China's Anti-Corruption Campaign and Credit Reallocation from SOEs to Non-SOEs*

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Abstract

We provide a novel empirical finding that the recent anti-corruption investigations in China are associated with credit reallocation from less productive, state-owned enterprises (SOEs) to more productive, non-SOEs. The empirical strategy exploits staggered investigations as exogenous shocks to bank loan issuance among rival firms in affected industry. The main finding extends to implicated firms and non-affected industries, proves strong for extensive margins and a supply shock, and remains solid for stock market reactions. We further single out the economic efficiency channel, and to a lesser extent, the political connection channel, through which the anti-corruption campaign leads to improved credit reallocation.

Keywords: Anti-corruption, credit reallocation, state ownership, economic efficiency, political connection.

JEL Classification: G30, G32, G34, P26.

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1. Introduction

In this paper, we provide a novel empirical finding that the financing impact of China's anti-corruption campaign on industry rivals differs decisively along the line of state ownership. Rival non-state-owned enterprises (non-SOEs) experience significant increases, while the rival state-owned enterprises (SOEs) experience significant decreases in bank lending, upon investigation announcements. In terms of the economic magnitude, non-SOEs receive a 28 percent increase in bank loan issuance one year after investigations, compared to SOEs, which experience a 13 percent less increase. The credit reallocation towards non-SOEs upon anti-corruption investigations is in stark contrast with the stylized fact that SOEs receive preferential treatment in bank lending during normal times, as illustrated in Figure 1 Panel A.

The identification strategy exploits a unique data set from the Central Commission for Discipline Inspection (CCDI) in China. Since 2012, the government required timely disclosure of investigation announcements of corruption officials to the public. We take advantage of the staggered investigations as exogenous shocks to identify the causal impact of corruption investigations on credit reallocation. By focusing on the rival firms in affected industries instead of the directly implicated firms, we make sure that the investigation announcements are uncorrelated with the rival firms' economic fundamentals. In addition, the targeted officials and exact timings of investigation announcements are considered largely unexpected to the general public, despite rumors and speculations surrounding these investigations.

To address the concern that SOEs and non-SOEs may differ in their economic fundamentals prior to the investigation events, we reconstruct the control and treatment groups using the propensity score matching and conduct a series of diagnostic tests to ensure that the parallel trends assumption is not violated. Furthermore, we verify that the credit shift from SOEs to non-SOEs is also present for the directly implicated firms, under the condition that investigation events are orthogonal to the implicated firms' economic fundamentals. In addition, we confirm that the credit shift effect remains strong even for the non-affected industries, under the condition that the investigation likelihoods are not systematically different across the affected and non-affected industries. Taken as whole, our findings are not only statistically sound but also economically broad.

We examine possible mechanisms through which the anti-corruption campaign leads to improved credit reallocation. First, the reallocation could be efficiency driven, where the corruption investigation forces bank lending to be more merit based. We find that non-SOE rivals experienced significant increases in total factor productivity (TFP) two years after the investigations, while the SOE rivals saw insignificant changes in TFP. Second, we verify that SOEs experienced significantly more reductions in political connections relative to non-SOEs; however, for connected firms, this does not lead bank loan to shift away from SOEs towards non-SOEs, which makes the political connection channel rather muted. Finally, there is no significant evidence for the mechanism of uncertainty aversion, as the stock market volatility proxy shows no systematic difference across SOEs and non-SOE upon investigation events. The economic efficiency mechanism is further corroborated by differential bank performances after issuing loans to SOEs and non-SOEs with reallocation taking place. Overall, the economic efficiency channel, and to a lesser extent, the political connection channel seem to explain how the credit reallocation effect is taking place.

Our main finding on bank loan reallocation can be strengthened and broadened along several dimensions. First, new bank loan initiations seem to be strongly favoring non-SOEs relative to SOEs following the investigations, which is particularly encouraging since non-SOEs have been traditionally largely deprived of credit access. Second, we identify an exogenous shock to the banking industry, which provides a unique setting to pin down the supply side effect of the credit reallocation. Third, turning over to equity market reactions upon investigations, we find that cumulative abnormal returns and seasonal equity issuances also clearly favor non-SOEs relative SOEs. Finally, our main finding is also robust with respect to total debt outstanding and geographical region variation.

Literature

A large literature documents the economic costs of corruption (Shleifer and Vishny, 1993; Shleifer and Vishny, 1994; Mauro, 1995; Fisman, 2001; Fisman and Svensson, 2007; Butler, Fauver, and Mortal, 2009; Bertrand, Kramarz, Schoar, and Thesmar, 2018). Our main finding of credit reallocation from less productive, SOEs to more productive non-SOEs is consistent with this line of research. In particular, our lead mechanism of economic efficiency confirmed by both firm-level TFP evidence and bank-level performance evidence, lands a strong support for the argument of economic costs of corruption. One closely related work in this regard is by Colonnelli and Prem (2017), who demonstrated the economic role played by anti-corruption crackdowns, using a Brazilian regional audit set. Our study adopts a similar empirical strategy but focuses on the industry dimension, yet reaches the same conclusion that corruption is not "greasing the wheels".

Political connections can mitigate financial frictions between firms and politicians (Faccio, 2006; Goldman, Rocholl, and So, 2009; Amore and Bennedson, 2013; Dreher and Gassebner, 2013). The relationship between political connections and bank financing decisions is quite complex, especially across countries (Sapienza, 2004; Khwaja and Mian, 2005; Leuz and Oberholzer-Gee, 2006; Claessens, Feijen, and Laeven, 2008; Zeume, 2016). Our finding suggests that the recent anti-corruption investigations in China severed significant political connections to SOEs but not much to non-SOEs, and tentatively this also lead to credit shift from SOEs to non-SOEs. A closely related paper along this angle is by Fan, Rui, and Zhao (2008), who show that the credit supply to firms dropped when links to high-level bureaucrats were severed. However, in our case, the political connection channel is less robust and significant than the economic efficiency channel.

In China, SOEs receive preferential treatment in bank lending during normal times (Brandt and Zhu, 2001; Boyreau-Debray and Wei, 2005; Song, Storesletten, and Zilibotti, 2011), and there exists severe credit misallocation (Hsieh and Klenow, 2009; Hsieh and Song, 2015; Song and Xiong, 2017). Megginson, Nash, and Randenborgh (1994), Dewenter and Malatesta (2001), Boubakri, Cosset, and Guedhami (2005), Liao, Liu, and Wang (2014) show that privatization can boost firm performance and align managerial incentives, while ownership structure also affects debt financing costs (Lin, Ma, Malatesta, and Xuan, 2013; Borisova, Fotak, Holland, and Megginson, 2015).

These strands of literature lend support to our focus on the state ownership as the deciding line for the credit reallocation effect, which seems reasonable for research on a transitional economy like China. In particular, Cong, Gao, Ponticelli, and Yang (2017) show that the 4-trillion economic stimulus in China following the global financial crisis has led to over extension of credit toward SOEs, which may or may not be surprising, given that government stimulus package during deep recessions typically aims at shovel ready public projects. However, a relevant question to our paper is, whether the credit reallocation to non-SOEs from the anti-corruption campaign turns out to be a correction or reversal to an early period over supply of credit to SOEs? Our preliminary diagnostics in Section 3B indicates that the likelihoods of corruption investigations are uncorrelated with industry characteristics and fundamentals (Table 4). Therefore, our finding of credit reallocation toward non-SOEs is genuinely driven by the anti-corruption investigations, since the macroeconomic trends and industry trends are excluded.

A growing literature shows that China's anti-corruption campaign has strong reactions on stock market (Griffin, Liu, and Shu, 2016; Lin, Morck, Yeung, and Zhao, 2016; Ang, Bai, and Zhou, 2016; Liu, Shu, and Wei, 2017). We find clear evidence that stock abnormal returns and seasonal stock offerings favor non-SOEs over SOEs around the investigations events. However, there is no clear evidence that stock return volatilities differ significantly along the lines of SOEs versus non-SOEs.

The rest of the paper is organized as follows. Section 2 describes data collection and summary statistics. Section 3 presents our main findings on bank credit reallocation effect. Section 4 investigates the potential mechanisms through which investigations affect credit provision. Section 5 presents various sensitivity analyses with alternative samples and markets. Section 6 concludes.

2. Corruption Cases, Summary Statistics, and Political Connections

In this section, we first introduce the unique data sample on China's anti-corruption campaign, linking the official under investigations to the implicated firms in affected industries. Then, we define key economic control variables and provide sample statistics on the firm characteristics. In the end, we track the changes in political connections for SOE and non-SOE rivals, respectively.

A. Data Sample on Corruption Cases

In the first phase, we collect our sample of corruption cases by searching the investigation documents on government officials between 2012 and 2015 from the website of Central Commission Discipline Inspection (CCDI).[1] Since late 2012, the government required the immediate disclosures to the public of the information regarding officials under corruption investigations, with the intention to improve the transparency of governance in the public sector. For each corruption case, the website discloses the name of the government official, the current position right before the investigation, the previous positions served as government officials or as CEOs of public firms, the type of corruption, and the degree of corruption (measured by the estimated monetary and non-monetary amounts of rent seeking activities).[2] We restrict our sample to only senior government officials---those hold positions at or above deputy minister level at the central government and deputy governor level at the provincial government, as they build extensive political network and have significant power in controlling the economic resources relative to lower ranked officials (see, also, Ding, Fang, Lin, and Shi, 2017). Appendix A provides the list of 78 senior government officials that were investigated, and the specific dates of investigations.

To identify the implicated firms, we manually search news articles and record any linkage between the investigated officials and the publicly-listed firms. Specifically, we consider key words related to five

[1] We choose the first quarter of 2015 as our last period of search for investigations because this procedure leaves two years lead time to identify the economic impact of anti-corruption campaign on financing capacity variables.

[2] Since the announcements may not contain the whole curriculum of the government official, we manually search all the previous positions served by the official to identify the political network of the investigated officials.

types of linkages: current employment, previous employment, business associations, relatives and friends, and law enforcement officers. The former three types of linkages follow the social network literature (Fracassi and Tate, 2012).[3] Current employments are typical directorships in the same firm. Prior employments capture overlapping prior employment in any firm. The last two types are specific to China's corruption culture. Given the fact that loyalty to family and clan can override loyalty to the state, we emphasize the influence of family and friend network on officials' bribing activities. The law enforcement officers refer to the circumstance when investigating officials and judges receive bribes from investigated officials and subsequently reduce the magnitude of penalty associated with the case under investigation.

In the second phase, we search linkages between the investigated senior government officials and public firms listed in the Shanghai and Shenzhen stock exchanges. In particular, we use an algorithm that allows us to manually trace the existence of political relationship and identify the type of linkage using the Baidu news search engine. We replicate the search through Google as well, and the results are essentially the same, due to the consistency in headline news releases. We further perform a pilot experiment with a random sample of 100 news articles to check the validity of our key word search.[4] Appendix B lists the 78 investigation cases that have established linkages with 61 implicated firms.

Since our paper focuses on the impact of anti-corruption announcements on the financing capacity of industry rivals, we keep only the earliest investigations of officials in an industry as our event dates. This filtering approach reflects the arrival of new information on corruption firms and the exogenous shocks on their industry rivals. This search method yields a total of 31 affected industries that contain at least one implicated firm directly linked to the investigated officials. To identify the industry peers within the affected industries that are not related to the implicated officials, we use the third-tier industry classification

[3] There is some tentative evidence that in China education-based network does not work or works in opposite direction as in the established studies (Griffin, Liu, and Shu, 2016).

[4] For each news article, two team members evaluate the key words independently, and the lists of key words are chosen if they are consistent more than 90 percent of the time. In the formal data collection stage, we use two independent groups to further evaluate each report to ensure consistent determination of the direct linkage.

according to the WIND China dataset.[5] Finally, we merge the industry peers in affected industries with the China Stock Market and Accounting Research Database (CSMAR), which provides comprehensive information about stock prices, financial statements, and ownership structure.[6] We further require that firms do not have missing information on stock prices, financial statements, and ownership structure from the fourth quarter of 2012 to the fourth quarter of 2017. Our final sample contains 1,560 public peer firms that operate in the same industry of investigation implicated firms. Appendix B lists the names of implicated firms with their state ownership dummies.

We construct the political connection measure from the curriculum vitae (CV) of the public companies' CEOs and directors, using the disclosures from annual reports. First, following Fan, Wong, and Zhang (2007) and Liu, Shu, and Wei (2017), we define a person as politically connected in China, if he or she is an official of the central government or a local government. Second, a company is connected through the Congress, if one of its top officers (CEO, president, vice-president, chairman, or secretary) is a member of the National People's Congress or a member of the China People's Political Consultative Conference (NCPCC) National Committee.[7] The connection through the Congress is similar to the measure in Faccio (2006) and Claessens, Feijen, and Laeven (2008), where a top officer is a member of parliament, a minister, or is closely related to a top politician or party. Third, we also track political connections through friendship or relatives as family ties with politicians in China are very important.[8] The political connection dummy *PoliticalConnection* equals one, if at least one top officer has connections with government officials through any of the three channels, and equals zero otherwise.

[5] The WIND classification has been extensively used by academia and practitioners in China. Our main results are robust to the alternative method of using the second-tier classification to identify industry peers.
[6] This merged dataset is similar to the merged COMPUSTAT-CRSP dataset in U.S.
[7] For example, Dong Mingzhu, a member of 10th, 11th and 12th National people's congress, is also the CEO of Gree Electric Appliances. Gree Electric Appliances is define as politically connected with a member of congress through the CEO.
[8] The relatives include parents, spouses, children, or siblings of CEOs.

B. Variable Definitions

Our main measure of industry rivals' financial capacity is the bank loan issuance *Log(LoanAmount)*, which equals the logarithm of one plus the amount bank loans issued from the fourth quarter of 2012 to the fourth quarter of 2017.

In our regressions, we control for determinants of financing that have been used in previous studies. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book*, and the *SOE* dummy. The government ownership dummy SOE follows prior literature (e.g., Wang, Wong, and Xia, 2008), which equals one if a firm is state-owned, given its largest ultimate shareholder is either a central or local government entity, and equals zero otherwise. The set of firm characteristics include the firm age (the number of years since IPO), size (the logarithm of total assets in millions of RMB), the book leverage ratio (total debt over total assets) to measure a firm's ex-ante debt capacity. We measure profitability using return on assets (ROA), which is the operating income before depreciation divided by total assets. The fraction of tangible capital is the amount of fixed investments on property, plant, and equipment divided by total assets. The market-to-book ratio is constructed as the sum of the market value of equity and book value of total liabilities, scaled by the book value of total assets. Detailed variable definitions are shown in Appendix C.

C. Sample Overview

Panel A of Appendix D tabulates the distribution of the numbers of investigations, affected industries, and peer firms in affected industries by quarter and year from the fourth quarter of 2012 to the first quarter of 2015.[9] We observe that 32 percent of the investigations occurred within the early period 2012-2013 and the remaining 68 percent occurred from 2014 to 2015. The increasing number of investigations in later periods reflects the fact that the anti-corruption campaign can be an intensive and persistent reform measure,

[9] We start the news article search on investigations from the fourth of quarter of 2012 since this period has been considered as the starting point of the anti-corruption campaign in the literature (Lin, Morck, Yeung, and Zhao, 2016).

which could have long lasting impact on the corporate sector. Panel B of Appendix D shows the detailed distribution of affected industries. If an industry experiences more than one investigation, we keep only the first event for each industry throughout the analysis. This filtering procedure avoids including the duplicates of corrupt-infested industries and the peer firms within. The balanced sample across industries gives peer firms equal weight in evaluating the effect of anti-corruption events. The investigations are more likely to affect real estate, chemical, mechanics, mining, and pharmaceutical industries as the numbers of peers in those industries are large.

