Target setting and Allocative Inefficiency in Lending: Evidence from Two Chinese Banks

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Abstract

We study the consequences of month-end lending incentives for Chinese bank managers. Using data from two banks, one state-owned and the other partially privatized, we show a clear increase in lending in the final days of each month, resulting from both more loan issuance and higher value per loan. We estimate that daily lending is 92 percent higher in the last 5 days of each month as a result of loan targets, with only a small amount plausibly attributable to shifting loans forward from the following month. End-of-month loans are 1.6 percentage points (12 percent) more likely to be classified as bad in the years following issuance relative to mid-month loans. Our work highlights the distortionary effects of target-setting on capital allocation, in a context in which such concerns have risen to particular prominence in recent years.

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1 Introduction

Many organizations provide performance targets to motivate workers and managers. This leads to a classic tradeoff — performance targets yield more effort, but possibly at the expense of distortions to the type of effort. One commonly described concern involves intertemporal shifts in the quality and quantity of effort in order to hit period-end targets.

While prior work has shown how target-setting by managers can distort employee effort or productivity across time – potentially at a cost to the firm – there is no obvious notion of efficiency that one may relate to the resultant distortion: Oyer (1998), in particular, shows how year-end targets lead to differences over the calendar cycle in the booking of sales revenues, and Larkin (2014) shows how non-linear incentives result in price cuts by salespeople that reduce the firm's revenues. While these findings indicate that there is a cost to the firm from high-powered incentives (to be weighed against any benefit) they do not necessarily imply efficiency costs.

In this paper, we study the loan portfolios of two large Chinese banks during the years 1997 - 2010. At the time, Chinese banks were reported to use month- and quarter-end loan quotas to motivate branch mangers, making it an apt setting to explore the effects of target-setting incentives on managerial decisions. Further, our focus on banking yields a natural measure of the efficiency consequences of targeting, since we may measure (ex post) loan quality as well as quantity. In particular, given the widely held belief that too much credit was available during our period of study, we argue that it is unlikely that the incremental lending that took place at month's end resulted in efficient capital allocation.

Our results are as follows: using two distinct data sets – one aggregated to the city level and the other at the level of the individual loan – we show that lending increases (via both more loans and larger loan sizes) as the final day of the month approaches, consistent with branch managers' need to hit month-end targets. 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 controls for national holidays, as well as the inclusion of 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. As one readily interpretable measure of the month-end effect, the probability that a branch makes a loan in the last 5 days of the month is 70 percent higher than the loan probability for a date in the middle of the month, while the loan probability in the first 5 days of the month is about 35 percent lower than mid-month. We also find that loans issued in the last 5 days of the month are, on average, 13 percent larger than those issued mid-month, leading to an overall end-of-month lending increase of about 92 percent.

This pattern suggests that branch managers may not simply be shifting loans forward in time but rather lowering end-of-month lending standards to meet their targets. We verify that this is the case using our loan-level data, which includes information on loan quality, to show that a month-end loan is more than 1.6 percentage points (12.8 percent) more likely to be classified eventually as a bad loan.

Given widespread concerns about excess leverage in the Chinese economy (as we document below China's debt-to-GDP ratio in 2018 was 255%, more than twice the emerging markets average), and the fact that most lending was directed toward the relatively unproductive state sector (Song *et al.* (2011), we argue that our results strongly suggest that the loan quantity targets set by the Chinese banks we study lead to distortions in the credit market. We present a back-of-the-envelope calculation which suggests that the overall size is large, with month-end targets resulting in the range of 5 billion dollars' (RMB 36 billion) worth of additional loan defaults by Chinese banks annually (assuming the state bank we study is roughly representative of other Chinese banks).

Most directly, our paper builds on the small body of research which studies empirically the effects of target setting in organizations. In particular, our work contributes to the small set of empirical papers that look at distortions created by targets or other non-linear incentives. These papers show that, across a range of settings and outcomes from accounting manipulation (Healy, 1985) to navy recruitment (Asch, 1990) to corporate sales (Oyer, 1998; Larkin, 2014), individuals manipulate the timing of results (e.g., booking sales early) and distort prices (as in Larkin (2014)) in order to hit targets or otherwise exploit non-linearities in their incentives. Our work is also related to the recent work of Liebman and Mahoney (2017) on year-end budget effects in U.S. government procurement. In a rather distinct setting, their findings parallel our own — they find that a much larger fraction of I.T. contracts are awarded at the end of the fiscal year, and that contracts awarded at year's end perform much more poorly. Our paper — which we see as complementary to these earlier efforts — has a number of distinctive elements. In contrast to earlier work on responses to non-linear incentives, we are better equipped to explore the efficiency and welfare consequences of period-end targeting, because of our focus on lending, which has a natural metric – default – for evaluating the economic consequences. Furthermore, given concerns that bad debt is building up in China, our finding that targets lead to more (bad-quality) loans is of direct policy interest. (The work of Liebman and Mahoney (2017) does not examine targeting as an incentive tool, but rather the distortions resulting from "use-it-or-lose-it" budgeting. Further, their analysis is for public sector budgeting, whereas we examine the responses of managers in a pair of banks, one of which is partially privatized, for which profit motives should, at least in theory, lead to efficiency-enhancing incentives.[1])

More broadly, our work connects to the vast literature on the distortionary effects of performance incentives which spans a range of social scientific disciplines. Within economics, this work is grounded in the foundational theoretical contributions of, for example, Baker (1992), Hölmstrom (1979), and Holmstrom and Milgrom (1991), while empirical applications have considered an array of settings in a range of organizational types. The results have been mixed, with some papers finding that target-setting improves performance without discernable side-effects on other dimensions of performance (e.g., Propper *et al.* (2010)), while others find that incentives lead to distortions in behavior and/or reporting of results (e.g., Gulati *et al.* (2016)). Most directly related to our work is that of Agarwal and Ben-David (2018), which documents the lower loan quality and greater reliance on hard information that results from high-powered incentives among managers. We similarly document a worsening of loan quality from incentives, focused on a setting in which there is plausibly excess lending, and resulting from non-linear (rather than high-powered versus weak) incentives.

In the next section, we provide a simple model to capture the essentials of end-of-month lending incentives faced by bank managers, to highlight the intuition behind our results: a forward-looking branch manager who faces monthly quantity incentives will lower his lending standards as month's end approaches. In our model, lending targets can lead to monthly lending cycles, even in the absence of present-bias or other 'behavioral' traits, as a framework for interpreting our results (though we emphasize that our main purpose is to present the empirical patterns rather than discern between standard versus "behavioral" explanations).

We describe the setting and the two distinct data sets we have collected in Section 3. We then present our analysis of the monthly cycle in lending in Section 4, both for the quantity and quality of loans. Section 5 concludes.

2 A simple model of lending quotas

We present a highly stylized model of credit provision to illustrate the intuition behind the monthly cycle in loan quantity and quality that may result from lending targets. As we document in the next section, the financial press has discussed the existence of such incentives for bank branch managers, and they became of sufficient concern as to raise concerns from government regulators. Our purpose in providing this model is to highlight that, within a

[1]Indeed, one might argue that to the extent that public sector procurement in the U.S. is captured by special interests, end-of-year budgeting with minimal oversight may be in the best interests of bidders.

transparent and straightforward framework, monthly lending cycles may exist even when the branch manager has correct beliefs about the distribution of loan applicants he will face, and without the presence of short-sighted lending officers (as in, for example, Cadena *et al.* (2011)).

Consider a two-period model in which loan officers are compensated based on the profitability of the loans they make, $p(repayment) * (1 + r) * Loans - Loans$. To focus on the incentives that are particular to lending targets, we assume no adverse selection or moral hazard. In the model, the loan officer takes the interest rate r as given which, as we argue in the next section, reflects the actual circumstances of loan officers in our sample. To further simplify our setup, we model the branch manager as receiving a single loan application of size 1 in each of the two periods (as such, we ignore the intensive margin of lending, which we will consider in the empirical analysis that follows). Finally, to simplify even further, we add the assumption that the first period loan must be made on receipt (i.e., before observing the second period application), though we show in Appendix A that our main results go through if the loan may be held in reserve until the second period.

The setup allows us to add a particularly straightforward lending quota, by requiring that the bank loan officer make at least one loan across the two periods. We assume a random arrival of loan applicants drawn from a uniform distribution of repayment probability, $[0, 1]$. The bank officer knows the distribution of borrower quality, and can observe p (based, for example, on prior credit history and the loan application).

It is straightforward that in the absence of the lending quota the loan officer will offer a loan if and only if $p \geq \frac{1}{R}$ (where $R = 1 + r$). In the last period, this will then be the decision rule if a loan has already been made. If no loan was made in the first period, then the decision rule is simply $p \geq 0$, since the quota is binding.

The second period expected payoffs then determine the first period decision rule. The loan officer makes a loan in the first period if and only if $\pi_{loan} > \pi_{noloan}$, taking into account the implications for the second period of fulfilling the quota in the first period:

$$Rp - 1 + \int_{\frac{1}{R}}^{1} [Rq - 1]dq > \int_{0}^{1} [Rq - 1]dq$$

This simplifies to a cutoff of:

$$p^* = \frac{1}{R}\left(1 - \frac{1}{2R}\right)$$

This expression defines both the probability of loan provision as well as the default probability, since the two move linearly in opposite directions in our model.

We may now calculate the probability of a loan in the second period (and as noted, by extension, the default probability). The probability that *no loan* is made is given by:

$$(1-p^*)\left(\frac{1}{R}\right)$$

This may easily be compared to the first period probability that no loan is made, as follows:

$$(1-p^*)\left(\frac{1}{R}\right)=\left(1-\frac{1}{R}-\frac{1}{2R^2}\right)\frac{1}{R}<\frac{1}{R}\left(1-\frac{1}{R}\right)<p^*$$

Thus, the probability of a loan is strictly higher in expectation in the second period (and the probability of default also strictly higher).

We emphasize that our objective in providing the model is to clarify how, in the absence of naive and/or shortsighted agents, a lending quota can nonetheless lead to a lowering of lending standards across a monthly cycle.[2] In our setting, it is because the loan officer trades off the option of waiting for the arrival of a higher value borrower in the second period against the benefits of loosening the quantity constraint earlier on. For reasonable assumptions on parameters, the benefit of waiting strictly outweighs the cost of having to lend to a low-quality borrower as the end of the month approaches. As a result of loan officers holding out for better borrowers by month's end, the average quality of month-end lending declines, while the quantity increases as loans are pushed out the door to meet the quota.

We finally observe that the lending quota increases the probability of lending even in the first period, relative to the no-quota benchmark. Thus, to the extent that we measure the effect of quotas based on comparisons in loan quantity and quality across the monthly cycle, we may underestimate the overall effect of lending quotas.

The model does not itself indicate whether incentives lead to inefficient allocation – it depends on whether there is an efficient quantity of lending in the absence of quotas. If, for example, bankers' risk aversion or spillovers from economic activity generated by new investment mean that there is insufficient lending, quantity incentives would be a natural way of promoting credit provision. If lending is optimized or even excessive in the absence of quantity incentives, month-end quotas will worsen the problem. Given the narrative we describe at the outset of the next section, we argue that the weight of the evidence is in line with incentives exacerbating the problem of excess credit.

[2] One *can* similarly get an end-of-month spike in lending as a result of short-sighted choices by "behavioral" agents, but our model shows that one does not have to resort to non-standard assumptions in order to get monthly credit cycles.

