Financial Corruption and Bank Lending: Evidence from China *

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Abstract

This paper explores the impact of the anti-corruption campaign that commenced in 2012 on Chinese firms through the bank lending channel. Using confidential data linking Chinese firms to their bank(s) and prefecture-level corruption indices, we find that banks located in more corrupt prefectures offered significantly less credit before the campaign, but this effect changed the direction following the campaign. Moreover, prior to the campaign, banks located in more corrupt prefectures tended to charge higher interest rates, provide loans with longer periods to maturity, and require more collateral, all of which changed the direction following the campaign. Our findings suggest that banks in more corrupt prefectures had more monopoly power, and thus charged higher markups and were less efficient. This monopoly effect is confirmed by the higher bank concentration ratios and bad-loan ratios in the more corrupt prefectures, but insignificant after the campaign.

Keywords: Financial corruption; Chinese bank system, Bank lending.

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1 Introduction

The anti-corruption campaign that commenced in 2012 has had a significant influence on the whole economy in China, especially the financial markets. More than 100,000 people have been indicted for corruption. The campaign 'netted' over high-ranking officials, including high-ranking military officers, senior executives of state-owned companies, and financial elites.[1] This paper studies the local effects of the anti-corruption campaign in China on banks' credit supply. The exogenous shock we consider was the anti-corruption campaign, which was a wide-ranging campaign against corruption that began in China following the conclusion of the 18th National Congress of the Communist Party of China in 2012.

The campaign is one of the most significant organized anti-corruption effort in the history of China. Figure 1 shows the significant rise of corruption control. We choose the anti-corruption campaign in 2012 as the supply side shock. Figure 2 shows the assets and return on assets (ROA) of Chinese banks. There is a distinct turning point appeared in 2012. From 2000 to 2012, the ROA of Chinese banks increased dramatically (apart from the financial crisis in 2008), but after 2012, it decreased significantly. This is partially due to a domestic supply-side shock in the form of the anti-corruption campaign.

Recent studies on the anti-corruption campaign in China have mainly focused on stock-price fluctuations (Griffin et al., 2016; Lin et al., 2016; Liu et al., 2017). However, bank finance remains a dominant source of corporate funding (about 85%), while equity finance accounts for only a tiny proportion in China (1.3 %) (Wang et al., 2016).[2] Li et al. (2017) present the novel empirical finding that the anti-corruption campaign in China is associated with credit reallocation from less productive state-owned enterprises (SOEs) to more productive non-SOEs.

We focus on anti-corruption campaign and Chinese bank credit in this paper. Different with the previous studies, we use a special data set obtained from the Center for Anti-corruption and Governance at Tsinghua University. Rather than investigating the

[1] Xiaomin Lai is a Chinese business executive and senior economist who served as party secretary and chairman of the board of China Huarong Asset Management from September 2012 to April 2018. He was sacked for corruption on 17 April 2018. On 5 January 2021, Lai was sentenced to death without reprieve for bribery, embezzlement, and bigamy. His private assets were seized as well. The sentence was carried out on 29 January 2021. This event was highly astonishing because Lai was the only person sentenced to death mainly because of corruption in recent decades in China.

[2] In 2016, China's total bank credit is 15.45 trillion USD, greater than that of the United States (12.44 trillion USD). This represented 137.95% of GDP, a much larger share than that of the United States (67.00%), implying that the credit market is more important in China than in the United States. Moreover, bank credit accounts for a greater share of capital than other financial instruments (stocks, fixed income, insurance, and investment funds) in China.

loan rebate in the literature, which is the application fee for an enterprise seeking to obtain credit, we focus on the bank's monopoly power, which is the bank's fee for obtaining monopoly power as the fund provider in a given prefecture. We test the local effects using difference-in-difference estimations to identify the differences in the level of corruption between various prefectures in China. Importantly, we analyze the behavior of local officials, rather than that of firm managers. Moreover, we use the extent of misreporting in a given prefecture as another proxy to measure the level of corruption. Baccini et al. (2021) find a strong and robust association between GDP manipulation, which they measure using night-lighting data, and incidence of corruption among local officials.

Then we use bank-firm matched loan-level data, which enables us to use the method proposed by Khwaja and Mian (2008) (firm-year fixed effects) to focus on variations in loans that are primarily the result of differences among the banks.[3] The stimulus-driven credit expansion disproportionately favored state-owned firms and firms with a lower average product of capital, reversing the process of capital reallocation toward private firms (Cong et al., 2019). We find that banks located in more corrupt prefectures offered significantly less credit before the campaign, but this effect changed the direction following the campaign. Moreover, prior to the campaign, banks located in more corrupt prefectures tended to charge higher interest rates, provide loans with longer periods to maturity, and require more collateral, all of which changed the direction following the campaign. Our findings suggest that banks in more corrupt prefectures had more monopoly power, and thus charged higher markups and were less efficient. This monopoly effect is confirmed by the higher bank concentration ratios and bad-loan ratios in the more corrupt prefectures, but insignificant after the campaign.

Most of the political science literature confirms that China is a highly centralized country, and neither provinces nor prefectures have their own laws, regulations, or policies. Thus, we can assume that enforcement is determined by the central government, and is similar across all regions. However, enforcement has differed over time. Thus, we conduct a robustness check using the difference between the index value in the initial year and the average of the index values in all of the pre-shock years to measure the level of corruption.

There is a growing body of literature studying the effects of corruption. Some studies have examined the negative effects of corruption and rent-seeking activities (Shleifer and

[3] Khwaja and Mian (2008) analyze how supply-side bank liquidity shocks are transmitted to the rest of the economy. They examined the impact of liquidity shocks by exploiting cross-bank liquidity variations induced by unanticipated nuclear tests in Pakistan. When Pakistan tested nuclear devices in 1998, the IMF suspended their exchange rate liquidity support. Consequently, the banks experienced the deposit run with larger dollar deposit accounts. The effect of the liquidity shock varied substantially across banks.

Vishny, 1993, 1994; Mauro, 1995; Fisman, 2001; Fisman and Svensson, 2007; Butler et al., 2009; Bertrand et al., 2018), while others have analyzed the positive impacts of corruption and political connections (Faccio, 2006; Goldman et al., 2008; Amore and Bennedsen, 2013; Dreher and Gassebner, 2013). Some studies have argued that the relationship between political connections and bank financing decisions is quite complex, especially across countries (Johnson and Mitton, 2003; Sapienza, 2004; Khwaja and Mian, 2005; Leuz and Oberholzer-Gee, 2006; Claessens et al., 2008; Zeume, 2017). This study is the first to analyze the impact of the anti-corruption investigation on China's bank lending channel using the prefecture-level corruption indices.

The article unfolds as follows. Section 2 illustrates the background of anti-corruption campaign and banking system in China. Section 3 describes the data and key indices used in this study. Section 4 discusses our empirical strategy and identification strategy, and reports our main finding regarding bank loan effects of the corruption as well as the results from many robustness checks. Section 5 investigates the mechanisms through which corruption may affect bank loans. Section 6 summarizes and concludes with a discussion of policy implications.

2 Background

With the commencement of China's economic system reform in 1978, the planned economy was discarded and a market economy involving a pricing system was introduced. The transition process included changes in the laws protecting property rights, which benefited various groups including the banks. Under the reform process, state-owned commercial banks replaced government finance as the primary source of corporate funds (Ting, 1997; Wedeman, 2004). These providers used the funds and powers granted by the government to obtain a monopoly position in the credit market. Although the central bank has since reduced their profits through interest rate controls, the banks can circumvent government-imposed restrictions using various other means in an attempt to acquire excess economic benefits, which will undoubtedly increase the financing costs of firms, both private and state-owned.

The anti-corruption campaign commenced in 2012. Most of the officials who were investigated were removed from office and faced accusations of bribery and abuse of power, although the range of alleged abuses varied widely. As of 2016, the campaign had netted more than 120 high-ranking officials, including about a dozen high-ranking military officers, several senior executives of state-owned companies, and five national leaders. In addition, more than 100,000 people had been indicted for corruption. Conducted mainly by the Central Commission for Discipline Inspection under the direction of its secretary Qishan Wang, along with various military and judicial bodies, the campaign was notable for implicating both incumbent and former leaders, and continues today. At the second plenary meeting of the 19th Central Commission for Discipline Inspection of the Communist Party of China held in Beijing on 11-13 January 2018, the party emphasized the necessity of increasing anti-corruption efforts in the financial sector. The meeting's communique also noted that it is essential to focus on resource-rich areas and critical positions, and to strengthen supervision in an effort to reduce the concentration of power.

In China, corruption in relation to bank credit can be classified into two forms. The first is the loan rebate, or the deducted benefit fee, which is the application fee payable by enterprises wanting to obtain credit. This kind of income can be referred to as the "entry fee," and most previous studies have focused on this form (Lu, 2000; Fan and Grossman, 2001; Ping and Lei, 2003; Yong and An-gang, 2003; Xie and Lu, 2005; Kwong, 2015). The second form is the bank's monopoly power as a provider of funds. Banks are able to abuse this power by applying significant markups to the interest rates they charge. The additional income they obtain from this monopoly power is referred to as "price rent." In this study, we focus on the second form. The traditional banking industry has obtained hidden profits through its monopoly position, with spread income accounting for the bulk of these hidden profits. It has been reported that interest income accounts for more than 80% of the total income of listed banks in China.

Xie and Lu (2005) investigate the central bank, as well as commercial banks and policy banks in 29 cities in China. They find that around 80.5% (975/1211) of bank staff surveyed admitted that rent-seeking by the right of financial resource allocation is very common to see or common to see in their work. Further, approximately 61.5% (652/1061) of staff in firms borrowing from banks considered that they needed to pay a significant markup to obtain the bank credit they required. Moreover, when the sample is limited to staff in private firms, the percentage increased from 61.5% to around 73.7% (350/475). Qian et al. (2015) find that the People's Bank of China (PBOC) limited the movement of interest rates in relation to both deposits and loans by setting base rates with upper and lower bounds. These rates and bounds varied over the business cycle and with differing loan maturities. Local commercial banks were able to adjust their interest rates within the prescribed bounds based on their specific needs.

3 Data and Descriptive Statistics

Below we describe our data, the definition and evolution of key indices, and summary statistics.

3.1 Data

We use several data sources to link using unique identifiers for each individual and prefecture. Thus, our data set combined four types of data: bank loan data, corruption data, night-lighting data, and economic data.

(i) Bank Loan Data. This study uses a novel data set containing information on bank-firm relationships in China, along with detailed bank- and firm-specific information. The sample period is from 2001 to 2016, providing a symmetrical time frame either side of the financial crisis in the United States. Chinese data were obtained from three primary data sets: Wind Datafeed Service (referred to as Wind), GTA The China Stock Market and Accounting Research (referred to as CSMAR) database, and the Almanac of China's Finance and Banking (2001-2016). Information about bank-firm relationships is obtained from the bank loan data in the CSMAR database. The CSMAR database compiles data from the Chinese stock market and the financial statements of China's listed companies. It is a unique, comprehensive database of Chinese stock returns, covering all companies listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. We collect information on bank loans to all of the listed firms in China.