Panel A of Table 1 provides summary statistics for the dependent variables and firm characteristics used throughout the analysis. We have 42,297 firm-quarter observations for the sample spans from the fourth quarter of 2012 to the fourth quarter of 2017. To prevent outliers from affecting our conclusions, we winsorize all variables at the 1 and 99 percent levels. On average, government ownership of the listed companies in our sample averaged 54 percent of firms' equity, which reflects the representativeness of our sample for both state-owned enterprise (SOEs) and privately-owned enterprises (non-SOEs). The leverage ratio has a mean of 0.451 and a median of 0.453.

Panel B of Table 1 presents the difference in summary statistics between the SOE and non-SOE peers. The SOE peer firms are fairly large in size, reflecting the fact that bribing activities often occur for firms with large amounts of economic resources. Further, the SOE peer firms have higher leverage, lower growth opportunities, and lower return on assets (i.e., lower productivity) compared to the non-SOE peer firms. Not surprisingly, SOE peers are more leveraged, having more access to bank loans and lower stock market volatility than non-SOE peers.

D. Government Ownership and Political Connection

In Table 2, we present the changes in political connection from 2012 to 2016. For each year, we calculate the average of the firm-level political connection across all public firms. For the entire sample of firms, Panel A illustrates the percentage of firms connected to government officials through the three channels listed above: government employment, member of the Congress, relatives or friends. The political connection dummy *PoliticalConnection* takes a value of one if the firm has at least one connection with government officials and zero otherwise. In 2012, approximately 25 percent of the observations in our sample correspond to firms that have at least one top official with political connections. From 2012 to 2016, the sample firms experienced substantial reductions in political connections to 19 percent. The decrease in political connections is concentrated in the top 50 and 100 firms in terms of the asset size and in the market capitalization weighted measures.

Panel B and C of Table 2 show the changes in political connections for SOEs and non-SOEs. For the SOE subsample, the percentage of politically connected firm decreases from 26 percent to 12 percent. The top 50 firms experience reduction from 64 percent to 30 percent, and the top 100 firms suffer reduction from 57 percent to 25 percent, respectively. In terms of the economic magnitude, approximately half of the sample SOE firms lost their political connections within three years. In contrast, for non-SOEs, the percentage of politically connected firm decreases only from 25 percent to 24 percent, and other columns exhibit a similar pattern. Figure 2 Panel A demonstrates the sharp declines in political connections for SOEs relative to non-SOEs during the anti-corruption campaign period, while Panel B demonstrates a similar yet stronger pattern surrounding the investigation event times.

Compared to the non-SOEs, the significant reduction in the political connection for SOEs suggests that they are more exposed to investigations, given the initiative of the anti-corruption campaign in reducing rent-seeking activities in the public sector. Therefore, the differential impact on SOEs versus non-SOEs provides tentative evidence that political connections could be instrumental in bringing about the credit reallocation effect, which we will give more thorough examination in Section 4.

3. Credit Reallocation Effect of Anti-Corruption Investigations

In this section, we first outline the testing hypotheses and empirical methodology. Then, we provide direct evidence on the credit relocation effect from SOEs to non-SOEs, due to heightened investigations since the anti-corruption campaign, mainly among investigation affected industry peers, but also among directly implicated firms and non-affected industry firms. To ensure a clean identification, we also conduct propensity-score matching and pre-trend analysis.

A. Hypothesis

The literature offers contradicting predictions about the effect of China's anti-corruption campaign on the financing capacity of SOEs versus non-SOEs. On the one hand, containing corruption cost and severing political connections may lead to more favorable borrowing conditions for non-SOEs. On the other hand, government guarantees lower default risk and borrowing cost, thus encourages bank lending to SOEs even during uncertain times.

There is a large literature studying the economic costs of corruption and examining the channels through which corruption fosters rent-seeking activities (see, e.g., Shleifer and Vishny, 1993; Shleifer and Vishny, 1994; Mauro, 1995; Fisman, 2001). Prior to the anti-corruption campaign, lenders may have been under pressure to make economically questionable loans to politically influential firms and politicians' friends. Since the campaign, as some of the powerful and implicated officials have been penalized or removed due to rent-seeking activities, lending decisions may be subject to less political interference of the state officials and with more discretion to maximize profit. This could lead to increases in lending to the more productive, non-SOEs, and reductions in lending to the less productive, SOEs.

Political connections are associated with preferential access to bank credit, as documented by Johnson and Mitton (2003), Sapienza (2004), and Khwaja and Mian (2005). Corruption investigations may convey negative information about SOEs, which could have previous connections with the investigated officials and have used bribes to obtain bank financing; therefore SOEs experience substantial losses of political connections since the campaign, as shown in Table 2 Panel B. In contrast, the investigations may convey positive information about non-SOEs, as they are less exposed to previous connections with the investigated officials, and their political connections are less severed by the anti-corruption campaign, as shown in Table 2 Panel C. Consequently, bank financing could tilt away from SOEs and toward non-SOEs.

Faccio, Masulis, and McConnell (2006) and Borisova, Fotak, Holland, and Megginson (2015) demonstrate that the implicit guarantee associated with government ownership lowers the perceived risk of default and the cost of debt. For SOEs, the value of a government guarantee increases financing capacity, as lenders factor into their lending decisions the high likelihood of bailout when encountering economic distress or political uncertainty. In contrast, for non-SOEs, a government bailout or restructuring intervention is unlikely; hence investigation events and political uncertainty may have only negative impact on their debt financing. Therefore, with implicit government guarantee under the state ownership, we expect credit provision shift from non-SOEs to SOEs, due to investors' aversion to political uncertainty.

We will provide clear empirical evidence in this section on which direction the anti-corruption campaign will shift bank lending toward---SOEs or non-SOEs, then, in the next section, we further examine the mechanisms through which this credit reallocation effect takes place.

B. Methodology

We adopt a difference-in-differences (hereafter, DID) method to overcome the potential endogeneity concerns. The approach compares the changes in bank financing for a treatment group of SOE rival firms versus a control group of non-SOE rival firms, which are otherwise comparable, before and after the investigation events. The staggered investigations across 31 affected industries and the DID approach rule out the possibility that the macroeconomic trend or policy in aggregate could drive the credit reallocation effect. We mainly focus on the SOE and non-SOE rival firms in the same 31 industries under corruption investigations, where the identification is rather clean. Our analysis also extends to 61 firms directly implicated with the corruption officials and to firms in the 33 non-affected industries by investigations.

Our generic regression specification is as follows:

$$Log(LoanAmount)_{i,j,t+1} = \beta_1 InvestigationAft_{j,t} + \beta_2 InvestigationAft_{j,t} * SOE_{i,t} + \beta_3 SOE_{i,t} + Firm\ Controls_{i,t} + QuarterFixed_t + IndustryFixed_j + QuarterIndustryFixed_{j,t} + \varepsilon_{i,t} \quad (1)$$

where $InvestigationAft_{j,t}$ is a dummy that equals one in affected industry *j* for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event. $SOE_{i,t}$ is a dummy that equals one for all rival firms classified as SOEs in quarter *t*, and equals zero for all rival firms classified as non-SOEs.[10] The key independent variable $InvestigationAft_{j,t}$ captures the change in bank lending before and after each investigation event that occurred in quarter *t*. The treatment firms consist of the SOE rivals in the affected industries, while the control firms consist of the non-SOE rivals in the affected industries. As the sample includes the 31 investigated industries, the coefficient estimate β_1 for the term $InvestigationAft_{j,t}$ captures the effect of the anti-corruption campaign for non-SOEs; the coefficient estimate β_2 for the interaction term $InvestigationAft_{j,t} * SOE_{i,t}$ captures a difference-in-differences effect between SOEs and non-SOEs. Consequently, the average effect associated with the anti-corruption campaign for SOEs can be deduced as $\beta_2 + \beta_3$. The key dependent variable bank loan issuance is the logarithm of one plus the amount of bank loans issued in the next quarter *t+1*. The set of *Firm Controls* are included to account for firm characteristics that might affect the corporate financing decision, which follows the existing literature: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book*, and the *SOE* dummy. Detailed variable definitions are shown in Appendix C.

We conduct preliminary tests to address the identification concern---whether the timing of the investigation is correlated with the economic fundamental of firms and the industries. First, in Table 3, we run probit regression of investigation likelihood in quarter *t* on the characteristics of the implicated firms in

[10] Note that the dummy variable $SOE_{i,t}$ has a subscript *t*, because there are five firms switching types between SOEs and non-SOEs, mainly due to the shares privatization program.

quarter *t-4* (one year before), after controlling for quarter fixed effects, and industry fixed effects. The insignificant coefficients on the firm controls suggest that the probability of the investigation is unlikely to be correlated with firm fundamentals. Second, we further test whether the announcement of investigation is exogenous to industry characteristics. Table 4 shows the probit regression of the investigation likelihood on the industry characteristics, after controlling for the set of firm characteristics. Specifically, we include the industry average value of firm controls in the affected industries in each model: *InduAge, InduSize, InduLeverage, InduProfitability, InduTangibility, InduMB and InduSOE*. Still, we observe insignificant correlation between the industry characteristics and the probability of being investigated. Therefore, both firm level and industry level evidence suggest that, there is little evidence that firm characteristics is systematically related to the probability of investigation, at least based on the observables we have in our samples.

C. The Impact of Investigations on Bank Lending

Figure 1 Panel B plots the changes in access to bank credit for SOE and non-SOE rivals, before and after investigations. We observe that anti-corruption investigations are associated with sharp increases in bank lending for non-SOE peers after the event quarter 0. In contrast, SOE rivals experience no significant changes in bank lending surrounding the announcement window. This provides a preliminary evidence that the bank credit allocation might have become more merit based, towards more productive firms during the anti-corruption campaign.

Table 5 displays the difference-in-differences regression result for bank loan issuance on key independent variables $InvestigationAft_{j,t}$ and its interaction with $SOE_{i,t}$ dummy. Column (1) controls for the set of firm level characteristics. Column (2) controls for firm level characteristics and quarterly fixed effects. Column (3) controls for firm level characteristics, quarterly fixed effects, and industry fixed effects.

To address the concern that the regression results might be driven by unobservable differences between SOEs and non-SOEs, Column (4) further controls for industry-quarter fixed effects.

In all columns, we observe positive coefficients on $InvestigationAft_{j,t}$ with significance level of 1 percent, indicating that non-SOE peer firms in affected industries experience substantial increases in bank lending after the investigations of government officials. In terms of the economic magnitude, for an investigation event that occurred in quarter *t*, on average the bank loan issuance to control firms (non-SOEs) increases by 28 percent in one year, after controlling for industry fixed effects, quarter fixed effects, and the industry-quarter fixed effects, as shown in Column (4). The industry-quarter fixed effect captures the time-varying industry specific characteristics that may drive the bank loan reallocation.

In contrast, the signs on the interaction term $InvestigationAft_{j,t} * SOE_{i,t}$ are all significantly negative across the four columns, at the 1 percent level, indicating that the financing gap between SOEs and non-SOEs shrinks in investigation affected industries. All else being equal, the negative effect suggests that SOE peers experience less increase in bank loan issuances, by 13 percent on average in Column (4), compared to non-SOE peers one year after investigations in affected industries.

D. Identification: Propensity-Score Matching and Pre-Trend Analysis

In order to more carefully address the concern that SOEs and non-SOEs may differ in their economic fundamentals prior to the investigations, we further construct the treatment group and the control group using propensity score matching. We start with estimating a probit model based on the initial sample of SOEs and non-SOEs within affected industries. The dependent variable equals one if the firm-quarter observation is a SOE and zero otherwise. The probit model includes all control variables from Equation (1), measured in the year-quarter immediately preceding investigations. We also include the political connection dummy, to capture the differences in the firms' ties with government officials, and include the amount of bank loans over the three years before investigations, to capture the differential trends in financing capacity.

We include firm control variables since the difference-in-differences approach requires the parallel trend assumption to be satisfied.

Panel A of Table 6 displays pre-match propensity score regression results in Column (1) and post-match diagnostic regression results in Column (2). In Column (1), some of the firm characteristics and political connection dummy have explanatory power, which suggests that initially the treatment group of SOEs and the control group of non-SOEs may differ along various dimensions. Using the predicted probabilities from Column (1), we conduct the nearest-neighbor propensity score matching without replacement, where each SOE in the treatment group is matched with a non-SOE from the control group. Specifically, we only retain the matching pair with the smallest distance between propensity scores, which yields 592 matched firms. The probit model regression for the matched sample is shown in Column (2). Given the insignificance of all the coefficient estimates on firm controls, the political connection dummy, and the pre-event bank lending, there should be little concern about observable trends between these two groups prior to the anti-corruption investigations.

We then conduct a series of diagnostic tests to verify that the parallel trends assumption is satisfied. Panel B shows the differences between the propensity scores of the treatment firms (SOEs) and those of the matched control firms (non-SOEs), which are essentially zero. Panel C further examines the mean differences between the treatment and control firms' characteristics prior to investigations, none of which is statistically significant, including political connection. These univariate comparisons suggest that the parallel trend assumption is unlikely to be violated, and our earlier finding on the credit reallocation effect is mainly driven by the exogenous change in anti-corruption investigations.

Panel D shows the difference-in-differences estimation, where the first two columns displays the average changes in bank lending for the treatment and control groups within one year and within three years, respectively. In the third column, the negative significant DID estimates indicate that the increases in bank lending are larger for the control non-SOE group than for the treatment SOE group. In terms of the economic magnitude, the exogenous shock of anti-corruption investigation leads to an increase of 9 percent in bank loan amounts for the control non-SOE group relative to the treatment SOE group in one-year period after the anti-corruption campaign.

Figure 3 illustrates the parallel trends and changes in financing capacity for the treatment and control groups. They share similar trend in years prior to investigations, consistent with the diagnostic tests results on the parallel trend assumption in Table 6. Post investigations, we observe sharp increases in bank lending for the control group of matched non-SOEs relative to the treatment group of matched SOEs.

We conduct pre-trend analysis in Table 7. Specifically, we conduct the DID test using observations centered on the investigations, including the pre-trend dummies and the post-event dummies in the regression. The variable *Treat* equals one for treatment firms (matched SOEs) and zero otherwise (matched non-SOEs). The time dummy $BeforeYear^{-1}$ equals one if a firm-year observation belongs to one year prior to investigations and zero otherwise. The time dummy $AfterYear^{1}$ equals one for the observation within one year after the investigation and zero otherwise. Since our sample spans the nine-year window around events, the omitted group constitutes observations four years after investigations, thus not shown in the table.

In all specifications, we observe statistically insignificant coefficient estimates for the pre-trend dummies, which supports the parallel trend assumption and the validity of the DID estimation. Moreover, the coefficient estimates on the post-event dummies are all positive and mostly significant, which indicates that control firms (matched non-SOEs) experience increases in bank lending compared to treatment firms (matched SOEs) in years following the investigations. The estimates on the interaction terms of treat dummies and post-event dummies are all negative and mostly significant, which is consistent with the reduction in bank lending among treatment SOE firms relative to control non-SOE firms after the investigations. [11]

[11] Importantly, the significance of the credit reallocation effect up to three years after the investigations suggests that the positive impact from the anti-corruption campaign can be long lasting.

E. Firms Directly Implicated by Corruption Investigations

Our main findings of this paper focus on the SOE and non-SOE rival firms that operate in the investigation affected industries, while excluding the directly implicated firms with officials under investigations, which could also be either SOEs or non-SOEs. In this section, we examine the impact of the anti-corruption investigations on the sample of implicated firms. In particular, we focus on the 78 high-ranked investigations that have direct linkages with 61 firms as shown in the Appendix A and B. Table 3 shows the insignificant correlation between implicated firm characteristics and the probability of being investigated. Thus, the variations in the investigation timings are unlikely to be related to the economic fundamentals of implicated firms.