3 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 2018, totalling an estimate of 228.9 trillion RMB (255% of GDP) in at the end of this period. The leverage ratio is twice as high as the average of emerging market economies excluding China. [3] 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.[4] Furthermore, as we document below, most of the lending in our data goes to state enterprises, which a large literature has documented as having relatively low productivity (see, e.g., Song *et al.* (2011)). Given these facts and patterns, we take as very likely that on the margin increased lending (with higher default) would not be welfare-improving.

We obtained data from two large Chinese banks, one partially privatized through a public offering and the other state-owned (referred to as the "private bank" and "state bank" respectively hereafter).

Both banks that we study have similar geographic structures. Within each bank, there are two types of branches: one main one for each city ("Fen Hang", or main branch, in Chinese) and smaller outposts located in counties within the city ("Zhi Hang", or sub-branch, in Chinese). For our private bank, all loans outstanding within a city (from both the main branch and sub-branches) were provided to us as city-level aggregates, so that we have a measure of total city-level lending for each day. For the state bank, we have data on individual loans, which we aggregate to the branch-level (separately for the main branch and each sub-branch). Thus, we will use city-level data in our analysis of the private bank's lending patterns, and branch-level data in our analysis of the state bank's lending.

For the private bank, this leads to a total of about 200 city-level aggregates of loans outstanding updated daily over the period January 2006 – June 2010. For the state bank, we obtained a sample of business loans made by each branch (both main and sub-branches), which number more than 1500. We do not list the precise number of cities or branches for each dataset as a way of shielding the banks' identities.

For the state bank, the loan-level sample was constructed as follows: for each branch, all firms which 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

[3]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

[4]See, for example, `http://www.xinhuanet.com//english/2017-07/09/c_136430117.htm`

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.)

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. From the private bank, we have obtained one "illustrative" evaluation formula, which incorporates a range of considerations, including costs, revenues, as well as more subjective outcomes such as employee evaluations. In the particular formula we were provided, "operating scale" is given a weight of 40 percent, while "operating performance" is given a weight of 60 percent. Non-performing loan rates are given a 10 percent weight within the "operating performance" criteria while total lending is weighted by 80 percent for "operating scale." While these criteria may vary over time and across regions, it indicates the potentially offsetting incentives to increase lending while maintaining a manageable default rate, though in this instance with greater weight on increased lending.

The formula described above does not explicitly account for monthly quantity targets (despite including some weight on quantity). However, the potential existence of such targets (and associated month-end increases in lending) has been noted by observers in China's financial press.[5] This issue of month-end targets did not go unnoticed 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.[6] This was followed in late September 2009 by a "window guidance" (effectively 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."[7] The article went on to describe various means by which banks can

[5]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://finance.people.com.cn/bank/GB/16558526.html` last accessed June 17, 2019), and "Banks pursue risky deposits at month's end," *First Financial Daily*, September 28, 2012 (`http://www.yicai.com/news/2114112.html` last accessed June 17, 2018); titles have been translated from Mandarin by the authors, both here and below.

[6]See `http://www.fsou.com/html/text/chl/1546/154692.html` (last accessed June 17, 2019) for the full text of this statement. The directive against end-of-month (and end-of-season) lending is in Article 3.

[7]"Regulators to strengthen window guidance to suppress banks' end-of-month red credit," *Se-*

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.

Beyond managerial incentives, there also could be a regulatory rationale for end-of-month lending. During the period we study, the CBRC had in place a deposit-to-loan ceiling of 75 percent, which was first set in its Commercial Banking Law issued in 1995, and later repealed under revisions to the law in 2015. Prior to June 2011, the CBRC only examined end-of-month ratios.[8] Because new loans appeared at least initially as deposits at the bank, one way of inflating the deposit-to-loan ratio in the short run was to issue loans late in the month, so that the funds were less likely to have been spent on the last day of the month (relative to loans issued early in the month). Note that this constraint binds at the bank (rather than branch or sub-branch) level, so that any incentives for increased end-of-month lending at the branch- or sub-branch-level would have to be the result of informal delegation to branch managers. It also appears that the deposit constraint was never binding for the private bank we consider here – across all branches, the deposit-to-loan ratio never rose above 70 percent during our sample period (we avoid giving a specific maximum as this would identify the bank). We will thus focus on managerial incentives rather than regulatory constraints in driving end-of-month lending in our results and discussion below. In closing, we also note that hitting end-of-month deposit-to-loan ratios has more obvious implications for loan timing rather than loan quality; the results we present on end-of-month decline in loan quality in Section 4 further indicate that regulatory incentives are unlikely to be the main driver of the patterns we document.

In the next two subsections, we provide a more detailed overview of each data set – first the private bank's city-level data set, followed by the state bank's loan-level data, as well as

curities Times, September 25, 2009 (`http://business.sohu.com/20090925/n266989261.shtml` last accessed June 17, 2019)

[8]Realizing that banks may manipulate these end-of-month ratios, in 2011 the CBRC set requirements based on the daily average deposit-to-loan ratio within each month.

its aggregation to the branch level.

3.1 Branch-level data from a private bank

The private bank provided daily balance sheets aggregated to the prefecture (city) level for the period January 2006 – June 2010. For each city-day, we observe the balance of total cumulative loans. The outcome we employ to capture efforts at hitting loan quantity targets is the change in the natural logarithm of cumulative loans outstanding ($\Delta log(Loans_{ct})$), where c indexes city and t the date.

We present summary statistics for the city-level data in Panel A of Table 1. Over our sample period, the mean (median) level of city-level cumulative loans outstanding is 106.19 million RMB (43.95 million RMB).[9] Observe that the average rate of change in lending is very low – of the order of 0.056 percent – though this aggregates up to a monthly average of about 1.7 percent. Additionally, we note that for just over 30 percent of city-day observations, loans outstanding is unchanged (17 percent if we exclude weekends and national holidays). As we will see shortly, this rate is much higher for our loan-level data set when we aggregate up to the branch-day level, since the loan-level data reflect lending to a subset of borrowers, and only for business (rather than individual) customers.

3.2 Loan-level data from a state bank

The loan-level data set contains a sample of more than 300,000 business loans issued by both its main and sub-branches, spanning the period 1998 – 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 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.

[9] To obtain the approximate U.S. dollar value one may divide by 7.

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.[10] (The two highest categories are "normal," in which case interest 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.)

Panels B and C of Table 1 contain summary statistics for our loan-level data, aggregated to the branch-level. In Panel B, we present summary statistics for a balanced panel of new loans issued, aggregated to the branch-day (bt) level. As is clear from the mean of $Prob(AnyLending_{bt})$, most branch-day observations include no new lending. This is in large part because, as noted previously, our loan data represent only a fraction of the overall lending portfolio of the bank. We will therefore need to scale up any effect size we measure to account for the fact that we are estimating month-end effects from a subset of the overall data.

Panel C of Table 1 shows 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 response to month-end incentives (i.e., does lending increase (via higher loan size or more loan contracts), conditional on a loan being made) as well as loan quality responses.

4 Results

4.1 End-of-month effect on loan quantity

For changes in loan value, we may utilize both our city-level and loan-level (aggregated to the branch-level) data sets. Recall that the city-level data set has the advantage of including

[10] 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.

all loans outstanding in a city on a given day, whereas the branch-level data set includes detailed data on all new loans issued to a random sample of the bank's borrowers. We will find it reassuring in what follows that we find broadly similar patterns in the data from both banks.

We present first the results from our city-level data, using a pair 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 allows us to capture changes in lending over the full range of a monthly cycle for months of any length.[11] Figure 1a shows $\Delta log(Loans_{b,d(t)}$, averaged over all branches b on dates t that fall on the day-of-the-month $d(t)$. The data show an average growth in lending on the final day of the month ($d = 0$) that is twice as large as any other day in the monthly cycle. In these data, we do not observe any evidence of loan-shifting from the beginning of one month to the end of the previous one, since lending at the beginning of the month is, if anything, slightly higher than at other times in the monthly cycle.

We next look at the pattern of lending over the month after netting out day-of-the-week fixed effects, month-year fixed effects, and city fixed effects. Specifically, we run the following regression:

$$\Delta log(Loans_{ct}) = \sum_{d=-13}^{13} \beta_d * I(d(t) = d) + dow_t + ym_t + city_c + \epsilon_{ct} \tag{1}$$

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 $\times$ year (ym_t), and city ($city_c$). To calculate confidence intervals on the coefficients, we cluster at the city-level. Figure 1b plots the regression coefficients, $\{\beta_{-13}, \ldots, \beta_{13}\}$, along with 95 percent confidence intervals. The patterns are virtually identical to those in Figure 1a.

We next turn to a graphical depiction of the patterns in our much richer data on lending from a state bank. Since the loan-level data provide information on new loan issuance, we do not have a ready measure of the stock of loans outstanding at each branch to measure a rate of change in lending. Furthermore, the data are much sparser than for the city-

[11] 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.

level data, with 98 percent of branch-date observations taking a value of zero. We thus use $log(1+NewLoans_{bt})$ to measure the overall flow of new borrowing at the branch-day level, so that zero values are defined. (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). [12]

We begin by graphing in Figure 2 the coefficients generated by a regression that follows the form of Equation 1, using $log(1+NewLoans_{bt})$ as the outcome variable (and clustering at the branch level for calculating standard errors; our standard errors are smaller in general if we cluster at the city level).[13] As before, we include day-of-the-week (dow_t) and month × year (ym_t) fixed effects. We include also city fixed effects.[14]

We once again observe an end-of-month spike in lending, this time clearly discernable in the last few days of the month. We also see a below average rate of lending at the beginning of the month. In our model, this is the result of more stringent lending standards early on, as loan officers exercise the option of waiting for higher-quality loan applicants to arrive later in the month. It could also result from branch managers shifting loans forward in time in order to make month-end quotas. Note, however, that the latter interpretation necessarily invokes a very high degree of short-termism for the bank officer, as it exacerbates the target problem in the following month. (We return to how this might affect the interpretation of our estimates below, though with the strong caveat that it requires an assumption of extreme short-run discounting and/or procrastination. Additionally, as we will argue shortly, the shifting of loans from the following month is harder to reconcile with the monthly cycle in loan quality that we document in the next section.)

Our loan-level data allow us 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 3, 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

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

[13]As with the private bank graphs above, the unconditional patterns over the month are very similar to those based on regression coefficients. We present this graph in Appendix Figure B2.

[14]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 B1 we show the monthly cycle with branch fixed effects included, and find that it is virtually identical.

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).[15]

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 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). The intensive margin graphs also show a substantial increase in the size and number of loans at ± 10 days (there is also an increase – albeit a relatively small one – in the extensive margin that is discernable in Panel A). While we did not predict this feature of the data in formulating our hypotheses, subsequent discussions with bank employees indicate that, at least informally, managers are also evaluated on the tenth and twentieth days of each month, which might account for these additional spikes. (Consistent with these interim evaluations appearing on the tenth and twentieth days of each month, the latter effect – which appears spread over two days in Panels B and C – appears more decisively on day 20 if we examine months with 30 and 31 days separately, or adjust our graphs to go from -5 to 22 days around the end of each month, rather than a ± 13 day window.)

In Table 2, for both the city- and branch-level data, we present the month-end effect in a regression framework which will allow us also to generate simple back-of-the-envelope calculations to gauge the magnitude and potential consequences of incentives to make month-end loans. Specifically, we focus on lending in the first and last 5 days of the month relative to the rest of the month: [16]

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

[15]We plot the analogous figures based on the raw data in Appendix Figure B3.

