Essays on Macroeconomics and Banking

by

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Abstract

This thesis contains three papers related to measures for improving the stability of the banking system, including regulations and public ownership.

The first chapter shows using a difference-in-differences strategy that the introduction of the U.S. bank stress tests led small businesses to concentrate their debt within a smaller number of banks. I explain this using a model of bank competition in which creditworthy but informationally opaque firms have an incentive to establish a small number of concentrated lending relationships to facilitate information acquisition by their lenders. Tightening credit standards reduces the rate of non-performing loans, but it also decreases the availability of credit. In response, firms strengthen their lending relationships by concentrating in a smaller number of lenders. When the model is calibrated to match the empirical estimates, tightening credit standards has zero net effect on efficiency, but it shifts the surplus from firms to banks because firms have fewer informed lenders with which to bargain over prices.

The second chapter, joint with Ali Kakhbod, illustrates channels by which regulations that require banks to hold liquid assets can either increase or decrease a bank's incentive to take risk with its remaining ineligible assets. A greater capacity to respond to liquidity stress increases the potential profits a bank would put at stake by making risky investments, but it also mitigates the illiquidity disadvantages of holding risky assets. We do not find evidence that the reserve requirement or the liquidity coverage ratio significantly affected measures of risk-taking such as non-performing loan ratios or credit default swap spreads.

The third chapter, joint with Eugenio Cerutti, shows that state-owned or public banks lent relatively more than domestic private banks during the Global Financial Crisis (GFC). Using a novel bank-level dataset covering 25 emerging market economies, we provide evidence that this was because they pursued an objective of helping to stabilize the economy, rather than because they had superior fundamentals or access to public or depositors' funding. Nonetheless, their countercyclical behavior seems unique to the GFC rather than a regular characteristic of public banks before and after the GFC.

JEL Codes: G21, G28, G01

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Chapter 1

The Effect of Tightening Credit Standards on Lending Relationships*

1.1 Introduction

In response to the 2008 financial crisis, the U.S. has implemented a host of regulatory reforms to strengthen the stability of the financial system. However, stricter regulations have been controversial due to their potential negative effects on economic growth. In particular, a recent literature is accumulating evidence that stricter regulations have led to tightening credit standards, or more cautious lending by banks,[1] resulting in lower credit supply, real investment by firms, and output.[2] While this may help to reduce lending to weak firms, it could also hinder efficient lending to viable but informationally

*I thank Rob Townsend, Alp Simsek, and David Thesmar for their guidance and support. I also thank participants at the MIT Macroeconomics Lunch, MIT Finance Lunch, and the Joint MIT/University of Chicago Graduate Student Conference for helpful and constructive comments. All remaining errors are my own.

[1]Most pointedly, Cortés et al. (2020) show that the U.S. bank stress tests cause affected banks to reduce their credit supply to small businesses, especially those for which they have relatively little information. Acharya, Berger and Roman (2018) also show that the stress tests cause banks to reduce their credit supply to small businesses as well as other relatively risk borrowers, consistent with increased cautiousness of lending.

[2]For example, Aiyar, Calomiris and Wieladek (2014), Behn, Haselmann and Wachtel (2016), Fraisse, Lé and Thesmar (2020), and Gropp et al. (2019) provide evidence from Europe that capital requirements cause affected banks to reduce lending. The latter two also show that capital requirements are associated with reduced investment, suggesting a limited ability of some firms to obtain alternative sources of finance. Furthermore, a review of studies on the costs and benefits of bank capital by Basel Committee on Banking Supervision (2019) indicates that, through the effects on credit supply and real investment, a percentage point increase in capital requirements can result in a 1 to 16 basis point reduction in GDP.

opaque firms whose credit risk is difficult to ascertain, such as many small businesses.[3]

A relevant factor affecting the impact of bank regulations on screening efficiency, or the degree to which banks accurately allocate credit to viable firms and deny credit to firms that are likely to default, is the response by firms. However, little is known about how firms adapt to tightening credit standards by adjusting their lending relationships. This question is important because an extensive literature has shown that lending relationships, or close ties between a firm and its banks, are a prevalent means by which lenders acquire information about the creditworthiness of opaque firms.[4] Firm financing arrangements in turn reflect the informational advantages of lending relationships insofar as relatively opaque firms without public accounting statements, credit ratings, or a strong reputation tend to concentrate their debt within a smaller number of lenders (Sufi (2007)). Finally, the general policy relevance of lending relationships has been underscored recently by evidence suggesting that the allocation of credit associated with the Paycheck Protection Program (PPP), a U.S. federal loan program implemented by the Small Business Administration (SBA) intended to support small businesses during the COVID-19 pandemic, was unrelated to exposure to the pandemic but significantly related to lending relationships with participating banks.[5]

This paper combines these two strands of the literature to examine the interaction between tightening credit standards and lending relationships. I first provide empirical evidence from the introduction of the U.S. bank stress tests that tightening credit stan-

[3]Small businesses are generally considered to be opaque because there is limited verifiable information about their quality, such as audited accounting statements (Berger et al. (2005)). However, access to credit for small businesses is important because small businesses play a key role in economic growth, with firms having fewer than 500 employees accounting for over 66% of net new jobs since 1993 according to data from the Bureau of Labor Statistics Business Employment Dynamics. In light of that consideration, Yellen (2017) reports that recent amendments to ease some bank regulations have been motivated on the basis of improving the availability of credit to small businesses, especially for particularly opaque firms with limited credit histories.

[4]In particular, small business lending is considered to be heavily dependent on close interactions through which a bank can acquire "soft", that is, unverifiable or hard to communicate, information about a firm's quality, such as first-hand knowledge about the character or competence of the manager (Rajan (1992), Petersen and Rajan (2002), Berger et al. (2005)). Consistent with this view, Petersen and Rajan (1994) find evidence that factors associated with close interactions between a firm and a lender, such as the length of the relationship and the degree to which the firm concentrates its debt with that lender, are associated with greater access to credit, while Agarwal and Hauswald (2010) reports a similar finding for physical proximity.

[5]Granja et al. (2020) find that the state-level percentage of small businesses receiving PPP loans is positively correlated with the local presence of banks with a high level of participation in the PPP but not with business shutdowns or reductions in hours worked, suggesting a limited ability of small businesses in hard-hit areas to obtain loans from active PPP lenders with whom they are less likely to have a pre-existing relationship. Similarly, Liu and Volker (2020) find that the state-level percentage of small businesses receiving PPP loans is positively correlated with the percentage of small businesses with bank financing in 2019 but not with the rate of COVID-19 cases or unemployment claims.

dards induces opaque firms, particularly small businesses, to concentrate their debt in a smaller number of lenders. I then explain this result within the context of a model of bank competition in which opaque firms have an incentive to establish a small number of concentrated lending relationships to reduce competition among their lenders, which in turn gives their lenders an incentive to screen efficiently.[6] Tightening credit standards causes firms to strengthen their lending relationships to maintain their access to credit, which can qualitatively influence the net effect on screening efficiency relative to a counterfactual without such an adjustment.[7]

To empirically examine how lending relationships adapt to tightening credit standards, I focus specifically on how U.S. small businesses responded to the introduction of stress tests conducted by the Federal Reserve. Since 2009, the Federal Reserve has conducted stress tests on an approximately annual basis for a subset of large banks to ensure they have sufficient capital to continue lending under potential adverse scenarios. I represent tightening credit standards by the introduction of the stress tests because they have been associated with reduced lending to risky firms (Cortés et al. (2020), Acharya, Berger and Roman (2018)). I focus on small businesses because they are considered to be relatively opaque and dependent on lending relationships (Petersen and Rajan (1994), Petersen and Rajan (2002), Berger et al. (2005)).

To track how small businesses adjusted their lending relationships in response the stress tests, I analyze data on loans supported by the Small Business Administration (SBA). I designate a firm as experiencing tightening credit standards if it had a pre-existing relationship with a stress-tested lender. This is motivated by evidence that it is costly for a firm to switch to a lender with which it does not have a relationship (Chodorow-Reich (2014)), making a firm indirectly exposed to regulations that affect its relationship lenders.[8]

I show using a difference-in-differences strategy that firms that borrowed from stress-

[6]The model is based on the classical idea that lending relationships facilitate the acquisition of information about a firm's creditworthiness, which can improve the availability of credit for viable firms but also allow the small number of informed lenders to extract rents due to the lack of competition (Rajan (1992), Sharpe (1990)). Firms choose the number of lenders to balance this trade-off.

[7]To evaluate the overall value of bank regulations, it is helpful to consider the trade-off between reducing the probability of financial crises and slowing down economic growth (Basel Committee on Banking Supervision (2019)). This paper focuses specifically on the effect of tightening credit standards on bank screening efficiency. This addresses the effect on economic growth since it encompasses the ability of productive firms to obtain credit. This paper does not directly address the value of bank regulations in mitigating financial crises, but it does examine the implications for non-performing loans, which are associated with financial crises and the severity of their effect on output (Ari, Chen and Ratnovski (2019)).

[8]Behn, Haselmann and Wachtel (2016), Fraisse, Lé and Thesmar (2020) and Gropp et al. (2019) also provide evidence that some firms have a limited ability to obtain financing from lenders with more looser regulations.

tested lenders decreased the number of lenders on outstanding loans compared to firms that borrowed from lenders that were exempt from the stress tests. Importantly, these firms also exhibited a greater decline in the number of lenders that were *exempt* from the stress tests, providing evidence that the consolidation of lending relationships was at least partly chosen by firms. A potential concern with using the stress tests as a measure of tightening credit standards is that they were not randomly assigned but rather targeted towards large banks. However, I show that this result is robust to restricting to bank holding companies with total assets near the threshold to be eligible for the stress tests, suggesting that it is not driven by factors related to bank size. I also provide correlative evidence that this consolidation of lending relationships was in turn associated with lower non-performing loan rates and higher interest rates.

I then explain these findings by developing a model in which relationship lenders compete for a firm's demand for credit. Similar to existing models of bank competition with credit screening, firms are informationally opaque in the sense that banks can make mistakes in determining which firms are likely to repay or default.[9] When a firm applies for a new loan, each of the relationship lenders first screens the firm by drawing a noisy signal about its creditworthiness. The lenders then compete in a manner analogous to Bertrand competition except that the costs are subjective estimates of a common cost of lending based on the borrower's quality. That is, if any lenders are willing to lend, the lender with the most optimistic signal supplies the loan. If the firm turns out to be creditworthy, the supplying lender also accrues a profit since the firm can only bargain down the interest rate to the level offered by the next best informed lender, analogous to the extraction of information rents discussed in Rajan (1992) and Sharpe (1990).[10]

In the course of interactions preceding the new loan application, a relationship lender can acquire costly information about a firm's credit risk to improve its screening accuracy. However, its incentive to do so decreases in the degree of competition it faces from the firm's other relationship lenders. Consistent with the documented importance of lending relationships in the financing of opaque firms, I consider parameters for which informa-

[9]Other papers that explore the interactions between bank competition and borrower screening include, for example, Broecker (1990), Thakor (1996), Cao and Shi (2001), Ruckes (2004), Dell'Ariccia and Marquez (2006), and Gorton and He (2008). Relative to this literature, I focus specifically on the connections between tightening credit standards, the number of competing lenders chosen by the firm, and the overall efficiency of credit allocation.

[10]Rent extraction by informed lenders is empirically supported by Petersen and Rajan (1994) and Agarwal and Hauswald (2010), who find that measures of relationship strength are more strongly associated with increased credit availability than lower prices. Additionally, Santos and Winton (2008) shows that bank-dependent firms exhibit relatively higher interest rates when it is easier to extract information rents, such as during recessions, and Hale and Santos (2009) shows that loan interest rates decrease when there is a public release of information about a firm, such as during an IPO.

tion acquisition is necessary to achieve a net surplus from lending. As a result, opaque firms have no incentive to substitute to non-relationship lenders.

A central feature of the model is that firms account for the information acquisition incentive when choosing the number of relationship lenders. In particular, a viable firm has an incentive to establish a small number of relationships to encourage its lenders to acquire information about its creditworthiness. However, for a given level of information acquisition, concentrating in a small number of relationships decreases the probability of receiving credit as well as the ability to bargain down the interest rate conditional on receiving credit. This provides a countervailing incentive to establish multiple relationships.[11]

In the model, tightening credit standards corresponds to lenders being unwilling to finance firms that are not perceived as sufficiently safe. Tightening credit standards thereby increases the probability that banks mistakenly deny credit to firms that are likely to repay. This intensifies the incentive for lenders to acquire information so that they can more accurately identify safe firms.[12] It also intensifies the incentive for creditworthy firms to concentrate in a smaller number of lenders so that lenders acquire additional information about them and have greater confidence in their ability to identify them as safe investments.[13]

The model also explains the finding that the consolidation of lending relationships was correlated with lower non-performing loan rates and higher interest rates. In particular, the consolidation of relationships increases the incentive for lenders to acquire information, which improves the ability of banks to screen out firms that are likely to default. It also softens competition among the relationship lenders, which reduces a firm's bargaining power and results in higher interest rates.

The model is also consistent with findings from the literature regarding the impli-

[11] The role of these channels in determining lender concentration is empirically supported by Sufi (2007) and Dennis and Mullineaux (2000), who show that the concentration of debt within a syndicated loan is increasing in the degree of asymmetric information between the borrower and lenders, and Farinha and Santos (2002), who provide evidence that firms with more to lose from rent extraction costs are more likely to have multiple lenders.

[12] In general, lenders could have a lower incentive to acquire information since they are less likely to lend, but they could also have a higher incentive to acquire information to mitigate this effect. The incentive to acquire information also depends on how tightening credit standards affects the degree of competition from other lenders. In numerical simulations, the positive channels dominate.

[13] In general, tightening credit standards can also encourage firms to establish more lending relationships via an insurance motive since, for a given level of information acquisition, doing so would increase the probability that at least one lender would be willing to lend. In numerical simulations, the incentive to encourage information acquisition dominates the incentive to diversify over more lenders, consistent with the observed effect in the empirical exercise.

cations of transparency for lending relationships. Variation in opacity reflects the fact that some firms may be more transparent due to public reporting requirements, credit ratings, or reputation. Transparent firms, which have less need to encourage information acquisition by their lenders, borrow from a greater number of lenders, consistent with the empirical findings in Sufi (2007). Additionally, tightening credit standards causes relatively transparent firms to substitute from bank loans to bonds, consistent with the finding from Becker and Ivashina (2014) that tightening credit standards increases the rate at which firms switch from loans to bonds.

To illustrate how lending relationships and tightening credit standards affect screening efficiency, I calibrate the model to match empirical analogs corresponding to the probability of obtaining credit, the number of lenders, the default rate, and the interest rate spread. At the calibrated parameters, firms designate too many relationship lenders from the perspective of screening efficiency. In particular, the constrained efficient number of relationship lenders for an opaque firm is equal to one because having a single relationship lender maximizes the incentive to screen efficiently and also avoids duplicating information acquisition costs. However, a firm designates a greater number of lenders to ensure that it has some bargaining power. Tightening credit standards induces firms to choose a more concentrated lending relationship configuration that is closer to the constrained optimum. The effect of this adjustment on screening efficiency can be significant. At the calibrated parameters, for example, tightening credit standards has an immediate effect of decreasing screening efficiency by 10.3% due to reducing the availability of credit for viable firms, but it has zero net effect after the adjustment of lending relationships.[14] However, even after the adjustment of relationships, the tightening shifts the distribution of the surplus from lending in favor of lenders.