Table 8 shows the regression results on the sample of implicated firms. The coefficient estimates on $InvestigationAft_{j,t}$ are all positive and statistically significant at the 1 percent level in all columns, indicating that the non-SOEs experience significant increases in the access to bank credit than SOEs after investigations. The magnitudes of the coefficient estimates here for implicated firms are nearly twice larger than those of rival firms reported in Table 5, an increase of 44 percent versus 28 percent annually, suggesting that the anti-corruption campaign could have stronger effects on non-SOE implicated firms. More importantly, the coefficient estimates on $InvestigationAft_{j,t} * SOE_{i,t}$, the variable of interest in the DID test, are all negative and statistically significant at the 1 percent level. The magnitudes of the coefficient estimates here for implicated SOE firms are nearly four times larger than those of rival SOE firms reported in Table 5, a decrease of 54 percent versus 13 percent annually, suggesting that the implicated SOE firms are much more affected to by the bank credit reallocation effect following the investigation events.

F. Non-Affected Industries

There is one important remaining concern about focusing on affected industries that, there may be unobservable differences in industry characteristics or fundamentals, such as size and growth opportunities, which could have differential correlations with the likelihoods of industries being investigated or not. To address this concern, we must conduct an "out-of-sample" test on the 33 non-affected industries---those without direct linkages to implicated officials. In the previous analysis, Table 4 shows the insignificant correlation between industry characteristics and the probability of being investigated. Thus, the variations in the investigation timings are unlikely to be related to the economic fundamentals of affected industries.

The variation in the investigation timings on implicated firms of affected industries is already shown in Table 4 to be exogenous, which is even more likely to be exogenous for firms in non-affected industries, since the latters have no obvious linkage with the officials under investigations. Nevertheless, we conduct the propensity score matching approach to match each investigated industry with the non-investigated industry by average firm size and growth opportunity (ROA). Panel A and Panel B of Figure 4 displays average firm size and ROA after the propensity score matching, where the investigation affected and non-affected industries look quite similar.[12] This evidence further supports that the investigation of implicated officials is unlikely to be correlated with the non-affected industry conditions leading up to the announcement.

Table 9 examines the impact of investigations on banks' lending decisions for firms in non-affected industries. The coefficient estimates on $InvestigationAft_{j,t}$ are all positive and statistically significant, suggesting that non-SOEs in non-affected industries also experience a 44 percent increase in one year (Column (4)) in bank lending upon exogenous increases in investigation shocks in affected industries. In contrast, the coefficient estimates on the interaction term $InvestigationAft_{j,t} * SOE_{i,t}$ are all negative and largely significant, which indicates that SOEs in non-affected industries experience an average 27 percent less increase in one year (Column (4)) in bank lending than non-SOE. Comparing to Table 5 on firms within affected industries, the loan amount increase for non-SOE rivals is by 28 percent in one year, while the loan amount increase for SOEs relative to non-SOEs is less by 13 percent in one year. Note that the magnitudes

[12] In an unreported figure, we also demonstrate that even before the propensity score matching, the investigated and non-affected industries are similar in firm size and operating performance.

of coefficient estimates after matching growth opportunity (Column (8)) are largely similar to those reported in Table 5. Therefore the implication is that, banks have equally strong incentive---if not stronger---to shift lending from SOEs to non-SOEs, even in the industries without associations with the anti-corruption investigations. We further corroborate such a pervasive credit reallocation effect with a case of pure credit supply shock in Section 5.

4. Potential Mechanisms

In this section, we explore the potential mechanisms that could drive our results on credit reallocation due to the anti-corruption campaign---economic efficiency, political connection, and uncertainty aversion.

A. The Economic Efficiency Channel

Shleifer and Vishny (1993) argue that corruption lowers economic growth. By initiating the anti-corruption campaign, the Chinese government intends to increase the costs associated with bribes. We expect that the anti-corruption campaign leads to reductions in rent-seeking activities, which forces credit allocation to be more merit based. Consequently, banks allocate less credit to less productive, SOEs and more credit to more productive, non-SOEs. We measure the firm operating performance using the total factor productivity (TFP).[13]

In Table 10, we report the effect of the anti-corruption investigations on a firm's TFP two year later. The coefficient estimates on $InvestigationAft_{j,t}$ are all positive and highly significant at the 1 percent level, which suggests that investigations increases the productivity of non-SOEs. In contrast, the coefficient estimates on the interaction terms are all negative and marginally significant at the 10 percent level, suggesting more limited efficiency gain on SOEs, given their relatively low growth opportunity (ROA). The

[13] Following Schoar (2002) and Giannetti, Liao, and Yu (2015), we compute a firm's total productivity by the industry and year. The TFP is computed as the residual from the firm level regression of the logarithm of the sales on the logarithm of the number of workers, the logarithm of the total assets, the logarithm of the expenses for material and other inputs. The estimate of total factor productivity captures a firm's deviation from the industry-level factor productivity in a given year.

TFP gain of non-SOEs and credit reallocation are consistent with the economic efficiency channel, where the anti-corruption campaign forces credit allocation to be more merit based.

B. The Political Connection Channel

Khwaja and Mian (2005) show that political connected firms receive substantial preferential treatment in bank lending in term of larger amounts of loans. They also demonstrate that constraints to rent seeking, e.g., checks imposed by electoral participation, alleviate such a preferential treatment. We test further whether changes in political connections triggered by the anti-corruption campaign could be a channel through which investigations lead to credit reallocation from SOEs to non-SOEs.

The regression results in Table 11 show that the impact of the anti-corruption campaign on political connections. Importantly, the decline in the political connection is larger for the SOEs than for the non-SOEs, as the interaction term is negative and statistically significant at the 1 percent level. The magnitude of coefficient estimates on the interaction term indicates that, on average, the exogenous anti-corruption investigations result in more decrease of about 43 percent of political connections for the SOEs than for the non-SOEs, in the three-year period following the investigations relative to the three-year period preceding the events. The negative coefficient estimates are consistent with the univariate analyses of the changes in political connections from 2012 to 2016, as shown in Table 2. However, non-SOEs only experience minor reduction of 5 percent in political connections, which is only significant at the marginal 10 percent level. The significant reduction in political connections among SOEs could be a mechanism, through which anti-corruption investigations affects bank credit reallocation toward non-SOEs.

C. The Uncertainty Aversion Channel

Following Pastor and Veronesi (2012), increases in political uncertainty could lead to rises in the discount rate and drops in stock prices. Using the index of economic policy uncertainty (EPU), Baker, Bloom, and Davis (2016) find that policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors. Under the uncertainty aversion view, SOE firms that are more exposed to anti-corruption investigations would face higher political uncertainty relative to the less exposed non-SOEs. We empirically test whether SOE firms are more likely to experience increases in uncertainty shock than non-SOE firms ex post, as proxied by the stock market volatility.

Table 12 reports how stock price volatility change after the anti-corruption events. The coefficient estimates on $InvestigationAft_{j,t}$ are all positive and statistically significant at the 1 percent level, indicating that the stock price volatility increases dramatically for non-SOEs. However, the insignificant DID estimator suggests that the treatment group (SOEs) and control group (non-SOEs) do not experience differential changes in stock price volatility. If the uncertainty aversion channel were to hold, then increases in stock price uncertainty would have led to reductions in bank lending to both SOEs and non-SOEs, which is inconsistent with our main finding of the credit reallocation effect from SOEs to non-SOEs. Overall, our evidence does not seem to support the political uncertainty aversion channel.

D. The Economic Efficiency Channel versus the Political Connection Channel

We have shown above some tentative evidence that the anti-corruption campaign contributes to credit reallocation through economic efficiency (increase) channel and/or the political connections (reduction) channel. In this section, we further examine the relative importance of these two mechanisms by testing them side-by-side. In particular, if the economic channel plays a dominant role, we should observe that the credit reallocation effect due to the TFP channel still holds even with the control for the political connection channel.

Table 13 presents this comparison result in the difference-indifferences framework. Column (1) displays our benchmark estimates similar to those reported in Table 5, but with a smaller sample size, due to the limitations of the political connection and TFP variables. Columns (2) to (4) control for political connection, TFP, and both. Note that the coefficient estimations for the bank loan changes for non-SOEs and DID effect on SOEs have similar magnitudes in Columns (2) to (4) and relative to the benchmark case in Column (1). The positive sign on political connection variable and negative sign on TFP variable imply that, on average, not considering anti-corruption investigations, highly connected and low TFP firms are more likely to get bank loans. However, the political connection effect is only marginally significant at the 10 percent level, while the TFP effect is highly significant at at the 1 percent level.

We further conduct sub-sample analyses on political connections and firms' TFP in columns (5) to (10). The credit reallocation effect from SOEs to non-SOEs seems to exist in the non-connected firm sample only, but not in the connected firm sample. While for the non-connected firm sample, the effect exists for both high TFP sample firms and low TFP sample firms, with statistical significance at the 1 percent level. These results seem to suggest that the economic efficiency channel could be the leading mechanism, and to a lesser extent, the political connection channel could also play a role.

E. More Evidence on the Economic Efficiency Channel: Bank Performance

The previous sections show that the banks allocate more credit towards non-SOEs, due to the anti-corruption campaign, which induces bank lending to become more merit based. To further demonstrate that such a credit reallocation is indeed beneficial to banks, we evaluate the bank performance before and after the anti-corruption investigations. We obtain bank financial information from the China Banking Regulatory Commission (CBRC) and link to the lender of each loan facility. Since there is no link table between lender name and the Bank ID reported by the CBRC, we manually match the largest 200 commercial banks ranked by asset size at the end of year 2016. These 200 largest banks include State-Owned Banks, National Shareholding Banks, City Commercial Banks, Rural Financial Institutions, and Foreign Banks.

For our sample of the largest 200 banks, we construct the following bank performance related dependent variables: *Log(SubprimeLoan)* equals the logarithm of the loan amount of subprime loans that issued to borrowers with high likelihood of defaulting according to bank's internal credit rating, non-performing loan measure *NPL* equals the percentage of the loans that is not paid in full at the maturity according to bank's internal reporting, *Log(ChargeOff)* equals the logarithm of the amounts of charge-offs from bank's balance sheet, and *Log(OperatingCost)* equals the logarithm of the amounts of operating costs.

Table 14 reports the marginal effect regression of bank performance measures on the interaction terms between bank loan issuances and post investigation indicator. In Columns (1), (3), (5), and (7), we include the industry, quarter, industry-quarter fixed effects, and control for borrower characteristics. In Columns (2), (4), (6), and (8), we add the bank-fixed effects to capture the heterogeneity of bank characteristics and risk preferences. In Column (2) and (4), we observe that increases in bank lending towards non-SOEs lead to reductions in subprime loans and a lower fraction of non-performing loans. The coefficients on the interaction terms between the post-investigation indicator and the bank lending are negative and statistically significant at the 1 percent level. In terms of the economic magnitude, in Column (4), a one standard deviation increase in the bank lending (8.424) towards non-SOEs lowers the non-performing loans by 0.577 standard deviations of the NPL (=8.424*(-0.028)/0.409) after the investigation events.

In contrast, we observe increases in the fraction of non-performing loans if a bank extends credit towards SOEs. In particular, the coefficient on the triple interaction term between the post-investigation, the bank lending, and the SOE indicator is positive and statistically significant at the 1% level, as shown in Column (4). The result indicates that a one standard deviation increase in the bank lending to SOEs leads to a larger increase in the non-performing loans by 0.309 standard deviations of the NPL (=8.424*(0.015)/0.409) after the investigations relative to bank lending to non-SOEs. Turning to the alternative measures of bank performance, we also find significant improvements for lending to non-SOEs relative to SOEs on the amount of subprime loans in Column (2), the amount of bank charge-offs in Column (6), and the amount of operating costs in Column (8).

These findings on bank performance support earlier findings on the economic efficiency channel at the firm level---the anti-corruption campaign forces bank credit allocation to be more merit based, and banks make rational business decisions by shifting credit toward more productive, non-SOE, rivals. As a result, the economic gain is further shared by both the more productive non-SOE firms and the more business oriented banking institutions.

5. Further Analysis and Robustness Checks

So far we have demonstrated that the anti-corruption campaign has a positive effect on the credit reallocation from SOE to non-SOE rival firms and the likely channels of economic efficiency and political connections through which the effect takes place. In this section, we provide additional evidence on the extensive margin---new loan issuance and exogenous credit supply shock. Furthermore, we connect to the existing literature of stock price reaction and seasonal equity issuance. Finally, we conduct some robustness checks, such as total debt issuance and regional effect analysis.

A. The Impact of Investigations on Extensive Margins

It is important to examine how anti-corruption investigations affect the likelihood of obtaining bank loans, especially for privately-owned, non-SOE firms that were previously largely deprived of bank credit access. We conduct regression analysis in an extensive margin framework. Columns (1)-(4) of Table 15 report the results from a probit regression on the likelihood of industry rivals obtaining new loans after anti-corruption investigations. In all columns, the positive and significant coefficients on $InvestigationAft_{j,t}$ indicate that non-SOE rivals have a large increase in the probability of obtaining bank loans, up by 17 percent, after the investigations of implicated firms in that industry. However, the negative coefficients on the interaction terms $InvestigationAft_{j,t} * SOE_{i,t}$ suggest that SOE rivals face a smaller increase in the likelihood of bank financing, less up by 6 percent, compared to non-SOE peers. The extensive margin results therefore support the credit reallocation effect earlier in the intensive margin based on the loan issuance amounts.

Columns (5) and (6) of Table 15 conduct additional tests on the extensive margin regression for industry rival firms that have never obtained bank loans prior to the anti-corruption investigations, which constitutes a much smaller sample size of 10,341 observations, one fourth of the regular sample size. The coefficient estimates on $InvestigationAft_{j,t}$ are all positive and significant at the 1 percent level. However, coefficient estimates on the interaction terms $InvestigationAft_{j,t} * SOE_{i,t}$ are all negative albeit insignificant. In terms of economic magnitudes, non-SOE rivals have a higher likelihood by 77 percent in obtaining a new loan, while SOE rivals has a less increase in likelihood by 12 percent in obtaining a new loan. These margins for previously unbanked non-SOE firms are larger than those for the whole sample in Columns (1) to (4). There seems to be more credit availability to the previously unbanked, more productive (ROA), non-SOE, rival firms.

B. Zero in on the Supply Side

China Minsheng Banking Corp., Ltd is the 11th largest bank in the nation. Its CEO Mao Xiaofeng resigned and was investigated on January 30, 2015, in a corruption case related to several high-profile government leaders.[14] On the same day, Mr. Mao had been detained for questioning by the Central Commission for Discipline Inspection (CCDI). Specifically, this investigation event was considered as an unexpected event, as CEO Mao was first promptly reported by *Caixin* on February 1, 2015, which is a leading and well-respected financial news media in China. According to *Financial Times* coverage on this case on February 1, 2015, Mr. Mao Xiaofeng became the latest top official in the financial industry ensnared in Chinese president Xi's Jinping's anti-corruption campaign. From a methodological perspective, the Minsheng Bank investigation provides a fruitful setup to explore the credit supply shock associated with the anti-corruption campaign on the subsequent bank credit allocation.

