# Policy Distortion in Credit Market: Evidence from an Economic Stimulus*

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This version: April, 2020

**Abstract**

This paper examines policy distortion in credit allocation across firms. Our empirical analysis is based on a unique proprietary loan-level dataset covering the period from August 2006 to July 2010 from one of the largest state-owned banks (SOBs) in China. We exploit the policy announcement (hereafter, PA) of a economic stimulus program in November 2008 as an exogenous shock to the bank's loan supply to show that policy intervention results in credit misallocation between state-owned enterprises (SOEs) and private-owned enterprises (POEs) in loan market. Our sample bank induces part of this credit misallocation by loosening credit risk management towards SOEs. As a result, there is a larger reduction in interest rate for SOEs than POEs after the PA. We further show that the credit misallocation is absent when the bank provides funding through discounting bankers' acceptance - a shadow banking activity which faces less government intervention than lending does.

* We would like to thank the data provider and a number of bank branch managers and loan officers who participated in our interviews. We are grateful to Loren Brandt, Avinash Dixit, Wei Jiang, Iftekhar Hasan, Hongzhong Liu, Zheng Song, Lijian Sun, Laura Wu, and all the participants of workshops at the Bank of Finland, China International Conference in Finance, Chinese Economic Society, Chinese University of Hong Kong, Fudan University, Hong Kong Baptist University, International Banking, Economics and Finance Association, Nanyang Technological University, Lingnan University of Hong Kong, Shanghai Jiao Tong University, Singapore Economic Review Conference, University at Albany - SUNY, University of Hong Kong for their valuable comments. This paper has been screened to ensure that no confidential data are disclosed.
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## 1. Introduction

A large literature stresses the role of finance on economic development (Levine, 2005). In particular, previous research shows that the quality of financial sector in terms of capital allocation can explain productivity difference across countries (Banerjee and Duflo, 2005). Although there are evidences of capital misallocation across firms in developing countries, few studies have identified sources of capital misallocation across firms. Among these few studies, however, Banerjee and Munshi (2004), Kwaja and Mian (2005), and Banerjee and Duflo (2014) show that community identity, political connections, and size-dependent policy constitute sources of capital misallocation across firms, respectively.

This paper examines policy distortion in credit allocation across firms. Because of the global financial crisis, GDP growth in China decreased from 10.6% in the first quarter of 2008 to 6.8% in the fourth quarter. To address the economic slowdown, the government announced an economic stimulus program accompanied by expansionary monetary policies in November 2008. The People's Bank of China (PBC) reduced the benchmark lending rate (BLR) by about 1 percentage point (see the dotted line in Figure 1). The policy intervention associated with the global economic conditions of reduced capital flows from industrialized economies thus provides a quasi-experiment for exogenous variation in banks' loan supply.

[Figure 1 about here]

Our empirical analysis exploits a proprietary corporate loan-level dataset from one of the largest SOBs in China. The data cover all corporate lending in an economically developed prefectural-level city for the period from August 2006 to July 2010 and include information on the interest rate, loan size, default status, collateral requirement, and maturity for each loan, as well as the borrowing firm's credit rating, ownership classification, firm size, industry sector, and lending bank branch. Importantly, Figures 1 depicts that our sample bank lends more at a lower interest rate on average after the PA (see the solid and dashed lines in Figure 1), which is consistent with the policy intervention from the PBC.

Credit misallocation is defined as that credit is not allocated according to firms' productivity. In our context, we employ state ownership as a source of credit misallocation. Credit misallocation is identified if our sample bank treats SOEs and POEs differently, *ceteris paribus*. Here, we provide anecdotal evidences with industry-level datasets for our studied city to examine how the return on capital (ROC) between SOEs and POEs changed over the period of 2007-2010, which serves as a basis to determine the existence of credit misallocation. We employ the Statistical Yearbooks of our studied city as a source for a glimpse of the performance of all firms above designated level in industrial, construction and service industries from

2007 to 2010.[5]

We compute three measures for ROC. The first measure, Profit/Assets, is calculated as the total profit (Profit before income tax) normalized by assets.[6] The second indicator, EBIT/Assets, is Earnings before Interest and Tax (EBIT, Profit before income tax and Financial costs) normalized by total assets. The first two measures are computed from the perspectives of investors or bank managers, in particular the second allows us to compare across industries by allowing different income taxes and capital structures. The last measure, Earnings before Interest and All Taxes/Assets, is calculated as EBIT + Non-income taxes (including value-added tax, business tax and other extra charges by government) normalized by total assets. Figure 2 displays the three measures of ROC for SOEs and POEs from 2007 to 2010.[7] For all measures, ROC reached the trough in 2008, which is consistent with the weak external demand due to the global financial crisis. More importantly, the ROC of SOEs dropped while that of POEs raised over the period 2007-2010.

[Figure 2 about here]

Given the evidence on productivity difference between SOEs and POEs, if our sample bank provides preferential treatments to SOEs after the PA, which can be viewed as an evidence of credit misallocation. More specifically, if the decrease in the interest rate or the increase in loan size is greater for SOEs than POEs, *ceteris paribus*, there is an evidence of credit misallocation between these two groups of firms. Our empirical analysis employs a difference-in-differences (DID) methodology to control for a set of time fixed effects, loan characteristics, borrower characteristics and branch characteristics, thus our comparison between SOEs and POEs are conditional on demand factor such as aggregate fluctuations, sectoral difference and borrower heterogeneity. Further, our empirical analysis does not subject to the problem of unobserved heterogeneity across banks because we compare lending behavior within a bank.

Our empirical analysis reports several interesting results. First, we find that the standardized interest rate charged to SOEs is reduced by an additional amount relative to that charged to POEs, *ceteris paribus*, after the PA. Interestingly, our data not only contain information on loan made but also the information on

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[5] For firms in industrial sector, including manufacturing, mining, and electricity, gas & water production & supply, the designated level is an annual sale of and above five million. For firms in service sector, the designated level varies across industries. For example, for wholesales business, the designated level is an annual sale of and above 20 million and the number of employees no less than 20. And for catering business, the designated level is an annual sale of and above 2 million and the number of employees no less than 40. For firms in the construction sector, the designated level is that the construction firms should achieve certain grade or above according to the Qualification Standard for Construction Enterprises.

[6] A better measure to capture a firm's profitability is the net profit, as the total profit minus the income tax. However, the data on income tax for firms in service sector and construction sector are not available. Hence, we can only use total profit as a measure for a firms' profitability. In China, the business income tax rate is 25%. If a loss occurs, the amount of loss can be deducted from the next year's income tax. Hence at the industry level, the observed ratio of the income tax over total profit is less than 25%. The consolidated income statement for the manufacturing firms in our studied city shows the ratio of the income tax over total profit is about 19%, which may vary over years.

[7] The yearbooks provide consolidated financial statements for firms grouped by their ownership: state, private and foreign (owned or controlled).

bankers' acceptance (hereafter, BA) discounted by our sample bank. Discounting BA is an alternative tool to provide short-term financing and a main off-balance sheet shadow banking activity conducted by Chinese banks after the economic stimulus program (Elloitt et al. 2015), and is subject less to government intervention than formal lending activities. We find no evidence to show our sample bank provides preferential treatment to SOEs relative POEs in discounting BA. Our results suggest that, even in an economically developed city with a large private sector, credit misallocation occurs between SOEs and POEs for our sample bank. Nonetheless, such misallocation only appears in making loan but not in discounting BA, which suggests that credit misallocation is more severe when government intervention is more pervasive.

Second, we find that the policy intervention induces credit misallocation of the bank by loosening its credit risk management in setting interest rate for SOEs relative to POEs, despite there is no evidence showing a reduction of default rate for SOEs relative to POEs. In particular, the credit misallocation between SOEs and POEs is more prevalent among firms with a worse credit rating than among firms with a better credit rating. Our counterfactual analysis shows that, on average, the standardized interest rate charged to SOEs should have been 0.36 SD higher if there had been no change in credit risk pricing after the PA. On the other hand, our sample bank tightens its credit risk management in shadow banking. Again, our sample bank behaves differently in formal and shadow banking markets, in which the extent of government intervention differs.

Our study contributes to several literatures. First, our study contributes a new micro-level evidence on how credit misallocation arises. Peek and Rosengren (2005) show that during the 1990s, troubled banks in Japan misallocated credit because they faced perverse incentives associated with a weak bank supervision system and government pressure to aid financially stressed firms. Financially troubled banks were more likely to increase the issuance of loans to financially stressed firms with a strong affiliation with the bank. Banerjee and Duflo (2014) show that Indian firms with lower profitability receive more loans than Indian firms with higher profitability and suggest that banks have an incentive to lend to these firms to save them from bankruptcy. Gropp et al. (2019) shows that firms with lower profitability invest more and maintain a higher rate of sales growth when government guarantee on German saving banks was in place. We add to the literature by using the comparison between formal and shadow banking, where the former is subject more to government intervention, to show policy intervention induces credit misallocation. We also extend the literature by showing such misallocation is conducted through applying less prudential credit risk management in setting loan contract.

Second, our study speaks to the broader literature on the effects of micro-level distortions on aggregate productivity (Restuccia and Rogerson, 2008; Hsieh and Klenow 2009). In particular, there are few recent studies, which includes Buera et al. (2011), Midrigan and Xu (2014) and Moll (2014), analyzes financial frictions and misallocation. These previous studies focus on the effect of financial frictions induced by collateral constraints, which can arise from the problems of limited commitment, limited enforcement and costly state verification, on productivity. Our work adds to these studies by showing that policy intervention also contributes to financial friction, which drives the dispersion of borrowing costs across firms.

Third, we contribute to the growing literature on capital misallocation in China, which accounts for a substantial TFP loss. Hsieh and Klenow (2009) report that 30% of the TFP loss in the Chinese manufacturing sector is due to capital misallocation. Brandt et al. (2013) report that 20% of the TFP loss in the non-agricultural sector in China is due to capital misallocation. Wu (2018) reports that 70% of the capital misallocation is contributed by policy distortion. A common approach to estimating unobserved capital market distortions is to compute the average revenue product according to the optimal condition of factor choices (Restuccia and Rogerson 2008; Hsieh and Klenow 2009). However, as criticized in Gilchrist et al. (2013), the accuracy of the average revenue product for measuring unobserved capital market distortions depends on the model specification. Our work extends the aforementioned literature by providing a direct micro-level evidence of capital misallocation based on the dispersion of borrowing costs across firms. Our work also differs from Wu (2018) in identifying policy distortion by focusing on a concrete episode of policy intervention.

In a closer relationship with our work, there are few works discussing the implications of economic stimulus program in China on capital allocation. Bai et al. (2016) argue that, although the economic stimulus program drives up the investment rate, it worsens capital misallocation and hence reduces productivity. Cong et al. (2019) show that firms with a lower marginal product of capital increases their loan more than firms with a higher marginal product of capital. However, none of them looks into the interest rate charged to borrowers. Our work differs from them in showing credit misallocation in the form of interest rate differential driven by state ownership after the economic stimulus program, but such misallocation is mainly generated from formal banking but not from shadow banking.