[16]Note that in this specification the number of days in the reference groups vary across months depending on the months' length. We present in Appendix Table B1 an alternative specification where the reference groups are the middle 5 days (13–17) of the month and the results are very similar.

The main variables of interest are $Last5Days$ and $First5Days$, indicator variables which denote the first and last 5 days of each month.[17] The results from specification 2 appear in columns (1) and (2) for the city- and branch-level data respectively. While the coefficients for the last-5-days average effect are very similar, it is clear from visual inspection of Figures 1b and 2 that much more of the end-of-month effect in the city-level data is concentrated on the final day of the month. For the branch-level analysis, the coefficient on $First5Days$ is negative, though only about a half the size of the estimated end-of-month effect.

Columns (3) – (6) 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 size is somewhat larger for the extensive margin: the coefficient of 0.012 on $Last5Days$ in column (3) indicates that the probability of a loan issuance at month's end is about 70 percent greater than during the middle of the month (which is 0.0172 on average), whereas the coefficient in the loan amount specification of 0.123 (column (4)) implies an increase in lending (conditional on at least one loan) of 13 percent ($exp(0.123) - 1$). 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 3.9 percent larger than a mid-month loan (column (5), since $exp(0.038) - 1 = 0.039$), while conditional on the issuance of at least one loan, the results in column (6) indicate that the number of loans is 8.9 percent larger at month's end.

Turning to the beginning-of-month effect, for the extensive margin we find (as with the overall effect) an effect size that is of the opposite sign and about a half of the magnitude of the end-of-month effect. We also observe a negative beginning-of-month effect that is about a third of the magnitude of the end-of-month effect for the intensive margins.

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 70 percent (0.012/0.0172), and conditional on the issuance of at least one loan, total lending increases by approximately 13 percent, indicating an overall end-of-month lending effect of just over 92 percent ($1.7 \times 1.13 - 1$). We reiterate that, in our model, the interpretation of

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

this increase in lending comes from a loosening of lending standards as the month progresses. The primary alternative interpretation – that end-of-month lending increases in part through a shift in loans from the following month – requires further assumptions of extreme short-termism on the part of loan officers, since it shifts his problem forward (and possibly makes it worse) by a month. In the next section, we will look at the monthly cycle in credit quality, which will further help us to rule out the "loan-shifting" hypothesis.[18]

To conclude our discussion of the end-of-month effects on credit quantity, we observe that while there are some distinct elements to the patterns in the two data sets we employ in this section, our overall takeaway is that both provide evidence of a robust month-end increase in lending; from our analysis of the loan-level data we may further conclude that this increase comes from both extensive and intensives margins.

4.2 End-of-month effect on loan quality

There are several primary ways that a bank manager might generate higher month-end lending. In our illustrative model, the loan officer loosens lending standards at month's end, making loans that, on the margin, would not be made were it not for the need to meet a month-end target. But he may also exert more effort to attract loans at month's end (and exert less effort at the beginning of each month), holding lending standards constant. Finally, as we have noted previously, he may shift the timing of already-approved loans forward, to make loan issuance occur before month's end.

One natural way of distinguishing among these various mechanisms – each of which has very different consequences for both loan profitability and capital allocation efficiency – is to look at the monthly cycle in loan quality. We present in Figure 4 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 measures of loan quality are 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).

[18]There is a version of loan-shifting that may be consistent with our data thus far, even without short-term planning, to the extent that bank managers shift loans from the following month to the current one in order to have the option value of finding new lenders in the next month. In a variant on the model in the Section 2, this will lead to a (perhaps slightly) lower lending standard in the next month, which will not be picked up by our analysis of monthly lending cycles. While we cannot fully rule out this possibility, we make a few observations on its plausibility and implications. First, this variant on loan-shifting still does not predict an improvement in loan quality at the beginning of each month, which we document in the next section. Second, this loan-shifting variant does lead to a decline in lending quality, but is one that would not be discernable via a monthly lending cycle.

We show the monthly cycle of the share of bad loans, weighted by loan amount, in Figure 4. Intriguingly, the pattern roughly parallels that of Figure 2, with an increase in the final few days of the month in the fraction of lending that is ultimately categorized as bad.

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 **??**, we present a disaggregated version of Figure 4, 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 directly from the shift to larger loans.

In Appendix Figure B5, we present a pair of alternative specifications to explore the robustness of the month-end increase in bad loans: Panel A uses the fraction of bad loan contracts (rather than fraction of loan amount) as the outcome variable, while Panel B shows the pattern for the raw data rather than estimated coefficients. The general pattern is very similar in these variants.

Again paralleling the presentation of results in Section 4.1, we show coefficients derived from regressions as specified in Equation (2), with our measure of loan quality as the outcome variable, and including city, day-of-week, and month-year fixed effects. These results appear in column (7) of Table 2. As already suggested by the patterns in Figure 4, the ratio of bad loans increases in the final few days of the month, roughly coinciding with the increase in lending. Once again, the estimated beginning-of-the-month effect on credit quality is of the opposite sign and half the magnitude of the end-of-month effect.

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.

We reiterate that our findings do not necessarily imply inefficiency unless the economy is over-leveraged. However, as we emphasized at the beginning of Section 3, the excess supply of low-quality loans is a well-recognized risk to China's economy during the period we study. Thus, in this context, the month-end incentives we have documented very plausibly contribute to and/or exacerbate the problem of excessive lending, leading to efficiency loss in the lending market.

4.3 Additional analyses

4.3.1 Robustness of the main results

In Appendix Tables B2 and B3, we present analyses that demonstrate our results' robustness to further controls. For the sake of brevity, we show the robustness via tables based on Equation (2) (the patterns we show in the Figures in the previous two sections are also unaffected by the inclusion of these controls). Appendix Table B2 includes dummy variables for each of China's national holidays (e.g., Chinese New Year, Labor Day, and the Dragon Boat Festival) and weekends, a total of approximately 116 days per year.[19] In Appendix Table B3 we show the results of a saturated specification that includes fixed effects for every city $\times$ month $\times$ year group. In both tables, we still observe significant end-of-month effects for both loan quantity and quality.

Finally, In Appendix Figure B6, we plot a number of other borrower characteristics around month's end. We look in particular at total assets, cash-to-assets, liabilities-to-assets, net-profits-to-assets, cashflow-to-assets and the Altman's Z-score.[20] Only total assets exhibits a monthly cycle, with larger borrowers appearing at month's end. The most straightforward interpretation of this result is that larger borrowers are better able – all else equal – to shoulder higher loans, and hence this simply reflects the intensive lending margin results we document above. Overall, the lack of clear monthly cycles in other borrower attributes emphasizes that monthly cycles are particular to loan quality and quantity.

4.3.2 Heterogeneity

We explore several dimensions of heterogeneity in monthly lending cycles in our loan-level dataset. The first two capture differences in borrower attributes: loans to those with positive versus negative borrowing history from the bank, and state-owned enterprises (SOEs) versus non-SOEs. We then explore heterogeneity as a function of differences in economic conditions in the areas where branches are located, based on local growth rates.

Focusing first on past borrower record, we split the sample of loans into those made to borrowers with at least one previous loan that was eventually classified as bad, and those made to borrowers who, to that point, had unblemished repayment records. In constructing this sample, two points are of note. First, our measure of past borrower performance is generated using our own data, so that loans made prior to 1998 are not incorporated in our

[19] 104 weekend days, and 12 national holidays until 2007, and 13 after.

[20] the Z-score is a weighted average of the following five terms: (1) current assets less current liabilities divided by total assets, (2) retained earnings divided by total assets, (3) earnings before interest and taxes divided by total assets, (4) book value of equity divided by total liabilities, and (5) sales divided by total assets.

assessment. (While we only have a subset of loans from the bank, recall that for a given borrower we have their complete loan history, so in this sense our measure of past borrower behavior does not suffer from missing data in the post-1997 period.) Second, the number of loans per firm is quite high – the median number of loans per firm is 21 – so that the chances that a given borrower has had at least one bad loan increases over time.[21] Note, however, that this should be absorbed by our year-month fixed effects, and in any event does not present an obvious confound to the monthly cycle that is our main interest.

In Figure 5 we split this sample based on whether the borrower had, to that point, had at least one bad loan. We do this to explore whether some of the month-end decline in loan quality results from branch managers making loans to borrowers with prior default, who have already shown themselves to be risky based on previous behavior. In panels (A) – (D), we present graphs paralleling Figures 2 – 4, showing the monthly cycles for each of these two loan types. In each graph, for each borrower group, we add back the mean of the dependent variable so that it is easy to discern whether the groups differ in their overall quantity and quality of credit. In the quantity figures (Panels A – C), the difference between the two groups is largely in their levels of borrowing: relatively little lending goes to borrowers with previous bad loans. The rate of lending to those with poor credit histories is considerably lower than the fraction of borrowers with bad loans overall — whereas nearly two thirds of repeat borrowers eventually have at least one loan that is classified as bad, only a quarter of lending to past borrowers goes to this group, indicating that branch managers do screen on past behavior in making loan decisions. Our main interest is in comparing the patterns across the monthly cycle, which is qualitatively similar for each group – each group sees an end-of-month increase in lending, along both the extensive (Panel B) and intensive (Panel C) margins.

Finally, in Panel D we look at bad loan rates for borrowers as a function of prior performance. Unsurprisingly, borrower repayment is correlated across loans – the bad loan rate is much higher for borrowers that had trouble repaying in the past. These patterns suggest that past repayment is informative of future reliability, so that the relatively low rate of lending to those with past bad loans is consistent with branch managers applying this information in screening for loan quality. Again, our main interest is in the monthly cycle in lending, which appears to show a month-end increase for both borrower types.

Overall, the differences based on past borrower behavior are consistent with the end-of-

[21] Given the high rate of repeat borrowing, there are relatively few loans to first-time borrowers in our sample. Because of their relative rarity, we omit first-time loans from our analysis, but when they are included they show similar monthly cycles to the overall sample – a month-end increase in lending quantity and a month-end decline in lending quality.

month effects coming from increases in lending to borrowers with both good and bad histories, rather than substantial shifts across groups with large average differences in reliability.

We next turn to examining differences in the monthly cycle for SOE versus non-SOE borrowers. This sample split is related to the previous one in the sense that SOE borrowers are perceived to be a higher credit risk for the bank. However, as a state bank it is under some obligation to provide financing to SOE enterprises. In Figure 6 we present four panels that parallel those in the preceding figure, splitting the sample by SOE versus non-SOE borrowers. Several patterns emerge. First, lending to SOEs is far higher than lending to non-SOEs overall, reflecting the bank's obligations to the state. The average loan size for SOEs is much smaller.[22]

As anticipated, default rates are far higher for SOEs. Focusing on monthly cycles, however, we again find no stark differences in end-of-month lending between the two groups: both experience a more than 10 percent increase in bad loans in the last 5 days of the month, relative to the mid-month benchmark (confirmed in regression analyses not shown). This finding may be related to the patterns we observed above as a function of borrower history: a disproportionate share of repeat borrowers with past bad loans are SOEs (96 percent, whereas SOEs constitute 82 percent of the overall sample), and given that we found no sharp differences in monthly lending cycles for borrowers as a function of their histories, the similar monthly patterns for SOEs and non-SOEs is perhaps unsurprising.

Overall, these findings suggest that, at least insofar as our two divisions of observable borrower risk are concerned, the increase in end-of-month lending (and decrease in end-of-month loan quality) is not driven by a disproportionate increase in lending to groups of riskier borrowers. Rather, loan quotas affect its quality threshold for all borrower classes, which is what we may expect if the bank has lending obligations to particular borrowers groups (i.e., SOEs).