Table 16 shows the regression findings by including the supply-side shock dummy $AftMao_t$, which equals one for the periods after January 30, 2015 and equals zero for the periods before and on January 30, 2015.[15] The dependent variable is the logarithm of the amount of bank loans. The coefficient estimates on

[14] According to the *Financial Times* coverage on this case on February 1, 2015, Mr. Mao Xiaofeng is closely related Mr. Ling Jihua, a top leader who rose up through the Chinese Youth League and in December 2015 became the latest top official ensnared in Chinese president Xi's Jinping's anti-corruption campaign.
[15] We also conducted placebo tests on both January 30, 2013 and January 30, 2014, without such a clear finding on supply shock for the credit reallocation. The tabulated results are available upon request.

the interaction term $AftMao_t * SOE_{i,t}$ are all negative and statistically significant at the 1 percent level. The negative sign indicates that after the investigation of CEO Mao, SOE firms experience an average 18 percent less increase in bank lending than non-SOEs in one year. In contrast, the coefficients on the term $AftMao_t$ are all positive and statistically significant at the 1 percent level---bankers have incentive to lend more towards non-SOEs, after the Mingsheng Bank scandal. The credit reallocation effect seems clear under a credit supply side story. This evidence from a pure credit supply shock is consistent with the evidence on the economic efficiency channel in Section 4, where bankers reallocate credit more merit based to more productive, non-SOEs, resulted in better bank performance.

Note that we do not completely rule out the demand side impact for the credit reallocation effect. However, since SOEs in China enjoy typical "preferential treatment" in obtaining bank financing in normal times (Brandt and Zhu, 2001; Boyreau-Debray and Wei, 2005; Song, Storesletten, and Zilibotti, 2011; Cong, Gao, Ponticelli, and Yang, 2017), it would be hard to reconcile with the credit demand story---SOEs would not be shy from obtaining bank financing even in difficult times. This argument is further corroborated by the fact that the credit reallocation effect is common and pervasive across affected industry rival firms, investigation implicated firms, and firms in non-affected industries.

C. Equity Market Response

Recent studies related to the anti-corruption campaign in China mainly focus on the stock market price reactions, see, e.g., Lin, Morck, Yeung, and Zhao (2016) and Liu, Shu, and Wei (2017). However, bank financing still constitutes a dominant source of corporate financing (about 85 percent), while equity financing is only a very small portion in China (1.3 percent) (Wang, Wang, Wang, and Zhou, 2016). In this section, we study the impact of the anti-corruption campaign on the equity market.

We estimate daily abnormal stock returns using Fama and French (1993) three factor model.[16] For each firm in the sample, we estimate the parameters over the 180 days in the pre-event period (Day -210 to Day -30). Figure 5 plots the cumulative abnormal returns (CARs) for both the non-SOEs (solid line) and SOEs (dash line) industry peer firms, over the 20 days event window. We observe that non-SOE peers experience substantial increases in abnormal returns in periods after the investigation events, while SOE peers experience significant decreases in abnormal returns in periods after the investigation events. Appendix E displays the mean and median CARs for the SOE and non-SOE peers, and the T-test for the difference in CARs. We report the mean and median CARs over the [-10,-2], [-10, +2], and [-10, +10] three windows. Non-SOE peer firms experience significant positive CARs, while SOE peer firms experience significant negative CARs.

We further exploit the implication of the anti-corruption campaign on the equity financing. The dependent variable in Appendix F is the total amount of seasonal equity issuance in each quarter. In Columns (1)-(4), the coefficients on $InvestigationAft_{j,t}$ are all positive and statistically significant at the 1 percent level, which suggests that non-SOE peer firms experience increases in equity issuance following the investigation of government officials. In contrast, for SOE peers, the coefficients on the interaction term $InvestigationAft_{j,t} * SOE_{i,t}$ in Columns (1) through (4) are all negative and statistically significant at the 1 percent level. This negative estimation result implies that, equity investors are much more cautious to invest towards SOE peer firms after the investigation events.

D. Robustness Checks---Total Debt and Regional Variation

We examine the credit reallocation effect for rival firms' total debt---both bank financing and non-bank financing---in Appendix G. The coefficient estimates on $InvestigationAft_{j,t}$ are positive and

[16] We estimate the following: $R_{i,t} = \alpha_i + \beta_i R_{M,t} + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$, where $R_{i,t}$ is the return to a firm on Day t ; $R_{M,t}$ is the return to the value-weighted market index on Day *t*; SMB_t and HML_t are the returns to the small-minus-big (SMB) and high-minus-low (HML) portfolios that captures size and book-to-market effects on Day *t*. We use the three-factor model instead of the market model as in Liao, Liu, and Wang (2014) to capture the systematic effect associated with firm size.

statistically significant in Columns (2) to (4) at the 1 percent level, which suggests that non-SOE firms experience increases in the amount of debt outstanding following the investigation of government officials. In terms of economic magnitude, after an investigation event, the total debt outstanding of control firms (non-SOEs) increases by 10 percent in one year, after controlling for industry and quarter fixed effects as shown in Column (4). In contrast, the total debt outstanding of treatment firms (SOEs) decreases, as the sum of coefficients estimates of $InvestigationAft_{j,t}$ and $InvestigationAft_{j,t} * SOE_{i,t}$ are negative on net in Column (4). These results confirm the earlier evidence on bank loan issuances.

We further examine how bank credit change with the anti-corruption investigations across geographic regions. Specifically, from the 78 high-ranked government officials that were investigated, we track their career paths during the past 30 years in different provinces. A province is affected upon the investigation of a government official who held high-ranked position in that province. The $InvestigationAft_{s,t}$ is a dummy that equals one in affected province *s* for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event.

Appendix Table H shows that impact of investigations on bank lending for firms in affected provinces. The coefficient estimates on $InvestigationAft_{s,t}$ are all positive and statistically significant at the 1 percent level, suggesting that non-SOEs experience a 13 percent increase in bank loan issuances one year after investigations in affected provinces. In contrast, the coefficient estimates on $InvestigationAft_{s,t} * SOE_{i,t}$ are all negative and statistically significant at the 1 percent level, which indicates that SOEs experience less increase in bank lending, by 34 percent on average, compared to SOEs one year after investigations in affected provinces.

Therefore, we also observe credit reallocation within geographic regions after the investigation of officials who held high-ranked position in those affected provinces. This finding is consistent with our main results in affected industries and non-affected industries. And a full-fledged study using regional variations is left for future research.

6. Conclusion

China's anti-corruption campaign causes bank credit reallocation from less productive SOE rivals to more productive non-SOE rivals in the investigation affected industries. This is in sharp contrast to the preferential treatment of SOEs in obtaining bank credit during normal times. The exogenous shocks from staggered investigations help to identify such a causal relationship. The credit relocation effect extends to corruption implicated firms and industries not affected by investigations. There are more evidence of the effect for new loan initiations, credit supply shock, and stock market reactions.

Two potential mechanisms---economic efficiency and political connection---may be causing the credit reallocation effect, while a third mechanism of uncertainty aversion does not seem to enjoy empirical support. Both firm TFP and bank performance are responding to the anti-corruption investigations, in favor of non-SOEs over SOEs, lending stronger support for the channel of economic efficiency. China's anti-corruption campaign could have long lasting impact on corporate investment, production, and employment, which we leave for future research.

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Table 1
Summary Statistics

This table presents the summary statistics of the dependent variables and firm controls based on the sample from the fourth quarter of 2012 to the first quarter of 2017. Panel A displays the summary statistics for the full sample of firms, and Panel B displays the summary statistics for the sample of SOEs and non-SOEs, respectively. The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. Age is the number of years after a firm's listing on Shanghai or Shenzhen Stock Exchange and first appearance in CSMAR database. Firm size is the logarithm of total assets. *Leverage* is long-term debt plus short-term debt divided by total assets. *Profitability* is operating income divided by total assets. *Tangibility* equals the amount of fixed investment divided by total assets. *MB* is constructed as the sum of the market value of equity and book value of total liabilities, scaled by the book value of total assets. The loan issuance amount *Log(LoanAmount)* equals the logarithm of one plus the loan amount issued in a quarter. The extensive margin measure of access to the credit market, *Prob(NewLoan)* is an indicator for whether a borrower obtained a new loan after the anti-corruption investigation. The total factor productivity, *TFP* is computed as the residual from the firm level regression of the logarithm of the sales on the logarithm of the number of workers, the logarithm of the total assets, the logarithm of the expenses for material and other inputs. The political connection dummy *PoliticalConnection* equals one if there exists any connection between firms' CEOs and officials through the following three types: central government or a local government, the Congress, or relative and friends, and zero otherwise. *StockVolatility* is computed using the standard deviation of a firm’s daily stock returns in percentage. The bank performance variables are also included to test the economic mechanism. *Log(SubprimeLoan)* equals the logarithm of the loan amount of subprime loans that issued to borrowers with high likelihood of defaulting according to bank's internal credit rating. The fraction of non-performing loan (NPL) equals the percentage of the loans that is not paid in full at the maturity according to bank's internal reporting. *Log(ChargeOff)* equals the logarithm of the amounts of charge-offs from bank's balance sheet. *Log(OperatingCost)* equals the logarithm of the amounts of operating costs.

Panel A: Full Sample						
Variables	N	Mean	SD	P25	P50	P75
SOE	42297	0.542	0.498	0.000	1.000	1.000
Age	42297	11.341	6.534	6.000	11.000	17.000
Size	42297	22.119	1.382	21.153	21.935	22.896
Leverage	42297	0.451	0.231	0.270	0.453	0.623
Profitability	42297	0.009	0.023	0.001	0.008	0.018
Tangibility	42297	0.224	0.170	0.092	0.191	0.327
MB	42297	2.074	1.529	1.122	1.564	2.425
Log(LoanAmount)	42297	14.481	8.424	13.459	18.543	19.967
Prob(NewLoan)	42297	0.754	0.431	1.000	1.000	1.000
TFP	39588	-0.002	0.286	-0.166	-0.015	0.157
PoliticalConnection	42297	0.229	0.420	0.000	0.000	0.000
StockVolatility	42297	0.029	0.010	0.023	0.027	0.033
Log(SubprimeLoan)	22564	9.380	1.524	8.579	9.717	10.412
NPL	23037	1.271	0.409	0.960	1.250	1.550
Log(ChargeOff)	22391	8.281	1.706	7.589	8.542	9.501
Log(OperatingCost)	23360	11.044	1.468	10.478	11.413	12.326

Panel B: The Comparision of Summary Statistics between SOEs and Non-SOEs								
	State-owned Enterprises (SOEs)			(Non-SOEs)			T-test	Sig
Variables	N	Mean	SD	N	Mean	SD		
Age	22937	13.509	5.694	19360	8.772	6.533	4.737	***
Size	22937	22.580	1.439	19360	21.573	1.083	1.007	***
Leverage	22937	0.508	0.221	19360	0.383	0.225	0.126	***
Profitability	22937	0.007	0.022	19360	0.012	0.025	-0.004	***
Tangibility	22937	0.250	0.189	19360	0.194	0.139	0.057	***
MB	22937	1.890	1.303	19360	2.293	1.735	-0.403	***
Log(LoanAmount)	22937	15.636	8.011	19360	13.114	8.693	2.522	***
Prob(NewLoan)	22937	0.799	0.401	19360	0.701	0.458	0.099	***
TFP	20459	0.009	0.280	19129	-0.014	0.291	0.023	***
PoliticalConnection	22937	0.196	0.397	19360	0.268	0.443	-0.072	***
StockVolatility	13336	0.028	0.009	7470	0.031	0.011	-0.003	***
Log(SubprimeLoan)	11263	9.423	1.522	11301	9.338	1.524	0.086	***
NPL	11558	1.270	0.409	11479	1.272	0.410	-0.002	
Log(ChargeOff)	11194	8.331	1.695	11197	8.231	1.716	0.100	***
Log(OperatingCost)	11728	11.062	1.484	11632	11.027	1.451	0.035	*

Table 2
Changes in Political Connections

This table presents the summary statistics of political connections based on the sample from 2012 to 2016. We focus on three types of political connections between firms and officials: 1) if CEO is an official of the central government or a local government; 2) if CEO is connected through the Congress, where CEO, president, vice-president, chairman, or secretary is a deputy to National People's Congress or a member of the CPPCC (China People's Political Consultative Conference) National Committee; 3) if CEO is connected through friends or relatives as family ties with politicians. The total number of political connection is the sum of the three types of connections. The percentage of firms connected through CEOs or CEOs' relatives is calculated as the number of firms connected with one connection with government officials, divided by the total number of listed firms in China in year *t* . The percentage of top 50 (100) firms connected is calculated among the largest 50 (100) firms (based on end of year market capitalization). Connected firms as the percentage of market capitalization is the number of connected firms weighted by their market value.

Year/Variables	% of firms connected through CEOs or CEOs' relatives	% of top 50 firms connected through CEOs or CEOs' relatives	% of top 100 firms connected through CEOs or CEOs' relatives	Connected firms as % of market capitalization
Panel A: The Changes in Political Connections				
2012	0.252	0.640	0.560	0.465
2013	0.249	0.540	0.470	0.419
2014	0.297	0.560	0.560	0.446
2015	0.195	0.380	0.340	0.291
2016	0.190	0.340	0.300	0.270
Panel B: The Changes in Political Connections for SOEs				
2012	0.255	0.640	0.570	0.506
2013	0.251	0.540	0.520	0.468
2014	0.241	0.560	0.510	0.465
2015	0.128	0.380	0.310	0.307
2016	0.116	0.300	0.250	0.262
Panel C: The Changes in Political Connections for Non-SOEs				
2012	0.249	0.420	0.390	0.324
2013	0.248	0.340	0.320	0.298
2014	0.342	0.520	0.490	0.396
2015	0.243	0.380	0.380	0.268
2016	0.240	0.400	0.380	0.282

Table 3
Probability of Investigation on Firm Characteristics

This table presents the probit regression of probability of being investigated on firm characteristics for the sample of implicated firms with link to officials being investigated. The dependent variable *Prob(Investigate)* equals one if an official linked to an implicated firm was investigated in *quarter t* and zero otherwise. We include the following firm level characteristics: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy.* The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Prob(Investigate)			
Age	0.006						
	(0.013)						
Size		0.039					
		(0.057)					
Leverage			-0.320				
			(0.359)				
Profitability				-1.634			
				(2.047)			
Tangibility					-0.506		
					(0.655)		
MB						-0.105*	
						(0.055)	
SOE							-0.170
							(0.165)
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	831	831	831	831	831	831	831
R-squared	0.043	0.043	0.046	0.043	0.043	0.053	0.044

Table 4
Probability of Investigation on Industry Characteristics

This table presents the probit regression of probability of being investigated on industry characteristics for the sample of implicated firms with link to officials being investigated. The dependent variable *Prob(Investigate)* equals one if an official linked to an implicated firm was investigated in *quarter t* and zero otherwise. We include the following firm level and industry level characteristics: *Age*, *Size*, *Leverage*, *Profitability*, *Tangibility*, *Market-to-book, and the SOE dummy.* The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Prob(Investigate)						
Age	-0.002	-0.000	-0.003	-0.003	-0.002	-0.005	-0.003
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Size	0.041	0.067	0.040	0.049	0.041	0.030	0.039
	(0.044)	(0.059)	(0.046)	(0.044)	(0.044)	(0.046)	(0.050)
Leverage	-0.022	-0.152	-0.083	-0.043	0.037	-0.065	-0.059
	(0.367)	(0.397)	(0.401)	(0.349)	(0.368)	(0.359)	(0.365)
Profitability	-1.922	-2.471	-1.945	-1.592	-1.691	-1.604	-1.921
	(2.703)	(2.805)	(2.653)	(2.699)	(2.728)	(2.674)	(2.670)
Tangibility	-0.253	-0.266	-0.263	-0.259	-0.049	-0.235	-0.245
	(0.463)	(0.462)	(0.464)	(0.443)	(0.552)	(0.464)	(0.504)
MB	-0.039	-0.040	-0.036	-0.037	-0.046	-0.030	-0.037
	(0.063)	(0.064)	(0.064)	(0.063)	(0.064)	(0.061)	(0.063)
InduAge	-0.012						
	(0.024)						
InduSize		-0.066					
		(0.091)					
InduLeverage			0.067				
			(0.539)				
InduProfitability				-3.725			
				(3.810)			
InduTangibility					-0.482		
					(0.683)		
InduMB						-0.125	
						(0.152)	
InduSOE							-0.008
							(0.282)
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,250	1,250	1,250	1,250	1,250	1,250	1,250
R-squared	0.036	0.037	0.036	0.039	0.037	0.038	0.036