Finally, our work is related to the recent studies on shadow banking in China. Previous works look into the roles of entrusted loan (He at al. 2016; Chen et al. 2018; Allen at el. 2019) and wealth management product (Hachem and Song 2016) in shadow banking. Our work differs from them in examining the role of BA in credit allocation. Although shadow banking has been criticized for undermining the stability of banking system in China, our results suggest that shadow banking allocates credit more efficiently than formal loan market.

The rest of the paper is organized as follows. Section 2 provides the institutional background. Section 3 discusses the empirical strategy and the data. Section 4 discusses the empirical results. Section 5 presents several robustness checks. The last section concludes.

## 2. Institutional Background

China has a bank-based financial system in which banks intermediate approximately 75% of the capital, more than double the percentage in the U.S. and 1.5 times the percentage in other Asian countries (Farrell et al., 2006). State ownership is far more prominent in the Chinese banking industry than that in most other countries. Indeed, either central or a local government owns more than 95% of all the approximately 170 domestic banks in China. The four biggest commercial banks, i.e., Agricultural Bank of China (ABC), Bank of China (BOC), China Construction Bank (CCB) and Industrial and Commercial Bank of China (ICBC), which accounted for 32.5% of the loan market in 2010, are all state owned (Almanac of China's Finance and Banking 2011). Other SOBs include joint-stock banks (JSBs), city commercial banks, and non-bank financial institutions.[8]

The central bank, PBC, operates under the guidance of the State Council. In addition to traditional monetary instruments, "other policy instruments" are heavily used, which include measures to directly influence the loan volume of banks (especially the biggest four SOBs) regardless of the prevailing interest rate, and to direct the allocation of loans. The commercial banking system therefore serves as a major instrument for monetary policy, which is subsumed into the government's wider economic agenda.

The global financial crisis in 2008 tightened credit constraints for firms in the U.S., Europe, and Asia, which in turn reduced their spending on employment, capital, and technology (Campello et al., 2010), and reduced not only firm inputs but also trade volumes worldwide (Chor and Manova, 2012). As an export-oriented country, China experienced a decrease in the growth rate of its total export value from 20.4% in 2007 to 7.4% in 2008. Consequently, its annual GDP growth rate decreased from 11.9% in 2007 to 9.0% in 2008 and, more strikingly, from 10.6% in the first quarter of 2008 to 6.8% in the fourth quarter. Moreover, a massive number of SMEs bankrupted, especially in the export sector.

In response to the sharp economic slowdown, Premier Jiabao Wen hosted an executive meeting of the State Council on November 5$^{th}$, 2008. In the meeting, the State Council determined that a four trillion RMB economic stimulus program, equivalent to 14% of the GDP in 2008, would be implemented in the following two years. Accompanying the economic stimulus program, expansionary monetary policies, such as lowering the interest rate and reservation ratio, canceling the loan volume ceiling for commercial banks,

[8] For detailed description of the Chinese banking industry, see Naughton (2007, p. 451-481).

and gradually increasing overall lending over the following two years, were adopted.

The BLR was reduced from 6.66% in November 2008 to 5.58% in December 2008 and was then further reduced to 5.31% in January 2009, where it remained until July 2010 (see the dotted line in Figure 1). The amount of bank loans increased from 3.18 and 3.63 trillion RMB in 2006 and 2007, respectively, to 4.91, 9.59, and 7.95 trillion RMB for the following three years (Almanac of China's Finance and Banking from 2007 to 2011). Further, Shen et al. (2016) and Liu et al. (2018) report that SOEs increase their borrowing more than POEs in 2009 and 2010, which in turn allow them to increase their capital investment. Deng et al. (2015) suggest that the increase in borrowing of SOEs after the economic stimulus program relate to their increased bids in land auction.

### *2.1 Shadow Banking through Discounting BA*

Shadow banking activities has surged in China since 2009 in response to the economic stimulus program. BA, together with trust loan and entrusted loan, are main off-balance-sheet shadow banking activities conducted by Chinese banks after the economic stimulus program (Elloitt et al. 2015).[9] Our paper focuses on one of shadow banking activities, namely discounting BA. BA is a secure money market instrument that usually arises in the course of international trade and commerce. A BA is a written draft issued by a borrower to a bank to repay borrowed funds at a future date. Before acceptance, the draft is not an obligation of the bank but simply an order by the drawer to the bank to pay a specified amount of money on a specified date to the bearer of the draft. Upon acceptance, which occurs when an authorized bank accepts and signs it, the draft becomes a primary and unconditional liability of the bank. Not only is it a primary obligation of the accepting bank, it is usually also a contingent liability of the drawer.

Depending on the bank's reputation, a payee may be able to sell the BA, that is, the time draft accepted by the bank, in an active market. The BA is negotiable and can be exchanged many times in the secondary market. The bearer who buys the acceptance can collect the amount loaned on maturity. BAs are also sold on a discounted basis if the bearer wants to collect the amount loaned before maturity. Paying discounted value for a time draft is called "discounting the draft". The interest rate that a bank charges a customer for discounting a BA depends on the interest rate at which the bank believes it will be able to sell it in the secondary market. A commission is added to this rate.

There are several reasons for a rising issuance of BA in response to the economic stimulus program since 2009. First, banks devoted more funding to long-term loan for financing the need of infrastructure

[9] Chinese banks often off-load the discounted bankers' acceptance from the asset side of their balance sheet by selling it to another financial institution in order to keep its loan scale remained intact. Further, the counterparty buying the discounted bankers' acceptance often hide it by using accounting loophole such as bookkeeping it as inter-bank purchase, which does not count towards the loan quota.

projects, which is the focus of the economic stimulus program. Since there is a regulatory restriction that the ratio of loan to deposit cannot exceed 0.75, banks need to finance the short-term projects with discounting BC instead of issuing short-term loan. The issuing bank of BA does not need to include it as a part of their loan, thus there is no impact on its ratio of loan to deposit. The bank discounting a BA often off-loads it from the asset side of its balance sheet by selling it to another financial institution, such as a trust company or a security brokerage. Overall, BA is categorized as a part of shadow banking because it is off-balance- sheet and subject to less regulation than formal banking.

## 3. Empirical Method and Data

In this section, we first discuss the reason why SOEs are a source of policy distortion in credit market. We then present the empirical specification for examining the credit misallocation between SOEs and POEs induced by the economic stimulus program. Finally, we discuss the data used in our empirical analysis.

### *3.1 SOEs as a Source of Policy Distortion*

Using provincial-level data, Brandt et al. (2013) show that almost all within-province factor market distortions result from capital misallocation between the state and the non-state sectors. However, the micro-mechanism underlying this capital misallocation remains unclear. In this section, we propose several explanations for policy distortion in credit market.

First, our sample bank may want to build a good relationship (Guanxi) with local governments. Our sample bank may thus lend to SOEs owned by local governments, which invest in infrastructure projects initiated by local governments in accord with the economic stimulus program. Supporting local government not only attracts deposits from local government but also indirectly helps bank managers receive promotions. Although senior bank management rather than a local government evaluates bank managers' performance, bank managers may nevertheless aim to please local government officials, as one bank manager explains: “When my superior is thinking of promoting someone out of several equally good candidates from sub-branches, he might consult his friends in the local branch of the People's Bank of China, the local branch of the China Bank Regulatory Commission and the local government. Therefore, we have to manage the relationships with these government departments very carefully and skillfully. Otherwise, it will ruin our career since the senior will not promote a bank manager who is unwelcomed by his friends in the related fields, which in turn might endanger his career…”.

Second, as suggested by Brandt and Li (2003), soft budget constraints and expected government bailouts for troubled SOEs induce banks to increase their loan supply to these SOEs. If bank managers expect only SOEs to receive a future government bailout for non-performing loans because of the economic stimulus program, then loan applications from SOEs are more likely to be approved than those from POEs, especially under the adverse economic environment of the global financial crisis. This tendency is intensified by the clawback system adopted by Chinese SOBs since the banking reform in 1998, which requires loan officer and bank manager to personally bear responsibility for any delinquencies in the loans they have granted. A bank manager's compensation can be clawed back if a loan defaults, even though he has been assigned to another department or promoted.[10] If such a loan default leads to a performance evaluation indicating that the bank manager is imprudent in lending, his career within the bank may be negatively affected (in some rare cases, he may even be dismissed).[11] The possible future bailout of non-performing loans issued to SOEs in accord with the economic stimulus program thus protects bank managers from any future clawbacks, as the loans issued to SOEs can be rolled over until the bailout occurs.

Finally, the personal costs to bank managers may be higher for defaults from a SOE than for defaults from a POE. According to the sample bank's internal documents related to performance evaluations, the penalty for loan officers and managers does not differ if a SOE or a POE defaults on a granted loan. The interviewed managers also confirmed that they are equally punished economically regardless of whether a SOE or a POE defaults on a loan.[12] However, the managers admitted that a default by a POE places them in a more disadvantaged position than a default by a SOE because they are more likely to be suspected of taking a bribe from a POE than from a SOE when a default occurs. This concern is intensified as the loans made in response to the economic stimulus program may reach a higher rate of default than those made during normal time because of the adverse economic situation.

### *3.2 Empirical Specification*

As the economic stimulus program of 2008 requires banks to increase their loan supply, we would expect our sample bank to provide loans of larger amounts and at lower interest rates to firms with equivalent characteristics if there is no credit misallocation. To examine the credit allocation across firms induced by the economic stimulus program at our sample bank, we use two sources of variation for identification: (1) the periods before and after the announcement of the economic stimulus program and (2) the cross-section of firms with different ownership types. The following regression is estimated:

[10]The clawback system is called a "lifetime responsibility system", which means that as long as a bank manager works for the same SOB, he has to take personal responsibility for the loans that he has issued for his entire life.
[11]For more information on the clawback system, see Allen and Li (2011).
[12]As described in an interview with a loan officer in Dobson and Kashyap (2006), the loan officer is not blamed for a loan defaulted by a SOE, but he is blamed for a loan defaulted by a POE.

$$Y_{it} = \beta_1 SOE + \beta_2(SOExPA) + X_{it}\gamma + \alpha_t + \alpha_j + \alpha_b + \varepsilon_{it} \qquad (1)$$

The dependent variables in $Y_{it}$ include the interest rate, logarithm of loan size, and default. The key variable of interest is the interaction term SOExPA, where PA is a dummy variable that takes a value of one if a loan is made in or after November 2008. This interaction term captures the differential effects of the economic stimulus program on loan contracts provided by our sample bank to SOEs versus POEs. If our sample bank provides preferential loan contract terms to SOEs relative to POEs, *ceteris paribus*, then we can infer that state ownership is a source of policy distortion in credit market.