For transparent firms, by contrast, the induced substitution to bonds decreases screening efficiency since bondholders are less efficient than banks at screening out weak firms. This is consistent with evidence from Becker and Ivashina (2014) that the substitution to bonds associated with tightening credit standards is more pronounced for firms with weak credit ratings.

Literature Review

This paper relates to four major themes in the literature.

First, this paper contributes to a recent empirical literature on bank regulations by showing that tightening credit standards causes opaque firms to concentrate their debt

[14] Note that the effect of tightening credit standards on screening efficiency likely underestimates the net value of heightened bank regulations since it does not capture the benefit from mitigating financial crises.

within a smaller number of lenders. It specifically relates to Cortés et al. (2020) and Acharya, Berger and Roman (2018), who show that the introduction of the stress tests in the U.S. led affected banks to decrease lending to relatively risky or unknown borrowers.[15] It relates more generally to a growing literature examining the effect of regulations on lending and the implications for real investment by firms (see, for example, Aiyar, Calomiris and Wieladek (2014), Behn, Haselmann and Wachtel (2016), Fraisse, Lé and Thesmar (2020), Gropp et al. (2019), Bassett and Berrospide (2018), Ayyagari, Beck and Martinez Peria (2018), Richter, Schularick and Shim (2018), and Boissay et al. (2019)).[16] It relates even more generally to a literature examining the effect of bank balance sheet shocks on credit supply (see, for example, Peek and Rosengren (1997) and Khwaja and Mian (2008)).[17] This literature provides mixed evidence on the extent to which firms can smooth credit supply shocks by substituting to alternative sources of finance and the implications for real outcomes.[18] This paper focuses particularly on how small businesses,

[15]Cortés et al. (2020) shows that stress-tested banks with a larger projected decline of capital in the stress tests reduce credit to small businesses in regions where they have no local knowledge and increase interest rates for firms for which they are likely to have more information. Acharya, Berger and Roman (2018) shows that banks that were subject to the stress tests increased interest rates compared to other banks, particularly for borrowers with greater default risk. They also exhibited reduced relatively risky types of credit such as commercial estate loans, credit card loans, and small business loans.

[16]Aiyar, Calomiris and Wieladek (2014) provide evidence from varying bank-specific capital requirements in the United Kingdom that capital requirements are associated with reduced lending. Behn, Haselmann and Wachtel (2016) provide evidence from Germany that banks experiencing an increase in capital requirements due to heightened borrower risk reduce lending. Fraisse, Lé and Thesmar (2020) show using loan-level data from France and variation in capital requirements across both banks and firms that capital requirements are associated with lower lending. Gropp et al. (2019) show that banks that were subject to the 2011 capital exercise conducted by the European Banking Authority reduced lending compared to a control group with matched characteristics. Bassett and Berrospide (2018) find that the extra capital required by the U.S. bank stress tests relative to banks' internal models is not unduly restricting credit growth. Ayyagari, Beck and Martinez Peria (2018) provide cross-country evidence that macroprudential policies targeting borrower characteristics, such as loan-to-value and debt-to-income limits, are associated with lower credit growth. Richter, Schularick and Shim (2018) provide cross-country evidence that tightening loan-to-value ratios decreases aggregate credit growth and, to a lesser extent, output. Boissay et al. (2019) describes a repository of studies on the effects of financial regulations maintained by the Bank for International Settlements (BIS) and finds that higher bank capital is on average associated with a negative effect on loans growth in the short-run but a positive effect in the long-run.

[17]Peek and Rosengren (1997) estimate the effect of capital requirements on credit supply by considering how a deterioration in capital ratios due to fluctuations in the Japanese stock market that were unrelated to U.S. credit demand led Japanese banks to reduce lending at their U.S. branches. Khwaja and Mian (2008) isolate the effect of losses in liquidity on credit supply by considering variation across banks lending to the same firm.

[18]In the U.S., Cortés et al. (2020) find evidence that the stress tests cause small businesses to substitute to small banks with less stringent regulations. However, Chen, Hanson and Stein (2017) finds that lending to small businesses by large banks in the U.S. has declined since the global financial crisis, which has been associated with reduced aggregate credit to small businesses. Additionally, Doerr (2019) show that the stress tests have been associated with reduced entry of small businesses. In other regions, Aiyar, Calomiris and Wieladek (2014) find evidence from the United Kingdom that unregulated banks can offset the decrease in credit associated with capital requirements. Behn, Haselmann and Wachtel (2016) find evidence from

which are considered to be especially dependent on lending relationships, respond by adjusting their lending relationships.

Second, this paper draws on concepts from a literature on lending relationships and illustrates how they interact with the tightness of credit standards to determine the way that firms manage multiple relationships. An extensive literature has explored the notion that lending relationships reduce information asymmetries for opaque firms, which increases the availability of credit but also allows lenders to extract rents from their private information. For example, this idea is theoretically formalized in Rajan (1992) and Sharpe (1990). It has also been empirically supported in Petersen and Rajan (1994), Berger and Udell (1995), Cocco, Gomes and Martins (2009) Santos and Winton (2008), Hale and Santos (2009), and Agarwal and Hauswald (2010).[19] Several papers specifically examine how these considerations affect firm financing choices. For example, Sufi (2007) and Dennis and Mullineaux (2000) provide evidence from syndicated loans that firms with less publicly available information such as accounting statements and credit ratings tend to concentrate their debt within a smaller number of lenders, while Rajan (1992), Farinha and Santos (2002), and Houston and James (1996) describe how firms try to avoid rent extraction costs.[20] I contribute to this literature by presenting a model in which this

Germany that capital requirements have a stronger negative effect on total firm borrowing than they do on bank lending. Fraisse, Lé and Thesmar (2020) find evidence from France that firms mitigate the reduction in credit associated with capital requirements to some extent by substituting towards alternative sources of finance like trade credit but that capital requirements are ultimately associated with lower real investment. Gropp et al. (2019) find evidence from Europe that firms that borrowed a large fraction of their debt from banks that were subject to the capital regulations decrease investment compared to other firms, especially if they have fewer alternative sources of funding like access to public equity markets. Ayyagari, Beck and Martinez Peria (2018) find cross-country evidence that macroprudential policies are associated with reduced real investment, especially for small and young firms that are relatively likely to be dependent on bank financing. Khwaja and Mian (2008) find evidence from Pakistan that small firms are less able to substitute to alternative sources of financing when their lenders experience liquidity shocks.

[19] Berger and Udell (1995) finds that borrowers with longer banking relationships face lower interest rates and collateral requirements, consistent with information acquisition by banks that reduces their perceived risk. Cocco, Gomes and Martins (2009) find evidence from the interbank lending market that concentrated lending relationships are associated with a greater probability of future lending and lower interest rates. Petersen and Rajan (1994) and Agarwal and Hauswald (2010) find evidence that factors associated with close interactions between a firm and a lender, such as the length of the relationship, the degree to which the firm concentrates its debt with that lender, and physical distance, are associated with greater access to credit. However, they also find that measures of relationship strength are more strongly associated with increased credit availability than lower prices. Consistent with the extraction of information rents by banks, Santos and Winton (2008) shows that bank-dependent firms exhibit relatively higher interest rates when information asymmetries are more severe, such as during recessions, and Hale and Santos (2009) shows that loan interest rates decrease when there is a public release of information about a firm, such as during an IPO. Boot (2000) contains a review of early work studying the costs and benefits of lending relationships.

[20] Rajan (1992) shows theoretically how firms cope with this trade-off when choosing how to distribute their debt between a single relationship lender and uninformed lenders. Farinha and Santos (2002) provide evidence that firms with more to lose from rent extraction costs, such as firms with more growth opportu-

trade-off interacts with the tightness of credit standards to determine how firms choose the number of relationship lenders. This paper is complementary to existing studies that examine other factors that could affect the number of lenders, such as the possibility that some lenders may become unavailable due to internal liquidity problems (Detragiache, Garella and Guiso (2000)) or the ease of renegotiation (Bolton and Scharfstein (1996)).

Third, this paper also examines the interaction between the tightness of credit standards with elements from the theoretical literature on bank competition with screening. For example, a foundational contribution in this literature is Broecker (1990). This paper is especially related to papers in this literature that incorporates the screening incentives of lenders, such as Thakor (1996), Cao and Shi (2001), Ruckes (2004), Dell'Ariccia and Marquez (2006), and Gorton and He (2008).[21] While some of these papers consider how competition between banks affects credit standards, I instead focus on how an exogenous tightening of credit standards, due to, for example, stricter regulations, affects the degree of competition among relationship lenders.

Fourth, the model presented in this paper is consistent with several results from the literature on the choice between bank versus bond financing and additionally examines the screening efficiency implications of policies that cause firms to substitute between them. In line with the existing literature on the choice between bank versus bond financing, the model in this paper shows that firms with less severe information frictions are more likely prefer bond financing (see, for example, Diamond (1991), Hale and Santos (2008)), Holmstrom and Tirole (1997)).[22] This paper differs by offering an explanation for this result based on screening incentives in the presence of adverse selection rather

nities, are more likely to initiate multiple relationships. Houston and James (1996) shows that measures of the severity of information asymmetries, such as the importance of growth options, are more negatively correlated with reliance on bank debt for firms with a single bank relationship compared to firms with multiple relationships.

[21] Thakor (1996) shows that capital requirements can reduce the incentive for banks to screen potential borrowers, resulting in increased credit rationing. Cao and Shi (2001) show that increasing screening costs can surprisingly improve the availability of credit since a smaller number of informed lenders mitigates the "winner's curse", or the tendency for lenders to discount their estimates of the borrower's creditworthiness because they recognize that the winning bidder is likely to be over-optimistic. Ruckes (2004) shows that increasing the profitability of borrowers can decrease the incentive for lenders to screen efficiently and result in relaxed credit standards. Dell'Ariccia and Marquez (2006) show that increasing the fraction of borrowers that have never been screened can also lead to looser credit standards since banks are less concerned that a firm applying for a loan was previously rejected by other banks. Gorton and He (2008) show that credit standards can vary over time purely due to changing perceptions of the credit standards of rival banks.

[22] Diamond (1991) presents a dynamic model in which firms initially acquire debt from banks in order to establish a strong credit reputation and then to transition bonds when they no longer need to be monitored. Consistent with this view, Hale and Santos (2008) find empirical evidence that establishing a strong reputation can accelerate a firm's decision to enter the public bond market. Holmstrom and Tirole (1997) also present a model in which firms with less severe information frictions, which in their case corresponds to a large enough equity stake to eliminate moral hazard incentives, prefer cheaper bond financing.

than monitoring in the presence of moral hazard.[23] This paper is also related to papers that investigate the effect of tightening bank lending on the choice between bank and bond financing (Holmstrom and Tirole (1997), Kashyap, Stein and Wilcox (1993), Becker and Ivashina (2014)).[24] This paper specifically examines how the choice between bank versus bond financing affects screening efficiency. In particular, the model predicts that the substitution to bonds allows a greater fraction of weak firms to obtain credit. This is consistent with the empirical findings in Becker and Ivashina (2014) showing that tightening credit standards increases the rate of substitution from bank loans to bonds, especially for firms with weak credit ratings.

The rest of the paper is organized as follows. Section 1.2 introduces the SBA loan data. Section 1.3 presents difference-in-differences estimates of the effect of the stress tests on lending relationships, non-performing loan rates, and interest rates. Section 1.4 presents a model of bank competition in which firms choose the number of relationship lenders. Section 1.5 calibrates the model using the empirical estimates and assesses how the adjustment of lending relationships affects the screening efficiency implications of tightening credit standards. Section 1.6 concludes.

1.2 Data: Small Business Administration loans

To analyze how opaque firms adapt to tightening credit standards, I use data on loans supported by the Small Business Administration (SBA) to assess how small businesses, which are considered to be opaque because they typically do not file public accounting statements or have credit ratings (Petersen and Rajan (1994), Petersen and Rajan (2002), Berger et al. (2005)), responded to the introduction of the stress tests, which was associated with increased cautiousness of lending. In particular, Acharya, Berger and Roman (2018)) shows that the stress tests cause banks to reduce credit supply to risky firms. Specifically regarding small businesses lending, Cortés et al. (2020) shows that the stress tests cause banks to stop lending to firms that are risky in the sense of being relatively

[23]The model in this paper is also distinct from models in which the choice between bank and bond financing depends on a firm's inherent risk rather than the degree of its opacity. For example, Chemmanur and Fulghieri (1994) and Bolton and Freixas (2000) present models in which banks have greater flexibility to restructure debt in the event of financial distress, which makes bank debt more attractive for inherently risky firms that are more likely to experience distress.

[24]Holmstrom and Tirole (1997) show that a reduction in bank capital increases the cost of bank financing and causes firms with relatively less severe information frictions to substitute to uninformed lenders. Kashyap, Stein and Wilcox (1993) show that tighter monetary policy leads to an aggregate shift from bank loans to commercial paper. Becker and Ivashina (2014) show using firm-level data that there is greater substitution from bank loans to bonds during periods of tight credit standards.

unknown and to increase prices for firms where they are more likely to have more information.[25]

In particular, I use data on loans issued under the SBA 7(a) loan program.[26] The SBA is a U.S. government agency whose mission is to support small business (Small Business Administration (2020)). The 7(a) loan program, which is named after section 7(a) of the 1953 Small Business Act that established the SBA, is the primary small business loan program administered by the federal government. The program is designed to facilitate credit access for small businesses by allowing banks to purchase a partial guaranty on newly originated loans. See Craig, Jackson and Thomson (2009) for a discussion of a theoretical rationale behind the program and a review of early related empirical work. Papers since then that analyze data from SBA loan programs include Brown and Earle (2017), Makridis and Ohlrogge (2018), and Granja et al. (2020).[27]

The SBA loan-level data is well suited for analyzing the effect of tightening credit standards on small business lending relationships because for each loan it identifies the lender, which gives rise to cross-sectional variation in the tightness of credit standards, and the borrower, which facilitates tracking how a firm responds over time by adjusting the number of lenders. Despite these advantages, a caveat with using the SBA data is that SBA loans are subject to various requirements and unique features, which could possibly limit external validity.[28] One could be especially concerned that factors such as the stress tests and lending relationships are relatively unimportant for partially guaranteed loans supported by the SBA since lenders are less exposed to the risk of default. However, Appendix Section 1.A provides evidence that the stress tests were associated with reduced SBA loan issues, consistent with the findings in Cortés et al. (2020) and Acharya, Berger and Roman (2018) that the stress tests were generally associated with reduced lending

[25]Note that there are multiple mechanisms by which the stress tests may have led to reduced small business lending. One channel is that the stress tests, by causing banks to hold more equity capital, reduce the risk-taking incentives of equityholders since they have more to lose. Another channel is that the stress tests increase the effective capital charges for risky assets, increasing the cost of funds relative to other investments. The model in Section 1.4 primarily focuses on the first channel, but the results of the model are qualitatively similar when modelling tightening credit standards via the second channel.

[26]Note that this data is available to the public and can be downloaded from the SBA website.