Table 5
Anti-Corruption Investigations and Credit Reallocation

This table presents the regression of the bank loan issuances around anti-corruption investigation events. The loan issuance amount *Log(LoanAmount)* equals the logarithm of one plus the total amount of bank loans issued in quarter *t* . *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t,* and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy* . The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
		Log(LoanAmount)		
InvestigationAft	1.352***	1.387***	1.011***	1.028***
	(0.112)	(0.112)	(0.111)	(0.112)
*InvestigationAft*SOE*	-0.444***	-0.484***	-0.537***	-0.545***
	(0.140)	(0.140)	(0.136)	(0.136)
SOE	-0.810***	-0.806***	-0.425***	-0.422***
	(0.107)	(0.107)	(0.106)	(0.106)
Age	-0.033***	-0.034***	-0.020***	-0.020***
	(0.007)	(0.007)	(0.007)	(0.007)
Size	1.315***	1.314***	1.931***	1.927***
	(0.038)	(0.038)	(0.036)	(0.036)
Leverage	13.341***	13.359***	11.988***	12.013***
	(0.220)	(0.220)	(0.227)	(0.227)
Profitability	-1.719	-1.435	-8.228***	-7.863***
	(1.942)	(1.947)	(1.871)	(1.893)
Tangibility	6.273***	6.255***	3.067***	3.068***
	(0.204)	(0.203)	(0.276)	(0.276)
MB	-0.683***	-0.687***	-0.542***	-0.545***
	(0.032)	(0.032)	(0.031)	(0.031)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	42,297	42,297	42,297	42,297
R-squared	0.299	0.300	0.350	0.351

Table 6
Propensity Score Matching (DID) Analysis

This table reports the propensity score matching DID tests examining how anti-corruption investigations affect loan issuances. Panel A presents parameter estimates from the probit model used to estimate propensity scores for firms in the treatment (SOEs) and control groups (non-SOEs). The dependent variable equals one if the firm-quarter observation belongs to the treatment group and zero otherwise. We include the following firm level controls in the propensity score matching: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, PoliticalConnection, and the bank loan issuances in the past 3 years* . Panel B reports the distribution of estimated propensity scores after the matching. Panel C reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding *t* -statistics and *p* -values. Panel D conducts the difference-in-differences tests of bank lending within one-year and within three-year period. The variable *Log(LoanAmount)* equals the logarithm of the total amounts of bank loans issued by banks in quarter *t* . All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

Panel A: Pre-match Propensity Score Regression and Post-match Diagnostic Regression

	Dummy=1 if in treatment group; =0 is in control group	
	(1)	(2)
	Prematch	Postmatch (w.o. replacement)
Age	0.075***	-0.012
	(0.007)	(0.010)
Size	0.448***	-0.036
	(0.043)	(0.072)
Leverage	-0.131	0.444
	(0.226)	(0.328)
Profitability	-9.239***	2.583
	(2.347)	(3.264)
Tangibility	1.137***	0.166
	(0.299)	(0.447)
MB	0.038	-0.007
	(0.034)	(0.048)
PoliticalConnection	-0.305***	-0.054
	(0.083)	(0.129)
Log(LoanAmount) $_{t-4}$	-0.011	0.011
	(0.007)	(0.011)
Log(LoanAmount) $_{t-8}$	0.001	-0.007
	(0.008)	(0.012)
Log(LoanAmount) $_{t-12}$	-0.000	0.003
	(0.007)	(0.011)
Industry fixed effects	Yes	Yes
Observations	1,636	592
p -value of χ^2	<0.001	0.999
Pseudo R^2	0.279	0.020

Panel B: Estimated Propensity Score Distributions						
Propensity Scores	Number of Obs.	Mean	SD	Min	P50	Max
Treatment (w.o. replacement)	296	0.475	0.231	0.060	0.475	0.961
Control (w.o. replacement)	296	0.475	0.231	0.056	0.476	0.967
Difference (w.o. replacement)	-	0.000	0.000	0.000	0.000	0.002

Panel C: Differences in Pre-investigation Characteristics						
	Treatment		Control		Difference	
Variable	N	mean	N	mean	*t* -statistics	*P* -value
Age	296	11.162	296	11.541	-0.747	0.455
Size	296	21.864	296	21.816	0.508	0.611
Leverage	296	0.463	296	0.438	1.351	0.177
Profitability	296	0.007	296	0.007	0.000	1.000
Tangibility	296	0.213	296	0.207	0.476	0.634
MB	296	2.057	296	2.139	-0.630	0.529
Political connection dummy	296	0.240	296	0.257	-0.474	0.635
Log(LoanAmount) $_{t-4}$	296	17.126	296	16.259	1.379	0.168
Log(LoanAmount) $_{t-8}$	296	16.342	296	15.747	0.897	0.370
Log(LoanAmount) $_{t-12}$	296	16.614	296	15.966	1.030	0.304

Panel D: Difference-in-Differences Test				
	Treatment Difference (after-before)	Control Difference (after-before)	Mean DiD Estimator (treat-control)	*t* -statistics for DiD Estimator
Log(LoanAmount) (one year)	0.605	1.817	-1.181***	-2.787
	(0.118)	(0.130)	(0.424)	
Log(LoanAmount) (three year)	3.007	6.073	-2.878**	-2.141
	(0.385)	(0.428)	(1.344)	

Table 7
Pre-Trend Analysis

This table shows the pre-trend analysis in the difference-in-differences tests using the nine-year observation centered on the investigations in the sample of matched treatment (SOEs) and control groups (non-SOEs), including the pre-trend dummies and the post-event dummies in the regression.

	(1)	(2)	(3)
		Log(LoanAmount)	
Treat	-0.046	1.082	1.082
	(0.547)	(0.668)	(0.668)
$BeforeYear^{-4}$		-0.989	-0.989
		(0.615)	(0.615)
$Treat*BeforeYear^{-4}$		-0.064	-0.064
		(0.826)	(0.826)
$BeforeYear^{-3}$	-0.574	-0.338	-0.338
	(0.481)	(0.568)	(0.568)
$Treat*BeforeYear^{-3}$	-0.480	-0.807	-0.807
	(0.678)	(0.764)	(0.764)
$BeforeYear^{-2}$	-0.232	-0.241	-0.241
	(0.463)	(0.565)	(0.565)
$Treat*BeforeYear^{-2}$	-1.063	-0.462	-0.462
	(0.655)	(0.758)	(0.758)
$BeforeYear^{-1}$	0.227	0.808	0.808
	(0.461)	(0.560)	(0.560)
$Treat*BeforeYear^{-1}$	-0.967	-0.949	-0.949
	(0.651)	(0.752)	(0.752)
$EventYear^{0}$	0.962**	0.553	
	(0.456)	(0.714)	
$Treat*EventYear^{0}$	-0.881	-0.736	
	(0.644)	(0.972)	
$EventYear^{0}$ & $AfterYear^{1}$			1.330**
			(0.547)
$Treat*EventYear^{0}$ & $AfterYear^{1}$			-1.372*
			(0.735)
$AfterYear^{1}$	1.262***	1.524***	
	(0.455)	(0.556)	
$Treat*AfterYear^{1}$	-1.222*	-1.531**	
	(0.645)	(0.750)	
$AfterYear^{2}$	1.593***	1.785***	1.785***
	(0.465)	(0.556)	(0.556)
$Treat*AfterYear^{2}$	-1.227*	-1.559**	-1.559**
	(0.660)	(0.750)	(0.750)
$AfterYear^{3}$	1.525***	3.330***	3.330***
	(0.519)	(0.557)	(0.557)
$Treat*AfterYear^{3}$	-0.509	-1.846**	-1.846**
	(0.732)	(0.756)	(0.756)
Observations	15,147	16,916	16,916
R-squared	0.011	0.023	0.023

Table 8

Credit Reallocation for Implicated Firms

This table presents the regression of the bank loan issuances on the anti-corruption investigations for the sample of implicated firms that have direct linkage with investigated officials. The dependent variable *Log(LoanAmount)* equals the logarithm of amount of bank loans issued by banks in quarter *t*. Detailed description of implicated firms is shown in Appendix B. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy*. The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
	Log(LoanAmount)			
InvestigationAft	2.407***	2.404***	1.746***	1.786***
	(0.508)	(0.510)	(0.470)	(0.478)
*InvestigationAft*SOE*	-1.509**	-1.503**	-1.842***	-1.961***
	(0.670)	(0.672)	(0.595)	(0.603)
SOE	-0.288	-0.310	0.403	0.455
	(0.511)	(0.510)	(0.599)	(0.615)
Age	-0.044	-0.046	-0.094***	-0.095***
	(0.030)	(0.030)	(0.035)	(0.035)
Size	0.705***	0.711***	1.535***	1.540***
	(0.164)	(0.164)	(0.178)	(0.180)
Leverage	17.075***	17.075***	5.855***	5.864***
	(1.135)	(1.137)	(1.269)	(1.271)
Profitability	10.668	9.933	-22.798***	-24.319***
	(8.662)	(8.671)	(8.260)	(9.099)
Tangibility	2.734**	2.760**	-2.616	-2.578
	(1.110)	(1.113)	(1.905)	(1.920)
MB	-0.912***	-0.908***	-0.293	-0.286
	(0.170)	(0.170)	(0.181)	(0.184)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Quarterly and industry fixed effects	No	No	No	Yes
Observations	1,870	1,870	1,870	1,870
R-squared	0.331	0.334	0.501	0.531

Table 9
Credit Reallocation within Non-Affected Industries

This table shows regression results for out-of-sample tests to assess the robustness of our credit reallocation findings in non-affected industries, those without linkage with implicated officials. The dependent variable *Log(LoanAmount)* equals the logarithm of the total amounts of bank loans issued by banks in quarter *t*. We conduct the propensity score matching approach to match each investigated industry with the non-investigated industry by average firm size (Columns (1)-(4)) and growth opportunity by market-to-book ratio (Columns (5)-(8)). *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy*. The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(LoanAmount)							
	Size				*MTB*			
InvestigationAft	1.711***	1.768***	1.595***	1.606***	2.191***	2.180***	1.598***	1.591***
	(0.212)	(0.212)	(0.213)	(0.214)	(0.212)	(0.213)	(0.212)	(0.213)
*InvestigationAft*SOE*	-0.803***	-0.866***	-0.973***	-0.973***	-0.629**	-0.645**	-0.628**	-0.623**
	(0.268)	(0.269)	(0.263)	(0.264)	(0.270)	(0.271)	(0.266)	(0.267)
SOE	0.470**	0.475**	0.764***	0.768***	0.280	0.280	0.445**	0.443**
	(0.191)	(0.191)	(0.197)	(0.197)	(0.195)	(0.195)	(0.200)	(0.200)
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Quarterly and industry fixed effects	No	No	No	Yes	No	No	No	Yes
Observations	13,535	13,535	13,535	13,535	13,535	13,535	13,535	13,535
R-squared	0.273	0.275	0.317	0.319	0.263	0.264	0.302	0.305

Table 10

Economic Efficiency Channel

This table presents the regression of the total factor productivity (TFP) on anti-corruption investigation events. The TFP is computed as the residual from the firm level regression of the logarithm of the sales on the logarithm of the number of workers, the logarithm of the total assets, the logarithm of the expenses for material and other inputs. The estimate of total factor productivity captures a firm's deviation from the industry-level factor productivity in a given year. The dependent variable *TFP* equals a firm's total factor productivity two years after the investigation. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy.* All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
Variables		*TFP*		
InvestigationAft	0.021***	0.021***	0.016***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
*InvestigationAft*SOE*	-0.010	-0.010	-0.012*	-0.012*
	(0.007)	(0.007)	(0.007)	(0.007)
SOE	0.040***	0.040***	0.043***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.002***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Leverage	0.076***	0.076***	0.050***	0.052***
	(0.009)	(0.009)	(0.010)	(0.010)
Profitability	2.200***	2.209***	2.248***	2.297***
	(0.088)	(0.089)	(0.091)	(0.093)
Tangibility	0.086***	0.086***	0.168***	0.168***
	(0.010)	(0.010)	(0.013)	(0.013)
MB	0.004***	0.004**	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Quarterly and industry fixed effects	No	No	No	Yes
Firm fixed effects	No	No	No	No
Observations	34,236	34,236	34,236	34,236
R-squared	0.034	0.035	0.044	0.044

Table 11
Political Connection Channel

This table presents the probit regression of changes in political connections around anti-corruption investigation events. We focus on three types of political connections between firms and officials: 1) if CEO is an official of the central government or a local government; 2) if CEO is connected through the Congress, where CEO, president, vice-president, chairman, or secretary is a member of National People's Congress or a member of the CPPCC (China People's Political Consultative Conference) National Committee; 3) if CEO is connected through friends or relatives as family ties with politicians. The political connection dummy *PoliticalConnection* equals one if there exists any connection between firms' CEOs and officials through the three types of connections in year *t+1* , and equals zero otherwise. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t* , and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy.* All regressions have standard errors clustered at the firm level, which is shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
		PoliticalConnection		
InvestigationAft	-0.033	-0.036*	-0.040*	-0.041*
	(0.021)	(0.021)	(0.022)	(0.022)
*InvestigationAft*SOE*	-0.443***	-0.440***	-0.427***	-0.427***
	(0.028)	(0.028)	(0.029)	(0.029)
SOE	-0.149***	-0.149***	-0.164***	-0.164***
	(0.020)	(0.021)	(0.021)	(0.021)
Age	-0.014***	-0.014***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Size	0.204***	0.204***	0.204***	0.204***
	(0.007)	(0.007)	(0.008)	(0.008)
Leverage	-0.415***	-0.415***	-0.409***	-0.409***
	(0.037)	(0.037)	(0.042)	(0.042)
Profitability	0.351	0.362	0.249	0.253
	(0.327)	(0.326)	(0.335)	(0.339)
Tangibility	0.115***	0.115***	0.111**	0.111**
	(0.042)	(0.042)	(0.056)	(0.056)
MB	-0.008	-0.008	-0.011*	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	42,297	42,297	42,268	42,268
R-squared	0.049	0.049	0.065	0.065

Table 12
Uncertainty Aversion Channel

This table presents the regression of stock volatility on anti-corruption investigations. The dependent variable *StockVolatility* is computed using the standard deviation of a firm's daily stock returns in percentage. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy*. All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
	StockVolatility			
InvestigationAft	0.601***	0.628***	0.662***	0.673***
	(0.023)	(0.023)	(0.024)	(0.024)
*InvestigationAft*SOE*	0.034	0.031	0.018	0.017
	(0.031)	(0.030)	(0.030)	(0.030)
SOE	-0.038*	-0.036	-0.027	-0.025
	(0.022)	(0.022)	(0.022)	(0.022)
Age	-0.009***	-0.009***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Size	-0.066***	-0.066***	-0.066***	-0.068***
	(0.008)	(0.008)	(0.008)	(0.008)
Leverage	0.118***	0.121***	0.167***	0.171***
	(0.043)	(0.042)	(0.045)	(0.045)
Profitability	-0.679***	-0.670***	-0.493***	-0.487***
	(0.127)	(0.126)	(0.129)	(0.129)
Tangibility	-0.292***	-0.292***	-0.190***	-0.190***
	(0.045)	(0.045)	(0.060)	(0.060)
MB	0.111***	0.110***	0.107***	0.106***
	(0.006)	(0.006)	(0.006)	(0.006)
Quarterly fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Quarterly and industry fixed effects	Yes	Yes	Yes	Yes
Observations	32,363	32,363	32,363	32,363
R-squared	0.077	0.088	0.096	0.098