In our final analysis we turn to examine whether lending patterns differ across prefectures with high versus low economic growth rates, by looking at cities at the top versus bottom quartile growth over the full sample period 1997 – 2010 (data on city-level growth come from *China Cities Statistical Year Book*). This may help us assess the extent to which the bank conditions its branch-level quotas on local economic conditions and hence credit demand. If central management fails to adjust for local circumstances, we may expect less end-of-month lending in high-growth cities, since branch managers do not need to boost lending to meet their quotas. If the requisite level of lending is branch-specific, we expect similar patterns for both high- and low-growth cities. We show the monthly lending patterns in Figure 7, panels

[22]SOEs borrowers also receive loans more frequently than non-SOEs, with comparable maturities, so that SOE borrowers may simply divide their borrowing into smaller increments.

A – D. The data once again show a consistency in the monthly cycle across groups: end-of-month increases in loan quantity and the bad loan rate appear for branches in both high and low growth cities. This is the pattern we would expect if quotas are set endogenously on the basis of anticipated local demand.

4.4 Estimating the overall impact of monthly lending incentives on loan quality and quantity

We may perform a set of simple back-of-the-envelope calculations to gauge the impact of end-of-month targets on the quality of the bank's loan portfolio. We begin by reiterating that, as we noted near the end of Section 2, our estimates plausibly provide a lower bound on the impact of targeting on loan quality. This will be the case if, as in our model, targeting lowers loan officers' quality thresholds even at the beginning of the month.

Our calculation in Section 4.1 suggests that lending quotas lead to a total increase in the quantity of lending at the end of the month of approximately 92 percent (a combination of both the extensive and intensive margin effects), relative to the middle of the month. We can similarly obtain an estimate of 38 percent for the decrease in lending at the beginning of the month. If we take observed beginning-of-month lending as an upper bound of what lending would be in the absence of loan targeting and use it as the benchmark, we get a lower bound for the end-of-month increase in lending from targeting of 210 percent ($(1+0.92)/(1-0.38)-1$); scaled by the begin-of-month and end-of-month periods each of 5 days, this corresponds to an extra 75 percent (the sum of 100% for the first five days, $\frac{1}{(1-0.38)} = 161\%$ for the middle 20 days, and 310% for the last 5 days, divided by a total of 30 days) in lending each month.

We may similarly estimate the decline in loan quality that comes from end-of-month targets as the difference between the end- and beginning-of-month coefficients in column (7) of Table 2, i.e., 0.021. Relative to the baseline bad loan rate of approximately 12 percent at the beginning of the month, this represents a 17.5 percent end-of-month increase. The bad loan rate of the *incremental* loans that result from lending targets is much higher than 17.5 percent: If we assume that, in the absence of targets, lending quantity and quality would be the same as in the first few days of the month, then the fraction of bad loans for the incremental lending that takes place at the end of the month, NPL, is defined by $(2.1 * NPL + 1 * 0.12)/3.1 = 0.125 + 0.016$, so that $NPL = 0.151$, or more than 25 percent higher than the 12% in the first few days.

We may finally calculate the overall effect that end-of-month lending has on the bank's total loan portfolio. Accounting for both the higher quantity of lending as well as the higher bad loan rate at the end of the month, we obtain an overall bad loan rate of $(0.12 * 1 * 5 +$

$0.125 * 1.61 * 20 + 0.141 * 3.1 * 5)/(1 * 5 + 1.61 * 20 + 3.1 * 5) = 0.129$ [23] Thus, end-of-month lending incentives increases the bank's bad loan rate by 0.9 percent (relative to the baseline of 12 percent at the beginning of the month).

If we account for the total loan portfolio of the bank, this multiplies up to RMB 4.5 billion in bad loans annually, given the bank's lending volume of approximately RMB 500 billion.[24]

There are reasons to think that the banks we analyze in this paper share a number of salient features with Chinese banks more broadly: as with the banks we study, the government owns or holds a substantial stake in most lending institutions in China. Furthermore, the discussion of target-setting in the media (see Section 3), as well as the government response to it, suggests that the phenomenon we study was a ubiquitous phenomenon. If we thus make the assumption that the banks we study (and their target-setting policies) are roughly representative of Chinese banks in general, monthly lending quotas may account for an extra RMB 36 billion in bad loans (based on the reported change in cumulative loans outstanding in China overall in 2010, which was RMB 4 trillion).

We reiterate a couple of caveats in interpreting the figures in this section. First, our estimates in this section may be seen as a lower bound on the impact of targets on the quantity and quality of the bank's loan portfolio: the impact of loan targets will be higher if we consider the possibility that targets also lead to more lending even at the beginning of the month, as discussed in our model section. Thus, in the context of the framework in Section 2, the estimates serve as a lower bound on the actual impact of targets on loan quality. Finally, we emphasize that, in coming up with an overall figure for credit distortion in the preceding paragraph, we are extrapolating on the basis of a single bank, albeit one that shares salient features with other Chinese financial institutions.

5 Conclusion

In this paper, we document a clear monthly cycle in lending at two large Chinese banks: credit quantity increases sharply near the end of each month, and lending quality declines. We suggest that these patterns are most easily explained by bank managers' efforts to hit

[23]To understand where this overall rate comes from, recall that 0.125 is the bad loan rate at the middle of the month, 1.61 is the amount of lending in the middle 20 days of the month (relative to the beginning of the month); 0.12=0.125-0.05 is the bad loan rate at the beginning of the month; 0.141=0.129+0.016 is the bad loan rate in the last 5 days of the month and 3.1 is the amount of lending in the last 5 days relative to the beginning of the month

[24]This figure is estimated based on average annual lending value over the period 1997 – 2010 in the sample, which is RMB 100 billion. Given that we sample just over 20 percent of borrowers, we multiply by 5 to obtain the estimated total loan portfolio of the bank.

monthly lending targets, as captured in the simple illustrative model we provide to motivate our analysis. The effects we document are very large – a back-of-the-envelope calculation suggests that lending is 210 percent higher in the last 5 days of each month as a result of loan targets, and the fraction of bad loans among the incremental loans made to hit monthly targets is more than 25 percent higher than the middle of the month. Our findings thus highlights the efficiency tradeoffs inherent in designing managerial incentives.

While it is beyond the scope of our data and analysis to make any decisive welfare 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 target-setting to increase loan quantity contributes to the capital misallocation that has raised concerns about the longer-term sustainability of China's economic boom. While the overall increment in bad loan rate we calculate is modest, when aggregated over banks' total loan portfolios the resultant misallocation runs into the billions of dollars, from this one channel alone.

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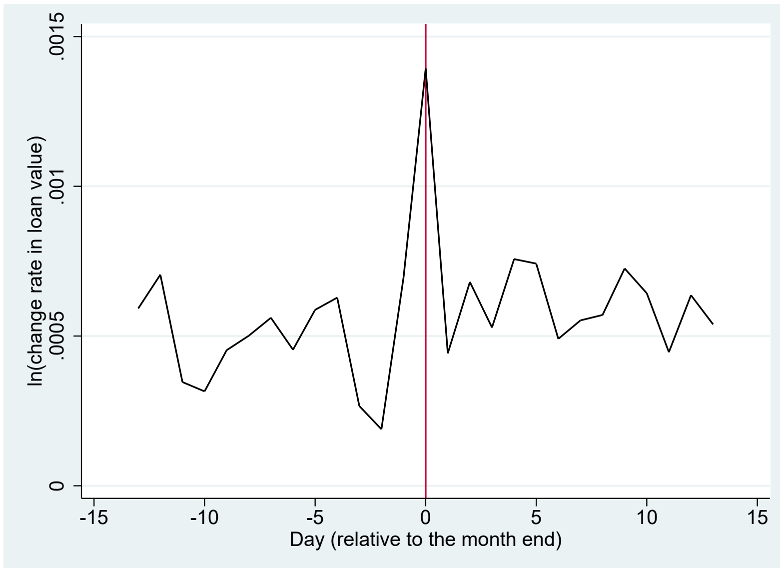
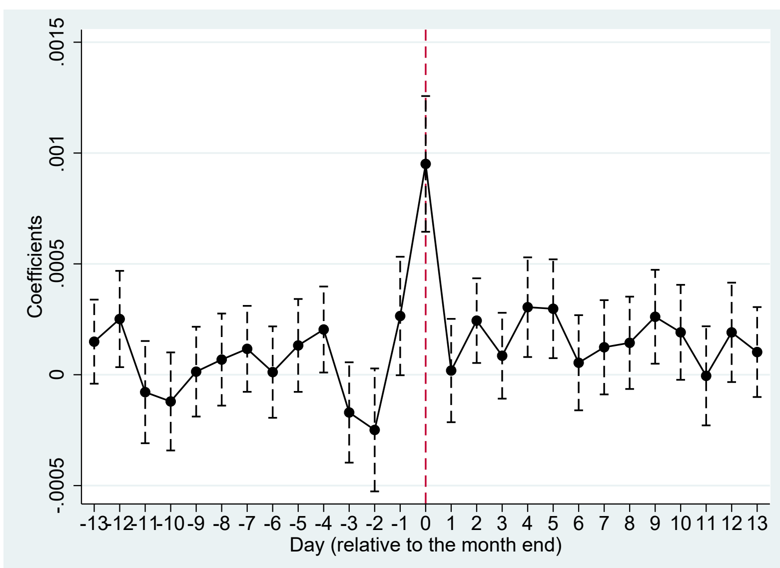
6 Figures and Tables

Figure 1: Log Changes in Loan Value (City-level data)