[27]Brown and Earle (2017) find that SBA loans are associated with increased job creation. Makridis and Ohlrogge (2018) find that foreclosures are associated with increased shares of SBA guarantees and decreased volumes of local SBA loans, possibly as a result of increased uncertainty and reduced optimism. Granja et al. (2020) find evidence that the allocation of credit associated with the Paycheck Protection Program (PPP), a federal loan program implemented by the SBA to support small businesses during the COVID-19 pandemic, is positively associated with the local presence of banks with a high level of participation in the PPP but not with business shutdowns or reductions in hours worked.

[28]In addition to being partially guaranteed, SBA loans are subject to restrictions on the loan amount, maturity, interest rates, collateral, and fees. There are also restrictions on eligible borrowers, including the requirement that a borrower does not have the ability to acquire credit without SBA assistance.

to small businesses. Additionally, Granja et al. (2020) show that lending relationships played a crucial role in the allocation of credit associated with the Paycheck Protection Program (PPP). Another caveat is that there could potentially be measurement error in cases where firms have other sources of finance besides SBA loans, although this is unlikely because a requirement for receiving an SBA loan is that a borrower cannot acquire financing without SBA assistance (Small Business Administration (2019)).

The loan-level SBA data includes the name of the borrower and lender, a set of borrower characteristics including state, business type, and NAICS industry code, and a set of loan characteristics including first disbursement date, total loan volume, volume of the loan insured by the SBA, term length, initial interest rate, an indicator for whether the loan is a revolver, and a loan status variable that can be used to determine whether a completed loan was paid in full or charged off as a non-performing loan.[29] I restrict to the subsample of firms that acquire SBA loans from at least two lenders over the period 2004-2014.[30] Including firms with only one SBA lender would mechanically hinder an analysis of lending relationship adjustments since a firm with only one observed lender cannot further increase the concentration of its loan portfolio.

I construct two additional variables to represent lending relationships and exposure to the stress tests. First, lending relationships are represented by the number of lenders on outstanding loans, which is determined using data on first disbursement dates, term lengths, and charge-off dates.

Second, I designate a firm as experiencing tightening credit standards if it had an outstanding loan, taken to represent a pre-existing relationship, with a lender that was included in the Supervisory Capital Assessment Program (SCAP), a stress test conducted in 2009 by the Federal Reserve for 19 bank holding companies with assets exceeding $100 billion.[31] The designation of the treatment group is motivated by empirical evidence that it is costly for a firm to substitute to a lender with which it does not have a relationship (Chodorow-Reich (2014)), making a firm indirectly exposed to regulations that affect its relationship lenders.

[29] Note that franchises are distinguished by name and zip code. Other firms are distinguished by name.

[30] About 50.2% of firms in this subsample have multiple lenders in 2009. For comparison, the fraction of firms with multiple lenders in the most recent Survey of Small Business Finance (SSBF) in 2003 is 38.4%, where, following Detragiache, Garella and Guiso (2000), I count the following institutions as lenders: commercial banks, savings banks, savings and loan associations, credit unions, and mortgage companies.

[31] Since the stress tests were not randomly assigned but targeted towards large bank holding companies, one might be concerned about unobserved factors related to lender size. To mitigate this concern, I find that these results are robust to restricting to the subset of firms with a lender that was eventually included in the stress tests after the threshold was lowered to $50 billion in 2014 and excluding firms with relationships to the four largest bank holding companies.

Most of the bank holding companies that were included in the SCAP were subject to continued regular stress testing at least until 2018, providing a basis for long-run adjustments of lending relationships. In particular, the Federal Reserve conducted annual stress tests for the same set of companies under the Comprehensive Capital Analysis and Review (CCAR) from 2011 to 2014, with the exception of one firm that delisted as a bank holding company in 2013. Additionally, starting in 2013, the Federal Reserve conducted the annual Dodd-Frank Act Stress Test (DFAST) as a complement to the CCAR for the same set of banks, as required by the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act.[32] Note that starting in 2014, the CCAR and DFAST were conducted for a wider set of bank holding companies with assets exceeding $50 billion. In 2018, the enactment of the Economic Growth, Regulatory Relief, and Consumer Protection Act increased the asset threshold for required annual tests to $250 billion and enabled the Federal Reserve to conduct stress tests for bank holding companies with assets between $100 billion and $250 billion on a less frequent basis.

Table 1.1 presents summary statistics aggregated to the firm level as of 2009. The loan-level characteristics are aggregated to the firm level by summing the volume of outstanding loans and calculating a weighted average of the other variables using loan volume as weights.[33] Loan volume is normalized to 2010 dollars using the GDP deflator. Note that a relatively small number of observations have data on interest rates since the SBA data does not report the initial interest rate on new issues until late 2008.

Table 1.2 compares firms that had a pre-existing relationship to a lender included in the SCAP to firms that did not as of 2009. Firms that were exposed to the stress tests have a larger number of lenders on average and a greater share of revolving loans, but the two groups otherwise appear to be similar in magnitude.

[32] This paper focuses on the stress tests conducted by the Federal Reserve, but note that the Dodd-Frank Act also requires some banks to periodically conduct their own stress tests. Starting in 2014, regulated financial companies with assets between $10 billion and $50 billion were required to conduct their own stress test each year, while those with assets exceeding $50 billion were required to conduct their own stress tests twice per year. As of 2018, only companies with assets exceeding $250 billion are required to conduct their own stress tests.

[33] The categorical variables corresponding to state, NAICS code, and business type are also aggregated to the firm level as follows. If a firm has multiple outstanding loans with discrepancies in a categorical variable, the categorical variable is set equal to the value associated with the largest outstanding loan. If discrepancies persist, then it is set to equal the value associated with the most recent loan among the largest loans. A small number of observations with residual discrepancies are not assigned a value.

Table 1.1: Summary statistics

This table presents firm-level summary statistics as of 2009 obtained from the dataset of SBA 7(a) program loan issues.

	N	Mean	SD	P25	P75
Stress test exposure	12932	0.408	0.492	0.000	1.000
Lenders	12932	1.743	1.363	1.000	2.000
Log volume	12932	12.623	1.394	11.707	13.648
Mean term (log months)	12931	4.972	0.562	4.431	5.497
Insured share	12932	0.700	0.121	0.625	0.754
Revolver share	12932	0.144	0.322	0.000	0.024
Non-performing loan share	12932	0.047	0.183	0.000	0.000
Mean spread (%)	1454	3.184	1.147	2.500	4.000

Table 1.2: Comparison

This table compares firms that had a pre-existing relationship to a lender included in the SCAP (and hence were "exposed" to the stress tests) to firms that did not (and hence were "unexposed") as of 2009. The first row presents the number of observations in each group, and the remaining rows present the mean.

	Exposed	Unexposed
N	5,282	7,650
Lenders	2.066	1.521
Log volume	12.60	12.64
Mean term (log months)	4.938	4.995
Insured share	0.668	0.722
Revolver share	0.211	0.0984
Non-performing loan share	0.0518	0.0439
Mean spread (%)	3.184	3.184

1.3 Empirical analysis

This section presents evidence using a difference-in-differences strategy that the introduction of the stress tests induced small businesses to concentrate their debt within a smaller number of lenders. This section also provides correlative evidence that this consolidation of lending relationships was in turn associated with lower non-performing loan rates and higher interest rates.

1.3.1 Number of lenders

Specification

To empirically assess the effect of tightening credit standards on the concentration of lending relationships, I implement a difference-in-differences strategy motivated by the empirical design in Acharya, Berger and Roman (2018) that compares the change in the number of lenders on outstanding loans before and after the introduction of the stress tests for firms that borrowed from a stress-tested lender relative to firms that borrowed from lenders that were exempt from the stress tests. I use the set of firms that borrowed from exempt lenders as a control group to isolate the effect of the stress tests from other concurrent events.

Tightening credit standards could be associated with a decline in the number of lenders either because lenders choose to stop financing risky firms or because firms choose to concentrate their debt within a smaller number of relationship lenders. To better capture the way in which small businesses willingly adjusted their lending relationships, I particularly focus on comparing the change in the number of lenders that were exempt from the stress tests.

The regression is as follows:

$$\Delta log\ lenders_i = \beta stress_i + \gamma X_i + \epsilon_i \tag{1.1}$$

where the dependent variable $\Delta log\ lenders_i$ is the change in the logarithm of the number of lenders that were exempt from the stress tests on outstanding SBA loans from 2009 to 2014 for firm i.[34] The treatment variable $stress_i$ is an indicator for whether in 2009 a

[34] Note that estimating a panel specification of the form $log\ lenders_{it} = \alpha_i + \psi_t + \beta_t stress_i \times 1_{t \geqslant 2009} + \epsilon_{it}$ for firms with outstanding loans extending through the same window from 2009 and 2014 yields similar results.

firm had an outstanding loan from a lender that was included in the SCAP.[35] To mitigate potential confounding due variation in observable loan terms and borrower characteristics, the set of control variables X_i as of 2009 that includes the logarithm of the number of lenders, a firm's business type (individual, partnership, or corporation), and firm-level summary statistics for set of loan-level characteristics variables: the logarithm of the volume of a loan, the term length of a loan expressed as the logarithm of the number of months, the fraction of a loan that is insured by the SBA, and an indicator for whether a loan is a revolver or term loan. To mitigate potential confounding due to variation in credit demand, I also include industry-region fixed effects aggregated to the level of 1-digit NAICS codes and census regions. The difference-in-differences coefficient β captures the extent to which firms exposed to the stress tests changed the number of lenders compared to firms that borrowed from lenders that were exempt from the stress tests.

The difference-in-differences design identifies the causal effect of stress test exposure on the number of lending relationships under the assumption that firms in the treatment and control groups would have experienced parallel trends in the absence of the stress tests. To assess the validity of this assumption, I also estimate the relative trend between the two groups using a panel specification

$$log\ lenders_{it} = \alpha_i + \psi_t + \sum_{t \neq 2009} \beta_t stress_i \times \psi_t + \epsilon_{it} \tag{1.2}$$

where α_i represents firm fixed effects and the other variables are the same as in equation (1.1). The yearly difference-in-differences coefficients β_t capture the average difference between the two groups relative to 2009.

Figure 1-1 presents the coefficients from estimating equation (1.2) with standard errors clustered by firm. The trends are approximately parallel before the introduction of the stress tests in 2009, but afterwards the treatment groups exhibits a notable relative decline.

Results

Table 1.3 presents the coefficients from estimating the cross-sectional specification (see equation (1.1)) with t-statistics computed using heteroscedasticity-consistent stan-

[35] Note that the results are robust to designating treatment based on whether a firm had an outstanding loan from a lender that was included in the SCAP as of 2008 or 2007. Determining treatment based on lending relationships in the years preceding the introduction of the stress tests eliminates the possibility that a firm's treatment status may have been determined after the policy was already in place, but it also introduces measurement error by ignoring how relationships may have changed in the intervening period.

dard errors in parentheses. The estimated effect of the stress tests in column (1) indicates that firms that were exposed to the stress tests exhibited an average decrease of 12.2% exempt lenders compared to firms that borrowed from lenders that were exempt from the stress tests. This suggests that the reduction in lenders was partly driven by the management of lending relationships by firms and not just the direct result of conservative lending by lenders. Section 1.4 offers an explanation for this finding with a model in which concentrating in a smaller number of lenders provides an incentive for lenders to screen more efficiently.

Column (2) addresses the concern is that the result could be confounded by unobserved factors related to lender size, especially since the stress tests were targeted towards large bank holding companies. For example, Chen, Hanson and Stein (2017) find that small business lending by the four largest banks decreased relative to other banks after 2008. Column (2) shows that the result is robust to restricting to the subset of firms with a lender that was eventually included in the stress tests after the threshold was lowered to $50 billion in 2014 and excluding firms with relationships to any the four largest bank holding companies by total assets, which includes Bank of America, Citigroup, JPMorgan Chase, and Wells Fargo.

Column (3) shows that a similar result obtains when using the total number of lenders.

Table 1.4 shows that the result is robust to various extensions. Column (1) omits the control variables other than the fixed effects. Column (2) estimates the specification using a finer set of industry-region fixed effects aggregated at the state × 6-digit NAICS level. Column (3) excludes franchises. Column (4) clusters by census region × 1-digit NAICS and business type.

1.3.2 Non-performing loan rates

Specification

To assess the effect of the stress tests and the associated change in the number of lenders on screening quality, I estimate a specification similar to equation (1.1) except replacing the dependent variable with the difference in the fraction of outstanding loans that are eventually charged-off as non-performing loans from 2009 to 2014 and including the difference in the logarithm of the number of exempt lenders as an independent variable:

$$\Delta NPL_i = \beta stress_i + \eta \Delta log\ lenders_i + \gamma X_i + \epsilon_i \tag{1.3}$$

Figure 1-1: Effect of the stress tests on lending relationships (yearly effects)

This figure presents the estimates β_t from running the regression $log\ lenders_{it} = \alpha_i + \psi_t + \sum_{t \neq 2009} \beta_t stress_i \times \psi_t + \epsilon_{it}$, where $log\ lenders_{it}$ is the number of lenders that were exempt from the stress tests, $stress_i$ is an indicator denoting whether in 2009 a firm had an outstanding loan from a lender that was included in the SCAP, α_i represents firm fixed effects, and ψ_t represents year fixed effects. Confidence intervals are constructed using firm-clustered standard errors. The vertical line at 2009 indicates the introduction of the stress tests.