Table 13
Economic Efficiency Channel versus Political Connection Channel

This table presents the regression of bank loan issuances on anti-corruption investigation events. The dependent variable loan issuance *Log(LoanAmount)* equals the logarithm of one plus the total amounts of bank loans issued in quarter *t* . *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t* , and equals zero for all other quarters prior to the investigation event. The political connection dummy *PoliticalConnection* equals one if there exists any connection between firms' CEOs and officials through the following three types: central government or a local government, the Congress, or relative and friends, and zero otherwise. *High TFP* includes firms with above the median level of total factor productivity, and zero otherwise. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy* . ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(LoanAmount)									
	Whole sample				*PoliticalConnection =1*	*PoliticalConnection =0*	*PoliticalConnection =1 & High TFP*	*PoliticalConnection =1 & Low TFP*	*PoliticalConnection =0 & High TFP*	*PoliticalConnection =0 & Low TFP*
InvestigationAft	0.636***	0.627***	0.620***	0.611***	0.432	0.450	0.432	0.450	0.811***	0.541**
	(0.131)	(0.131)	(0.131)	(0.131)	(0.409)	(0.383)	(0.409)	(0.383)	(0.237)	(0.224)
*InvestigationAft*SOE*	-0.726***	-0.706***	-0.718***	-0.699***	-0.702	0.040	-0.702	0.040	-0.780***	-0.878***
	(0.126)	(0.126)	(0.126)	(0.127)	(0.474)	(0.437)	(0.474)	(0.437)	(0.230)	(0.227)
SOE	-0.130	-0.136	-0.043	-0.052	0.852	0.825	0.852	0.825	0.382	-0.012
	(0.259)	(0.259)	(0.261)	(0.261)	(1.141)	(1.022)	(1.141)	(1.022)	(0.497)	(0.442)
Political connection		0.202*		0.193*						
		(0.107)		(0.107)						
TFP			-1.405***	-1.411***						
			(0.166)	(0.166)						
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,974	35,974	35,974	35,974	8,336	27,638	4,168	4,152	13,707	13,660
R-squared	0.587	0.606	0.587	0.587	0.640	0.590	0.668	0.642	0.617	0.619

Table 14
Economic Efficiency Channel---Bank Performance

This table presents the regression of bank performance on anti-corruption investigation events. The dependent variable *Log(SubprimeLoan)* equals the logarithm of the amount of subprime loans that issued to borrowers with high likelihood of defaulting according to bank's internal credit rating. The dependent variable on non-performing loan measure *NPL* equals the percentage of the loans that is not paid in full at the maturity according to bank's internal reporting. The dependent variable *Log(ChargeOff)* equals the logarithm of the amount of charge-offs from bank's balance sheet. The dependent variable *Log(OperatingCost)* equals the logarithm of the amounts of operating costs. The loan issuance *Log(LoanAmount)* equals the logarithm of the total amounts of bank loans in quarter *t* . *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter t, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book and SOE* . The loan facility guarantee information *Collateral dummy, and Guarantee dummy* captures the implicit or explicit guarantees. All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(SubprimeLoan)		*NPL*		*Log(ChargeOff)*		*Log(OperatingCost)*	
InvestigationAft	0.637***	0.961***	0.608***	0.665***	0.735***	0.964***	0.083	0.586***
	(0.130)	(0.035)	(0.027)	(0.020)	(0.146)	(0.043)	(0.126)	(0.019)
*InvestigationAft*Log(LoanAmount)*	-0.030	-0.052***	-0.021***	-0.028***	-0.031	-0.035***	0.020	-0.042***
	(0.028)	(0.008)	(0.006)	(0.004)	(0.031)	(0.009)	(0.027)	(0.004)
*InvestigationAft*Log(LoanAmount) *SOE*	-0.041	0.016	0.007	0.015***	0.007	0.034***	-0.047	0.017***
	(0.036)	(0.010)	(0.008)	(0.006)	(0.040)	(0.012)	(0.035)	(0.005)
SOE	0.313**	0.050	0.067***	0.066***	0.456***	0.099**	0.234*	0.074***
	(0.124)	(0.034)	(0.026)	(0.019)	(0.139)	(0.041)	(0.121)	(0.018)
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	18,294	18,294	18,663	18,663	18,146	18,146	18,915	18,915
R-squared	0.091	0.935	0.431	0.692	0.101	0.924	0.054	0.980

Table 15
Anti-Corruption Campaign and Extensive Margin

This table presents the probit regression of the likelihood of industry rivals obtain new loans around anti-corruption investigation within the affected industries. The dependent variable *Prob(NewLoan)* is an indicator for whether a borrower obtained a new loan after the anti-corruption investigation. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter *t*, and equals zero for all other quarters prior to the investigation event. Columns (5) and (6) display regression results for unbanked borrowers that have never borrowed from banks before. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy*. All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Prob(NewLoan)					
	Whole sample				Without previous access to credit	
InvestigationAft	0.247***	0.252***	0.165***	0.169***	0.758***	0.770***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.040)	(0.041)
*InvestigationAft*SOE*	-0.059*	-0.066**	-0.061*	-0.062**	-0.079	-0.080
	(0.030)	(0.030)	(0.031)	(0.031)	(0.057)	(0.057)
SOE	-0.140***	-0.140***	-0.083***	-0.083***	-0.118***	-0.119***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.046)	(0.046)
Age	-0.008***	-0.008***	-0.005***	-0.005***	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Size	0.192***	0.192***	0.353***	0.353***	0.266***	0.265***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.018)	(0.018)
Leverage	2.239***	2.247***	2.067***	2.077***	1.132***	1.144***
	(0.047)	(0.047)	(0.052)	(0.052)	(0.075)	(0.075)
Profitability	-0.528	-0.468	-2.046***	-1.962***	-3.179***	-3.122***
	(0.374)	(0.375)	(0.388)	(0.392)	(0.568)	(0.581)
Tangibility	1.313***	1.311***	0.742***	0.744***	0.165	0.165
	(0.057)	(0.057)	(0.069)	(0.069)	(0.117)	(0.118)
MB	-0.113***	-0.113***	-0.087***	-0.088***	-0.043***	-0.044***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)
Quarterly fixed effects	No	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes	No	Yes
Observations	0.205	0.206	0.243	0.245	0.155	0.160
R-squared	42,297	42,297	42,045	42,023	10,341	10,341

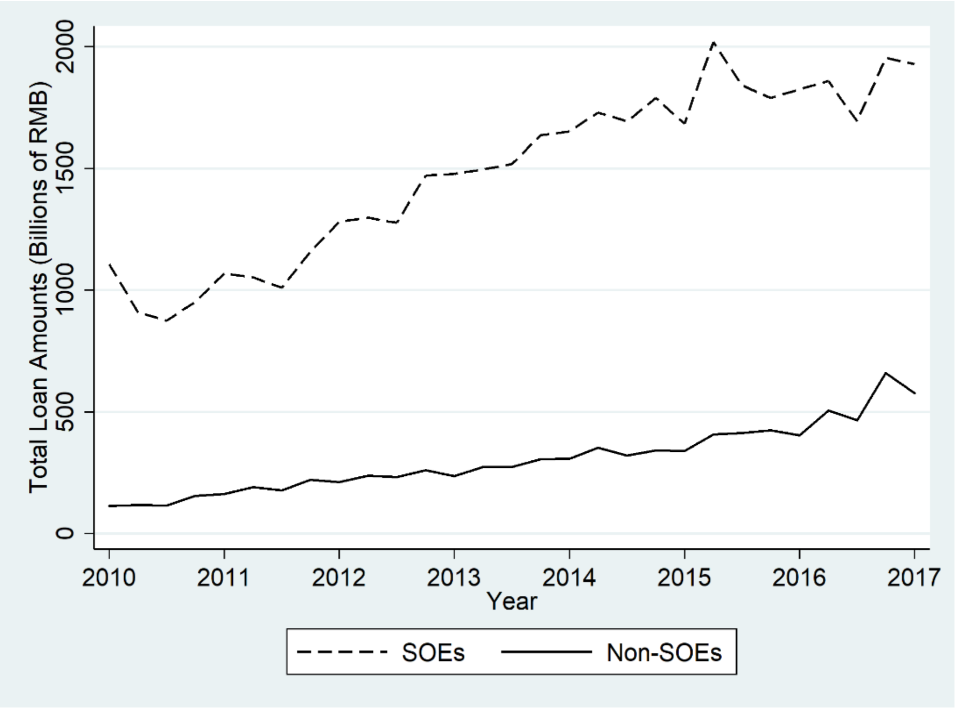
Table 16
Supply-Side Shock

This table presents the regression using the financial industry shock from the investigation of Minsheng Bank Governor Mao Xiaofeng. The banking sector shock indicator *AftMao* equals one for the periods after and on January 30, 2015, and equals zero for the period before January 30, 2015. The loan issuance *Log(LoanAmount)* equals the logarithm of one plus the total amounts of bank loans issued. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy.* All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
	Log(LoanAmount)			
AftMao	1.920***	1.934***	1.329***	1.330***
	(0.123)	(0.123)	(0.121)	(0.121)
*AftMao*SOE*	-0.827***	-0.832***	-0.663***	-0.665***
	(0.154)	(0.154)	(0.149)	(0.149)
SOE	-0.945***	-0.939***	-0.629***	-0.629***
	(0.095)	(0.095)	(0.094)	(0.094)
Age	-0.036***	-0.036***	-0.023***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Size	1.300***	1.294***	1.912***	1.910***
	(0.039)	(0.039)	(0.037)	(0.037)
Leverage	13.102***	13.124***	11.625***	11.635***
	(0.226)	(0.225)	(0.233)	(0.233)
Profitability	1.542	2.234	-4.158**	-4.101**
	(1.967)	(1.975)	(1.905)	(1.927)
Tangibility	5.907***	5.902***	2.786***	2.791***
	(0.208)	(0.208)	(0.282)	(0.283)
MB	-0.716***	-0.716***	-0.546***	-0.548***
	(0.034)	(0.034)	(0.033)	(0.033)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	40,976	40,976	40,976	40,976
R-squared	0.288	0.289	0.338	0.339

Figure 1
Changes in Bank Loan Issuances

Panel A: The Aggregate Changes in Bank Loan Issuances 2010-2017



Panel B: The Changes in Bank Loan Issuances around Investigation Events

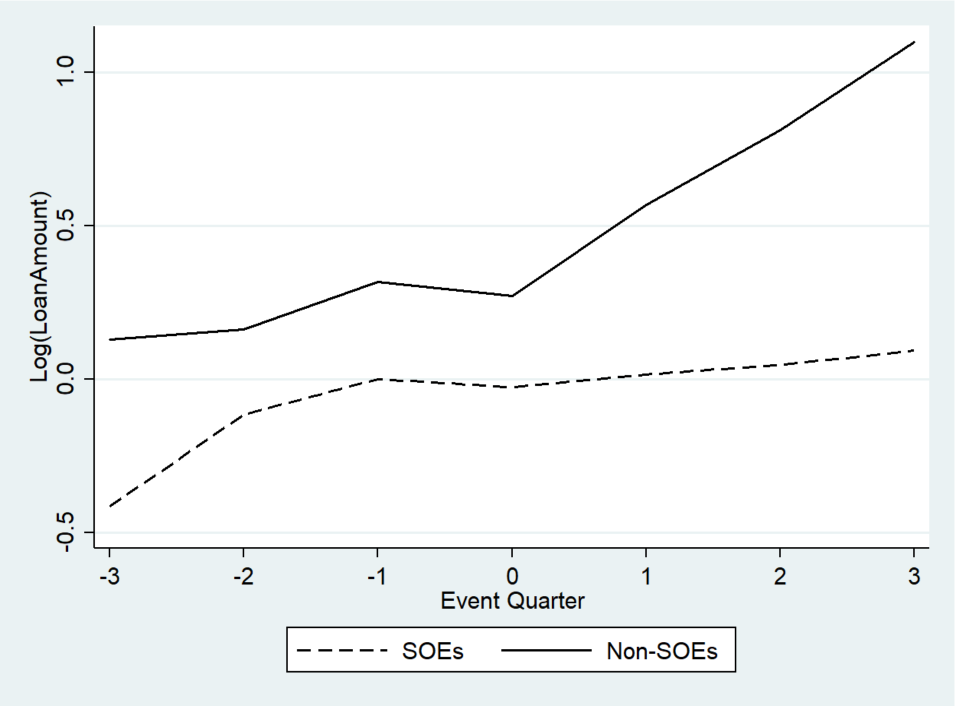
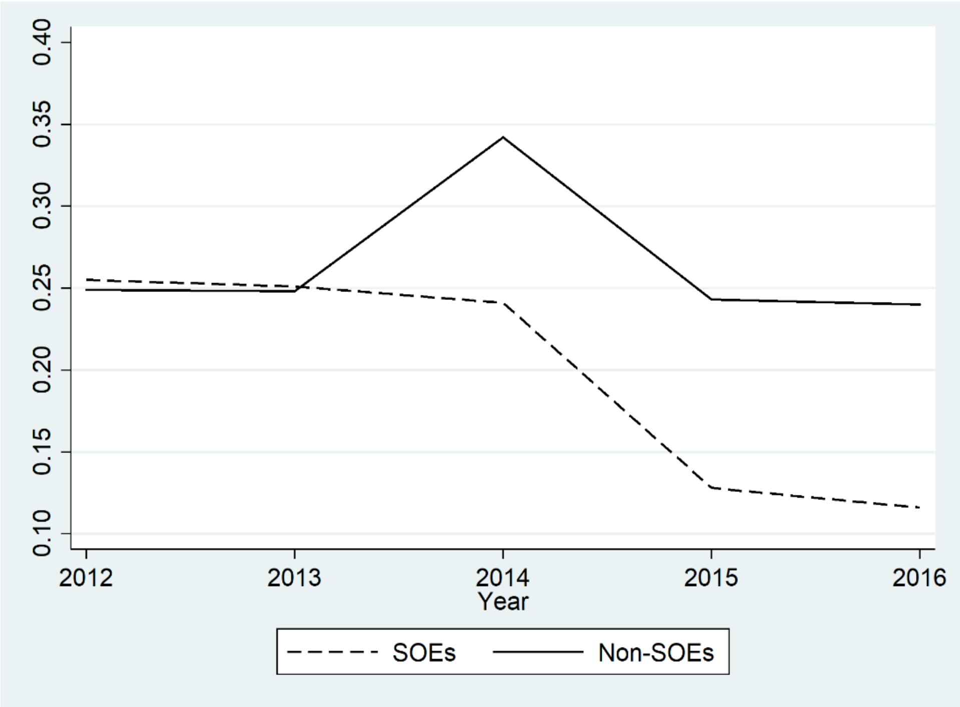


Figure 1: Changes in Bank Loan Issuances. Panel A displays the aggregate changes in bank loan issuances from 2010 to 2017 in both affected and non-affected industries. The aggregate bank loan issuances *Total Loan Amounts* equals the total amounts of bank loans issued. Panel B shows the changes in bank loan issuances around investigation events. The bank loan issuances *Log(LoanAmount)* equals the logarithm of one plus the amounts of bank loans issued. The solid line represents the non-SOE peer firms, and the dash line represents the SOE peer firms.

