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The Great Recession and Bank Lending to Small Businesses

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Abstract:

This paper investigates whether small firms have experienced worse tightening of credit conditions during the Great Recession than large firms. To structure the empirical analysis, the paper first develops a simple model of bank loan pricing that derives both the interest rates on loans actually made and the marginal condition for loans that would be rationed in the event of an economic downturn. Empirical estimations using loan-level data find evidence that, once we account for the contractual features of business loans made under formal commitments to lend, interest rate spreads on small loans have *declined* on average relative to spreads on large loans during the Great Recession. Quantile regressions further reveal that the relative decline in average spread is entirely accounted for by loans to the riskier borrowers. These findings are consistent with the pattern of differentially more rationing of credit to small borrowers in recessions as predicted by the model. This suggests that policy measures that counter this effect by encouraging lending to small businesses may be effective in stimulating their recovery and, in turn, job growth.

JEL Classifications: G21, G01, G32, E51

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I. Introduction

The most recent U.S. recession has been dubbed the Great Recession in recognition of its severity. The economy suffered longer and steeper losses in output and employment in this recession than in any other post-war downturn. Despite the depth of the slump, the recovery has been disappointingly anemic. In particular, it has been noted that net job losses by small firms have been unusually deeper than net job losses by large firms. At the same time, lending to small businesses has also been hard hit.[1] Since small firms are deemed by many to be vital for job creation, the supply of credit to small businesses, or the lack thereof, has garnered much attention, as policymakers seek to stimulate employment growth in the aftermath of the Great Recession.[2]

The bursting of the housing bubble in the United States triggered a system-wide financial shock. Financial institutions suffered sizeable subprime-mortgage-related losses that have likely amplified the negative shock to the economy. To the extent that supply-side credit constraints have played a larger than usual role in this economic downturn, small businesses likely have been affected more adversely than large firms. A number of previous studies have suggested that financial constraints are more binding on small firms (see, for example, Gertler and Gilchrist 1994). For one thing, bank-dependent firms are found to display more signs of being financially constrained (for example, Kashyap et al. 1994), and small businesses depend almost exclusively on bank financing (Cole et al. 1996). If the lack of availability of credit to small firms, as opposed to a lack of demand for credit by small firms, is an important impediment to the

[1] Net employment changes by firm size are based on the Business Employment Dynamics database compiled by the Bureau of Labor Statistics. Total small commercial and industrial loans in the balance sheets of commercial banks declined 7.1 percent between 2008 and 2010, according to the June Call Reports.

[2] For instance, Federal Reserve Chairman Bernanke highlighted the contribution to gross job creation by startup enterprises and enumerated the various programs that the Federal Reserve and other government agencies have initiated to facilitate credit flows to small businesses, in his speech at the July 12th capstone event for a series of more than 40 meetings aimed at addressing the financing needs of small businesses,.

recovery, then the policy response should include measures that encourage small business lending.[3]

In this paper we investigate whether small firms have experienced worse deterioration in the cost and availability of credit during the Great Recession than large firms have. To this end, the paper first develops a simple model of bank loan pricing to offer structural guidance for the empirical analysis. It adapts the costly state verification model to derive loan interest rates as a function of the aggregate state of the economy as well as borrowers' credit quality and loan attributes, such as size and collateral status. The model can produce credit rationing in equilibrium and derives the condition for the interest rate paid by the marginal borrower. It shows that credit rationing exhibits countercyclical movements, the degree of which can vary in the cross section depending on borrower quality, loan attributes, and the lender's financial health. In particular, the model yields the result that small firms can be more subject to rationing during recessions than large firms, because small firms incur higher monitoring costs per dollar of funds borrowed. This finding implies that the quality of the marginal small borrower who obtains credit will in fact *increase* in a downturn relative to the quality of the marginal large borrower.

These results imply that the presence of greater credit constraint on small firms during a downturn can be detected through shifts in the distribution of interest rates among loans *actually made* (and thus observed). All else being equal, interest rates on loans to the riskiest firms should rise *less* for small firms than for large ones. More specifically, for the empirical analysis given our data, the upper quantiles of loan interest rates would be expected to rise less for small firms than for large ones if the former faced more rationing during the recession.

The paper then uses a loan-level dataset to explore relative changes in the terms of business loans during the Great Recession. We focus on the relative change in the

[3] Such as the $30 billion of funds made available through the Small Business Jobs Act (signed by President Obama on September 27, 2010).

interest rates of small versus large loans. This is akin to a difference-in-differences analysis in that we compare the interest rates on small versus large loans before and after the onset of the recession. We also examine the extent to which bank-level indicators of financial health that have been found to influence a bank's willingness to supply credit have affected the relative terms of its small business loan origination.[4] Furthermore, taking advantage of the large cross-section of loans in our dataset, we conduct quantile regressions to investigate whether the relative changes in the distribution of loan interest rate spreads exhibit signs of credit rationing as suggested by the model.

Our analysis reveals that specific features of different types of loan contracts, largely neglected to date, can overturn the conclusion regarding the relative change in terms on small loans during the Great Recession. In particular, our regression analysis explicitly accounts for two main contractual features of loans made under formal commitments to lend. First, since they are drawdowns under existing commitments, most of these loans carry a spread (over a base interest rate) that is predetermined—fixed at the level set in the commitment contract. Second, multiple types of base rates are used in commitment contracts, and the base rate is almost invariably allowed to float with the market. These loans under fixed commitment contrast with new term loans, for which the entire interest rate is negotiated at the time of the loan contract.

Once we take into account these features of loans made under existing commitments, we find a significant *reduction* in the average interest rate spread of small loans (relative to large ones) in this downturn. The quantile regressions then reveal that the biggest relative reduction in loan rates occurred in the top percentiles, corresponding to the riskiest borrowers. These results are consistent with the pattern predicted by the model when credit rationing increases more for small firms than for large firms in an

[4] A large body of research highlights the importance of bank health and bank capital constraints for credit availability, both theoretically (for example, Bernanke and Blinder 1988, Holmstrom and Tirole 1997) and empirically (for example, Peek and Rosengren 2000, Paravisini 2008, among many others). More recently, Ivashina and Scharfstein (2010) have shown that reductions in bank capital had an adverse effect on bank lending during the Great Recession.

economic downturn. Further analysis of bank health indicators provides additional supporting evidence: the biggest relative decline in loan interest rates occurs for banks with an a priori high nonperforming loan ratio and a low share of small business loans in the total commercial and industrial (C&I) loan portfolio, as well as for banks with greater exposure to the crisis—meaning banks that are more dependent on wholesale funding, are large, and/or have a high ratio of unrealized losses.

Our findings have important policy implications. If lack of credit is a nonnegligible impediment to recovery, then the policy response should include measures that encourage lending. For instance, policies such as expanding government guarantees on small business loans through programs run by the Small Business Administration can prove effective in speeding up the recovery. Regulatory and supervisory policy can also play a useful role in this regard. For example, if it is true to some degree that supervisors' concerns about bank safety may have, inadvertently, constrained lending to small firms that are fundamentally sound but experiencing cash flow shortfalls in the near term, then the remedy should in principle be straightforward: reduce such supervisory constraints to the fullest extent feasible. In addition, banks should be compelled to raise capital if a current or expected capital shortfall is hindering the growth of their loan portfolios.

The remainder of the paper is organized as follows. Section II presents the model that derives both the conditions for observed interest rates on loans actually made and the likely manifestation of credit rationing by banks. It also discusses briefly what the model implies about empirical specifications. Section III describes the data and the empirical specification. Section IV presents the empirical analysis, focusing on the change in loan terms for small loans relative to large ones. It then discusses policy implications of the empirical findings. Section V concludes.

II. A Model of Bank Lending and the Distribution of Loan Interest Rates

This section develops a model of the optimization problem that banks solve in setting the contractual interest rate to charge on each loan, based on that borrower's risk profile as well as other relevant factors such as the aggregate state of the economy. This model incorporates several features that have often been adopted to rationalize credit rationing. Accordingly, it investigates how the business cycle may affect the types of borrowers who receive credit and in turn the distribution of loan interest rates. In particular, it explores the following question: if, for plausible reasons, small firms are more likely than large firms to be denied credit during economic downturns, how would this phenomenon be manifest in the distribution of interest rates paid by those borrowers who are, in fact, granted credit?

2.1 Model Setup

As an extensive literature on financial intermediation has established, banks facilitate credit supply by screening and monitoring borrowers to mitigate the asymmetric information problem. Here we adapt the widely used "costly state verification" (CSV) model to characterize the informational friction that gives rise to bank loan contracts. Specifically, a borrower's realized return or collateral value is assumed to be costlessly observable only to herself, while anyone else must conduct costly monitoring to find out the true *ex post* value. As Townsend (1979) and Gale and Hellwig (1985) have shown, with ex post information asymmetry, risky debt is the optimal contract for external financing. Williamson (1987) further shows that the CSV model can give rise to credit rationing.[5]

Since the focus in this paper is bank C&I loans, which tend to be short-term loans with variable interest rates, we consider one-period debt contracts. At the maturity of a loan, if the borrower does not repay the interest as set out in the contract, the lending

[5] Stiglitz and Weiss (1981) develop an alternative framework in which credit rationing can arise because of ex ante asymmetry of information between borrowers and lenders. Their model, however, does not naturally generate a near continuous distribution of interest rates.

bank conducts monitoring and receives all the residual payoff or liquidation value of collateral, or both.[6] In the model, the cost of this monitoring will play the key role in distinguishing small borrowers from large ones. Specifically, we assume that the monitoring cost per dollar of funds lent is a decreasing function of loan size. Therefore, smaller borrowers face a higher cost of funds, all else being equal, due to the information processing cost.[7]

Since a key objective of the model is to study how aggregate fluctuations along with heterogeneity in credit quality across borrowers affect the price of credit, we follow Bernanke, Gertler, and Gilchrist (BGG 1999) in modeling the return on each project as subject to both idiosyncratic and aggregate shocks. Specifically, we assume that a project i invested at the beginning of period t realizes its return at the end, and $R_{i,t+1} = \theta_i \omega_{i,t+1} R_{t+1}$ describes i's realized gross return. θ_i represents the project-specific productivity that is known ex ante.[8] We assume that there is a continuum of potential projects indexed by θ_i that are independent and identically distributed (i.i.d.) across projects as well as over time, with E(θ) = 1. All else being equal, θ_i gives rise to the distribution of contractual interest rates on loans.[9]

Ex post, each project is subject to idiosyncratic return shocks denoted by $\omega_{i,t+1}$. The ω's too are assumed to be i.i.d. random draws across projects following a time-invariant differentiable cumulative distribution function (c.d.f.) $G(\omega)$ over a non-negative support with E(ω) = 1. Moreover, $\omega_{i,t+1}$ is independent of the firm type θ_i. Each project's exposure to aggregate risk is represented by R_{t+1}, the common component of

[6] The monitoring here does not alter the intrinsic risk profile of the projects that banks fund, keeping the model more tractable without loss of the key feature of bank lending for our purpose—potentially a higher cutoff level of borrower creditworthiness during economic downturns. See Diamond (1991) for a model of monitoring that mitigates the moral hazard problem by altering borrowers' incentive and in turn the risk-return profile of the project.

[7] Petersen and Rajan (2002) show that, for small business loans, the size of the fees is independent of the size of the loan and so the fee percentage declines with loan size.

[8] In reality, θ_i can be interpreted as a sufficient statistic of indicators of a borrower's default risk, such as credit score, leverage, etc., that are perfectly observable to the bank ex ante. Here, we ignore the cost banks incur to uncover such signals since its effect on loan terms is qualitatively similar to monitoring cost, which is our focus and will be discussed at length below.

[9] We will see that, if every loan had identical terms, there would be a one-to-one (inverse) mapping between θ_i and default probability as well as loss, given default.

returns that will be realized on all projects funded at the beginning of period t. Loan approval and terms on the whole fluctuate over the business cycle because the conditional distribution of R_{t+1} varies from period to period. Denote the time-t c.d.f. of R_{t+1} as $H_t(R)$. In each period t, individual borrower i is assumed to have one project with a predetermined scale, denoted by K_{it}. This assumption simplifies the analysis but is stronger than necessary; all we need is for K_{it} to be uncorrelated with θ_i.[10] The borrower puts up part of her own net worth and borrows the rest (denoted B_{it}) to finance the project.

Regarding the monitoring technology, we assume that the lender's cost consists of two parts, a fixed component M_{it} plus a variable component proportional to the realized payoff. It is common to assume that only a fraction (denoted as δ) of the project return is recovered in the default process, while the fixed cost is motivated by expenses, such as fees paid to law and accounting firms, that vary little within a wide range of firm sizes.

In the following sections we solve the lenders' optimization problem. We examine how a bank determines whether to lend to a borrower and what interest rate to charge. We pay special attention to how these decisions are influenced by the state of the aggregate economy and financial health of the lender. Next, we derive comparative statics and empirical implications.

2.2 Equilibrium Condition for Individual Loan Interest Rates

We start by deriving the condition that a bank j should use to decide whether to grant credit to a borrower of type θ_i and, if so, what loan interest rate to charge. Denote borrower i's contractual interest rate (also referred to as the yield to maturity) as $\hat{Z}_{i,t+1}$.[11] Borrower i is deemed in default if, at the end of period t, i's return falls short of the

[10] This allows a distribution of interest rates among large as well as small loans, instead of a monotonic mapping between θ_i and the optimally chosen K_i. It is a reasonable assumption for modeling lending behavior in a short run over which the scale of operation is more-or-less fixed.

[11] Even though $\hat{Z}_{i,t+1}$ is contracted and known at the beginning of t, we keep the (t+1) subscript to signify that whether it can be collected by the bank depends on the realization of $\omega_{i,t+1}$ and R_{t+1}.

promised interest payment, that is, $\theta_i \omega_{i,t+1} R_{t+1} K_{it} < \hat{Z}_{i,t+1} B_{it}$.[12] Rearrange terms and express the default condition as

$$\left(\theta_i b_{it}^{-1}\right) \omega_{i,t+1} R_{t+1} < \hat{Z}_{i,t+1}, \tag{1}$$

where $b_{it} := B_{it}/K_{it}$ is i's leverage ratio (that is, debt-to-asset ratio). Equation (1) indicates that, in terms of the prospect of repayment, higher leverage is equivalent to lower productivity. As will be shown later, we can interpret θ_i as inclusive of a leverage adjustment and omit explicit references to b_{it}. Default thresholds can be defined according to (1) as follows:

Definition: For given θ_i and b_{it}, there is a one-to-one mapping between $\hat{Z}_{i,t+1}$ and a threshold value, known at time t, for the composite return $\omega_{i,t+1}R_{t+1}$, denoted $\hat{R}_{i,t+1}$, below which loan i is considered in default. If aggregate return R_{t+1} is also given, an analogous threshold can be defined for the idiosyncratic return $\omega_{i,t+1}$, denoted $\hat{\omega}_{i,t+1}$:

$$\hat{R}_{i,t+1} := \hat{Z}_{i,t+1} \Big/ \left(\theta_i b_{it}^{-1}\right) \text{ and } \hat{\omega}_{i,t+1} := \hat{Z}_{i,t+1} \Big/ \left(\theta_i b_{it}^{-1} R_{t+1}\right). \tag{2}$$

Note that $G(\hat{\omega}_{i,t+1})$ is the probability of default (PD) of borrower *i* for a given aggregate return R_{t+1}, while $\mathrm{E}_R\left[G(\hat{\omega}_{i,t+1})\right]$ is *i*'s PD with $\mathrm{E}_R[.]$ denoting the expectation over all possible values of R_{t+1}. PD rises in the loan rate charged $\hat{Z}_{i,t+1}$, all else being equal, because there is less chance that the cash flow will be sufficient to cover the loan payment. Consistent with intuition, (2) also shows that, for any given $\hat{Z}_{i,t+1}$, a higher value of θ_i lowers $\hat{\omega}_{i,t+1}$, and hence a borrower's odds of default. In fact, if every loan had identical terms, θ_i would be the sufficient statistic for PD. By comparison, a good state of the economy (that is, a higher R_{t+1}) lowers the PD for all borrowers.

We now analyze how a bank should set the interest rate when lending to a type *i* borrower. From the bank's perspective, the interest rate charged must generate an expected rate of return (net of the monitoring cost) no less than its risk-adjusted

[12] We ignore technical default of loan covenants, primarily because we have no data on covenants.

opportunity cost of funds. The lending bank can charge a markup in accordance with its market power. This is one reason a bank's required rate of return can deviate from that on market securities with comparable risk. For simplicity, we assume that this markup is a constant multiple over the bank's ex ante cost of funds. Note, however, that our empirical analysis is valid as long as the markup on small loans relative to large loans does not vary systematically over the business cycle; the absolute or even relative markup need not be constant.[13] Accordingly, in all the ensuing derivations, the cost of funds is interpreted as inclusive of the bank-specific markup.

The contractual interest rate $\hat{Z}_{i,t+1}$ must satisfy:

$$\hat{Z}_{i,t+1} B_{it} \int_0^\infty \int_{\hat{\omega}_{i,t+1}}^\infty dG(\omega) dH_t(R_{t+1}) + \int_0^\infty \int_0^{\hat{\omega}_{i,t+1}} \left(\delta R_{i,t+1} K_{it} - M_{it} \right) dG(\omega) dH_t(R_{t+1}) = R_{M,t} B_{it} . \quad (3)$$

The first term on the left-hand side of (3) is the expected interest payment. The second term is the expected net liquidation value of the project. Together they equal the lender's overall payoff from the loan in expectation. As noted above, δ denotes the recovery rate, as $(1-\delta)$ of the payoff on a defaulted loan is spent on monitoring. M_{it} denotes the fixed component of the monitoring cost. The overall monitoring cost likely varies over time and across banks as well as projects, since it is a reduced-form representation of a bank's cost function for its monitoring technology. Here, for brevity we omit the bank-specific element from the subscript. In this model, monitoring cost is the friction responsible for driving a wedge between internal and external funds for a firm.

On the right-hand side of equation (3), $R_{M,t}$ is the ex ante (marginal) cost of funds for the bank (inclusive of the markup); the bank subscript is omitted for convenience. The cost of funds should equal a weighted average of the bank's cost of debt and (shadow) cost of equity. If the lending bank itself faced no additional frictions (due to information or agency problems) in raising external funds, then the cost of funds for a loan should equal the rate on a market debt instrument with the same risk profile (primarily maturity and risk rating). Otherwise, arbitrage opportunities would arise.

[13] In reality, a bank is likely to vary the markup both across borrowers and over time. We will later discuss plausible scenarios that may bias our empirical estimates.

However, we know from previous studies, such as Froot and Stein (1998), that financial institutions themselves face frictions in raising external funds other than insured deposits. In particular, a bank facing capital constraint can be thought of as having a prohibitively high shadow cost of equity and hence facing a higher cost of raising debt as well.

Substituting (2) into (3), dividing through by B_{it}, and rearranging terms, we can express (3) entirely in terms of rate of return as follows:

$$\hat{Z}_{i,t+1} - \int_0^{\infty} \int_0^{\hat{\omega}_{i,t+1}} \left(\hat{Z}_{i,t+1} + m_{it} - \delta R_{i,t+1} b_{it}^{-1} \right) dG(\omega) dH_t(R_{t+1}) = R_{M,t} . \tag{4}$$

$m_{it} := M_{it} / B_{it}$ is the monitoring expense normalized by the size of the loan. As explained above, we take m_{it} to be the key distinction between large and small loans. Anecdotal data suggest that there is a somewhat fixed component of the monitoring cost, including the variety of fees (such as to accounting and law firms) related to restructuring and liquidation, and that the cost in general does not rise proportionally with the size of the loan. Therefore, the monitoring cost per unit of loan balance is most likely a concave function of loan size, meaning that the smaller a loan, the greater its unit monitoring cost m_{it}. Everything else being equal, this implies that the smaller the loan, the higher the interest rate $\hat{Z}_{i,t+1}$, as will be shown below. Furthermore, this renders small borrowers more susceptible to credit rationing, especially during severe economic downturns.

The first term in (4) is the loan's expected return if it were free of default risk. This risk-free payoff is reduced by the expected default cost, that is, the second composite term. Should the borrower default, the lender would not be able to collect the contractual interest $\hat{Z}_{i,t+1}$ but would receive the project's payoff after paying the monitoring expenses. This expected default cost term is always positive as $\hat{Z}_{i,t+1} - \delta b_{it}^{-1} \mathrm{E}\left(R_{i,t+1} \mid R_{i,t+1} \le \theta_i \hat{R}_{i,t+1} \right) > 0$ given that $\hat{Z}_{i,t+1} = \theta_i \hat{R}_{i,t+1} b_{it}^{-1}$ and $\delta < 1$.