We use four sets of control variables: 1) the fixed effects for 43 months ($\alpha_t$) are included to control for the effects of aggregate fluctuations on loan contract terms and the default rate; 2) loan characteristics, including a dummy variable for whether the borrower provides collateral (Collateral) and the maturity of the loan (Maturity); 3) firm characteristics, including the borrower's internal credit rating (Rating), a dummy variable for whether the borrower defaulted previously (Defaulter), a dummy variable for whether the borrower is a small and medium enterprise (SME), a dummy variable for whether the borrower is a frequent borrower (FREQ) and the fixed effects for 17 sectors ($\alpha_j$); 4) branch characteristics, i.e. the share of the branch's loans in the total loans issued by all branches in the last year (BSize) and the fixed effects for 8 branches ($\alpha_b$).[13]

Further, we examine the credit risk management of our sample bank after the PA to determine whether the bank's credit risk management contributes to the credit misallocation between SOEs and POEs. We estimate the following regression:

$$\begin{aligned} Y_{it} = {} & \beta_1 SOE + \beta_2(PAxSOE) + \beta_3(PAxRating) + \beta_4(SOExRating) + \beta_5(PAxSOExRating) \\ & + X_{it}\gamma + \alpha_t + \alpha_j + \alpha_b + \varepsilon_{it}. \qquad (2) \end{aligned}$$

Equation (2) allows us to estimate the average effects of firms' credit risk rating on changes in the interest rate, loan size, and default risk after the PA. The triple interaction term captures the differential effects of borrowers' internal credit rating on the interest rate between SOEs and POEs after the PA. For example, in the regression with the interest rate as the dependent variable, a negative coefficient for $\beta_3$ indicates that the interest rate becomes more sensitive to borrowers' internal credit rating after the PA. And, a positive

[13] By including the collateral requirement for loans as an explanatory variable, we control for the differential loan contract terms induced by limited commitment problems. We also control for the differential loan contract terms due to loan demand by including the internal credit rating, which summarizes the balance sheet, cash flow, income statement and qualitative information of borrowers.

coefficient for $\beta_5$ indicates that the change in interest rate sensitivity against borrowers' internal credit rating after the PA is less positive for SOEs than POEs.

Note that the group of POEs is not a standard "control" group in our empirical strategy because they are also affected by the policy intervention. Thus, our estimate $\beta_2$ does not identify the effect of the policy intervention on the bank's lending to SOEs. Instead, our estimate $\beta_2$ captures only the changes in the bank's differential treatment toward SOEs and POEs before and after the PA. We thus exploit this policy intervention as an exogenous source of differential treatment in loan contract terms between SOEs and POEs. Since we are interested in investigating the credit misallocation induced by the economic stimulus program toward SOEs relative to POEs after the PA, the potential effect of the policy intervention on POEs does not invalidate our identification strategy (Banerjee and Duflo 2014).

### *3.3 Data*

Our empirical analysis is based on a proprietary dataset of corporate loans from one of the largest SOBs in China. This bank is highly internationalized and diversified, providing financial services not only in China but also in many other countries. Consequently, it is one of the Chinese banks that have been seriously hit by the subprime crisis. In mainland China, our sample bank has a nationwide network with more than 10,000 branches, which are organized into the following five levels from highest to lowest: the headquarter in Beijing, provincial-level branches, prefectural-level branches, county-level sub-branches, and street-level sub-branches.[14] The lower-level branches report to and are monitored by their nearest higher branch. The branch levels are set according to not only administrative structure but also business needs and hence, our sample bank sets a provincial-level branch in the capital city of each province as well as in several highly economically developed cities.

Our dataset is obtained from a provincial-level branch in an economically developed prefecture-level city (but not the capital city) of a leading province in economic development that is located in the coastal area of China. The city has a population of about six million and a GDP per capita more than triple the nationwide average. Our sample provincial-level branch manages over 100 prefecture-level, county-level, and street-level sub-branches across the city (including the urban area, subordinate counties, and rural areas).

Although our sample is limited to one economically prosperous city, it serves our objective to examine credit misallocation. Brandt et al. (2013) show that within-province factor market distortions are worse than between-province factor market distortions and that the cost of within-province distortions is negatively

[14] According to the literal translation, the five different levels from highest to lowest are the headquarter, the first-level branches, the second-level branches, the first-level sub-branches, and the second-level sub-branches.

correlated with income across provinces. Thus, our study on one city allows us to focus on the main part of factor market distortions, i.e., within-province distortions. In addition, our study provides a lower bound for within-province distortions. Namely, if there is evidence of distortion in our city after the PA, distortion in other provinces is likely more severe since first, our city is highly economic developed, and second, the economic stimulus program mainly focuses on the inland part of China to foster the infrastructure development and hence the intervention in bank lending should be more severe in the inland China than that in the coastal, where the infrastructure has been better developed.

Our data represent the universe of corporate lending in the city of our sample bank between August 2006 and July 2010.[15] Since the information of branches and loans in previous year is used in constructing explanatory variables, our sample period for empirical analysis covers from January 2007 to July 2010. Table 1 reports the industry distribution of loans over the sample period.[16] First, the largest portion of loans is issued to the manufacturing sector (C), followed by the wholesale & retail sector (F). Second, the largest two portions of BAs are discounted to the same two sectors as those for loans. Nonetheless, the sample of BAs covers fewer sectors than that of loans.

[Table 1 about here]

For each outstanding loan, the data contain information on the loan's interest rate, principal amount, collateral requirement, maturity, and quality, as well as the borrowing firm's size (denoted by large, medium or small), internal credit rating with the lending bank, ownership classification, industry sector, and lending bank branch.[17] Table 2 provides variable definitions.

[Table 2 about here]

Loan quality refers to a quarterly evaluation of the default risk of a loan based on the Bank of International Settlements' classification scheme, which includes five categories: standard, special mention, substandard, doubtful, and unrecoverable. The evaluation is used by the headquarters to prepare loan loss

[15] Unfortunately, the bank does not keep information on loan applications; therefore, we do not know the acceptance ratios for loan applications from SOEs and POEs.

[16] At the beginning of each year, the bank headquarters provides guidelines for loan allocation across industrial sectors to branches. In most cases, the branches follow these guidelines in allocating their loans across sectors.

[17] The standard adopted by banks for categorizing firm size varies across industries. For example, for the manufacturing industry (C), a firm with more than 2,000 employees is regarded as large, a firm with between 300 and 2,000 employees is classified as medium, and a firm with fewer than 300 employees is considered small. For the construction industry (E), a firm with more than 3,000 employees is categorized as large, a firm with between 600 and 3,000 employees is classified as medium, and a firm with less than 600 employees is considered small. In addition to number of employees, annual sales and assets are used as benchmarks to divide firms into different size categories.

provisions. According to the bank managers we interviewed, loans belonging to or below the category of special mention are very likely to become non-performing loans.[18] In our empirical analysis, we thus simplify loan quality to a dichotomy dummy variable: Default, which takes a value of 1 if the loan is within or below the category of special mention and 0 otherwise.

The primary measure of borrowers' ex-ante credit risk is borrower's internal credit rating score, which ranges from 1 (worst) to 10 (best). The rating process follows a rigorous procedure, based solely on objective information according to internal bank documents. This information includes the size of the borrower, the turnover of CEOs in the two years before the credit evaluation, financial information (such as balance sheet, income statement and cash flow statement), the credibility of the auditing company that audits and provides the borrower's financial statements, the credit record of the borrower (whether the borrower has ever defaulted or has loans overdue), and the relationship of the borrower with the bank (the number of years that the firm has been doing business with the bank and the year in which the bank granted the first loan to the firm). The sample bank uses the internal credit rating to evaluate loan application. Previous studies show that borrowers' internal credit rating is useful for analyzing loan transactions. For example, Chang et al. (2014) find that internal credit ratings predict loan defaults, and Qian et al. (2015) find that internal credit ratings affect loan contract terms and predict loan defaults.

[Figure 3 about here]

We filter our sample by using the following steps. First, inter-branch loans are excluded to avoid counting loans twice. Second, since there are very few (about 3%) observations for long-term loans, we restrict our sample to short-term loans, i.e., loans with maturity equal to or less than one year. Third, we remove 468 firms because of their ambiguous ownership nature. Fourth, to ensure that our results are robust to outliers, we delete observations with values for loan size, interest rate, and maturity above the top 0.1% and below the bottom 0.1% in the distribution. The final dataset contains 12,725 observations of loans issued to 1,839 firms, and 920 observations of BAs discounted to 277 firms.

### *3.4 Descriptive statistics*

The left Panel A of Table 3 provides descriptive statistics for our sample of loans. The average amount is 6.69 million RMB, and the average annual interest rate is 6.40%.[19] Firms default on 4% of loans on

[18] Dobson and Kashyap (2006) cites a report in which a senior advisor at CCB alleged that many loans classified as special mention loans, as well as loans in lower categories,were in fact non-performingloans.

[19] Yeung (2009) argues that bank branches sometimes divide large loans to SOEs into several smaller loans to avoid the monitoring mechanisms established by the headquarters because each branch at the various levels has a different ceiling for loans that can be approved

average. Further, borrowers have average credit rating at 4.86 and provide collateral for 66% of all loans. Since our sample contains only short-term loan, the average maturity is 261 days, and 93% of the loans issued are made to SMEs, 3% to SOEs, and 12% to frequent borrowers. On average, each branch accounts for 16% of the total loans issued by all branches in the last year.

[Table 3 about here]

The right Panel A of Table 3 provides descriptive statistics for the characteristics of BAs discounted to existing firms. There is no default for BAs in our sample. The average amount is RMB 6.46 million and the average annual interest rate is 3.68%. The interest rate regulation does not apply to BA, thus the interest rate of BA can be lower than the BLR set by the PBC. Further, borrowers have average credit rating at 5.50 and provide collateral for 95% of all BA. Since BA is a type of short-term loans with maturity up to 6 months, the average maturity is 128 days. 85% of the BAs discounted are made to SMEs, 9% to SOEs, and 6% to frequent borrowers. On average, each branch accounts for on average of 26% of the total BA discounted by all branches in the last year.

Table 3 conducts bivariate difference-in-difference (DID) analyses for interest rate, loan size made, default and explanatory variables. Qian et al. (2015) suggest that the use of raw interest rates may generate biased coefficients because higher rates accompany a larger standard deviation of rates. Thus, we follow their approach to normalize actual rates by the standard deviation of rates on all loans in a given year. Since the mean standardized interest rate move in opposite directions as that of raw interest rate, we rely on the standardized interest rate for our empirical analysis.

The left panel reports the results for sample of loan. For SOEs, on average, we find that the standardized interest rate increases from 8.18 to 8.97. For POEs, on average, we find that the standardized interest rate increases from 8.35 to 9.41. The bivariate DID estimates show that the standardized interest rate charged to SOEs decreases 0.28 units (at 10% significant level) more than that to POEs.