Figure 2
Changes in Political Connections

Panel A: The Time Series of Changes in Political Connections



Panel B: The Changes in Political Connections around Investigations

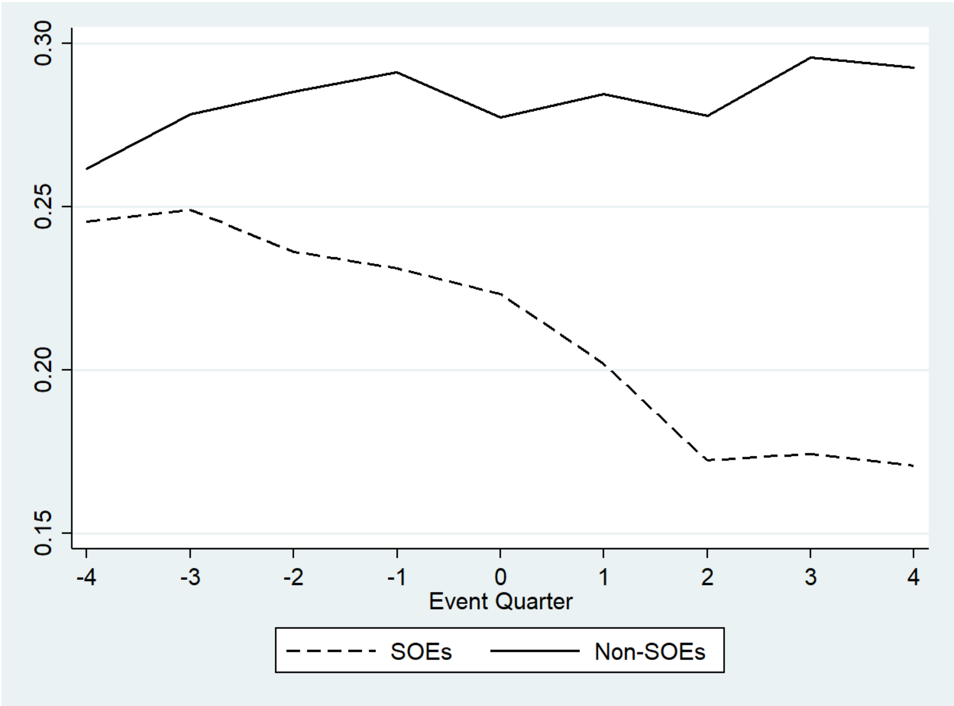


Figure 2: Changes in Political Connections. Panel A displays the changes in political connections from 2012 to 2016. Panel B shows the changes in political connections around investigation events. The political connection dummy equals one if there exists any connection between firms' CEOs and officials through the following three types: central government or a local government, the Congress, or relative and friends, zero otherwise. The solid line represents the non-SOE peer firms, and the dash line represents the SOE peer firms. Quarter 0 is the quarter during which the investigation occurs.

Figure 3
Propensity Score Matching (DID) Analysis of Bank Loan Issuances

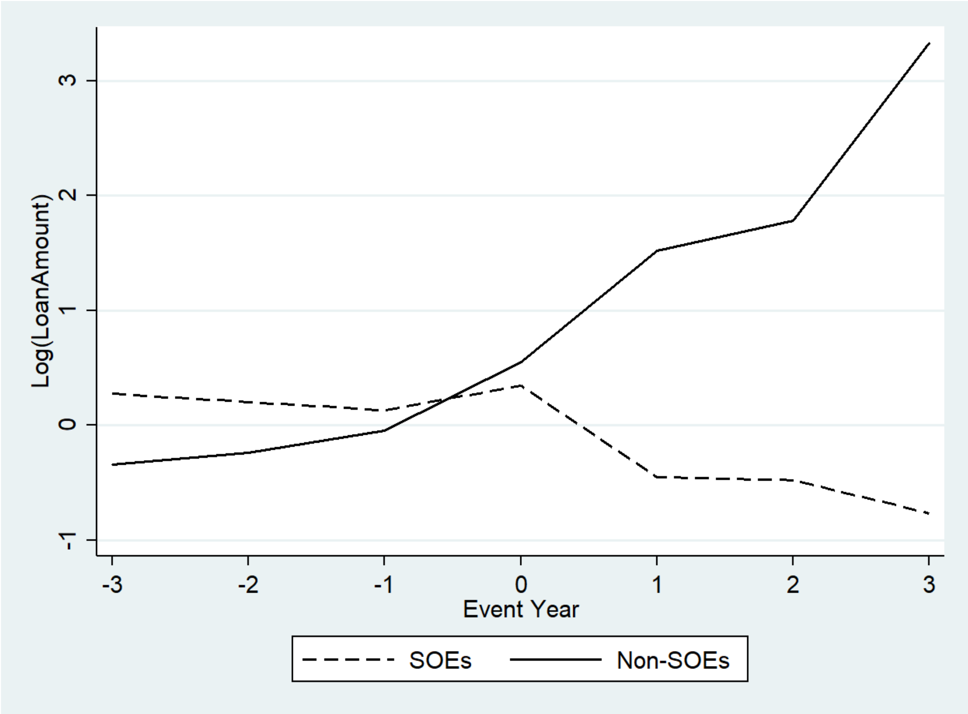
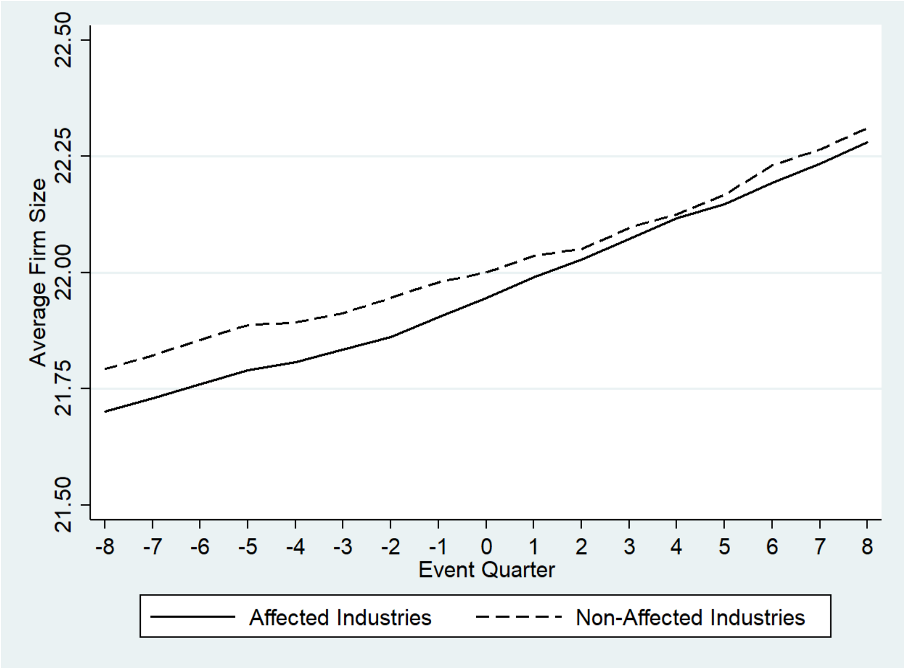


Figure 3: Propensity Score Matching (DID) Analysis of Bank Loan Issuances. This figure displays the changes in bank loan issues before and after the anti-corruption campaign for the difference-in-differences match sample of SOEs and non-SOEs in the three-year period after investigations relative to three-year period preceding investigations. The bank loan issuances *Log(LoanAmount)* equals the logarithm of one plus the amount of bank loans issued. The solid line represents the non-SOE peer firms, and the dash line represents the SOE peer firms. The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. Quarter 0 is the quarter during which the investigation occurs.

Figure 4
Propensity Score Matching of Affected and Non-Affected Industries

Panel A: The Change in Average Firm Size



Panel B: The Change in Average ROA

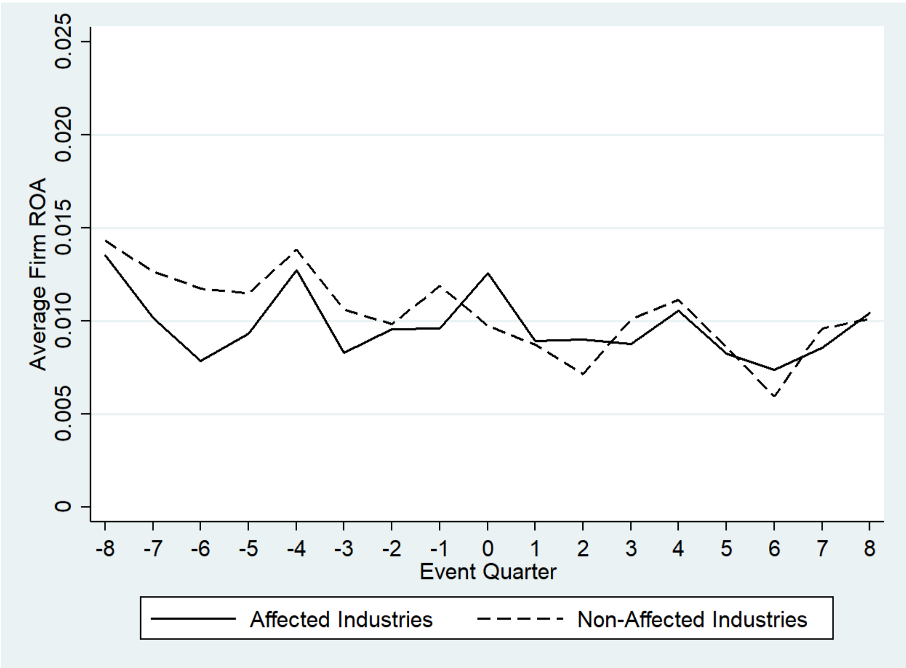


Figure 4: Firm Characteristics after Propensity Score Matching. Panel A and Panel B display the key variables after the propensity score matching. In Panel A shows the change in average firm size prior to the anti-corruption campaign and the after the campaign for the matched sample of affected industries and non-affected industries. For each industry, we take the average of the firm-level measures among all rival firms in that industry. The solid line represents the non-SOE peer firms, and the dash line represents the SOE peer firms.

Figure 5
Cumulative Abnormal Returns (CARs)

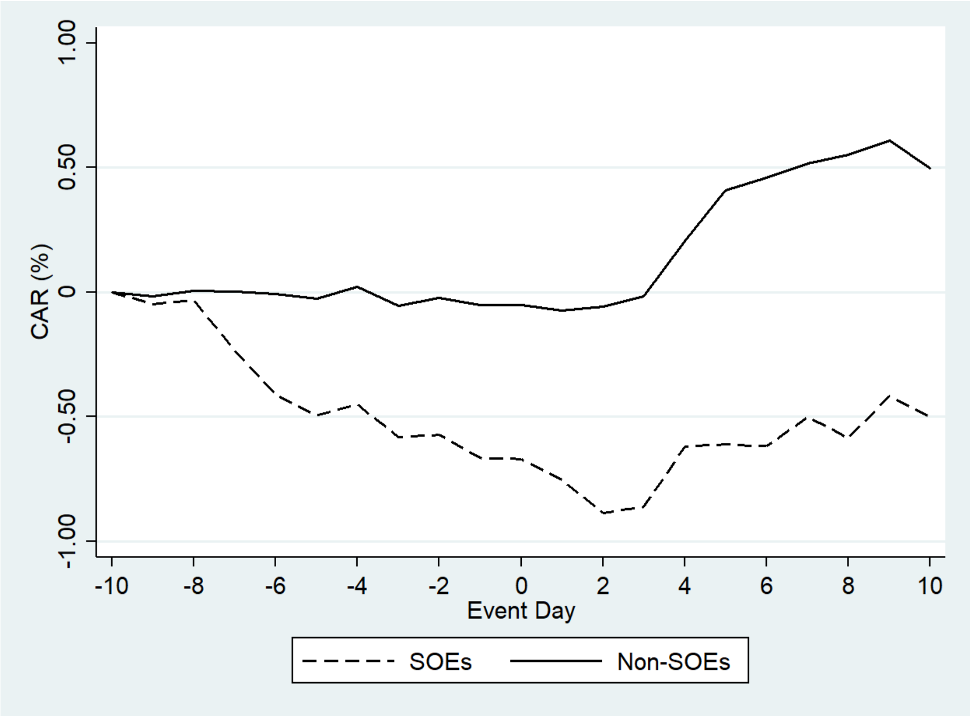


Figure 5: Cumulative Abnormal Returns (CARs) for State-Owned Enterprises (SOEs) and Privately-Owned Enterprises (non-SOEs). This figure plots the cumulative abnormal returns (in percentage points) associated with events surrounding anti-corruption investigations for peers firms that are privately-owned enterprises (non-SOEs) and state-owned enterprises (SOEs) respectively. The government ownership dummy SOE equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. Quarter 0 is the quarter during which the investigation occurs. Cumulative abnormal returns (CARs) are calculated with the Fama-French three factor model over the 180 days estimation window in the pre-event period (Day -210 to Day -30) and over the event windows of [-10, +10]. The solid line represents the non-SOE peer firms, and the dash line represents the SOE peer firms.

Appendix A
List of Investigated Officials

This table displays the distribution of the sample of the list of officials that are investigated, and the specific date of investigations between 2012 and 2015 from the website the Central Commission for Discipline Inspection (CCDI) in China. For each corruption case, the website discloses the name of the government official, the current position right before the investigation, the previous positions served as government officials or as CEOs of public firms, the type of corruption, and the degree of corruption (measured by the estimated monetary and non-monetary amounts of rent seeking activities. We restrict our sample to the investigation of senior government officials as they build extensive political network and have significant power in controlling the economic resources relative to lower ranked officials.

Panel A: The Investigations of Officials

Implicated government officials	Date of investigation	Implicated government officials	Date of investigation	Implicated government officials	Date of investigation
Liu Zhijun	2/12/2011	Jin Daoming	2/27/2014	Bai Enpei	8/29/2014
Tian Xueren	11/5/2011	Shen Peiping	3/9/2014	Bai Yun	8/29/2014
Huang Sheng	11/24/2011	Xu Caihou	3/15/2014	Ren Runhou	8/30/2014
Zhou Zhenhong	1/16/2012	Yao Mugen	3/22/2014	Sun Zhaoxue	9/15/2014
Bo Xilai	4/10/2012	Shen Weichen	4/12/2014	Pan Yiyang	9/17/2014
Yang Kun	5/20/2012	Song Lin	4/17/2014	Qin Yuhai	9/21/2014
Li Chuncheng	12/6/2012	Mao Xiaobing	4/24/2014	He Jiacheng	10/11/2014
Ni Fake	6/4/2013	Zhao Yaping	4/25/2014	Zhao Shaolin	10/11/2014
Guo Yongxiang	6/22/2013	Tan Qiwei	5/3/2014	Liang Bin	11/20/2014
Wang Suyi	6/30/2013	Wang Shuaiting	5/16/2014	Sui Fengfu	11/27/2014
Li Daqiu	7/6/2013	Yang Baohua	5/26/2014	Zhu Mingguo	11/28/2014
Yang Hanzhong	8/3/2013	Zhao Zhiyong	6/3/2014	Wang Min	12/18/2014
Wang Yongchun	8/26/2013	Su Rong	6/14/2014	Ling Jihua	12/22/2014
Li Hualin	8/27/2013	Ling Zhengce	6/19/2014	Han Xuejian	12/22/2014
Jiang Jiemin	9/1/2013	Du Shanxue	6/19/2014	Sun Hongzhi	12/26/2014
Ji Jianye	10/17/2013	Wan Qingliang	6/27/2014	Yang Weize	1/4/2015
Liao Shaohua	10/28/2013	Tan Li	7/8/2014	Ma Jian	1/16/2015
Chen Baihuai	11/19/2013	Han Xiancong	7/12/2014	Lu Wucheng	1/23/2015
Guo Youming	11/27/2013	Zhang Tianxin	7/12/2014	Si Xinliang	2/16/2015
Chen Anzhong	12/6/2013	Wu Changshun	7/20/2014	Xu Aimin	2/17/2015
Tong Mingqian	12/18/2013	Yang Senlin	7/23/2014	Jing Chunhua	3/3/2015
Li Dongsheng	12/20/2013	Chen Tiexin	7/24/2014	Li Zhi	3/11/2015
Yang Gang	12/27/2013	Zhou Yongkang	7/29/2014	Xu Jianyi	3/15/2015
Li Chongxi	12/29/2013	Liu Tienan	8/8/2014	Qiu He	3/15/2015
Ji Wenlin	2/18/2014	Chen Chunping	8/23/2014	Liao Yongyuan	3/16/2015
Zhu Zuoli	2/19/2014	Nie Chunyu	8/23/2014	Xu Gang	3/20/2015

Appendix B

List of Implicated Firms

This table displays the distribution of the sample of implicated firms with linkage to investigated officials, the affected industries, and the government ownership of implicated firms.