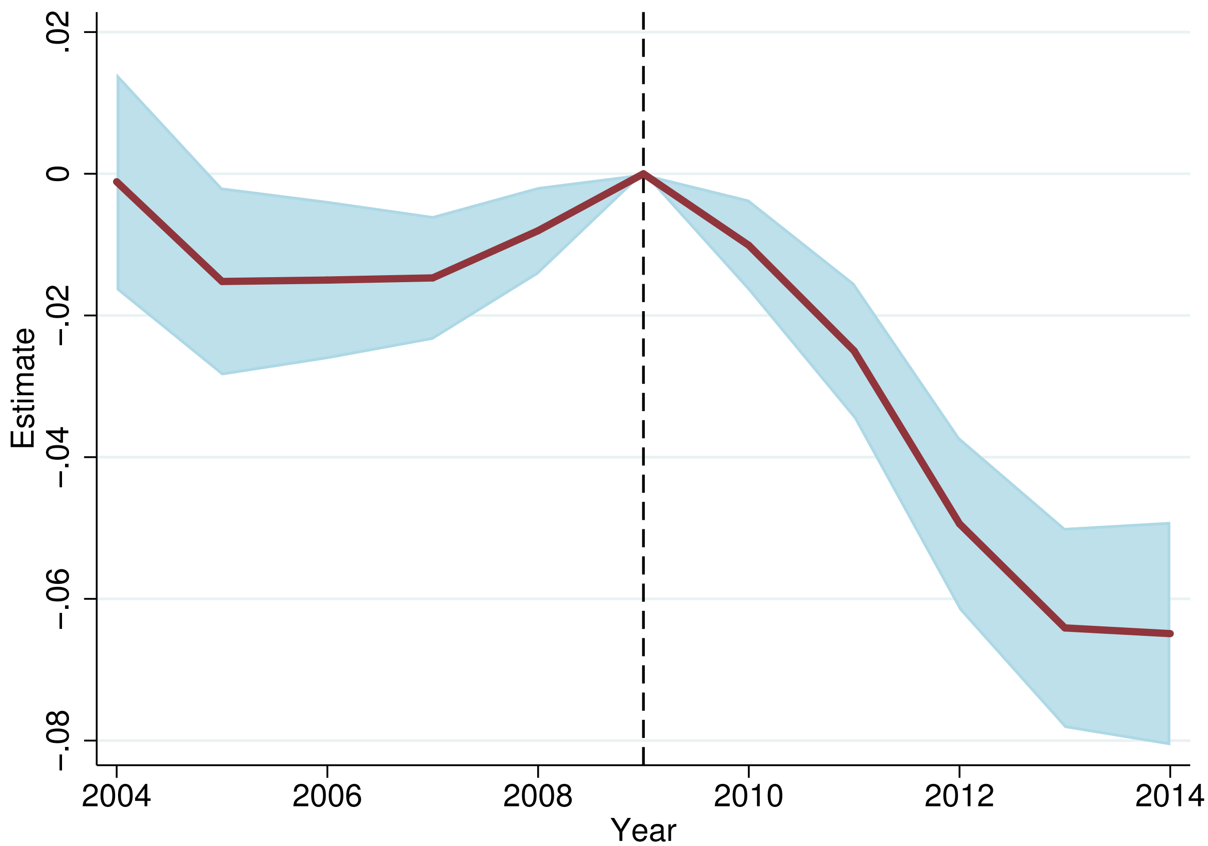


Table 1.3: Effect of the stress tests on lending relationships (cross-sectional analysis)

This table presents results from estimating variations of the regression $\Delta log\ lenders_i = \beta stress_i + \gamma X_i + \epsilon_i$, where the dependent variable $\Delta log\ lenders_i$ is the change in the logarithm of the number of lenders that were exempt from the stress tests on outstanding SBA loans from 2009 to 2014 for firm i. The treatment variable $stress_i$ is an indicator for whether in 2009 a firm had an outstanding loan from a lender that was included in the SCAP. The set of controls X_i as of 2009 includes the logarithm of the number of lenders, business type fixed effects, industry-region fixed effects aggregated to the level of 1-digit NAICS codes and census regions, and firm-level summary statistics for set of loan-level characteristics: the logarithm of the volume of a loan normalized to 2010 dollars using the GDP deflator, the term length of a loan expressed as the logarithm of the number of months, the fraction of a loan that is insured by the SBA, and an indicator for whether a loan is a revolver or term loan. Column (1) estimates the baseline specification. Column (2) restricts to firms with a lender that was eventually included in the stress tests and that did not have a relationship with any of the four largest banks. Column (3) estimates the specification using the total number of lenders as the dependent variable. T-statistics computed using heteroscedasticity-consistent standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Δ Log exempt lenders		Δ Log total lenders
	(1)	(2)	(3)
Stress test exposure	-0.122***	-0.137***	-0.053***
	(-14.76)	(-8.31)	(-6.98)
Observations	8809	2349	11531
R^2	0.413	0.444	0.467
Controls	Yes	Yes	Yes
Industry-region FE	Yes	Yes	Yes
Legal type FE	Yes	Yes	Yes
Lender size subsample	No	Yes	No

Table 1.4: Effect of the stress tests on lending relationships (robustness)

This table presents results from estimating a variation of the regression $\Delta log\ lenders_i = \beta stress_i + \gamma X_i + \epsilon_i$, where the dependent variable $\Delta log\ lenders_i$ is the change in the logarithm of the number of lenders that were exempt from the stress tests on outstanding SBA loans from 2009 to 2014 for firm i. The treatment variable $stress_i$ is an indicator for whether in 2009 a firm had an outstanding loan from a lender that was included in the SCAP. The set of controls X_i as of 2009 includes the logarithm of the number of lenders, business type fixed effects, industry-region fixed effects aggregated to the level of 1-digit NAICS codes and census regions, and firm-level summary statistics for set of loan-level characteristics: the logarithm of the volume of a loan normalized to 2010 dollars using the GDP deflator, the term length of a loan expressed as the logarithm of the number of months, the fraction of a loan that is insured by the SBA, and an indicator for whether a loan is a revolver or term loan. Column (1) omits the control variables other than the fixed effects. Column (2) estimates the specification using state × 6-digit NAICS fixed effects. Column (3) excludes franchises. Column (4) clusters by census region × 1-digt NAICS fixed effects and business type. T-statistics computed using heteroscedasticity-consistent standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Δ Log exempt lenders			
	(1) Omit controls	(2) Disaggregated FE	(3) No franchises	(4) Clustering
Stress test exposure	-0.095***	-0.084***	-0.115***	-0.122**
	(-11.69)	(-7.12)	(-13.36)	(-5.96)
Observations	8809	5918	8564	8809
R^2	0.393	0.536	0.409	0.413
Controls	No	Yes	Yes	Yes
Industry-region FE	Yes	Yes	Yes	Yes
Legal type FE	Yes	Yes	Yes	Yes

Note that the results for non-performing loans are documented as correlations and cannot necessarily be interpreted causally.

Results

Table 1.5 presents the coefficients from estimating equation (1.3). As a baseline, column (1) estimates the regression without including the difference in the number of lenders as a regressor. The estimate indicates that exposure to the stress tests was not strongly correlated with changes in non-performing loan rates. Column (2) includes the difference in the logarithm of the number of lenders. The estimates suggest the concentration of lending relationship was associated with lower non-performing loan rates. This correlation motivates the model developed in Section 1.4, which incorporates the idea that concentrating in a smaller number of lenders provides an incentive for lenders to screen more efficiently. Column (3) shows that this result is robust to restricting to the subset of lenders whose size was near the regulatory threshold, as described in Section 1.3.1.

1.3.3 Interest rates

Specification

To assess the effect of the stress tests and the associated consolidation of lending relationships on the ability of firms to bargain with their lenders over prices, I estimate a specification similar to equation (1.3) except replacing the dependent variable with the difference in the average interest rate spread relative to the prime rate on outstanding loans. Note that the results for interest rate spreads are documented as correlations and cannot necessarily be interpreted causally.

Results

Table 1.6 presents the estimates from the cross-sectional regression. Column (1) indicates that exposure to the stress tests may not have been strongly correlated with spreads, although the correlation is positive and significant in Column (2) after including the change in the number lenders.[36] Column (2) also indicates that the concentration of

[36]Note that there are mixed results in the literature regarding the extent to which the effect of capital requirements is transmitted through either loan quantities or prices. For example, Acharya, Berger and Roman (2018) and Cortés et al. (2020) find evidence of both quantity and price effects, whereas Behn, Haselmann and Wachtel (2016) only find evidence of quantity effects.

Table 1.5: Effect of the stress tests on non-performing loans (cross-sectional analysis)

This table presents results from estimating variations of the regression $\Delta NPL_i = \beta stress_i + \eta \Delta log\ lenders_i + \gamma X_i + \epsilon_i$, where the dependent variable ΔNPL_i is the difference between 2009 and 2014 in the fraction of outstanding SBA loans of firm i that are eventually charged off. The treatment variable $stress_i$ in an indicator denoting whether in 2009 a firm had an outstanding loan from a bank that was included in the SCAP, and $\Delta log\ lenders_i$ is the difference in the logarithm of the number of lenders that were exempt from the stress tests on outstanding SBA loans. The set of controls X_i as of 2009 includes the logarithm of the number of lenders, business type fixed effects, industry-region fixed effects aggregated to the level of 1-digit NAICS codes and census regions, and firm-level summary statistics for set of loan-level characteristics: the logarithm of the volume of a loan normalized to 2010 dollars using the GDP deflator, the term length of a loan expressed as the logarithm of the number of months, the fraction of a loan that is insured by the SBA, and an indicator for whether a loan is a revolver or term loan. Column (1) estimates the baseline specification with the total set of lenders. Column (2) estimates the baseline specification with the set of exempt lenders. Column (3) estimates the same specification as column (2) while restricting to firms with a lender that was eventually included in the stress tests and omitting the four largest banks. T-statistics computed using heteroscedasticity-consistent standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Δ NPL		
	(1)	(2)	(3)
Stress test exposure	-0.002	-0.009**	-0.007
	(-0.77)	(-2.49)	(-0.99)
Δ Log exempt lenders		0.044***	0.028***
		(9.74)	(3.33)
Observations	11531	8809	2349
R^2	0.042	0.048	0.070
Controls	Yes	Yes	Yes
Industry-region FE	Yes	Yes	Yes
Legal type FE	Yes	Yes	Yes
Lender size subsample	No	No	Yes

lending relationships was associated with higher spreads. This motivates the model developed in Section 1.4, which incorporates the idea that concentrating in a smaller number of lenders reduces the bargaining power of firms. Column (3) shows that this result has a similar magnitude when restricting to the subset of lenders whose size was near the regulatory threshold, as described in Section 1.3.1.

Table 1.6: Effect of the stress tests on interest rate spreads (cross-sectional analysis)

This table presents results from estimating variations of the regression $\Delta spread_i = \beta stress_i + \eta \Delta log\ lenders_i + \gamma X_i + \epsilon_i$, where the dependent variable $\Delta spread_i$ is the difference between 2009 and 2014 in the average interest rate spread on outstanding SBA loans of firm i. The treatment variable $stress_i$ in an indicator denoting whether in 2009 a firm had an outstanding loan from a bank that was included in the SCAP, and $\Delta log\ lenders_i$ is the difference in the logarithm of the number of lenders that were exempt from the stress tests on outstanding SBA loans. The set of controls X_i as of 2009 includes the logarithm of the number of lenders, business type fixed effects, industry-region fixed effects aggregated to the level of 1-digit NAICS codes and census regions, and firm-level summary statistics for set of loan-level characteristics: the logarithm of the volume of a loan normalized to 2010 dollars using the GDP deflator, the term length of a loan expressed as the logarithm of the number of months, the fraction of a loan that is insured by the SBA, and an indicator for whether a loan is a revolver or term loan. Column (1) estimates the baseline specification with the total set of lenders. Column (2) includes the change in the number of lenders . Column (3) estimates the same specification as column (2) while restricting to firms with a lender that was eventually included in the stress tests and omitting the four largest banks. T-statistics computed using heteroscedasticity-consistent standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Δ Spread		
	(1)	(2)	(3)
Stress test exposure	-0.087	0.099**	0.165
	(-1.65)	(2.10)	(1.54)
Δ Log exempt lenders		-0.224***	-0.190
		(-4.22)	(-1.35)
Observations	1380	1169	258
R^2	0.115	0.122	0.249
Controls	Yes	Yes	Yes
Industry-region FE	Yes	Yes	Yes
Legal type FE	Yes	Yes	Yes
Lender size subsample	No	No	Yes

1.4 Model

To explain the estimated effects of the stress tests on lending relationships, non-performing loan rates, and interest rates, this section introduces a model of bank competition in which firms choose the number of lenders they designate as relationship lenders.

The model captures the incentive for a firm to establish a small number of lending relationships to encourage its lenders to acquire information about its creditworthiness. It then illustrates how tightening credit standards that increase a firm's risk of being denied credit intensify this incentive.

1.4.1 Agents

There are two types of agents: firms and lenders. All agents are risk neutral.

A firm can either undertake a project that requires 1 unit of external investment or take an outside option whose value is normalized to zero. There are two quality types θ of firms: bad firms produce a gross return of 0 while good firms produce a positive net return $A > 0$. Lenders cannot perceive the type of an individual firm, but they know the frequencies of the two types in the population, $\lambda_b \leqslant \frac{1}{2}$ and $\lambda_g = 1 - \lambda_b$. Firms are also differentiated by their transparency, which is observable and independent from inherent quality.

Each lender can issue a loan at a cost of 1. The parameters are normalized so that indiscriminate lending produces zero expected profits

$$(1 + A)\lambda_g - 1 = 0 \tag{1.4}$$

This assumption isolates accurate screening as the sole source of surplus in the model.

1.4.2 Timeline overview

The timeline is divided into three periods $t = 0, 1, 2$ which capture the formation of lending relationships, the role of relationships and bank regulations in determining the allocation of credit, and, in cases where a firm obtains credit, loan repayment outcomes.

In period $t = 0$, lending relationships are formed.[37] A firm designates a number of relationship lenders to maximize its expected profits, which depends on its ability to obtain credit at a low interest rate. In particular, designating a relationship lender can be interpreted as initiating interactions that could allow a lender to acquire information about the firm, which could include prior loans or potentially a broader range of financial services such as deposit accounts. The relationship lenders then acquire information about the firm's credit risk to maximize their expected rents from information. This could

[37]The formation of lending relationship in period $t = 0$ can be interpreted as taking place over time through a history of interactions between a firm and its lenders.

include information that is difficult for a firm to convey directly or credibly, such tacit knowledge about the competence or character of a firm's management acquired through personal interactions. When deciding the extent of information acquisition, lenders take into account the degree of competition from the other lenders.[38]

In period $t = 1$, the firm applies for a new loan at each of its relationship lenders.[39] The lenders first estimate the firm's creditworthiness and then compete in an oligopolistic manner to determine which lender supplies the loan and the interest rate. In this process, bank regulations can constrain lenders from financing firms that they perceive as too risky. Note that for any particular loan application, the firm acquires credit from only one of the relationship lenders. The number of relationship lenders is primitively defined as the number of lenders that acquire information about the firm, but it can also be thought of as the expected number of lenders on outstanding loans if one thinks of the firm as applying for multiple loans over time, consistent with the empirical representation of lending relationships described in Section 1.2. For simplicity, the model focuses on a single loan application.

In period $t = 2$, the firm receives the outside option payoff of zero if it did not obtain funding, otherwise it either repays the loan or defaults. Note that bad firms always default while good firms can always repay since a lender has no incentive to set an interest rate higher than the return of a good firm.

Figure 1-2 presents a graphical overview of the timeline. An elaboration of the model follows in approximately backwards order.

1.4.3 New loan application

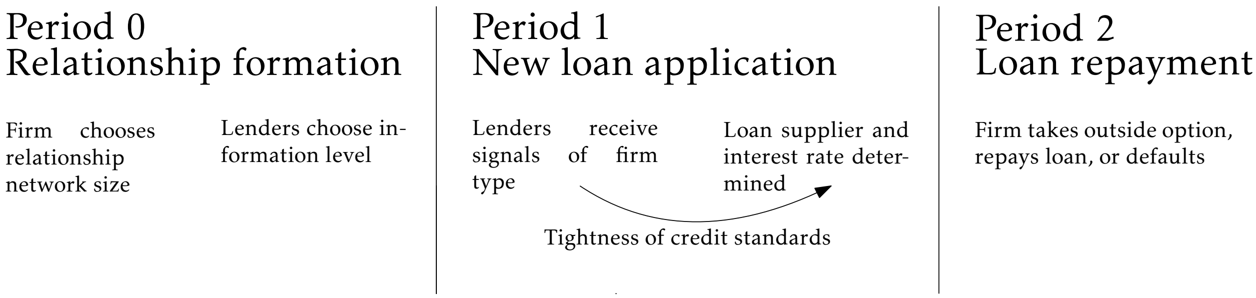
The new loan application in period $t = 1$ captures how lending relationships and bank regulations affect the supply and terms of credit. When a firm applies for a new loan with its relationship lenders, each lender first estimates the firm's default risk. This is represented allowing each lender to independently draw a signal whose informativeness

[38] Allowing banks to be aware of a firm's number of lenders is justified on the basis that lenders can acquire this information from credit reporting agencies Detragiache, Garella and Guiso (2000). Additionally, the finding in Petersen and Rajan (1994) that increasing the number of lenders can negatively affect the price and availability of credit for small businesses is consistent with the idea that a lender's investment in a lending relationship is sensitive to the presence of other informed lenders.

