SOEs and Soft Incentive Constraints in State Bank Lending

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Abstract

We study how Chinese state bank managers' lending incentives impact lending to state-owned enterprises. We show lending quantity increases and quality decreases at month's end, indicating monthly lending targets that decrease lending standards. Increased quantity comes from both SOEs and private lending, whereas decreased quality is from only SOEs, which continue to receive loans even after prior defaults (particularly at month's end). We suggest that SOE lending may thus be beneficial for state bank managers, who lend to delinquent state enterprises to meet targets, which in turn may exacerbate SOEs' soft budget constraints.

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1 Introduction

State-owned enterprises in many economies are supported financially by governments. It may be hard for policymakers to force SOEs to adhere to a fixed budget, leading to bailouts via government transfers or write-offs of bad debt owed to state banks – what Kornai (1979) famously referred to as the soft budget constraint. A large literature documents, both theoretically and empirically, the reasons that a government may wish to prop up SOEs, as well as the social cost-benefit tradeoffs from doing so.[1] Less well-studied are the motivations and incentives of organizations and agents – most notably state banks and the loan officers they employ – that provide the financial support that enables the soft budget constraint. That is, it is straightforward to see how easy access to capital benefits managers of badly-run SOEs, but little work looks at why those running state banks willingly provide credit to these troubled firms.

Conventional wisdom is that state banks lend to SOEs because they are compelled to do so by the government, and loan officers happily oblige because the government takes eventual responsibility for any SOE defaults (see, for example, Lu *et al.*, 2005; Tian *et al.*, 2005; Lou, 2000, among others). We show, however, that bank managers may have their own incentives to lend to SOEs, as such lending provides an easy way for them to meet lending targets that are also common in banking – state or otherwise. That is, the opportunity to lend to SOEs provides bank managers facing loan targets with what we call a "soft incentive constraint" since it can easily be managed by lending to SOEs, with lesser concern for their creditworthiness.

We study the loan portfolio of a large Chinese state bank during the period 1997 – 2010, with the ultimate goal of understanding what motivates their lending to SOEs versus private firms. Specifically, we examine how branch managers respond to month- and quarter-end loan

[1] See, among many examples, Dewatripont and Maskin (1995), Maskin (1999), and Kornai *et al.* (2003) for early theoretical contributions; Estrin *et al.* (2009) on government ownership and privatization in transition economies; Guriev (2018) for a recent discussion of SBCs and the failure to privatize; Caballero *et al.* (2008) on lending to insolvent firms in Japan, a market economy.

quotas that Chinese banks (both state-owned and private) were reported to use to motivate them during the period we study.[2]

We begin by discussing and presenting evidence of lending targets for bank branch managers. We show that these incentives led to very strong monthly cycles in both the quantity and quality of lending in our data. Specifically, both the number and size of loans increase as the final day of the month approaches, consistent with branch managers' need to hit month-end targets. Our intensive and extensive margin estimates combined imply an overall end-of-month lending increase of about 92 percent. This pattern is distinct from any day-of-week or month-of-year effects, and is invariant to a wide range of robustness tests, including branch $\times$ month fixed effects. Consistent with Oyer (1998), we also find a lower rate of lending at the beginning of each month, though the shortfall does not come close to offsetting the end-of-period increase. Consistent with a month-end lowering of lending standards, we also show that a month-end loan is more than 1.1 percentage points (8 percent) more likely to be classified eventually as a bad loan. These findings echo those of Tzioumis and Gee (2013), which finds similar patterns for U.S. mortgage lending for loan officers motivated by month-end targets.

We next turn to exploring the composition of lending over the monthly cycle, focusing on two main features of borrowing firms: SOE status and past borrowing history. We document several drivers of the overall monthly cycles in loan quantity and quality that may be useful for understanding bank managers' incentives to lend to SOEs. First, we find that, while the end-of-month increase in bank lending appears for both SOE and private borrowers, the quality decline is driven primarily by loans to SOEs. If banks were driven to lend to SOEs simply via government fiat, we would not expect to see this monthly cycle. Rather, SOEs would simply have higher default rates over the entire month, rather than a pronounced increase at month's end when lending quotas become more of an immediate concern.

When we further disaggregate both SOEs and private firms into those with clean borrow-

[2]Such incentives are pervasive in the banking industry. See Tzioumis and Gee (2013) for evidence on short-term lending quotas in U.S. mortgage lending, also discussed further below.

ing records versus those with past default, we see a much starker contrast: first, non-SOEs with past defaults receive almost no loans whatsoever from the bank, accounting for just 1.5 percent of overall lending on average. SOE borrowers with past defaults, by contrast, constitute 30 percent of the bank's new lending during the period we study, and the monthly cycle of lending to SOEs is comparable for those with clean credit histories and those with past defaults.[3] That is, state banks seem not to discriminate against SOEs with poor credit history at the end of each month when they increase lending to meet targets. Finally, focusing on non-SOE borrowers, we observe no monthly cycle among those with clean credit histories (which, recall, constitute the vast majority of non-SOE loans).

Overall, the patterns we document suggest a pecking order, with bank managers turning to (higher-risk) SOEs as needed to meet loan quantity targets, while maintaining relatively high standards for non-SOE lending. This in turn suggests that bank managers' performance is less impacted by bad loans to SOEs, which the bank expects to write off. SOEs' soft budget constraints may thus have a counterpart in state banks: a "soft incentive constraint" as a result of ready (and forgivable) opportunities of lending to SOEs. We emphasize that our purpose is *not* to show merely that state banks lend preferentially to SOEs, but rather to study how this preferential treatment interacts with bank managers' own incentives to further exacerbate excessive lending to SOEs. This interpretation presents the intriguing possibility that the soft budget constraint serves to undermine performance incentives for bank managers, by providing a readily available set of loan opportunities to help them reach lending targets. And these targets, in turn, further slacken the financial constraints of SOEs, since branch bank managers face incentives (rather than just pressure from higher-level government officials), to push loans to already insolvent state-owned firms. Potentially, these two effects lead to a vicious cycle of inefficient lending reinforced by *both* borrower and lender incentives. The consequences of softer incentives for the quality of loans to SOEs may

[3]The 30 percent figure is much higher than the analogous 1.5 percent for private firms, even after we account for the fact that private firms default less often, and SOEs are a larger fraction of the bank's overall lending portfolio.

have a substantial impact on overall productivity because of the lower efficiency of SOEs: a back-of-the-envelope calculation suggests that total factor productivity for the Chinese economy overall is 2.5% lower as a result of the soft lending constraint that we document. (Note that our point is related to, but distinct from, the general concern that bank managers may be penalized less severely (if at all) for bad loans to SOEs (e.g., Elliott and Yan, 2013). Rather, our focus is on how this lack of consequence interacts with, and is amplified by, the distortions resulting from quantity incentives. Further, our explanation is more nuanced than the common narrative, in which state banks are pressed to lend to inefficient SOEs by higher-level officials (Mo, 1999).)

We contribute to what has been heretofore a largely unstudied topic: the managerial incentives of state banks, which are a dominant feature of financial systems worldwide (La Porta *et al.*, 2002). Our analyses of these incentives sits at the intersection of two much larger literatures: research on SOEs, particularly their access to state capital, and work on target-setting and the distortions that results.

The conceptual foundations of the soft budget constraint and SOE financing were laid by Kornai (1979).[4] Of particular relevance for our own findings is research on the preference of Chinese state banks for SOE lending (Wei and Wang, 1997) and, at least historically, relative efficiency of bank-funded SOEs (compared to those funded by government transfers), as documented by Cull and Xu (2003). Consistent with these earlier results, our findings suggest that branch managers preferentially lend to SOEs with clean credit records, but that the incentives to make good loans are overridden by month-end quantity targets that lead to high-default loans to SOEs.

Our work also builds on the body of research which studies empirically the effects of target setting in organizations. Empirically, researchers have studied this topic across a range of settings and outcomes from accounting manipulation (Healy, 1985) to navy recruitment (Asch, 1990) to corporate sales (Oyer, 1998; Larkin, 2014). Of most direct relevance, Tzioumis

[4]See Kornai *et al.* (2003) for a summary of earlier work on the topic.

and Gee (2013) show that mortgage loan officers in the U.S. increase their output (and also loan delinquency) as the end of the month approaches; also closely related, Agarwal and Ben-David (2018) documents lower loan quality and greater reliance on hard information following the implementation of high-powered incentives among managers at a U.S. bank. Our results echo these findings, which we obtain in an distinct organizational setting, though our main interest is in using these month-end incentives to better understand state banks' SOE lending incentives.

2 Background and Data

China has experienced one of the largest and longest credit booms in history (Chen and Kang, 2018) – total credit to the non-financial sector more than quadrupled between 2008 and 2019, totaling an estimated 255.9 trillion RMB (259% of GDP) at the end of this period. This leverage ratio is twice as high as the average of emerging market economies excluding China. [5] The non-performing loan ratio also increased substantially during this period, posing sufficient risks to China's economy that policymakers considered ways of encouraging corporate deleveraging in recent years.[6]

Furthermore, of particular relevance for our work, much of this lending goes to state enterprises: in our own data, SOEs account for 80 percent of total lending, and as of 2018 SOE borrowing accounted for nearly half of Chinese debt overall. Thus, understanding the drivers of SOE lending – particularly to SOEs that are poor credit risks – is of relevance to larger macro questions, most notably the economy's productive efficiency, which we discuss in more detail below.

We obtained loan-level data from a large state-run bank in China, for the years 1997–2010.

[5]For example, the debt-to-GDP ratios for Argentina, India, and South Africa are 112%, 123%, and 131% respectively. Calculated by authors using Bank of International Settlements Statistics for credit to the non-financial sector in Dec 2018.

[6]See, for example, `http://www.xinhuanet.com//english/2017-07/09/c_136430117.htm`, last accessed August 10, 2021.