We augment the data on bank-firm relationships with bank- and firm-level data taken from Wind, which provides historical reference data, real-time market data, and historical intraday market data, covering stocks, bonds, futures, foreign exchange, funds, indices, warrants, and macro market data, as well as descriptions, real-time market data, financial data, dividend data, corporate actions, and historical intraday data. We combine this data set with bank-level information (trade settlements) from the Almanac of China's Finance and Banking (2001-2016). The Almanac of China's Finance and Banking is a highly informative yearbook sponsored by China society for finance and banking that has been published annually and supervised by People's Bank of China (PBOC) since 1986.

(ii) Corruption Data. Our data on city officials are obtained from Transparency International China (TIC). TIC, which is based at Tsinghua University, China, is a member unit of Transparency International, an organization that collects corruption-related data for academic and policy research. TIC provides demographic data (gender, education, and birth year) and appointment data on city officials, and maintains a database of corruption investigations, prosecutions, and convictions of those city officials. City officials include

city party secretaries and mayors. Their corruption cases, if they have met the criminal criteria, are transferred to the judicial system and publicized on provincial government websites and in newspapers. TIC tracks these public information sources to establish and maintain its corruption database. No confidential data are included in the TIC database. Whether a city official is corrupt or not is reported in the TIC database in the form of a corruption indicator that displays a value of 1 if the official is corrupt and 0 otherwise. Corrupt officials are defined as those investigated and transferred by provincial Discipline Inspection Commissions (DICs) to the judicial system. As of 2020, all the corrupt officials in our data set have been prosecuted and convicted by the Chinese judicial system.

We use the TIC database to construct our working sample. City officials (termed as persons) hold office in different cities for different periods of time. Each person-city combination involves a tenure of at least one year. We use both tenure- and person-level data in our analysis. Since the corruption indicator Corrupt in the TIC database is available at the person rather than the tenure level, a corrupt official has all his or her tenures designated as 1. Our sample covered 3223 persons who held tenures in 364 cities during the period 1994-2018 for a total of 21,990 tenures. Since each tenure is linked to a city for at least one year, it has corresponding bank loan and night-lighting statistics. The prefecture list can be found in Appendix 6.

(iii) Night-lighting Data. Night-lighting data are gathered by Air Force satellites that have been circling Earth 14 times a day since the 1970s, and measure the light intensity emanating from specific geographic locations. Henderson et al. (2012) argue that the night-lighting data are a good proxy for economic activity because the consumption of goods in the evening requires lighting. The night-lighting data include latitudes and longitudes. We use QGIS codes to locate them on a GIS map of China. Area (prefecture) codes are automatically assigned by the QGIS. The night-lighting data include total, average, median, minimum, and maximum levels of lighting. We also have information on how many lighting observations are summed up in each prefecture.

(iv) Economic Data. We combine our data set with economic information obtained from the GTA CSMAR Database. The economic data set contains information on all of the essential prefecture-level economic characteristics including GDP, government revenue, government spending, employment, FDI, population, financial assets, consumption, loans, deposits, and other economic variables. The definitions of all variables used are presented in Table 1.

3.2 Measure of Corruption

There are numerous methods available to measure corruption. Given the data in this study, the corruption index is defined as the probability of being investigated and removed by the central government at the prefecture level, and is measured as follows:

$$Corruption\ Index_{p,t} = \sum_{o'=1}^{O} W_{o',p,t} \times \mathbb{1}(Corrupted_{o',p,t} = 1), \tag{1}$$

where o represents official for prefecture, p represents prefecture, and t represents year. $Corrupted_{o,p,t}$ equals 1 if official o is investigated and removed, 0 otherwise. $W_{o,p,t}$ is the weights given to each official regarding the characteristics of the position (1/m to leaders, 0.5/m to vice officials for Economics, 0.2/m to others), where $\sum_{o'=1}^{O} W_{o',p,t} = 1$.

To enable a greater understanding of the variations in and evolution of corruption in China over time, we plot several figures to illustrate. Figure 3 shows the corruption index from 1994 to 2018. The index increased from 2001 to 2011, when it peaked, and then gradually decreased after 2012. We acknowledge that this trend may have been influenced by construction bias. However, in this study, we focus on the variations among different prefectures, rather than on the overall trend. Moreover, Figure 4 presents the coefficient of variation of the corruption index from 1994 to 2018. It can be seen that the variation substantially decreased around the year 2012. Figure 5 reports the percentiles of the corruption index from 1994 to 2018. We find that the dispersion of the corruption index increased significantly by percentile. In other words, the variation in the corruption index is greatest for the 90th percentile. Moreover, the index peaked around 2011 for the 60th, 70th, 80th, and 90th percentiles.

Figure 6 shows the average variations in our measure of corruption across prefectures from 2001 to 2016. It can be seen that the northern regions were more corrupt than the southern regions, which is consistent with the findings of previous studies that the southern regions are more developed, market-oriented, transparent, and independent from the central government than the northern regions of China. Since we focus on the dispersion of corruption among different prefectures over time, we plot the variations in the corruption index across prefectures over time (every four years). The results are shown in Figure 7. From the period of 2001-2004 to the period of 2005-2008, the dispersion increased significantly, and then increased even more from 2009 to 2012. This trend in variations coincided with China's rapid economic growth and increasing openness from 2001 to 2012. From the period of 2009-2012 to the period of 2013-2016, the dispersion is significantly reduced following the commencement of the anti-corruption campaign in 2012.

The misreporting index measures the difference between the reported data and the night-lighting data at the prefecture level, which could be standardized and represented by

$$Misreporting\ Index_{p,t} = ln(\frac{GDP_{p,t}}{sd(GDP_{p,t})}) - ln(\frac{light(sum)_{p,t}}{sd(light(sum)_{p,t})}), \tag{2}$$

where p represents prefecture and t represents year. By construction, a higher misreporting index implies the more exaggerated prefecture-level GDP reported by the local government.

To reduce measurement error, we winsorize all variables at the 1% and 99% levels to reduce the influence of outliers. Regarding the sample selection problem, our data set provides more comprehensive coverage of small, micro, and rural banks than other data sets, as we include all banks, both listed and non-listed. Panel A of Table 2 presents summary statistics for the loan-level variables in our primary data set. Since our data cover all business loans to listed firms, there is considerable variation in loan size. The average loan size is about 358.828 million yuan, and the standard deviation is around 2418.99 million yuan. Given the considerable size of variation, we use the log of loan size instead of loan size. Panel A of Table 2 also shows that the average log of the loan size of state-owned banks is similar to that of private banks (18.842 vs. 18.548), and the average change in the log of the loan size of state-owned banks is also similar to that of private banks (11.4% vs. 12.3%). Panel B of Table 2 presents summary statistics for the bank-level and prefecture-level variables in our data set. It can be seen that the average corruption index is higher for state-owned banks, indicating that state-owned banks were more likely to be located in more corrupt areas than private banks. Moreover, the average misreporting index is higher for state-owned banks, which implies that state-owned banks were more likely to be located in prefectures that were more subject to misreporting than private banks.

4 Effects of Corruption on Bank Lending

Figure 8 plots the yearly amounts of the bank loans from 2001 to 2016. It shows a clear parallel trend prior to the onset of the anti-corruption campaign, and the amounts of banks loans from the banks located in more corrupt prefectures were significantly lower than the amounts from less corrupt prefectures. However, after 2012, the amounts of bank loans from more corrupt prefectures increased significantly and exceeded those from less corrupt prefectures. Then, it continued to show a clear parallel trend after 2012. The divergence in bank loans following the onset of the anti-corruption campaign suggests that the campaign is not anticipated by the financial market in China.

4.1 Bank Loan Effects

4.1.1 Identification

For the level effect of the bank-firm matched loans, we employ the following specification for bank i and firm j in the prefecture p and year t:

$$Y_{ijpt} = \beta_1 Index_{p,t-1} + \beta_2 Index_{p,t-1} \times Post_t + \gamma X_{i,t-1} + \mu_i + \lambda_{jt} + \epsilon_{ijpt}, \tag{3}$$

where i represents bank, j represents firm, p represents prefecture, t represents year. Y_{ijct} could be the log of the loan amount, the log of the interest rate, the log of the maturity, and the collateral, respectively. $Post_t$ is an indicator variable equals one after 2012. $X_{i,t}$ is the bank level control variables, which include State-owned, Policy, Rural, Size. Specifically, Size is ln(assets), and State-owned is an indicator variable that equals 1 if the bank is state-owned. Policy is an indicator variable that equals 1 if the bank is a policy bank. Policy banks are unique to China. The difference between policy and commercial banks is that the goal of policy banks is not profit maximization. Rather, their goal is to try to implement government policy in the financial markets. Notwithstanding, there are numerous differences between the central bank and the policy banks. However, the most significant difference for the purposes of this study is that the central bank cannot lend money directly to firms. It can only lend money to policy or commercial banks, which can then provide loans to firms. Rural is also an indicator variable that equals 1 if the bank is located in a rural area. μ_i is the bank fixed effects, λ_{jt} is the firm-year fixed effects. $Index_{p,t}$ could be $Corruption\ Index_{p,t}$ and $Misreporting\ Index_{p,t}$ respectively. All the bank branches located in the same prefecture share the unique $Corruption\ Index_{p,t}$, and the prefecture level $Corruption\ Index_{p,t}$ is the probability of been investigated and removed because of corruption. All the bank branches located in the same prefecture share the unique $Misreporting\ Index_{p,t}$, and the prefecture level $Misreporting\ Index_{p,t}$ is the standardized differences between GDP and the night-lighting data. Since we focus on the banks' behavior over time, the standard errors are clustered at the bank level and robust to heteroskedasticity.

We use the technical method proposed by Khwaja and Mian (2008) to simultaneously estimate the bank lending and firm borrowing channels stems from identification concerns, which arise because events that trigger changes in liquidity supply, such as monetary policy innovations or financial shocks, are often accompanied by changes in investment returns and, consequently, credit demand. Therefore, changes in firm borrowing reflect changes in both credit supply and credit demand. We use firm-year fixed effects to control for credit shocks on the demand side.

One concern is the endogeneity problem in relation to the corruption or misreporting index. Suppose that firms borrowed from pre-campaign banks located in less corrupt prefectures could switch to banks located in more corrupt prefectures at no cost, with no reason to expect differential outcomes to those at the pre-campaign level of corruption or misreporting for different banks. We use prior period rather than current period levels of the corruption or misreporting index to avoid the endogeneity problem. In addition, we change the prior period to the initial year or the average of the pre-shock years in the robustness analysis section.

Another concern about the omitted variable problem is the heterogeneity in bank response to political shocks. It is possible that the lending channel coefficient is driven by inherent differences in how banks respond to the shocks induced by the anti-corruption campaign in China, if there is such response heterogeneity, and it is systematically correlated with a bank's liquidity shock. For example, perhaps the lending channel estimate is picking up differences in how state-owned and private banks react to political shocks since we know that the Chinese government has more control power on state-owned banks.