[39] The new loan application in period $t = 1$ is interpreted as taking place over a relatively short period of time in the sense that the long-term relationship structure established in period $t = 0$ is taken as fixed. Similar to existing models from the literature on bank competition with screening, it is equivalent to think of the firm as either applying to all of the lenders simultaneously or applying to the banks at different times since lenders must make their offers without knowing the decisions of the other lenders (Cao and Shi (2001)).

Figure 1-2: Timeline overview

This figure presents an overview of the timeline.



depends on the information it acquired about the firm's creditworthiness in period $t = 0$. After estimating the default risk of the firm, lenders that perceive the firm as too risky relative to the tightness of credit standards reject the firm's application, while the remaining lenders compete in an oligopolistic manner that is represented as a second-price sealed-bid auction where they bid interest rates.

Risk estimates

This section shows how lenders estimate the default risk of a firm, which can be described in two parts. First, each lender draws a signal from a distribution that depends on its information level and the firm's quality. Second, a lender then adjusts this estimate to take into account the additional information that it would learn if it won the auction.

Consider a firm that applies for a new loan conditional on having established relationships with n lenders in period $t = 0$. Suppose also that in period $t = 0$ the lenders acquired the same level of information about the firm, which is represented by the variable ψ. At the beginning of the loan application phase, each lender independently draws a privately observed signal that depends on the firm's quality type and the information level of the lenders according to the distribution[40]

[40] Up to a first order approximation in ψ, this distribution system can be assumed without loss of generality conditional on the following set of intuitive properties: the predictive distribution does not depend on the information level, the conditional distributions converge to the predictive distribution when the information level is equal to zero, and the first order effect of information on the conditional pdf for a good signal is given by the probability of receiving as high a signal under the predictive distribution. See Appendix 1.C for details.

$$f(s|b;\psi) = \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_b}\right)1_{[0,1]} \tag{1.5}$$

$$f(s|g;\psi) = \left(1 + \left(s - \frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)1_{[0,1]} \tag{1.6}$$

Note that nonnegativity of the conditional pdfs requires the information level to be bounded by

$$\psi_{max} = 2\lambda_b \tag{1.7}$$

This signal structure generates several intuitive properties for the posterior risk of default. The posterior risk of default conditional on receiving signal s with information ψ can be expressed as

$$\begin{aligned} D(s;\psi) &\equiv Pr(b|s;\psi) \\ &= \lambda_b + \left(\frac{1}{2} - s\right)\psi \end{aligned} \tag{1.8}$$

The properties of the posterior risk are represented graphically in Figure 1-3. The posterior risk is decreasing in the signal and equal to the prior λ_b at the threshold point $s = \frac{1}{2}$. The strength of a signal in shifting the prior is increasing in its distance from this threshold as well as the information level.

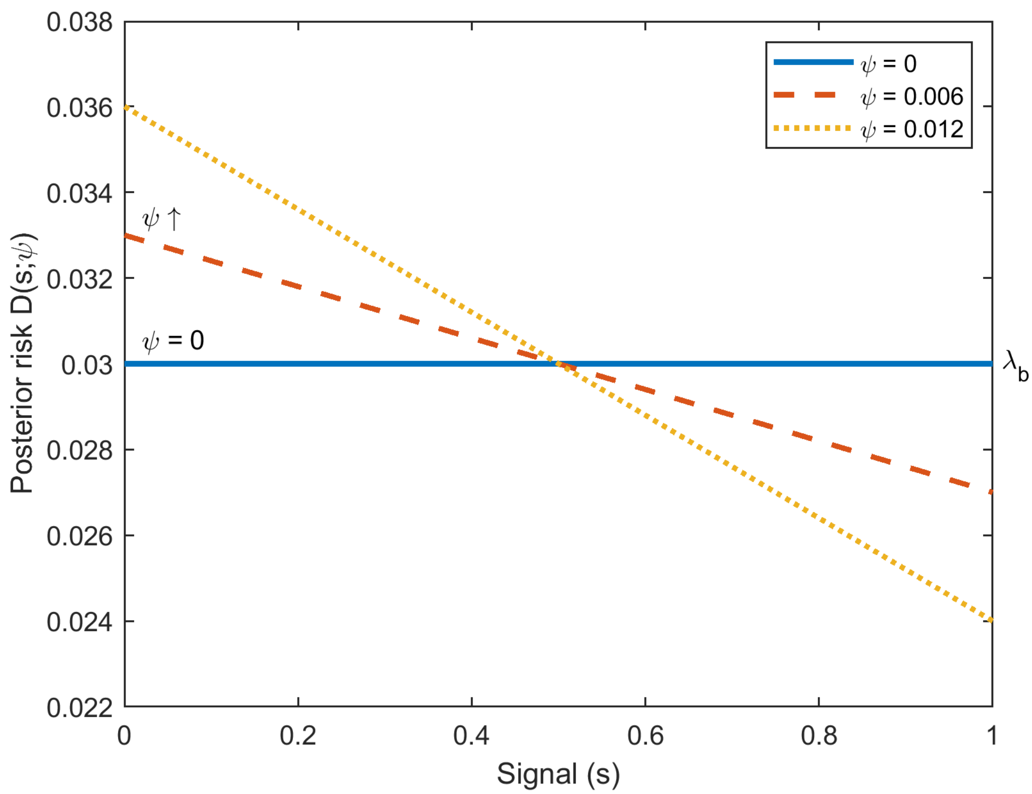
Conditional on the signals, competition among the lenders is formally represented as a second-price sealed-bid auction where they bid interest rates.[41] Applying a general result for common value auctions from Milgrom (1981), I determine that there is a symmetric equilibrium in which each lender's bid is based on the minimum posterior risk of default that it could have conditional on winning the auction with the signal that it receives. Conditioning on winning the auction accounts for the "winner's curse", or the tendency for the winning bidder of a common value auction to have an over-optimistic assessment, and the information implicitly conveyed in the equilibrium interest rate.

The posterior risk conditional on winning the auction is determined as follows. Since the signal is inversely related to the posterior risk (see equation (1.8)), the equilibrium

[41]The auction is analogous to Bertrand competition except that the perceived costs of producing loans are based on estimates of a common cost based on the borrower's quality. For simplicity, the auction is assumed to be sealed-bid so that the condition of winning the auction and the equilibrium interest rate are the only sources of information about the signals of the other lenders. The assumption that banks cannot observe each other's offers is similar to other models of bank competition with screening, such as Broecker (1990), Cao and Shi (2001), and Ruckes (2004).

Figure 1-3: Posterior risk

This figure shows how a lender's posterior risk $D(s;\psi)$ varies with its signal s and information level ψ.



interest rate corresponds to the second highest signal. The posterior risk conditional on drawing signal s and inferring from the equilibrium interest rate that the highest signal among the $n-1$ competing lenders is equal to t can be expressed as[42]

$$D(s,t;\psi,n) \underset{\psi\approx 0}{\approx} \lambda_b + \frac{1}{2}(n-2s-nt)\psi \tag{1.9}$$

The *minimum* posterior risk conditional on winning with signal s occurs when the greatest signal among the $n-1$ competing lenders is also equal to s, which can be expressed as

$$D(s,s;\psi,n) = \lambda_b + \frac{1}{2}(n-(n+2)s)\psi \tag{1.10}$$

The minimum posterior risk conditional on winning the auction with n bidders $D(s,s;\psi,n)$ qualitatively inherits some of the properties of the posterior risk conditional on just the signal $D(s;\psi)$. Specifically, the minimum posterior risk is decreasing in the signal, and information increases the strength of the signal. A difference is that minimum posterior risk is equal to the prior at the threshold point $s=\frac{n}{n+2}$, which is increasing in the number of lenders to account for the fact that the severity of the winner's curse is increasing in the number of bidders.

Tightness of credit standards

Regulations that encourage conservative lending practices constrain lenders from financing firms that they perceive as too risky. In particular, a lender only bids if the expected posterior risk of default conditional on winning the auction occurs below a bound $B \leqslant \lambda_b$ representing the looseness of credit standards.[43] This determines an equivalent lower bound that must be satisfied by a lender's signal.[44]

Lemma 1.1. *A lender rejects the a firm's loan application if it draws a signal less than the threshold*

$$\underline{s} = \frac{n}{n+1} + \frac{2(\lambda_b - B)}{(n+1)\psi} \tag{1.11}$$

[42]See Appendix 1.B.1 for a calculation. The notation $\underset{\psi\approx 0}{\approx}$ indicates that the expression is a first order approximation around $\psi = 0$.

[43]Note that a bound $B > \lambda_b$ is equivalent to $B = \lambda_b$ since a lender who perceives the expected posterior risk to be greater than the prior never has an incentive to bid. Under the normalization for the cost of funds (see equation (1.4)), the return for a good firm is too low for such a lender to make positive expected profits.

[44]See Appendix 1.B.2 for a calculation.

The threshold $\underline{s}$ is then inversely related to the probability that a lender is willing to finance the firm.[45]

Tightening credit standards corresponds to decreasing B.[46] This choice for modeling tightening credit standards is motivated by the findings in Cortés et al. (2020) and Acharya, Berger and Roman (2018) showing that the stress tests were associated with decreasing loan quantities and increasing interest rates. In particular, similar to the results in Cortés et al. (2020), it causes banks to withdraw credit from firms about which they have uninformative signals, which in equilibrium also leads to an increase in interest rates for the firms where they have informative signals because there is less competition for their credit demand (see Section 1.5). One interpretation behind this choice of modeling tightening credit standards is that regulations that require a lender to hold more capital, such as the stress tests, decrease a bank's appetite for risk since shareholders have more to lose. I represent this increased cautiousness as occurring directly through a bank's decision about whether to lend because that is what a bank can control, whereas the interest rate is determined in equilibrium since there is generally some degree of competition. For simplicity, the model abstracts from microfounding this risk aversion channel.[47]

An important observation is that tightening credit standards decreases credit access, but this effect is mitigated by the information level of the lenders. This plays a crucial role in shaping how lending relationships respond to tightening credit standards.

Corollary 1.1. The immediate effect of tightening credit standards is a reduction in credit access:

$$\frac{\partial \underline{s}}{\partial B} = -\frac{2}{(n+1)\psi} \leqslant 0 \tag{1.12}$$

This effect is mitigated by the information level of the lenders:

$$\frac{\partial^2 \underline{s}}{\partial \psi \partial B} = \frac{2}{(n+1)\psi^2} \geqslant 0 \tag{1.13}$$

---

[45] Note that if $\underline{s} \geqslant 1$ then this probability is equal to zero.

[46] For simplicity, I assume that the tightening affects all lenders equally, abstracting from the potential incentive for firms to substitute to lenders with looser regulations. This could reflect various reasons for some firms to prefer to strengthen their existing relationships with regulated enders that are not explicitly modeled. For example, for some firms regulated lenders could be closer in terms of physical distance, which has generally been associated with relationship strength (see, for example, Agarwal and Hauswald (2010), Cortés et al. (2020), and Sufi (2007)).

[47] Note that the results from numerical simulations of the model are qualitatively similar if tightening credit standards are alternatively represented by an increase in the cost of funds, which could represent higher effective capital charges associated with the stress tests.

Interest rate bids

A lender that is willing to lend to the firm participates in the auction by bidding an interest rate R. Conditional on the posterior risk D, a lender's expected profits can be expressed by the probability of repayment with interest minus the cost of funds

$$(1-D)(1+R)-1 \tag{1.14}$$

The zero-profits interest rate can be written as a markup over the cost of funds that corresponds to the risk[48]

$$\underline{R}(D) \underset{D\approx\lambda_b}{\approx} A+\frac{1+A}{\lambda_g}(D-\lambda_b) \tag{1.15}$$

If at least one other lender participates in the auction, a lender's bid is equal to the zero-profits interest rate corresponding to the minimum posterior risk conditional on winning the auction (see equation (1.10)).

Lemma 1.2. *A lender's bid is equal to*

$$\underline{R}(D(s,s;\psi,n)) = A+\frac{1+A}{\lambda_g}\frac{1}{2}(n-(n+2)s)\,\psi \tag{1.16}$$

Since the interest rate bid is an affine transformation of the minimum posterior risk, it inherits many of the key intuitive properties. In particular, the bid is decreasing in the signal since a high signal indicates that the firm is likely to repay the loan. Additionally, information increases the strength of the signal. Finally, if the information level is zero, then the bid is always equal to the maximum feasible interest rate, which is the return of a good project A. This reflects the fact that the parameters are normalized to isolate accurate screening as the sole source of surplus in the model (see equation (1.4)).

If only one lender has a sufficiently optimistic signal to offer a loan, then it fully appropriates any potential surplus by charging an interest rate that is equal to the return of a good firm A.[49]

[48] See Appendix 1.B.3 for a calculation.

[49] In this case the winning lender's posterior risk is averaged over cases where the second highest signal is less than $\underline{s}$. It can be checked that the posterior risk is less than the tightness bound B as long as the expected posterior risk before bidding is also less than B. In other words, a lender that is willing to bid is still willing to supply a loan after it wins the auction.

Auction summary

The resolution of the auction is summarized as follows. If more than one lender is willing to lend, then the lenders bid $\underline{R}(D(s,s;\psi,n))$ and the lender with the lowest bid supplies the loan at the second lowest bid $\underline{R}(D(s_{n-1:n},s_{n-1:n};\psi,n))$. If only one lender has a sufficiently optimistic signal to offer a loan, then it charges an interest rate that is equal to the return of a good firm A.[50] If no lender obtains a sufficiently optimistic assessment to be willing to offer credit, then the firm takes the outside option.[51]

1.4.4 A lender's information acquisition decision

Relationship lenders choose the level of information to acquire about a firm's creditworthiness to maximize their rents from information net of an information acquisition cost. A key implication is that lenders have little incentive to acquire information about a firm with many competing lenders.

Decision problem

There are two sources of information that are differentiated by their costs. The first is easily accessible information such as bond ratings and public filings, which is represented by a firm's transparency $z \geqslant 0$. The other is information $\eta \geqslant 0$ acquired by a lender through close interactions with the firm, which has a convex acquisition cost $\mu\frac{\eta^2}{2}$. A lender's total information level is equal to the sum from these two sources, $\psi = z + \eta$.

The value of information to a lender consists in efficiently providing credit to firms that are likely to repay as well as undercutting competitors with noisier signals. For simplicity, consider a symmetric equilibrium in which all lenders commit to acquire the same information level.[52] In particular, relationship lenders choose the level of informa-

[50]This formal convention is consistent with the motivating intuition that a firm's bargaining power derives from leveraging competing offers from other informed lenders.

[51]Note that the firm could not do better by alternatively applying to a lender with which it does not have a relationship, as the normalization in equation (1.4) implies that a lender with no information has a zero profits interest rate that is equal to the return of a good project. If an uninformed lender additionally internalized that the firm had been rejected by its relationship lenders, then the zero-profits interest rate would be strictly greater than the return of a good project and the lender would strictly prefer to reject the loan application. As a precedent, Detragiache, Garella and Guiso (2000) also present a model in which, for some parameter specifications, it is impossible for opaque firms to obtain credit from uninformed lenders.