The right panel of Table 3 reports the results of BA. On average, we find that the standardized interest rate decreases from 5.55 to 4.13. For POEs, on average, we find that the interest rate decreases from 5.45 to 4.49. The interest rate reduction for BA is larger than that for loan because the interest rate regulation does not apply to loan but not to BA. The bivariate DID estimates show that the standardized interest rate

within its authority. Such behavior in our sample bank may explain why we find that the bank grants smaller loans to SOEs than to private firms. However, when we asked the managers of our studied branches about whether such situations occur in our sample bank, they replied that these situations are rare because the lower-level sub-branches in the city do not have authority to approve loans. Rather, loan approvals are centralized in the provincial-level branch, which has a very high ceiling for loans that can be approved (the ceiling varies according to industry and other characteristics); thus, the loans usually do not exceed the ceiling.

charged to SOEs decreases 0.46 units (at 10% significant level) more than that to POEs.

Turning to a key explanatory, i.e. Rating. Figure 3 depicts that the distributions of Rating for SOEs and POEs both shift to the left. On average, the internal credit rating becomes worse after the PA. However, we do not find any bivariate DID estimate on Rating is statistically significant at any conventional level. It does not support the bivariate DID estimates in standardized interest rate and loan size are driven by the changes in internal credit rating. It is an anecdotal evidence of credit misallocation in loan market towards SOEs after the economic stimulus program. Nonetheless, the bivariate DID estimates on other explanatory variables are mostly significant. To rule out for the possibility that the results of bivariate DID analysis reported in Panel B of Table 3 are driven by confounding variables, we proceed with the multivariate regression outlined in the previous section.

## 4. Empirical Results

We first report the results for the sample of loans and then followed by those for the sample of BAs. The similarity and difference between results in these two samples allow us to discuss the credit misallocation in formal and shadow banking. Finally, we examines the role of credit risk management in contributing to the credit misallocation between SOEs and POEs reported in previous sub-sections, if any.

### *4.1 Loan*

In this sub-section, we report the differential effects of the economic stimulus program on the interest rate and size of loans issued to SOEs and POEs after the PA. Column 1-2 of Table 4 present the empirical results of estimating Equation (1) with the standardized interest rate as the dependent variable. We test the robustness of our results by first including the fixed effects only and then adding loan, firm and branch characteristics in Columns 1-2. We use the results presented in Column 2 as our benchmark results because the estimation includes a complete set of control variables.

Column 2 shows that the coefficients for the interaction between PA and SOE ($\beta_2$) are negative and significant at the 1% level. Specifically, there is a 0.36 SD larger reduction in interest rate for SOEs than their equally good private counterparts after the PA. It suggests that there is a policy distortion in credit allocation induced by the economic stimulus program. The policy intervention thus not only induces banks to reduce overall interest rates but also affects the credit allocation by decreasing the cost of borrowing to a greater extent for SOEs than for their equivalent private counterparts.

[Table 4 about here]

Columns 4-5 of Table 4 present the empirical results of estimating Equation (1) with the logarithm of loan size as the dependent variable. According to our benchmark results reported in Column 5, the loan size for SOEs is 30% larger than that for POEs before the PA; however, no significant change in the difference in loan size between SOEs and POEs occurs after the PA. Thus, SOEs receive larger loans over the entire sample period. From a boarder perspective, SOEs in the studied prefecture-level city account for less than 1% of local employment and industrial output, while they account for more than 10% of the total amount of loans issued by our sample bank in the city. Although these results do not point to any credit misallocation towards SOEs after the PA, it supports the use of empirical specification as the results on relative loan size between SOEs and POEs are consistent with previous studies (Brandt and Li, 2003; Allen at al. 2005; Firth et al, 2009).

### *4.2 Banker's Acceptance (BA)*

In this sub-section, we report the differential effects of the economic stimulus program on the interest rate and size of BAs discounted to SOEs and POEs. Columns 1-2 and Columns 4-5 of Table 5 present the empirical results of estimating Equation (1) with the standardized interest rate and size of BA as the dependent variables, respectively. We test the robustness of our results by first including the fixed effects only and then adding loan, firm and branch characteristics. We use the results presented in Columns 2 and 5 as our benchmark results because the estimation includes a complete set of control variables.

[Table 5 about here]

Columns 2 and 5 of Table 5 report that the coefficients of PA x SOE ($\beta_2$) are insignificant. There is no evidence to show our sample bank provides preferential treatments to SOEs relative to POEs in setting interest rate and loan size when it discounts BA. Taking the results of these two sub-sections together, credit misallocation of our sample bank only appear in loan market but not in BA market, which suggests that credit misallocation is more severe when government intervention is more pervasive.

### *4.3 Credit Risk Management*

To examine the role of credit risk management in driving our results reported in the previous sub-sections, we estimate Equation (2) with the standardized interest rate (logarithm of loan size) as the dependent variable.

Column 3 of Table 4 reports the results for sample of loan. We focus our discussion of credit risk management on the derivative of standardized interest rate w.r.t. Rating, i.e.[20]

$$\frac{\partial(Std\ Interest\ Rate)}{\partial Rating} = \beta_{Rating} + \beta_3 PA + \beta_4 SOE + \beta_5 PA \times SOE$$
$$= \begin{cases} -0.0431^{***}\ for\ PA = 0\ and\ SOE = 0 \\ -0.0538^{***}\ for\ PA = 1\ and\ SOE = 0 \\ -0.0047\quad for\ PA = 0\ and\ SOE = 1 \\ 0.0461^{*}\quad for\ PA = 1\ and\ SOE = 1 \end{cases}$$

The coefficient of Rating is negative and significant, whereas the coefficient $\beta_4$ is positive and significant. More specifically, our sample bank charges a lower standardized interest rate for POEs with a better internal credit rating, but do not vary standardized interest rate for SOEs with internal credit rating. It suggests that the credit risk pricing for SOEs is looser than that for POEs before the PA. Further, the coefficient $\beta_5$ for the triple interaction term among PA, SOE and Rating is significantly positive. Since the derivative of standardized interest rate w.r.t. Rating increase significantly more for SOEs than POEs, it suggests that that our sample bank becomes less prudent in its credit risk pricing toward SOEs relative to POEs after the PA.

Column 3 of Table 5 reports the results for sample of BA. The derivative of standardized interest rate w.r.t. Rating, i.e.[21]

$$\frac{\partial(Std\ Interest\ Rate)}{\partial Rating} = \begin{cases} -0.0063\ for\ PA = 0\ and\ SOE = 0 \\ -0.0285\ for\ PA = 1\ and\ SOE = 0 \\ 0.0743^{**}\ for\ PA = 0\ and\ SOE = 1 \\ -0.0479\ for\ PA = 1\ and\ SOE = 1 \end{cases}$$

The coefficient of Rating is negative and insignificant, whereas the coefficient $\beta_4$ is positive and significant. Our sample bank charges a higher standardized interest rate for SOEs with a better internal credit rating, which does not support the use of credit risk pricing. Further, the coefficient $\beta_5$ for the triple interaction term among PA, SOE and Rating is significantly negative. Since the derivative of standardized interest rate w.r.t. Rating decrease significantly more for SOEs than POEs, it suggests that, for discounting

[20] ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
[21] ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

BA, our sample bank becomes more prudent in its credit risk pricing toward SOEs relative to POEs after the PA.

We then estimate Equation (2) with the logarithm of loan size as the dependent variable, and report the results in Column 6 of Tables 4 and 5 for the samples of loan and BA, respectively. For the sample of loan, the coefficient of Rating is positive and significant, whereas the coefficient $\beta_4$ is negative and significant. More specifically, our sample bank provides a larger (smaller) loan for POEs (SOEs) with a better internal credit rating, which suggests that the credit risk management in loan size is only applied to POEs. Further, the coefficient $\beta_5$ for the triple interaction term among PA, SOE and Rating is insignificant, which shows that there is no differential change in the derivative of loan size w.r.t. Rating between SOEs than POEs after the PA. Further, Column 6 of Table 5 reports that the size of BA discounted to borrowers is not significantly relate to internal credit rating.

The above results indicate that our sample bank loosens (tightens) interest rate pricing more for SOEs relative to POEs in loan (BA) market after the PA. We examine the economic effect of such interest rate pricing by performing a counterfactual experiment. Specifically, we compare the predictions from two models: 1) our empirical model employed to estimate Column 3 of Tables 4 and 5; and 2) a counterfactual model with the same specification as the first one but assuming $\beta_2 = \beta_5 = 0$. The second model differs from the first model in assuming that the interest rate pricing of our sample bank does not change for SOEs after the PA. Thus, these two models only provide different predictions for SOEs after the PA. We only discuss the results on standardized interest rate because the coefficients $\beta_2$ and $\beta_5$ are insignificant in Column 6 in Tables 4 and 5 for the logarithm of loan size.

[Table 6 about here]

The left panel of Table 6 reports that, for the sample of loan, our model predicts the standardized interest rate for SOEs are 8.18 before and 8.97 after the PA, respectively. On the other hand, our model predicts that there is 1.06 SD increase in standardized interest rate for POEs after the PA. The predicted DID of standardized interest rate for SOEs relative to POEs is -0.27. However, the counterfactual model predicts that the DID of interest rate for SOEs relative to POEs could have been raised by 0.09 if there had been no change in interest rate pricing for SOEs after the PA.

The right panel of Table 6 reports that, for the sample of BA, our model predicts the standardized interest rate for SOEs are 5.55 before and 4.13 after the PA, respectively. On the other hand, our model predicts that there is 0.96 decrease in standardized interest rate for POEs after the PA. The predicted DID of standardized interest rate for SOEs relative to POEs is -0.46. However, the counterfactual model predicts that the DID of interest rate for SOEs relative to POEs could have been reduced by -0.49 if there had been no change in credit risk pricing for SOEs after the PA.

Overall, we find that the policy intervention induces credit misallocation between SOEs and POEs in loan market, and such misallocation is partly driven by the loosening of credit risk management of our sample bank. The loosening of credit risk management towards SOEs produce a larger reduction in interest rate for SOEs than POEs. On other hand, after the PA, our evidences only show that our sample bank tightens its credit risk pricing in shadow banking, but there is no evidence of credit misallocation.

### *4.4 Control Variables*

Before closing this section, several empirical results on control variables deserve further discussion. For the sample of loan, Table 4 show the coefficients for the other control variables. Firms that provide collateral (Collateral) borrow less. Longer maturity (Maturity) is associated with a larger loan at a higher interest rate. SMEs, non-frequent borrowers (1-FREQ) and firms that have previously defaulted (Defaulter) borrow less at a higher interest rate. Nonetheless, defaulted SOEs can offset the disadvantages imposed on defaults firms. Turning to the control variables reported in Table 5 for the sample of BA. Consistent with the behavior in extending loan, our sample bank discounts a larger size of BA for longer maturity, but a smaller size of BA to SMEs and firms that provide collateral (Collateral).