This equation also makes it clear that, in terms of the prospect of a lender's return, higher leverage is equivalent to lower productivity, since we can characterize a project's quality with the composite term $\theta_i b_{it}^{-1}$ —productivity normalized by leverage. If, with a slight abuse of notation, we redefine θ_i to equal $\theta_i b_{it}^{-1}$, then condition (4) becomes:

$$\hat{Z}_{i,t+1} - \int_0^{\infty} \int_0^{\hat{\omega}_{i,t+1}} \left(\hat{Z}_{i,t+1} + m_{it} - \delta R_{i,t+1} \right) dG(\omega) dH_t(R_{t+1}) = R_{M,t} . \tag{5}$$

So, in all the following derivations, we interpret θ_i as inclusive of a leverage adjustment and omit explicit references to b_{it}. In short, equation (5) implicitly defines loan rate $\hat{Z}_{i,t+1}$ as a function of θ_i, $m_{it,}$ and distributions of idiosyncratic and aggregate returns $G(\omega)$ and $H_t(R_{t+1})$, respectively. We will base our empirical specifications on this equation.

2.3 Conditions for Credit Rationing

In this section we derive the maximal interest rate ($\overline{Z}_{i,t+1}$) that a lender would charge a borrower. Under some conditions, this corresponds to the maximal expected rate of return on the loan and can be derived by differentiating the left-hand side of equation (5) with respect to the loan rate $\hat{Z}_{i,t+1}$. We obtain the following first-order condition:

$$\int_0^{\infty} \left\{ \left[1 - G\left(\overline{\omega}_{i,t+1} \right) \right] - \left[(1-\delta) \overline{Z}_{i,t+1} + m_{it} \right] g\left(\overline{\omega}_{i,t+1} \right) \Big/ \theta_i R_{t+1} \right\} dH_t(R_{t+1}) = 0 , \tag{6}$$

where $\overline{\omega}_{i,t+1} \coloneqq \overline{Z}_{i,t+1} / \theta_i R_{t+1}$. In words, the marginal gain from raising the loan interest rate should on net average to zero over all possible realizations of aggregate return R_{t+1}. The intuition is that a marginal increase in the loan rate $\hat{Z}_{i,t+1}$ has two opposite effects on a lender's return: on the one hand it raises the marginal return by $\mathrm{E}_R \left[1 - G\left(\hat{\omega}_{i,t+1} \right) \right]$ through a higher non-default payoff, but on the other hand it raises the probability and hence the net cost of default by $\mathrm{E}_R \left\{ \left[(1-\delta) \hat{Z}_{i,t+1} + m_{it} \right] g(\hat{\omega}_{i,t+1}) \Big/ \theta_i R_{t+1} \right\}$. $\overline{Z}_{i,t+1}$ is the value at which these two effects offset. It becomes the unique interior solution that maximizes the lender's expected return if we further assume that the second-order condition holds:

$$-\frac{1}{\theta_i R_{t+1}}\left[g(\bar{\omega}_{i,t+1})(2-\delta)+\left[(1-\delta)\bar{Z}_{i,t+1}+m_{it}\right]g'\left(\bar{\omega}_{i,t+1}\right)\Big/\theta_i\, R_{t+1}\right]<0\,. \tag{7}$$

This is surely satisfied if $\bar{Z}_{i,t+1}$ is small enough relative to $E_t(R_{i,t+1})$ so that $g'\left(\bar{\omega}_{i,t+1}\right)>0$.

If this maximal expected return falls short of the lender's opportunity cost of funds (inclusive of the desired markup), then the lender would rather not make the loan than charge a rate higher than $\bar{Z}_{i,t+1}$, which would only diminish her expected payoff. In other words, $\bar{Z}_{i,t+1}$ is the maximal yield a lender would charge and so no value of $\hat{Z}_{i,t+1}$ would satisfy equation (4). We can interpret this situation as rationing—such borrowers are shut out of the credit market:

Result 1: In equilibrium, it is optimal for lenders to ration borrowers whose $\bar{Z}_{i,t+1}$, *as defined implicitly in (6), result in a maximal expected return that is lower than the lender's opportunity cost of funds.*

Appendix A derives the solution for $\bar{Z}_{i,t+1}$ in the specific case where ω and R_{t+1} both follow lognormal distributions. For general distribution functions, a clearly stronger than necessary condition for (6) to hold is if the expression inside the curly bracket, denoted as $\mathrm{E}\left(\bar{R}_{i,t+1}\right)$, equals 0. It can be expressed as

$$\bar{\omega}_{i,t+1}\eta\left(\bar{\omega}_{i,t+1}\right)=\bar{Z}_{i,t+1}\Big/\left[(1-\delta)\bar{Z}_{i,t+1}+m_{it}\right], \tag{8}$$

where $\eta(\omega)\equiv g(\omega)/[1-G(\omega)]$ is the hazard rate.[14] This means that the marginal condition of zero net gain is satisfied in every possible aggregate state of the economy. This condition in fact becomes necessary if we characterize aggregate fluctuations in the

[14] If we further assume $\partial\left[\omega\eta(\omega)\right]/\partial(\omega)>0$, then $\bar{Z}_{i,t+1}$ is the unique interior solution that maximizes the lender's expected return. As shown in BGG (1999), this condition is satisfied by any monotonic transformation of the normal distribution.

form of first-order stochastic dominance of the distribution of aggregate return R_{t+1} in good times over that in bad times (see Appendix A2 for details).

2.4 Comparative Statics on the Degree of Credit Rationing and the Marginal Borrower

How $\overline{Z}_{i,t+1}$ changes with the borrower- and loan-specific attributes can be examined by fully differentiating (6) or (8). We illustrate with the comparative static of $\overline{Z}_{i,t+1}$ with respect to θ_i in the appendix, particularly for the case where ω and R_{t+1} follow lognormal distributions. We derive that $d\overline{Z}_{i,t+1} / d\theta_i > 0$, that is, the cutoff loan rate is increasing in θ_i. This result conforms to our intuition: all else being equal, borrowers with higher credit quality are less likely to hit the upper limit of the loan rate and face rationing.

Assuming condition (8) holds, then θ_i and the aggregate return R_{t+1} have symmetric effects on $\overline{Z}_{i,t+1}$ for an individual borrower, and so $d\overline{Z}_{i,t+1} / dR_{t+1} > 0$. This is also intuitive: more optimistic expectations about the aggregate state of the economy lower the likelihood of borrowers being rationed, all else being equal. It is readily shown with similar algebra that $d\overline{Z}_{i,t+1} / dm_{it} < 0$ and $d\overline{Z}_{i,t+1} / d\delta > 0$. That is, lower audit cost (relative to the loan size, in terms of both the fixed and the variable components) enables a borrower to remain viable to a lender at higher interest rates and thus less likely to face rationing.

Result 2: All else being equal, a borrower is more likely to be rationed the lower is θ_i and δ, and the higher is m_{it} and $R_{M,t}$. That is:

$$\frac{d\overline{Z}_{i,t+1}}{d\theta_i} > 0, \quad \frac{d\overline{Z}_{i,t+1}}{d\delta} > 0, \quad \frac{d\overline{Z}_{i,t+1}}{dm_{it}} < 0, \text{ and } \frac{d\overline{Z}_{i,t+1}}{dR_{M,t}} < 0.$$

These results are illustrated in the diagram below, which depicts a lender's expected rate of return (that is, the left-hand side of (5)) as a function of loan yields.

Parameters m_{it}, θ_{it}, etc. shift the expected return curve and thus alter the solution of $\hat{Z}_{i,t+1}$ and $\overline{Z}_{i,t+1}$. Specifically, it shows that $\overline{Z}_{i,t+1}$ falls in m_{it}, whereas $\hat{Z}_{i,t+1}$ rises in m_{it}, all else being equal.

Note also that Figure 1a illustrates a case of credit rationing. The curve corresponding to m_J characterizes the marginal borrower, while the curve corresponding to m_j depicts one firm that is rationed out of the market. Denote borrower J's vector of attributes as $X_J{}' = \{\theta_J, m_{Jt}\}$, conditional on the aggregate return R_{t+1}. By definition, we have $\hat{Z}_{J,t+1} = \overline{Z}_{J,t+1}$. If there exists another borrower j with a higher unit audit cost m_{jt}, then j's expected return will lie entirely below the lender's cost of funds μ, such as the curve labeled m_{jt} in Figure 1a. Therefore, j would not receive credit. In order for j to still be eligible for credit, she would need to have a higher intrinsic credit quality θ_j—generally any parameter changes that shift up the expected return for the lender. This is perhaps a case particularly relevant for small loans, since they tend to have a high audit cost relative to the size of their borrowing. This may well be a reason why, all else being equal, a bigger fraction (in terms of the range of θ's) of small borrowers than of larger borrowers may be rationed.

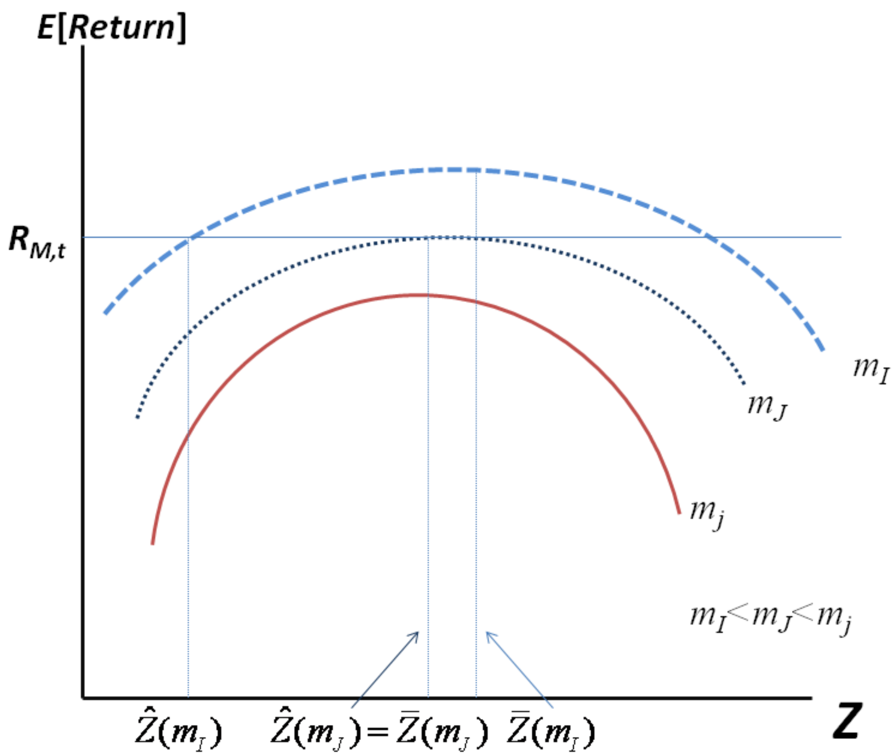

Figure 1a. Comparative statics of $\hat{Z}_{i,t+1}$ and $\bar{Z}_{i,t+1}$

This upper bound on the loan rate may not be reached for any borrowers within the given range of values for θ_i, m_{it}, and $R_{M,t}$. In particular, such an outcome is more likely during good times, represented here by on average relatively high R_{t+1}. More generally,

Result 3: There exists an equilibrium with no rationing, that is, $\hat{Z}_{i,t+1} < \bar{Z}_{i,t+1}, \forall i$, *for sufficiently large values of* θ_i *and* $E_t(R_{t+1})$, *or small values of* m_{it} *and* $R_{M,t}$.

This would be represented in Figure 1a as a case where none of the expected return curves lie entirely below the opportunity-cost-of-funds line. Since $\bar{Z}_{i,t+1}$ rises in R_{t+1}, a bigger fraction of borrowers are likely to face credit rationing if expectations of the overall health of the economy deteriorate, corresponding to downward shifts of all the expected return curves. According to the comparative statics above, the borrowers most likely to be rationed in recessions are those already marginal—with worse return profiles, less collateral, or higher unit monitoring cost (such as small borrowers), or a combination of all three. In other words, the marginal borrower in recessions is likely to be of a better return type (higher θ_i). The more severe the downturn, the bigger the shift in the marginal borrower's attributes. This can be a reason to suspect that more borrowers, especially small borrowers, are being rationed in this recession.[15]

Yet another force that can also help to drive up the intrinsic credit quality θ_i of the marginal borrower in recessions is banks' cost of funds $R_{M,t}$. This parameter captures the supply effects of lending. To the extent that a bank raises funds at the margin from sources other than insured deposits, the risk premium it faces on its funding rises during bad economic times. This would in turn require the bank to raise the interest rates it charges on loans, since it is shown in Result 3 that $\partial \hat{Z}_{i,t+1} / \partial R_{M,t} > 0$. However, this may not be feasible for those marginal borrowers who were already paying interest rates closest to maximal feasible rates during good times. So banks that experience an increase in the cost of funds are forced to stop lending to the previously near-marginal borrowers.

2.5 Comparative Statics on the Interest Rates Paid by Funded Borrowers

In this section we derive the comparative statics regarding the interest rate charged on loans that are actually made. We illustrate with the comparative static of $\hat{Z}_{i,t+1}$ with respect to θ_i in the appendix. We derive that $d\hat{Z}_{i,t+1} / d\theta_i < 0$. The intuition for this result is that projects of better types have a lower default probability $G(\omega)$ beyond the marginal effect of better intrinsic returns, because they also enjoy lower interest rates.

[15] Another element that may have played a bigger than usual role in curtailing credit availability during this latest downturn is the loss of collateral value, as a result of the slump in both the residential and the commercial real estate markets.

Since R_{t+1} and θ_i have symmetric effects on $\hat{Z}_{i,t+1}$, we know that $d\hat{Z}_{i,t+1} \big/ dR_{t+1} < 0$, meaning that loan interest rates tend to be lower during times of better expected aggregate states of the economy. Similar algebra shows that $d\hat{Z}_{i,t+1} \big/ d\delta < 0$, and $d\hat{Z}_{i,t+1} \big/ dm_{it} > 0$. In words, loan interest rates need to be higher if the recovery rate is lower or for borrowers with higher unit monitoring cost.

Result 4: Other things being equal, the interest rate on a loan decreases with θ_i and δ, and increases with m_{it} and $R_{M,t}$. That is:

$$\frac{d\hat{Z}_{i,t+1}}{d\theta_i} < 0, \quad \frac{d\hat{Z}_{i,t+1}}{d\delta} < 0, \quad \frac{d\hat{Z}_{i,t+1}}{dm_{it}} > 0, \text{ and } \frac{d\hat{Z}_{i,t+1}}{dR_{M,t}} > 0.$$

The bank's cost of funds $R_{M,t}$ is assumed in (3) to be identical for every type of borrower, although in reality it is more likely to be a decreasing function of observable indicators of the borrower's credit quality, that is, θ_i in the context of this model. Research on publicly traded corporate bonds finds a considerable risk premium that rises (in absolute level) for lower-rated bonds (see, for example, Berndt et al. 2005 and Elton et al. 2001), and risk premia on low-rated bonds are also more countercyclical. To the extent that these aggregate factors underlying the risk premia on market debt also influence the cost to banks of external funds at the margin, we should see interest rates increase more than linearly (in the expected default loss) for lower-rated loans.

On the other hand, the premia on riskier loans may not be as cyclical as they are on risky market debt if there is an implicit contract between banks and their borrowers under which banks offer some degree of rate-spread smoothing. Alternatively, some may interpret the "stickiness" revealed by significant coefficients on the lagged market spreads as evidence of credit rationing, in that bank loan spreads do not adjust as quickly as they otherwise would because banks restrict the type of borrowers who can obtain credit.[16] One sign that may distinguish between these two hypotheses is that rigidity due to rationing is possibly more asymmetric than rigidity due to implicit spread smoothing. The intuition is that banks are likely to shut out low-quality borrowers more swiftly when the aggregate economy turns sour and default risk premia rise, and they are slower to extend credit to lower-quality borrowers when the overall economy improves.

2.6 Countercyclical Credit Rationing and Cross-Sectional Heterogeneity

Combining the comparative statics for the necessary loan rate $\hat{Z}_{i,t+1}$ and the maximal feasible loan rate $\overline{Z}_{i,t+1}$, we see that parameter differences either across borrowers or over time (for example, a higher m or a lower θ) that push up the former also simultaneously push down the latter. The combined effect is to change the distance between $\hat{Z}_{i,t+1}$ and $\overline{Z}_{i,t+1}$ more than would be implied by the equilibrium condition for either rate alone.

Result 5: Credit rationing is countercyclical and the degree of this cyclicality decreases in θ_i *and* a_{it}*, and increases in* m_{it} *and* μ_t*.*

This result has the potential implication that a larger percentage of small borrowers may become credit constrained when the economy heads south. Figure 1b illustrates this result. The intuition is as follows: assume that large and small borrowers share the same distribution of θ's and that the only difference between them is that small firms have higher m_{it}'s (that is, $m_1 < m_2$, where 1 denotes a large firm and 2 denotes a small firm). Further assume that no firm was rationed during the good economic times. Then, the comparative statics derived above that $d\hat{Z}_{i,t+1}/dm_{it} > 0$ while

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[16] See, for example, Berger and Udell (1992), although note that they regress spreads on Treasury yields instead of maturity- and credit-quality-matched market spreads.

$d\overline{Z}_{i,t+1}/dm_{it} < 0$ imply that $d\left(\overline{Z}_{i,t+1} - \hat{Z}_{i,t+1}\right)/dm_{it} < 0$. In words, $\hat{Z}_{J,t+1}$ for the marginal borrower *J* is closer to her ceiling $\overline{Z}_{J,t+1}$ for small borrowers than for large ones. When a negative aggregate shock hits the economy (that is, R_{t+1} falls on average), every $\hat{Z}_{i,t+1}$ is raised even while the ceiling $\overline{Z}_{i,t+1}$ is lowered. Given the marginal small borrower's closer distance to her maximal feasible loan rate, the same R_{t+1} shock will push a bigger fraction of small borrowers beyond this rate ceiling and shut them out of the bank loan market. This implies that the marginal small borrower who still receives financing in a recession is of higher intrinsic quality than the marginal small borrower during a boom. Therefore, conditional on receiving a loan, small borrowers should on average experience a smaller increase in loan interest rates in a recession than large borrowers do. Moreover, this effect should be larger for the lower-quality borrowers; that is, those that in good times paid high interest rates are rationed out of the market in bad times.

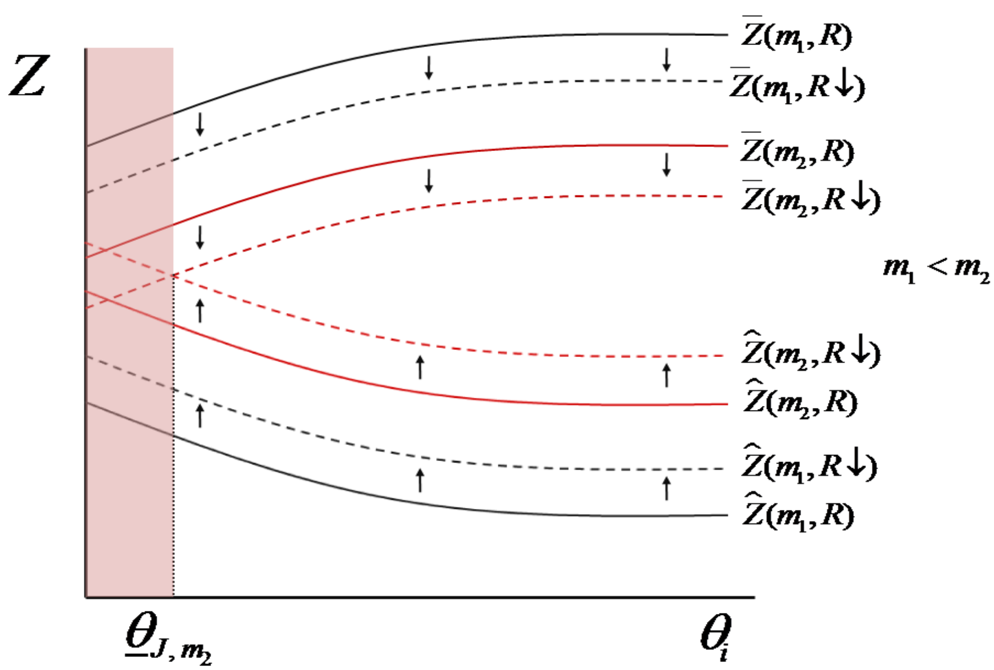

Figure 1b. The effect of a negative aggregate shock on equilibrium conditions

2.7 Empirical Specifications Implied by the Model

Following the model in equation (5), the determinants of the loan interest rate can be specified in a regression model as follows:

$$d_{ijt} = \alpha + \beta_I S_I + \beta_t D_t + \beta_{It}(S_I D_t) + \beta_j D_j + \sum\nolimits_{k=1}^{K} \gamma_k X_{jt,k} + \sum\nolimits_{n=1}^{N} \lambda_n Z_{ijt,n} + \varepsilon_{ijt}\,. \tag{9}$$

The dependent variable d_{ijt} is the yield of loan i at bank j in quarter t. S_I denotes the loan size category dummies. Our primary coefficients of interest are those on the interaction between loan size dummies and time dummies, that is, the β_{It}'s. These measure how the interest rates or spreads on small loans relative to large ones vary from period to period. This is akin to a difference-in-differences approach.