Another concern regarding the omitted variable problem is heterogeneity in terms of banks' responses to political shocks. Could the lending channel coefficient be driven by inherent differences in how banks respond to the shock induced by the anti-corruption campaign in China? This is possible if there is response heterogeneity that is systematically correlated with the banks degree of liquidity shock. For example, perhaps the lending channel estimate picks up differences in how state-owned and private banks react to a political shock, as we know that the Chinese government has more control over state-owned banks. Since state-owned banks should have been more affected by the changes of government policies, we use a dummy variable for state-owned banks to capture any differences. We also address these concerns by including other bank characteristics as a proxy for such differential lending sensitivity as controls, such as the bank's size, dummies for policy and rural banks. These bank-level controls are designed to capture a bank's sensitivity to political shocks. In particular, we use lagged values to avoid the endogeneity problem. The results showed that the lending channel coefficient remained robust to all bank-level controls.

Although firm-year fixed effects address the main concerns regarding identification noted in the literature, there may be additional problems. Since the fixed effects strategy does not require any assumptions about the correlation between liquidity supply and demand shocks, the concern regarding the reverse causality problem is that if the liquidity supply shocks are anticipated, either banks may adjust their lending or firms may adjust their borrowing prior to the shock. This would lead to either an under- or overestimate of the impact on the bank lending channel depending on the direction of the pre-shock loan adjustments. However, in this study, the natural experiment anti-corruption campaign is unanticipated in China. Furthermore, it happened outside the financial market, precisely speaking, at the field of political science. Therefore, it would have been difficult for Chinese banks and firms to anticipate this type of liquidity supply shock. In particular, the underlying assumption regarding all regressions in this study is that prior-year financial positions are not positively correlated with unobserved within-bank changes in loan lending following the onset of the anti-corruption campaign.

To reduce measurement error, as noted before, we winsorize all variables at the 1% and 99% levels to reduce the influence of outliers. Regarding the sample selection problem, our data set provides more comprehensive coverage of small, micro, and rural banks than other data sets, as we include all banks, both listed and non-listed. Our main concern regarding the sample selection problem is that our data set only provides information about listed firms. However, there are also numerous unlisted firms in China. Gertler and Gilchrist (1994) suggest that because size could serve as a proxy for financial constraints, a higher sensitivity of small firms would provide evidence in favor of the "financial accelerator," whereby financial friction is expected to exacerbate downturns. Crouzet and Mehrotra (2020) use new, confidential data obtained from the income statements and balance sheets of United States manufacturing firms to examine this idea. Thus, our analysis of the impact of the anti-corruption campaign on the Chinese bank lending channel could be regarded as an analysis of the "lower bound" impact. Since we only consider listed firms, if these firms were affected by the anti-corruption campaign, small and micro firms should have been affected even more.

4.1.2 Baseline Results

Table 3 presents the results from the regression model given by equation (3). Column (3) shows that a 1% increase in the leader's probability of being investigated and removed is associated with a 0.161% decline in the average bank loan amount, and that this changed direction and became significantly positive following the commencement of the anti-corruption campaign in 2012. Column (6) shows that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.122% decline in the average bank loan amount, and that this also changed direction and became significantly positive following the commencement of the anti-corruption campaign in 2012.

The estimated effects on interest rates are presented in Table 4. Column (3) shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.547% increase in the interest rate. This effect became significantly negative following the commencement of the anti-corruption campaign in 2012. Column (6) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.245% increase in the interest rate, and this effect also became significantly negative following the commencement of the anti-corruption campaign in 2012.

Table 5 focuses on the period until maturity of the loan. Column (3) shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.637% increase in the period until maturity, and this effect changed direction following the commencement of the anti-corruption campaign in 2012. Column (6) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.487% increase in the period until maturity, and this effect also changed direction following the commencement of the anti-corruption campaign in 2012.

Table 6 focuses on collateral. Column (3) shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.106% increase in collateral, and this effect is significantly reduced following the commencement of the anti-corruption campaign in 2012. Column (6) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.120% increase in collateral, and this effect is also significantly reduced following the commencement of the anti-corruption campaign in 2012.

4.2 Year-specific Effects

To further explore the relationship between the bank loan amount and corruption, we employ the following specification for bank i and firm j in year t for the year-specific effects.

$$L_{ijpt} = \beta_1 Index_{p,t-1} \times Year\ Dummy_t + \gamma X_{i,t-1} + \lambda_{jt} + \epsilon_{ijpt}, \tag{4}$$

where i represents bank, j represents firm, t represents year, L_{ijpt} is the log loan size, Year Dummy equals one for each specific year, otherwise it equals zero, $X_{i,t-1}$ is the bank-level control variables, λ_{jt} is the firm-year fixed effects. Figure 9 shows the year-specific effects estimated using equation (4). It can be seen that the coefficient of the interaction term for the corruption index and the year dummy, β_1, increased significantly around 2012, suggesting that banks in more corrupt prefectures increased their credit supply significantly following the commencement of the anti-corruption campaign.

4.3 Loan Allocation Effects

For the level effect of the bank-firm matched loans, we employ the following specification for bank i and firm j in the prefecture p and year t:

$$\begin{aligned} L_{ijpt} &= \beta_1 Index_{p,t-1} + \beta_2 Index_{p,t-1} \times Post_t \\ &+ \beta_3 Index_{p,t-1} \times Post_t \times State\text{-}owned(Firm)_{jt} + \mu_i + \lambda_{jt} + \epsilon_{ijpt}, \end{aligned} \tag{5}$$

where i represents bank, j represents firm, p represents prefecture, t represents year. Y_{ijct} could be the log of the loan amount, the log of the interest rate, the log of the maturity, and the collateral. $Post_t$ is an indicator variable equals one after 2012, $X_{i,t}$ is the bank level control variables, μ_i is the bank fixed effects, λ_{jt} is the firm-year fixed effects. $Index_{p,t}$ could be $Corruption\ Index_{p,t}$ and $Misreporting\ Index_{p,t}$ respectively. All the bank branches located in the same prefecture share the unique $Corruption\ Index_{p,t}$, and the prefecture level $Corruption\ Index_{p,t}$ is the probability of been investigated and removed because of corruption. All the bank branches located in the same prefecture share the unique $Misreporting\ Index_{p,t}$, and the prefecture level $Misreporting\ Index_{p,t}$ is the standardized differences between GDP and the night-lighting data. $State\text{-}owned(Firm)_{jt}$ equals one if the firm is a state-owned firm. Since we focus on the banks' behavior over time, the standard errors are clustered at the bank level and robust to heteroskedasticity.

In Section 4.1, we find that banks located in more corrupt areas increased their lending more following the commencement of the anti-corruption investigation. Here, we discuss whether the increase in the credit supply went to state-owned firms or private firms. Table 7 reports the results of the regression model given by equation (5). Banks located in more corrupt areas were more likely to increase their lending following the commencement of the anti-corruption campaign. Moreover, they showed a preference for allocating the increase of their lending to private firms, although this trend is not significant. The results also indicate that banks located in areas with more misreporting of GDP increased their lending more following the commencement of the anti-corruption campaign, and were more likely to allocate the increase of their lending to private firms, but again, this trend is not significant. The results are consistent with the main findings in Li et al. (2017).

4.4 Robustness

It can be seen that our estimates are robust to the inclusion of a wide range of controls and fixed effects. We now present the results of additional specification checks to further increase our confidence in the estimates. To further address concerns regarding a possible endogeneity problem in relation to the corruption and misreporting indices, we use the index in the initial year and the average of the indices in all of the pre-shock years to measure corruption and misreporting. Table 8 presents the estimates from the regression model given by equation (3) using the corruption or misreporting index for the initial year instead of a lag of one year. The results regarding loan amounts are nearly identical to our baseline estimates. Table 9 shows the results obtained from equation (3) using the average of the corruption or misreporting indices for all the pre-shock years. Once again, these results are close to our baseline estimates. Moreover, Table 10 shows the interest rate effects given by equation (3) using the corruption or misreporting index for the initial year. Once again, we obtain similar results to our baseline estimates. Table 11 reports the interest rate effects also given by equation (3) using the average of the corruption or misreporting indices from all of the pre-shock years. It is reassuring to find no evidence that our results are driven by the endogeneity bias in either the corruption or misreporting index.

We use firm-year fixed effects, λ_{jt}. The use of such tight firm-level fixed effects enabled us to focus primarily on the variations in loans as a result of the banks' decisions. However, a concern arises in that we may ignore all the Chinese manufacturing firms that only receive one loan from one prefecture each year. Thus, the use of tight fixed effects may hurt our results, as substantial variations are eliminated (i.e., there are no cross-bank loans; just one loan from one prefecture in a given year). To alleviate such concerns, we calculate the percentage of firms in our sample obtaining multiple loans from different prefectures each year. This number proved to be 61.85%, which is higher than the threshold of 60%, and the average loan term for those firms is 3.13 years. Therefore, the tight fixed effects used in this study are justified.

5 Mechanism

The corruption index can disclose the extent of the market competition or marketization, corrupt banks bribe the government of the local prefecture in an effort to obtain increased market power. Banks with sufficient market power have a greater ability to set interest rates and control loan amounts. Thus loan amounts and interest rates can be affected by the level of market competition, and banks in corrupt areas might charge higher markups and supply less credit. Moreover, firms who want to obtain loans from banks with a relatively high level of market power must pay a higher fixed cost (entry cost) and higher variable costs (interest rate). Thus, they are more likely to provide collateral and obtain a loan with a longer period to maturity. In addition, banks in corrupt areas might be less efficient and at greater risk of default. Thus, they may experience higher rates of bad loans. Therefore, this section explores the mechanisms underlying the effects of bank loans on both bank concentration and bank health.

5.1 Bank Concentration Effects

To justify this mechanism, we examine the effects of corruption and misreporting on both the market share of the top three banks and the HHI index in the specific prefecture as follows.

We employ the bank share to measure the banks' bargaining power in a specific prefecture in China. The Bank share is a variable used to measure the share of bank i in year t and prefecture p, and it could be written as

$$Bank\ Share_{it} = \frac{Size_{it}}{Total\ size_{pt}}. \tag{6}$$

Bank size can be measured in terms of either bank assets or loans provided. Here, we consider not only assets but also loans because banks in China vary in their operations, and some banks might be relatively small in terms of assets, but provide a considerable amount of credit. Since we focus on bank lending, we need to consider the size of the banks' loans. For the bank-level information, we employ the following specification for bank i in the prefecture p and year t:

$$Bank\ Share_{ipt} = \beta_1 Index_{p,t-1} + \beta_2 Index_{p,t-1} \times Post_t + \gamma X_{i,t-1} + \mu_p + \lambda_t + \epsilon_{ipt}, \tag{7}$$

where i represents bank, p represents prefecture, t represents year, Bad Loan$_{i,t}$ is (Subprime loan$_{i,t}$+Doubt loan$_{i,t}$+Loss loan$_{i,t}$)/Asset$_{i,t}$ or (Subprime loan$_{i,t}$+Doubt loan$_{i,t}$+Loss loan$_{i,t}$)/Total Loan$_{i,t}$, $Post_t$ is an indicator variable equals one after 2012, $X_{i,t}$ is the bank level control variables, μ_p is the prefecture fixed effects, λ_t is the year fixed effects. $Index_{p,t}$ could be $Corruption\ Index_{p,t}$ and $Misreporting\ Index_{p,t}$ respectively. All the bank branches located in the same prefecture share the unique $Corruption\ Index_{p,t}$, and the prefecture level $Corruption\ Index_{p,t}$ is the probability of been investigated and removed because of corruption. All the bank branches located in the same prefecture share the unique $Misreporting\ Index_{p,t}$, and the prefecture level $Misreporting\ Index_{p,t}$ is the standardized differences between GDP and the night-lighting data. Since our main variable of interest varies at the prefecture level over time, the standard errors are clustered at the prefecture level and robust to heteroskedasticity.