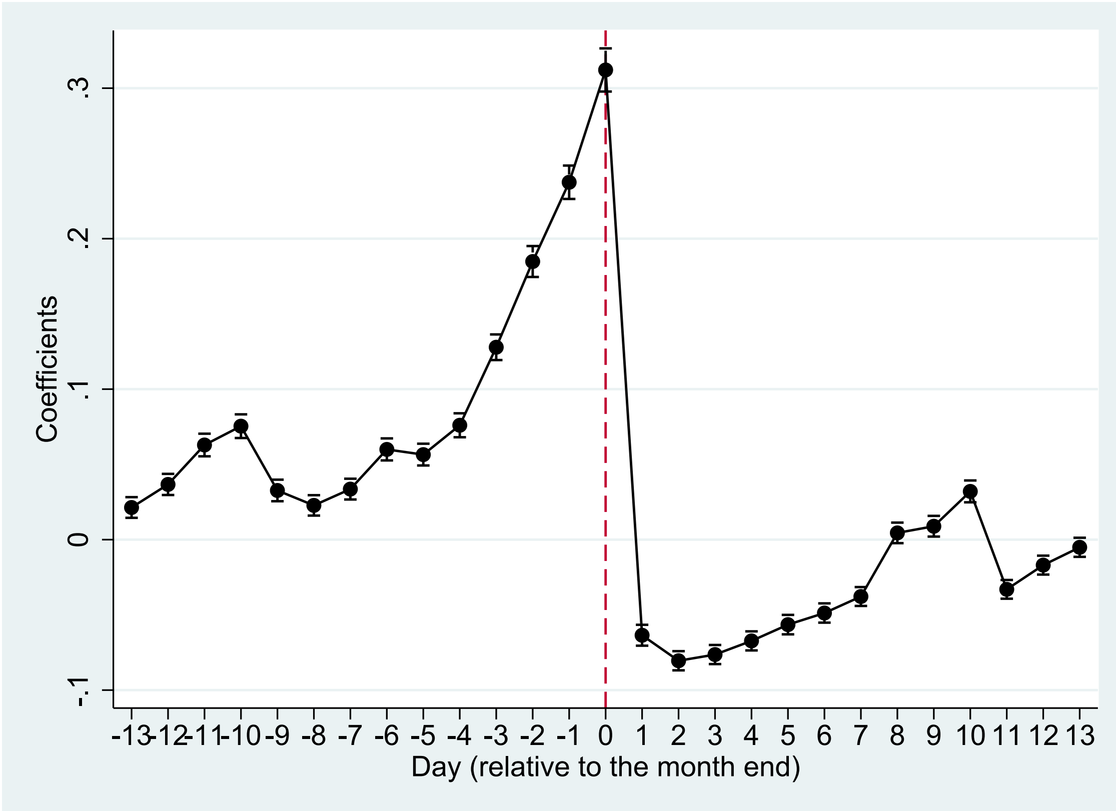
(a) Raw plots



(b) Coefficients plots

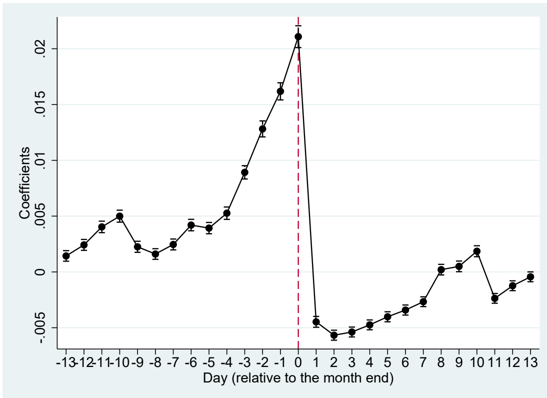
Note: dates more than +/-13 days away from the month end are excluded from the raw data graph; days outside of the +/-13 day window are the omitted category in the coefficient plots, which are conditional on year-month, day-of-week, and city fixed effects. Standard errors are clustered at the city level.

Figure 2: Value of New Lending Issued, Coefficients Plots (Branch-level data)

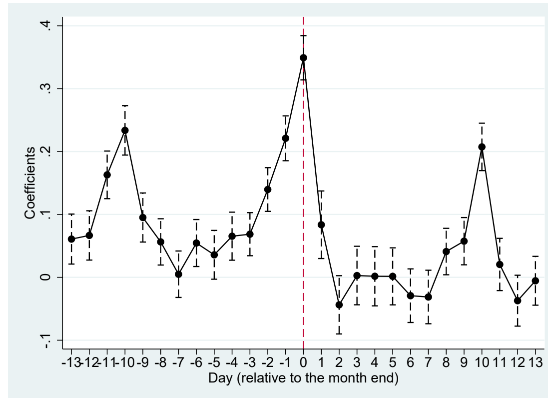


Note: dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

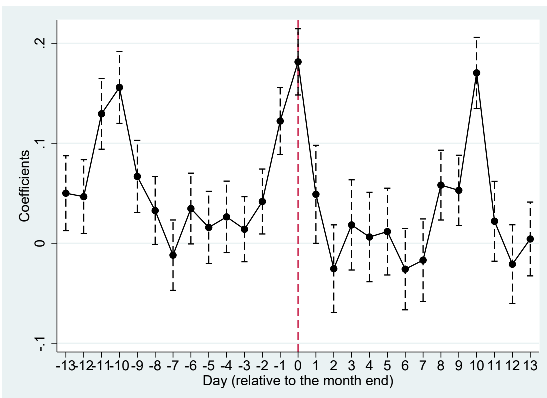
Figure 3: Extensive and Intensive Margins of New Loan Issued



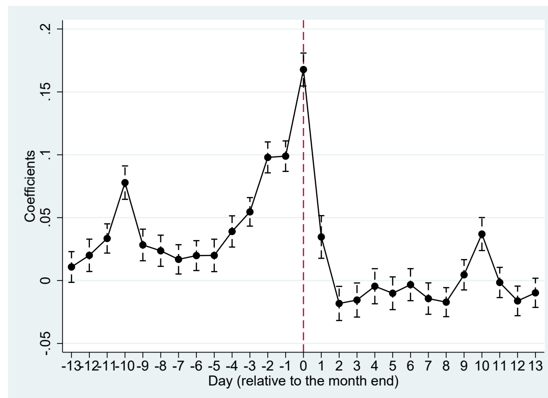
(a) Extensive: $Prob(Anylending)$



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



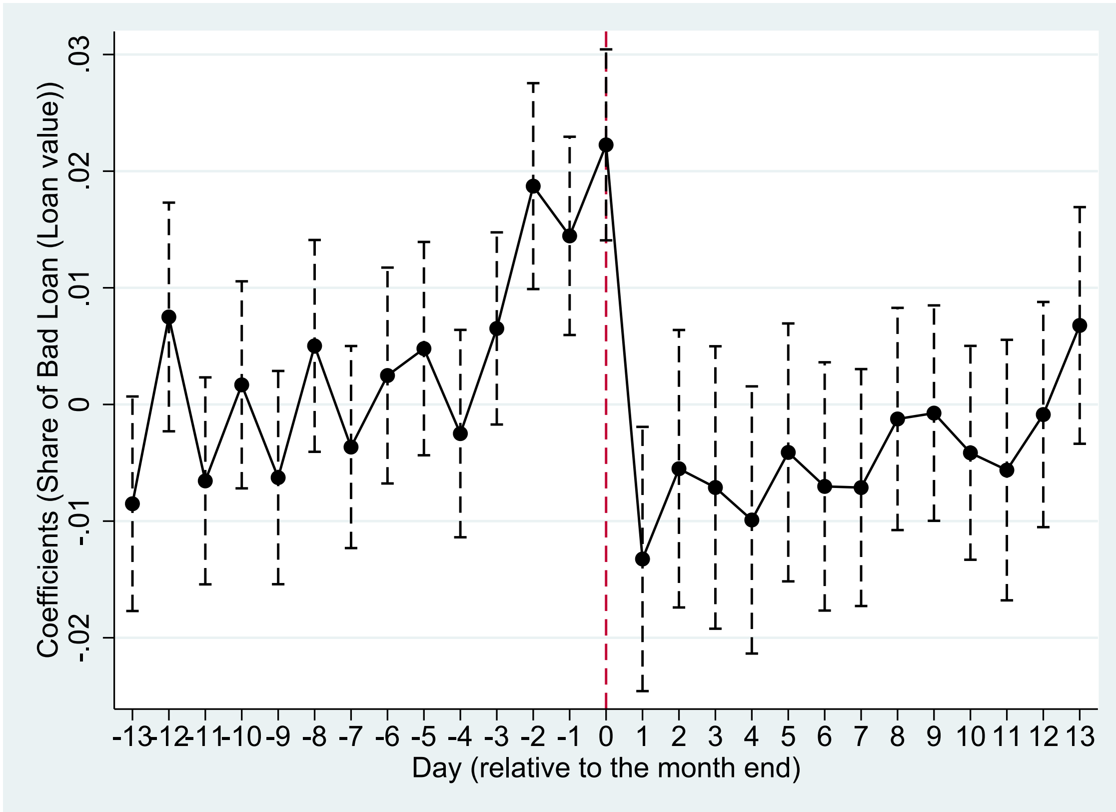
(c) Intensive: $log(AverageSize)$



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

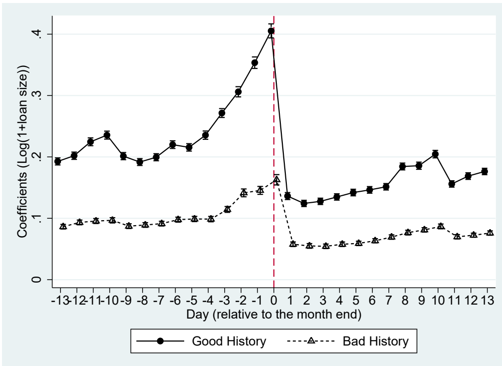
Note: dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

Figure 4: Share of Bad Loans (weighted by loan amount), Coefficients Plots

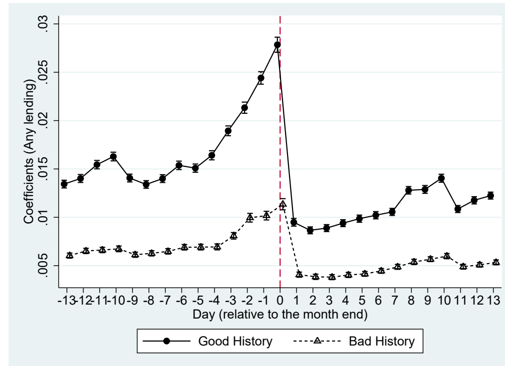


Note: dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

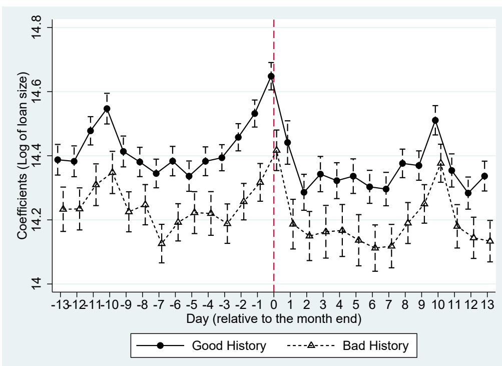
Figure 5: Firms with good vs bad previous history, Coefficients Plots



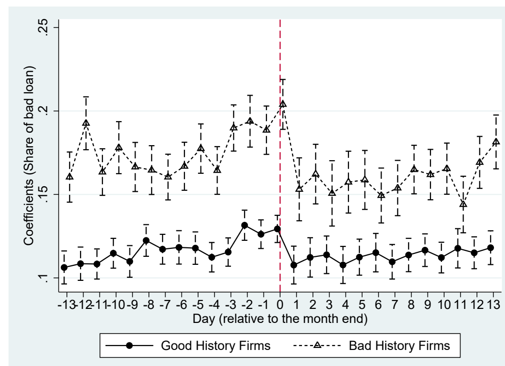
(a) Overall Effects



(b) Extensive Margin



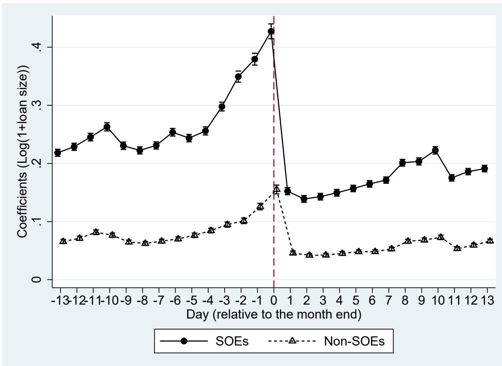
(c) Intensive Margin



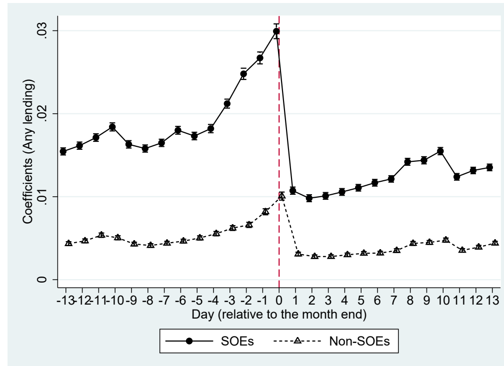
(d) Quality

Note: good-history firms are defined as firms with unblemished repayment records up to that points; bad-history firms are defined as those with at least one previous loan that had been classified as bad up to that points. 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.