Bank dummies D_j's account for bank fixed effects. A full set of time dummies (D_t) is also included, to account for aggregate fluctuations not picked up by other control variables. As shown in the model, the loan interest rate or spread is influenced by a set of bank- and loan-level characteristics, that is, the vectors $\{X_{jt}\}_{K\times 1}$ and $\{Z_{ijt}\}_{N\times 1}$, respectively. We discuss in the next section the variables included as controls.

III. Data and Empirical Specification

3.1 Data

The loan-level data used in this study are collected in the Federal Reserve's quarterly Survey of Terms of Business Lending (STBL). During the first full business week of the middle month in each quarter, a sample of up to 348 domestically chartered commercial banks and 50 U.S. branches and agencies of foreign banks are asked to report terms of all the loans originated within that week. For this study, we use only data reported by domestically chartered banks. The primary reason is that the branches and agencies of foreign banks tend to originate C&I loans in the largest size category, while domestic banks originate mostly smaller loans, about 90 percent of which in fact have original principal less than $1 million and thus would be labeled small business loans. This makes domestic banks the suitable sample given the focus of this study—to examine the dynamics of terms on small business loans during the Great Recession. To better approximate the behavior of loan terms for the population of all domestic banks, we re-weight the survey sample using bank-specific scaling factors calculated by Federal Reserve Board staff.[17]

The survey collects the following attributes of each loan contract: interest rate, maturity, repricing frequency, internal credit rating, whether it has a prepayment penalty, whether it is secured, and whether it is made under an existing commitment contract.[18] Data on each bank's internal credit rating of every loan are reported only since 1997.[19] Two aspects of the rating data have especially important implications for our regression specifications. First of all, the ratings are loan-specific and not fully exogenous in that they are determined jointly with the terms of the loan. The survey instructions state explicitly that "definitions [of internal risk ratings] provided here take account of both the characteristics of the borrower and the protections provided in the loan contract."[20] So, rating is particularly dependent on loan attributes such as whether the loan is secured, the ratio between the value of collateral and the loan principal, and the loan covenants. For instance, a borrower can improve the rating of her loan by putting up high-value collateral or accepting more restrictive covenants. In the model's notation, this just means that rating depends on not only borrowers' type θ_i's but also on collateral a_{it} and monitoring cost m_{it}. In contrast, individuals' credit scores correspond to θ_i's and are exogenous to terms a consumer may receive on any incremental credit.

The second feature of these loan-level credit ratings is that they should, in theory, be comparable across banks. The survey instructions describe in reasonable detail the borrower credit conditions corresponding to each rating class. For instance, among other

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[17] The survey overweights the largest banks in that most of the top 50 banks are included and account for a bigger share in the sample (in terms of both the number and dollar volume of loans) than their share in the C&I loan portfolio of the banking industry as a whole. For large banks that report only the originations on some but not all business days in the survey week, these scaling factors also adjust for the partial reporting.
[18] For documentation and more details, see data release E.2 at http://federalreserve.gov/releases/e2/.
[19] See English and Nelson (1998) for a detailed account of the survey design for the rating variable and a characterization of early vintages of the data. In particular, they found the ratings to be less than reliable when first collected in 1997:Q2, so we start our sample in 1998:Q1.
[20] In fact, loan terms and risk rating are in general jointly determined, according to our conversations with bank examiners and bankers.

criteria, Rating 1 (minimal risk) is to be assigned to a "customer who has been with your institution for many years and has an excellent credit history."[21] Moreover, for loans rated 1 and 2, the instructions specify the credit mapping to publicly rated corporate debt. Ratings 1 and 2 are for customers with, respectively, AA and BBB or higher public debt rating. Every respondent bank is instructed to enter the numerical designation that "most closely matches the definition of the internal rating assigned to this loan," but *not* the institution's own internal risk rating.

Starting in 2003, the survey further distinguishes between formal commitments and informal lines of credit. According to the instructions, a formal commitment is defined as "a commitment for which a bank has charged a fee or other consideration or otherwise has a legally binding commitment." Otherwise, it is considered an informal line of credit. Especially important for our purpose is that a formal commitment "is usually evidenced by a binding contract, to lend a specified amount, frequently at a predetermined spread over a specific base rate."[22] Furthermore, for each loan made under a formal commitment, the banks since 2003:Q3 also report the date on which the commitment contract itself was signed. Since the median and mean number of days between the commitment and the drawdown as reported in the 2003:Q3 survey were around 270 and 650 days, respectively, we use data on loan commitments signed in 2000:Q1 and after in our regression analysis. The latest quarter in the dataset is 2009:Q4.

For those commitment loans whose base rates are defined by the lending bank to be prime, a supplemental section asks the banks to record the exact prime rate used on every day of the survey week. This prime rate can either be specific to the reporting bank or as reported in the financial press.[23] Figure 2 plots the distribution of the bank-specific prime rates over time, along with the prime rate posted in the Federal Reserve's data release H.15, which has been set at 3 percentage points above the fed funds target

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[21] For more details, see survey instructions at http://www.federalreserve.gov/reportforms/ReportDetail.cfm.

[22] For further details on distinctions between the two types of commitments, again see the survey instructions.

[23] Such as the prime rate reported by the majority of the top 25 U.S. chartered banks and published in the Federal Reserve data release H.15, http://federalreserve.gov/releases/h15/.

rate since 1994.[24] This time series shows that the vast majority of loans are priced off a common prime rate in every period, despite a fat right-tail—a few banks use prime rates up to 4 plus percentage points above the modal prime rate.

The bank-level financial data are from the Consolidated Reports of Condition and Income (generally referred to as the Call Reports).[25] These comprise balance-sheet and income statements filed quarterly by all commercial banks operating in the United States with their corresponding regulators. The bank-level controls are based on the financial data from one quarter prior to the survey quarter. Table A.1 in the appendix details the definition of the variables used to construct these bank-specific controls.

Table A.1 also describes the loan-specific reference market yield and spread, based on the market security whose maturity is closest to the loan's next repricing date and whose rating best matches the comparable market securities if specified in the survey instructions. For loans rated 1, the reference securities are AA-rated market bonds or A1/P1 commercial paper if the maturity is less than a year. For loans rated 2, the reference is A- and BBB-rated market bonds or A2/P2 commercial paper. Since the comparable market rating classes are not specified for loans rated 3 through 5, we choose BB, B, and CCC bonds as the respective market reference.

3.2 Empirical Specification for Regression Analysis

The specification (9) for the interest rate or spread regressions is recapped below:

$$d_{ijt} = \alpha + \beta_I S_I + \beta_t D_t + \beta_{It}(S_I D_t) + \beta_j D_j + \sum_{k=1}^{K} \gamma_k X_{jt,k} + \sum_{n=1}^{N} \lambda_n Z_{ijt,n} + \varepsilon_{ijt}\,. \qquad (10)$$

Our primary coefficients of interest are those on the interaction between loan size dummies and time dummies, that is, the β_{It}'s. This regression will be estimated using

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[24] Since the funds rate essentially hit the zero lower bound in December 2008, the prime rate has been held at 3.25 percent—three points above the upper bound of the 0-to-25-basis-points range for the funds rate. For the evolution of the relationship between this bank prime rate and the fed funds rate, see Kobayashi (2009).

[25] For the reporting forms and instructions, see http://www.ffiec.gov/ffiec_report_forms.htm. Data used in this study come exclusively from FFIEC 031 and 041.

ordinary least squares (OLS) as well as quantile regressions. The OLS estimates provide the conditional mean of the dependent variable. The quantile regressions enable us to explore the full conditional distribution of interest rates.

We consider two dependent variables: the yield and the spread of loan i at bank j in quarter t. The overall rate paid on a loan should arguably be the ultimate price variable of interest, since it is the borrowing firm's cost of capital (along with the shadow rental price of its equity capital). However, the information content of the overall loan yield has changed in recent decades and is no longer uniform in the cross-section. In particular, a growing and now dominant share of business loans is made under outstanding commitment contracts or lines of credit. The interest rate on the funds drawn under formal commitments is almost always specified as a base rate plus a fixed spread. The spread is a predetermined "markup" chosen at the time when the commitment contract was negotiated. The base rate, on the other hand, is left to vary with the spot market value of the interest rate to which it is indexed. The most prevalent choice of base rate is the prime rate, but many other types are used in practice, including the LIBOR (London interbank offered rate).

It seems reasonable to argue that the base-rate component of the overall yield on a loan drawn under a formal commitment is by and large exogenous with respect to bank- and loan-level attributes relevant for setting the loan rate (such as μ_t and m_{it} in equation (5)). The spread, on the other hand, should be set according to considerations underlying (5) at the time of the commitment contract. Since our analysis aims to uncover how the small-versus-large firm differential (in borrowing cost) varies over time, controlling for bank and loan characteristics, spread is the more appropriate dependent variable for loans under formal commitments. Moreover, since spread is set in the commitment contract, the time dummies should be indexed to the time of commitment instead of the time of drawdowns.

In contrast, for loans made under informal lines of credit, the yield is usually not pre-set but is determined at the time of the drawdown, based on the spot market condition, according to equation (5) above. In this respect, loans made under informal lines of credit are akin to new loans. For these loans, it is the overall yield that is relevant for comparing the cost of borrowing across large and small firms. And the time dummies should naturally be indexed to the time of the loan contract itself. On the other hand, since informal commitments constitute a very small proportion of the loans originated (2.6 percent), they have little impact on the estimation results. We run a robustness test regressing spreads over prime rates on informal commitments and new loans together and obtain qualitatively the same coefficient estimates (results available upon request).

The size categories used for S_I follow those in the Call Reports, which classify all C&I loans with original amounts of less than $1 million as small business loans. These loans are further divided into three size categories: I) below $100,000, II) between $100,000 and $250,000, and III) between $250,000 and $1 million. There is the distinct possibility that some small loans are in fact made to large firms, especially for loans made under existing commitments, since every drawdown is recorded as a new origination. In addition, a bank participating in syndicated lending deals need only report the amount of its participation, not the amount of the deal as a whole.

For our sample, one potentially more accurate way to classify the loans, at least for those made under existing commitments, is to use the size of the commitment. It seems an intuitive argument that each firm would choose a size of loan commitment that is in keeping with the scale of its operation, while the size of a particular drawdown depends more on the funding need at that point in time. In the data, the correlation between the loan size and the underlying commitment size is indeed modest: seldom more than 0.3. On the other hand, there do not appear to be cyclical variations in the correlation between commitment size and drawdown size. So we have little reason to suspect that the loan-size-based classification significantly biases our estimates, even for new term loans for which only the loan size is observed.[26] Nevertheless, for loans under commitment, our baseline regressions use the following cutoffs for commitment sizes: I') below $500,000, II') between $500,000 and $1.25 million, and III') between $1.25 and $5 million.[27] These cutoffs are chosen to be multiples of five over their counterparts for loan sizes because individual drawdowns under existing formal or informal commitments represent on average about 15 percent of the overall commitment balance.

We also specify the time dummies in two different ways and compare the resulting coefficient estimates of the β_{lt}'s. The first set of regressions includes a full set of quarter dummies (D_t), each of which is then interacted with the three loan-size dummies. This is the most flexible specification in that the marginal effect of loan size on the interest rate is allowed to vary quarter by quarter. The second specification contains simply a recession dummy, which equals 1 from 2008:Q1 to 2009:Q4 and 0 otherwise. The coefficient on its interaction with the three size dummies measures how interest rates or spreads on small loans relative to large ones changed since the onset of this recession. This is more restrictive but also more intuitive and suitable for the quantile regressions.

The remaining controls in the loan interest rate or spread regressions are a set of bank- and loan-level characteristics, that is, the vectors $\{X_{jt}\}_{K\times1}$ and $\{Z_{ijt}\}_{N\times1}$, respectively. Additionally, bank dummies D_j's account for bank fixed effects.

The primary purpose of bank-level controls is to account for unobserved time-varying bank characteristics that influence a bank's opportunity cost of funds (inclusive of the bank-specific markup, μ_t in question (5)). Some bank-level variables also help control cross-bank variations in m_{it} (monitoring cost), which likely depend on a bank's operating efficiency. Previous banking studies suggest such relevant variables as bank

[26] Moreover, according to a recent informal survey by Federal Reserve Board staff, most of the banks with C&I portfolios concentrated in small loans are in fact engaged primarily in lending to small businesses.

[27] There is anecdotal evidence that a nontrivial fraction of small business loans are above $1 million. See, for example, http://dpc.senate.gov/pdf/wh/treasury_smallbus_recession.pdf. This dimishes the likelihood of finding a significant change in the relative cost of borrowing across the two size groups since the recession.

size, liquidity ratio, capital adequacy, bank profitability, quality of the loan portfolio, and a bank's funding structure.

The bank capital ratio here serves as a proxy for the shadow cost of equity. It can be regarded as a reduced-form measure of a bank's capital "shortfall," to the extent that banks have similar target ratios for capital.[28] The bigger the shortfall, the higher the shadow cost of external financing, since banks likely face frictions themselves in raising external funds. In addition to the more standard measure of the ratio of tier-one regulatory capital over risk-weighted assets, we also experiment with the ratio of tangible common equity over total risk-weighted assets, which has been found to better reflect the true capital adequacy of banks during this financial crisis.[29]

Another explanatory variable aiming to capture time-series variations in the opportunity cost of funds (μ_t) is the interest rate or spread on market debt securities that most closely match the repricing frequency as well as the credit quality of a loan. Table 1 details the maturity and credit-rating-matched market reference interest rate or spread for loans in each rating class. If the lending bank itself faced no additional frictions (due to information or agency problems), then this repricing-frequency and rating-matched market rate should be the exact cost of funds for the loan; otherwise arbitrage opportunities would arise. On the other hand, many banks raise funds via deposits exclusively, so their actual cost of debt financing differs from the market rate relevant for private firms of comparable credit quality. To capture the deviation of a bank's cost of debt financing from the market reference, we control for a bank's funding sources, particularly the share of deposits in total liabilities.

Portfolio quality is measured as the share of nonperforming loans, either those within the C&I portfolio or the entire loan portfolio. The former may be correlated with unobserved quality differentials (within a rating class) in C&I portfolios across banks,

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[28] What should matter is presumably the deviation from a bank's optimal target capital ratio. One can use procedures that explicitly estimate an individual bank's target capital ratio, such as those in Berger et al. (2008).
[29] See, for example, Duffie (2009).

while the latter may contain an additional signal related to the unobserved capital pressure on the bank.

Given that the dependent variable should have no time trend in steady state, we use a normalized measure of bank size—assets of bank *j* divided by total assets of all domestically chartered banks in a given quarter. Alternatively, dummy variables for bank size categories are used. Liquidity is defined as the ratio of cash and market securities to total assets. Alternatively, it can be measured as the share of deposits in transaction accounts. According to the literature on banks as providers of liquidity insurance (see, for example, Kashyap, Rajan, and Stein 2002 and Gatev and Strahan 2006), banks with a high percentage of transaction deposits have a comparative advantage in liquidity insurance and thus may offer either lower spreads on average or better spread smoothing over the business cycle. As a measure of bank profitability we use the return over assets (ROA).

The loan-level controls should include those loan attributes most relevant for determining the interest rate. The model suggests the following variables: probability of default or expected default loss, maturity, and collateral status. The expected default loss is rarely observable and therefore is approximated by discrete credit ratings. The credit ratings enter as dummy variables, that is, there are five binary dummies corresponding to the five rating classes, respectively. This measure allows different ratings to have flexible influence on the loan interest rate or spread. Loan maturity is included as an extra control for unobserved quality attributes of the loan.[30] Since over 20 percent of the loans have no stated maturity, we introduce a missing-maturity dummy that equals 1 for such loans to avoid losing them and set their maturities to be one year.[31]

Another binary variable identifies whether a loan is secured (equal to 1 if the loan is secured and 0 otherwise). Unfortunately, there is no information on the collateral

[30] For instance, all else being equal, we may expect loans of higher quality to have longer maturity. Note that the cross-maturity differentials in yield or spread are accounted for in part also through the repricing-frequency and credit-rating-matched market interest rate or spread (as explained above).

[31] The results are robust to excluding the loans with missing maturity from the regression analysis.

value relative to the loan principal. We also include a dummy variable identifying floating-rate vs. fixed-rate loans (equal to 1 if the loan rate is floating and 0 otherwise). In pooled regressions that include all types of loans, a commitment status dummy is added (equal to 1 if the loan is made under an existing commitment or line of credit, and 0 otherwise).

As previous studies have argued or demonstrated, elements of a loan's terms are jointly determined and so none can be considered exogenous and entered as explanatory variables for the others in a structural manner. The internal credit rating of a loan is not strictly exogenous either. For our purpose, the endogenous nature of the non-price loan terms and the credit rating is not a concern in the usual sense because we do not attempt to interpret their coefficients as structural. Instead, we include them as controls to account, as much as possible, for the unobserved true creditworthiness that differs across small versus large borrowers to varying degrees over the business cycle. Note that only the *time varying* aspect of the unobserved quality composition of small borrowers relative to large ones matters for our empirical analysis, since the difference-in-differences estimation strategy removes the influence of any constant (including unobserved) credit quality differentials across small and large borrowers. Any residual changes in the composition of large vs. small borrowers' quality during the recession unobserved by the econometrician will load on the coefficient of the interaction term.

3.3 Descriptive Statistics

Table 1 reports the summary statistics for the variables that enter the regression analysis. It shows that slightly over 95 percent of the loans have an initial principal amount less than the $1 million cutoff and thus would be classified as small business loans according to the Call Reports convention. Among these, over 73 percent have balances below $100,000—in fact, the median loan size is only $45,000—and the rest are about evenly divided between the remaining two size categories. Classifying borrowers according to commitment size, which is arguably a better proxy for the size of the firm, gives a more even distribution across four corresponding size groups. Thirty-four percent of the loans have a commitment size of less than $500,000; 16 percent of between $500,000 and $1.25 million; 26 percent of between $1.25 and $5 million, and 24 above $5 milion.

Nearly 90 percent of the loans have floating rates, and around 80 percent are secured. About 23 percent of the loans have no stated maturity; these loans are most likely drawdowns priced based on the prime rate, judging by the survey instructions. According to bankers, these tend to be working capital loans with maturities on average of less than a year. Among the rest, the median and mean maturities are around 270 days and 470 days, respectively. These figures indicate that the majority of bank loans have maturities comparable to commercial paper.

In terms of the distribution of individual loan credit ratings, the bulk are rated 3 (moderate risk) or 4 (acceptable risk)—about 45 percent and 36 percent, respectively. A tiny fraction (2 percent) are in rating class 1 (minimal risk), and about an equal percentage (8 percent) in rating classes 2 and 5. This suggests that few bank customers satisfy the high standards laid out in the instructions for rating 1 borrowers. Rating 5 should be rare too, especially among new loans, since it applies to loans that must immediately incur capital charges. Given the low share of rating-5 new loans, we omit them as a robustness check, and this has virtually no effect on the parameter estimates.[32]

There are about 1.375 million loan observations from 1998:Q1 to 2009:Q4 after we drop loans with missing values for any of the variables used in the regressions. The sample is adjusted for bank mergers and acquisitions as follows: the target and acquirer for each deal are treated as separate entities until the quarter prior to the effective date of the merger; then, the merged bank is treated as yet another distinct entity. After adjusting for mergers, a total of 1,090 banks constitute our sample. In all the regressions, standard errors are clustered at the merger-adjusted bank level.

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[32] Results available upon request from the authors.