Finally, we do not attempt to interpret the coefficients of BSize because those results may confound with other branch characteristics. Nonetheless, we include that variable as one of our control variables.

## 5. Further Analyses and Robustness Checks

This section first verifies our main results with the information on loan default. Then, we suggest the credit misallocation towards SOEs after the PA was exacerbated by a policy favoring a set of preferential industries. Finally, we provide robustness checks with confounding factors and an alternative control group of firms.

### *5.1 Ex-Post Risk Measure*

Our main results suggest that our sample bank loosens the interest rate pricing towards SOEs relative to POEs. An alternative explanatory is that SOEs become safer borrowers after the PA, thus our sample bank reduces interest rate towards SOEs. In this sub-section, we examine default risks between SOEs and POEs after the PA. Note that there are only defaults for the sample of loan. The left panel B of Table 3 reports that the default rate of SOEs increases 6% more than that of POEs after the PA. It suggests that our sample bank provides preferential treatment to SOEs relative to POEs in setting interest rate, despite SOEs experience a larger rise in default rate than POEs.

To control other confounding factors affecting loan default, we presents the empirical results of Equations (1) and (2) with loan default as the dependent variable in Table 7.

[Table 7 about here]

There are two relevant results. First, the coefficient estimates of borrowers' internal credit rating on loan default are reasonable. We find that firms with a better credit rating are less likely to default on their loans than firms with a worse credit rating. Particularly, Column 3 of Table 7 indicates that firms in credit rating group 10 (the best credit rating group) face a 1.3% higher likelihood of default than firms in credit rating group 1 (the worst credit rating group), respectively. Our results regarding the predictive power of borrowers' internal credit rating on default rate largely agree with the results reported by Chang et al. (2014) and Qian et al. (2015).

Second, we find no significant change in the default rate between SOEs and POEs after the PA (see Column 2), indicating that the decrease in interest rates charged to SOEs relative to POEs after the PA is not related to the change in default risks between SOEs and POEs. Also, there is no significant change in the predictive power of internal credit rating between SOEs and POEs after the PA. Thus, the relative change in credit risk pricing between SOEs and POEs is not driven by the relative change in informativeness of internal credit rating for those two types of firm. These results support the view that the differential reduction in interest rates between SOEs and POEs is evidence of credit misallocation induced by the economic stimulus program.

### *5.2 A Source of Favoritism towards SOEs*

We explore a policy that may contribute a part of credit misallocation between SOEs and POEs after the PA. The economic stimulus program aims to foster the development of the agricultural sector, improve health and pension system coverage, provide low-income housing, and increase investment in infrastructure, research and development, education, culture, and environmental protection. Hence, the government encourages banks to lend to firms in the industries providing those goods and services, i.e. preferential industries. Table 1 reports that there are several preferential industries coincide with a higher share of SOEs, such as Electricity, gas & water production and supply (CSIS Code = D).

We construct a dummy variable Prefer, which takes the value one for firms belonging to preferential industries, and zero otherwise. Panel A of Table 8 includes the interaction term between PA and Prefer, and the triple interaction term among PA, Prefer and Rating. The coefficients of those two interaction terms are significant in most specifications. Also, the inclusion of those two interaction terms weaken the significance of PA x SOE x Rating, i.e. $\beta_5$, in Column 1. It suggests that the loosening of credit risk pricing towards SOEs is driven by this favorable policy towards preferential industries. Nonetheless, the coefficient of PA x SOE, i.e. $\beta_2$, remains significant, which suggests that a part of interest rate reduction towards SOEs is a favoritism towards them.

[Table 8 about here]

### *5.3 A SOE-specific Trend*

The use of Equation (1) assumes that the dependent variables of SOEs and POEs share the parallel trends before the PA. Appendix 1 provides supports of the assumption. Further, the use of Equation (2) assumes the derivative of dependent variable w.r.t. Rating for SOEs and POEs share the parallel trends before the PA. Although we are not able to test this assumption, we estimate Equation (2) with a SOE-specific trend. The SOE-specific trend intends to capture the relative trend of dependent variable between SOEs and POEs that may confound the effect of adjusting credit risk management. We report the results in Panel B of Table Table 8, and find consistent results with those in Tables 4 and 5.

### *5.4 Alternative Control Group of Firms*

We categorize the borrowers into two groups: SOEs and POEs (privately owned firms, joint-stock companies, proprietorships, foreign-owned firms, or Sino-foreign joint ventures). However, since foreign firms are also privately owned and the number is large in our studied city, we include this group of firms in our analysis. This definition of POEs assumes that private domestic and foreign firms receive similar treatment from our sample bank. In order to make sure that our results are comparable to those from the literature which only contains domestic private firms, we replicate the analysis by comparing our sample bank's treatment toward domestic SOEs and POEs in Panel B of Table 8. The results for the sample excluding foreign firms are generally consistent with our main results for the whole sample.

## 6. Conclusion

This paper examines policy distortion in credit allocation across firms. Our empirical analysis is based on a loan-level data set covering the period from August 2006 to July 2010 from one of the largest SOBs in China. We exploit how the announcement of the economic stimulus program in November 2008 as an exogenous shock may affect the bank's lending behavior. We find that the policy intervention results in credit misallocation between SOEs and POEs. A part of such credit misallocation is generated by loosening credit risk management toward SOEs. On the other hand, we do not find that our sample bank misallocates credit between SOEs and POEs in shadow banking. There are two potential welfare losses related to the credit misallocation in the loan market. First, credit misallocation may reduce the aggregate productivity because credit is not allocated according to borrowers' productivity. Second, the over-supply of credit to SOEs may result in allocative inefficiency in the loan market (see Appendix 2).

Our findings have general implication for the capital misallocation in China as a whole. We find that credit misallocation exists in a highly commercialized, privatized and economic developed city in China. We infer that credit misallocation will be more severe in the rest of China, especially in inland China, where banks were more pressed by the local government due to its access to very limit financial resources and a higher presence of SOEs in local economy. Further, the major part of economic stimulus program consisted of infrastructure development, especially in inland China, where the infrastructure development lags behind the national average. Banks in less developed region would have been more pressed to support the stimulus plan than their counterparts in developed region. Hence, credit allocation by banking sector in less developed region can be more distorted than that in developed region. Policymakers may argue preferential treatments toward SOEs, especially during period of financial crisis can be well justified if these firms better serve the society, such as job provision and infrastructure development. The welfare implication of supporting SOEs during financial crisis is beyond the scope of our paper. Clearly, credit misallocation found in our paper is a cost for pursuing such policy.[22]

[22] In March 2010, the China Banking Regulatory Commission required SOBs to re-evaluate loans issued to local government-owned SOEs established between the PA and the end of 2009, as the central government realized that local government debt accrued owing to the four trillion RMB economic stimulus program amounted to six trillion RMB. Further, an estimated 97% of the debt was from the banking system.

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**Figure 1**

This figure displays 1) the benchmark lending rate (BLR) for 6-12 months loan (dotted line); 2) the average interest rate for the loans issued and BAs discounted to firms by our sample bank (dashed line); and 3) the associated amount of loans issued and BAs discounted (solid line) over the period of January 2007-July 2010. The interest rate is in % per annum. The average interest rate can be lower than the BLR because there is no regulation on interest rate to discount BA. The unit of loan size is one billion RMB.

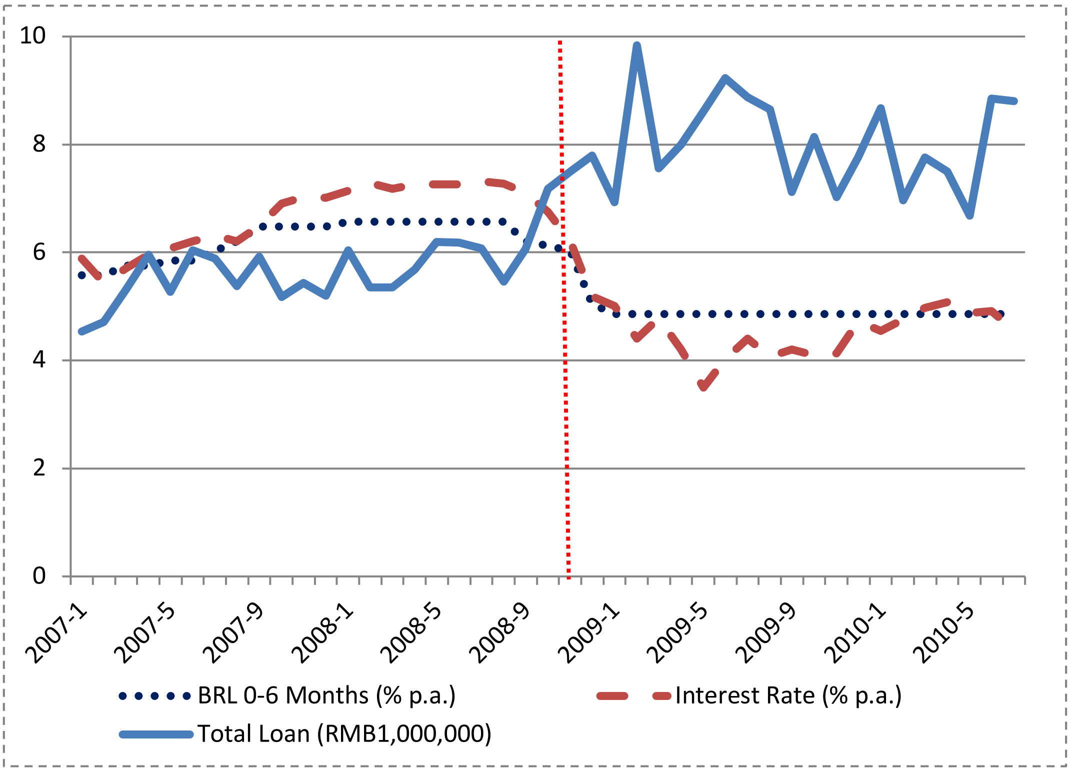
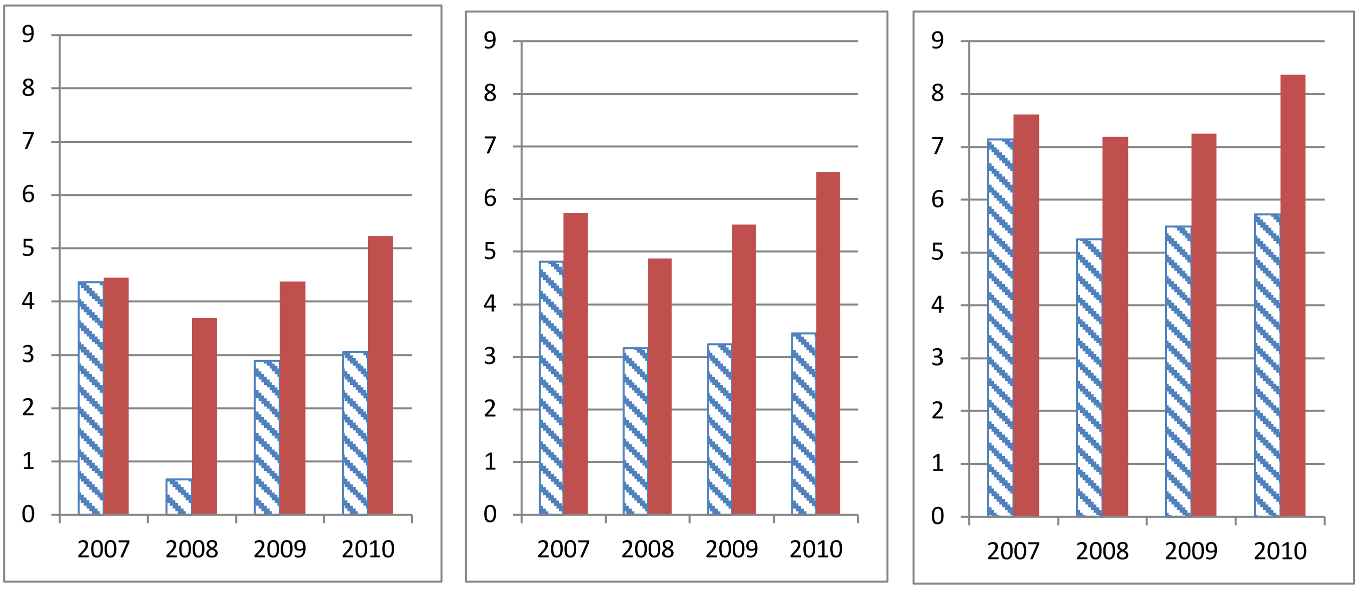


