$, where $T$ is equal to 1, 5, 10, 15, and 20 for different event windows. In Panel A, the sample includes 418 treated firms and 418 controlled firms matched with the treatment group. In Panel B and C, I report the subsample results for SOEs and non-SOEs, respectively. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: full sample | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
|---|---|---|---|---|---|
| $PCID$ | 0.519* | 1.086* | 2.413*** | 2.013*** | 1.352** |
| | (0.262) | (0.567) | (0.450) | (0.463) | (0.513) |
| Size | -0.195 | -0.444 | -0.627 | -0.383 | 0.273 |
| | (0.351) | (0.539) | (0.538) | (0.549) | (0.653) |
| Leverage | -0.190 | 0.609 | 2.070 | 1.479 | 0.491 |
| | (0.806) | (1.583) | (1.790) | (2.197) | (2.499) |
| B/M | -2.032* | -2.142 | -1.515 | -3.354* | -4.308** |
| | (1.065) | (1.487) | (1.791) | (1.668) | (1.916) |
| Growth | 0.293 | 0.074 | 0.150 | -0.336 | -0.542 |
| | (0.220) | (0.368) | (0.518) | (0.568) | (0.727) |
| ROE | 0.135* | 0.491*** | 0.767*** | 0.908*** | 0.877*** |
| | (0.076) | (0.165) | (0.208) | (0.190) | (0.249) |
| Top1 | 1.366 | 2.616 | 0.842 | 2.318 | 0.515 |
| | (2.446) | (5.472) | (5.720) | (5.853) | (6.816) |
| Ivol | -0.014*** | -0.036*** | -0.069*** | -0.107*** | -0.063*** |
| | (0.004) | (0.011) | (0.016) | (0.016) | (0.016) |
| SOE | 0.352 | -0.753 | -1.159 | -1.308 | -1.635 |
| | (0.504) | (0.857) | (1.075) | (1.369) | (1.410) |
| Constant | 4.305 | 10.092 | 12.729 | 6.999 | -6.208 |
| | (6.839) | (9.872) | (9.691) | (10.028) | (11.951) |
| N | 836 | 836 | 836 | 836 | 836 |
| Adj. $R^2$ | 0.026 | 0.030 | 0.035 | 0.035 | 0.028 |

Table 3.5 Continued

| Panel B: SOEs | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
|---|---|---|---|---|---|
| *PCID* | 0.445 | 0.750 | 1.186 | 0.929 | 0.912 |
| | (0.587) | (1.307) | (1.089) | (1.015) | (0.883) |
| Size | -0.375 | -0.427 | -0.600 | -0.540 | 0.178 |
| | (0.398) | (0.541) | (0.742) | (0.510) | (0.627) |
| Leverage | -0.604 | -1.424 | -0.820 | -1.582 | -2.366 |
| | (0.874) | (1.806) | (2.030) | (2.024) | (2.395) |
| B/M | -0.615 | 0.011 | 0.948 | 0.608 | 0.378 |
| | (1.181) | (1.740) | (2.056) | (2.111) | (2.492) |
| Growth | 0.223 | -0.541 | 0.276 | -0.603 | -1.747* |
| | (0.162) | (0.579) | (0.887) | (0.774) | (0.811) |
| ROE | 0.617 | 3.310 | 7.585 | 6.165 | 4.434 |
| | (2.012) | (5.155) | (8.491) | (7.806) | (6.977) |
| Top1 | 1.712 | 2.011 | 0.956 | 6.405* | 4.246 |
| | (1.551) | (3.313) | (3.085) | (3.238) | (3.283) |
| Ivol | 0.682*** | 1.663*** | 1.815** | 2.281*** | 2.676*** |
| | (0.170) | (0.424) | (0.810) | (0.689) | (0.718) |
| Constant | 6.944 | 6.531 | 8.495 | 2.945 | -14.683 |
| | (8.350) | (11.056) | (14.433) | (9.993) | (12.358) |
| N | 460 | 460 | 460 | 460 | 460 |
| Adj. $R^2$ | 0.052 | 0.059 | 0.073 | 0.066 | 0.059 |