IV. Empirical Results

4.1 Linear Regression Analysis of Yields on All Loans

We first examine how interest rates on small business loans vary on average relative to rates on large business loans, especially how the relative rates behaved during this recession. In Table 2 we report the results of a baseline regression of loan yields that includes all loans, as well as separate regressions for new term loans and loans made under commitments. First, for the regressions with all loans, we run two specifications that differ only in the time fixed effects. The first one uses two recession dummies that equal 1 for the quarters during the 2001 recession as well as the quarters since 2008:Q1 and 0 otherwise; all the coefficients are listed in column 1. The second regression includes a full set of quarterly time dummies, with 1998:Q1 being the omitted quarter. Figure 4 plots the coefficients on the interaction terms between quarter dummies and loan size category dummies (along with the 1-standard-deviation band). Column 2 of Table 2 presents coefficient estimates on the rest of the explanatory variables.

Loans with an original balance greater than $1 million (large loans) are the omitted group. So the positive and significant coefficients on the three small-loan-size dummies are consistent with the prior suggested by the model as well as with findings of previous studies (for example, Kwan 2010)—small loans on average carry a higher rate. Note that the relationship is monotonic: relative to the above-million-dollar loans, yields are higher for small loans in decreasing size groups.

The first column in Table 2 shows that yields have in fact declined on average since the onset of this recession. Moreover, the coefficients on the interaction terms between the recession dummy and the loan size dummies are also all negative. On average, the interest rates on small loans declined relative to large loans in the recession by 48, 35, and 27 basis points for the three small-loan categories, respectively. This is in sharp contrast with the 2001 recession, where all three interaction terms for small-loan dummies are positive.

The credit-quality-matched market yield is positive and significant. For a 1-percentage-point increase in the market yields, bank loan yields rise 46 basis points on average. The bank-level controls are not consistently significant except for the unused C&I ratio, which is significantly negative in all specifications. The sometimes significant positive coefficient on ROA indicates that more profitable banks charge higher interest rates on average. The negative and occasionally significant coefficient of the nonperforming loan ratio indicates that banks with a higher percentage of bad loans charge lower rates. The significant positive coefficient on the capital ratio in some specifications may be due to the fact that small banks tend to hold more capital and also charge higher than average interest rates. The coefficient on normalized bank size is negative, albeit insignificant in most regressions.

Among the loan-level controls, credit ratings have the intuitive effect on yields—the better the rating, the lower the yield. Relative to loans rated 1, which is the omitted category, yields rise about 30 basis points for every notch of increase in the rating number (that is, lower credit quality). Fixed-rate loans carry marginally higher yields than floating-rate ones: only 11 basis points. By comparison, yields on secured loans are lower by 25 basis points. Maturity has a very marginal impact on yields.

Next, we turn to the specification with a full set of quarterly time dummies to gauge the time-series variations in relative yields on loans of different sizes. The top left panel of Figure 4 indicates that, compared with loans larger than $1 million (the omitted size category), there has been a downward trend in the average yield charged on the smallest C&I loans (less than $100,000), which was interrupted slightly by the 2001 recession and then petered out since 2006. Their yields were on average lower than those on the large loans throughout the sample period, with a cumulative decline of around 1 percentage point. During the financial crisis and the ensuing recession, yields on the smallest loans did not rise more than on loans larger than $1 million.

Similarly, the relative spreads on the other two categories of small loans have trended down as well (as shown in the top right and bottom left panels), albeit more modestly. Unlike the trend of the smallest loans, the downward trend in relative yields for these two small loan categories was essentially uninterrupted by either of the recessions in the sample. By comparison, the bottom right panel shows that the average yield on loans larger than $1 million (that is, the coefficients on the time dummies) exhibits little trend and its variations over time closely follow the movement of short-term risk-free interest rates.

We conduct Wald tests of the null hypothesis that the relative yields on small loans did not change significantly during this recession, that is,

$$H_0\text{: mean of } \beta_{It} = 0,\ t \in [2008\text{:Q1, 2009:Q4}],\ I = 1, 2, 3.$$

As can be inferred from the plots in Figure 4, the tests indicate that for the two smaller loan categories the test cannot reject the null that the mean of the recession coefficients is statistically equal to zero. On the other hand, we find that yields on the third category of small loans (with principal between $250,000 and $1 million) rose less in this crisis-recession than yields on the above-$1-million loans (p-value 0.011).[33] Given this finding of the relative change in yields between large and small loans, it is no surprise that qualitatively the same result emerges for loan spreads over a common base rate (fed funds rate) as the dependent variable. Spreads on small loans have risen less on average than those on large ones during this downturn.

These pooled regressions, however, suffer from important mis-specifications because they ignore two special institutional features of loans made under commitments. As discussed above, the information content of yield differs qualitatively between most drawdowns under a formal commitment and the other types of loans. To recap briefly, the entire yield on a new loan or loans under an informal line is determined according to the spot market condition when the *loan* is made, whereas the yield on loans under a formal commitment is typically the sum of a spread that is fixed at the earlier time of the *commitment* plus a floating base rate. This means it is incorrect to

[33] This test result is essentially the same as that in Kwan (2010).

regress either the spread or the yield on a formal commitment loan on variables indexed to the *later* time of the drawdown.

Second, different types of base rates are used in formal commitment contracts, all corresponding to risk-free or nearly risk-free short-term debt. As we show below, small loans are largely indexed to a prime rate, which is essentially pegged to the fed funds rate, whereas large loans are more often indexed to the LIBOR. These rates are almost identical under most circumstances, but some of them (such as the LIBOR) rose to unprecedented heights and persisted at those levels for months during the financial crisis. This means that the yields on some large loans may have jumped during the crisis quarters merely because of spikes in the LIBOR, without any active tightening of terms by banks. Since the pooled regressions ignore this contractual feature, their conclusion regarding the relative change in yields between large and small loans is potentially vulnerable to this exogenous shock to the base rate. The analysis below therefore seeks to assess the extent to which spikes in the LIBOR account for the bigger increase in yields on large loans.

4.2 Regressions of Yields on New Loans versus Loans Made under Commitments

We now consider how the coefficient estimates are affected by the type of base rate set in the commitment contract. According to data on the specific type of base rate used on each loan, which are only available between 1986:Q1 and 2003:Q2, the most widely used base rate is a prime rate, while the LIBOR typically ranks second. In addition, the fed funds rate, other domestic money market rates, and other unspecified rates are used. The bar charts showing the frequency of different types of base rates (Figure 3) reveals a clear pattern: prime rates are used noticeably more often on loans smaller than $1 million, while the LIBOR rate is used more often on larger loans.[34] And the share accounted for by either LIBOR-based or prime-based loans is stable within

[34] This is consistent with the pattern for loans to large corporations reported in the DealScan database, where the LIBOR is the most commonly used base rate. See, for example, Ivashina and Scharfstein (2010).

large and small loan size categories over that sample period. By comparison, the incidence of these two base rates does not differ nearly as much across banks of different sizes.

So one reason that interest rates rose more on large loans than on small ones during this crisis-downturn could simply be mechanical. The LIBOR skyrocketed during the peak of the crisis and persisted at those elevated levels for months. It resulted in much higher yields on large loans made under existing formal commitments that had set the LIBOR as the base rate. Since a noticeably higher fraction of large loans use the LIBOR as base, while small loans are more likely to use a prime rate or CD rates, shocks to the LIBOR manifested as bigger increases in yields on large loans relative to small loans.

Unfortunately, since loan-level data of the base rate are available only through 2003:Q2, we can test this hypothesis only indirectly. Our solution is to run separate yield regressions for new vs. commitment loans, to account for their different contractual features. We conjecture that, if spikes in the LIBOR were mostly responsible for the relative increase in yields on large loans found above, this should manifest more among loans made under formal commitments than among new loans. This is because, for new originations, the bank and the borrower can negotiate about the entire yield with minimal prior contractual constraints, unlike the case for loans drawn under formal commitments. So spikes in the LIBOR are not necessarily transmitted fully to yields on new loans, let alone to yields on large loans only. Another implication of the LIBOR-based hypothesis regarding the relative increase in yields on large loans is that the timing should coincide with movements in the LIBOR. In our data, this means that the biggest relative increase in large loan yields should occur in the fourth quarter of 2008, which corresponds to the survey (in November) amid the market turmoil following the Lehman bankruptcy.

Columns 3 and 4 of Table 2 report results of regressions with recession dummies and all quarter dummies, respectively, for the subsample of commitment loans only.[35] Figure 5 plots the time and interaction coefficients (from the latter regression). The time dummies reflect the time of the drawdown—when the loan was made. Note that here we index time dummies to loan date solely to be consistent with the specification of all-loan regressions above. For loans made under formal commitments, we will later index time dummies to the economically relevant date of the signing of the commitment contract. As can be seen in the regression results in column 3, the interaction terms are negative and significantly different from zero. These results are consistent with the hypothesis that an increase in the LIBOR during the recession could be a driver of our results.

Columns 5 and 6 of Table 2 report the new-loan-only regressions. Figure 6 plots the coefficients on quarter dummies and quarter dummies interacted with the three small-loan size dummies. One clear message is that the relative increase in rates on all three categories of small loans during this recession is now insignificantly different from zero. The coefficients on the other explanatory variables remain qualitatively the same. This suggests that for term loans originated "on the spot," whose rates should be determined mostly by market and borrower conditions at the time of the origination, there was no significant change in the relative yield between large and small loans during the recession.

Nevertheless, it should be noted that the pattern of interaction coefficients in Figures 5 and 6 are not consistent with the conjecture that the LIBOR was at least partly responsible for boosting yields on large loans as compared to small loans during this recession. As discussed above, most pronounced LIBOR spikes should manifest in our

[35] Ideally, we would group loans drawn under informal lines together with new loans, since both types of loan have terms set mostly according to conditions at the time the loan is made. But the survey only started distinguishing between informal lines and formal commitments in 2003. Since, for comparability, we want the same sample period for commitment loans in these regressions as for all loans and new loans above, we report results for commitment loans as a whole from 1998 to 2009. We doubt this would have significant impact on the estimates, since only about 4 percent of loans were drawn under informal lines.

data in the fourth quarter of 2008. However, the most significant negative coefficients occurred instead in the last quarter of 2009. In order to further investigate this hypothesis, we explore the interest rate spreads in the next section.

4.3 Linear Regression Analysis of Loan Spreads

Next, we address how the predetermined nature of spreads (that is, yields net of base rates) on loans under formal commitments influences the estimate of the relative change in spreads between large and small loans. Under the hypothesis that the crisis-induced shock to the LIBOR base rate was mostly responsible for the steeper increase in yields on large loans, we should expect spreads to show no significant relative change between small and large commitment loans during the crisis. This test, however, can be conducted only on loans priced based on prime rates, since only for such loans are data on base rates available for the entire sample period. Throughout the sample years, around 40 percent of the loans are priced based on prime rates.

Columns 1 and 2 in Table 3 and Figure 7 report the coefficient estimates from the regression of spreads on prime-based loans made under formal commitments. The time dummies and bank controls are indexed to the time when the *commitment* contract was signed (lagged by one quarter for bank controls), as opposed to when the *loan* was made. Likewise, the maturity- and rating-matched market reference spread on the right-hand side is from the week prior to the signing of the commitment instead of from the date of the drawdown. As discussed above, this is the correct mapping, since spreads on these loans are determined when the formal commitment contracts are signed and thus reflect the economic conditions then. Given that the median number of days till a drawdown is 200 in our sample, spread-relevant credit conditions likely have evolved meaningfully between the commitment and the drawdown dates for the majority of these loans.

The coefficient on the interaction between the recession dummy and the smallest loan category is negative and significant. On average, the spreads on small loans declined relative to large loans by 20 basis points since the onset of the recession. The interaction coefficients for the other two small-loan categories are negative but insignificant. Given that these spread regressions use only prime-based loans, we conclude that spikes in the LIBOR during the crisis do not fully explain results of the above yield regressions.

For comparison, we also run a similar regression for new loans.[36] Naturally, here all the right-hand-side variables (time dummies plus bank controls) are indexed to the time when the loan was made. Columns 3 and 4 in Table 3 and Figure 8 report the coefficient estimates from the regression of spreads on prime-based new loans. As in the yield regressions, most coefficients are insignificant, including those on the interaction terms.

Since these regressions are based only on those loans that use the prime rate as the base rate, it is natural to ask whether the endogenous choice of base rate reflects certain sample selection characteristics that can bias the regression results. From conversations with former loan officers, we learned of one rationale for some large borrowers' preference for the LIBOR as the base rate. These borrowers favor the LIBOR because the market for LIBOR-based interest rate swaps is considerably deeper than that for prime-based swaps. These borrowers can thus achieve the objective of a cheaper fixed rate for interest payments over an extended period by obtaining a floating-rate loan from a bank while simultaneously entering into a swap agreement with a third party. Such arrangements are made predominantly by large banks. Given that our regressions include bank fixed effects, we can think of no obvious reason why this rationale for choosing the LIBOR as the base rate should bias our main results.

4.4 Changes in the Full Distribution of Loan Spreads for Formal Commitments

[36] Compared with commitment loans, in the case of new loans it is less clear to the borrower what exactly the meaning of spread on a new loan is, since what she should care about is the cost of capital, which corresponds to the yield. The spread on a new loan can be meaningful for the lender, to the extent that her cost of funds covaries closely with the base rate. In the STBL data, 40 percent of new loans report a prime rate as the base rate.

Our main empirical result so far can be summarized as follows: once we account for the contractual features of business loans made under formal commitments to lend, interest rate spreads on small loans have declined *on average* relative to spreads on large loans since the beginning of the Great Recession in 2008:Q1. Our model, on the other hand, has empirical implications for changes in the shape of the *full distribution* of interest rates during the recession. The model suggests that, if spreads on small loans decline relative to large loans during an economic downturn mainly because a bigger fraction of the small borrowers—the riskiest ones that were near the margin before the downturn—are rationed out of the market, we should observe the steepest relative decrease in spreads in the part of the distribution occupied by the riskier borrowers. Being near the margin, these borrowers should have been paying the highest interest rates before the recession, and were later shut out of the credit markets during the recession.

To test this hypothesis, we examine the changes in the full distribution of interest rate spreads for formal commitments before and after the recession. We start by plotting the unconditional distribution of spreads by loan size and over time. To this end, we employ the so-called box plot in Figure 9, where the top and bottom edges of each box define the 25th and 75th percentiles of the distribution, respectively, while the horizonal line in-between represents the median. The whiskers depict the tails of the distribution —1.5 times the inter-quartile range beyond the 25th and 75th quartiles, respectively. Consistent with the OLS regression results, small loans on average pay higher spreads than large loans. Likewise, spreads increase more for large loans than for small loans during the recession.

More importantly, comparing the size of the inter-quartile boxes and upper tails of the spread distributions, we can see that during the recession the spread dispersion among the largest loans widens more than the spread dispersion on smaller loans. In sum, the unconditional distributions suggest that spreads increased more for large loans than for small loans during the recession and that this relative increase was mainly driven by the upper tail of the spread distribution. This finding is consistent with the pattern that would be predicted by the model in the case where credit rationing is more acute in downturns for small borrowers than for large ones. In consequence, the credit quality of the marginal small borrowers who obtained loans in this recession rose more than the quality of the marginal large borrowers, and the former thus saw their loan spreads widen less.

We now turn to examine the changes in the *conditional* distribution of interest rate spreads, that is, after taking account of the loan- and bank-level control variables. To obtain the conditional rate spread, we regress the spread on loan- and bank-level controls as well as time dummies, that is, we estimate specification (10) without loan-size dummies and interactions of time and size dummies on the right-hand side. Residuals from this regression (conditional spreads) are then divided into two groups according to commitment size—above versus below \$5 million—and labeled large versus small loans. To represent the relative position of the spread distribution for small loans vis-à-vis large loans, we first sort the residuals separately among large and small loans and next, for each percentile in the conditional spread distribution for small loans, map out the corresponding percentile in the large-loan distribution. For instance, the 5th percentile for small loans is mapped to the 15th percentile for large loans if they correspond to the same value of spreads. These calculations are done separately for the subsample periods before and during the recession, that is, the years 2004 to 2007 and 2008 to 2009.

Figure 10 depicts these mappings for the before- and during-recession sample periods, facilitating the comparison of the conditional distribution of spreads on small loans versus large loans before and during the recession. Specifically, percentiles of spreads on small loans are shown on the x-axis, while those of large loans are shown on the y-axis. Not surprisingly, both curves in Figure 10 are above the 45-degree line, illustrating the fact that spreads are bigger on small loans than on large loans both before and since the onset of the recession. More importantly, the figure demonstrates significant reductions in relative spreads on small loans since the recession began only for the highest quantiles of the conditional spread distribution. The 30th percentile of the small- loan spread distribution corresponds roughly to the 50th percentile of the large-loan spread distribution both before and during the recession. On the other hand, the 80th percentile of the small loan spread distribution corresponds to roughly the 95th percentile of the large loan spread distribution before the recession. During the recession, it drops to approximately the 85th percentile. The pattern of reduction in relative spreads on small loans during the recession is consistent with heightened credit rationing of the riskiest small borrowers.

To further analyze the changes in the distribution of spreads for formal commitments, we estimate specification (10) using quantile regressions.[37] The dependent variable is the interest rate spread on commitment loans that use a prime rate as the base rate. Quantile regressions allow us to account for heterogeneous effects of covariates at different points of the conditional spread distribution, as the partial effect of each explanatory variable is allowed to vary across the distribution. At each chosen quantile, coefficient estimates on the interaction terms measure how differently spreads on small loans behaved relative to the spreads on large loans during the recession for loans at that percentile, given the other conditioning variables. We estimate the model at every five percentile intervals, that is, the 5th, 10th,… and 95th percentiles. Figure 11 plots the 19 quantile regression estimates (the solid line) along with 95-percent confidence bands (the shaded gray area) against the corresponding percentiles on the horizontal axis. We again include the bank fixed effects to control for unobserved time-invariant bank characteristics. All the explanatory variables are measured at the time of the commitment contract.

According to the OLS estimates of the mean relative change in spreads, small loans paid on average 20 basis points less during the recession. Figure 11 points to

[37] We follow the procedure described by Canay (2010), except that we eliminate the bank fixed effects by de-meaning the data at the bank level instead of first-differencing the data.

important differences across the conditional distribution of spreads. Reductions in the relative spread on the small loans under formal commitments mainly occur within the higher percentiles of the interest rate distribution: the interaction coefficients are negative and significant for the 70th percentile and above. At the lower tail of the distribution, however, the interaction coefficients are insignificant. For example, spreads on small loans are statistically the same as those on large loans during the recession at the 5th percentile but are 80 basis points lower at the 90th percentile. Also observe that for a given quantile, the coefficient on the interaction term is more negative for the smallest loan category. The conventional OLS estimation cannot capture such disparate partial effects of the covariates. More importantly, this pattern is consistent with increased credit rationing of the riskiest small borrowers during the recession as implied by the model.

4.5. *Robustness Tests*

Our interpretation of the results obtained so far is that small firms may have been subject to greater credit rationing by banks than larger firms in this recession. To further substantiate this interpretation, we conduct robustness tests that focus on those loans that were more likely to be rationed (such as those of low quality) and on those banks that were more likely to cut lending because they had suffered grave losses in the financial crisis.

First of all, we estimate regression (10) by loan rating. The results, reported in Table 4, show that the most negative coefficients on the interaction terms occur in the subsample of loans with rating 5. To a lesser degree, loans with ratings 3 and 4 also produce negative albeit insignificant coefficients on the recession-loan-size interaction dummies. In sum, rationing appear to be concentrated in the lower-quality borrowers.

Next, we run regression (10) by bank subsamples sorted according to the degree of strain on the banks' balance sheets. We divide banks into above- and below-median subsamples based on a variety of relevant attributes and provide the results in paired columns in Table 5. The premise is that banks more exposed to the financial crisis are more likely to ration credit to their borrowers. For clarity of exposition, only the coefficients of interest—on the recession dummy and its interaction with the loan size dummies—are reported. In Panel A we divide the sample of banks according to bank attributes before the crisis; we use the average value of each over the years 2004 to 2006. In Panel B we explore the effect of certain bank characteristics during the recession, averaged over the years 2008 and 2009. We find that banks with a nonperforming-loan ratio above the median, both before and during the crisis (columns 1 and 9, respectively), a deposit ratio below the median (column 4) and asset size above the median before the recession (column 5), unrealized losses (column 11), and nonperforming loans over allowance for loan and lease losses above the median during the recession (column 13) have the most negative and significant coefficients on the interaction terms. These regressions provide support for the supply-side interpretation of our findings.