As with many large Chinese banks, the one we study has two types of branches: one main one for each city ("Fen Hang", or main branch, in Chinese) and smaller outposts located in districts or counties within the city ("Zhi Hang", or sub-branch, in Chinese). While we have data on individual loans, we aggregate to the branch-level (separately for the main branch and each sub-branch), since loan targets, as described below, operate at the branch (both main and sub-branches) level.

2.1 Branch manager incentives

As with loan officers worldwide, branch managers at the banks we study are assessed based on the quality and quantity of lending. These evaluations are conducted monthly. We do not have access to a specific evaluation formula, but from conversations with bank officials, performance is based on a combination of monthly evaluation of "operating scale" – primarily the total value of lending – and "operating performance" which includes non-performance loans, profits per employee, return on assets, cost to revenue ratio and others. Managers are also evaluated based on more subjective criteria such as employee ratings. Based on conversations with leaders at a private Chinese bank, operating scale had a weight of 40 percent, primarily loan volume. The same bank put a substantially smaller weight on loan defaults. (One reason for the modest weight on default is the difficulty in tying particular managers to defaults on specific loans, since it may take some time for a loan to turn bad, by which time a manager may have moved to a different branch or retired.)

Beyond information gleaned from officials at the bank we study, there has been much discussion in the Chinese financial press of the widespread existence of quantity incentives, in the specific form of monthly lending targets that will be our focus in what follows. [7] This issue

[7] See, for example, "Four big banks pursue small and medium-sized enterprise loans, at the expense of quality," *People's Daily*, September 12, 2011 (`http://roll.sohu.com/20111209/n328451399.shtml`, last accessed August 9, 2020), and "Banks pursue risky deposits at month's end," *First Financial Daily*, September 28, 2012 (`http://www.yicai.com/news/2114112.html` last accessed August 9, 2021); titles have been translated from Mandarin by the authors, both here and below.

of month-end targets was also addressed by regulators – near the end of our sample period, in June 2009, the CBRC (China Bank Regulatory Committee) issued a statement emphasizing that *all* banks, including state-owned ones, should prevent "end of month lending practices" and also urged banks to gradually abolish quota-based incentive systems.[8] This was followed in late September 2009 by a "window guidance" (a recommendation without force of explicit legal enforcement) from the CBRC against end-of-month lending to hit loan targets. A story reporting on this window guidance further noted that the CBRC had become concerned in large part because, as a result of bank officials' pursuit of increased lending to meet targets, "credit risk has become a secondary consideration."[9]

The article went on to describe various means by which banks can boost month-end credit: by accepting higher-risk loans, shortening review times, or even encouraging borrowers to submit loan applications based on false information. (Given that the press continued to discuss end-of-month spikes in lending as late as 2012, it appears that the CBRC's attempt at policy-via-suasion was unsuccessful.)

If loan officers had discretion over interest rates, some of the profit effects of increased (risky) month-end lending might be recovered via higher interest rates. However, credit risk is rarely priced in our setting. In the state bank we study, the bank's policies until 2006 required that all loans have a uniform interest rate (set by the central bank) that varied solely based on maturity, so that higher month-end risk (for a given maturity) could not be priced. After 2006, managers at the province-level were given discretion to increase rates up to 130 basis points above the base-level (central bank dictated) interest rate, still leaving local branches without discretion in rate-setting.

While we heard no explicit mention of differential incentives for branch managers to

[8] See `http://www.fsou.com/html/text/chl/1546/154692.html`, last accessed August 9, 2021, for the full text of this statement. The directive against end-of-month (and end-of-season) lending is in Article 3.

[9] "Regulators to strengthen window guidance to suppress banks' end-of-month red credit," *Securities Times*, September 25, 2009 (`http://business.sohu.com/20090925/n266989261.shtml` last accessed August 9, 2021)

approve SOE loans, the preferential treatment of SOEs been described by observers of the Chinese financial system (Elliott and Yan, 2013). [10] We will find that our data are consistent with preferential lending to SOEs, even those with poor repayment records. Our main interest is in exploring how this preference interacts with monthly lending targets. Furthermore, given our main result of an increase in low-quality lending to SOEs at month's end, our results emphasize a tension between regulators' apparent interest in reducing bad loans that result from quantity targets, while at the same time taking a permissive approach toward lending to SOEs in general. These conflicting objectives further suggest that the monthly cycles we will document are unlikely to result from a monthly pattern in government pressure on banks to lend to SOEs, which could otherwise result from SOEs' own cash needs over the course of the month.

2.2 Data

We obtained a sample of business loans made by each of the bank's more than 1500 branches. We do not list the precise number of cities or branches as a way of shielding the bank's identity. The loan-level sample was constructed as follows. For each branch, all firms that obtained a loan during 1998 – 2010 were ranked by average assets over this period, and divided into terciles (small/medium/large). Within each group, we obtained data on more than 20 percent of firms, selected at random. For this random subset of firms, we were provided with the complete loan history of each firm. (We do not provide the exact proportion of firms, again as a way of shielding the bank's identity. Also note that we, not the bank, selected the firms for the analysis.)

Our loan-level data set contains a sample of more than 300,000 business loans issued

[10] There are a few reasons why SOEs may have preferential access to bank loans. First, banks may discriminate against private firms because of taste or as required by the government. Second, banks may have access to more soft information on SOEs than on private firms. Third, SOEs may be deemed less risky because the government can repay the firm's loan in the event of default. Finally, bank managers may have incentives to build connections with government officials by lending to SOEs (Brandt and Li, 2003). However, none of these channels would generate a monthly lending cycle peaking at month's end in the absence of managers' lending targets.

by both the bank's main and sub-branches, spanning the period 1997 – 2010. For each loan contract, we observe its date of issuance, loan value, loan type, quality classification by the bank, as well as the borrowers' income statements. We aggregated the loan data to the branch-date level (since lending incentives operate at the branch-level) and constructed two data sets to study the loan quantity responses to month-end incentives. The first is a balanced panel in which branch-days with no lending are coded as 0. We will use this data set to examine the "extensive" margin of quantity responses (i.e., the probability of any lending on a given date) as well as the overall effects (i.e., does the total amount of lending increase). The second data set is comprised of a sub-sample of the balanced panel, restricted to branch-day observations for which at least one new loan was issued. We use this sample to evaluate the "intensive" margin of the month-end responses (i.e., does lending increase, via higher loan size or more loan contracts, conditional on at least one loan being made). In both data sets, we calculated the number of contracts and the aggregated loan amount for each branch on each date.

We also use the second data set (branch-day level, conditional on at least one loan) to evaluate loan quality responses to month-end incentives. Our quality measure is based on the 5-class loan classification that the bank itself uses, which is updated over the life of the loan. The final assessment in our data was in July, 2011. To avoid misclassifying loans that occurred late in the period, when we examine loan quality we limit our sample to loans issued in 2008 or earlier, to provide at least 2.5 years of repayment history (our results are insensitive to the particular choice of cutoff). We use the bank's own "bad loan" classification as our measure of loan quality: in the 5-class system, any loan in the bottom three categories – "secondary (ciji)", "suspicious (keyi)" or "loss (sunshi)" – is classified as bad. The loan remains as an asset on the bank's balance sheet until it reaches the "loss" classification, but loans that fall into the secondary and suspicious categories eventually go into default at relatively high rates.[11] (The two highest categories are "normal," in which case interest

[11] To the extent that some loans in our data are renegotiated (and hence do not appear as at risk of default), our bad loan measure represents a lower bound on the true bad loan rate in the data.

and principal repayment are up-to-date, and "special mention (guanzhu)", which occurs if the borrower is still able to service the loans currently, but the repayment of loans might be adversely affected by some factors.)

Table 1 contains summary statistics for our loan-level data, aggregated to the branch-day level. In column (1) we include all loans, while columns (2) and (3) provide summary statistics for SOE and non-SOE loans (aggregated to the branch-day level) respectively; the differences in attributes between SOE and non-SOE loans are given in column (4).

In the top part of the table, we present summary statistics for a balanced panel of new loans, as captured by total loan value and also an indicator variable denoting at least one loan in a given branch on a particular day. As is clear from the mean of $AnyLoan$, most branch-day observations include no new lending. This is in large part because, as noted previously, the firms included in our loan data represent only a fraction of the overall lending portfolio of the bank (though recall also that for a given firm we have their complete loan history during our sample period). Comparing SOE and non-SOE borrowers, we observe that the likelihood of an SOE loan is more than three times that of a non-SOE loan; total daily lending is just over twice as high for SOEs versus non-SOEs.

We next turn to summary statistics for all branch-day cells when at least one new loan was issued. This is the subsample we will use to evaluate the "intensive" margin of lending, conditional on a loan being made, as well as loan quality responses. SOE loans are smaller on average than non-SOE loans. In our sample (and for the Chinese economy more broadly) SOEs are far larger on average than private firms: the average SOE borrower reports assets of RMB 452 million, as compared to RMB 243 million for non-SOE borrowers. This suggests that borrowing at SOEs is broken up into smaller increments, both from the bank we study as well as potentially from other lenders. If we aggregate at the borrower-level over our entire sample period, the average SOE borrower takes out an average of 45.8 loans, as compared to 16.1 loans for an average private borrower; median total borrowing per firm is RMB 187 million for SOEs versus RMB 127 for non-SOEs.

Turning to borrower type and loan quality, we see very sharp differences between SOE and private firms. The share of loans to SOEs with past default is substantial – 36.7 percent on average – as compared to non-SOEs, for which the comparable figure is only 6.1 percent. Thus, while private firms are largely shut out of borrowing as a result of prior non-payment, the same does not seem to be the case for SOEs.

Finally, we find that SOEs are much more likely to default on their loans – 14.7 percent of SOE loans are eventually classified as bad loans, as compared to 6.4 percent of loans for private firms.

In the next section, we will explore the difference in lending to SOEs versus non-SOEs with greater rigor, and also examine how loans to the two types of borrowers differ over the monthly cycle. We do so via monthly "event plots" as well as regression analyses that provide ready measures of effect sizes, and allow us to better control for other factors that may affect the quantity and quality of lending.