| Panel C: non-SOEs | (-1,+1) | (-1,+5) | (-1,+10) | (-1,+15) | (-1,+20) |
|---|---|---|---|---|---|
| *PCID* | 0.707* | 2.025** | 4.554*** | 4.009*** | 2.529* |
| | (0.379) | (0.778) | (0.993) | (1.058) | (1.420) |
| Size | -0.102 | -1.008 | -1.710 | -1.220 | -0.847 |
| | (0.775) | (1.301) | (1.049) | (0.810) | (0.823) |
| Leverage | 0.475 | 3.439 | 6.075** | 6.381** | 4.636 |
| | (2.111) | (2.845) | (2.570) | (2.162) | (3.581) |
| B/M | -2.993* | -3.015 | -1.080 | -4.566 | -6.008 |
| | (1.685) | (2.366) | (2.801) | (3.210) | (4.070) |
| Growth | 0.347 | 0.200 | 0.049 | -0.271 | -0.032 |
| | (0.279) | (0.398) | (0.674) | (0.758) | (0.757) |
| ROE | 0.127 | 0.524* | 0.789*** | 0.960*** | 0.953*** |
| | (0.131) | (0.255) | (0.194) | (0.100) | (0.126) |
| Top1 | 2.143 | 6.478 | 6.563 | 3.391 | 2.947 |
| | (3.570) | (6.826) | (5.960) | (8.002) | (10.601) |
| Ivol | -0.024*** | -0.055*** | -0.086*** | -0.135*** | -0.091*** |
| | (0.005) | (0.008) | (0.011) | (0.012) | (0.011) |
| Constant | 1.702 | 19.090 | 31.237 | 22.523 | 17.215 |
| | (15.045) | (24.793) | (19.633) | (15.591) | (15.653) |
| N | 376 | 376 | 376 | 376 | 376 |
| Adj. $R^2$ | 0.045 | 0.052 | 0.067 | 0.077 | 0.073 |

## Table 3.6: Loss of PCID and Operating Performance

This table reports change of firm's operating performance after politically connected independent director (PCID) resignation using the following regression model: $y_{it} = \alpha + \beta_1 PCID_i + \beta_2 PCID_i \times Post_t + Controls_{t-1} + \omega_j + \gamma_t + \epsilon_{it}$, where $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, $Post_t$ is a dummy variable which is equal to 1 after the PCID resignation takes effect and 0 otherwise, $\omega_j$ and $\gamma_t$ are industry and year fixed effect. The firm is in the treatment group if it has PCID resignation to comply with Regulation No.18. Operating performance is measured using ROE in Panel A and cash flow from operations (CFO) in Panel B. ROE is defined as the ratio of net profit to book value of equity and CFO is defined as the ratio of cash flows from operations to total assets. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. I report results for the full sample, SOEs subsample, and non-SOEs subsample. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: ROE | Full sample | SOEs subsample | Non-SOEs subsample |
|---|---|---|---|
| $PCID$ | 0.009 | 0.017* | 0.003 |
| | (0.006) | (0.009) | (0.006) |
| $PCID \times Post$ | -0.000 | -0.006 | 0.004 |
| | (0.004) | (0.006) | (0.008) |
| Size | 0.032*** | 0.035*** | 0.032*** |
| | (0.005) | (0.005) | (0.006) |
| Tangibility | -0.165*** | -0.227*** | -0.103*** |
| | (0.023) | (0.030) | (0.023) |
| Leverage | -0.001 | -0.035 | 0.112 |
| | (0.028) | (0.033) | (0.086) |
| B/M | -0.114*** | -0.097*** | -0.157*** |
| | (0.021) | (0.027) | (0.015) |
| Growth | 0.014*** | 0.022*** | 0.004 |
| | (0.003) | (0.006) | (0.003) |
| Top1 | 0.020** | -0.025 | 0.077** |
| | (0.008) | (0.019) | (0.028) |
| Age | 0.010* | 0.015* | 0.000 |
| | (0.005) | (0.007) | (0.007) |
| Independence | 0.006 | -0.027 | 0.064 |
| | (0.038) | (0.052) | (0.053) |
| Board size | -0.004 | -0.008 | 0.031 |
| | (0.016) | (0.023) | (0.018) |
| SOE | -0.026*** | | |
| | (0.006) | | |
| Constant | -0.573*** | -0.593*** | -0.768*** |
| | (0.076) | (0.091) | (0.079) |
| N | 4,871 | 2,747 | 2,124 |
| Adj. $R^2$ | 0.089 | 0.096 | 0.100 |