Finally, we explore whether those banks that specialize in small business lending behaved differently during the crisis and recession than other banks in our sample. The premise here is that we should find less evidence of rationing among small business lenders. We again divide banks into above- and below-median subsamples, in this case based on the share of (less than $1 million) small loans in total C&I loan portfolio according to the data in June Call Reports. Columns 7 and 8 in Table 5 present the coefficients for the above- and below-median subsamples, respectively. We find that the interaction terms have negative and significant coefficients only for the below-median banks, suggesting that these banks rationed more small businesses during the recession than banks focused on lending to small businesses. This finding is consistent with previous results from the banking literature documenting that firms with close banking relationships experience a smaller decline in credit availability during economic downturns (see, for example, Hancock and Wilcox 1998; Ferri, Kang, and Kim 2001; Vickery 2005).

4.6. Alternative Explanations

There are several possible alternative explanations of our findings. In this section we evaluate the ones that are most plausible. We conduct additional robustness checks based on subsamples of banks that display the traits most conducive to the suggested alternative mechanisms to assess how much they can help to explain the main results of our paper.

4.6.1 Loan Restructuring

First of all, some have suggested that loan restructuring may be responsible for the changes in relative interest rate spreads found in this paper.[38] Restructuring generally means reducing the payment per period, which is often achieved in part by a reduction of the interest rate. Our data likely contain restructured loans, because the survey instructions specifically ask respondents to include conversions of revolving credit into term loans, which is a typical way to restructure loans under commitments. Unfortunately, our data do not identify whether an originated loan is truly a new origination or the restructuring of an existing loan.

So we rely on the Call Reports data to investigate this hypothesis. The Call Reports provide the total dollar amount of restructured C&I loans at the bank level, but no breakdowns by the original loan amount. If our finding is largely driven by restructuring of riskier small business loans, then it should be more pronounced for those banks that have a higher proportion of restructured loans. We again divide banks into two subgroups, here according to whether the ratio of restructured C&I loans over total C&I loans is above or below the median. The results are reported in columns 15

[38] Rice and Rose (2010) show that small banks have conducted more restructuring of business loans during this recession than large banks have. Since small banks are understood to specialize in lending to small businesses, it is likely that small loans have been more subject to restructuring than large loans. Furthermore, it is possible that among small loans, the riskier ones have experienced a higher incidence of restructuring than the less risky ones, and this may help to explain our finding of the relatively smaller increase in spreads on riskier small loans.

and 16 of Table 5 (Panel B), respectively. We observe that the interaction terms are negative and significant for the above-median banks. This suggests that loan restructuring may have played a role in our finding of a relative decline in interest rate spreads on small loans compared to large loans during the recession. However, in order for restructuring to explain the shift in the overall distribution of spreads between small and large loans, one would have to argue that banks were more willing to restructure the riskier small loans relative to the riskier large loans. There seems no obvious rationale for such a differentiation.

4.6.2 Cyclicality of Firms

Another conjecture is that the cyclicality of volatility may be different between large and small firms. For instance, if a bigger fraction of the riskiest small firms fail and exit during downturns than their counterparts among large firms, then we could observe that loan interest rate spreads rise less for surviving small firms than for large firms. On the other hand, the creation of new firms is procyclical, and these startups are usually small firms. If economic downturns depress the creation of new small firms, which are likely to be among the riskiest small borrowers, then again we could observe that loan interest rate spreads rise less for existing small firms than for large firms.

We interpret this conjecture as fully consistent with the credit rationing story, albeit in a somewhat different form. Although we cannot quantify it with our data, it is quite likely that the lack of bank financing has played a role in both the failure of the riskiest small firms and the low birth rate of new small firms. Also, note that existing studies of the creation and growth of small businesses over the business cycle are inconclusive and that therefore the conjecture above is subject to debate. For example, Moscarini and Postel-Vinay (2009) find that small businesses create more jobs in periods of high unemployment and recessions than in periods of recovery. Haltiwanger, Jarmin, and Miranda (2010) show that when one controls for firm age, firm size has no systematic relationship with firm growth and so larger firms may experience faster growth.

4.6.3 Tightening on Other Credit Standards: Fees and Collateral

Strictly speaking, a borrower's cost of capital equals the all-in cost of each loan contract, which includes various fees (such as the origination fee paid upfront) in addition to the interest rate. The absence of fee data in the STBL can especially bias down the estimate of the full cost on loans made under formal or informal lines of credit, since the overall cost of either type of loan contract typically comprises a bigger share of fees, routinely a fee on the unused portion of the line and sometimes also an annual fee on the entire line.

To the extent the heterogeneity in these unobserved fees is largely across banks and reasonably stable over time, the bank fixed effects should absorb most of this variation. But if the fees vary differently over business cycle across small versus large loans within a bank, then the inability to control for fees associated with each loan can bias our results and even reverse them. For instance, it is possible that even though small loans on average saw no bigger increase in interest rates than large loans during this recession, the all-in cost of funding in fact rose more for small borrowers if they had to pay higher fees than large borrowers did. Nonetheless, there is no a priori reason to expect the fee portion of borrowing to rise *more* for small borrowers than for large ones during bad times. Nor are we aware of anecdotal evidence to this effect. In fact, for loans made under existing commitments, which constitute the bulk of our data, the marginal cost of funds equals the interest rate net of the fee on the unused commitment. So if small borrowers faced higher fees, their marginal cost of funds would actually be lower.

Yet another explanation of our findings could be that small borrowers, especially the riskier ones, have been posting more collateral or subject to more stringent covenants in general since the downturn began. Consequently, the rates paid by riskier small borrowers have not risen as much as the large loans. Even though this is not rationing, it would still be a form of tightening of credit to small businesses. Both explanations are consistent with the broad conjecture that credit became relatively harder to get for small firms than for large firms during this recession.

4.6.4 Change in the Composition of Large Borrowers

Next, we address the alternative explanation that our finding of the shift in the relative distribution of large versus small loan interest rates is the result of the riskier among large borrowers being shut out of the public debt market and thus having to turn to banks. In particular, if large risky borrowers were shut out of the commercial paper market, they would have to tap into their lines of credit. We would then likely observe interest rates going up more for large than for small borrowers.[39] Unfortunately, our data do not report whether a borrower has access to public markets or not. So we further divide large loans into three size groups according to the commitment amount: between $5 million and $10 million, between $10 million and $25 million, and $25 million and above. We identify the last subgroup as loans most likely made to large firms with access to the commercial paper and bond markets. We observe that the only negative and significant interaction coefficient corresponds to loans under commitment below $5 million. This observation does not appear to support this alternative hypothesis of market rationing of riskier large firms. One caveat with this robustness test is that the below $5 million category likely includes some, albeit few, instances of individual banks' participation in syndicated loan commitments.[40]

A related alternative hypothesis is that the markup charged by banks increases more for large risky borrowers than for other borrowers in recessions, and did so more markedly during the Great Recession when these firms were shut out of public debt markets. This is, however, not supported by the above finding that none of the coefficients on the recession-loan-size interaction dummies are significantly negative for the small-loan commitment category. So it seems reasonable to maintain our assumption that the markups charged by banks do not vary systematically across large and small borrowers over the business cycle.

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[39] The market for A2/P2 commercial paper of nonfinancial firms experienced severe strain during the crisis—spreads spiked, maturities shortened, overall issuance plummeted—while the market for A1/P1 paper experienced little change.

[40] The survey instructions ask banks to report their share in the syndicated loan, not the full loan amount.

4.6.5 Large Firms Applying for Small Loans

Another potential explanation is that more of the small loans were made to large firms during the recession because demand fell and firms borrowed less. However, we observe no significant changes during the recession in the proportion of small loans that were made under commitments greater than $5 million. Furthermore, none of our analysis based on the commitment size instead of the loan amount should be subject to this concern, to the extent that the relationship between the size of a firm and its credit line is nearly monotonic.

V. Conclusion

A public policy issue that has gained prominence over the past year is whether credit constraint has been largely responsible for the unusually severe net job losses suffered by small businesses relative to large firms since the onset of the Great Recession. The answer to this question can have important implications for the kind of policy solutions that will likely be most effective in stimulating recovery and growth of small businesses.

This study develops a simple model of bank loan pricing and applies it to analyze the dynamics of interest rates on small business loans relative to large loans over the past decade or so. It then compares the relative terms on small business loans before and during this recession, to assess whether small business loans have experienced greater tightening of loan terms during the Great Recession.

The empirical analysis finds that small business loans experienced a relative decrease in interest rate spreads compared to large business loans during the Great Recession, once we take in account the fact that most of these loans were made under existing commitments to lend and so their interest rates equal a pre-chosen floating base rate plus a pre-set fixed spread. Moreover, the relative decline appears to concentrate on loans to the riskiest borrowers, that is, those facing rates or spreads in the upper quantiles of the distribution. These findings are consistent with signs of credit rationing as implied by the model.

Our results are also consistent with findings in corporate finance studies that lines of credit are not a perfect substitute for holding liquid securities such as cash and cash equivalents (see, for example, Sufi 2009). Our results imply that lines of credit do not fully insure small businesses against liquidity shocks in the event of an economic downturn.

In summary, our findings suggest that credit availability may have played a role in hampering the recovery of small businesses. This implies that policy measures that focus on encouraging credit supply to small businesses may have an effect in encouraging the expansion of existing small firms or the creation of new ones. However, our analysis cannot assess whether tight credit supply is a major hindrance to small businesses. Hence, it is prudent to continue policy efforts that aim to stimulate aggregate demand.

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Appendix A. Banks' Optimal Lending Decision and Comparative Statics

A1. Bank optimization problem when returns are lognormal

First we analyze a case where the gross return on project i $R_{i,t+1} = \theta_i \omega_{i,t+1} R_{t+1}$ is distributed lognormally, as both $\omega_{i,t+1}$ are R_{t+1} assumed to be lognormal. Specifically, since $r_{i,t+1} := \ln\left(R_{i,t+1}\right) = \ln\theta_i + \ln\omega_{i,t+1} + \ln R_{t+1} \equiv \widehat{\theta}_i + \widehat{\omega}_{i,t+1} + r_{t+1}$, we assume $\widehat{\omega}_{i,t+1}$ and r_{t+1} are both normally distributed as follows: $\widehat{\omega}_{i,t+1} \sim N(\mu_{\widehat{\omega}}, \sigma^2_{\widehat{\omega}})$ while time-t conditional distribution of $r_{t+1} \sim N(\mu_{rt}, \sigma^2_{rt})$. Recall that $\omega_{i,t+1}$ is independent of R_{t+1}, so $r_{i,t+1} \sim N(\mu_{it}, \sigma^2_{it})$ with $\mu_{it} = \widehat{\theta}_i + \mu_{\widehat{\omega}} + \mu_{rt}$ and $\sigma^2_{it} = \sigma^2_{\widehat{\omega}} + \sigma^2_{rt}$.

Given the distributional assumption, the marginal condition (5) for setting the loan interest rate $\hat{Z}_{i,t+1}$ becomes[41]

$$e^{\hat{z}_{i,t+1}} - \left(e^{\hat{z}_{i,t+1}} + m_{it}\right)\Phi\left(\frac{\hat{z}_{i,t+1} - \mu_{it}}{\sigma_{it}}\right) + \delta \mathrm{E}_t\left(R_{i,t+1}\right)\Phi\left(\frac{\hat{z}_{i,t+1} - \mu_{it}}{\sigma_{it}} - \sigma_{it}\right) = R_{M,t}. \tag{A.1}$$

$\hat{z}_{i,t+1} := \ln\left(\hat{Z}_{i,t+1}\right)$ while $\mathrm{E}_t(R_{i,t+1}) = \exp\left(\mu_{it} + \sigma^2_{it}/2\right)$ is the conditional mean of $R_{i,t+1}$. Note that $\Phi\left[\left(\hat{z}_{i,t+1} - \mu_{it}\right)/\sigma_{it}\right]$ is the probability of default.

Next we derive the comparative statics of $\hat{Z}_{i,t+1}$ with respect to θ_i, m_{it}, etc. To streamline notations, denote the left-hand side of equation (5) and hence equation (A.1) as $\mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)$; note that it is the lender's expected return from the loan. Then

$$\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}} = e^{\hat{z}_{i,t+1}} - \frac{\left(e^{\hat{z}_{i,t+1}} + m_{it}\right)\phi_1}{\sigma_{it}} - e^{\hat{z}_{i,t+1}}\Phi_1 + \frac{\delta \mathrm{E}_t\left(R_{i,t+1}\right)\phi_2}{\sigma_{it}},$$

where $\Phi_1 \equiv \Phi\left[\left(\hat{z}_{i,t+1} - \mu_{it}\right)/\sigma_{it}\right]$ and $\phi_1 \equiv \phi\left[\left(\hat{z}_{i,t+1} - \mu_{it}\right)/\sigma_{it}\right] = \partial\Phi_1/\partial\hat{z}_{i,t+1}$, while $\phi_2 \equiv \phi\left[\left(\hat{z}_{i,t+1} - \mu_{it}\right)/\sigma_{it} - \sigma_{it}\right]$. Denote $\Phi_2 \equiv \Phi\left[\left(\hat{z}_{i,t+1} - \mu_{it}\right)/\sigma_{it} - \sigma_{it}\right]$, then

[41] Note that the mean of lognormal $R_{i,t+1}$ truncated at $\hat{Z}_{i,t+1}$ is $\exp\left(\mu_{it} + \sigma^2_{it}/2\right)\Phi\left\{\left[\hat{z}_{i,t+1} - \left(\mu_{it} + \sigma^2_{it}\right)\right]/\sigma_{it}\right\}$ with $\Phi(.)$ denoting the standard normal distribution function.

$$\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \widehat{\theta}_i} = \frac{\left(e^{\hat{z}_{i,t+1}} + m_{it}\right)\phi_1}{\sigma_{it}} - \delta \mathrm{E}_t\left(R_{i,t+1}\right)\left[\frac{\phi_2}{\sigma_{it}} - \Phi_2\right].$$

We can sign $d\hat{Z}_{i,t+1}/d\theta_{it}$ through $d\hat{z}_{i,t+1}/d\widehat{\theta}_{it}$ since:

$$\frac{d\hat{z}_{i,t+1}}{d\widehat{\theta}_i} = \frac{d\widehat{Z}_{i,t+1}}{d\theta_i}\frac{\theta_i}{\widehat{Z}_{i,t+1}} = -\left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \widehat{\theta}_i}\right] \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right].$$

If we assume $\delta \mathrm{E}_t\left(R_{i,t+1}\right)\Phi_2 + \left(1-\Phi_1\right)e^{\hat{z}_{i,t+1}} > \partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial \hat{z}_{i,t+1} > 0$, that is, the lender's expected return increases in the loan rate at a moderate pace, then $\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial \widehat{\theta}_{i,t+1} > 0$. In this case $d\hat{Z}_{i,t+1}/d\theta_{it} < 0$. This result conforms to the intuition that more creditworthy borrowers face lower loan interest rates.

Similarly, assuming $\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial \hat{z}_{i,t+1} > 0$, we derive

$$\frac{d\widehat{Z}_{i,t+1}}{dm_{it}} = \frac{e^{\hat{z}_{i,t+1}} d\hat{z}_{i,t+1}}{dm_{it}} = -e^{\hat{z}_{i,t+1}}\left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial m_{it}}\right] \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] = e^{\hat{z}_{i,t+1}}\Phi_1 \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] > 0.$$

$$\frac{d\widehat{Z}_{i,t+1}}{dR_{M,t}} = -e^{\hat{z}_{i,t+1}}\left[\frac{\partial\left[\mathrm{E}\left(\mathfrak{R}_{i,t+1}\right) - R_{M,t}\right]}{\partial R_{M,t}}\right] \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] = e^{\hat{z}_{i,t+1}} \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] > 0.$$

$$\frac{d\widehat{Z}_{i,t+1}}{d\delta} = -e^{\hat{z}_{i,t+1}}\left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \delta}\right] \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] = -e^{\hat{z}_{i,t+1}}\mathrm{E}_t(R_{t+1})\Phi_2 \Big/ \left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{z}_{i,t+1}}\right] < 0.$$

These are again intuitive results: all else being equal, the interest rate to charge on a loan rises in the per-dollar monitoring cost and the bank's opportunity cost of funds but falls in the recovery rate.

If we characterize good macro conditions in terms of a higher conditional mean of aggregate return μ_{rt}, we know that $d\hat{Z}_{i,t+1}/d\mu_{rt} < 0$ because

$$\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial \mu_{rt} = \partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial \widehat{\theta}_i > 0.$$

This says that the better a lender's expectation of the economy-wide return, the lower the loan interest rates charged, all else being equal.[42] Alternatively, if we map good economic times into lower volatilities for R_{t+1}, equal to $\exp\left(2\mu_{rt}+\sigma_{rt}^2\right)\left[\exp\left(\sigma_{rt}^2\right)-1\right]$, while keeping its mean $\mathrm{E}_t(R_{t+1})=\exp\left(\mu_{rt}+\sigma_{rt}^2/2\right)$ the same, lower values for σ_{rt} need to be compensated for by increases in μ_{rt} to maintain the same $\mathrm{E}_t(R_{t+1})$: $d\mu_{rt}=-\sigma_{rt}d\sigma_{rt}$. Since

$$\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial\sigma_{rt}}=\frac{\sigma_{rt}\left(\hat{z}_{i,t+1}-\mu_{it}\right)\left(e^{\hat{z}_{i,t+1}}+m_{it}\right)\phi_1}{\sigma_{it}^3}-\delta\mathrm{E}_t\left(R_{i,t+1}\right)\left[\phi_2\frac{\sigma_{rt}}{\sigma_{it}}\left(1+\frac{\hat{z}_{i,t+1}-\mu_{it}}{\sigma_{it}^2}\right)-\Phi_2\sigma_{rt}\right]$$
$$=\frac{\sigma_{rt}\left(\hat{z}_{i,t+1}-\mu_{it}\right)}{\sigma_{it}^2}\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial\mu_{rt}}-\delta\mathrm{E}_t\left(R_{i,t+1}\right)\sigma_{rt}\left[\frac{\phi_2}{\sigma_{it}}-\Phi_2+\Phi_2\frac{\hat{z}_{i,t+1}-\mu_{it}}{\sigma_{it}^2}\right],$$

we have

$$-\sigma_{rt}\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial\mu_{rt}}+\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial\sigma_{rt}}=\frac{-\sigma_{rt}\left(e^{\hat{z}_{i,t+1}}+m_{it}\right)\phi_1}{\sigma_{it}}+\frac{\sigma_{rt}\left(\hat{z}_{i,t+1}-\mu_{it}\right)}{\sigma_{it}^2}\left[\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial\mu_{rt}}-\delta\mathrm{E}_t\left(R_{i,t+1}\right)\Phi_2\right].$$

For this to be negative, it is sufficient to assume $\partial\mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial\mu_{rt}<\delta\mathrm{E}_t\left(R_{i,t+1}\right)\Phi_2$, since under most circumstances $\hat{z}_{i,t+1}<\mu_{it}$, that is, the project's expected payoff exceeds the loan yield. Then we have $d\hat{Z}_{i,t+1}/d\sigma_{rt}>0$, mirroring the result $d\hat{Z}_{i,t+1}/d\mu_{rt}<0$.

Next we consider the comparative statics of $\overline{Z}_{i,t+1}$, the loan yield that maximizes the lender's expected return $\mathrm{E}(\mathbf{R}_{i,t+1})$. So $\overline{Z}_{i,t+1}$ is the solution to $\partial\mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)/\partial\hat{z}_{i,t+1}=0$. Assuming the second-order condition of return maximization (7) is satisfied implies that

$$\frac{\partial\mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial\left(\overline{z}_{i,t+1}\right)^2}=\left(1-\Phi_1\right)e^{\overline{z}_{i,t+1}}-\frac{2e^{\overline{z}_{i,t+1}}\phi_1}{\sigma_{it}}-\frac{\left(e^{\overline{z}_{i,t+1}}+m_{it}\right)\phi_1'}{\sigma_{it}^2}+\frac{\delta\mathrm{E}_t\left(R_{t+1}\right)\phi_2'}{\sigma_{it}^2}<0.$$

$\phi_i'(.)$, i=1, 2, is the derivative of the standard normal probability function corresponding to $\phi_i(.)$.

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[42] Here we ignore the general equilibrium effect that during good times banks' required rate of return $R_{M,t}$ also tends to rise because of tighter monetary policy.