3 Results

Before turning to our SOE versus non-SOE comparison, we first present a set of results which indicate that, overall, lending quantity increases and lending quality decreases at month's end. We view this initial set of results as a contribution in itself, as it provides a compelling case study on the consequences of non-linear incentives for lending. We thus provide evidence from a very different context that supports the conclusions of Tzioumis and Gee (2013) that lending targets lead to standard-cutting to boost output at the expense of loan quality.[12]

We then turn to our main analysis, which provides a decomposition of this overall effect, by comparing monthly cycles for SOEs and private firms, which we suggest sheds light

[12] Beyond the obvious distinctions implied by the fact that the two papers study banking in very different economies, our focus is on the *commercial* loan portfolios of a Chinese state bank while they look at a *mortgage* lending at a private U.S. bank. Because, as Tzioumis and Gee (2013) note, commercial lending may involve team production, it may be more difficult to tie output to individual effort. We show that even in this case there are both quality and quantity effects from target-setting.

on bank officials' incentives to lend to SOE versus private firms. We do so to examine the differential incentives to lend to SOE versus non-SOE borrowers, and in particular how these incentives interact with monthly targets, potentially encouraging branch managers to lend to SOEs with poor credit histories.

3.1 End-of-month effect on loan quantity and quality

We begin with a set of figures which show how lending evolves over the monthly cycle. In these figures — and all that follow — we set $d = 0$ for the final day of the month, and show in each figure the change in lending ±13 days from the last day of the month. This formulation allows us to capture changes in lending over the full range of a monthly cycle for months of any length.[13] To net out day-of-the-week fixed effects, month-year fixed effects, and city fixed effects, we plot coefficients from the following regression:

$$\Delta log(1 + NewLoans_{bt}) = \sum_{d=-13}^{13} \beta_d * I(d(t) = d) + dow_t + ym_t + city_b + \epsilon_{bt} \quad (1)$$

where $NewLoans_{bt}$ are new loans issued at branch b on date t. Observe that we use $log(1 + NewLoans_{bt})$ to measure the overall flow of new borrowing at the branch-day level, so that zero values are defined.[14] (When we look at the intensive margin of lending below, where we condition on at least one loan being made, we use $log(NewLoans_{bt})$ to measure borrowing, for ease of interpretation). The variables of interest, $I(d(t) = d)$, are a set of dummy variables denoting that date t is on day-of-the-month d; the other regressors include fixed effects for day-of-the-week (dow_t), month × year (ym_t), and city where branch b is

[13]It makes no difference for our calculation if we widen the excluded category, narrowing the figure to have, say, ±12 days or ±11 days to estimate end-of-month and beginning-of-month effects.

[14]The patterns we document here are virtually identical if we use the *arcsinh* transformation as in, for example, Kline *et al.* (2017).

located ($city_b$). To calculate confidence intervals on the coefficients, we cluster at the branch-level.[15]

Figure 1 plots the regression coefficients, $\{\beta_{-13}, \ldots, \beta_{13}\}$, along with 95 percent confidence intervals. The figure shows a clear increase in lending as the end of the month ($d = 0$) approaches, with a sharp drop as the next month begins. Furthermore, the coefficients on beginning-of-month dates are negative, indicating less lending at the beginning of the month relative to the omitted category of mid-month dates. However, as is visually discernable, the beginning-of-month drop is not so large as to offset the end-of-month increase, a point we will return to in discussing the regression results below.

We may use our loan-level data to distinguish, at the branch level, between the "extensive" margin (the likelihood that a loan is made) and "intensive" margin (the size of a loan, conditional on a loan being made) in generating the patterns we observe over the monthly cycle. In Figure 2, Panel A, we show the extensive margin using as the outcome in equation 1 an indicator variable which denotes whether any loan was made in branch b at date t. In Panel B we show the intensive margin, which is generated using $log(NewLoans_{bt}|NewLoans_{bt} > 0)$, i.e., the logarithm of the value of loans issued conditional on at least one issuance. Given that we condition on a loan being issued in branch b at time t, there are far fewer observations underlying the figure in Panel B (and also Panels C and D). Panels C and D disaggregate the intensive margin into end-of-month effects on average loan size and the number of loan contracts (again, conditional on at least one loan being issued at branch b at time t).

In all panels, we observe an end-of-the-month effect, indicating that branches increase lending toward month's end through a combination of more loan contracts and larger loan sizes. The effect is most pronounced for the extensive margin – the month-end coefficient (at

[15]Given that quotas are plausibly assigned at the city rather than (county) branch level, we do not include branch fixed effects in our preferred specifications. In Appendix Figure A1 we show the monthly cycle with branch fixed effects included, and find that it is virtually identical to the figure we show in the main text. We additionally note that the unconditional patterns over the month are very similar to those based on regression coefficients. We present this graph in Appendix Figure A2.

date $d = 0$) is slightly above 0.02 which, given the sample average of 0.018, implies a doubling of the probability of making a loan on the last day of the month. The specifications underlying Panels B – D also imply large end-of-the-month effects. For example, the coefficients in Panel B indicate that, relative to mid-month, loan issuance is about 40 percent higher ($exp(0.34) - 1$) on the last day of the month, with the effect coming through both higher loan sizes (Panel C) and more loans (Panel D).

In Table 2, we present the month-end effect in a regression framework. We focus on lending in the first and last 5 days of the month relative to the middle 5 days (13–17th) of each month, which is the omitted category:[16]

$$\Delta log(1 + Loans_{bt}) = \beta_1 * Last5Days_{bt} + \beta_2 * First5Days_{bt} + dow_t + ym_t + City_b + \epsilon_{bt} \quad (2)$$

The main variables of interest are $Last5Days$ and $First5Days$, which denote the last and first 5 days of each month respectively.[17] The coefficients on both variables are highly significant ($p < 0.01$) and of expected signs; the coefficient on $First5Days$ is negative, and about a third of the size of the estimated end-of-month effect.

Columns (2) – (5) show the results of specifications that take the form of Equation 2, with our extensive margin measure ($Anyloan$) and intensive margin measures ($log(Loans)$, $log(Loans/Contracts)$ and $log(Contracts)$) as outcome variables. The intensive margin regressions, as noted earlier, include far fewer observations than the extensive margin analyses, since the outcome variables are defined only for branch-days when loan disbursement is non-zero. We observe a positive month-end coefficient on both margins, though the implied effect

[16] In practice our results are very similar if we use all other days outside of the first and last five, rather than just the middle five, as the benchmark.

[17] As one might expect, we generate larger point estimates for daily month-end effects if we use shorter windows, given the patterns we observe in the figures above.

size is somewhat larger for the extensive margin: the coefficient of 0.0129 on $Last5Days$ in column (2) indicates that the probability of a loan issuance at month's end is about 76 percent greater than during the middle of the month (which is 0.0172 on average), whereas the coefficient in the loan amount specification of 0.182 (column (3)) implies an increase in lending (conditional on at least one loan) of 20 percent ($exp(0.182) - 1$). When we disaggregate the intensive margin into the effect on average loan size versus number of loans, we find an effect on both: the coefficient on the log of average loan size implies that the average end-of-month loan is 10 percent larger than a mid-month loan (column (4), since $exp(0.095) - 1 = 0.1$), while conditional on the issuance of at least one loan, the results in column (5) indicate that the number of loans is 9 percent larger at month's end.

It is straightforward to generate a rough sense of overall magnitude of the end-of-month effect on loan quantity (relative to the sample mean) by simply adding up the extensive and intensive margin effects in columns (3) and (4): the likelihood of loan issuance increases by 76 percent (0.013/0.0172), and conditional on the issuance of at least one loan, total lending increases by approximately 20 percent, indicating an overall end-of-month lending effect of just over 111 percent ($1.76 \times 1.2 - 1$).

We will elaborate on these figures in Section 3.3 below, where we calculate the consequences of end-of-month targets for the quantity and quality of SOE lending.

Finally, we look at loan quality over the monthly cycle, to examine whether standards are lowered in order to reach month-end targets. We present in Figure 3 the results of a specification that parallels that of Figure 1, with $BadLoanPct$ as the outcome variable. As with our intensive margin graphs, the results in this specification are based on an unbalanced branch-day panel, since our measure of loan quality is only defined for branch-day observations in which the bank issues at least one loan (recall also that for our credit quality analysis we limit the sample to loans issued in 2008 or earlier to allow time for a loan to go into arrears). We show the monthly cycle of the share of bad loans, weighted by loan amount, in Figure 3. Intriguingly, the pattern roughly parallels that of Figure 1, with an increase in the final few days of the month in the fraction of lending that is ultimately categorized as bad. The implied magnitude is substantial, with a 1.1 percentage point increase in the bad loan rate in the last 5 days relative to mid-month. Given the sample mean of 14.8 percent, this implies an increase of just under 8 percent. Note that the bad loan rate is substantially lower at the beginning of the month: the coefficient on $First5Days$ implies a bad loan rate that is 0.9 percentage points lower than mid-month. [18]

Overall, the results in this section indicate a month-end decline in loan quality, consistent with a relaxation of lending standards to make month-end loan quantity targets.

3.2 Monthly cycles in SOE versus private lending

We now build on the results in the preceding section – which established higher lending quantity and lower lending quality at month's end – to examine how much is driven by SOE versus private lending. We begin with a set of graphs that look at the quantity and quality of loans made to SOEs versus private firms. These graphs exactly parallel those presented in Section 3.1, now splitting the sample into loans given to SOE versus non-SOE borrowers.

We present four graphs in Figure 4, Panels A – D. These include the monthly cycle in overall lending (Panel A); the extensive and intensive margins of lending (Panels B and C respectively); and the monthly cycle in bad loan rates (Panel D).