Regarding the banks' share of the bank assets of top three banks in the specific prefecture, column (1) in Table 12 shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.101% increase in the bank's share of assets, and that this effect changed direction following the commencement of the anti-corruption campaign in 2012. Column (3) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.655% increase in the bank's share of assets, and that this effect also changed direction following the commencement of the anti-corruption campaign in 2012. Regarding the bank's share of total loans of top three banks in the specific prefecture, column (2) shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.0883% increase in the bank's share of total loans, and this effect is significantly reduced following the commencement of the anti-corruption campaign in 2012. Column (4) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.607% increase in the bank's share of total loans, and that this effect is significantly reduced following the commencement of the anti-corruption campaign in 2012.

Since the above analysis of the banks' shares of assets and total loans only considered the change of the share for the top three banks, we need to discuss the effects on all of the banks to obtain a complete picture. Therefore, we use the Herfindahl-Hirschman Index (HHI) to calculate the banks' monopoly power in a specific prefecture in China. The HHI values for banks at the prefecture level were calculated as

$$HHI_{pt} = (s_1^2 + s_2^2 + s_3^2 + ... + s_n^2)/10000, \tag{8}$$

where s_n is the market share percentage of bank n. For the prefecture-level information, we employ the following specification for prefecture p and year t:

$$HHI_{pt} = \beta_1 Index_{p,t-1} + \beta_2 Index_{p,t-1} \times Post_t + \mu_p + \lambda_t + \epsilon_{pt}, \tag{9}$$

where p represents prefecture and t represents year. $Post_t$ is an indicator variable equals one after 2012, $X_{i,t}$ is the bank level control variables, μ_p is the prefecture fixed effects, λ_t is the year fixed effects. $Index_{p,t}$ could be $Corruption\ Index_{p,t}$ and $Misreporting\ Index_{p,t}$ respectively. All the bank branches located in the same prefecture share the unique $Corruption\ Index_{p,t}$, and the prefecture level $Corruption\ Index_{p,t}$ is the probability of been investigated and removed because of corruption. All the bank branches located in the same prefecture share the unique $Misreporting\ Index_{p,t}$, and the prefecture level index $Misreporting\ Index_{p,t}$ is the standardized differences between GDP and the night-lighting data. Since our main variable of interest varies at the prefecture level over time, the standard errors are clustered at the prefecture level and robust to heteroskedasticity.

Table 13 presents the bank concentration effects estimated using the HHI. Column (1) shows the HHI calculated using the banks' shares of assets. It can be seen that the HHI is higher in the more corrupt areas prior to the commencement of the anti-corruption investigation, and decreased substantially following the commencement of the anti-corruption campaign. Column (2) shows the HHI calculated using the banks' shares of total loans. It can be seen that the results barely move, if anything, the estimates became more significant. Moreover, column (3) shows that the HHI based on the banks' share of assets is higher in prefectures with high levels of misreporting prior to the commencement of the anti-corruption campaign, and is significantly reduced following the commencement of the anti-corruption investigation. Column (4) shows the HHI calculated using the banks' shares of total bank loans. It can be seen that the results are similar to those presented in column (3), but somewhat more significant.

In summary, we find that banks located in more corrupt prefectures or prefectures with more misreporting of GDP had greater monopoly or bargaining power, and applied higher interest-rate markups in addition to being less efficient. As noted in Section 4, these monopoly effects resulted in higher interest rates and smaller bank loans in the more corrupt areas prior to the commencement of the anti-corruption investigation. After 2012, the higher interest rates and smaller loans disappeared with the collapse of the banks' monopoly or bargaining power. In addition, the bargaining power held by the banks in the more corrupt prefectures enable them to ask for longer period until maturity and more collateral.

5.2 Bank Health Effects

We use bad-loan data to analyze the effect of corruption and misreporting on bank balance sheets. The bad loan ratio is a variable used to measure the health of a specific bank i in year t, and it is constructed as

$$Bad\ Loan_{it} = \frac{Subprime\ loan_{it} + Doubt\ loan_{it} + Loss\ loan_{it}}{Size_{it}}, \tag{10}$$

where assets or total loans could measure size. Similar to our previous analysis, we consider both assets and loans to avoid situations where a bank has relatively few assets but provided a relatively high amount of credit. In these cases, even though bad loans might have been high in relation to assets, they might have been acceptable when considering the amount of credit provided. For the bank-level information, we employ the following specification for bank i in the prefecture p and year t:

$$Bad\ Loan_{ipt} = \beta_1 Index_{p,t-1} + \beta_2 Index_{p,t-1} \times Post_t + \gamma X_{i,t-1} + \mu_p + \lambda_t + \epsilon_{ipt}, \tag{11}$$

where i represents bank, p represents prefecture, t represents year, Bad Loan_{ipt} is (Subprime loan_{ipt}+Doubt loan_{ipt}+Loss loan_{ipt})/Asset_{ipt} or (Subprime loan_{ipt}+Doubt loan_{ipt}+Loss loan_{ipt})/Total Loan_{ipt}, Bank Share_{ipt} is $\text{Asset}_{ipt}/\sum_{i=1}^{I}\text{Asset}_{ipt}$ or $\text{Loan}_{ipt}/\sum_{i=1}^{I}\text{Loan}_{ipt}$, $Post_t$ is an indicator variable equals one after 2012, $X_{i,t}$ is the bank level control variables, μ_p is the prefecture fixed effects, λ_t is the year fixed effects. $Index_{p,t}$ could be $Corruption\ Index_{p,t}$ and $Misreporting\ Index_{p,t}$ respectively. All the bank branches located in the same prefecture share the unique $Corruption\ Index_{p,t}$, and the prefecture level $Corruption\ Index_{p,t}$ is the probability of been investigated and removed because of corruption. All the bank branches located in the same prefecture share the unique $Misreporting\ Index_{p,t}$, and the prefecture level $Misreporting\ Index_{p,t}$ is the standardized differences between GDP and the night-lighting data. Since our main variable of interest varies at the prefecture level over time, the standard errors are clustered at the prefecture level and robust to heteroskedasticity.

Regarding bad loans in relation to bank assets, column (1) in Table 14 shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.218% increase in bad loans as a fraction of assets. This effect is significantly reduced following the commencement of the anti-corruption campaign in 2012. Column (3) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.346% increase in bad loans as a fraction of assets, and this effect is also significantly reduced following the commencement of the anti-corruption campaign in 2012. Furthermore, regarding bad loans in relation to total loans provided, column (2) in shows that a 1% increase in the leaders' probability of being investigated and removed is associated with a 0.359% increase in bad loans as a fraction of total loans provided, and this effect is significantly reduced following the commencement of the anti-corruption campaign in 2012. Column (4) presents that a 1% increase in the difference between the logs of the economic and night-lighting data is associated with a 0.692% increase in bad loans as a fraction of total loans provided, and this effect is also significantly reduced following the commencement of the anti-corruption campaign in 2012.

Therefore, we find that the anti-corruption campaign improved the banks' health, as reflected in their balance sheets. This finding is consistent with the results presented in Table 5, banks located in more corrupt prefectures had high bad loan ratio because they chose to give loans with longer period until maturity. This finding is also consistent with the results presented in Table 6, banks located in more corrupt areas asked for more collateral to reduce the losses from the default. Further, this finding is also consistent with the results presented in Section 4.3, banks located in the more corrupt prefectures chose to allocate more loans to private firms following the onset of the anti-corruption campaign, which enjoy greater profitability and debt-paying ability than state-owned firms.

6 Conclusion

In this paper, we show that banks located in more corrupt prefectures provided significantly less credit prior to the commencement of the anti-corruption campaign, and this effect changed the direction following the commencement of the campaign. Moreover, banks located in more corrupt prefectures tended to charge higher interest rates, offer loans with longer periods to maturity, require more collateral, and experience a higher rate of bad loans prior to the commencement of the anti-corruption campaign, and all of these characteristics were reduced or reversed following the commencement of the campaign.

The corruption index indicates the extent of market competition (marketization), and corrupt banks bribe local governments in an effort to obtain increased market power. First, higher levels of corruption lead to a reduced credit supply and higher interest rates through the channel of the reduced competition and higher interest rate markups. Second, higher levels of corruption lead to higher interest rates through the channel of less competition, lower efficiency, and higher variable costs. Third, higher levels of corruption lead to longer loan periods until maturity as a result of less competition, lower efficiency, and higher fixed costs. This monopoly effect is confirmed by the finding that the bank concentration ratio is higher in more corrupt areas, and that this characteristic disappeared following the introduction of the anti-corruption campaign.

The findings of our study foster the understanding of the unfolding of the impact of the anti-corruption campaign on China's bank lending channel. Our results also indicate that both market-oriented and government-oriented effects are critical in relation to China's financial markets. Moreover, the results of our study provide evidence of the crucial role of monopoly power in determining the allocation of bank credit. An examination of the industries that were most affected by the anti-corruption campaign would be a worthwhile topic for future research.

Tables

Table 1: Variable Definitions

Variable	Definition
Dependent Variables (winsorized at the 1% level)	
L	Natural logarithm of bank loans
ΔL	ln(bank loan$_{t+1}-$bank loan$_t$)
$Bad\ Loan_{i,t}$ (Asset)	(Subprime loan$_{i,t}$+Doubt loan$_{i,t}$+Loss loan$_{i,t}$)/Asset$_{i,t}$
$Bad\ Loan_{i,t}$ (Total loan)	(Subprime loan$_{i,t}$+Doubt loan$_{i,t}$+Loss loan$_{i,t}$)/Total loan$_{i,t}$
$Bank\ Share_{i,t}$ (Asset)	Asset$_{i,t}$/Total asset$_{p,t}$
$Bank\ Share_{i,t}$ (Loan)	Loan$_{i,t}$/Total loan$_{p,t}$
$HHI_{p,t}$ (Asset)	$(s_{1A}^2 + s_{2A}^2 + s_{3A}^2 + ... + s_{nA}^2)/10000$
$HHI_{p,t}$ (Total loan)	$(s_{1TL}^2 + s_{2TL}^2 + s_{3TL}^2 + ... + s_{nTL}^2)/10000$
Key Explanatory Variables (winsorized at the 1% level)	
$Post_t$	Dummy equals one if the year is after 2012.
$Bad\ Loan_{i,t}$	(Subprime loan$_{i,t}$+Doubt loan$_{i,t}$+Loss loan$_{i,t}$)/Asset$_{i,t}$
$Corruption\ Index_{i,t}$	$\sum_{o'=1}^{O} W_{o',p,t} \times \mathbb{1}(Corrupted_{o',p,t} = 1)$
$Misreporting\ Index_{i,t}$	$ln(\frac{GDP_{p,t}}{sd(GDP_{p,t})}) - ln(\frac{light(sum)_{p,t}}{sd(light(sum)_{p,t})})$
$State\text{-}owned_i(Firm)$	Dummy equals one if the firm is a state-owned firm.
Control Variables (winsorized at the 1% level)	
$State\text{-}owned_i(Bank)$	Dummy equals one if the bank is a state-owned bank.
$Policy_i$	Dummy equals one if the bank is a policy bank.
$Rural_i$	Dummy equals one if the bank is a rural bank.
$Size_{i,t}$	ln(Bank Assets$_{i,t}$)