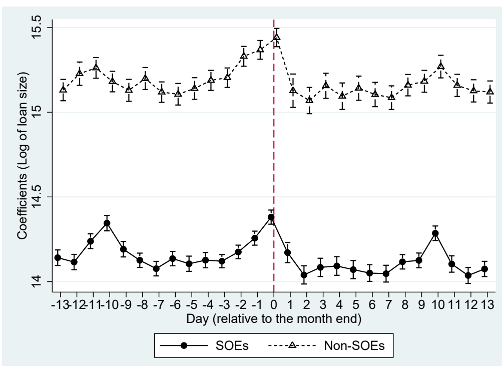
Figure 6: SOE vs Non-SOE Firms, Coefficients Plots



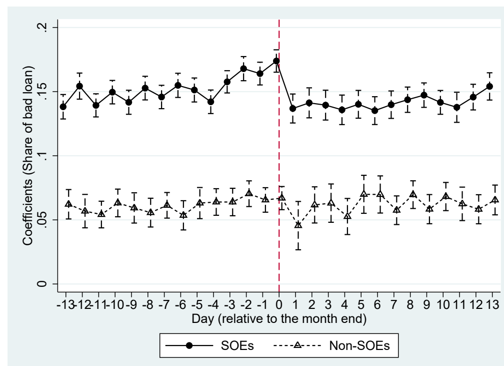
(a) Overall Effects



(b) Extensive Margin



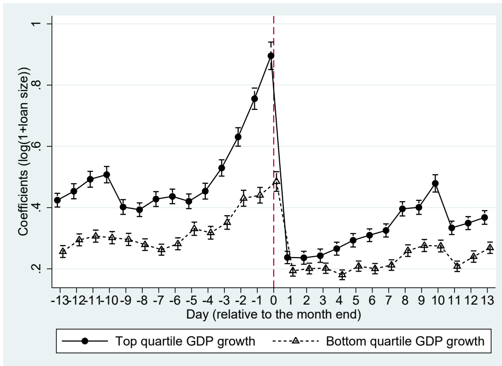
(c) Intensive Margin



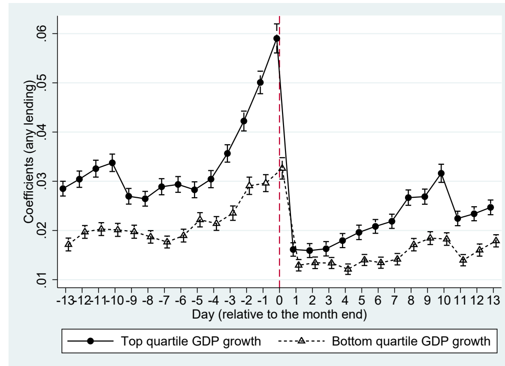
(d) Quality

Note: 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.

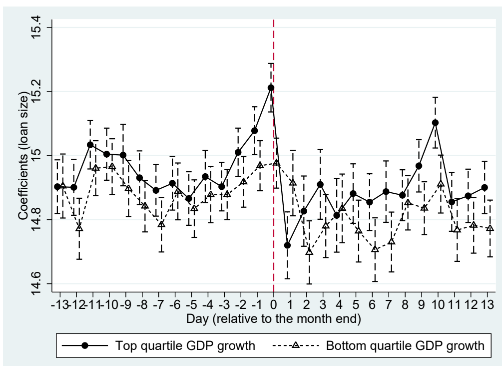
Figure 7: High Growth vs Low Growth Cities, Coefficients Plots



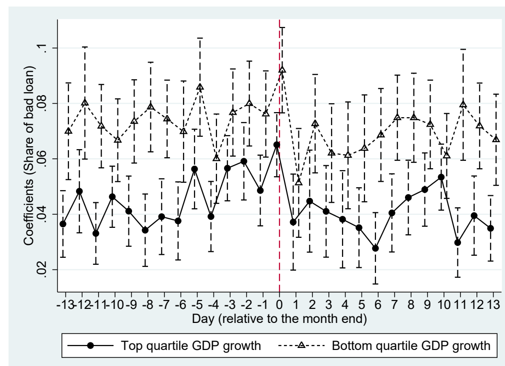
(a) Overall Effects



(b) Extensive Margin



(c) Intensive Margin



(d) Quality

Note: high-growth cities are defined as cities with GDP growth rates above the sample's 75 percentile value in a given year; low-growth cities are defined as those with GDP growth rates below the sample's 25 percentile value in a given year; the set of high- and low-growth cities vary across years. 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

	Mean	Median	Std	Obs
Panel A: City-level data				
Cumulative Loan Value (million RMB)	106.19	43.95	195.00	499,346
Change Rate in Lending (%)	0.056	0	1.13	494,241
Panel B: Loan-level data aggregated to the branch level (balanced)				
Loan Value (million RMB)	0.13	0	6.39	10,137,096
Prob(Any Lending) (%)	1.82	0	13.37	10,137,096
Panel C: Loan-level data aggregated to the branch level (unbalanced sub-sample)				
Loan Value (million RMB)	7.23	2.00	46.9	183,744
Average Loan Size (million RMB per contract)	5.60	1.50	41.1	183,744
Number of Contracts	1.50	1.00	2.55	183,744
Share of Bad Loans (%)	12.90	0	32.48	183,744

Notes.

The branch-level summary statistics in Panel A are based on city-level daily aggregates of loans outstanding to a partially privatized bank during the years 2006 – 2010. The loan-level data in Panels B and C are based on the daily new loans issued to a randomly selected subset of borrowers from a state bank during the years 1997 – 2010, aggregated to the subbranch level. In Panel B, branch-day observations in which there was no lending to these borrowers are coded as zeros. In Panel C branch-day observations with no lending are excluded. See the text for further details on the sample construction and detailed variable definitions.

Table 2: Loan Quantity and Quality Responses to Month End Incentives

	Dependent Variables: Quantity Response						Quality Response
	$\Delta log(Loans)$	$log(1+NewLoans)$	AnyLoan	$log(NewLoans)$	$log(Loans/Contracts)$	$log(Contracts)$	Share of Bad Loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Last 5 days	0.121	0.173***	0.012***	0.123***	0.038***	0.085***	0.016***
	(0.0694)	(0.00320)	(0.000224)	(0.00863)	(0.00800)	(0.00314)	(0.00207)
First 5 days	0.000	-0.084***	-0.006***	-0.042***	-0.026**	-0.016***	-0.005
	(0.0000618)	(0.00186)	(0.000130)	(0.0106)	(0.00989)	(0.00329)	(0.00243)
R^2	0.005	0.026	0.025	0.490	0.554	0.117	0.313
Observations	494241	10131984	10131984	183744	183744	183744	158762
Sample	A	B	B	C	C	C	C
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.

Column (1) uses branch level data (the sample from Table 1(A)), and the coefficients and standard errors have been multiplied by 1000 for ease of exposition; columns (2) – (3) 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(B)); columns (4) – (7) 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(C)).

The reference groups are all other days not in the first or last 5 days.

OLS estimates, robust standard errors in parentheses are clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix: Modeling Delayed Lending

The model in Section 2 assumes that a branch manager cannot defer a loan application until later, effectively removing the option value of holding a potential loan in reserve in case later loan applications are of low quality. In this appendix, we present a model which highlights that, as long as there is some probability that a deferred loan is no longer available at the point at which the quality of later loan applicants is realized, we still obtain the model's main intuition that loan quantity increases over the month and loan quality decreases.

We again assume a two-period model where the branch manager receives a single loan application of size 1 in each period. We depart from the baseline model (in which lending decisions have to be made at the time of loan application), we allow the branch manager (if he wishes) to defer a decision on the first-period application until the next period. If the manager choose to postpone the decision, she risks losing the application with probability β. This may reflect, for example, the risk that a borrower switches to another lender, or the termination of the project due to the failure to obtain funds in time. However, with probability $(1-\beta)$, the manager will have two applicants in hand to choose from in the second period.

The decision rule for the second period depends on the first-period lending decision, and also whether the first-period loan is still available. As in our baseline model, if a loan has already been made in the first period, the manager makes a second loan if and only if $p > \frac{1}{R}$. If no loan was made during the first period, the manager offers a loan to the higher quality applicant if the first-period applicant is still available, and to any second-period applicant with $p \geqslant 0$ if the first-period loan application is unavailable.

In the first period, the branch manager offers a loan if and only if $\pi_{loan} > \pi_{noloan}$:

$$Rp - 1 + \int_{\frac{1}{R}}^{1}(Rq-1)dq \geqslant \beta \cdot \int_{0}^{1}(Rq-1)dq + (1-\beta)[(Rp-1)p + \int_{p}^{1}(Rq-1)dq]$$

This simplifies to

$$(1-\beta)(Rp)^2 - 2R(RP) + 2R - 1 \leqslant 0$$

.

We first notice that the benchmark model we presented in Section 2 is a special case of this expression, in which $\beta = 1$, leading to the same cutoff of $p^* = \frac{1}{R}(1 - \frac{1}{2R})$ as before.

With the option of delay in lending, the manager will set a higher cutoff p^{**} in the first period. To see this, we notice from the first-period decision rule that

$$0 \leqslant (1-\beta)(Rp^{**})^2 = 2R(Rp^{**}) - 2R + 1$$

which simplifies to

$$p^{**} \geqslant \frac{1}{R}(1 - \frac{1}{2R}) = p^*$$

Now we can compare the probability of no lending in the first period (p^{**}) and in the second period ($(1-p^{**})\frac{1}{R}$):

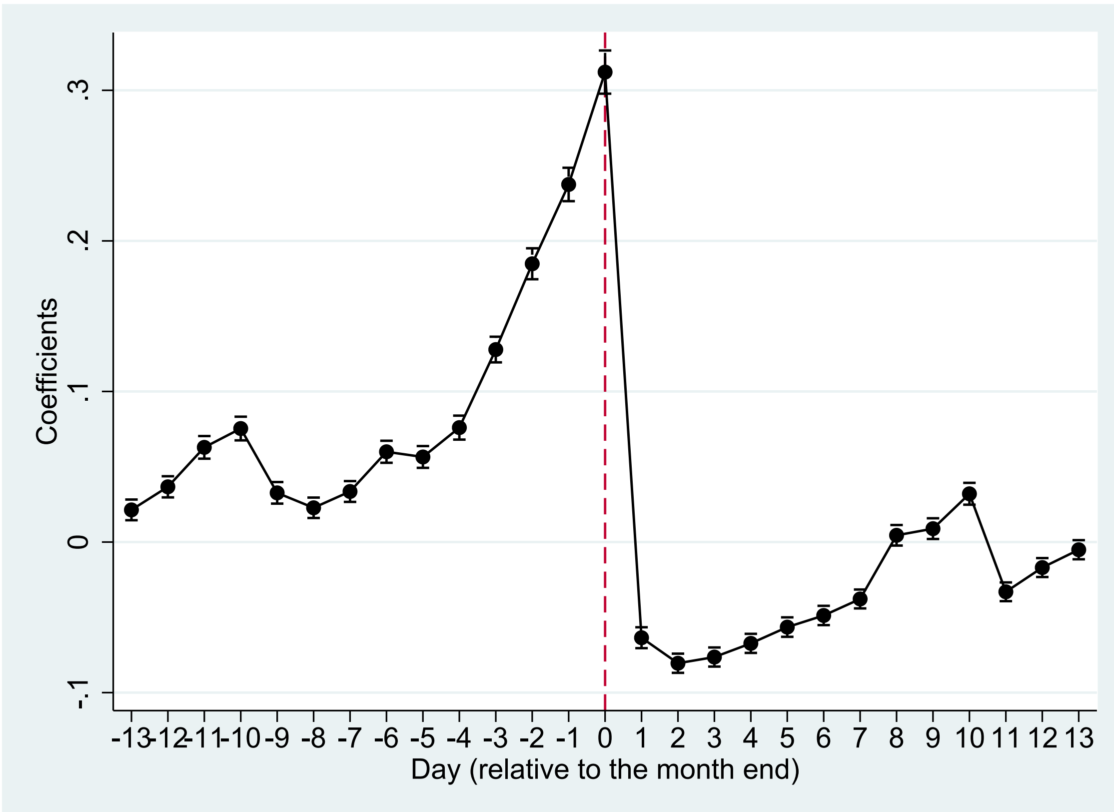
$$(1-p^{**})\frac{1}{R} \leqslant (1-p^{*})\frac{1}{R} < p^{*} \leqslant p^{**}$$

.