Then we have the relationship that the loan yield ceiling is decreasing in m_{it}:

$$\frac{d\overline{Z}_{i,t+1}}{dm_{it}} = \frac{e^{\overline{z}_{i,t+1}} d\overline{z}_{i,t+1}}{dm_{it}} = -e^{\overline{z}_{i,t+1}} \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \overline{z}_{i,t+1} \partial m_{it}} \right] \Big/ \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \left(\overline{z}_{i,t+1}\right)^2} \right] = e^{\overline{z}_{i,t+1}} \left(\frac{\phi_1}{\sigma_{it}} \right) \Big/ \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \left(\overline{z}_{i,t+1}\right)^2} \right] < 0.$$

Likewise we derive that the loan yield ceiling rises in the recovery rate because

$$\frac{d\overline{Z}_{i,t+1}}{d\delta} = -e^{\overline{z}_{i,t+1}} \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \overline{z}_{i,t+1} \partial \delta} \right] \Big/ \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \left(\overline{z}_{i,t+1}\right)^2} \right] = e^{\overline{z}_{i,t+1}} \left[\frac{\mathrm{E}_t\left(R_{t+1}\right)\phi_2}{\sigma_{it}} \right] \Big/ \left[\frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \left(\overline{z}_{i,t+1}\right)^2} \right] > 0.$$

Similarly, $d\overline{Z}_{i,t+1} \big/ d\theta_{it} > 0$ – the loan yield ceiling also rises in the borrower's quality—since assumptions regarding the first- and the second-order conditions imply that

$$\begin{aligned} \frac{\partial \mathrm{E}^2\left(\mathfrak{R}_{i,t+1}\right)}{\partial \overline{z}_{i,t+1} \partial \theta_i} &= \frac{e^{\overline{z}_{i,t+1}}\phi_1}{\sigma_{it}} + \frac{\left(e^{\overline{z}_{i,t+1}} + m_{it}\right)\phi_1'}{\sigma_{it}^2} + \frac{\delta \mathrm{E}_t\left(R_{t+1}\right)}{\sigma_{it}} \left(\phi_2 - \frac{\phi_2'}{\sigma_{it}} \right) \\ &> \left(1-\Phi_1\right) e^{\overline{z}_{i,t+1}} - \frac{e^{\overline{z}_{i,t+1}}\phi_1}{\sigma_{it}} + \frac{\delta \mathrm{E}_t\left(R_{t+1}\right)\phi_2}{\sigma_{it}} > 0. \end{aligned}$$

A2. Comparative statics of $\overline{Z}_{i,t+1}$ under general distributions of R_{t+1}

First we show that the sufficient condition (8) for the maximal feasible loan yield becomes necessary when we model good macroeconomic times as characterized by distributions of aggregate return R_{t+1} that first-order stochastically dominate those during bad times.[43] Recap the general condition for the maximal feasible loan yield (6) below:

$$\int_0^\infty \left\{ \left[1 - G\left(\overline{\omega}_{i,t+1}\right)\right] - \left[\left(1-\delta\right)\overline{Z}_{i,t+1} + m_{it}\right] g\left(\overline{\omega}_{i,t+1}\right) \Big/ \theta_i R_{t+1} \right\} dH_t(R_{t+1}) = 0\,.$$

[43] Note that this is equivalent to a higher mean in the case of a normal distribution.

Denote the term inside the curly bracket as $\mathrm{E}\left(\overline{R}_{i,t+1}\right)$, then (8) means $\mathrm{E}\left(\overline{R}_{i,t+1}\right)$ = 0. If this condition does not hold, then $\int \mathrm{E}\left(\overline{R}_{i,t+1}\right) dH(R_{t+1})$ does not equal 0, that is (6) cannot be satisfied, at all times. This is because the integrand $\mathrm{E}\left(\overline{R}_{i,t+1}\right)$ is a decreasing function of R_{t+1}:

$$\partial \mathrm{E}\left(\overline{R}_{i,t+1}\right) \big/ \partial R_{t+1} = -\left[\left(1-\delta\right)\overline{Z}_{i,t+1} + m_{it}\right] \Big/ \theta_i R_{t+1}^2 \left[g\left(\varpi\right) + g' \big/ \theta_i R_{t+1}\right] - g\left(\varpi\right)\overline{Z}_{i,t+1} \Big/ \theta_i R_{t+1}^2 < 0.$$

This implies that $\int \mathrm{E}\left(\overline{R}_{i,t+1}\right) dH(R_{t+1}) \leq \int \mathrm{E}\left(\overline{R}_{i,t+1}\right) dH'(R_{t+1})$ if $\mathrm{E}\left(\overline{R}_{i,t+1}\right)$ is not always 0, where H(.) and H'(.) denote the distribution function of R_{t+1} during good and bad times, respectively. So equation (8) must be satisfied for (6) to hold at all times.

To derive the comparative statics of $\overline{Z}_{i,t+1}$, we further assume the second-order condition (7) for the maximal expected return holds so that

$$\frac{\partial \mathrm{E}\left(\overline{R}_{i,t+1}\right)}{\partial \overline{Z}_{i,t+1}} = -\frac{1}{\theta_i R_{t+1}}\left[g(.)\left(2-\delta\right) + \frac{\left[\left(1-\delta\right)\overline{Z}_{i,t+1} + m_{it}\right] g'}{\theta_i R_{t+1}}\right] < 0 .$$

Since

$$\frac{\partial \mathrm{E}\left(\overline{R}_{i,t+1}\right)}{\partial \theta_i} = \frac{\left(1-\delta\right)\overline{Z}_{i,t+1} + m_{it}}{\theta_i^2 R_{t+1}}\left[g\left(\overline{\omega}_{i,t+1}\right) + \frac{g'\overline{Z}_{i,t+1}}{\theta_i R_{t+1}}\right] - \frac{\overline{Z}_{i,t+1} g(.)}{\theta_i^2 R_{t+1}} > 0 ,$$

we derive that the cutoff loan rate $\overline{Z}_{i,t+1}$ is increasing in θ:

$$\frac{d\overline{Z}_{i,t+1}}{d\theta_i} = -\left[\frac{\partial \mathrm{E}\left(\overline{R}_{i,t+1}\right)}{\partial \theta_i}\right] \Bigg/ \left[\frac{\partial \mathrm{E}\left(\overline{R}_{i,t+1}\right)}{\partial \overline{Z}_{i,t+1}}\right] > 0.$$

Comparative statics of $\overline{Z}_{i,t+1}$ with respect to other parameters m_{it}, $R_{M,t}$ etc. can be derived analogously.

A3. Comparative statics of $\hat{Z}_{i,t+1}$ under general distributions of R_{t+1}

To derive how the interest rate charged on realized loans varies with borrower type θ_i, recall that we denote the left-hand side of equation (5) as $\mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)$ and that its derivative with respect to $\hat{Z}_{i,t+1}$ equals the left-hand side of equation (6):

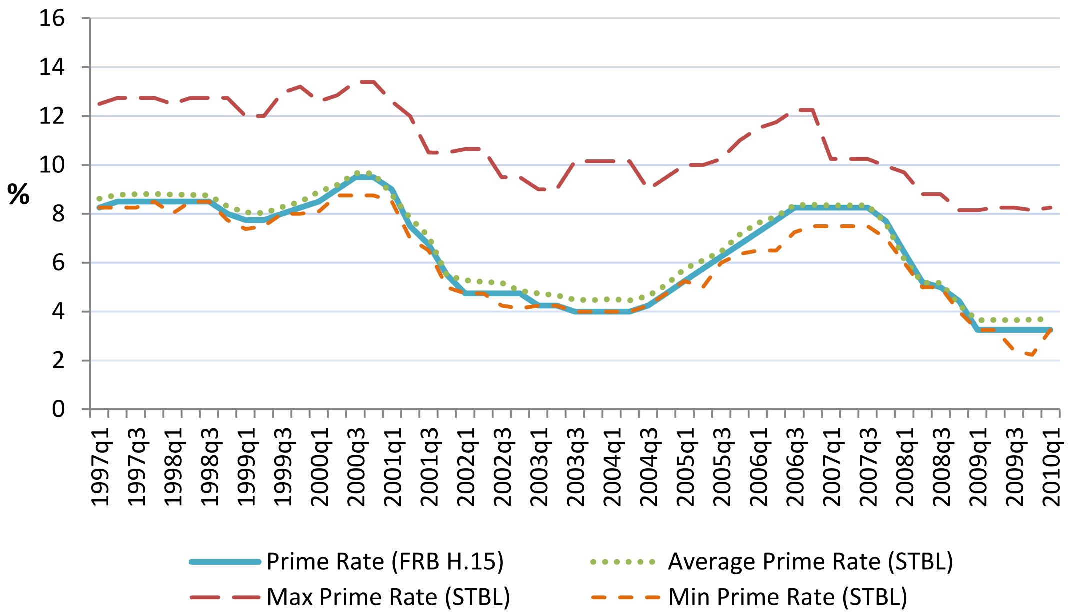
$$\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right)}{\partial \hat{Z}_{i,t+1}} = \int_0^\infty \left\{\left[1 - G\left(\hat{\omega}_{i,t+1}\right)\right] - \left[(1-\delta)\hat{Z}_{i,t+1} + m_{it}\right] g\left(\hat{\omega}_{i,t+1}\right) \Big/ \theta_i R_{t+1}\right\} dH_t(R_{t+1}).$$

Assuming the second-order condition for a unique maximal expected return on the loan holds, we have $\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right) \big/ \partial \hat{Z}_{i,t+1} > 0$ when $\hat{Z}_{i,t+1} < \bar{Z}_{i,t+1}$. There then follows the intuitive result that the better a project's type, the lower the loan interest rate $\hat{Z}_{i,t+1}$ and hence the cutoff level $\hat{\omega}_{i,t+1}$. That is, $d\hat{Z}_{i,t+1} \big/ d\theta_i < 0$, since

$$\frac{d\hat{Z}_{i,t+1}}{d\theta_i} = -\frac{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right) \big/ \partial \theta_i}{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right) \big/ \partial \hat{Z}_{i,t+1}} = -\frac{\int_0^\infty \left\{\left[(1-\delta)\hat{Z} + m\right] g\left(\hat{\omega}\right) + \delta \int_0^{\hat{\omega}} \omega R dG(\omega)\right\} dH(R)}{\partial \mathrm{E}\left(\mathfrak{R}_{i,t+1}\right) \big/ \partial \hat{Z}_{i,t+1}}.$$

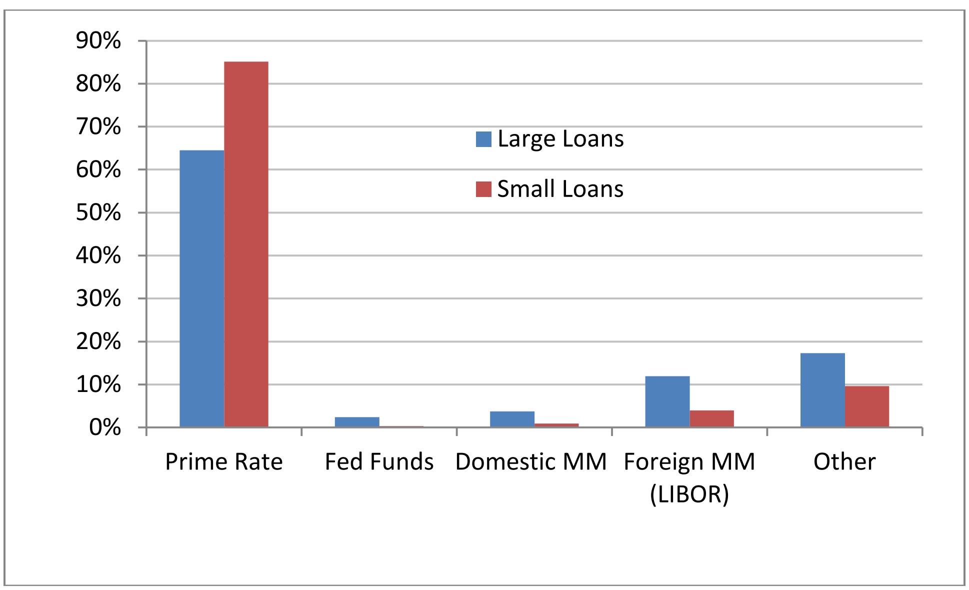
Comparative statics of $\hat{Z}_{i,t+1}$ with respect to the other parameters m_{it}, $R_{M,t}$, etc. can be derived analogously.

Figure 2. Distribution of prime rates across banks



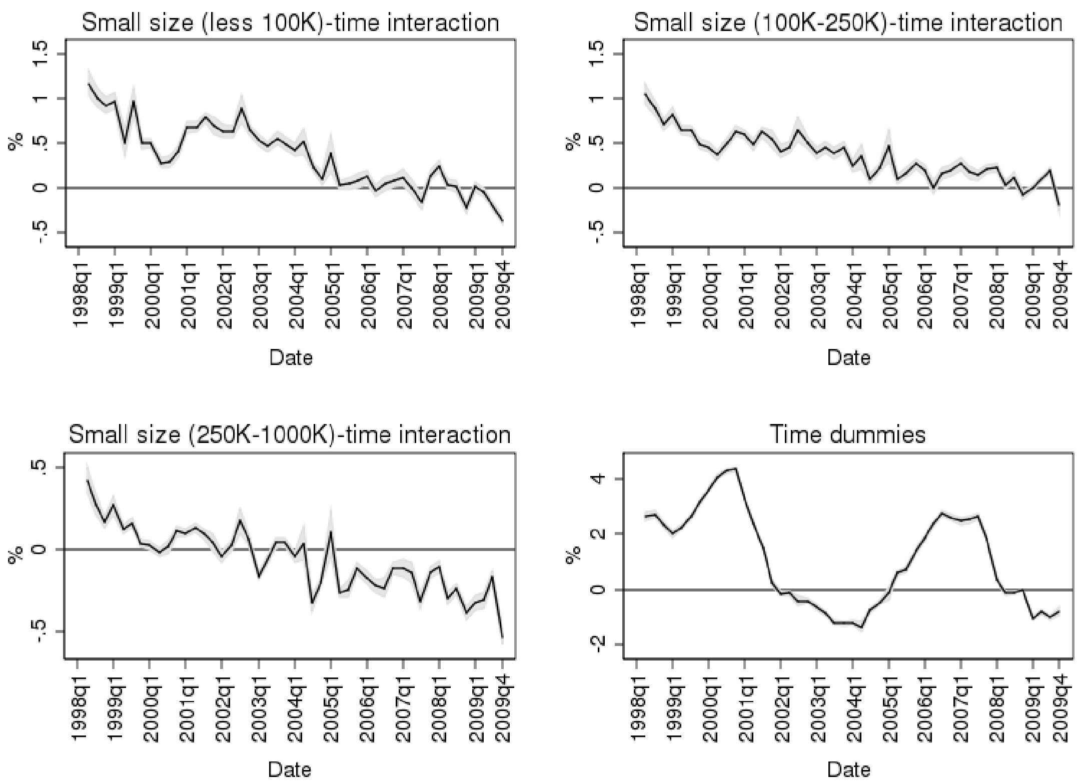
Note – The figure plots the prime rate as reported by the Federal Reserve System (H.15), joint with the minimum, maximum, and average prime rate reported by the banks in the STBL dataset.

Figure 3. Choice of base rates across loan size categories



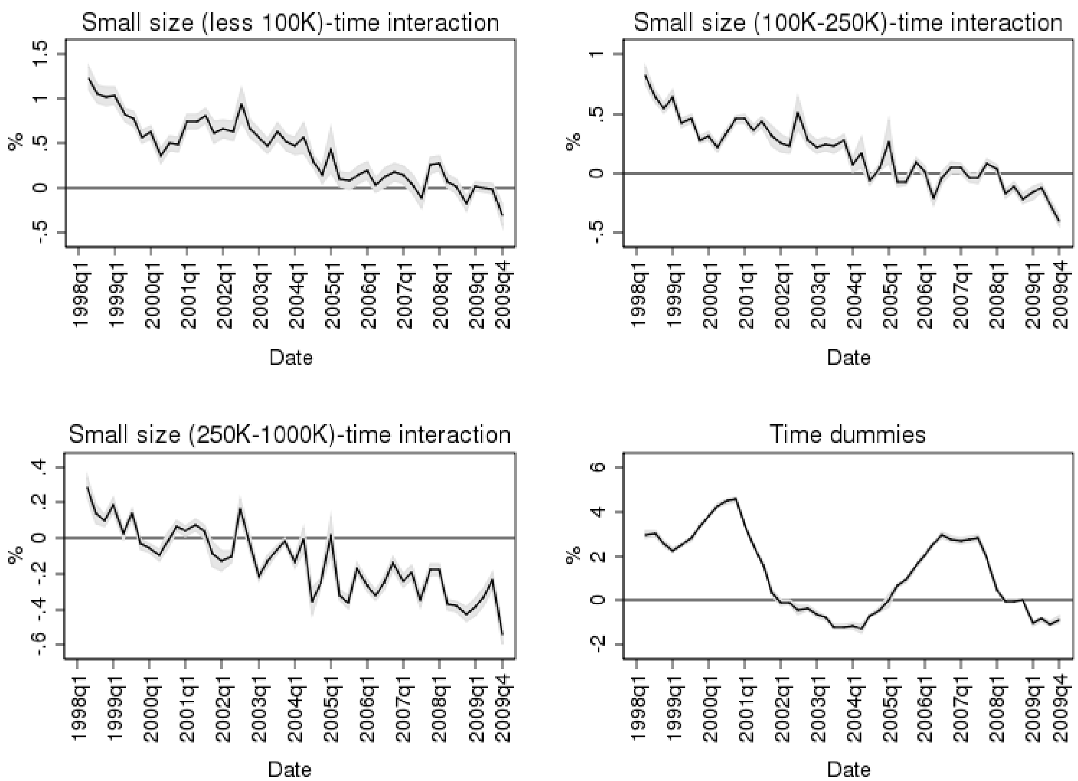
Note – This figure shows the percentage of loans that use each base rate by size of the loan. Source: STBL data between 1986:Q1 and 2003:Q2 (not available after that).

Figure 4. Coefficient estimates on quarter dummies and interaction between quarter and small-loan size category dummies. Yield regression. All loans.



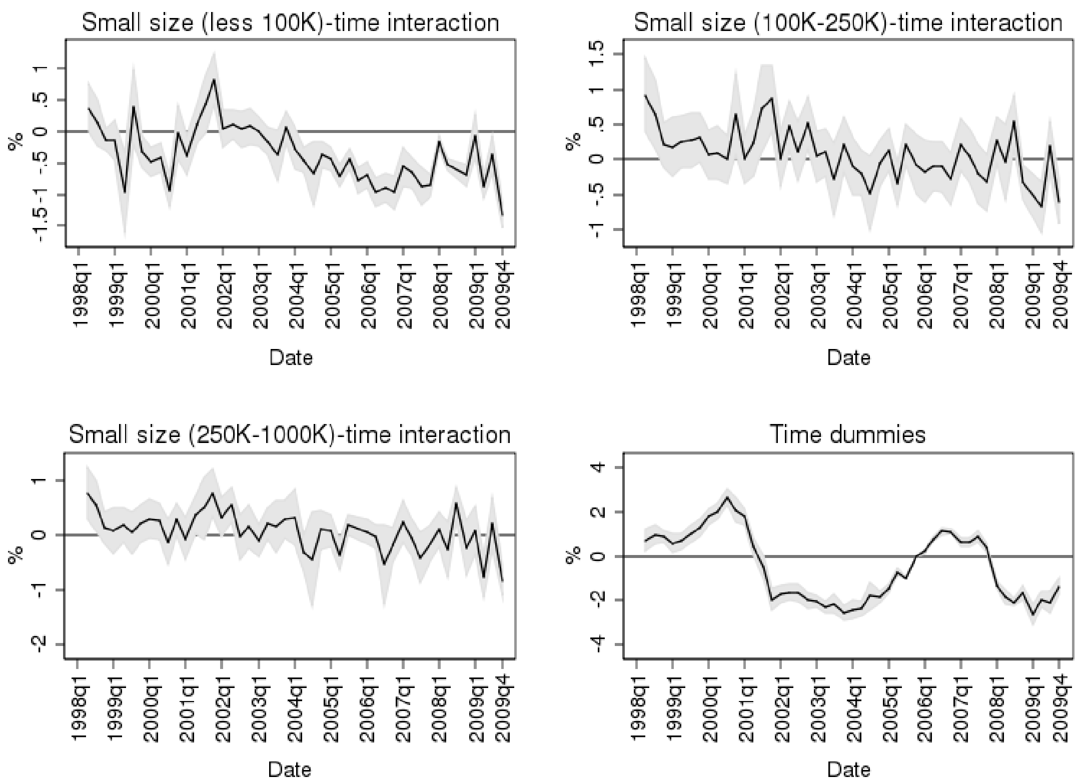
Note – The figure plots the time quarter dummies and the interaction terms between the quarter dummies and the three loan size categories. The remaining regression coefficients are in column 2 of Table 2. The dependent variable is the interest rate on all loans. All the explanatory variables are measured at the time of the loan.