Table 2: Summary Statistics

	State-owned Banks			Private Banks			All Banks		
	mean	sd	count	mean	sd	count	mean	sd	count
Panel A: Loan-level variables									
loan	502.619	3,717.35	9,840	264.614	780.71	15,018	358.828	2,418.99	24,858
lnloan	18.842	1.38	9,840	18.548	1.22	15,018	18.664	1.29	24,858
dlnloan	0.114	0.91	4,822	0.123	0.77	6,655	0.119	0.83	11,477
Observations	9840			15018			24858		
Panel B: Bank/prefecture-level variables									
Corruption Index	0.105	0.03	122	0.084	0.17	912	0.087	0.16	1,034
Misreporting Index	0.048	0.42	106	-0.173	0.60	658	-0.142	0.58	764
Size	28.367	1.83	103	25.401	1.32	756	25.757	1.69	859
State-owned (Bank)	1.000	0.00	122	0.000	0.00	912	0.118	0.32	1,034
Policy	0.344	0.48	122	0.000	0.00	912	0.041	0.20	1,034
Rural	0.000	0.00	122	0.154	0.36	912	0.135	0.34	1,034
Observations	122			912			1034		

Notes. A "loan" is defined as a bank-firm pair, i.e., multiple loans of a firm from the same bank are aggregated up. Panel A presents descriptive statistics of firm-bank pairwise dependent variables split into state-owned and private banks. Panel B presents descriptive statistics of bank-level explanatory variables split into state-owned and private banks. State-owned is an indicator variable equals one if the bank is a state-owned bank. The sample consists of all banks that are located in China. The sample consists of all firms that are listed in the A-share, B-share, H-share, and oversea stocks market.

Table 3: The Bank Lending Channel—Loan Amount

Log(Loan)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	0.160***	0.108*		0.0970**	0.0160	
	(0.0530)	(0.0600)		(0.0442)	(0.0788)	
Policy	0.512***	0.794***		0.493***	0.704***	
	(0.123)	(0.0804)		(0.0101)	(0.0309)	
Rural	0.161*	0.0340		0.143	-0.00184	
	(0.0888)	(0.147)		(0.116)	(0.211)	
Size	0.0809***	0.0982***		0.0932***	0.130***	
	(0.0160)	(0.0214)		(0.0189)	(0.0314)	
Index	-0.210*	-0.199	-0.161*	-0.135***	-0.173***	-0.122***
	(0.120)	(0.143)	(0.0931)	(0.0319)	(0.0643)	(0.0280)
Index x Post	0.317**	0.468***	0.314**	0.0721**	0.0615*	0.0638*
	(0.124)	(0.133)	(0.158)	(0.0363)	(0.0362)	(0.0358)
Observations	23630	23630	23296	13485	13485	12999
R^2	0.576	0.112	0.579	0.576	0.119	0.577
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	162	162	160	144	144	141

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of log loan volume. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 4: The Bank Lending Channel—Interest Rate

Log(Interest)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	-0.106***	-0.00990		-0.0943**	-0.0725*	
	(0.0370)	(0.0385)		(0.0371)	(0.0370)	
Policy	-0.934***	-1.236***		-0.135	-0.189***	
	(0.0999)	(0.0665)		(0.106)	(0.0579)	
Rural	-0.00535	0.00564		-0.0929	0.109	
	(0.0897)	(0.0958)		(0.125)	(0.122)	
Size	0.00304	0.0592***		0.0327**	0.00181	
	(0.0107)	(0.0105)		(0.0127)	(0.0123)	
Index	0.409***	0.617***	0.547***	0.0107	-0.0703	0.245**
	(0.129)	(0.151)	(0.141)	(0.0482)	(0.0443)	(0.111)
Index x Post	-0.501***	-0.640***	-0.498***	-0.141**	-0.156***	-0.185***
	(0.137)	(0.158)	(0.158)	(0.0583)	(0.0559)	(0.0636)
Observations	806	806	661	603	603	494
R^2	0.880	0.507	0.885	0.841	0.332	0.849
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	73	73	65	61	61	56

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of the log interest rate. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 5: The Bank Lending Channel—Maturity

Log(Maturity)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	0.116***	0.122***		0.200*	0.0959	
	(0.0430)	(0.0467)		(0.108)	(0.102)	
Policy	1.849***	2.388***		1.560***	2.112***	
	(0.0960)	(0.259)		(0.125)	(0.257)	
Rural	0.366***	0.452***		0.586*	0.782***	
	(0.107)	(0.0948)		(0.334)	(0.203)	
Size	0.0847***	0.106***		0.177***	0.239***	
	(0.0137)	(0.0152)		(0.0344)	(0.0318)	
Index	0.829***	0.931***	0.637**	-0.292**	-0.223***	0.487
	(0.268)	(0.329)	(0.274)	(0.113)	(0.0824)	(0.324)
Index x Post	-0.824***	-1.003***	-0.854***	-0.412**	-0.453***	-0.431**
	(0.280)	(0.333)	(0.286)	(0.210)	(0.152)	(0.180)
Observations	12379	12379	12410	4869	4869	4733
R^2	0.478	0.077	0.566	0.536	0.098	0.589
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	141	141	142	125	125	122

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of log maturity. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 6: The Bank Lending Channel—Collateral

Collateral	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	0.0206***	0.0358***		0.0352***	0.0667***	
	(0.00688)	(0.00989)		(0.00967)	(0.0135)	
Policy	0.00790	-0.0264		-0.00305	0.0164	
	(0.0137)	(0.0215)		(0.00669)	(0.0205)	
Rural	0.0167	-0.000975		-0.0253	-0.0266	
	(0.0215)	(0.0249)		(0.0304)	(0.0370)	
Size	-0.000713	-0.0240***		-0.00508	-0.0263***	
	(0.00357)	(0.00325)		(0.00479)	(0.00477)	
Index	0.0651*	0.139***	0.106**	0.0343**	0.0431**	0.120**
	(0.0366)	(0.0445)	(0.0490)	(0.0151)	(0.0178)	(0.0530)
Index x Post	-0.0877**	-0.139***	-0.0240	-0.0324*	-0.0408**	-0.0375**
	(0.0355)	(0.0492)	(0.0527)	(0.0170)	(0.0201)	(0.0190)
Observations	23630	23630	23296	13485	13485	12999
R^2	0.572	0.123	0.622	0.582	0.157	0.629
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	162	162	160	144	144	141

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is an indicator variable equals one if the loan is a collateral loan. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 7: The Bank Lending Channel—Loan (Credit Allocation across Firms)

Log(Loan)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned (Bank)	0.161***	0.110***		0.101**	0.00936	
	(0.0298)	(0.0331)		(0.0472)	(0.0302)	
Policy	0.508***	0.778***		0.479***	0.683***	
	(0.0669)	(0.0556)		(0.132)	(0.112)	
Rural	0.161***	0.0303		0.146***	-0.00804	
	(0.0310)	(0.0588)		(0.0443)	(0.115)	
Size	0.0803***	0.0970***		0.0934***	0.133***	
	(0.00570)	(0.00844)		(0.0125)	(0.00903)	
Index	-0.224*	-0.190	-0.154	-0.122***	-0.185***	-0.275***
	(0.131)	(0.122)	(0.156)	(0.0365)	(0.0386)	(0.101)
Index x Post	0.367***	1.224***	0.169*	0.0631*	0.352***	0.197*
	(0.142)	(0.127)	(0.0928)	(0.0380)	(0.0492)	(0.118)
Index x Post x State (Firm)	-0.0614	-1.291***	-0.0585	-0.0215	-0.428***	-0.0390
	(0.0880)	(0.168)	(0.0868)	(0.0307)	(0.0399)	(0.0407)
Observations	23175	23175	22845	13027	13027	12556
R^2	0.579	0.117	0.582	0.582	0.129	0.584
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	162	162	160	144	144	141

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of log loan volume. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 8: The Bank Lending Channel—Loan (Initial Year)

Log(Loan)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	0.160***	0.0931***		0.115***	0.0390	
	(0.0208)	(0.0268)		(0.0285)	(0.0344)	
Policy	0.509***	0.807***		0.471***	0.670***	
	(0.0455)	(0.0615)		(0.0479)	(0.0662)	
Rural	0.161***	0.0351		0.148*	0.0155	
	(0.0495)	(0.0679)		(0.0789)	(0.105)	
Size	0.0797***	0.101***		0.0703***	0.0969***	
	(0.00684)	(0.00847)		(0.0107)	(0.0124)	
Index	-0.120	-0.103		-0.173***	-0.269***	
	(0.0920)	(0.117)		(0.0427)	(0.0479)	
Index x Post	0.109**	0.275***	0.120*	0.0789**	0.0748**	0.0603*
	(0.0471)	(0.0642)	(0.0667)	(0.0308)	(0.0371)	(0.0324)
Observations	23630	23630	23296	13485	13485	12999
R^2	0.576	0.112	0.579	0.577	0.120	0.577
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	162	162	160	144	144	141

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of log loan volume. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 9: The Bank Lending Channel—Loan (Average of the pre-shock Years)

Log(Loan)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	0.159***	0.0802**		0.0957**	0.0132	
	(0.0313)	(0.0322)		(0.0460)	(0.0309)	
Policy	0.513***	0.813***		0.489***	0.699***	
	(0.0683)	(0.0560)		(0.133)	(0.110)	
Rural	0.161***	0.0336		0.150***	0.0115	
	(0.0312)	(0.0594)		(0.0477)	(0.124)	
Size	0.0808***	0.103***		0.0891***	0.125***	
	(0.00501)	(0.00902)		(0.0116)	(0.00994)	
Index	-0.108	-0.114		-0.193***	-0.255***	
	(0.0817)	(0.0746)		(0.0633)	(0.0685)	
Index x Post	0.102***	0.234***	0.109**	0.0670*	0.0629*	0.0603*
	(0.0334)	(0.0272)	(0.0547)	(0.0366)	(0.0381)	(0.0305)
Observations	23630	23630	23296	13485	13485	12999
R^2	0.576	0.112	0.579	0.577	0.119	0.577
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	162	162	160	144	144	141

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of log loan volume. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 10: The Bank Lending Channel—Interest Rate (Initial Year)

Log(Interest)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	-0.0748**	0.0574		-0.0949***	-0.0633*	
	(0.0361)	(0.0373)		(0.0364)	(0.0363)	
Policy	-0.957***	-1.287***		-0.145	-0.206***	
	(0.101)	(0.0666)		(0.106)	(0.0579)	
Rural	0.00317	0.0214		-0.0643	0.121	
	(0.0906)	(0.0968)		(0.125)	(0.122)	
Size	0.00311	0.0619***		0.0266**	-0.00883	
	(0.0109)	(0.0109)		(0.0131)	(0.0124)	
Index	0.249	-0.102		-0.0748	0.0806*	
	(0.222)	(0.206)		(0.0485)	(0.0473)	
Index x Post	-0.176*	-0.0825	-0.165	-0.104**	-0.0463	-0.101**
	(0.104)	(0.112)	(0.181)	(0.0436)	(0.0433)	(0.0511)
Observations	806	806	661	603	603	494
R^2	0.877	0.496	0.877	0.842	0.332	0.846
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	73	73	65	61	61	56