**Figure 2**

The three figures display three proxies for measuring return on capital for industries in the studied city from 2007 to 2010 for SOEs and POEs, respectively. The first indicator, Profit/Assets (a), is calculated as the total profit (Profit before income tax) normalized by assets. The second indicator, EBIT/Assets (b), is Earnings before Interest and Tax (EBIT, Profit before income tax and Financial costs) normalized by total assets. The last indicator, Earnings before Interest and All Taxes/Assets (c), is calculated as EBIT + Non-income taxes (including value-added tax, business tax and other extra charges by government) normalized by total assets.




(a) Profit/Assets (b) EBIT/Assets (c) EBIT + Non-Income Tax/Assets

SOEs POEs

**Figure 3**

These two figures display the internal credit rating of borrowing firms before and after the policy announcement (PA). The upper and lower figures report the internal rating for SOEs and POEs, respectively. The x-axis is the rating, which from 1 (the worst) to 10 (the best). The y-axis is the percentage distribution.

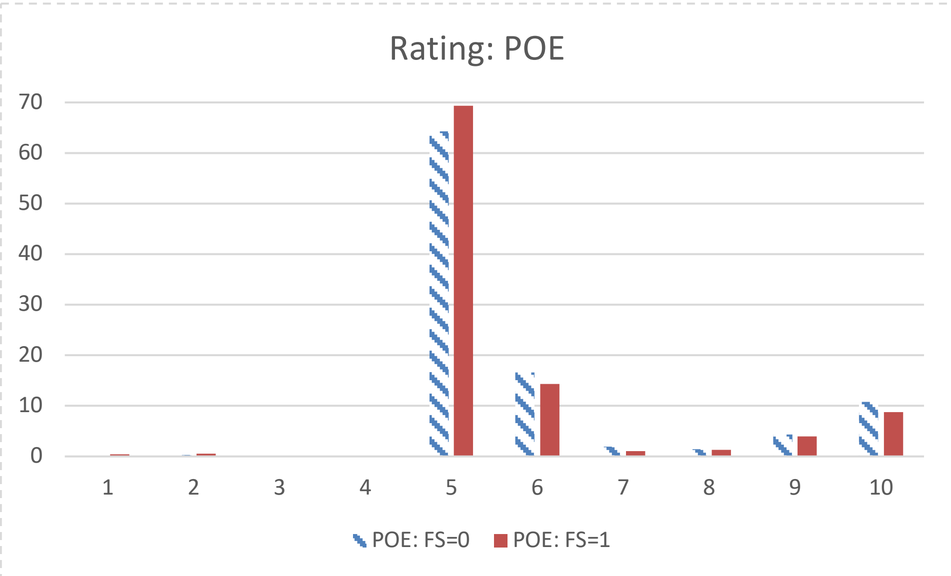



**Table 1**
This table presents the industry distribution of our sample of loans and BAs from January 2007 to July 2010. CSIC stands for Chinese Standard Industrial Classification. Column Prefer indicates whether the industry is a preferential industry. Column % refers to the percentage share of loans or BAs issued to that industry among total loans or Bas issued.

| | | | Loan | | | BA | | |
|---|---|---|---|---|---|---|---|---|
| CSIC Code | Sector | Prefer | Obs | SOE | % Loan | Obs | SOE | % BA |
| A | Agriculture, forestry, animal husbandry & fishery | 1 | 21 | 0.05 | 0.09 | | | |
| B | Mining | 0 | | | | 2 | 0 | 0.35 |
| C | Manufacturing | 0 | 10,497 | 0.01 | 76.82 | 669 | 0.04 | 65.01 |
| D | Electricity, gas & water production & supply | 1 | 37 | 0.69 | 1.94 | 6 | 0.67 | 3.43 |
| E | Construction | 1 | 147 | 0.01 | 1.55 | 2 | 0 | 0.15 |
| F | Wholesale & retail trade | 0 | 1,644 | 0.07 | 14.31 | 230 | 0.19 | 29.23 |
| G | Transportation, storage & postal services | 1 | 163 | 0.16 | 2.00 | 7 | 0.14 | 0.91 |
| H | Accommodation & catering | 0 | 11 | 0 | 0.11 | | | |
| I | Information transmission, computer services & software | 1 | 14 | 0.07 | 0.05 | | | |
| K | Real estate | 0 | 5 | 0 | 0.16 | | | |
| L | Leasing & business services | 0 | 72 | 0.38 | 1.42 | 3 | 0.67 | 0.82 |
| M | Scientific research, technical services & geological prospecting | 0 | 7 | 0 | 0.01 | | | |
| N | Water, environment & public facilities management | 1 | 35 | 0.89 | 0.82 | | | |
| O | Resident services & other services | 0 | 14 | 0.2 | 0.09 | 1 | 0 | 0.11 |
| P | Education | 1 | 17 | 0.38 | 0.19 | | | |
| Q | Health, social security & social welfare | 1 | 30 | 1 | 0.33 | | | |
| R | Culture, sports & entertainment | 1 | 11 | 0.82 | 0.09 | | | |
| | Total | | 12,725 | | 100 | 920 | | 100 |

Table 2

Variable definitions.

| | Definition |
|---|---|
| ***Dependent Variables*** | |
| Interest | Interest rate charged to a loan in % p.a. |
| Std Interest | Interest / SD(Interest), where SD(Interest) is computed for each year |
| Size | Loan amount in RMB 1,000,000 |
| Default | Dummy variable equal to one if a loan is not healthy |
| ***Loan Characteristics*** | |
| Collateral | Dummy variable equal to one if a borrower provides collateral for a loan |
| Maturity | Maturity of a loan in days |
| ***Borrower Characteristics*** | |
| Rating | Quantitative credit rating score that the bank uses upon loan application to facilitate the lending decision process, from 0 (Worst) to 9 (Best) |
| SOE | Dummy variable equal to one if the borrower is a state-owned enterprise |
| SME | Dummy variable equal to one if the borrower is a small or medium-sized enterprise |
| FREQ | Dummy variable equal to one if a firm has borrowed from the bank more than 16 times (the 90 percentile of the number of times firms have borrowed from the bank) |
| Defaulter | Dummy variable equal to one if the borrower had defaulted before since the beginning of the sample period |
| Prefer | Dummy variable equal to one if the borrower operating in a preferential industry, and = 0 otherwise. *(Only in Robustness Checks)* |
| ***Branch Characteristics*** | |
| BSize(t-1) | Branch size measured by the loan share of a branch among all branches in the last year |

**Table 3**
Summary statistics.

| | Loan | | | | | BA | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A** | Mean | SD | Min | Median | Max | Mean | SD | Min | Median | Max |
| ***Dependent Variables*** | | | | | | | | | | |
| Interest | 6.40 | 1.13 | 4.37 | 6.37 | 9.71 | 3.68 | 1.61 | 1.56 | 3.32 | 8.1 |
| Size | 6.69 | 11.2 | 0.15 | 3 | 200 | 6.46 | 13.7 | 0.05 | 2.43 | 190 |
| Default | 0.04 | 0.19 | 0 | 0 | 1 | | | | | |
| ***Loan Characteristics*** | | | | | | | | | | |
| Collateral | 0.66 | 0.46 | 0 | 1 | 1 | 0.95 | 0.19 | 0 | 1 | 1 |
| Maturity | 261 | 96.5 | 14 | 251 | 366 | 128 | 43.2 | 16 | 137 | 183 |
| ***Borrower Characteristics*** | | | | | | | | | | |
| Rating | 4.86 | 1.69 | 0 | 4 | 9 | 5.50 | 2.05 | 1 | 4 | 9 |
| SOE | 0.03 | 0.16 | 0 | 0 | 1 | 0.09 | 0.28 | 0 | 0 | 1 |
| SME | 0.93 | 0.26 | 0 | 1 | 1 | 0.85 | 0.36 | 0 | 1 | 1 |
| FREQ | 0.12 | 0.32 | 0 | 0 | 1 | 0.06 | 0.23 | 0 | 0 | 1 |
| Defaulter | 0.05 | 0.21 | 0 | 0 | 1 | | | | | |
| ***Branch Characteristics*** | | | | | | | | | | |
| BSize(t-1) | 0.16 | 0.11 | 0.03 | 0.12 | 0.36 | 0.26 | 0.19 | 0 | 0.28 | 0.50 |
| Observations | 12,725 | 12,725 | 12,725 | 12,725 | 12,725 | 920 | 920 | 920 | 920 | 920 |
| **Panel B** | PA=0 SOE | PA=1 SOE | PA=0 POE | PA=1 POE | DID | PA=0 SOE | PA=1 SOE | PA=0 POE | PA=1 POE | DID |
| ***Dependent Variables*** | | | | | | | | | | |
| Interest | 7.06 | 5.25 | 7.19 | 5.53 | -0.16* | 4.95 | 2.87 | 4.95 | 2.83 | 0.05 |
| Std Interest | 8.18 | 8.97 | 8.35 | 9.41 | -0.28* | 5.55 | 4.13 | 5.45 | 4.49 | -0.46* |
| Ln(Size) | 1.82 | 2.33 | 0.97 | 1.28 | 0.20 | 1.54 | 2.05 | 0.62 | 0.96 | 0.17 |
| Default | 0.06 | 0.10 | 0.04 | 0.03 | 0.06*** | | | | | |
| ***Loan Characteristics*** | | | | | | | | | | |
| Collateral | 0.53 | 0.41 | 0.66 | 0.67 | -0.13** | 0.77 | 1.00 | 0.93 | 0.98 | 0.18*** |
| Maturity | 266 | 278 | 244 | 280 | -24.2** | 125 | 128 | 126 | 129 | -0.40 |
| ***Borrower Characteristics*** | | | | | | | | | | |
| Rating | 5.18 | 4.95 | 4.95 | 4.77 | -0.04 | 6.43 | 6.67 | 5.47 | 5.35 | 0.35 |
| SME | 0.72 | 0.73 | 0.92 | 0.94 | -0.01 | 0.50 | 0.72 | 0.87 | 0.87 | 0.23*** |
| FREQ | 0.00 | 0.13 | 0.02 | 0.22 | -0.07** | 0.07 | 0.44 | 0.00 | 0.06 | 0.31*** |
| Defaulter | 0.07 | 0.12 | 0.05 | 0.04 | 0.05** | | | | | |
| Observations | 181 | 155 | 6,549 | 5,840 | | 44 | 36 | 324 | 516 | |