Again, the probability of a loan (as well as the probability of default) is strictly higher in expectation in the second period.

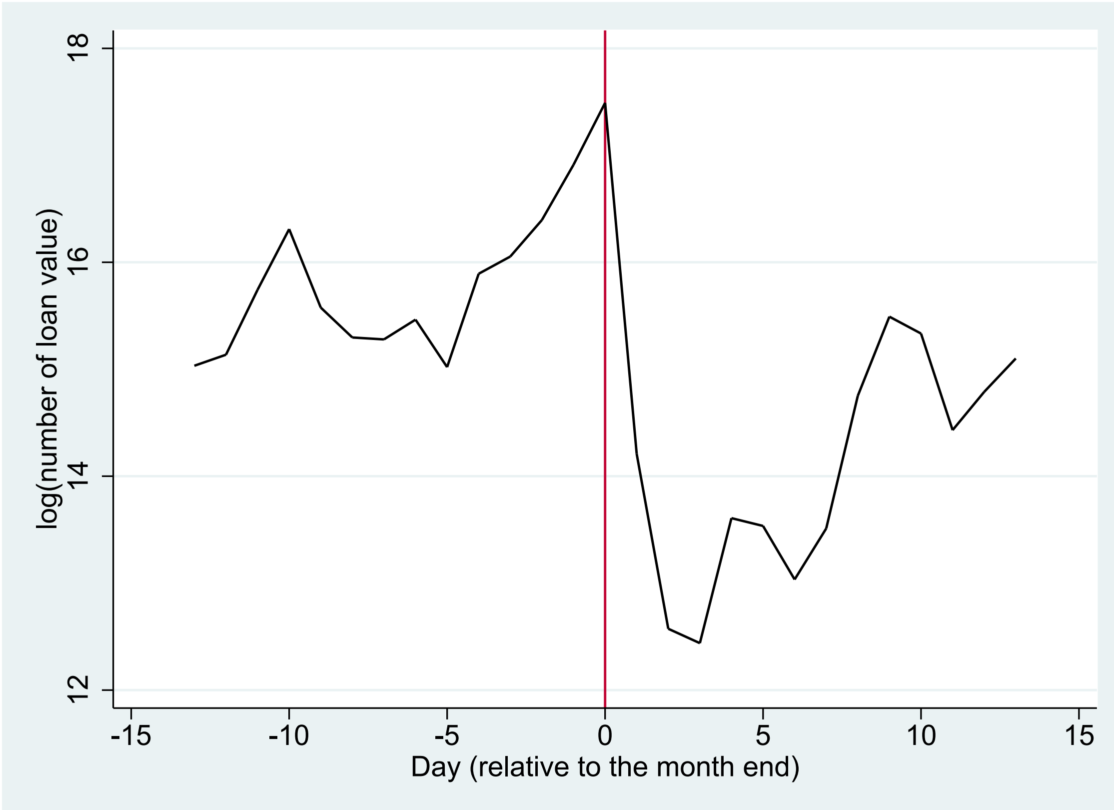
B Appendix Figures and Tables

Figure B1: Value of New Lending Issued with Branch Fixed Effects



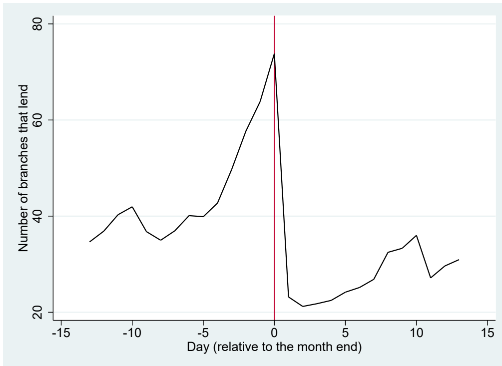
Note: dates more than +/-13 days away from the month end are the omitted category; coefficient plots are conditional on year-month, day-of-week, and branch fixed effects; standard errors are clustered at the branch level.

Figure B2: Value of New Lending Issued (Branch-level data)

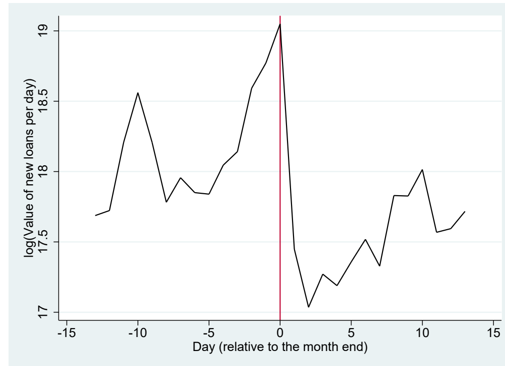


Note: dates more than +/-13 days away from the month end are excluded from the raw data graph.

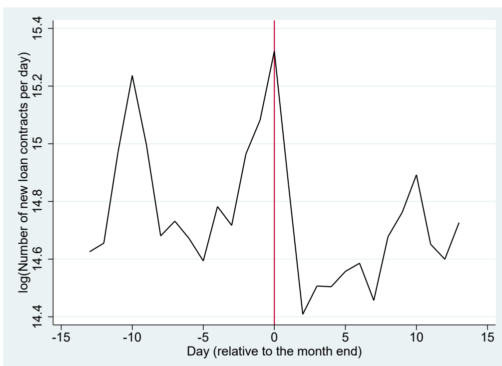
Figure B3: Extensive and Intensive Margins of New Loans Issued, Raw plots



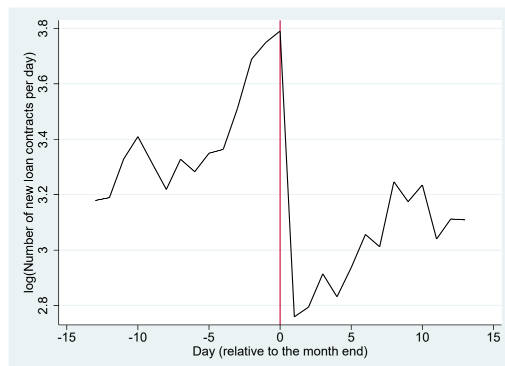
(a) Extensive: $Prob(anylending)$



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



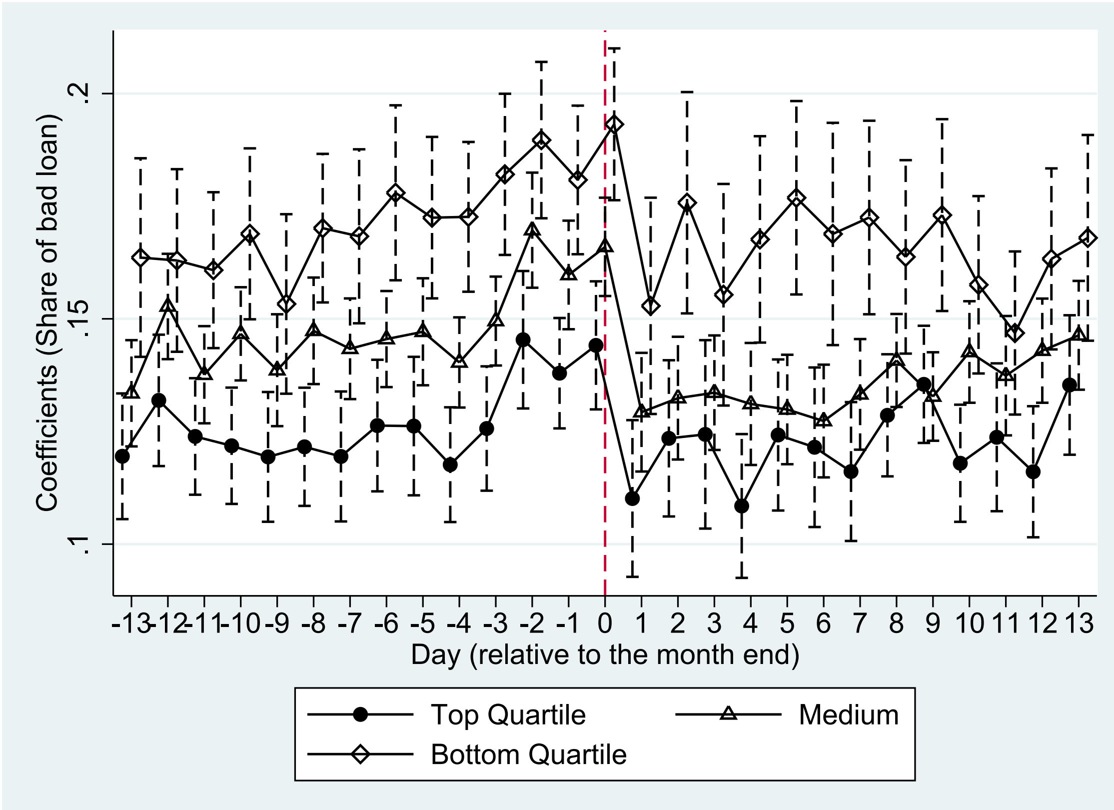
(c) Intensive: $log(AverageSize)$



(d) Intensive: $Log(Contracts)$

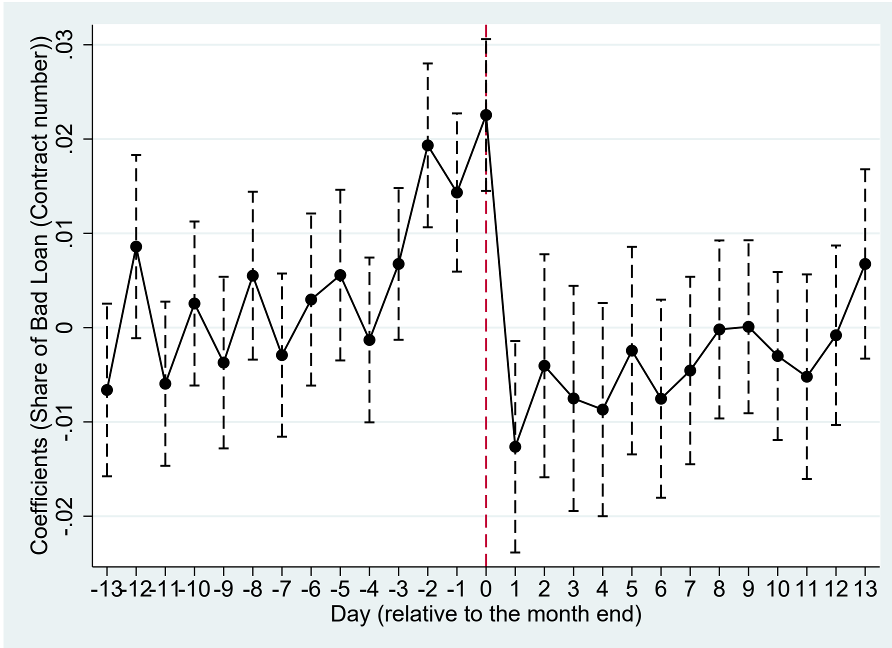
Note: dates more than +/-13 days away from the month end are excluded from the raw data graph.