Firms connected to implicated officials	Firm ID	SOE	Firms connected to implicated officials	Firm ID	SOE
China Vanke Co.,Ltd.	000002	1	Rongsheng Petrochemical Co., Ltd.	002493	0
FAWER Automotive Parts Limited Company	000030	0	Huawei Culture Co., Ltd.	002502	0
Yihua Healthcare Co.,Ltd.	000150	0	Beijing Ultrapower Software Co.,Ltd.	300002	0
Dong-E-E-Jiao Co., Ltd.	000423	1	Lepu Medical Technology (Beijing) Co.,Ltd.	300003	1
Sichuan Jinlu Group Co.,Ltd.	000510	0	Chengdu CORPRO Technology Co.,Ltd.	300101	0
Hengyi Petrochemical Co., Ltd.	000703	0	Leshi Internet Information & Technology Corp.	300104	0
Suning Universal Co.,Ltd.	000718	0	Risen Energy Co., Ltd.	300118	0
Faw Car Co., Ltd.	000800	1	China Minsheng Banking Corp., Ltd.	600016	1
Skyworth Digital Co.,Ltd.	000810	1	Huadian Power International Corporation Limited	600027	1
Hangjin Technology Co., Ltd.	000818	1	Zhejiang Guangsha Co.,Ltd.	600052	0
Shanxi Taigang Stainless Steel Co.,Ltd.	000825	1	Beijing Wandong Medical Technology Co., Ltd.	600055	1
Aerospace Hi-Tech Holding Group Co.,Ltd.	000901	1	China Resources Double-Crane Co.,Ltd.	600062	1
Tianjin FAW Xiali Automobile Co.,Ltd.	000927	1	Ginwa Enterprise(Group)Inc.	600080	0
Shanxi Xishan Coal and Electricity Power Co.,Ltd.	000983	1	Xin Jiang Ready Health Industry Co., Ltd.	600090	1
China Sanjiu Medical & Pharmaceutical Co., Ltd.	000999	1	Shanxi Lanhua Sci-Tech Venture Co.,Ltd.	600123	1
Shenzhen Bauing Construction Holding Group Co.,Ltd.	002047	0	Changchun Yidong Clutch Co., Ltd.	600148	1
Suzhou Gold Mantis Construction Decoration Co., Ltd.	002081	0	Heilongjiang Interchina Water Treatment Co.,Ltd.	600187	1
Jiangsu Yuyue Medical Equipment & Supply Co., Ltd.	002223	0	Jiangsu Wuzhong Industrial Co., Ltd	600200	0
Qiming Information Technology Co.,Ltd.	002232	1	Shandong Nanshan Aluminium Co., Ltd.	600219	0
Guangdong Taiantang Pharmaceutical Co.,Ltd.	002433	0	Guangxi Guiguan Electric Power Co.,Ltd.	600236	1

Firms connected to implicated officials	Firm ID	SOE
Sichuan Hongda Co.,Ltd.	600331	0
Jiangxi Lianchuan Gopto-Electronic Science&Technology Co	600363	1
Zhangzhou Pientzehuang Pharmaceutical.Ltd.	600436	1
Jiangxi Hongcheng Waterworks Co., Ltd.	600461	1
Shenzhen Geoway Co.,Ltd.	600462	1
China Shipbuilding Industry Group Power Co.,Ltd.	600482	1
Zhongjin Gold Corp., Ltd.	600489	1
Changjiang & Jinggong Steel Building (Group) Co.,Ltd.	600496	0
Fangda Special Steel Technology Co.,Ltd.	600507	0
Fangda Carbon New Material Co.,Ltd.	600516	0
Heilongjiang Agriculture Company Limited	600598	1
Changchun FAWAY Automobile Components Co., Ltd.	600742	1
GD Power Development Co.,Ltd.	600795	1
Chengdu B-Ray Media Co.,Ltd.	600880	1
Yihua Lifestyle Technology Co., Ltd.	600978	0
Western Mining Co., Ltd	601168	1
Aluminum Corporation of China Limited	601600	1
Shanxi Lu'An Environmental Energy Development Co., Ltd.	601699	1
Petrochina Company Limited	601857	1
China Shipbuilding Industry Company Limited	601989	1
Industrial and Commercial Bank of China Limited	601398	1

Appendix C
Variable Definitions

Variable	Definition
SOE	The government ownership dummy SOE equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise
Age	The number of years after a firm's listing on Shanghai or Shenzhen Stock Exchange and first appearance in CSMAR database
Size	The logarithm of total assets
Leverage	The long-term debt plus short-term debt divided by total assets
Profitability	The operating income divided by total assets
Tangibility	The amount of fixed investment divided by total assets
MB	The sum of the market value of equity and book value of total liabilities, scaled by the book value of total assets
Log(LoanAmount)	The logarithm of one plus the amount of bank loans issued in a quarter
Prob(NewLoan)	An indicator for whether a borrower obtained a new loan after the anti-corruption investigation
TFP	The residual from the firm level regression of the logarithm of the sales on the logarithm of the number of workers, the logarithm of the total assets, the logarithm of the expenses for material and other inputs
PoliticalConnection	A dummy variable that equals one if there exists any connection between firms' CEOs and officials through the following three types: central government or a local government, the Congress, or relative and friends, zero otherwise
StockVolatility	The standard deviation of a firm’s daily stock returns in percentage
Log(SubprimeLoan)	The logarithm of the loan amount of subprime loans that issued to borrowers with high likelihood of defaulting according to bank's internal credit rating
NPL	The fraction of non-performing loan equals the percentage of the loans that is not paid in full at the maturity according to bank's internal reporting
Log(ChargeOff)	The logarithm of the amounts of charge-offs from bank's balance sheet
Log(OperatingCost)	The logarithm of the amounts of operating costs

Appendix D
Distribution of Anti-Corruption Cases by Year Quarter and Industry

This table displays the distribution of the sample of investigation of senior government officials and rival firms in affected industries. Panel A shows the number of announcement of investigations of government officials, the number of industries that are investigated, and the number of peer firms in the same industry. The year-quarter refers to the calendar year and quarter that the investigation occurred. Panel B displays the number of peer firms in each affected industry, which is classified using the WIND China third-tier classification. We keep only the first announcement of investigations in each industry throughout the analysis.

Panel A: The Number of Investigations

Year-quarter	Number of investigations	Number of affected industries	Number of peer firms
2012-4	1	3	201
2013-1	1	0	0
2013-2	6	8	520
2013-3	6	0	0
2013-4	11	2	65
2014-1	4	0	0
2014-2	14	9	447
2014-3	15	2	51
2014-4	9	5	216
2015-1	11	2	60
Total	78	31	1560

Panel B: Number of Peer Firms across Industries

Industry	Number of peer firms
Semiconductor products and semiconductor devices	26
Electric power	44
Electrical equipment	88
Electronic equipment, instruments and components	95
Independent power producer and energy	7
Real estate and development	139
Aerospace and defense	18
Internet software and services	14
Chemical industry	163
Mechanics	145
Household consumer durables	49
Building material	38
Building products	21
Construction and engineering	42
Mining	141
Media	44
Automobile	21
Auto parts	50
Software	21
Business services and supplies	19
Oil and natural gas	44
Food	81
Water	13
Information technology services	29
Leisure equipment and supplies	12
Health care technology	2
Medical and health care equipment and supplies	11
Paper products	29
Pharmacy	100
Drinks	31
Other	23
Total	1560

Appendix E
Abnormal Returns Surrounding Anti-Corruption Investigations

This table reports the stock returns associated with events surrounding anti-corruption investigations for rival firms that are privately-owned enterprises (non-SOEs) and state-owned enterprises (SOEs) respectively. The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. The sample includes rival firms operate in the same industry as investigated firms between 2012 and 2015. Cumulative abnormal returns (CARs) are calculated with the Fama-French three factor model over the 180 days estimation window in the pre-event period (Day -210 to Day -30) and over the event windows of [-10,-2], [-10,+2], and [-10, +10] respectively. This table displays the mean and median cumulative abnormal returns for the non-SOE peers and SOE peers respectively, and the T-test for the difference in cumulative abnormal returns. The *p*-values for statistical significance are shown below the difference in CARs.

T-test for Differences in CARs between SOE and non-SOE Peer Firms

	Privately-owned enterprises (Non-SOEs)			State-owned enterprises (SOEs)			Diff (non-SOEs-SOEs)	
Event window	N	Mean	Median	N	Mean	Median	T-test mean	T-test median
[-10,-2]	2699	-0.024	-0.695	2285	-0.572	-0.986	0.548	0.291
		0.860	0.000		0.000	0.000	0.004	0.006
[-10,+2]	2681	-0.056	-0.989	2279	-0.884	-1.464	0.828	0.476
		0.730	0.000		0.000	0.000	0.000	0.001
[-10,+10]	2681	0.497	-0.587	2271	-0.502	-1.389	0.999	0.802
		0.019	0.001		0.017	0.000	0.001	0.001

Appendix F
Seasonal Equity Issuance Surrounding Investigations

This table presents the regression of seasonal equity issuance on the anti-corruption investigation events. The dependent variable equity issuance *Log(EquityIssue)* equals the logarithm of one plus the total amount of seasonal equity issued. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy.* All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
Variables		*Log(EquityIssue)*		
InvestigationAft	0.788***	0.791***	0.872***	0.879***
	(0.065)	(0.065)	(0.066)	(0.066)
*InvestigationAft*SOE*	-0.401***	-0.401***	-0.427***	-0.428***
	(0.082)	(0.082)	(0.082)	(0.082)
SOE	-0.201***	-0.201***	-0.165***	-0.164***
	(0.047)	(0.047)	(0.047)	(0.047)
Age	-0.018***	-0.018***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Size	0.123***	0.123***	0.115***	0.114***
	(0.020)	(0.020)	(0.021)	(0.021)
Leverage	1.027***	1.027***	1.303***	1.311***
	(0.099)	(0.098)	(0.107)	(0.108)
Profitability	3.466***	3.456***	4.120***	4.259***
	(0.825)	(0.822)	(0.838)	(0.853)
Tangibility	0.204*	0.205*	-0.036	-0.036
	(0.113)	(0.114)	(0.151)	(0.151)
MB	0.079***	0.078***	0.053***	0.052***
	(0.015)	(0.015)	(0.016)	(0.016)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	39,464	39,464	39,464	39,464
R-squared	0.014	0.014	0.018	0.018

Appendix G
Total Debt Surrounding Investigations

This table presents the regression of total debt outstanding on the anti-corruption investigation events. The dependent variable total debt outstanding *Log(TotalDebt)* equals the logarithm of one plus the total short-term debt and long-term debt outstanding. *InvestigationAft* is a dummy that equals one for all quarters after and including the investigation quarter, and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy*. All regressions have standard errors clustered at the firm level, as shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
Variables		*Log(TotalDebt)*		
InvestigationAft	0.280**	0.284***	0.365***	0.357***
	(0.109)	(0.110)	(0.111)	(0.111)
*InvestigationAft*SOE*	-0.287**	-0.291**	-0.414***	-0.416***
	(0.129)	(0.130)	(0.128)	(0.128)
SOE	0.365***	0.366***	0.585***	0.584***
	(0.098)	(0.098)	(0.098)	(0.098)
Age	0.110***	0.110***	0.100***	0.100***
	(0.006)	(0.006)	(0.006)	(0.006)
Size	2.630***	2.629***	2.577***	2.579***
	(0.029)	(0.029)	(0.031)	(0.032)
Leverage	10.205***	10.207***	10.581***	10.570***
	(0.172)	(0.172)	(0.194)	(0.194)
Profitability	-7.253***	-7.157***	-4.739***	-5.017***
	(1.588)	(1.591)	(1.601)	(1.619)
Tangibility	5.724***	5.718***	5.538***	5.540***
	(0.164)	(0.164)	(0.242)	(0.242)
MB	-0.383***	-0.384***	-0.382***	-0.381***
	(0.028)	(0.028)	(0.028)	(0.028)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	41,228	41,228	41,228	41,228
R-squared	0.451	0.452	0.471	0.471

Appendix H
Credit Reallocation across Geographic Regions

This table presents the regression of the bank loan issuances on the investigation of a high-ranked official given his career path in different geographic regions. The loan issuance amount *Log(LoanAmount)* equals the logarithm of one plus the total amount of bank loans issued in year *t+1* . *InvestigationAft* is a dummy that equals one in affected province *s* for all quarters after and including the investigation quarter *t,* and equals zero for all other quarters prior to the investigation event. We include the following firm level controls: *Age, Size, Leverage, Profitability, Tangibility, Market-to-book, and the SOE dummy* . The government ownership dummy *SOE* equals one if a firm is state-owned, given its largest ultimate shareholder is either a government or local entity, and equals zero otherwise. All regressions have standard errors clustered at the firm level, which are shown in the parentheses. ***, **, or * indicates that the regression coefficient is statistically significant from zero at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)
	Log(LoanAmount)			
InvestigationAft	0.814***	0.808***	0.416***	0.409***
	(0.090)	(0.090)	(0.089)	(0.089)
*InvestigationAft*SOE*	-1.344***	-1.339***	-1.107***	-1.105***
	(0.114)	(0.114)	(0.111)	(0.111)
SOE	-0.256***	-0.267***	0.007	0.007
	(0.065)	(0.065)	(0.066)	(0.066)
Age	-0.069***	-0.068***	-0.052***	-0.052***
	(0.005)	(0.005)	(0.005)	(0.005)
Size	1.800***	1.802***	2.079***	2.079***
	(0.026)	(0.026)	(0.025)	(0.025)
Leverage	9.201***	9.194***	8.332***	8.332***
	(0.159)	(0.159)	(0.161)	(0.161)
Profitability	-4.579***	-4.658***	-5.576***	-5.479***
	(0.944)	(0.950)	(0.931)	(0.933)
Tangibility	2.834***	2.835***	1.670***	1.670***
	(0.150)	(0.150)	(0.182)	(0.182)
MB	-0.590***	-0.589***	-0.550***	-0.550***
	(0.026)	(0.026)	(0.025)	(0.025)
Quarterly fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Industry-quarter fixed effects	No	No	No	Yes
Observations	90,862	90,862	90,862	90,862
R-squared	0.188	0.188	0.226	0.228