As we already observed in the summary statistics, lending to SOEs is far higher than lending to non-SOEs overall (Panel A), reflecting the bank's obligations to the state. This is driven entirely by the extensive margin, as illustrated in Panel B – in fact, the average loan

[18] The higher loan size we document in the preceding section might potentially account for the decline in loan quality, if moral hazard is increasing in loan size, as suggested by standard "too big to fail" arguments. To examine this possibility, we split the sample by (within branch-year) loan size, and investigate whether the monthly cycle of bad loan rates is the result of a compositional shift in lending from smaller to larger loans. In Appendix Figure A3, we present a disaggregated version of Figure 3, with portfolios divided into three groups based on loan size. First, we note that overall larger loans are less likely to default, which is inconsistent with the most straightforward version of the loan size and moral hazard argument. More importantly, for all three groups, there is a comparable month-end deterioration in loan quality, which suggests that the full sample end-of-month increase in bad loans does not result from the shift to larger loans.

size for SOEs is much smaller (Panel C).[19] Turning to bad loan rates (Panel D), the overall average is nearly three times higher for SOEs relative to private borrowers.

The figures also provide visual evidence on any differences in monthly loan cycles between the two groups of borrowers. Focusing first on quantity measures, SOE and non-SOE lending looks quite similar, relative to their monthly averages. That is, both groups contribute, in proportional terms, roughly equally to the month-end increase in loan quantity.

We may see this even more straightforwardly in Table 3, which presents the SOE versus non-SOE lending quantity comparison in regression form. As before, we compare lending in the first and last 5 days of each month to mid-month lending, after accounting for city, year$\times$month and day-of-week fixed effects. Focusing first on overall lending quantity in columns (1) and (2) for SOEs and non-SOEs respectively, we observe that, while the month-end lending increase is greater for SOEs, the end-of-month effect is quite similar as a fraction of the sample average in each case.

Turning to credit quality in Table 4, we see a sharper increase in bad loans to SOEs relative to non-SOEs, even relative to their very different base rates. The coefficient on $Last5days$ is 0.0170 for SOEs ($p < 0.001$), while for non-SOE loans the coefficient is 0.0024 and insignificant at conventional levels ($p < 0.49$). The point estimates imply that, even relative to their much higher baseline, SOE loans have an increase in bad loan rates that is 3 times higher than that of non-SOEs. In the remaining columns of Tables 3 and 4, we further disaggregate SOE and non-SOE borrowers into those with prior bad loans in our data and those with clean credit histories. The rationale for this further sample split is straightforward: a lender aiming to reduce defaults should be well-motivated to avoid lending to past defaulters both to signal the costs of non-compliance, and also because credit quality may be serially correlated. (For completeness, we also provide the full monthly patterns disaggregated by both SOE status and credit history in Figure A4. For ease of exposition, we focus on the regression tables in describing the results.) We start by looking at loan quantity; several

[19] As also noted earlier, SOEs borrowers receive loans more frequently than non-SOEs so that SOE borrowers may simply divide their borrowing into smaller increments.

noteworthy patterns emerge. First, there is a month-end increase in lending to all types of borrowers. However, the increase for private firms with past defaults is extremely small relative to the other three categories, simply because private defaulters receive very little lending *at any time* whereas SOEs with past default are able to obtain new loans. The month-end increase overall is thus driven by a combination of non-SOEs with clear credit histories, and SOEs largely irrespective of past repayment status.

These drivers of month-end lending are a useful backdrop when we turn to examine the credit quality of month-end lending in Table 4, columns (3) – (6). One particularly noteworthy difference emerges in this comparison: while SOEs default on month-end loans at substantially higher rates, regardless of credit history, we do not observe any such increase for non-SOEs without past defaults: the coefficient on $Last5days$ is small in magnitude and does not approach statistical significance for this subgroup. [20]

We conclude our empirical analysis by comparing patterns in the earlier versus later parts of the period we study. As Hsieh and Klenow (2009) document, SOE productivity increased substantially during the early 2000s, as the government implemented a suite of reforms that aimed to harden SOEs' soft budget constraints. We are interested in whether related reforms reduced managers' incentives to fill loan quotas via SOE lending. We split the sample based on the implementation of China's Enterprise Bankruptcy Law (EBL) executed in June 2007, which had as one of its main objectives to limit bailouts of state enterprises (see Booth). (As already noted above, other correlated policies may have been implemented at around the same time, so any difference we observe across time periods reflects the overall impact of the full set of changes.)

The patterns are shown in Appendix Figure A5, which exactly parallels the structure of

[20] For the small number of observations where we observe loans to non-SOEs with past defaults, we observe much higher default rates for month-end loans (p¡0.1); note however, that the sample size is far, far smaller for this subgroup, since there are simply very few loans given to non-SOEs with past defaults. Finally, we observe similar patterns if we proxy for creditworthiness using return on assets (profits divided by total assets) rather than past default. Both high- and low-profit SOEs receive end-of-month loans, whereas only high-profit private firms do; the end-of-month increase in default is driven by both high- and low-profit SOEs.

Figure 4. While the *level* of lending converges for private versus state-owned firms, we observe a clear end-of-month increase for both groups before as well as after bankruptcy reform. Interestingly, there is also a reduction (and convergence) in default rates for both private firms and SOEs, with no discernable monthly cycle in the post-reform period, suggesting that the discipline imposed by the EBL and other policy shifts may have disciplined lending to SOEs (as well as private firms). Note, however, that because our data end in 2010, it is possible that loans made later in the sample have yet to have a chance to go bad (though as noted in our data description, we only include loans through to the middle of 2008 in our default analysis for this reason).

3.3 Interpretation and discussion of results

We begin by recapping the main patterns we have documented thus far:

1. Lending increases substantially in the final days of each month, and these month-end loans default at substantially higher rates.

2. SOEs with past bad loans constitute 37 percent of all borrowing by SOEs, as compared to 6 percent of borrowing by non-SOEs with past bad loans.

3. SOEs and non-SOEs both contribute to the month-end increase in loan quantity. However, for non-SOEs the increase comes almost exclusively from those with clean credit histories, while for SOE borrowers the month-end lending increase is similar for firms with clean records and those with past defaults.

4. The end-of-month increase in bad loan rates is 3 times higher for SOEs versus non-SOEs. Furthermore, there is no increase in bad loan rates among non-SOEs with clean credit histories.

The standard tools that agents have for meeting quantity targets is greater effort and relaxing standards. For non-SOE lending, the increase appears to come (particularly for firms in good standing) from increased effort, as we do not observe an increase in default. Since SOE lending quantity increases and quality declines, month-end loans to state-owned enterprises may be facilitated by a decline in standards.

Particularly when combined with the high overall default rate for SOEs as well as the high rate of repeat borrowing for SOEs with past bad loans, it suggests lesser consequences to branch managers for making bad loans to SOEs.

As we have emphasized throughout, while prior work has observed the high default rate among SOEs, our results on monthly cycles in low-quality lending are new.

The monthly cycle itself is less plausibly the result of patterns in government pressure or SOEs' own financial needs – particularly given that regulators were putting pressure on banks to limit end-of-month lending during the period we study, it is harder to attribute the end-of-month cycle increase in lending to SOEs with bad credit histories to direct government pressure, rather than bank manager incentives. Thus, our focus on the monthly cycle in lending helps us to distinguish between government pressure on banks to increase SOE lending and the willing participation of bank officials to slacken their quantity-based incentives. That is, it may be in branch managers' interests to have a set of borrowers for which quality is less of a concern, given their need to meet quantity targets – SOEs may offer a reservoir of lending opportunities to draw on if they are short on loan quantity near the end of the month. Thus, the possibility of lending to SOEs softens the quantity incentives faced by branch managers.

We emphasize that under the resulting "soft incentive constraint" branch managers themselves benefit from the option of lending to already over-leveraged SOEs; thus, rather than grudgingly acquiescing to government demands to make SOE loans, they may actively promote it. The soft budget constraint enjoyed by SOEs thus serves to undermine the role that target-based incentives have in motivating bank officials, and conversely the soft incentive constraint on the part of bank managers may exacerbate the lack of financial discipline in SOEs. And this, in turn, is of relevance to the broader economy, given the relatively low productivity of SOEs versus private firms, and also because of rising concerns of excess leverage in China, particularly among SOEs.[21]

3.4 Estimating the consequences of the soft incentive constraint

We may use the point estimates from our preceding analysis to provide a back-of-the-envelope calculation of how much target-setting may have exacerbated the problem of unproductive lending to SOEs. We take two approaches to measure the consequences for China's credit market and economy more broadly. First, we estimate the consequences for loan default rates, which is one measure of resource misallocation. This approach has the benefit of being derived directly from our own estimates, but it also fails to account fully for the allocative consequences of higher lending to SOEs – the bank may make relatively unproductive loans to SOEs that are nonetheless paid back, for example because of government subsidy. We therefore also provide an estimate of the consequences for total factor productivity (TFP), building on the findings of Hsieh and Klenow (2009).

Both of these estimates have the same starting point of calculating the increase in lending to SOEs that results from month-end incentives. Let us take beginning-of-month lending as a benchmark for behavior in the absence of any quantity targets. This would be appropriate if, for example, we assume a standard model in which a bank official faced with a loan target gradually reduces his standards over the course of the month as the option value of waiting for high-quality borrowers to arrive declines. Naturally the implied effects are marginally smaller if we use mid-month values as the benchmark.

On the extensive margin, month-end lending to SOEs is 75 percent higher than the mid-month average of 0.0135 (0.0101/0.0135), based on figures from column (1) of Table A1, while the intensive margin increase is $e^{0.146} - 1 == 16\%$. Thus, the total end-of-month increase is

[21] In recognition of these worries, towards the end of 2018 the Chinese Banking Regulatory Commission urged all large banks to lend more to private firm. Lending to private firms was required to account for a third of all lending (two-thirds for and small mid-sized banks), rising to half of all loans within three years.

$1.75 * 1.16 - 1 == 103\%$. Similarly, lending is 26 % lower $(1 - (1 - 0.0037/0.0135) * e^{0.0130})$ at the beginning of the month relative to mid-month. If we add these two effects (again, assuming that start-of-the-month lending reflects what we might observe in the absence of quantity targets), targeting raises SOE lending by 52% $(5 * 1 + 20 * 1/(1 - 0.26) + 5 * (2.03 * 1/(1 - 0.26)))/30)$.