[52]It is also possible to allow the lenders to compete in a symmetric Nash equilibrium when choosing the information level. Calibrating the version of the model with the coordinated equilibrium achieves a closer fit to the data compared to the version with the Nash equilibrium, but the comparative statics are qualitatively similar. See Appendix 1.D for details. Besides being simpler and better able to fit the data,

tion $\psi \in [0, \psi_{max}]$ to maximize their net rents from information

$$\pi_L = \lambda_g E\left[(\min\{\underline{R}(D(s_{n-1:n}, s_{n-1:n}; \psi, n)), A\} - \underline{R}(D(s, s_{n-1:n}; \psi, n)))\, 1_{\{s=s_{n:n}\geqslant \underline{s}\}}|g;\psi\right] \\ -\mu\frac{(\psi - z)^2}{2} \tag{1.17}$$

where the expectation averages over cases where the lender wins the auction for a good firm and obtains a profit corresponding to the difference between the interest rate that it collects and its zero-profits interest rate.[53]

Determinants of information acquisition

The chosen information level satisfies a few key properties.

First, a lender's total information level increases in a firm's transparency due to the reduced marginal acquisition cost.[54]

Lemma 1.3. *A lender's total information level increases in a firm's transparency:*

$$\frac{\partial \psi}{\partial z} \geqslant 0 \tag{1.18}$$

Second, lenders have little incentive to acquire information about a firm with a large and competitive network of relationship lenders.[55]

Lemma 1.4. *Acquired information converges to zero as the number of lenders increases. Equivalently, the total information level converges to the firm's transparency:*

$$\lim_{n\to\infty} \psi = z \tag{1.19}$$

In particular, increasing the number of lenders increases the likelihood of being undercut by a rival and also decreases the expected profit margin conditional on supplying the

the coordinated equilibrium in the model is also qualitatively consistent with the fact that many U.S. banks coordinate on the prime interest rate. In particular, the model analog of the prime interest rate, or the lowest interest rate that a bank would be willing to charge after receiving the most optimistic signal, is equal to $R(D(1,1;\psi,n))$, which, conditional on n, is uniquely determined by the information level ψ.

[53]See Appendix 1.B.4 for a calculation of a lender's problem.

[54]See Appendix 1.B.5 for a calculation. Note that the level of acquired information η is decreasing in z at the parameters that are calibrated in Section 1.5.1, but the total information level is still increasing in z.

[55]See Appendix 1.B.6 for a calculation.

loan, decreasing the return to information.[56]

Third, tightening credit standards can in general either increase or decrease the incentive to acquire information. In particular, tightening credit standards has the immediate effect of decreasing the probability that a lender is willing to finance the firm (see equation (1.12)), but increasing the information level mitigates this effect (see equation (1.13)). Additionally, decreasing the probability that a lender is willing to finance the firm has a direct negative effect on the incentive to acquire information, but it also has a positive effect by dampening the degree of competition. The total impact on a lender's incentive to acquire information depends in part on the relative strengths of these effects.[57]

1.4.5 A firm's lending relationship concentration decision

A firm chooses a number of relationship lenders to maximize its expected profits, which depends on its ability to obtain credit at a low interest rate. A key implication is that tightening credit standards can intensify the incentive for opaque firms to concentrate within a smaller number of lenders and encourages transparent firms to substitute to bonds.

Decision problem

A good firm chooses the number of relationship lenders to maximize its expected profits

$$\pi_F = E\left[(A - \min\{\underline{R}(D(s_{n-1:n}, s_{n-1}; \psi, n)), A\})\, 1_{\{s_{n:n} \geqslant \underline{s}\}} | g; \psi\right] + 0 * Pr(s_{n:n} < \underline{s} | g; \psi) \qquad (1.20)$$

where the first term averages over cases where the firm obtains funding and accrues whatever fraction of the return to the project remains after paying interest and the second term averages over cases where the firm does not obtain credit.

A firm may alternatively prefer to borrow from a disperse set of $n = \infty$ non-monitoring lenders, which is interpreted as issuing debt to bondholders. Bondholders are not affected by tightening credit standards and have $B_{bond} = \lambda_b$.[58]

Bad firms always obtain zero profits and are therefore indifferent to the number of relationship lenders. Since it is costless for bad firms to imitate good firms, I consider an

[56] Locally, the number of lenders also affects the incentive to acquire information through other channels that are described in a formal decomposition in Appendix 1.B.7.

[57] Appendix 1.B.8 provides a formal decomposition.

[58] See Appendix 1.B.9 for a calculation of a firm's problem.

equilibrium in which good and bad firms both choose the number of lenders that maximizes equation (1.20). This induces a pooling equilibrium in which the quality type of a firm cannot be inferred from its chosen number of lenders. Note that a bad firm's choice can be made unique without affecting the conclusions of the model by supposing that borrowers receive a positive but arbitrarily small private benefit of control from running the project. In that case, bad firms have an incentive to imitate good firms to have a positive probability of receiving credit and capturing the private benefit of control.[59]

Determinants of lending relationship concentration

Firms face a trade-off in which, holding the information level of lenders fixed, increasing the number of relationship lenders has the benefit of increasing the probability of receiving credit as well as the ability to bargain down the interest rate conditional on receiving credit. However, it also has the cost of decreasing the incentive for lenders to acquire information.

Opaque firms have a relatively strong incentive to concentrate their debt in a small number of lenders to encourage the acquisition of information, whereas transparent firms have a relatively strong incentive to borrow from a more disperse set of lenders to increase their bargaining power. At the extremes, highly opaque firms with $z = 0$ can only make positive profits if lenders acquire information about them and therefore always choose a finite number of lenders, whereas maximally transparent firms with $z = \psi_{max}$ cannot encourage further information acquisition and therefore always issue bonds.[60]

Tightening credit standards can intensify the incentive for opaque firms to concentrate their debt within a smaller number of lenders. In particular, tightening credit standards reduces the probability that a firm's lenders are willing to compete for its demand for credit (see equation (1.12)). This can reduce a firm's expected profits.[61] However, information mitigates this effect by increasing the probability that a lender receives a sufficiently strong signal of the firm's creditworthiness to compete in the auction (see equation (1.13)). This can intensify the incentive for an opaque firm to concentrate in a smaller number of lenders, which encourages greater information acquisition and par-

[59]Considering a pooling equilibrium in which bad types mimic good types is similar to other models of capital structure, such as Bolton and Freixas (2000).

[60]Locally, transparency also affects a firm's number of relationship lenders through other channels that are described formally in Appendix 1.B.10.

[61]It is straightforward to see that a firm makes zero expected profits in the boundary case where $B = 0$. Locally, the tightness of credit standards also affects a firm's expected profits through other channels that are described in a formal decomposition in Appendix 1.B.11.

tially restores its access to credit.[62]

By contrast, tightening credit standards encourages transparent firms to substitute from bank loans to bonds. In particular, since tightening credit standards has no effect on the expected profits that a firm could obtain when borrowing from bondholders, moderately transparent firms that were nearly indifferent between the two types of debt before the tightening substitute. This is similar to the result in Holmstrom and Tirole (1997) that tightening bank lending decreases the relative cost of uninformed finance for moderately transparent firms, although they consider a different mechanism involving moral hazard.

1.5 Calibration and screening efficiency analysis

This section first calibrates the parameters of the model and shows that it is capable of qualitatively matching the estimated effects of tightening credit standards from Section 1.3. It then formally defines screening efficiency and shows that the induced concentration of lending relationships by opaque firms can substantially mitigate the negative effect of tightening credit standards on screening efficiency. Finally, it shows that tightening credit standards can also cause relatively transparent firms to substitute to bonds, which decreases screening efficiency.

1.5.1 Calibration

The model is calibrated for opaque firms with $z = 0$ using data on small businesses. The calibrated parameters include the scale of the information acquisition cost μ, the fraction of bad firms λ_b, the level of looseness before the introduction of the stress tests B_{loose}, and the level of looseness after the introduction of the stress tests B_{tight}. These parameters are selected to minimize a variance-weighted sum of squared deviations between the empirical and model-generated values for a set of eight observable variables. First I consider the pre-tightening levels of four variables:[63]

- The first variable is the access to credit, which in the model is the fraction of firms

[62] Note that tightening credit standards can also intensify an incentive to establish more lending relationships via an insurance motive in which, for a given level of information acquisition, firms have an incentive to establish more lending relationships to increase the probability that at least one lender would be willing to lend. The total impact on a firm's chosen number of lenders depends in general on the relative strengths of these channels. Appendix 1.B.12 provides a formal decomposition.

[63] Appendix 1.E formally defines these variables within the model.

that obtain credit. The empirical analog is the fraction of firms seeking credit in the most recent Federal Reserve Survey of Small Business Finance (SSBF) as of 2003 that report always being approved for credit as opposed to sometimes or always being denied credit or not applying in anticipation of being denied.

- The second variable is the number of relationship lenders. The empirical analog is the average number of lenders for firms in the SBA dataset, as reported in Table 1.1.[64]

- The third variable is the default rate, which in the model is the fraction of the firms receiving credit that are bad. The empirical analog is the fraction of outstanding loans in 2009 in the SBA dataset that are eventually charged off as non-performing loans, as reported in Table 1.1.

- The fourth variable is the average interest rate spread, which in the model is the expected net interest charged conditional on receiving credit. The empirical analog is the average interest rate spread relative to the prime rate on outstanding loans in 2009 in the SBA dataset, as reported in Table 1.1.

The remaining four variables in the calibration correspond to the respective changes in these variables from 2009 to 2014 associated with the stress tests.[65]

Table 1.7 presents the calibrated parameters and Table 1.8 compares the empirical and model-generated values for the observables. The model generally appears to fit the data well. Notably, the model is capable of matching the decrease in the number of lenders, which is because opaque firms have an incentive to mitigate the reduced access to credit by encouraging their lenders to acquire more information.

1.5.2 Screening efficiency

This section defines screening efficiency and shows how it is affected by tightening credit standards. As an overview, tightening credit standards reduces screening efficiency by decreasing the availability of credit to good firms, but the adjustment of lending relationships can mitigate this effect. I decompose the adjustment into two phases. First,

[64] Note that to match the average number of lenders I abstract from interpreting the number of lenders in the model n as an integer.

[65] These are estimated in Section 1.3 for the variables based on data on SBA loans. Note that there does not exist a version of the SSBF after the introduction of the stress tests to estimate the change in the access to credit. Instead, the change in the access to credit is interpreted to correspond to the change in the number of new loan issues estimated in Appendix Section 1.A.

Table 1.7: Calibrated parameters

This table presents the calibrated parameter values.

Parameter	Value
Information cost (μ)	1.800
Fraction of bad firms (λ_b)	0.030
Pre-tightening looseness (B_{loose})	0.028
Post-tightening looseness (B_{tight})	0.025

Table 1.8: Comparison of empirical and model-generated variables

This table presents the empirical and model-generated values for a set of targeted variables.

Variable	Empirical	Model
Pre-tightening levels		
Access to credit	0.561	0.499
Number of lenders	1.741	1.727
Default rate	0.047	0.021
Interest rate spread (%)	3.184	2.803
Tightening-induced difference		
Access to credit	–0.200	–0.176
Number of lenders	–0.053	–0.054
Default rate	–0.002	–0.003
Interest rate spread (%)	–0.087	0.015

holding the number of lenders fixed, tightening credit standards increases the incentive for lenders to acquire information. Second, it also increases the incentive for firms to concentrate their debt in a smaller number of lenders to encourage further information acquisition. The tightening in combination with the adjustment of lending relationships shifts the distribution of the surplus from lending in favor of lenders.

Screening efficiency is represented by the total surplus from lending, which is defined as the expected return from financed projects minus the costs of investment and information acquisition. This can be expressed as

$$S = \underbrace{(1+A)\lambda_g P_g + 0 * \lambda_b P_b}_{\text{return from financed projects}} - \underbrace{(\lambda_g P_g + \lambda_b P_b)}_{\text{investments costs}} - \underbrace{n\mu\frac{(\psi - z)^2}{2}}_{\text{information costs}}$$

where P_g is the probability that a good firm obtains a loan and P_b is the probability that a bad firm obtains a loan.

I consider two decompositions of the surplus. First, in a "losses" decomposition I express it as the maximum possible surplus in a perfect information or first best environment (where a firm receives credit if and only if it is good) minus losses due to missed good loans (not supplying credit to good firms), losses due to bad loans (supplying credit to bad firms), and information acquisition costs:

$$S = \underbrace{A\lambda_g}_{\text{perfect information}} - \underbrace{A\lambda_g(1-P_g)}_{\text{missed good loans}} - \underbrace{\lambda_b P_b}_{\text{bad loans}} - \underbrace{n\mu\frac{(\psi - z)^2}{2}}_{\text{information costs}} \tag{1.21}$$

Second, in a "distributional" decomposition I express the surplus as firm profits plus the profits accrued collectively by the lenders

$$S = \underbrace{\lambda_g \pi_F}_{\text{firm profits}} + \underbrace{n\pi_L}_{\text{lender profits}} \tag{1.22}$$

Note that screening efficiency does not encompass the benefits of bank regulations in mitigating financial crises except insofar as it includes bad loans, which are associated with the degree to which financial crises affect output (Ari, Chen and Ratnovski (2019)). The effect of tightening credit standards on screening efficiency therefore likely underestimates the net value of heightened bank regulations.

At the calibrated parameters, the constrained efficient number of lenders for an opaque firm with $z = 0$ is equal to $n_{ce} = 1$. To illustrate this, Figure 1-4 shows how the surplus and its components in the losses decomposition (see equation (1.21)) vary with the number of lenders at the pre-tightening level of looseness. There are two regions that can be used to decompose the effect of varying the number of lenders into a direct effect without a simultaneous adjustment of information acquisition and a full effect that also includes an associated adjustment of information acquisition.

When the number of lenders is small, the information level acquired by lenders is constrained by the maximum $\psi_{max} = 2\lambda_b$ (see equation (1.7)) and does not vary with the number of lenders. In that case, increasing the number of lenders decreases losses from missed good loans since a good firm has a greater probability of finding at least one lender that is willing to lend to it. However, the same logic for bad firms implies that there is also an increase in losses from bad loans. The total information cost also increases with the number of lenders, which can be thought of as a duplication of information costs (Diamond (1984)). The sum of these effects results in a decreasing relationship between the total surplus and the number of lenders.

When the number of lenders is large enough that the information level is not constrained, then increasing the number of lenders has the additional effect of inducing lenders to acquire less information. In this case, the reduction in information acquisition is severe enough that increasing the number of lenders actually decreases total information costs. However, the reduction in information acquisition is also associated with greater losses due to mistakenly providing credit to bad firms and rejecting good firms. The sum of these effects results in a decreasing relationship between the total surplus and the number of lenders in this region. Finally, since the surplus is everywhere decreasing in the number of lenders, the efficient choice of lenders is equal to the lowest possible number, which is one.

In equilibrium, firms always choose to have more than the constrained efficient number of relationship lenders. In particular, a firm never chooses to have a single lender since in that case it has no bargaining power and receives zero expected profits. To illustrate how firms choose their lending relationships, Figure 1-5 shows how the components from the distributional decomposition of the surplus (see equation (1.22)) vary with the number of lenders. By choosing to have more but weaker relationships, firms sacrifice some of the total potential surplus to increase their share.