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of the log interest rate. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 11: The Bank Lending Channel—Interest Rate (Average of the pre-shock Years)

Log(Interest)	(1) Index (Corruption)	(2) Index (Corruption)	(3) Index (Cor.)	(4) Index (Misreporting)	(5) Index (Misreporting)	(6) Index (Misr.)
State-owned	-0.0700*	0.0525		-0.101***	-0.0767**	
	(0.0358)	(0.0368)		(0.0371)	(0.0371)	
Policy	-0.958***	-1.283***		-0.134	-0.193***	
	(0.101)	(0.0662)		(0.106)	(0.0576)	
Rural	-0.000397	0.0231		-0.0804	0.119	
	(0.0910)	(0.0971)		(0.125)	(0.122)	
Size	0.00157	0.0608***		0.0343***	-0.000492	
	(0.0108)	(0.0106)		(0.0124)	(0.0120)	
Index	0.118	0.0686		-0.0424	0.0967**	
	(0.176)	(0.171)		(0.0499)	(0.0480)	
Index x Post	-0.221**	-0.1733	-0.316**	-0.107**	-0.161***	-0.101**
	(0.109)	(0.117)	(0.161)	(0.0492)	(0.0499)	(0.0511)
Observations	806	806	661	603	603	494
R^2	0.877	0.496	0.877	0.841	0.333	0.846
Bank Fixed Effect	NO	NO	YES	NO	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO
Year Fixed Effect	NO	YES	NO	NO	YES	NO
Firm-Year Fixed Effect	YES	NO	YES	YES	NO	YES
Clusters at Bank Level	73	73	65	61	61	56

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-firm-year. The dependent variable is the level of the log interest rate. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the bank level.

Table 12: Bank Share (Top 3 Banks in the Specific Prefecture)

	(1) Bank Share (Asset) Index (Corruption)	(2) Bank Share (Total Loan) Index (Corruption)	(3) Bank Share (Asset) Index (Misreporting)	(4) Bank Share (Total Loan) Index (Misreporting)
State-owned	0.135***	0.111***	0.0182	0.000422
	(0.0420)	(0.0150)	(0.0310)	(0.0171)
Policy	-0.146***	-0.0851***	-0.156***	-0.0886***
	(0.0480)	(0.0163)	(0.0216)	(0.00509)
Rural	-0.220***	-0.143***	-0.234***	-0.135***
	(0.0195)	(0.0207)	(0.00807)	(0.0164)
Index	0.101*	0.0883*	0.655***	0.607***
	(0.0592)	(0.0519)	(0.0756)	(0.0696)
Index x Post	-0.139**	-0.197***	-0.0548*	-0.143**
	(0.0703)	(0.0596)	(0.0318)	(0.0548)
Constant	0.282***	0.0802	0.292***	0.107***
	(0.0964)	(0.0518)	(0.0128)	(0.0134)
Observations	2019	2358	1431	1695
R^2	0.633	0.612	0.669	0.646
Year Fixed Effect	YES	YES	YES	YES
Prefecture Fixed Effect	YES	YES	YES	YES
Clusters at Prefecture Level	113	123	109	123

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-year. The dependent variable is the bank share. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the prefecture level.

Table 13: Bank Concentration (Herfindahl-Hirschman Index)

	(1) HHI (Asset) Index (Corruption)	(2) HHI (Total Loan) Index (Corruption)	(3) HHI (Asset) Index (Misreporting)	(4) HHI (Total Loan) Index (Misreporting)
Index	0.0813*	0.0881**	0.245***	0.216***
	(0.0441)	(0.0405)	(0.0306)	(0.0336)
Index x Post	-0.0979*	-0.107**	-0.0342*	-0.0411**
	(0.0561)	(0.0517)	(0.0186)	(0.0169)
Constant	0.535***	0.126**	0.494***	0.0879***
	(0.0598)	(0.0537)	(0.0152)	(0.0150)
Observations	724	841	529	616
R^2	0.555	0.533	0.599	0.577
Year Fixed Effect	YES	YES	YES	YES
Prefecture Fixed Effect	YES	YES	YES	YES
Clusters at Prefecture Level	129	137	124	137

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-year. The dependent variable is the (Herfindahl-Hirschman Index/10000). All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the prefecture level.

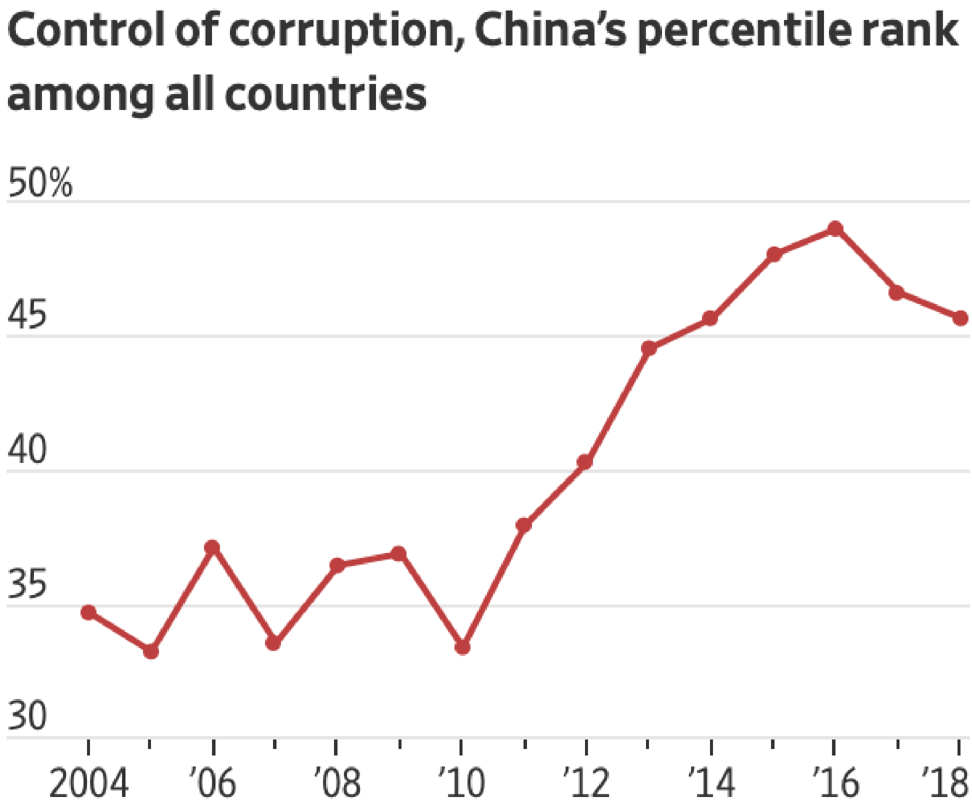
Table 14: Bank Health

	(1) Bad Loan/Asset Index (Corruption)	(2) Bad Loan/ Total Loan Index (Corruption)	(3) Bad Loan/Asset Index (Misreporting)	(4) Bad Loan/ Total Loan Index (Misreporting)
State-owned	1.697***	3.142***	1.846***	3.507***
	(0.469)	(0.707)	(0.545)	(0.834)
Policy	-1.428**	-4.301***	-1.557**	-4.548***
	(0.669)	(0.900)	(0.706)	(0.953)
Rural	1.164***	1.677***	1.462***	2.081***
	(0.121)	(0.147)	(0.185)	(0.230)
Index	0.218	0.359	0.346***	0.692***
	(0.233)	(0.372)	(0.110)	(0.174)
Index x Post	-0.212**	-0.827**	-0.308***	-0.710***
	(0.107)	(0.413)	(0.108)	(0.169)
Constant	4.956***	11.42***	5.029***	11.26***
	(1.324)	(2.314)	(1.319)	(2.287)
Observations	1273	1530	1099	1327
R^2	0.454	0.510	0.466	0.524
Year Fixed Effect	YES	YES	YES	YES
Prefecture Fixed Effect	YES	YES	YES	YES
Clusters at Prefecture Level	95	100	84	89

Notes. This table presents the results of a Chinese bank lending channel regression. The unit of observation is a bank-year. The dependent variable is the bad loan rate. All regressions include fixed effects. ***, **, or * indicates that the coefficient estimate is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors given below coefficient estimates are clustered at the prefecture level.

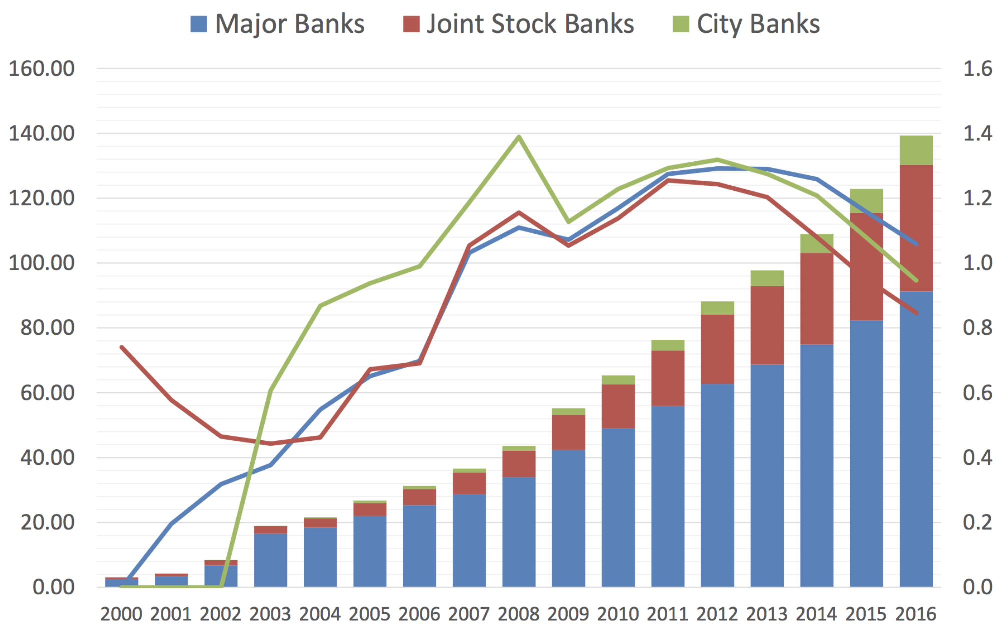
Figures

Figure 1: Cleanup Costs



Source: "China's Corruption Paradox", The Wall Street Journal.

Figure 2: Bank Assets (RMB Trillion) and ROA (%)



Source: Jiang Wang (MIT), "China's Financial System: Developments and Challenges", MIT Golub Center for Finance and Policy 4th Annual Conference.