Focusing first on the consequences for delinquent loans, the increment in bad loans relative to the beginning of the month is 2.6 percent $(0.017 + 0.009)$, based on the estimates in Table 4, column (1). Given that the average beginning-of-month bad loan rate is 14.2 percent, this implies a 18 percent month-end increase over the already-high rate of bad loans among SOEs. Thus, target-setting leads to substantial loan increases to SOEs that already have high default rates, and furthermore these incremental loans themselves default at even higher rates than the SOE average.

Turning to our calculation of the consequences for the overall productivity of China's economy, we estimate the incremental TFP loss that results from target-setting. We will assume that overall TFP is a weighted average of TFP for SOEs and for private firms, and further that TFP from incremental capital investment is comparable to average TFP for both SOEs and private firms. These are substantial assumptions, but they allow us to utilize readily available estimates on average TFP and total credit in the Chinese economy to generate a measure of TFP loss from incentives to lend to SOEs. In 2018, SOE borrowing accounted for nearly half of Chinese debt overall, so that TFP from capital investment is $0.5TFP_{SOE} + 0.5TFP_{nonSOE}$, under the targeting regime that we observe in our data. Using the preceding calculation that targeting raised SOE lending by approximately 50%, we calculate that without the additional lending that SOEs received as a result of target incentives, the share of SOE lending would have been $\frac{0.5/1.5}{0.5+0.5/1.5} = 0.4$. According to Hsieh and Klenow (2009, Table VII), TFP of SOE firms is 41% lower than that of private firms. Therefore, the TFP in the absence of targeting would have been $\frac{0.4\times0.6+0.6\times1}{0.5\times0.6+0.5\times1} = 105\%$ that of TFP with targeting. This implies an approximately 5% incremental TFP gain in capital investment, had there not been higher lending to SOEs as a result of target-setting.

The final step in our calculation is to consider how much the TFP loss on debt-financed investment implies for the economy overall. As of 2018, the total capital stock in China was approximately 500 trillion RMB, and total debt was estimated to be around 250 trillion RMB. If we take approximately half of capital to be debt-financed, the TFP gain from removing loan targets with then simply be half of the 5% gain from improved lending practices, i.e., 2.5%.[22] As we have observed, there are many assumptions that go into these rough calculations. The takeaway, though, is that there is quite plausibly a substantial efficiency loss from bank managers using SOEs as a convenient channel to fulfill their lending quotas, which in turn plausibly amplifies the problem of soft budget constraints at Chinese SOEs.

4 Conclusion

In this paper, we document a clear monthly cycle in lending at a state bank in China: credit quantity increases sharply near the end of each month, and lending quality declines, most plausibly resulting from bank managers' efforts to hit monthly lending targets. Our main focus is on comparing loan patterns for SOEs versus private borrowers. We find that the month-end increase in lending quantity comes from both types of firms, whereas the quality decline is largely driven by SOE lending. We additionally find that the bank continues to offer loans to SOEs after a default, while lending is very low to past-defaulting private firms; furthermore, even past-defaulting SOEs receive a boost in lending at the end of the month. Overall, these findings suggest that, not only do branch managers face little consequence from making bad loans to SOEs, but they may even find benefit in having this ready outlet for lending available, given their own quantity-based incentives.

While it is beyond the scope of our data and analysis to make any decisive welfare

[22] In fact, this is an underestimate – potentially a very significant one – of the relevance of debt-financed investment. During 2002-2018, for example, equity accounted for only 1-7% of new financing in China, while bank credit accounted for 51-99%. By this metric, debt-financed investment should receive a much greater weight in the preceding calculation.

calculation (we do not capture the net benefits that come from motivating Chinese banks to issue loans at a higher rate), our results indicate that the twin phenomena of soft budget constraints at SOEs and target-based incentives at state banks may together exacerbate the capital misallocation that some have suggested afflicts the Chinese economy (Hsieh and Klenow, 2009).

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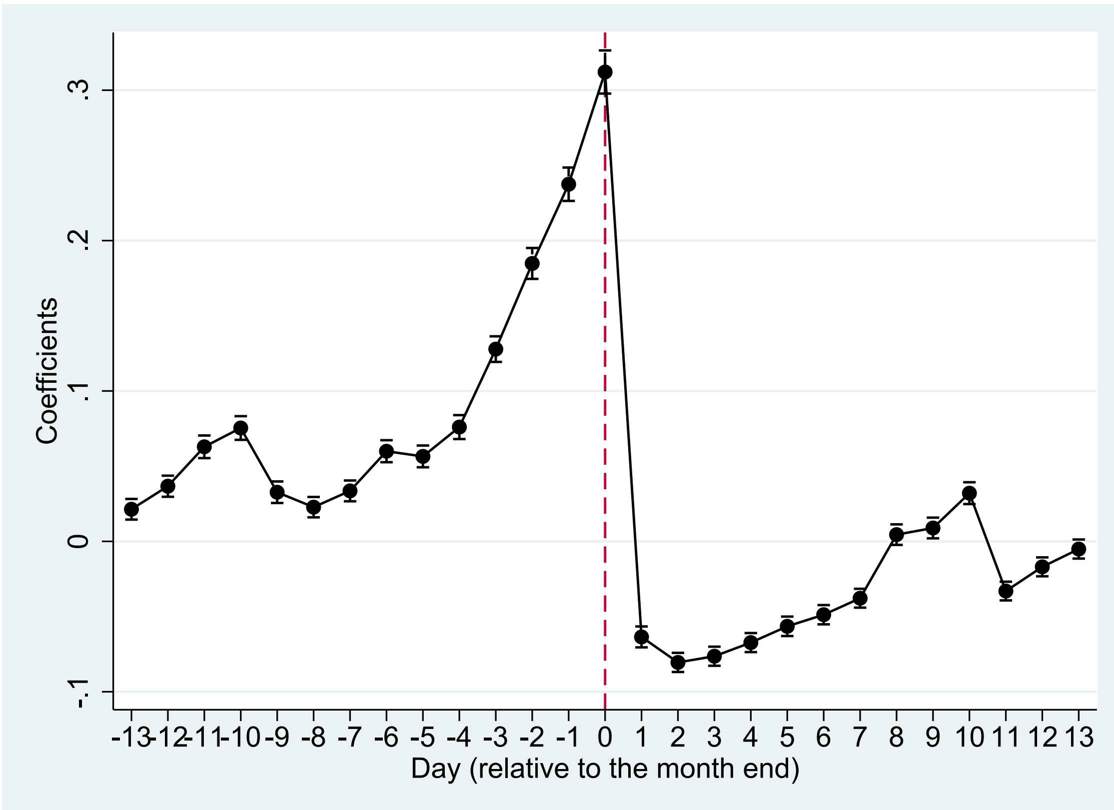
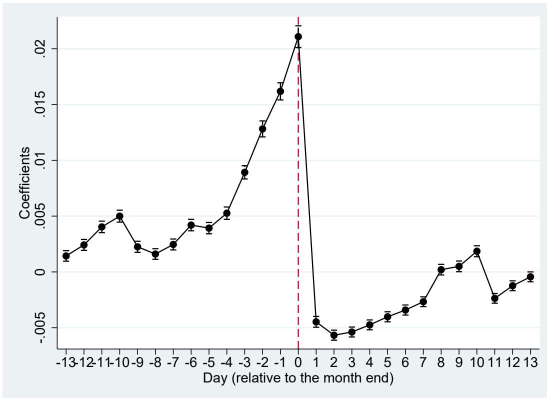
5 Figures and Tables

Figure 1: Value of New Lending Issued, Coefficients Plots

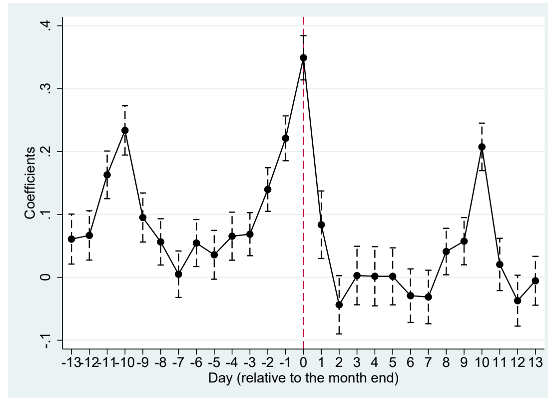


Note: The dependent variable is the value in RMB of new loans issued by branch b on date t. Dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

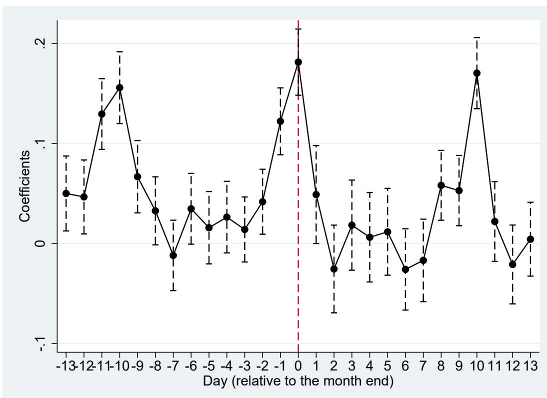
Figure 2: Extensive and Intensive Margins of New Loan Issued