Table 3.6 Continued

| Panel B: cash flow from operations (CFO) | | | |
|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample |
| $PCID$ | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.003) | (0.004) |
| $PCID \times Post$ | 0.002 | 0.004 | 0.001 |
| | (0.003) | (0.005) | (0.003) |
| Size | 0.008*** | 0.008*** | 0.009*** |
| | (0.001) | (0.002) | (0.003) |
| Tangibility | -0.024*** | -0.022 | -0.034** |
| | (0.008) | (0.014) | (0.012) |
| ROA | -0.040* | -0.013 | -0.145*** |
| | (0.021) | (0.016) | (0.023) |
| Leverage | 0.255*** | 0.220*** | 0.268*** |
| | (0.041) | (0.038) | (0.066) |
| B/M | -0.013 | -0.013 | -0.011 |
| | (0.010) | (0.008) | (0.026) |
| Growth | -0.009*** | -0.010*** | -0.007** |
| | (0.003) | (0.003) | (0.003) |
| Top1 | 0.033*** | 0.020* | 0.058*** |
| | (0.007) | (0.010) | (0.016) |
| Age | 0.004* | 0.008 | 0.001 |
| | (0.002) | (0.005) | (0.002) |
| Independence | -0.002 | 0.002 | -0.017 |
| | (0.029) | (0.032) | (0.023) |
| Board size | 0.008 | 0.012 | 0.002 |
| | (0.007) | (0.011) | (0.008) |
| SOE | -0.001 | | |
| | (0.002) | | |
| Constant | -0.121*** | -0.156*** | -0.022 |
| | (0.041) | (0.036) | (0.036) |
| N | 4,871 | 2,747 | 2,124 |
| Adj. $R^2$ | 0.118 | 0.109 | 0.138 |

## Table 3.7: Loss of PCID and Firm Risk

This table reports change of firm risk after politically connected independent director (PCID) resignation using the following regression model: $y_{it} = \alpha + \beta_1 PCID_i + \beta_2 PCID_i \times Post_t + Controls_{t-1} + \omega_j + \gamma_t + \epsilon_{it}$, where $PCID_i$ is a dummy variable which is equal to 1 if the firm is in the treatment group and 0 otherwise, $Post_t$ is a dummy variable which is equal to 1 after the PCID resignation takes effect and 0 otherwise, $\omega_j$ and $\gamma_t$ are industry and year fixed effect. The firm is in the treatment group if it has PCID resignation to comply with Regulation No.18. In Panel A, the dependent variable is stock price volatility, which is defined as the standard deviation of daily stock return, multiplied by 100. The sample includes 418 treated firms and 418 controlled firms matched with the treatment group. I report results for the full sample, SOEs subsample, and non-SOEs subsample. In Panel B, the dependent variable is political sensitivity, which is defined as the sum of absolute cumulative abnormal return over the three-day window around announcements of the new regulatory documents issued by China Securities Regulatory Commission (CSRC) estimated using market model each year. All variables are winsorized at 1% to 99% except dummy variables. All variables are defined in Appendix A. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * represent statistical significance at the 1% level, 5% level, and 10% level, respectively. Data source: CSMAR and website of Shanghai Stock Exchange and Shenzhen Stock Exchange.

| Panel A: stock price volatility | | | |
|---|---|---|---|
| | Full sample | SOEs subsample | Non-SOEs subsample |
| $PCID$ | -0.002 | 0.001 | 0.012 |
| | (0.011) | (0.010) | (0.026) |
| $PCID \times Post$ | -0.022 | -0.010 | -0.054*** |
| | (0.014) | (0.019) | (0.016) |
| Size | -0.137*** | -0.130*** | -0.136*** |
| | (0.007) | (0.009) | (0.019) |
| Leverage | 0.223*** | 0.334*** | 0.064 |
| | (0.039) | (0.042) | (0.041) |
| Tangibility | -0.018 | 0.011 | 0.230 |
| | (0.089) | (0.121) | (0.333) |
| ROA | -0.611*** | -0.579*** | -0.768** |
| | (0.155) | (0.178) | (0.272) |
| B/M | 0.069** | 0.050 | 0.083 |
| | (0.028) | (0.038) | (0.077) |
| Growth | 0.067** | 0.034 | 0.084** |
| | (0.025) | (0.021) | (0.029) |
| Top1 | 0.081** | 0.026 | 0.187* |
| | (0.028) | (0.042) | (0.094) |
| Age | -0.052*** | -0.037 | -0.060*** |
| | (0.015) | (0.031) | (0.011) |
| Independence | -0.264** | -0.323** | -0.328 |
| | (0.117) | (0.148) | (0.191) |
| Board size | -0.068** | -0.055 | -0.131*** |
| | (0.029) | (0.049) | (0.035) |
| Beta | 0.377*** | 0.372*** | 0.340*** |
| | (0.029) | (0.051) | (0.022) |
| Ivol | 0.217*** | 0.250*** | 0.190*** |
| | (0.016) | (0.020) | (0.013) |
| SOE | -0.010 | | |
| | (0.016) | | |
| Constant | 4.769*** | 4.500*** | 4.750*** |
| | (0.243) | (0.293) | (0.297) |
| N | 4,867 | 2,745 | 2,122 |
| Adj. $R^2$ | 0.741 | 0.754 | 0.720 |