Figure 3: Corruption Index over Time

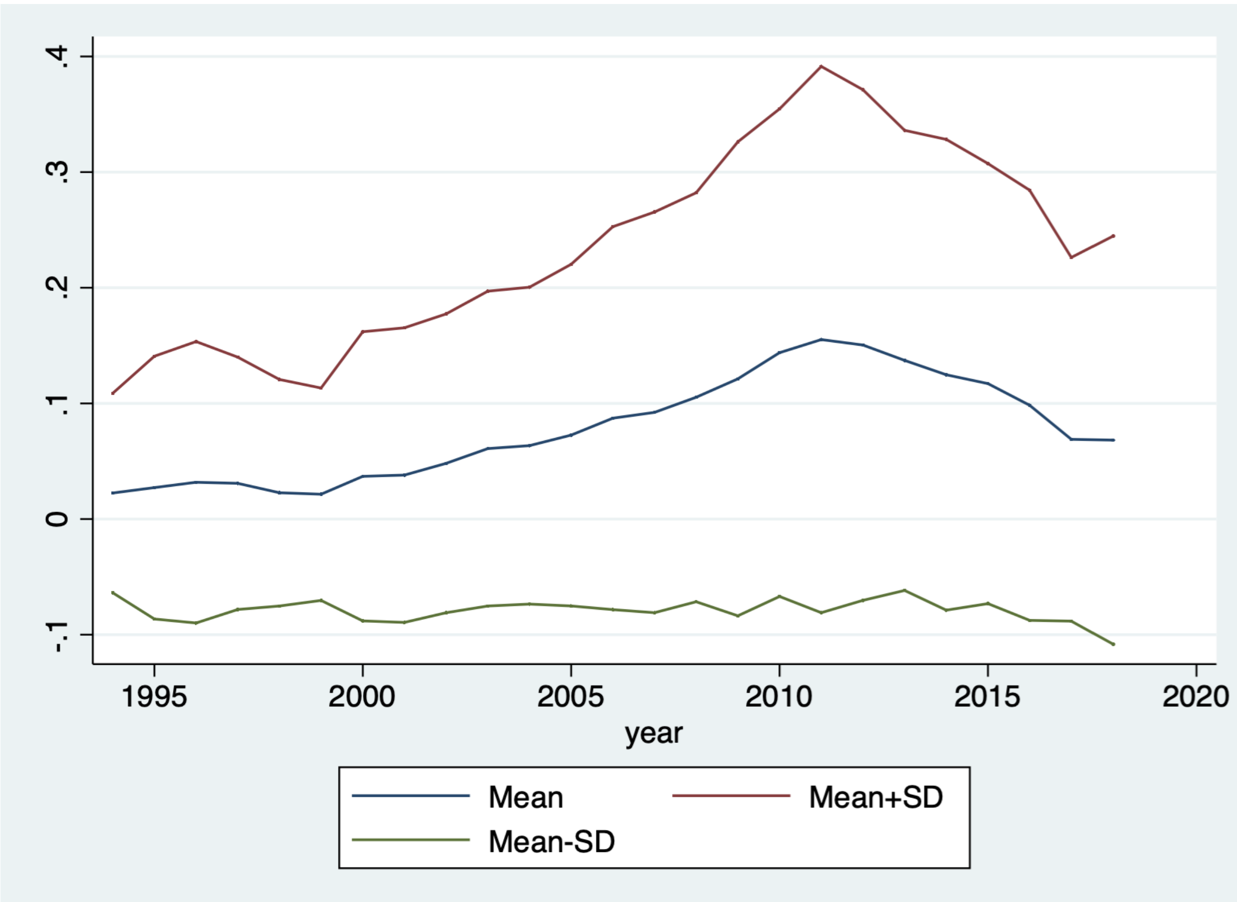


Figure 4: Corruption Index (Coefficient of Variation) over Time

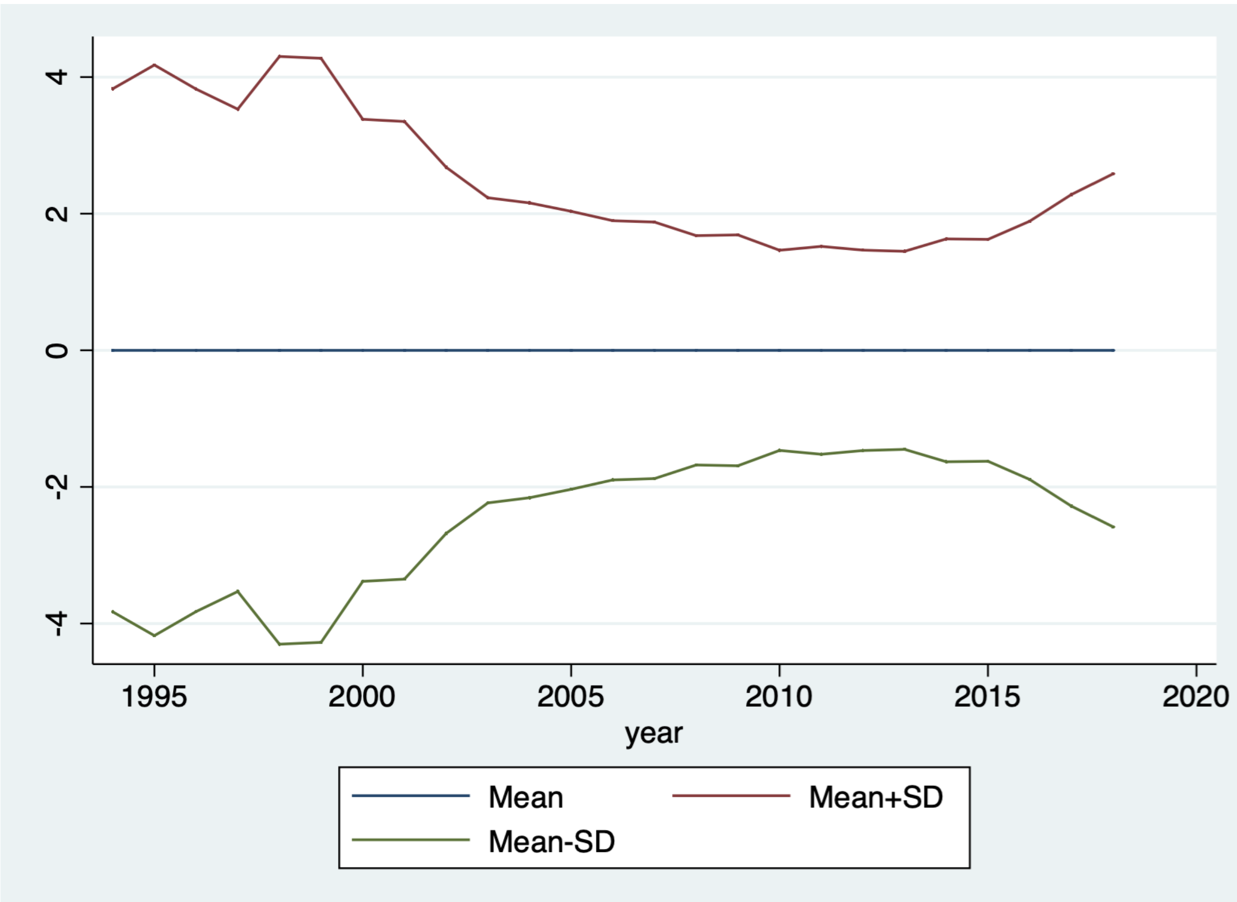


Figure 5: Corruption Index over Time

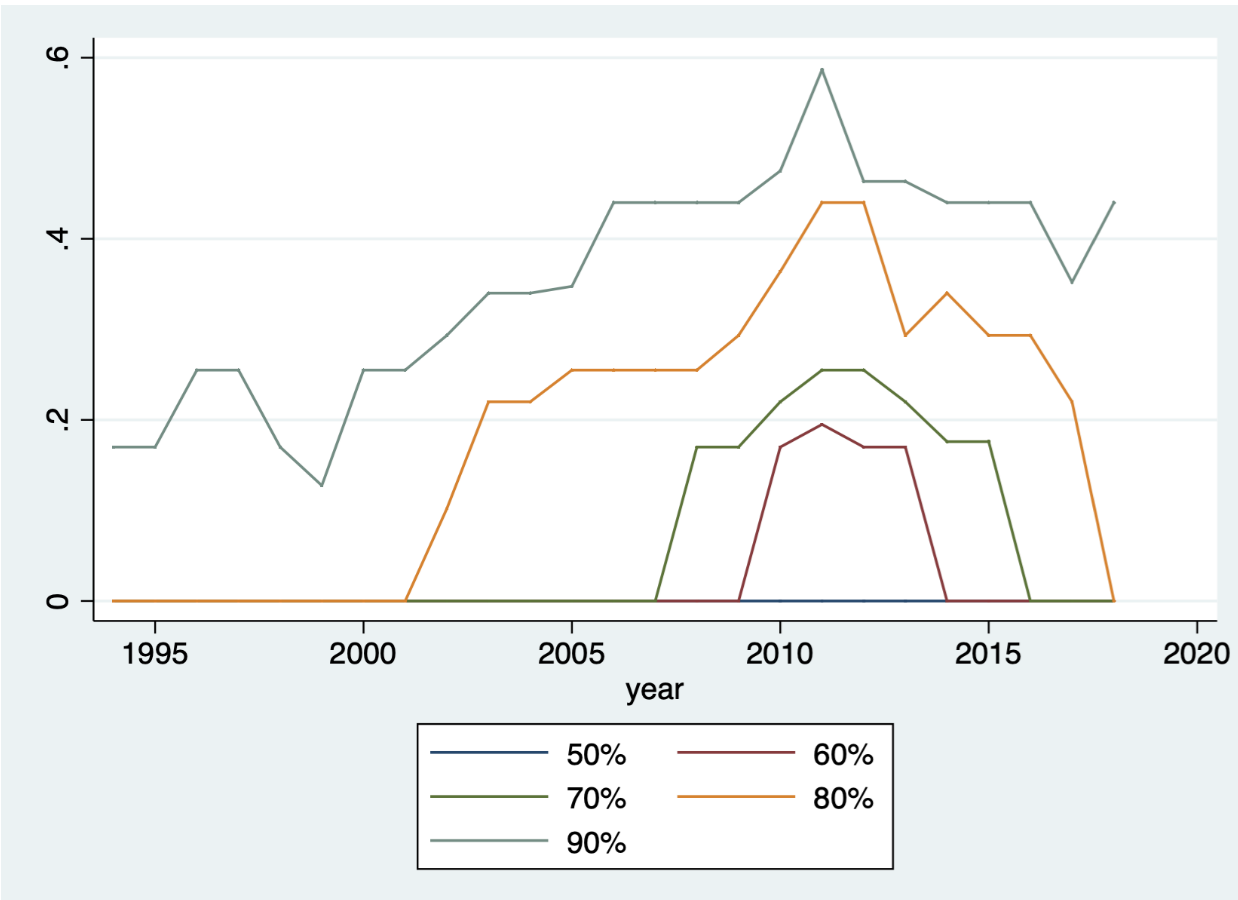


Figure 6: Corruption Index (DM) Map (2001-2016)