The adjustment of lending relationships can qualitatively influence the effect of tightening credit standards on screening efficiency. To illustrate this at the calibrated parameters, Table 1.9 shows how the surplus and its components in the losses decomposition

Figure 1-4: Losses decomposition of surplus from lending

This figure shows how the surplus from lending S and its components in the losses decomposition vary with the number of lenders n for an opaque firm ($z = 0$) at the pre-tightening level of looseness (B_{loose}).

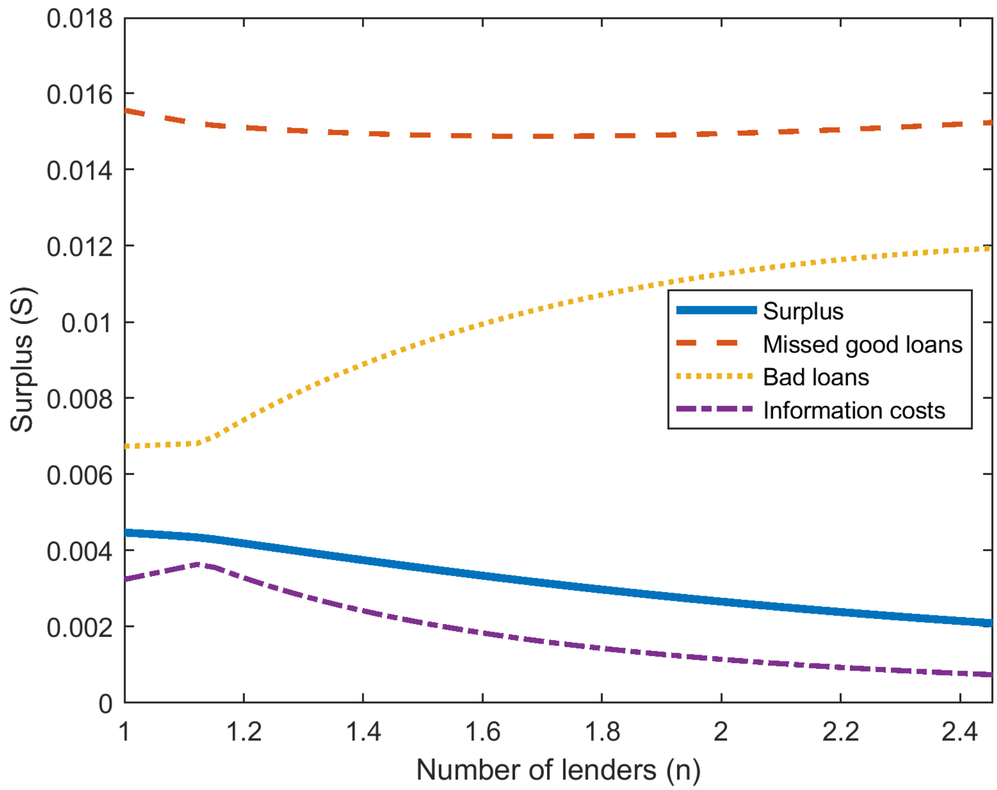
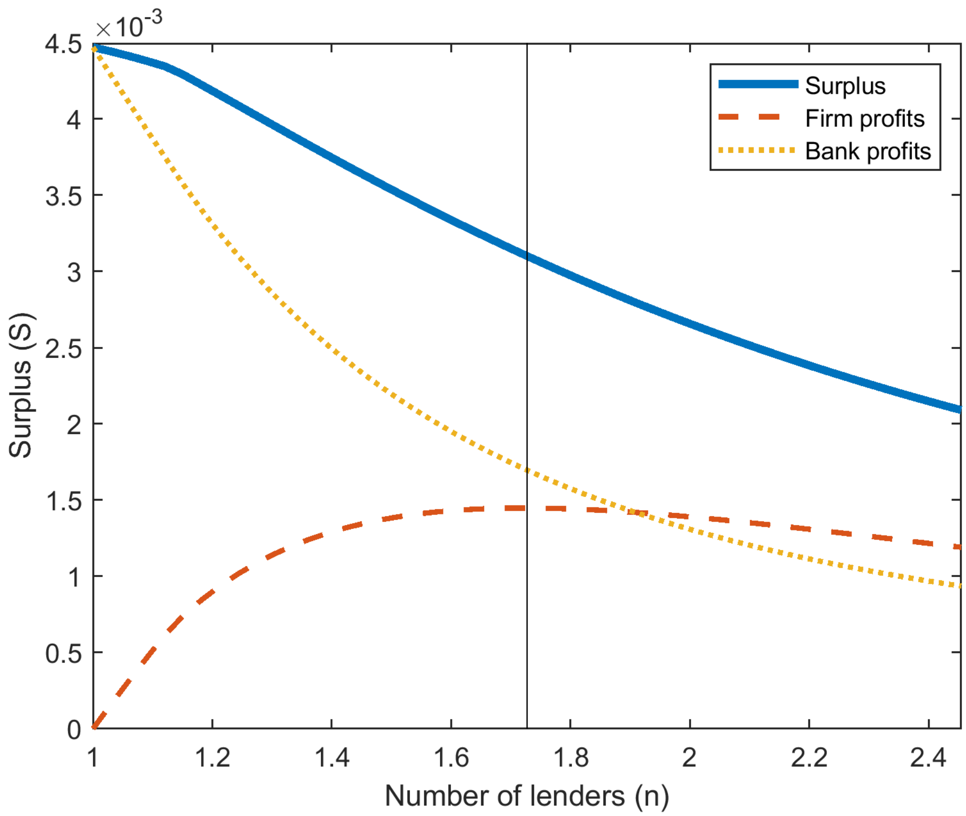


Figure 1-5: Distributional decomposition of surplus from lending

This figure shows how the surplus from lending S and its components in the distributional decomposition vary with the number of lenders n for an opaque firm ($z = 0$) at the pre-tightening level of looseness (B_{loose}). The vertical line indicates the equilibrium number of lenders chosen by the firm.



vary with the looseness of credit standards. It also illustrates the differences between fixing lending relationships at the pre-tightening configuration, only allowing lenders to adjust to the observed tightening, and taking into account the full adjustment of lending relationships by both the firm and its lenders.

Table 1.9: Losses decomposition of surplus from lending

This table presents the surplus and its decomposition in the losses distribution at four different states: loose credit, tight credit with no adjustment by any agents, tight credit with adjustment of only information ψ by lenders, and tight credit with adjustment of both information by lenders ψ and relationship lenders n by firms. Values have been multiplied by 100.

	Surplus	Perfect info.	Missed good loans	Bad loans	Info. costs
Loose credit	0.310	3.000	1.488	1.046	0.156
Tight credit: no adjustment	0.278	3.000	1.783	0.783	0.156
Tight credit: lenders adjust	0.294	3.000	1.744	0.777	0.185
Tight credit: full adjustment	0.310	3.000	1.729	0.760	0.202

Screening efficiency is notably less sensitive to the degree of looseness after accounting for the adjustment of lending relationships. In particular, the immediate effect of the observed tightening without taking into account the adjustment of relationships reduces the surplus by 10.3% from the pre-tightening level. This is driven by an increase in losses from missed good loans as good firms find it difficult to obtain credit. To partially offset this effect, lenders increase the acquisition of information, mitigating the loss in screening efficiency to 5.16%. In addition, to partially restore the access to credit, firms strengthen their lending relationships by concentrating in a smaller number of lenders. Tightening credit standards thereby induces firms to choose a lending relationship configuration that is closer to the constrained optimum, recovering the remaining losses from the tightening. Additionally, the concentration of lending relationships is also associated with a decrease in losses from bad loans, consistent with the empirical findings in Table 1.5.

Finally, tightening credit standards and the resulting adjustment in lending relationships shift the surplus from lending from firms to lenders. To illustrate this, Table 1.10 shows how the components of the distributional decomposition of the surplus vary with the looseness of credit standards. The immediate effect of the observed tightening decreases firm profits by 30.7% from the pre-tightening level. This reflects two effects. First, firms are less likely to obtain credit from any of their lenders. Second, firms that obtain credit face higher interest rates since a smaller fraction of their relationship lenders are willing to compete. The adjustment of lending relationships mitigates the loss to 20%. In particular, the concentration of lending relationships increases the likelihood of obtaining credit, but it is also associated with an increase in the interest rate, consistent with the empirical findings in Table 1.6. Finally, the induced concentration of relationships by firms also benefits lenders by supporting more efficient lending.

Table 1.10: Distributional decomposition of surplus from lending

This table presents the surplus and its decomposition in the losses distribution at four different states: loose credit, tight credit with no adjustment by any agents, tight credit with adjustment of only information ψ by lenders, and tight credit with adjustment of both information by lenders ψ and relationship lenders n by firms. Access to credit is and the interest rate spread are reported as a percentage, and values for the other columns have been multiplied by 100.

	Surplus	Firm profits	Lender profits	Access to credit	Interest rate spread
Loose credit	0.310	0.140	0.170	49.945	2.803
Tight credit: no adjustment	0.278	0.097	0.181	40.140	2.844
Tight credit: lenders adjust	0.294	0.111	0.183	41.372	2.816
Tight credit: full adjustment	0.310	0.112	0.198	41.871	2.818

1.5.3 Variation in transparency

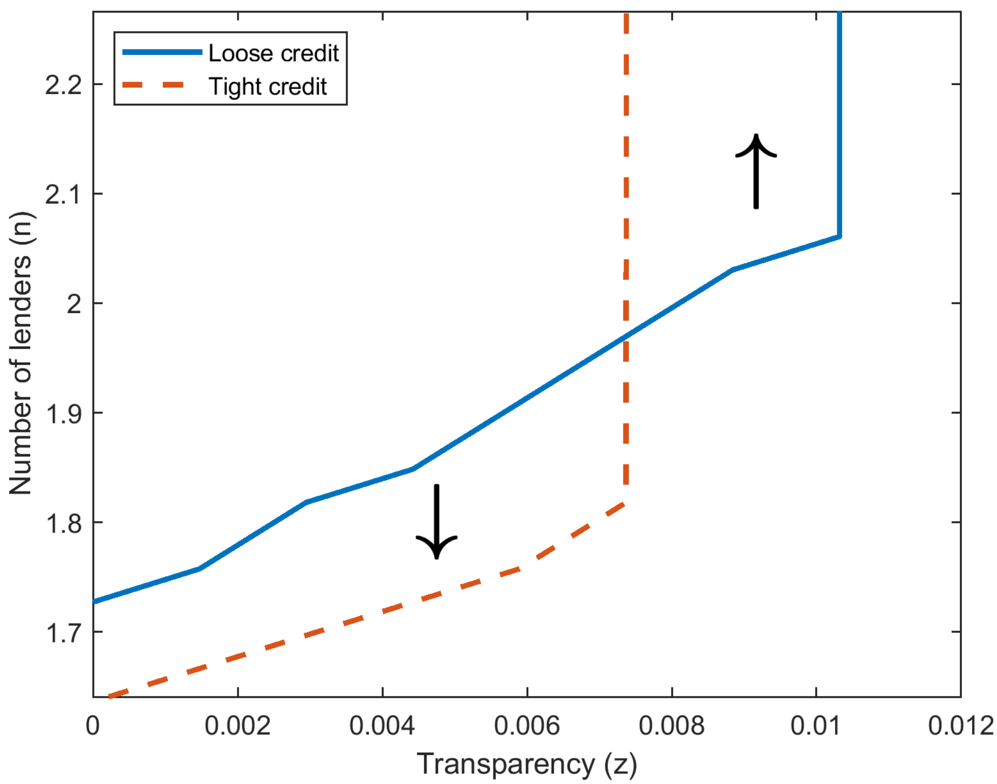
This section shows that the model qualitatively matches results from the literature about how lending relationships vary with transparency.

First, as shown in Figure 1-6, the number of lenders increases with a firm's transparency, which is consistent with empirical evidence that more transparent firms, as determined by having publicly available SEC filings, credit ratings, or a strong reputation, are more likely to borrow from multiple concentrated lenders or issue bonds (Sufi (2007), Dennis and Mullineaux (2000), Hale and Santos (2008)). Second, tightening credit standards induces sufficiently transparent firms to substitute to bonds, which is consistent with the empirical finding in Becker and Ivashina (2014) that tightening credit standards increases the rate of substitution from bank loans to bonds.

Screening efficiency decreases for firms that substitute from bank loans to bonds. To illustrate this, Figure 1-7 shows how the surplus and its components in the losses decomposition vary with firm transparency. Screening efficiency decreases at the threshold

Figure 1-6: Effect of transparency on the number of lenders

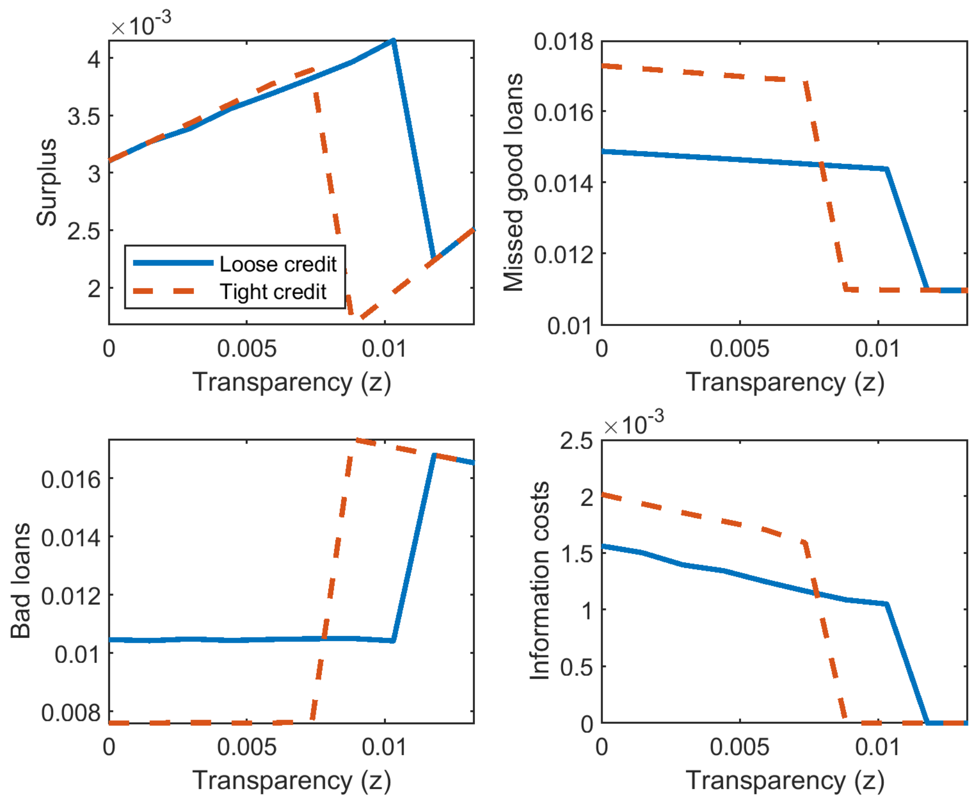
This figure shows how the number of relationship lenders chosen by a firm n varies with its transparency z for different levels of the looseness of credit standards B. An undefined number of lenders indicates that the firm borrows from bondholders. The arrows indicate the direction of the change in the number of lenders associated with a tightening of credit standards.



transparency level where firms substitute to bonds. This is largely driven by an increase in losses from bad loans, reflecting the fact that bondholders are less efficient than concentrated lenders at screening out bad borrowers. The increasing share of credit lent to bad firms is qualitatively consistent with the empirical finding in Becker and Ivashina (2014) that the tightening-induced substitution to bonds is stronger for firms with weaker credit ratings.