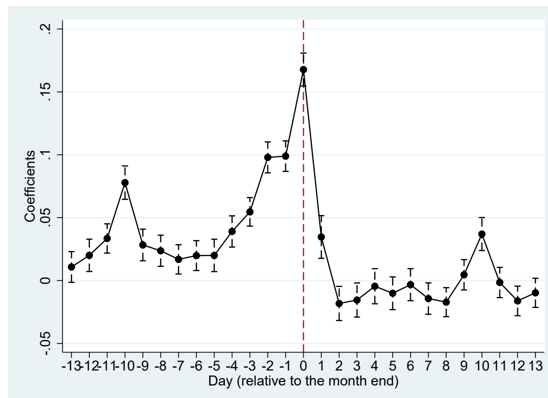
(a) Extensive: $Prob(Anylending)$



(b) Intensive: $log(NewLoans|NewLoans > 0)$



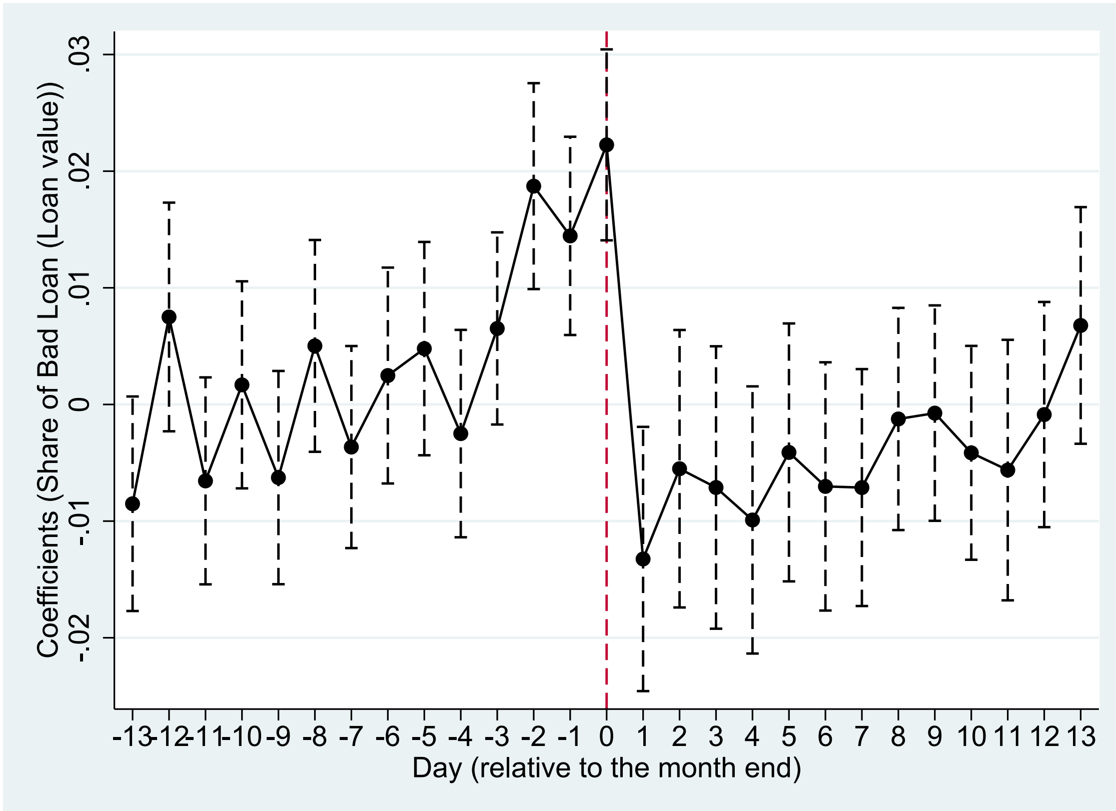
(c) Intensive: $log(AverageSize)$



(d) Intensive: $log(Contracts)$)

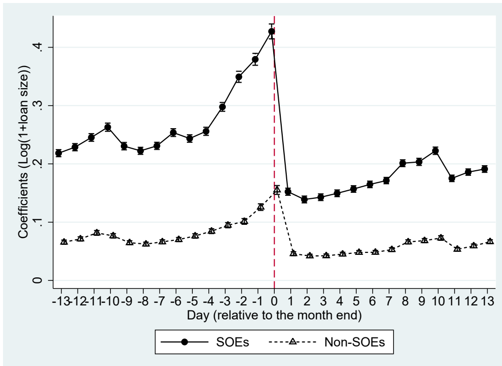
Note: $AnyLending$ is an indicator variable denoting that the branch b issued at least one loan to a firm in our dataset on date t. $NewLoans$ is the value in RMB of new loans issued by branch b on date t. $AverageSize$ is the average size of new loans issued by branch b on date t. $Contracts$ is the number of loans issued by branch b on date t. Dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

Figure 3: Share of Bad Loans (weighted by loan amount), Coefficients Plots

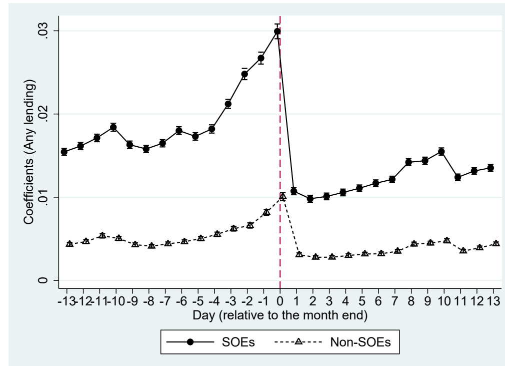


Note: The dependent variable is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). Dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

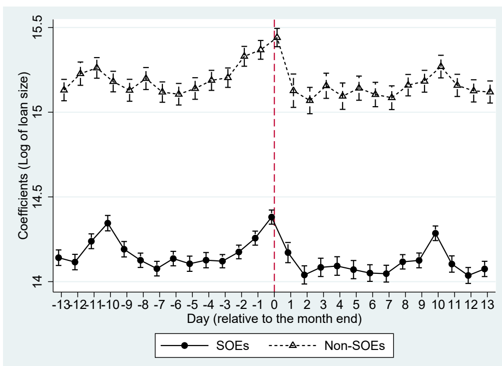
Figure 4: SOE vs Non-SOE Firms, Coefficients Plots



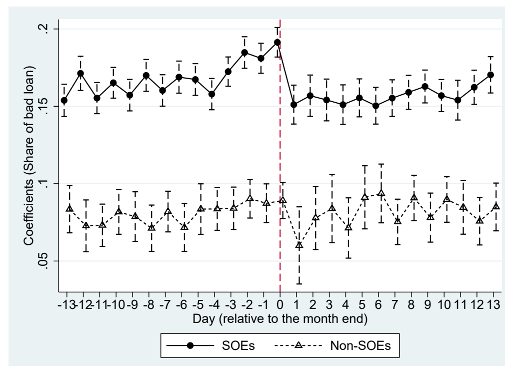
(a) Overall Effects



(b) Extensive Margin



(c) Intensive Margin



(d) Quality

Note: The dependent variable in panel (a) is the value in RMB of new loans issued by branch b on date t. The dependent variable in panel (b) is an indicator variable denoting that the branch b issued at least one loan to a firm in our dataset on date t. The dependent variable in panel (c) is the value in RMB of new loans issued by branch b on date t conditional on at least one loan being issued. The dependent variable in panel (d) is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). SOE firms are defined as firms owned or controlled by the state. Dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

Table 1: Summary Statistics

	All firms	SOEs	nonSOEs	Difference
	(1)	(2)	(3)	(2)-(3)
	Full Sample			
Loan value per branch-day (million RMB)	0.131	0.092	0.039	0.054
	(6.393)	(5.891)	(2.468)	[0.002]
AnyLoan (%)	1.821	1.426	0.408	1.018
	(13.370)	(11.856)	(6.374)	[0.004]
N	10137096	10137096	10137096	.
	Sub-sample with at least 1 loan			
Loan value conditional on lending (million RMB)	7.229	6.479	9.471	-2.992
	(46.943)	(48.910)	(37.463)	[0.225]
Loan value per contract (million RMB)	5.599	4.903	8.077	-3.174
	(41.117)	(45.128)	(20.287)	[0.155]
# of loan contracts conditional on lending	1.505	1.565	1.216	0.348
	(2.554)	(2.809)	(1.000)	[0.009]
Share of bad loans (%)	14.804	16.198	8.420	7.778
	(34.381)	(35.597)	(27.384)	[0.185]
Share of loans to firms with bad repayment history (%)	0.300	36.690	6.212	30.478
	(0.453)	(47.748)	(23.963)	[0.172]
N	183744	144565	41358	.

For details on variable definitions, please see text. Standard deviations in parentheses; Standard errors in square brackets.

Table 2: Loan quantity and quality responses to month end incentives

	Dependent Variables:					
	Quantity					Quality
	$log(1 + NewLoans)$	AnyLoan	$log(NewLoans)$	$log(Loans/Contracts)$	$log(Contracts)$	Share of Bad Loans
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.1884***	0.0129***	0.1817***	0.0952***	0.0865***	0.0110***
	(0.0035)	(0.0002)	(0.0113)	(0.0037)	(0.0109)	(0.0028)
First 5 days	-0.0681***	-0.0048***	0.0043	-0.0027	0.0070	-0.0090***
	(0.0022)	(0.0002)	(0.0133)	(0.0040)	(0.0126)	(0.0032)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	0.269	0.019	14.337	0.235	14.102	0.152
# Observations	4992658	4992658	95236	95236	95236	82087
Adjusted R^2	0.023	0.022	0.414	0.100	0.477	0.223

Notes: Columns (1) – (2) use the balanced panel of loans aggregated to the branch level, in which days without any recorded loans are coded as zero (the sample from Table 1(A)); columns (3) – (6) use the sub-sample of the balanced panel that includes only branch-day observations when at least one loan was issued (the sample from Table 1(B)). $NewLoans$ is the value in RMB of new loans issued by branch b on date t. $AnyLoan$ is an indicator variable denoting that the branch b issued at least one loan to a firm in our dataset on date t. $Loans/Contracts$ is the average size of new loans issued by branch b on date t. $Contracts$ is the number of loans issued by branch b on date t. Share of bad loans is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). In each case, the reference group is the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Loan Quantity and SOE Status