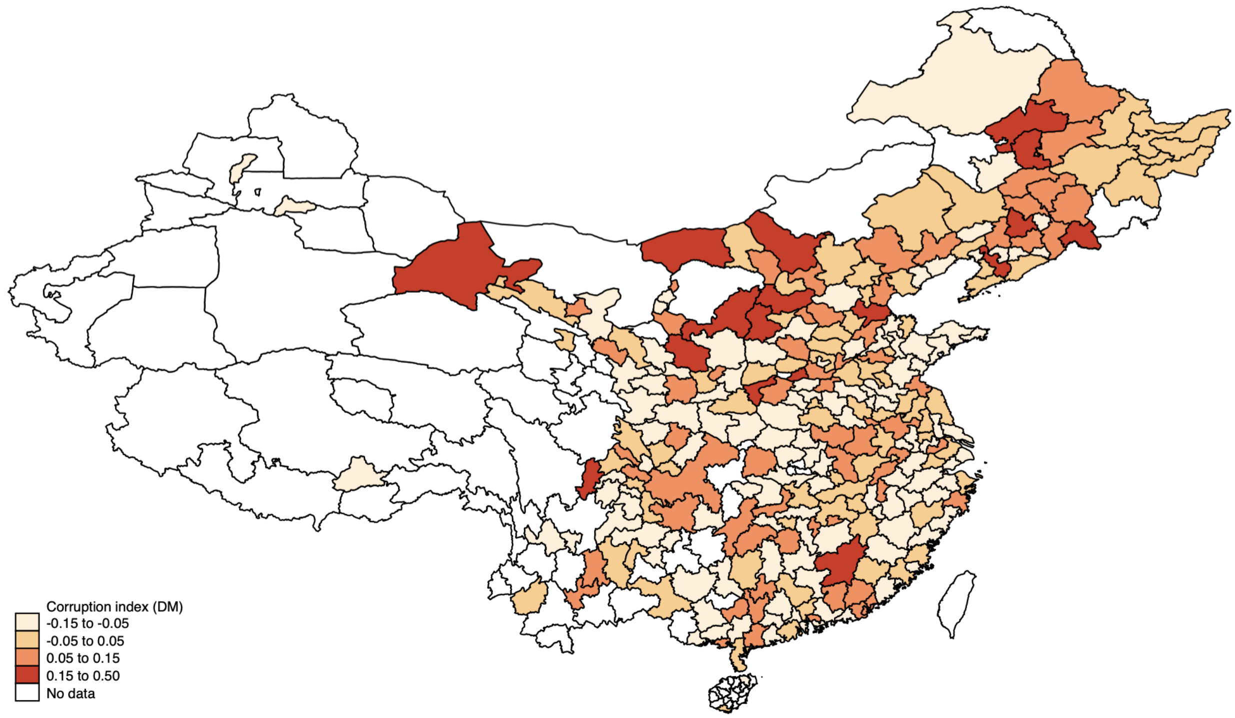


Figure 7: Evolution of Corruption Index (DM) (2001-2016)

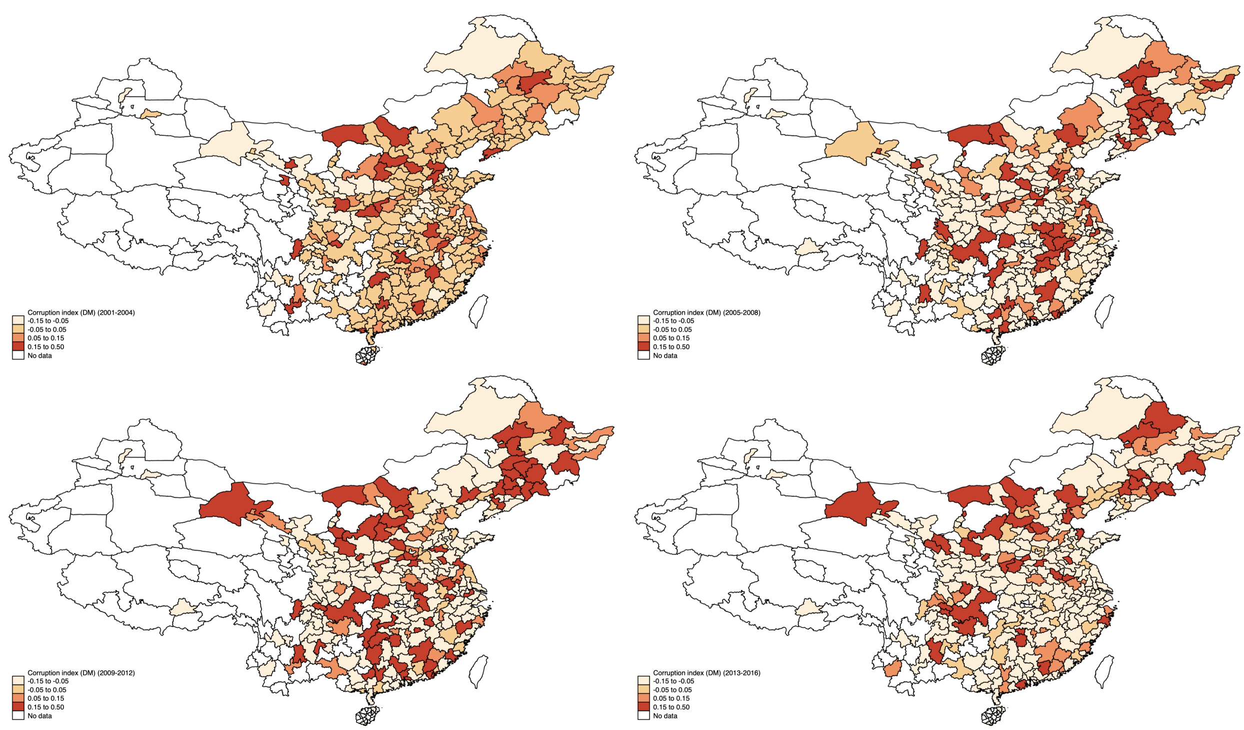
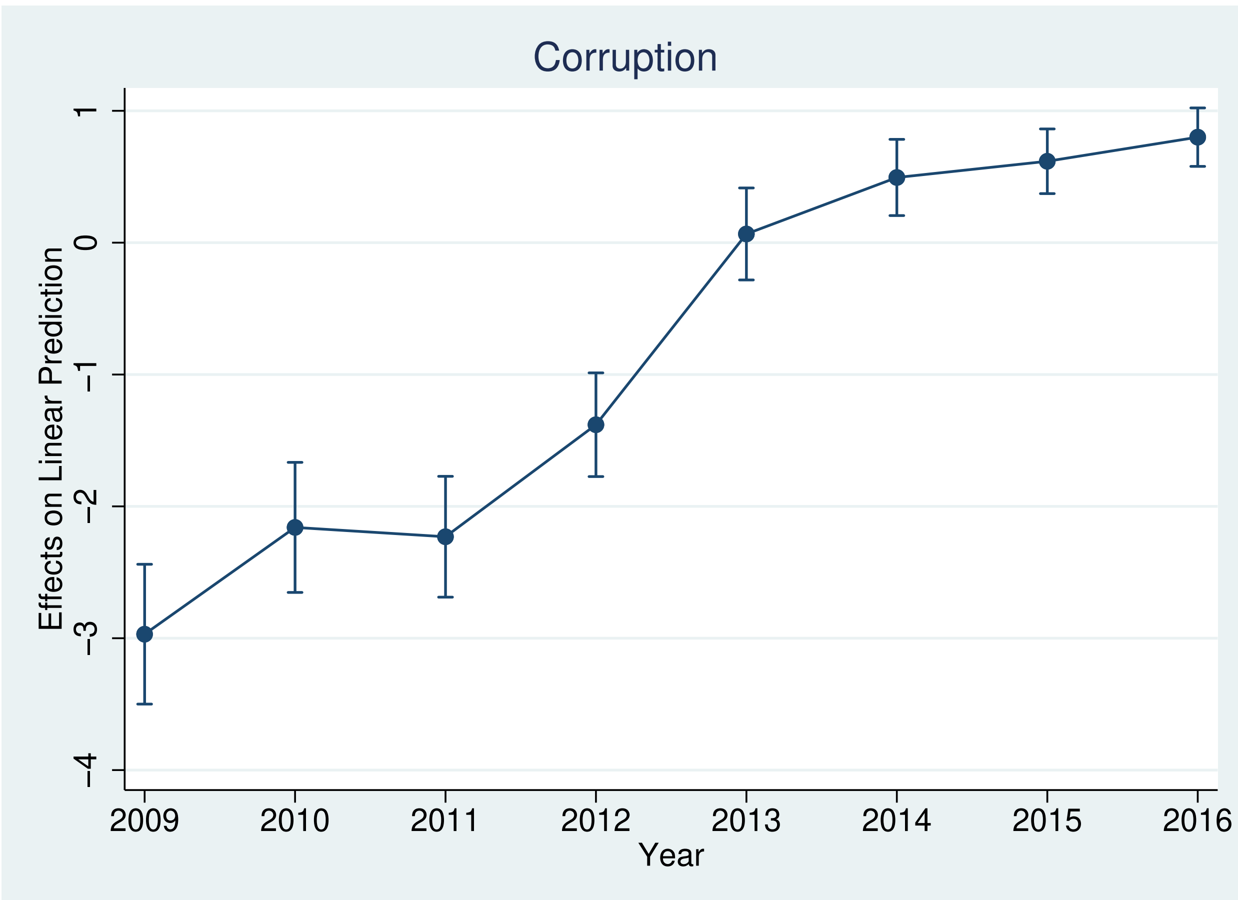


Figure 8: Parallel Trend (The Log Amount of the Loan)

Notes. Bank loans are sorted into more corrupt (upper half) and less corrupt (lower half) based on the corruption index in the prefectures the banks' headquarters located in.

Figure 9: Year-specific Effects (Coefficients β_1)



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Appendix: Prefecture List

Anshan
Anyang
Baotou
Beijing (Districts)
Cangzhou
Changchun
Changsha
Changzhou
Chaoyang
Chengde
Chengdu
Chongqing (Districts)
Dalian
Datong
Dazhou
Deyang
Dezhou
Dongguan
Dongying
Foshan
Fushun
Fuxin
Fuzhou
Guangzhou
Guilin
Guiyang
Haerbin
Handan
Hangzhou
Hefei
Huhehaote
Huludao
Huzhou
Jiangmen
Jiaozuo
Jiaxing
Jinan
Jincheng
Jinhua
Jining
Jinzhou
Jiujiang
Kaifeng
Kelamayi
Kunming
Laiwu
Lanzhou
Leshan
Linyi
Liuzhou
Longyan
Luoyang
Luzhou
Mianyang
Nanchang
Nanchong
Nanjing
Nanning
Ningbo
Ningde
Panzhihua
Pingdingshan
Qingdao
Qinhuangdao
Quanzhou
Qujing
Rizhao
Shanghai (Districts)
Shantou
Shaoxing
Shenyang
Shenzhen
Shijiazhuang
Shizuishan
Suining
Suzhou
Taian
Taiyuan
Taizhou
Tangshan
Tianjin (Districts)
Tongling
Weifang
Weihai
Wenzhou
Wuhan
Wuhu
Wulumuqi
Wuxi
Xiamen
Xining
Yancheng
Yangzhou
Yantai
Yibin
Yinchuan
Yingkou
Yuxi
Zaozhuang
Zhanjiang
Zhengzhou
Zhuhai
Zibo
Zigong