Figure 5. Coefficient estimates on quarter dummies and interaction between quarter and small-loan size category dummies. Yield regression. Commitment loans.



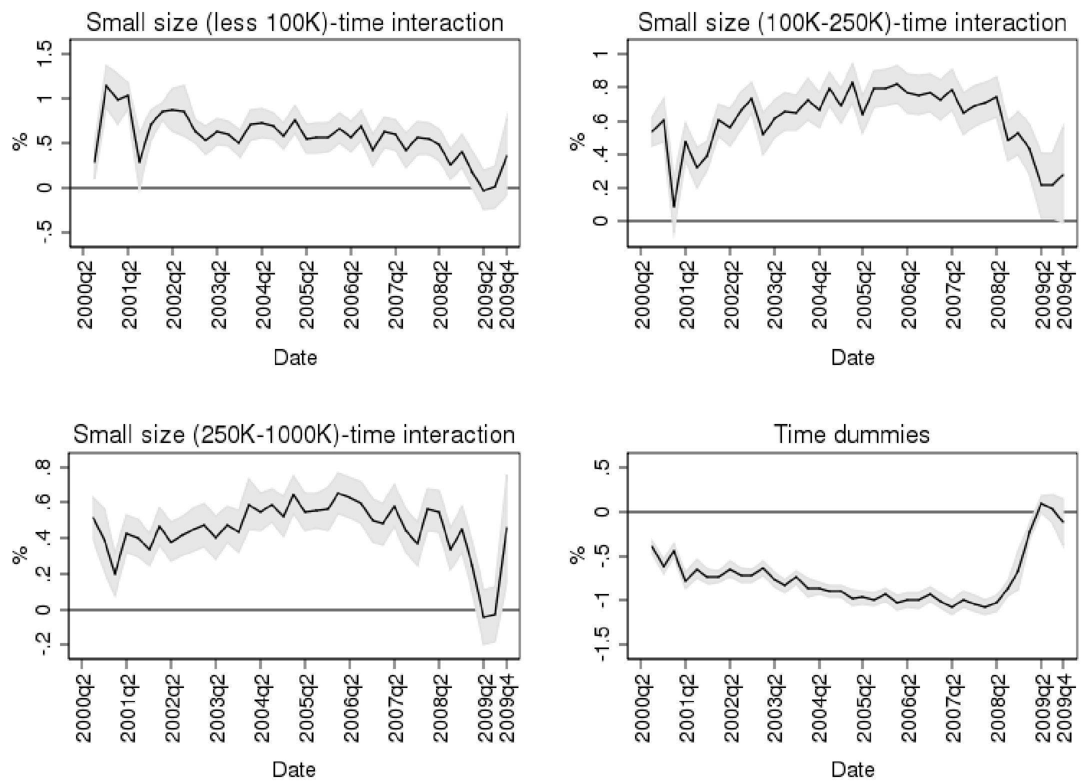
Note – The figure plots the time quarter dummies and the interaction terms between the quarter dummies and the three loan size categories. The remaining regression coefficients are in column 4 of Table 2. The dependent variable is the interest rate on commitment loans. All the explanatory variables are measured at the time of the loan.

Figure 6. Coefficient estimates on quarter dummies and interaction between quarter and small-loan size category dummies. Yield regression. New loans.



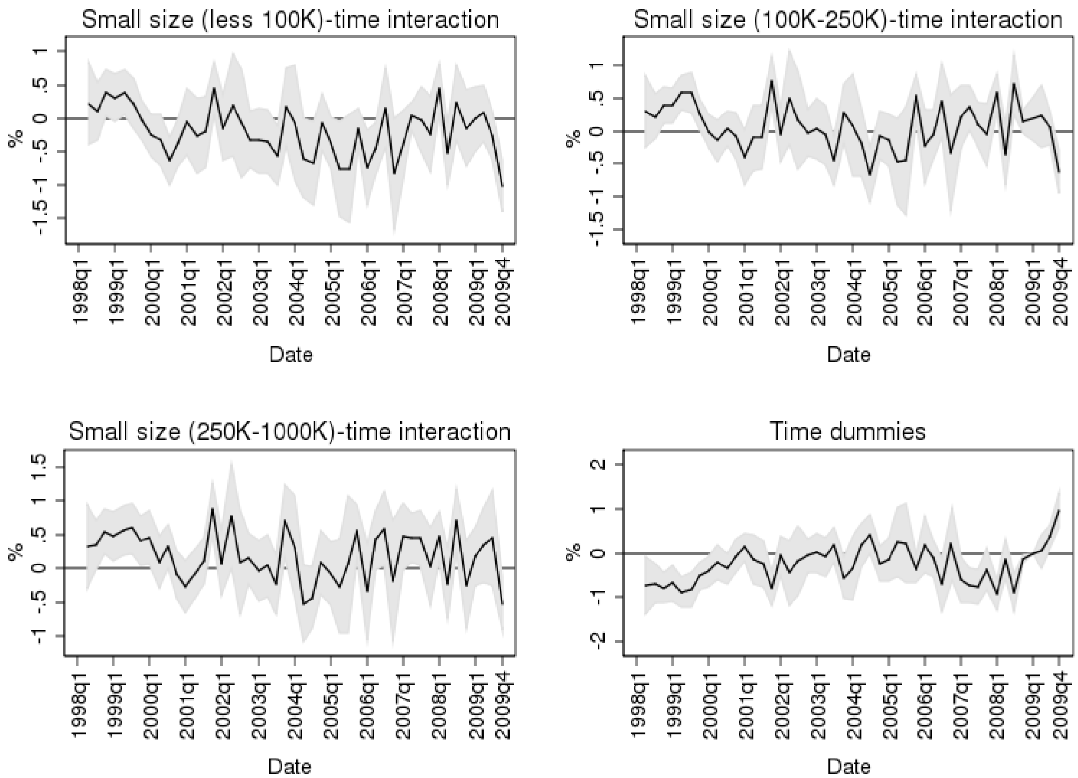
Note – The figure plots the time quarter dummies and the interaction terms between the quarter dummies and the three loan size categories. The remaining regression coefficients are in column 6 of Table 2. The dependent variable is the interest rate on new loans. All the explanatory variables are measured at the time of the loan.

Figure 7. Coefficient estimates on quarter dummies and interaction between quarter and small-loan size category dummies. Spread regression (prime based). Formal commitments at time of commitment.



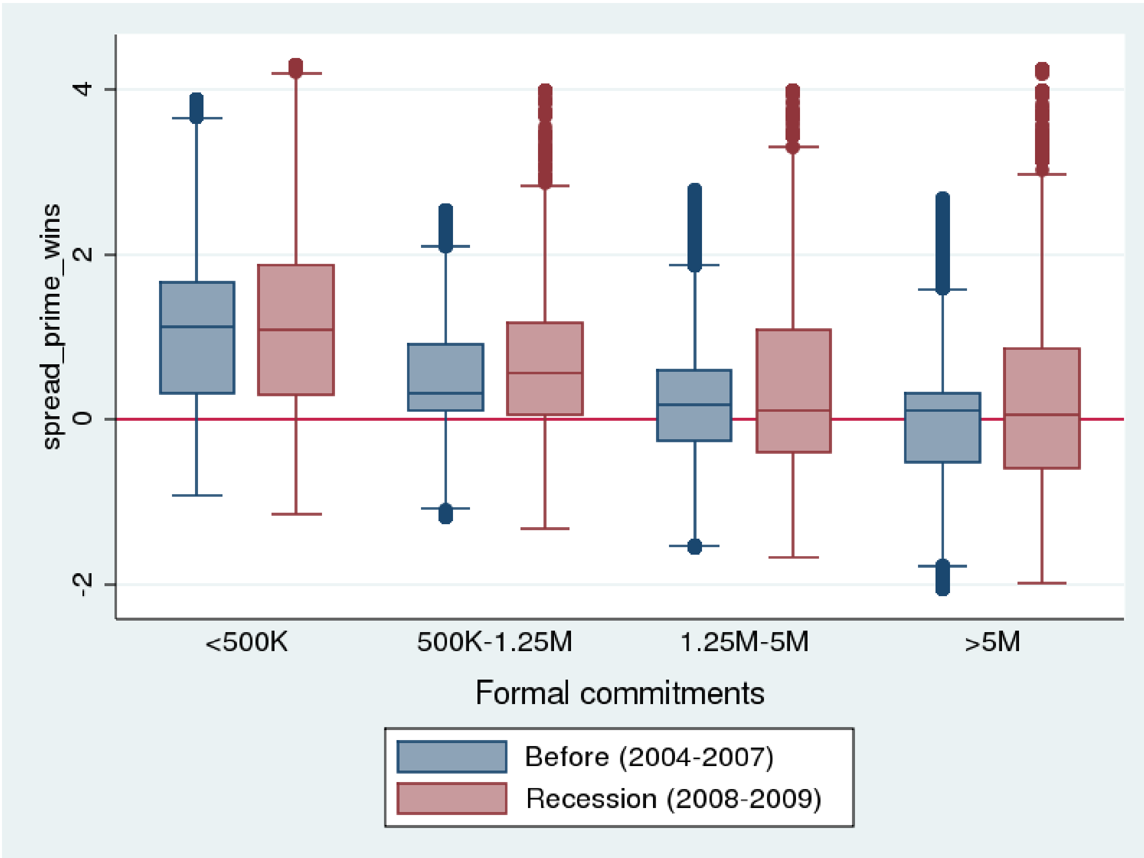
Note – The figure plots the time quarter dummies and the interaction terms between the quarter dummies and the three loan size categories. The remaining regression coefficients are in column 2 of Table 3. The dependent variable is the interest rate spread on commitment loans that use the prime rate as reference rate. All the explanatory variables are measured at the time of the commitment contract

Figure 8. Coefficient estimates on quarter dummies and interaction between quarter and small-loan size category dummies. Spread regression (prime based). New loans.



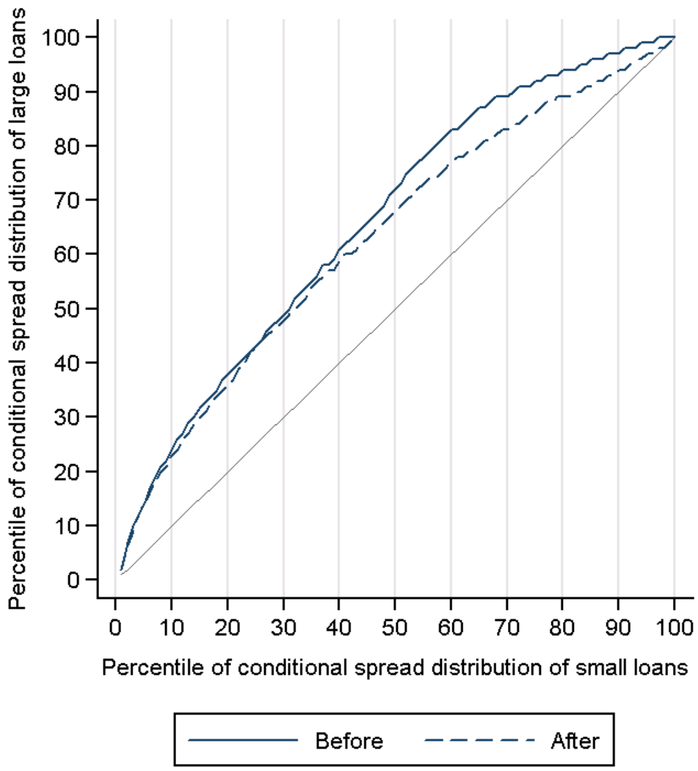
Note – The figure plots the time quarter dummies and the interaction terms between the quarter dummies and the three loan size categories. The remaining regression coefficients are in column 4 of Table 3. The dependent variable is the interest rate spread on new loans that use the prime rate as reference rate. All the explanatory variables are measured at the time of the loan.

Figure 9. Unconditional distribution of prime based spreads by loan size, before and during the recession (boxplot).



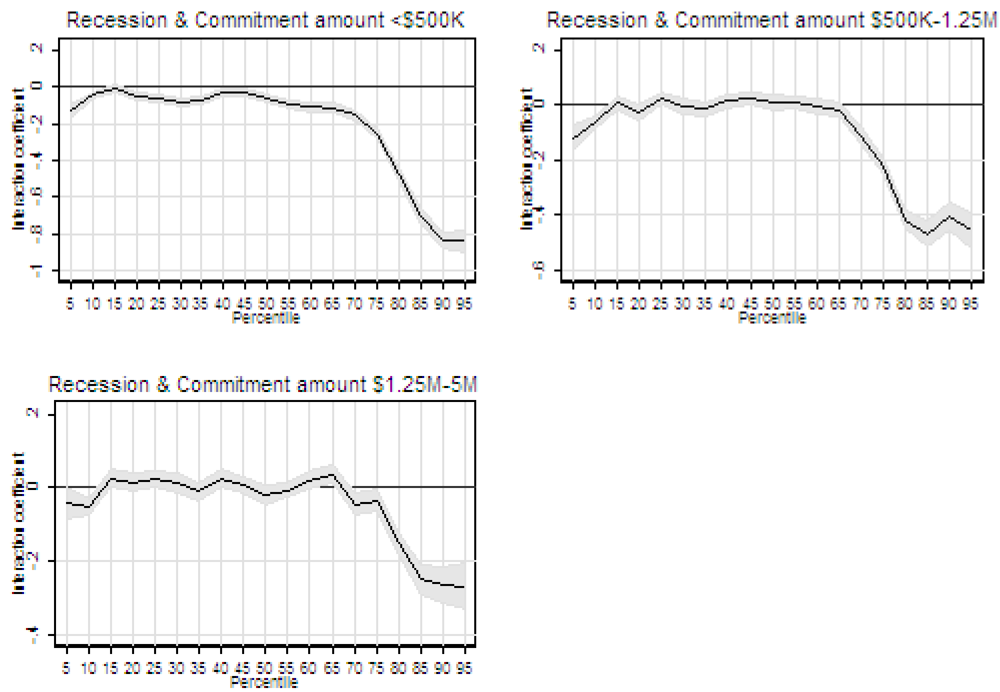
Note – The figure shows the box plots of interest rate spreads for formal commitments that use the prime rate as base rate. The sample of loans has been divided by the size of the commitment into four categories (specified in the x axis) and into two time periods (before the recession and recession period). The top and bottom edges of each box define the 25th and 75th percentiles of the distribution, respectively, while the horizonal line in between represents the median. The whiskers depict the tails of the distribution—1.5 times the inter-quartile range beyond the 25th and 75th quartiles, respectively.

Figure 10. The impact of the Great Recession on loan spreads of small loans versus large loans (rankplot).



Note – The figure shows the location of small loans in the distribution of spreads of large loans before and after the Great Recession. The results in the figure are obtained using the following procedure: First, I calculate residuals for small and large loans from specification (9). The dependent variable is the interest rate spread on commitment loans that use the prime rate as reference rate. I keep 100 small loans, each corresponding to a different percentile of the small loans conditional spread distribution. Next, I calculate their position in the large loans spread distribution. I repeat this procedure before (solid line) and during (dashed line) the recession.

Figure 11. Quantile regressions. Plot of interaction coefficients of loan size and recession dummies. Prime based spreads. Formal commitment loans at time of the commitment.



Note – The figure plots the interaction coefficients of the recession dummy with each of the three small size classes for 19 quantile regressions. We estimate specification (10) using quantile regressions with bank fixed effects. We estimate the model at every five percentile intervals, that is, the 5, 10,… and 95 percentiles. We plot the 19 distinct quantile regression estimates for each percentile as the solid line with 95 percent confidence bands (shaded gray area). To account for bank fixed effects, we follow the procedure described by Canay (2010), except that we eliminate the bank fixed effects by de-meaning the data at the bank level instead of first-differencing the data. The dependent variable is the interest rate spread on commitment loans that use the prime rate as reference rate. All the explanatory variables are measured at the time of the commitment contract (coefficients not reported).

Table 1. Summary statistics of regression variables

	All loans N=1,375,031		New loans N=174,033		Formal commitments N=593,074	
	mean	median	mean	median	mean	median
Loan yield	7.062	7.208	7.403	7.496	6.106	5.904
Loan spread (prime based)	0.825	0.605	0.970	0.819	0.640	0.360
Dummy for prime based loans	0.396	0	0.333	0	0.761	1
Prime rate	6.462	7.000	6.584	7.500	5.696	5.250
Dummy for rating 2	0.086	0	0.131	0	0.078	0
Dummy for rating 3	0.451	0	0.432	0	0.433	0
Dummy for rating 4	0.363	0	0.354	0	0.386	0
Dummy for rating 5	0.080	0	0.057	0	0.086	0
Dummy for secured loans	0.813	1	0.821	1	0.821	1
Maturity (missing set to 1 year)	438	353	615	365	404	328
Dummy for missing maturity	0.232	0	0.412	0	0.186	0
Dummy for floating-rate loans	0.893	1	0.767	1	0.925	1
Reference market yield	7.113	7.15	7.082	7.15	6.599	6.46
Reference market spread	1.866	1.66	1.815	1.67	1.855	1.48
Dummy for loans < $100K	0.733	1	0.791	1	0.738	1
Dummy for loans in [$100K, $250K]	0.126	0	0.103	0	0.129	0
Dummy for loans in [$250K, $1M]	0.093	0	0.065	0	0.093	0
Dummy for loans in > $1M	0.048	0	0.041	0	0.041	0
Dummy for commitment amount < $500K					0.338	0
Dummy for commitment amount [$500K, $1.25M]					0.160	0
Dummy for commitment amount [$1.25M, $5M]					0.260	0
Dummy for commitment amount in > $5M					0.243	0
Dummy for new loans	0.127	0	1	1	0	0
Dummy for commitment loans	0.873	1	0	0	1	1
Dummy for informal commitments	0.026	0	0	0	0	0
Dummy for formal commitments	0.431	0	0	0	1	1
Liquidity ratio	0.203	0.189	0.201	0.177	0.194	0.183
ROA	0.003	0.003	0.003	0.003	0.003	0.003
Capital ratio	0.095	0.092	0.097	0.094	0.095	0.093
Asset size (normalized)	0.014	0.006	0.008	0.004	0.018	0.010
NPL ratio	0.008	0.006	0.008	0.006	0.010	0.007
Unused C&I ratio	1.358	1.245	1.176	0.889	1.410	1.351
(Loans<1M)/(Total C&I)	0.280	0.246	0.375	0.320	0.262	0.222
Restructured loans ratio	0.0004	0	0.0002	0	0.0005	0
Unrealized losses	-0.070	-0.010	0.038	-0.001	-3.523	-0.031
NPL over ALLL	0.788	0.647	0.738	0.631	0.973	0.748
Deposit ratio	0.701	0.699	0.701	0.682	0.709	0.708
Dummy for year 1998	0.093	0	0.089	0	0.000	0
Dummy for year 1999	0.097	0	0.119	0	0.000	0
Dummy for year 2000	0.085	0	0.105	0	0.000	0
Dummy for year 2001	0.091	0	0.086	0	0.000	0
Dummy for year 2002	0.085	0	0.074	0	0.000	0
Dummy for year 2003	0.076	0	0.066	0	0.094	0
Dummy for year 2004	0.082	0	0.069	0	0.160	0
Dummy for year 2005	0.073	0	0.062	0	0.139	0
Dummy for year 2006	0.084	0	0.079	0	0.160	0
Dummy for year 2007	0.079	0	0.072	0	0.154	0
Dummy for year 2008	0.079	0	0.062	0	0.157	0
Dummy for year 2009	0.077	0	0.118	0	0.137	0