	Dependent Variables: ln(1 + new lending)					
	SOE status		(SOE status, repayment history)			
	SOE	nonSOE	(SOE, good)	(SOE, bad)	(nonSOE, good)	(nonSOE, bad)
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.1430***	0.0496***	0.0967***	0.0499***	0.0413***	0.0039***
	(0.0033)	(0.0018)	(0.0026)	(0.0022)	(0.0016)	(0.0005)
First 5 days	-0.0509***	-0.0181***	-0.0299***	-0.0215***	-0.0160***	-0.0007***
	(0.0020)	(0.0011)	(0.0014)	(0.0013)	(0.0010)	(0.0003)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	0.207	0.065	0.131	0.078	0.057	0.004
# Observations	4992658	4992658	4992658	4992658	4992658	4992658
Adjusted R^2	0.019	0.012	0.012	0.014	0.011	0.002

Notes: New lending is the value in RMB of new loans issued by branch b on date t. SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. In all specifications, the reference group is the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Loan Quality and SOE Status

	Dependent Variables: share of bad loans					
	SOE status		(SOE status, repayment history)			
	SOE	nonSOE	(SOE, good)	(SOE, bad)	(nonSOE, good)	(nonSOE, bad)
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.0170***	0.0024	0.0167***	0.0193***	-0.0031	0.0310
	(0.0032)	(0.0042)	(0.0039)	(0.0051)	(0.0043)	(0.0249)
First 5 days	-0.0091**	-0.0078	-0.0051	-0.0144**	-0.0048	-0.0674**
	(0.0036)	(0.0058)	(0.0044)	(0.0061)	(0.0064)	(0.0275)
log(loan size)	-0.0145***	-0.0008	-0.0126***	-0.0156***	0.0005	0.0059
	(0.0014)	(0.0025)	(0.0016)	(0.0023)	(0.0024)	(0.0142)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	0.167	0.085	0.155	0.195	0.077	0.215
# Observations	66651	16492	42454	24872	13967	1181
Adjusted R^2	0.216	0.396	0.201	0.308	0.401	0.490

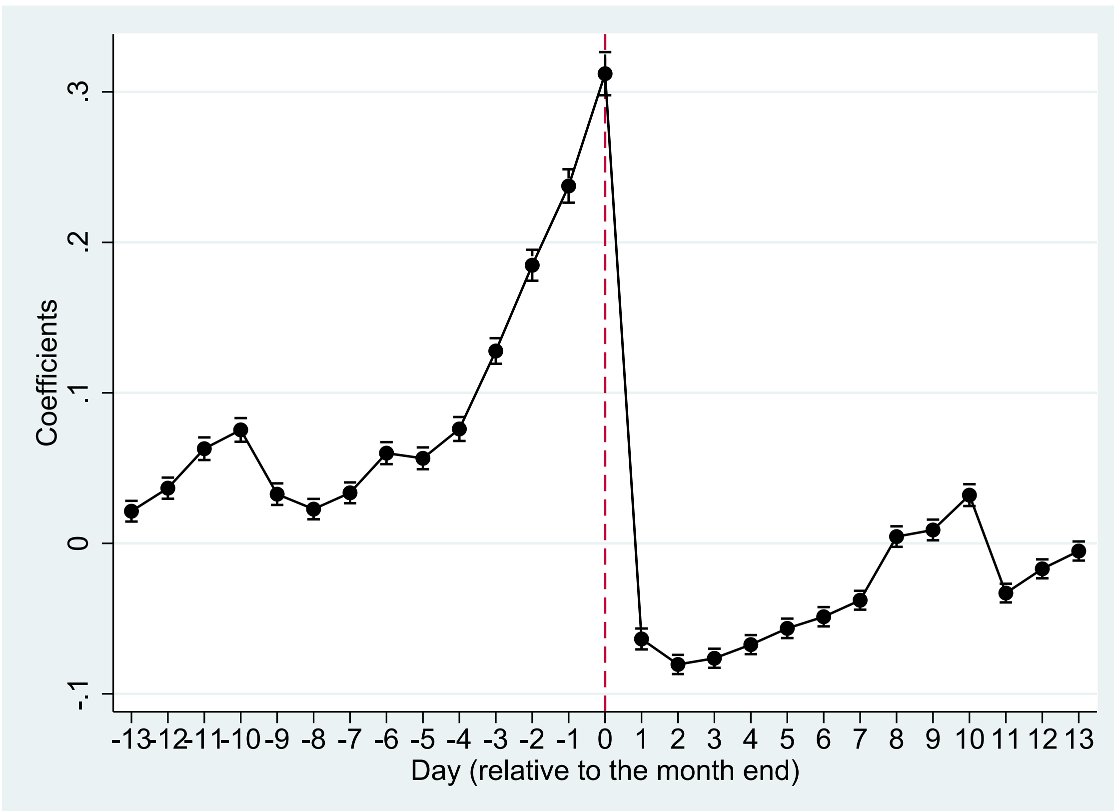
Notes: Share of bad loans is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. In all specifications, the reference group is the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Online Appendix for: SOE and Soft Incentive Constraints in State Bank Lending

Yiming Cao, Raymond Fisman, Hui Lin, and Yongxiang Wang

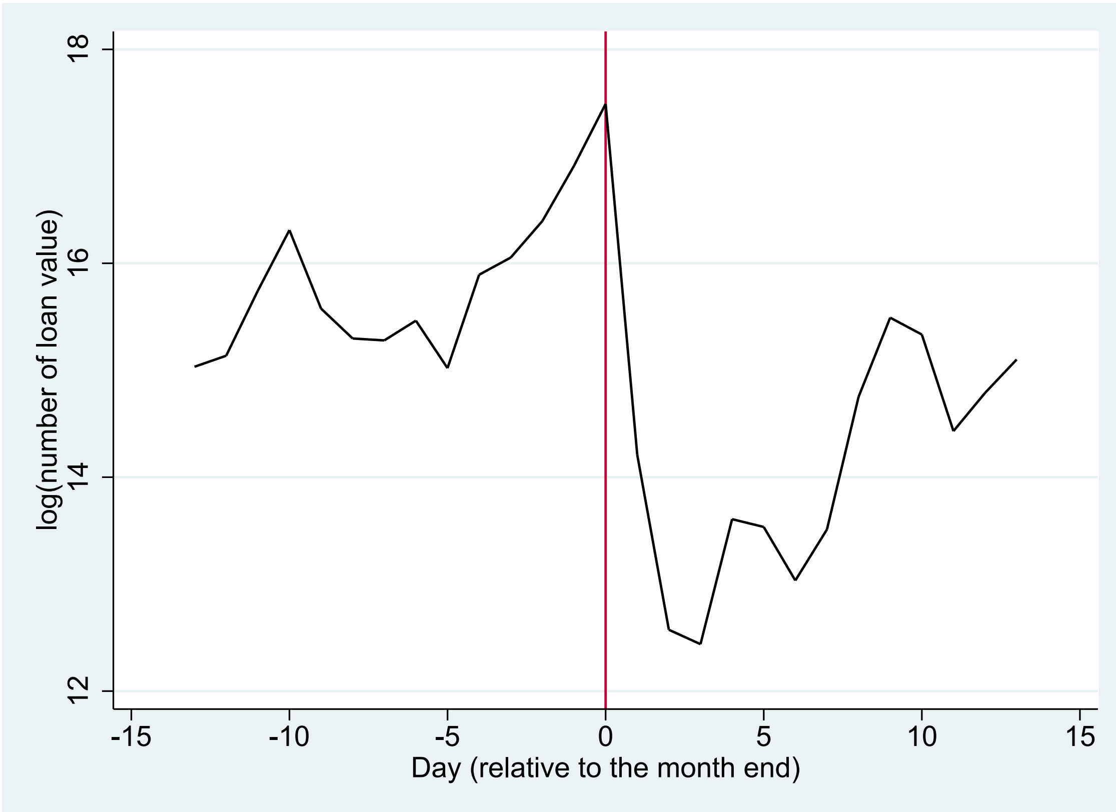
A Additional Results

Figure A1: Value of New Lending Issued with Branch Fixed Effects



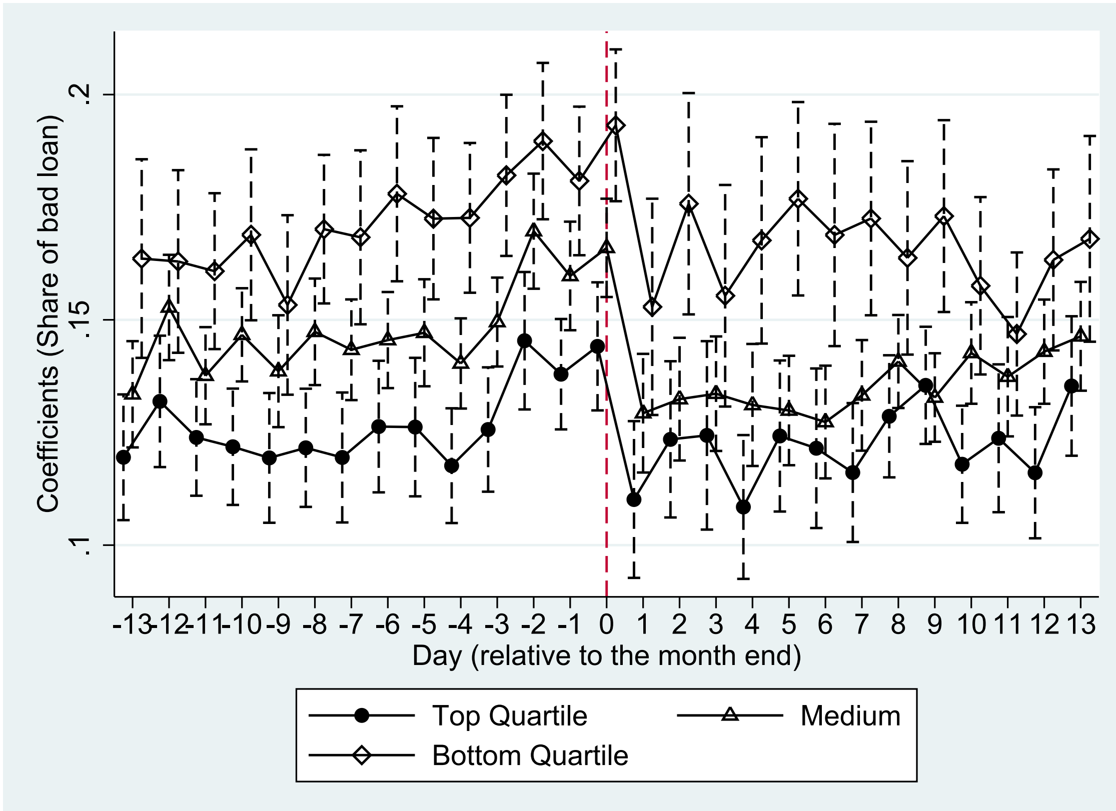
Note: The dependent variable is the value in RMB of new loans issued by branch b on date t. Dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and branch fixed effects; standard errors are clustered at the branch level.