Table 3.7 Continued

| Panel B: political sensitivity | Full sample | SOEs subsample | Non-SOEs subsample |
|---|---|---|---|
| *PCID* | -0.028 | 0.018 | -0.027 |
| | (0.023) | (0.045) | (0.046) |
| *PCID* × *Post* | -0.114 | -0.058 | -0.190*** |
| | (0.072) | (0.122) | (0.054) |
| Size | -0.158*** | -0.151*** | -0.183*** |
| | (0.018) | (0.030) | (0.035) |
| Leverage | 0.383*** | 0.309** | 0.386*** |
| | (0.107) | (0.138) | (0.126) |
| Tangibility | 0.268 | 0.419 | 0.113 |
| | (0.345) | (0.314) | (1.055) |
| ROA | -2.168*** | -2.456*** | -1.773** |
| | (0.383) | (0.486) | (0.698) |
| B/M | -0.188** | -0.125* | -0.333* |
| | (0.066) | (0.061) | (0.160) |
| Growth | 0.168** | 0.190** | 0.106* |
| | (0.060) | (0.064) | (0.050) |
| Top1 | -0.007 | -0.101 | 0.217 |
| | (0.130) | (0.214) | (0.144) |
| Age | -0.256*** | -0.362*** | -0.191*** |
| | (0.052) | (0.076) | (0.047) |
| Independence | -0.137 | -0.329 | -0.749 |
| | (0.413) | (0.443) | (0.635) |
| Board size | -0.172 | -0.019 | -0.471* |
| | (0.107) | (0.136) | (0.233) |
| Beta | 0.177*** | 0.186** | 0.145 |
| | (0.051) | (0.069) | (0.086) |
| Ivol | 0.305*** | 0.333*** | 0.262*** |
| | (0.035) | (0.052) | (0.025) |
| SOE | -0.182*** | | |
| | (0.041) | | |
| Constant | 8.602*** | 8.405*** | 9.688*** |
| | (0.720) | (1.071) | (0.741) |
| N | 4,862 | 2,743 | 2,119 |
| Adj. $R^2$ | 0.286 | 0.267 | 0.304 |

# Conclusions

This thesis studies several important issues of China's financial market. In Chapter 1, we show that China stocks have lower correlation with the global market compared with all other major markets. From the perspective of international investors, adding China stocks into a well-diversified portfolio can further increase its Sharpe Ratio. In addition, China stocks are less affected by global financial contagion when diversification benefits are most valuable. We further find that mainland China stocks with high policy sensitivity provide greater diversification benefits. While holding Hong Kong listed Chinese stocks is less affected by friction-related policy risks, it cannot reap the same diversification benefits with that from mainland China stocks. The global market integration can mitigate concerns on policy risks and boost foreign investor holdings, but also diminish diversification benefits. We find that the effect of foreign ownership in increasing the correlation of China's stock market with the global market is still limited. China's stock market still provides valuable diversification opportunity for international investors up till most recent time in late 2010s.

Chapter 2 exploits the recent bond defaults to investigate the industry contagion effect of financial distress in China. The abnormal return analysis shows that while SOE peers of defaulted firms overall do not have significant decrease in firm value, non-SOE peers suffer from significant drop in firm value, especially in high competition and high debt-dependent industries. In addition, debt financing of industry peers decreases because of the bond defaults, especially bank loans, which is the main debt financing source for Chinese firms. Beside debt financing, industry peers also suffer from drop in investment. However, the contagion effect on peers' debt financing and investment only affects non-SOE peers but not SOE peers. This is because SOEs in China have superior access to debt financing through both bond issuance and bank loans.

The Regulation No.18 issued in 2013 during the anti-corruption campaign in China leads to a wave of PCID resignation in the following two years. Using this regulation as a quasi-natural experiment, I investigate the effects of losing PCIDs on Chinese listed firms in Chapter 3. I find that firms with PCIDs have negative CAR around the release of the new regulation because of increase in political risk. However, firms have significantly positive CAR around resignation announcement of PCIDs, because their political risk decreases after replacing PCIDs and complying with the new regulation. The positive CAR is more prominent for non-SOEs than SOEs as SOEs may have more other connections with the government and thus their political risk does not change significantly. Last, I show that firms' operating performance does not change after replacing PCIDs, casting doubt on the "helping hand" theory of political connections. Although connections may bring benefits to firms and increase firm value, it can also increase firm risk and thus decrease firm value, especially during the anti-corruption campaign.

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