Table 2. Regression analysis of C&I loan yields

	All Loans (1998Q1-2009Q4)		Commitment Loans (1998Q1-2009Q4)		New Loans (1998Q1-2009Q4)	
	Recession dummies	Qtr dummies	Recession dummies	Qtr dummies	Recession dummies	Qtr dummies
	(1)	(2)	(3)	(4)	(5)	(6)
(Loans <$100k)*(2008-9 recession)	-0.480***		-0.474***		-0.155	
	[0.141]		[0.145]		[0.238]	
(Loans $100-250k)*(2008-9 recession)	-0.356***		-0.316***		-0.131	
	[0.122]		[0.120]		[0.252]	
(Loans $250k-1M)*(2008-9 recession)	-0.272***		-0.246***		-0.189	
	[0.0941]		[0.0888]		[0.253]	
Dummy for loans < $100K	1.347***	0.848***	1.244***	0.708***	1.682***	1.962***
	[0.0781]	[0.128]	[0.0755]	[0.168]	[0.112]	[0.247]
Dummy for loans in [$100K, $250K]	0.904***	0.439***	0.827***	0.562***	1.137***	1.022***
	[0.0659]	[0.139]	[0.0611]	[0.111]	[0.112]	[0.363]
Dummy for loans in [$250K, $1M]	0.694***	0.663***	0.625***	0.666***	0.928***	0.829**
	[0.0547]	[0.103]	[0.0478]	[0.105]	[0.106]	[0.321]
Dummy for 2008-2009 recession	-1.674***		-1.771***		-1.639***	
	[0.187]		[0.200]		[0.291]	
Dummy for 2001 recession	-0.123		-0.0762		-0.745**	
	[0.203]		[0.230]		[0.344]	
(Loans <$100k)*(2001 recession)	0.404***		0.424***		0.815**	
	[0.140]		[0.151]		[0.367]	
(Loans $100-250k)*(2001 recession)	0.284**		0.291**		0.661*	
	[0.124]		[0.133]		[0.360]	
(Loans $250k-1M)*(2001 recession)	0.203**		0.205**		0.505	
	[0.0985]		[0.102]		[0.365]	
Dummy for commitment loans	-0.478***	-0.343***				
	[0.0614]	[0.0614]				
Reference market yield	0.462***	-0.266***	0.424***	-0.248***	0.617***	-0.135
	[0.0704]	[0.0555]	[0.0729]	[0.0569]	[0.108]	[0.0889]
Liquidity ratio	-2.728*	0.0908	-3.815**	-0.00155	0.830	0.737
	[1.478]	[0.462]	[1.788]	[0.454]	[1.555]	[0.645]
ROA	8.468*	-1.569	10.08*	-1.746	-2.840	-3.597
	[4.996]	[2.100]	[5.479]	[2.466]	[9.451]	[6.485]
Capital ratio	-3.527	3.185**	-6.109	4.666***	0.0515	0.480
	[5.586]	[1.515]	[6.497]	[1.504]	[7.407]	[2.717]
Asset size (normalized)	-42.00	-14.67	-57.86	-11.46	55.06	5.674
	[90.61]	[14.52]	[95.23]	[12.26]	[103.7]	[40.93]
NPL ratio	-20.44*	-1.227	-21.06*	1.005	-18.81	-4.761
	[10.74]	[2.389]	[10.98]	[1.979]	[14.11]	[6.324]
Unused C&I ratio	-0.00122***	-0.00222***	0.000914**	-0.000276	-0.00154***	-0.00193***
	[0.000181]	[9.61e-05]	[0.000389]	[0.000284]	[0.000220]	[0.000142]
Dummy for rating 2	0.435***	0.500***	0.253**	0.373***	0.885***	0.898***
	[0.0951]	[0.0651]	[0.106]	[0.0687]	[0.135]	[0.121]
Dummy for rating 3	0.467***	1.312***	0.379***	1.180***	0.655***	1.521***
	[0.106]	[0.0971]	[0.114]	[0.101]	[0.170]	[0.171]
Dummy for rating 4	0.703***	1.657***	0.610***	1.526***	0.893***	1.907***
	[0.112]	[0.0993]	[0.115]	[0.102]	[0.224]	[0.193]
Dummy for rating 5	1.019***	2.033***	0.916***	1.910***	1.334***	2.311***
	[0.144]	[0.103]	[0.155]	[0.105]	[0.221]	[0.204]
Dummy for secured loans	-0.254***	-0.203***	-0.206***	-0.146**	-0.412**	-0.339***
	[0.0710]	[0.0631]	[0.0721]	[0.0668]	[0.205]	[0.103]
Maturity	2.27e-05	3.19e-05**	5.97e-05***	5.89e-05***	-5.15e-05*	-3.79e-05
	[1.65e-05]	[1.54e-05]	[2.12e-05]	[1.87e-05]	[2.78e-05]	[2.45e-05]
Dummy for missing maturity	0.247***	0.231***	0.262***	0.224***	0.114	0.161
	[0.0762]	[0.0598]	[0.0801]	[0.0616]	[0.123]	[0.127]
Dummy for floating-rate loans	-0.112*	-0.0895*	-0.0735	-0.0303	-0.286***	-0.257***
	[0.0652]	[0.0517]	[0.0814]	[0.0658]	[0.0776]	[0.0595]
Observations	1,375,029	1,375,031	1,201,130	1,201,132	174,033	174,033
Number of banks (clusters)	1,090	1,090	1,001	1,001	828	828
R-squared	0.598	0.764	0.604	0.779	0.566	0.712

Note – The table reports OLS regressions according to specification (10). The dependent variable is the loan interest rate. Bank fixed effects included in all regressions. All loans are included in columns 1 and 2. Columns 3 and 4 report the coefficients for commitment loans. Columns 5 and 6 report the coefficients for new loans. Columns 1, 3, and 5 include a dummy variable for each recession in the sample period (2001 and 2008-09) plus interaction terms of the recession and the three loan size categories. Columns 2, 4, and 6 include a full set of time quarter dummies plotted in Figure 4, 5, and 6, respectively. The size of the loan is used to classify loans into four groups according to the break-points: $100k, $250k and $1M. All the explanatory variables are measured at the time of the loan. Sampling weights used in all regressions.

Table 3. Regression analysis of C&I loan spreads: prime-based loans only

	Formal Commitments (2000Q1-2009Q4)		New Loans (1998Q1-2009Q4)	
	Recession at com.date	Qtr dummies at com.date	Recession dummies	Qtr dummies
	(1)	(2)	(3)	(4)
(Loans <$100k)*(2008-9 recession)	-0.198**		-0.0199	
	[0.0934]		[0.192]	
(Loans $100-250k)*(2008-9 recession)	-0.110		0.00619	
	[0.0821]		[0.192]	
(Loans $250k-1M)*(2008-9 recession)	-0.105		-0.0825	
	[0.0666]		[0.195]	
Dummy for loans < $100K	0.943***	0.334	0.687***	0.909**
	[0.0660]	[0.284]	[0.133]	[0.382]
Dummy for loans in [$100K, $250K]	0.374***	-0.326	0.353***	0.309
	[0.0487]	[0.235]	[0.122]	[0.332]
Dummy for loans in [$250K, $1M]	0.163***	-0.360	0.218*	0.0113
	[0.0283]	[0.237]	[0.113]	[0.379]
Dummy for 2008-2009 recession	0.150**		0.0934	
	[0.0659]		[0.224]	
Dummy for 2001 recession	0.137**		-0.0349	
	[0.0591]		[0.230]	
(Loans <$100k)*(2001 recession)	0.127		0.341	
	[0.154]		[0.261]	
(Loans $100-250k)*(2001 recession)	-0.356***		0.0536	
	[0.0679]		[0.224]	
(Loans $250k-1M)*(2001 recession)	-0.175***		0.0364	
	[0.0591]		[0.213]	
Reference market spread	0.00278	0.00421	0.00287	-0.0638
	[0.0141]	[0.0545]	[0.0562]	[0.0742]
Liquidity ratio	0.608	0.484	0.392	0.0475
	[0.484]	[0.337]	[0.719]	[0.814]
ROA	0.595	-0.776	-6.472	5.583
	[2.101]	[1.371]	[10.46]	[10.82]
Capital ratio	1.805	1.261	1.673	1.017
	[1.179]	[0.783]	[2.427]	[2.341]
Asset size (normalized)	-3.708	-5.071	47.49**	27.23
	[3.642]	[4.405]	[23.94]	[28.20]
NPL ratio	4.889*	1.732	12.99*	9.892
	[2.591]	[2.392]	[7.532]	[6.560]
Unused C&I ratio	-0.0280	-0.0525	-0.123	-0.132
	[0.0365]	[0.0332]	[0.0854]	[0.0981]
Dummy for rating 2	0.282***	0.273***	0.452***	0.410***
	[0.0600]	[0.0589]	[0.0979]	[0.100]
Dummy for rating 3	0.651***	0.633***	0.801***	0.821***
	[0.0571]	[0.0602]	[0.121]	[0.137]
Dummy for rating 4	0.921***	0.896***	1.190***	1.199***
	[0.0570]	[0.0578]	[0.139]	[0.157]
Dummy for rating 5	1.445***	1.419***	1.559***	1.571***
	[0.0749]	[0.0732]	[0.154]	[0.172]
Dummy for secured loans	-0.173***	-0.165***	-0.163*	-0.132**
	[0.0655]	[0.0620]	[0.0840]	[0.0517]
Maturity	0.000105***	0.000108***	-6.62e-05	-2.73e-05
	[2.89e-05]	[2.87e-05]	[6.42e-05]	[2.83e-05]
Dummy for missing maturity	0.0649	0.0307	0.102	0.112
	[0.0829]	[0.0714]	[0.145]	[0.133]
Dummy for floating-rate loans	-0.128	-0.160*	-0.159	-0.198
	[0.0839]	[0.0833]	[0.133]	[0.130]
Observations	385,390	385,390	111,168	111,168
Number of banks (clusters)	425	425	759	759
R-squared	0.408	0.422	0.438	0.455

Note – The table reports OLS regressions according to specification (10). The dependent variable is the interest rate spread on loans that use the prime rate as reference rate. Bank fixed effects included in all regressions. Columns 1 and 2 report the coefficients for commitment loans. Columns 3 and 4 report the coefficients for new loans. Columns 1 and 3 include a dummy variable for each recession in the sample period (2001 and 2008–09) plus interaction terms of the recession and the three loan size categories. Columns 2 and 4 include a full set of time quarter dummies plotted in Figure 7 and 8, respectively. For formal commitments (columns 1 and 2) the size of the commitment is used to classify loans into four groups according to the break-points: \$0.5M, \$1.25M and \$5M, and all the explanatory variables are measured at the time of the commitment. For new loans (columns 3 and 4) the size of the loan is used to classify loans into four groups according to the break-points: \$100k, \$250k and \$1M, and all the explanatory variables are measured at the time of the loan. Sampling weights used in all regressions.

Table 4. Regressions by loan rating. Prime based spreads. Formal commitment loans at time of the commitment.

	ALL	Rating=1	Rating=2	Rating=3	Rating=4	Rating=5
	(1)	(2)	(3)	(4)	(5)	(6)
(Loans <$100k)*(2008-9 recession)	-0.198**	0.204	-0.0105	-0.180	-0.128	-0.465***
	[0.0934]	[0.218]	[0.128]	[0.127]	[0.0922]	[0.136]
(Loans $100-250k)*(2008-9 recession)	-0.110	0.322	-0.0276	-0.117	-0.0275	-0.317*
	[0.0821]	[0.239]	[0.108]	[0.111]	[0.0865]	[0.172]
(Loans $250k-1M)*(2008-9 recession)	-0.105	0.282	-0.00216	-0.118	-0.0605	-0.288**
	[0.0666]	[0.220]	[0.0736]	[0.0993]	[0.0716]	[0.114]
Dummy for loans < $100K	0.943***	1.049***	0.974***	1.039***	0.819***	0.499***
	[0.0660]	[0.126]	[0.0899]	[0.0892]	[0.0552]	[0.0621]
Dummy for loans in [$100K, $250K]	0.374***	0.551***	0.577***	0.432***	0.318***	0.196***
	[0.0487]	[0.100]	[0.0756]	[0.0593]	[0.0415]	[0.0678]
Dummy for loans in [$250K, $1M]	0.163***	0.279***	0.231***	0.172***	0.152***	0.118**
	[0.0283]	[0.0979]	[0.0435]	[0.0389]	[0.0242]	[0.0592]
Dummy for 2008-2009 recession	0.150**	-0.279*	0.176*	0.151*	0.0644	0.295***
	[0.0659]	[0.164]	[0.106]	[0.0879]	[0.0717]	[0.0983]
Dummy for 2001 recession	0.137**	0.311	0.497***	0.122	0.112	-0.277***
	[0.0591]	[0.347]	[0.137]	[0.0922]	[0.0788]	[0.0922]
(Loans <$100k)*(2001 recession)	0.127	-0.0718	-0.298	-0.176	0.317*	-0.421
	[0.154]	[0.419]	[0.231]	[0.113]	[0.173]	[0.316]
(Loans $100-250k)*(2001 recession)	-0.356***	-0.788**	-0.509**	-0.195*	-0.415***	-0.110
	[0.0679]	[0.369]	[0.208]	[0.104]	[0.0755]	[0.129]
(Loans $250k-1M)*(2001 recession)	-0.175***	-0.555	-0.650***	-0.195**	-0.212***	0.0997
	[0.0591]	[0.577]	[0.166]	[0.0864]	[0.0596]	[0.153]
Observations	385,390	4,707	25,611	170,078	151,873	33,121
Number of banks (clusters)	425	228	277	370	334	257
R-squared	0.408	0.582	0.616	0.502	0.344	0.341

Note – The table reports OLS regressions according to specification (10) dividing the sample of loans according to their rating (1 to 5). The dependent variable is the interest rate spread on commitment loans that use the prime rate as reference rate. Bank fixed effects included in all regressions. All regressions include a dummy variable for each recession in the sample period (2001 and 2008–09) plus interaction terms of the recession and the three loan size categories. All the explanatory variables are measured at the time of the commitment. The size of the commitment is used to classify loans into four groups according to the break-points: $0.5M, $1.25M and $5M. Sampling weights used in all regressions.

Table 5. Regressions by bank characteristics. Prime based spreads. Formal commitment loans at time of the commitment.

Panel A. Median of variables before the crisis (2004-06)

	Non-performing loans		Deposit ratio		Share assets		Small business lender	
	above median	below median	above median	below median	above median	below median	above median	below median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Loans <$100k)*(2008-9 recession)	-0.355***	0.0493	-0.0697	-0.221**	-0.291***	0.154	0.440**	-0.242**
	[0.104]	[0.118]	[0.116]	[0.104]	[0.106]	[0.145]	[0.175]	[0.108]
(Loans $100-250k)*(2008-9 recession)	-0.206**	0.0255	-0.0596	-0.0960	-0.139	0.136	0.413***	-0.0981
	[0.0943]	[0.113]	[0.0932]	[0.0916]	[0.0894]	[0.123]	[0.157]	[0.0906]
(Loans $250k-1M)*(2008-9 recession)	-0.147**	0.0509	0.00810	-0.0861	-0.108	0.0204	0.364**	-0.0837
	[0.0719]	[0.112]	[0.0709]	[0.0714]	[0.0684]	[0.104]	[0.184]	[0.0727]
Observations	248,860	136,530	145,835	239,555	335,259	50,131	26,878	279,543
Number of banks (clusters)	206	219	208	217	187	238	174	192
R-squared	0.388	0.440	0.444	0.330	0.306	0.457	0.485	0.320

Panel B. Median of variables during the crisis (2008-09)

	Non-performing loans		Unrealized losses		NPL/ALLL		Restructured loans	
	above median	below median	above median	below median	above median	below median	above median	below median
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(Loans <$100k)*(2008-9 recession)	-0.262**	0.161	-0.610***	-0.154	-0.254**	-0.133	-0.225**	-0.0730
	[0.105]	[0.139]	[0.172]	[0.152]	[0.104]	[0.176]	[0.106]	[0.118]
(Loans $100-250k)*(2008-9 recession)	-0.167*	0.307**	-0.452***	-0.0898	-0.151*	-0.0394	-0.181**	0.119
	[0.0869]	[0.121]	[0.128]	[0.110]	[0.0904]	[0.178]	[0.0876]	[0.122]
(Loans $250k-1M)*(2008-9 recession)	-0.139**	0.311**	-0.264**	-0.0573	-0.104	-0.0685	-0.153**	0.128*
	[0.0670]	[0.130]	[0.113]	[0.0886]	[0.0693]	[0.166]	[0.0702]	[0.0769]
Observations	291,176	94,214	138,542	179,516	284,616	100,774	220,426	164,964
Number of banks (clusters)	243	182	68	100	253	172	211	214
R-squared	0.373	0.491	0.309	0.305	0.371	0.488	0.340	0.497

Note – The table reports OLS regressions according to specification (10) by bank subsamples sorted according to the median of the variable in the top row. In Panel A we divide the sample of banks according to bank attributes before the crisis (average over 2004 to 2006). In Panel B divide the sample of banks according to bank attributes during the recession (average over 2008 and 2009). The dependent variable is the interest rate spread on commitment loans that use the prime rate as reference rate. Bank fixed effects included in all regressions. All regressions include a dummy variable for each recession in the sample period (2001 and 2008–09) plus interaction terms of the recession and the three loan size categories. All the explanatory variables are measured at the time of the commitment. The size of the commitment is used to classify loans into four groups according to the break-points: \$0.5M, \$1.25M and \$5M. Sampling weights used in all regressions.

Table A.1. Description of variables

Variable	Description	Source	Variable Mnemonic(s)
Loan yield	Effective interest rate on the loan	STBL	QTBL7961
Loan spread (prime based)	Effective interest rate on the loan minus prime rate	STBL	QTBL7961-QTBL7923
Dummy for prime based loans	Prime rate used as base pricing rate (Yes/No)	STBL	QTBLC430
Prime rate	Prime rate (percent)	STBL	QTBL7923
Loan amount	Face amount of loan (in dollars)	STBL	QTBL1921
Commitment amount	Amount of total commitment, formal or informal	STBL	QTBL1915
Dummy for secured loans	Dummy =1 if a collateralized loan	STBL	QTBL1929
Maturity (in days)	Maturity date minus date loan is made	STBL	QTBL9914-QTBL9912
Dummy for rating 1	Dummy for loans rated 1	STBL	QTBLA344
Dummy for rating 2	Dummy for loans rated 2	STBL	QTBLA344
Dummy for rating 3	Dummy for loans rated 3	STBL	QTBLA344
Dummy for rating 4	Dummy for loans rated 4	STBL	QTBLA344
Dummy for rating 5	Dummy for loans rated 5	STBL	QTBLA344
Dummy for floating-rate loans	Dummy =1 if a loan has floating rate	STBL	QTBLA341
Dummy for commitment loans	Dummy =1 if a loan made under a commitment	STBL	QTBL1915
Reference market yield	A1/P2 CP rate if re-pricing frequency less than one year and rated 1,2	FRB H.15	
	A2P2 CP rate if re-pricing frequency less than one year and rated 3,4,5	FRB H.15	
	AAA bond rate if re-pricing frequency greater than one year and rated 1,2	FRB H.15	
	BAA bond rate if re-pricing frequency greater than one year and rated 3,4,5	FRB H.15	
Reference market spread	A1/P2 CP rate minus 3-Month Treasury if re-pricing freq<1yr and rating of 1,2	FRB H.15	
	A2/P2 CP rate minus 3-Month Treasury if re-pricing freq<1yr and rating of 3,4,5	FRB H.15	
	AAA bond rate minus 10-Year Treasury if re-pricing freq<1yr and rating of 1,2	FRB H.15	
	BAA bond rate minus 10-Year Treasury if re-pricing freq<1yr and rating of 3,4,5	FRB H.15	
Liquidity ratio	(cash+securities) over assets	Call Reports	(RCFD0010+RCFD1754+RCFD1773) /RCFD2170
ROA (Return over assets)	Quarterly income over assets	Call Reports	RIAD4340/RCFD2170
Capital ratio	Capital over assets	Call Reports	RCFD3210/RCFD2170
Asset size (normalized)	Assets of bank j over aggregate banking sector assets	Call Reports	RCFD2170
NPL ratio	non-performing loans over assets	Call Reports	(RCFD1403+RCFD1407)/RCFD2170
Unused C&I ratio	Other unused commitments over total C&I loans	Call Reports	RCFD3818/RCFD1766
Restructured loans ratio	Loans restructured and in compliance with modified terms over total loans	Call Reports	RCFD1616/RCFD2122
Unrealized losses	Other comprehensive income over total trading assets	Call Reports	RIADB511/RCFD3545
Deposit ratio	Total deposits over assets	Call Reports	RCFD2200/RCFD2170
NPL over ALLL	Non-performing loans over allowance for loan and leases losses	Call Reports	(RCFD1403+RCFD1407)/RCFD3123
Small business lender	Loans with original amount <1M over total C&I loans	Call Reports	(RCON5571+RCON5573+RCON557 5)/RCON1763