**Table 4**

Loan Sample. The sample and dependent variable are in the first and second rows, respectively. All variables are defined in Table 2. The models are estimated with OLS. We perform the Wald Test under the null hypothesis that all coefficients equal 0 and find that the null hypothesis is rejected at p-value<0.01 in all cases. SEs are clustered at the sector-time level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | Loan | Loan | Loan | Loan | Loan | Loan |
| Variable | Std Interest | Std Interest | Std Interest | Ln(Size) | Ln(Size) | Ln(Size) |
| SOE ($\beta_1$) | 0.0329 | 0.0312 | -0.183 | 0.541*** | 0.301*** | 0.814*** |
| | [0.0632] | [0.0549] | [0.115] | [0.0792] | [0.0687] | [0.177] |
| Rating | -0.0769*** | -0.0459*** | -0.0431*** | 0.0965*** | 0.0515*** | 0.0427*** |
| | [0.00553] | [0.00466] | [0.00500] | [0.00596] | [0.00596] | [0.00686] |
| PA x SOE ($\beta_2$) | -0.377*** | -0.359*** | -0.674*** | 0.0673 | 0.155 | 0.0665 |
| | [0.0877] | [0.0791] | [0.194] | [0.104] | [0.105] | [0.322] |
| PA x Rating ($\beta_3$) | | | -0.0107 | | | 0.0257** |
| | | | [0.00955] | | | [0.0114] |
| SOE x Rating ($\beta_4$) | | | 0.0384* | | | -0.0945*** |
| | | | [0.0202] | | | [0.0290] |
| PA x SOE x Rating ($\beta_5$) | | | 0.0613* | | | 0.0157 |
| | | | [0.0323] | | | [0.0547] |
| Collateral | | 0.0203 | 0.0221 | | -0.468*** | -0.472*** |
| | | [0.0216] | [0.0216] | | [0.0299] | [0.0297] |
| Maturity | | 0.00414*** | 0.00415*** | | 0.00119*** | 0.00117*** |
| | | [0.000139] | [0.000140] | | [0.000168] | [0.000167] |
| SME | | 0.468*** | 0.477*** | | -1.322*** | -1.348*** |
| | | [0.0235] | [0.0239] | | [0.0434] | [0.0434] |
| FREQ | | -0.120*** | -0.119*** | | 0.116*** | 0.113*** |
| | | [0.0303] | [0.0302] | | [0.0275] | [0.0278] |
| Defaulter | | 0.521*** | 0.521*** | | -0.551*** | -0.554*** |
| | | [0.0382] | [0.0379] | | [0.0621] | [0.0620] |
| SOE x Defaulter | | -0.674*** | -0.603*** | | 1.031*** | 0.868** |
| | | [0.230] | [0.229] | | [0.348] | [0.344] |
| BSize(t-1) | | -2.888*** | -2.933*** | | 1.128 | 1.193 |
| | | [0.940] | [0.932] | | [0.806] | [0.808] |
| PA x Control | No | Yes | Yes | No | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | No | Yes | Yes |
| Branch FE | Yes | Yes | Yes | No | Yes | Yes |
| Observations | 12,725 | 12,725 | 12,725 | 12,725 | 12,725 | 12,725 |
| R-squared | 0.713 | 0.780 | 0.780 | 0.146 | 0.265 | 0.266 |

**Table 5**

BA Sample. The sample and dependent variable are in the first and second rows, respectively. All variables are defined in Table 2, Panel A. The models are estimated with OLS. We perform the Wald Test under the null hypothesis that all coefficients equal 0 and find that the null hypothesis is rejected at p-value<0.01in all cases. SEs are clustered at the sector-time level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | BA | BA | BA | BA | BA | BA |
| Variable | Std Interest | Std Interest | Std Interest | Ln(Size) | Ln(Size) | Ln(Size) |
| SOE ($\beta_1$) | -0.0705 | -0.0655 | -0.570** | 0.710*** | 0.150 | 0.523 |
| | [0.0698] | [0.0752] | [0.234] | [0.245] | [0.269] | [0.906] |
| Rating | -0.0321*** | -0.0182** | -0.00716 | 0.103*** | 0.0182 | 0.0124 |
| | [0.00938] | [0.00870] | [0.00883] | [0.0234] | [0.0216] | [0.0298] |
| PA x SOE ($\beta_2$) | 0.0359 | 0.0859 | 0.773** | -0.0907 | 0.354 | -0.542 |
| | [0.120] | [0.135] | [0.339] | [0.318] | [0.378] | [1.146] |
| PA x Rating ($\beta_3$) | | | -0.0214 | | | 0.00683 |
| | | | [0.0179] | | | [0.0425] |
| SOE x Rating ($\beta_4$) | | | 0.0810** | | | -0.0599 |
| | | | [0.0344] | | | [0.132] |
| PA x SOE x Rating ($\beta_5$) | | | -0.108** | | | 0.141 |
| | | | [0.0478] | | | [0.169] |
| Collateral | | 0.108 | 0.0850 | | -0.711** | -0.691** |
| | | [0.0694] | [0.0612] | | [0.307] | [0.299] |
| Maturity | | 0.000230 | 0.000248 | | 0.00440*** | 0.00439*** |
| | | [0.000424] | [0.000399] | | [0.00164] | [0.00163] |
| SME | | 0.0307 | 0.108** | | -1.413*** | -1.468*** |
| | | [0.0539] | [0.0504] | | [0.190] | [0.193] |
| FREQ | | 0.0487 | -0.158 | | 0.424 | 0.575 |
| | | [0.136] | [0.137] | | [0.304] | [0.390] |
| BSize(t-1) | | 1.325*** | 1.213*** | | -1.289* | -1.193 |
| | | [0.288] | [0.307] | | [0.688] | [0.734] |
| PA x Control | No | Yes | Yes | No | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | No | Yes | Yes |
| Branch FE | Yes | Yes | Yes | No | Yes | Yes |
| Observations | 920 | 920 | 920 | 920 | 920 | 920 |
| R-squared | 0.826 | 0.846 | 0.847 | 0.204 | 0.345 | 0.346 |

**Table 6**

Counterfactual experiment for loans (left panel) and bankers' acceptance (right panel). Left panel: We employ the results reported in Column 3 (6) of Table 4 to predict the interest rate (the logarithm of loan size) for SOEs and POEs and report the results in the panel Predicted. Panel Counterfactual reports the results predicted from the results in Column 3 (6) of Table 6 by assuming $\beta_2 = \beta_5 = 0$. Right panel: We employ the results reported in Column 3 (6) of Table 5 to predict the interest rate (the logarithm of BA size) for SOEs and POEs and report the results in the panel Predicted. Panel Counterfactual reports the results predicted from the results in Column 3 (6) of Table 5 by assuming $\beta_2 = \beta_5 = 0$.

| | Loan | | | | | BA | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | PA=0 SOE | PA=1 SOE | PA=0 POE | PA=1 POE | DID | PA=0 SOE | PA=1 SOE | PA=0 POE | PA=1 POE | DID |
| **Panel A: Predicted** | | | | | | | | | | |
| Std Interest | 8.18 | 8.97 | 8.35 | 9.41 | -0.27 | 5.55 | 4.13 | 5.45 | 4.49 | -0.46 |
| Ln(Size) | 1.82 | 2.33 | 0.97 | 1.28 | 0.20 | 1.54 | 2.05 | 0.62 | 0.96 | 0.17 |
| Observations | 181 | 155 | 6,550 | 5,840 | | 44 | 36 | 324 | 516 | |
| **Panel B: Counterfactual** | | | | | | | | | | |
| $\beta_2 = \beta_5 = 0$ | | | | | | | | | | |
| Std Interest | 8.18 | 9.34 | 8.35 | 9.41 | 0.10 | 5.55 | 4.10 | 5.45 | 4.49 | -0.49 |
| Ln(Size) | 1.82 | 2.18 | 0.97 | 1.28 | 0.05 | 1.54 | 1.70 | 0.62 | 0.96 | -0.18 |
| Observations | 181 | 155 | 6,550 | 5,840 | | 44 | 36 | 324 | 516 | |

**Table 7**

Default in loan sample. The sample and dependent variable are in the first and second rows, respectively. All variables are defined in Table 2. The models are estimated with OLS. We perform the Wald Test under the null hypothesis that all coefficients equal 0 and find that the null hypothesis is rejected at p-value<0.01 in all cases. SEs are clustered at the sector-time level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Sample | Loan | Loan | Loan |
| Variable | Default | Default | Default |
| SOE ($\beta_1$) | 0.00196 | 0.00528 | -0.0267 |
| | [0.0172] | [0.00876] | [0.0306] |
| Rating | -0.00660*** | -0.00142*** | -0.00129** |
| | [0.00108] | [0.000509] | [0.000549] |
| PA x SOE ($\beta_2$) | 0.0272 | -0.0169 | -0.0628 |
| | [0.0276] | [0.0149] | [0.0543] |
| PA x Rating ($\beta_3$) | | | -0.000930 |
| | | | [0.00103] |
| SOE x Rating ($\beta_4$) | | | 0.00573 |
| | | | [0.00549] |
| PA x SOE x Rating ($\beta_5$) | | | 0.00894 |
| | | | [0.00910] |
| Collateral | | -0.00857*** | -0.00835*** |
| | | [0.00233] | [0.00234] |
| Maturity | | 3.97e-05*** | 4.06e-05*** |
| | | [1.12e-05] | [1.14e-05] |
| SME | | -0.0222*** | -0.0212*** |
| | | [0.00740] | [0.00752] |
| FREQ | | 0.00716** | 0.00713** |
| | | [0.00284] | [0.00283] |
| Defaulter | | 0.807*** | 0.807*** |
| | | [0.0187] | [0.0187] |
| SOE x Defaulter | | -0.231* | -0.220* |
| | | [0.128] | [0.126] |
| BSize(t-1) | | -0.0203 | -0.0249 |
| | | [0.0865] | [0.0867] |
| PA x Control | No | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Sector FE | No | Yes | Yes |
| Branch FE | No | Yes | Yes |
| Observations | 12,725 | 12,725 | 12,725 |
| R-squared | 0.026 | 0.665 | 0.665 |