Figure B4: Share of Bad Loans by loan size, Coefficients Plots

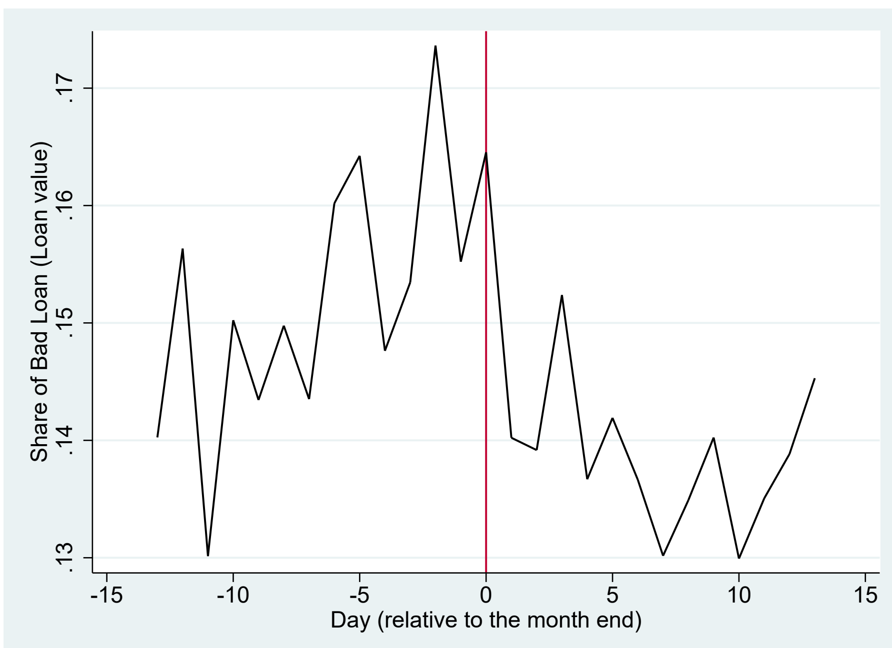


Note: dates more than +/-13 days away from the month end are the excluded category; coefficient plots are conditional on year-month, day-of-week, and city fixed effects; standard errors are clustered at the branch level.

Figure B5: Alternative Presentations of Loan Quality Response



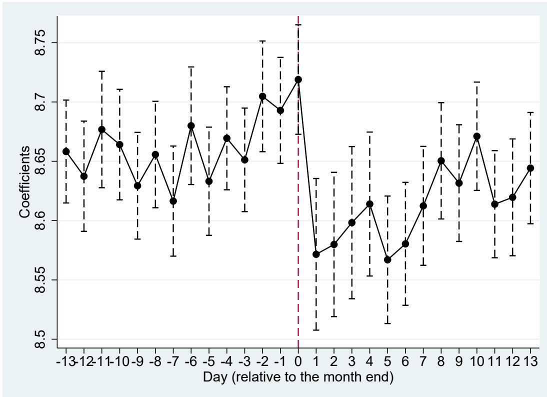
(a) Share of Bad Loans (unweighted), Coefficients Plots



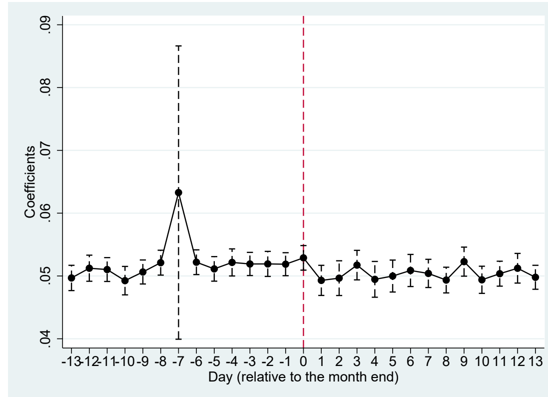
(b) Share of Bad Loans (weighted by loan amount),Raw Plots

Note: dates more than +/-13 days away from the month end are excluded from the raw data graph; days outside of the +/-13 day window are the omitted category in the coefficient plots, which are conditional on year-month, day-of-week, and city fixed effects. Standard errors are clustered at the branch level.

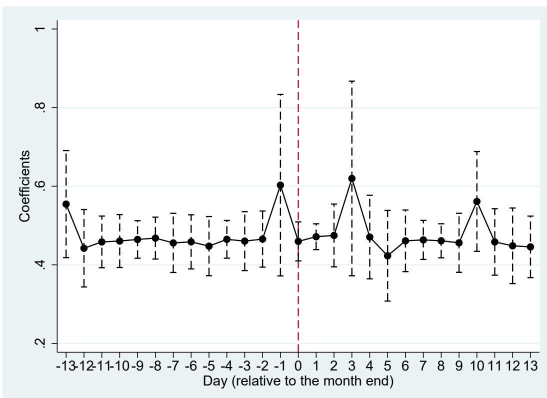
Figure B6: Firm Characteristics



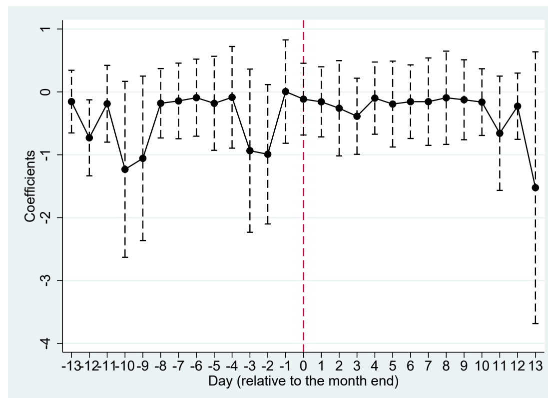
(a) Total assets (log)



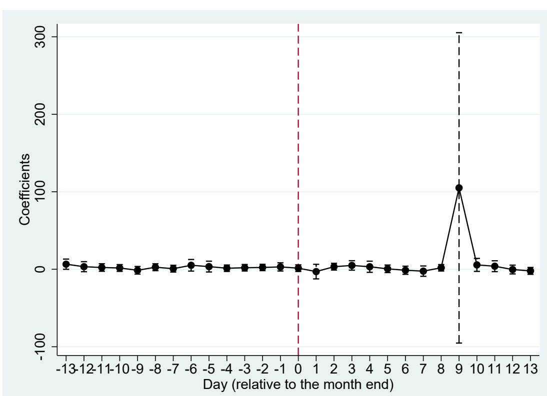
(b) Cash to assets ratio



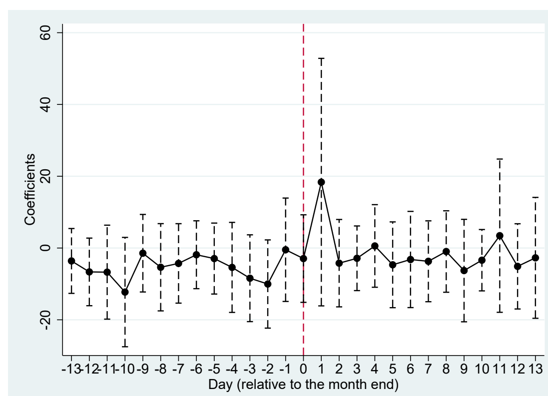
(c) Liabilities to assets ratio



(d) Profits to assets ratio



(e) Net cash flow to assets ratio



(f) Altman's Z-score

Note: 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.

Table B1: Loan Quantity and Quality Responses Relative to the Middle 5 Days of the Month

	Dependent Variables: Quantity Response						Quality Response
	$\Delta log(Loans)$	$log(1 + NewLoans)$	AnyLoan	$log(NewLoans)$	$log(Loans/Contracts)$	$log(Contracts)$	Share of Bad Loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Last 5 days	0.179*	0.188***	0.013***	0.170***	0.075***	0.095***	0.014***
	(0.0785)	(0.00355)	(0.000247)	(0.0111)	(0.0105)	(0.00373)	(0.00276)
First 5 days	0.000*	-0.068***	-0.005***	0.005	0.008	-0.003	-0.007*
	(0.0000751)	(0.00216)	(0.000151)	(0.0129)	(0.0121)	(0.00412)	(0.00307)
R^2	0.006	0.027	0.027	0.488	0.557	0.144	0.315
Observations	243175	4992658	4992658	95236	95236	95236	82087
Sample	A	B	B	C	C	C	C
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.

Column (1) uses city level data (the sample from Table 1(A)), and the coefficients and standard errors have been multiplied by 1000 for ease of exposition; columns (2) – (3) 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(B)); columns (4) – (7) 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(C)).

The reference groups are days (the 13^{th} – 17^{th}) in the middle of the month.

OLS estimates, robust standard errors in parentheses are clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Loan Quantity and Quality Responses Controlling for Holidays

	Dependent Variables: Quantity Response						Quality Response
	$\Delta log(Loans)$	$log(1+NewLoans)$	AnyLoan	$log(NewLoans)$	$log(Loans/Contracts)$	$log(Contracts)$	Share of Bad Loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Last 5 days	0.188*	0.189***	0.013***	0.168***	0.074***	0.094***	0.014***
	(0.0782)	(0.00355)	(0.000247)	(0.0111)	(0.0105)	(0.00374)	(0.00277)
First 5 days	0.000**	-0.055***	-0.004***	-0.001	0.004	-0.005	-0.007*
	(0.0000781)	(0.00207)	(0.000144)	(0.0129)	(0.0121)	(0.00415)	(0.00308)
R^2	0.006	0.028	0.027	0.488	0.557	0.144	0.315
Observations	243175	4992658	4992658	95236	95236	95236	82087
Sample	A	B	B	C	C	C	C
Holiday Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.

Column (1) uses branch level data (the sample from Table 1(A)), and the coefficients and standard errors have been multiplied by 1000 for ease of exposition; columns (2) – (3) 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(B)); columns (4) – (7) 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(C)).

The reference groups are days (the 13^{th} – 17^{th}) in the middle of the month.

OLS estimates, robust standard errors in parentheses are clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Loan Quantity and Quality Responses with Year-month-city FEs

	Dependent Variables: Quantity Response					Quality Response
	$log(1 + NewLoans)$	AnyLoan	$log(NewLoans)$	$log(Loans/Contracts)$	$log(Contracts)$	Share of Bad Loans
	(1)	(2)	(3)	(4)	(5)	(6)
Last 5 days	0.188***	0.013***	0.141***	0.053***	0.087***	0.009*
	(0.00311)	(0.000213)	(0.0149)	(0.0136)	(0.00539)	(0.00367)
First 5 days	-0.068***	-0.005***	0.023	0.023	-0.000	-0.007
	(0.00222)	(0.000154)	(0.0176)	(0.0163)	(0.00580)	(0.00426)
R^2	0.060	0.059	0.673	0.717	0.409	0.551
Observations	4992658	4992658	94290	94290	94290	81334
Sample	B	B	C	C	C	C
$Year \times Month \times City(branch)$ FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes

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(B)); 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(C)).
The reference groups are days (the $13^{th} - 17^{th}$) in the middle of the month.
OLS estimates, robust standard errors in parentheses are clustered at the branch level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.