Figure A2: Value of New Lending Issued (Branch-level data)



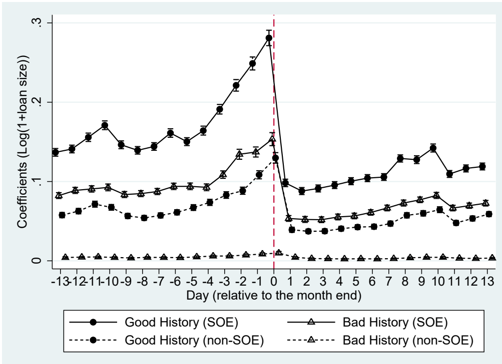
Note: The y-axis is the log value in RMB of new loans issued by branch b on date t.dates more than +/-13 days away from the month end are excluded from the raw data graph.

Figure A3: Share of Bad Loans by loan size, Coefficients Plots

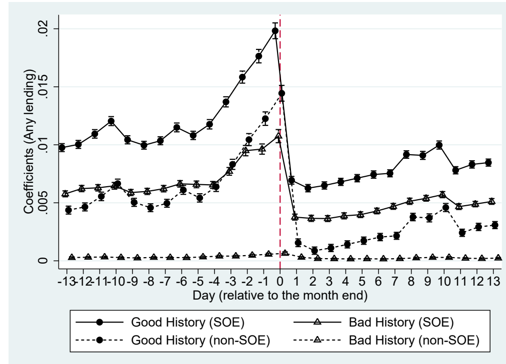


Note: The dependent variable is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). Dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

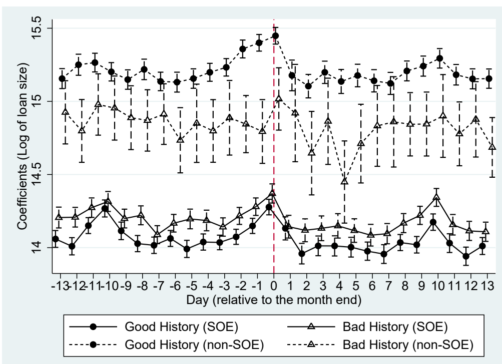
Figure A4: SOE status and repayment history decomposition, Coefficients Plots



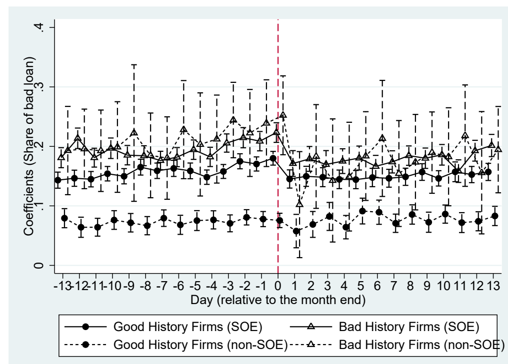
(a) Overall Effects



(b) Extensive Margin



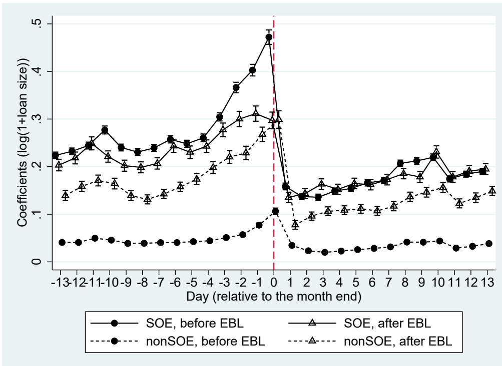
(c) Intensive Margin



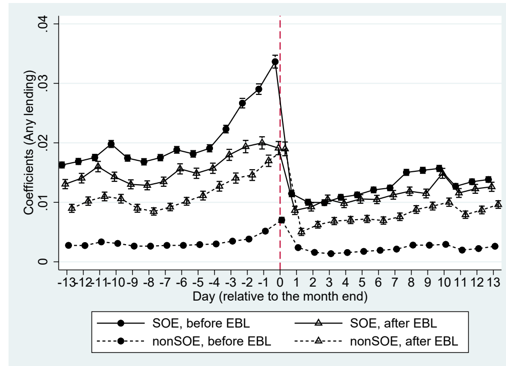
(d) Quality

Note: The dependent variable in panel (a) is the value in RMB of new loans issued by branch b on date t. The dependent variable in panel (b) is an indicator variable denoting that the branch b issued at least one loan to a firm in our dataset on date t. The dependent variable in panel (c) is the value in RMB of new loans issued by branch b on date t conditional on at least one loan being issued. The dependent variable in panel (d) is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. Dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

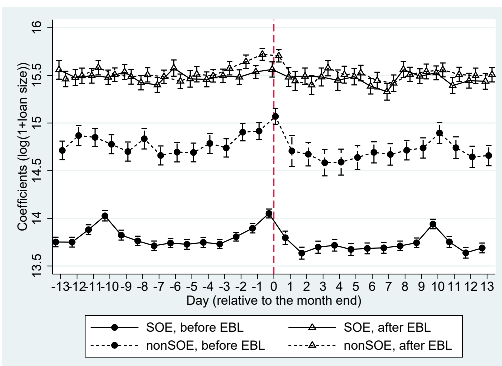
Figure A5: Sample splits by the enaction of the Enterprise Bankruptcy Law (EBL)



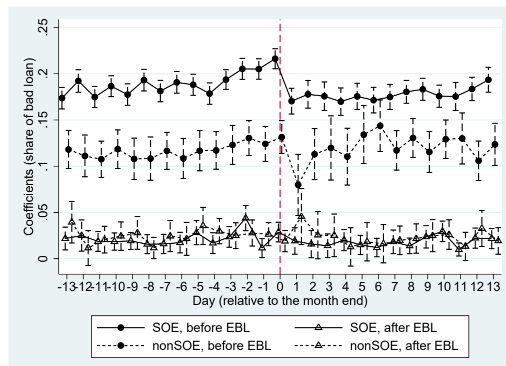
(a) Overall: $log(NewLoan)$



(b) Extensive: $Prob(anylending)$



(c) Intensive: $log(NewLoan|NewLoan > 0)$



(d) Quality: Share of bad loan

Note: dates more than +/-13 days away from the month end are excluded from the raw data graph.

Table A1: Loan Quantity and SOE Status, Extensive Margin

	Dependent Variables: Anylending					
	SOE status		(SOE status, repayment history)			
	SOE	nonSOE	(SOE, good)	(SOE, bad)	(nonSOE, good)	(nonSOE, bad)
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.0101***	0.0032***	0.0069***	0.0035***	0.0026***	0.0003***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
First 5 days	-0.0037***	-0.0012***	-0.0022***	-0.0015***	-0.0011***	-0.0000***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	0.015	0.004	0.009	0.006	0.004	0.000
# Observations	4992658	4992658	4992658	4992658	4992658	4992658
Adjusted R^2	0.019	0.012	0.012	0.014	0.011	0.002

Notes: *Anylending* is an indicator variable denoting that the branch b issued at least one loan to a firm in our dataset on date t. SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. In each specification, the reference group is the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A2: Loan Quantity and SOE Status: Intensive Margin

	Dependent Variables: ln(value of new lending)					
	SOE status		(SOE status, repayment history)			
	SOE	nonSOE	(SOE, good)	(SOE, bad)	(nonSOE, good)	(nonSOE, bad)
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.1463***	0.1985***	0.1329***	0.1071***	0.1992***	-0.0335
	(0.0132)	(0.0178)	(0.0163)	(0.0197)	(0.0188)	(0.0656)
First 5 days	0.0130	-0.0050	0.0308	-0.0146	0.0100	-0.1161
	(0.0153)	(0.0222)	(0.0193)	(0.0233)	(0.0233)	(0.0880)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	14.081	15.168	14.003	14.133	15.187	14.961
# Observations	74282	22169	47069	27956	19440	1402
Adjusted R^2	0.392	0.431	0.412	0.408	0.445	0.565

Notes: new lending is the value in RMB of new loans issued by branch b on date t. SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. In each specification, the reference group is the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3: Loan Quality and SOE Status without controlling for loan size

	Dependent Variables: share of bad loans					
	SOE status		(SOE status, repayment history)			
	SOE	nonSOE	(SOE, good)	(SOE, bad)	(nonSOE, good)	(nonSOE, bad)
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.0147***	0.0022	0.0149***	0.0175***	-0.0030	0.0306
	(0.0032)	(0.0042)	(0.0039)	(0.0052)	(0.0043)	(0.0252)
First 5 days	-0.0091**	-0.0078	-0.0053	-0.0140**	-0.0048	-0.0684**
	(0.0036)	(0.0058)	(0.0044)	(0.0061)	(0.0064)	(0.0271)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean(Dep.var)	0.167	0.085	0.155	0.195	0.077	0.215
# Observations	66651	16492	42454	24872	13967	1181
Adjusted R^2	0.212	0.396	0.199	0.305	0.401	0.490

Notes: Share of bad loans is the fraction of loans issued by branch b on date t that eventually are classified as bad (see text for details). SOE firms are defined as firms owned or controlled by the state. Repayment status of a firm is defined as bad if at least one of the borrowers previous loans was classified as bad, and good otherwise. The reference groups are the middle 5 (13–17) days of the month. OLS estimates, standard errors are clustered at the city level. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.