**Table 8**

Robustness checks. The sample and dependent variable are in the first and second rows, respectively. All variables are defined in Table 2. The models are estimated with OLS. We perform the Wald Test under the null hypothesis that all coefficients equal 0 and find that the null hypothesis is rejected at p-value<0.01 in all cases. SEs are clustered at the sector-time level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

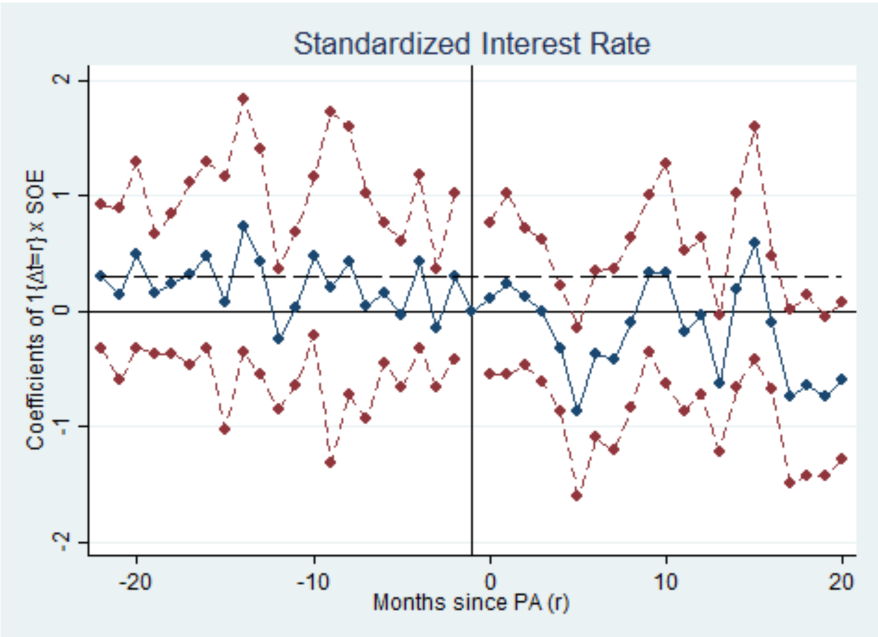
| | (1) | (2) | (4) | (5) |
|---|---|---|---|---|
| Sample | Loan | Loan | BA | BA |
| Variable | Std Interest | Ln(Size) | Std Interest | Ln(Size) |
| Panel A: Preferential | | | | |
| SOE ($\beta_1$) | -0.206* | 0.835*** | -0.625*** | 0.677 |
| | [0.117] | [0.179] | [0.221] | [0.886] |
| Rating | -0.0433*** | 0.0427*** | -0.00899 | 0.0177 |
| | [0.00499] | [0.00685] | [0.00890] | [0.0298] |
| PA x SOE ($\beta_2$) | -0.491** | -0.279 | 1.015*** | -1.352 |
| | [0.213] | [0.353] | [0.331] | [1.096] |
| PA x Rating ($\beta_3$) | -0.0122 | 0.0312*** | -0.0215 | 0.00887 |
| | [0.00973] | [0.0114] | [0.0180] | [0.0422] |
| SOE x Rating ($\beta_4$) | 0.0402** | -0.0965*** | 0.0881*** | -0.0799 |
| | [0.0204] | [0.0291] | [0.0331] | [0.131] |
| PA x SOE x Rating ($\beta_5$) | 0.0367 | 0.0715 | -0.137*** | 0.244 |
| | [0.0343] | [0.0583] | [0.0465] | [0.164] |
| PA x Prefer | -0.373** | 0.807*** | -1.371*** | 4.557*** |
| | [0.173] | [0.268] | [0.393] | [1.412] |
| PA x Prefer x Rating | 0.0491* | -0.146*** | 0.0907* | -0.365* |
| | [0.0286] | [0.0470] | [0.0490] | [0.220] |
| Observations | 12,725 | 12,725 | 920 | 920 |
| R-squared | 0.780 | 0.267 | 0.848 | 0.354 |
| Panel B: SOE-Specific Trends | | | | |
| PA x SOE ($\beta_2$) | -0.507** | -0.0238 | 0.883** | -0.499 |
| | [0.200] | [0.345] | [0.394] | [1.344] |
| PA x SOE x Rating ($\beta_5$) | 0.0649** | 0.0138 | -0.112** | 0.139 |
| | [0.0329] | [0.0547] | [0.0486] | [0.172] |
| SOE x Time | -0.00886 | 0.00480 | -0.00345 | -0.00134 |
| | [0.00562] | [0.00756] | [0.00862] | [0.0249] |
| Observations | 12,725 | 12,725 | 920 | 920 |
| R-squared | 0.780 | 0.266 | 0.847 | 0.346 |
| Panel C: Foreign firms excluded | | | | |
| PA x SOE ($\beta_2$) | -0.686*** | 0.209 | 0.466 | -0.806 |
| | [0.200] | [0.330] | [0.366] | [1.183] |
| PA x SOE x Rating ($\beta_5$) | 0.0625* | -0.00934 | -0.0641 | 0.217 |
| | [0.0334] | [0.0559] | [0.0535] | [0.174] |
| Observations | 7,518 | 7,518 | 578 | 578 |
| R-squared | 0.782 | 0.266 | 0.860 | 0.427 |
| Control + PA x Control included | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes |
| Branch FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |

**Appendix 1: Parallel Trends Analysis**

We use the following non-parametric event study approach to search for the structural break in our data and demonstrate that standardized interest rate falls at the policy announcement (PA).

$$Std\ Interest_{it} = (\Sigma_{r=-22,\ldots,-2}\,\beta_r \cdot 1_{\{\Delta t=r\}} + \Sigma_{r=0,\ldots,20}\,\beta_r \cdot 1_{\{\Delta t=r\}}) \times SOE_i + X_{it}\gamma + \alpha_t + \alpha_j + \alpha_b + \varepsilon_{jt}$$

The dependent variable is standardized interest rate $Std\ Interest_{it}$ for firm $i$ at time $t$. We only examine that dependent variable because only the DiD estimate for standardized interest rate is significant in our empirical analyses. Let $\Delta t \equiv t - t_{PA}$ so the event time indicator $1_{\{\Delta t=r\}}$ represents $r$ months before ($r < 0$) or after ($r \geq 0$) the month of the PA ($t_{PA}$). The set of $\beta_r$'s includes the coefficients of the interactions between the event time indicators and $SOE_i$, i.e., $1_{\{\Delta t=r\}} \times SOE_i$. Since we choose October 2008 (the month before PA, i.e., $r$ = -1) as the baseline month in the analysis, $\beta_r$ measures the difference in standardized interest rate between SOEs and POEs at time $r$ relative to the omitted $\beta_{-1}$ which is the difference in the month before the PA.

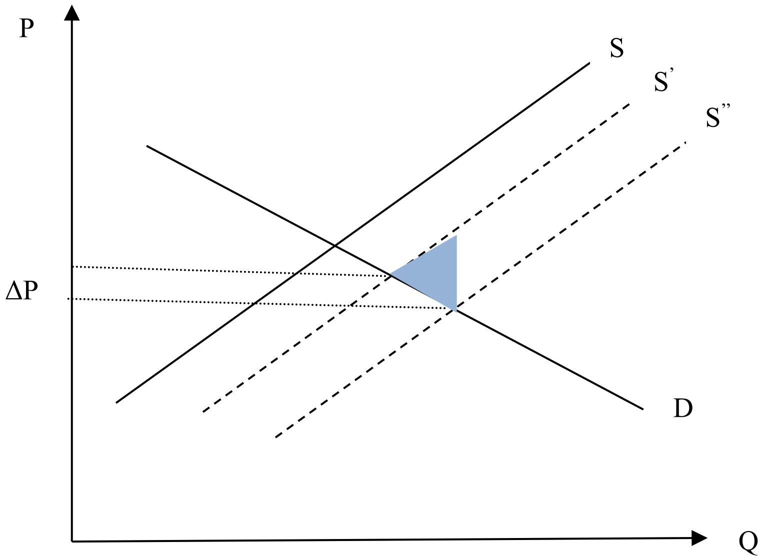



The estimated $\beta_r$'s in the above equation are plotted in the following figure with $\beta_{-1}$ normalized to zero for the month before the PA which is marked by the solid vertical line (see Appendix A for the coefficient plots for the alternative measures of luxury dining.) The dash-dotted lines represent the pointwise 95 percent confidence intervals based on the standard errors clustered at the sector-time level. The figure show a visually apparent change in standardized interest rate four months after the PA, i.e. in March 2009. In subsequent months, the standardized interest rate fluctuates at lower levels than that before the PA. The delay in the impact of the PA was primarily due to the seasonal increase in standardized interest rate dining in the first quarter. Overall, we do not find a no pre-trend of standardized interest rate for SOEs relative to POEs because there is no clear trend for the set of $\beta_r$'s before the PA.

**Appendix 2**

This appendix provides a simple framework to discuss the allocative inefficiency resulting from the credit misallocation. We assume that our sample bank maximizes the following profit function $\pi = [P(1\text{-}d)\text{-}c]Q(P)$ by choosing P. The parameters P, d and c are loan interest rate, default rate of loan and cost of funding, respectively. The variable Q is loan demand, which depends on loan interest rate. The first order condition is $P = c/(1\text{-}d) + Q/(\partial Q/\partial p)$, which implies that loan supply is increasing in Q linearly if loan demand is linear, i.e. $\partial Q/\partial P$ is a constant. The loan supply shifts to the right if the cost of funding or the default rate decreases.

We represent the situation before the PA with the solid lines in the following figure:




After the PA, the reduction in cost of funding shifts the loan supply from S to S', which in turn reduce interest rate charged to all firms. Nonetheless, if our sample bank perceives the default rate of SOEs decreases, this policy distortion increases the loan supply to SOEs even further. As a result, the loan supply to SOEs shift to S″ instead. Thus, we treat the difference between S′ and S″ is driven by governmental intervention because such shift in loan supply was not driven by productivity. The extra loan amount lent to SOEs results in a welfare loss, which is illustrated by the shaded triangle. If loan demand and supply are linear, for example $Q_d = a - bP$ and $Q_s = c + dP$, then the deadweight loss can be represented by $0.5(1\text{-}b/d)b(\Delta P)^2$. It suggests that the welfare loss due to credit misallocation is proportional to $\Delta P$, which positively relates to the DID estimate of standardized interest rate for SOEs relative to POEs.