Figure 1-7: Effect of transparency on the surplus from lending

This figure shows how the surplus from lending S and its components in the losses decomposition vary with transparency z for different levels of the looseness of credit standards B.



1.6 Conclusion

This paper examines how tightening credit standards affects lending relationships. I show using a difference-in-differences approach and loan-level data from the Small Business Administration (SBA) that the introduction of bank the stress tests, which was associated with tightening credit standards, led small businesses to decrease the number of lenders on outstanding loans. I explain these findings with a model of bank competition in which firms choose the number of relationship lenders to balance a trade-off between providing an incentive for lenders to screen and retaining some bargaining power over the interest rate. Tightening credit standards leads firms to concentrate in a smaller number of lenders to encourage greater information acquisition. Tightening credit standards directly reduces screening efficiency by decreasing the availability of credit to viable firms, but this induced adjustment of lending relationships significantly mitigates this loss. However, tightening credit standards shifts the surplus from lending in favor of lenders.

Overall, these results underscore the importance of accounting for lending relationships when analyzing the welfare impacts of financial stability policies.

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Appendices for Chapter 1

1.A Loan issues

This section provides evidence that the introduction of the stress tests led lenders to tighten credit standards on SBA loans.

1.A.1 Specification

I implement a difference-in-differences specification motivated by the approach in Acharya, Berger and Roman (2018) comparing the change in the number of SBA loan issues from before 2009, when the stress tests were introduced, until 2014, when the stress tests were expanded to include a larger subset of lenders, for stress-tested lenders relative to lenders that were exempt from the stress tests. In particular, I estimate the regression

$$log\ issues_{ijkt} = \alpha stress_i + \beta stress_i \times STactive_t + \phi_j + \gamma_{kt} + \epsilon_{ijkt} \tag{1.23}$$

where $log\ issues_{ijkt}$ is the logarithm of the number SBA loan issues by lender i to firms with business type (individual, partnership, or corporation) j in industry-region k during year t, $stress_i$ is an indicator for whether a lender was included in the 2009 SCAP, $STactive_t$ is an indicator for whether a year is greater than or equal to 2009, ϕ_j represents business type fixed effects, and γ_{kt} represents industry-region-year fixed effects aggregated at the level of 1-digit NAICS codes and census regions to control for local demand. The difference-in-differences coefficient β captures the extent to which stress-tested lenders changed the number of loan issues after the introduction of the stress tests relative to lenders that were exempt from the stress tests.

I also estimate the relative trend between the two groups using a panel specification

$$log\ issues_{ijkt} = \alpha stress_i + \sum_{t \neq 2009} stress_i \times \beta_t + \phi_j + \gamma_{kt} + \epsilon_{ijkt} \quad (1.24)$$

The yearly difference-in-differences coefficients β_t capture the average relative difference between the two groups relative to 2009.

1.A.2 Results

Figure 1-8 presents the estimates from a panel regression corresponding to the cross-sectional specification given by equation (1.23) with standard errors clustered by lender. There is a relative decline starting in 2008, which suggests that the banks that were eventually included in the stress tests may have also been more vulnerable to the preceding financial crisis. The relative trend partially recovers after 2010, but there is a general relative decline from before to after the introduction of the stress tests. This is consistent with the result in Chen, Hanson and Stein (2017) that big bank lending to small businesses exhibited a sustained relative decline after the financial crisis. One factor that may have contributed to the persistence of this effect is tightening credit standards on SBA loans due to the introduction of the stress tests.

Table 1.11 presents the coefficients from estimating equation (1.23) with t-statistics computed using lender-clustered standard errors in parentheses. The estimated coefficient on the interaction term is negative and statistically significant, indicating that loan issues decreased by approximately 20% for stress-tested lenders relative to other lenders after the introduction of the stress tests.

Figure 1-8: Effect of the stress tests on loan issues

This figure presents the estimates β_t from estimating the regression $log\ issues_{ijkt} = \alpha stress_i + \sum_{t\neq 2009} stress_i \times \beta_t + \phi_j + \gamma_{kt} + \epsilon_{ijkt}$, where $log\ issues_{ijkt}$ is the logarithm of the number of SBA loan issues by lender i to firms with business type j in industry-region k during year t, $stress_i$ is an indicator for whether a lender was included in the 2009 SCAP, and γ_{kt} represents industry-region-year fixed effects aggregated at the level of 1-digit NAICS codes and census regions. Confidence intervals are constructed using lender-clustered standard errors. The vertical line at 2009 indicates the introduction of the stress tests.

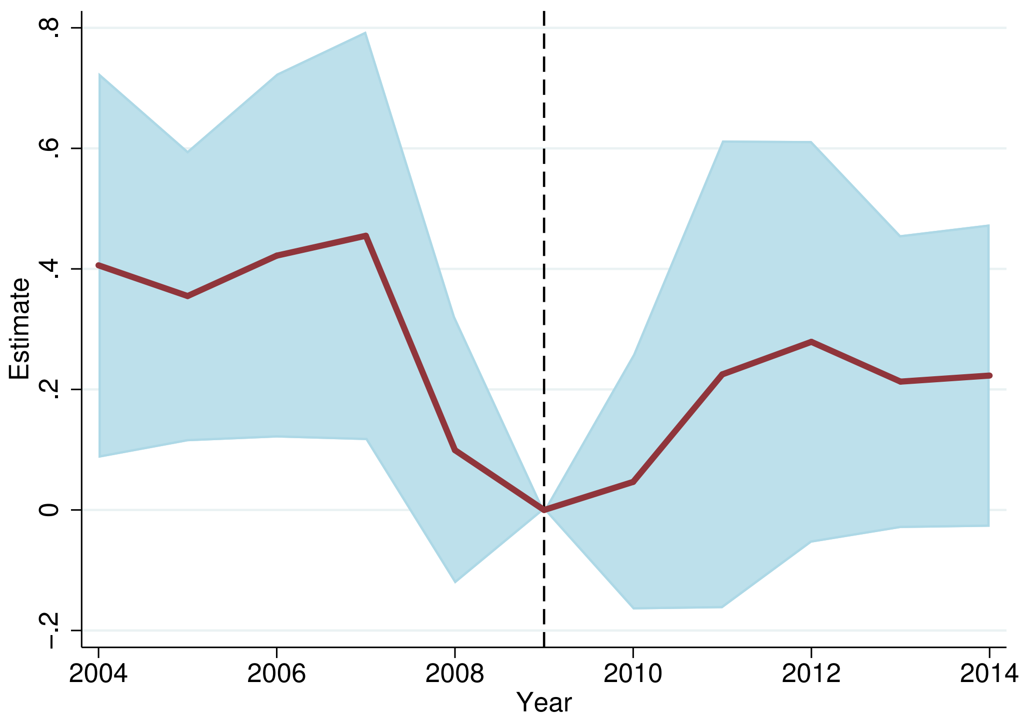


Table 1.11: Effect of the stress tests on loan issues

This table presents results from estimating the regression $log\ issues_{ijkt} = \alpha stress_i + \beta stress_i \times active_t + \phi_j + \gamma_{kt} + \epsilon_{ijkt}$, where $log\ issues_{ikt}$ is the logarithm of the number of SBA loan issues exhibited by lender i to firms with business type j in industry-region k during year t, $stress_i$ is an indicator for whether a lender was included in the 2009 SCAP, $STactive_t$ is an indicator for whether a year is greater than or equal to 2009, ϕ_j represents business type fixed effects, and γ_{kt} represents industry-region-year fixed effects aggregated at the level of 1-digit NAICS codes and census regions. T-statistics computed using lender-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Log loan issues
Stress test exposure × STactive	-0.200**
	(-2.03)
Observations	18582
R^2	0.169

1.B Calculations

1.B.1 Calculation for equation (1.9)

This section shows

$$D(s,t;\psi,n) = \lambda_b + \frac{1}{2}(n-2s-nt)\,\psi$$

First, observe that the predictive distribution of the maximum signal from k draws, which is obtained by marginalizing over the distributions of the maximum signals for the two firm types, can be approximated by the distribution of the maximum signal of k draws from the predictive distribution of a single draw

$$\begin{aligned}
f_{k:k}(s;\psi) &= \lambda_b k f(s|b;\psi) F(s|b;\psi)^{k-1} + \lambda_g k f(s|g;\psi) F(s|g;\psi)^{k-1} \\
&= \lambda_b k \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_b}\right)\left(s + \frac{1}{2}\left(s - s^2\right)\frac{\psi}{\lambda_b}\right)^{k-1} \\
&\quad + \lambda_g k \left(1 + \left(s - \frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)\left(s + \frac{1}{2}\left(s^2 - s\right)\frac{\psi}{\lambda_g}\right)^{k-1} \\
&\underset{\psi\approx 0}{\approx} \lambda_b k \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_b}\right)\left(s^{k-1} + (k-1)s^{k-2}\frac{1}{2}(s - s^2)\frac{\psi}{\lambda_b}\right) \\
&\quad + \lambda_g k \left(1 + \left(s - \frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)\left(s^{k-1} + (k-1)s^{k-2}\frac{1}{2}(s^2 - s)\frac{\psi}{\lambda_g}\right) \\
&\underset{\psi\approx 0}{\approx} \underbrace{k s^{k-1}}_{\equiv f_{k:k}(s)}
\end{aligned} \tag{1.25}$$

Then, since the signals are independently distributed we have

$$\begin{aligned}
D(s,t;\psi,n) &\equiv Pr(b|s,t;\psi,n) \\
&= \lambda_b \frac{f(s|b;\psi) f_{n-1:n-1}(t|b;\psi)}{f(s) f_{n-1:n-1}(t)} \\
&= \lambda_b \frac{f(s|b;\psi)}{f(s)} \frac{f(t|b;\psi)}{f(t)} \left(\frac{F(t|b;\psi)}{F(t)}\right)^{n-2} \\
&= \lambda_b \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_b}\right)\left(1 + \left(\frac{1}{2} - t\right)\frac{\psi}{\lambda_b}\right)\left(1 + \frac{1}{2}(1-t)\frac{\psi}{\lambda_b}\right)^{n-2}
\end{aligned}$$

$$
\begin{aligned}
&\underset{\psi \approx 0}{\approx} \lambda_b \left(1 + \left(\frac{1}{2} - s\right)\frac{\psi}{\lambda_b}\right)\left(1 + \left(\frac{1}{2} - t\right)\frac{\psi}{\lambda_b}\right)\left(1 + (n-2)\frac{1}{2}(1-t)\frac{\psi}{\lambda_b}\right) \\
&\underset{\psi \approx 0}{\approx} \lambda_b + \frac{1}{2}(n - 2s - nt)\psi
\end{aligned}
$$

1.B.2 Calculation for equation (1.11)

The threshold $\underline{s}$ is determined by

$$
\begin{aligned}
B &= E\left[D(\underline{s}, t; \psi, n) | \underline{s}\right] \\
&\underset{(1.9)}{=} \lambda_b + \frac{1}{2}\left(n - 2\underline{s} - nE[t|\underline{s}]\right)\psi
\end{aligned}
\tag{1.26}
$$

Conditional on $\underline{s}$, the second highest signal t is distributed as the maximum of $n-1$ signals that are uniformly distributed on $[0, \underline{s}]$. Therefore $E[t|\underline{s}] = \frac{n-1}{n}\underline{s}$. Substituting this into equation (1.26) and rearranging obtains the result.

1.B.3 Calculation for equation (1.15)

Setting the lender's expected profits (see equation (1.14)) equal to zero and rearranging obtains

$$
\underline{R}(D) = \frac{D}{1-D}
$$

Taking a first order approximation at $D = \lambda_b$ and applying the normalization from equation (1.4) obtains

$$
\begin{aligned}
\underline{R}(D) &\underset{D \approx \lambda_b}{\approx} \frac{\lambda_b}{1-\lambda_b} + \frac{1}{(1-\lambda_b)^2}(D - \lambda_b) \\
&\underset{(1.4)}{=} A + \frac{1+A}{\lambda_g}(D - \lambda_b)
\end{aligned}
$$

1.B.4 Calculation for equation (1.17)

First I compute a lender's net information rents as a function of primitives. First note that

$$
\begin{aligned}
f_{n:n}(s|g;\psi) &= nf(s|g;\psi)F(s|g;\psi)^{n-1} \\
&= n\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)\left(s^{n-1}+(n-1)s^{n-2}\frac{1}{2}(s^2-s)\frac{\psi}{\lambda_g}\right) \\
&\underset{\psi\approx 0}{\approx} \underbrace{ns^{n-1}}_{f_{n:n}(s)} + \psi \underbrace{ns^{n-1}\left((n+1)s-n\right)\frac{1}{2\lambda_g}}_{\equiv h_{n:n}(s)}
\end{aligned} \tag{1.27}
$$

Then a lender's expected profits can be written

$$
\pi_L = \lambda_g E\left[\left(\min\{\underline{R}(D(s_{n-1:n},s_{n-1:n};\psi,n)),A\} - \underline{R}(D(s,s_{n-1:n};\psi,n))\right)1_{\{s=s_{n:n}\geqslant \underline{s}\}}|g;\psi\right] - \mu\frac{(\psi-z)^2}{2} \tag{1.28}
$$

$$
\begin{aligned}
&= \lambda_g \int_{\underline{s}}^{1}\left[\int_0^{\underline{s}}[A-\underline{R}(D(s,t;\psi,n))]f_{n-1:n-1}(t|g;\psi)dt\right]f(s|g;\psi)ds \\
&\quad + \lambda_g \int_{\underline{s}}^{1}\left[\int_{\underline{s}}^{s}[\underline{R}(D(t,t;\psi,n))-\underline{R}(D(s,t;\psi,n))]f_{n-1:n-1}(t|g;\psi)dt\right]f(s|g;\psi)ds - \mu\frac{(\psi-z)^2}{2}
\end{aligned} \tag{1.29}
$$

Substituting the zero profits interest rate (see equation (1.15)) associated with the posterior risk (see equation (1.9)) and approximating at $\psi\approx 0$ obtains

$$
\begin{aligned}
\pi_L &= \lambda_g \int_{\underline{s}}^{1}\left[\int_0^{\underline{s}}\frac{1+A}{\lambda_g}\frac{1}{2}[nt+2s-n]\psi\left(f_{n-1:n-1}(t)+\psi h_{n-1:n-1}(t)\right)dt\right]f(s|g,\psi)ds \\
&\quad + \lambda_g \int_{\underline{s}}^{1}\int_{\underline{s}}^{s}\left[\frac{1+A}{\lambda_g}\frac{1}{2}2(s-t)(n-1)t^{n-2}\psi dt\right]ds - \mu\frac{(\psi-z)^2}{2} \\
&\underset{\psi\approx 0}{\approx} \frac{1+A}{2}\left[(-n+1)\underline{s}^{n-1}+(2n-1)\underline{s}^{n}-n\underline{s}^{n+1}\right]\psi \\
&\quad + (1+A)\left[\frac{1}{n(n+1)}-\frac{1}{2}\underline{s}^{n-1}+\frac{n-1}{n}\underline{s}^{n}+\frac{-n+1}{2(n+1)}\underline{s}^{n+1}\right]\psi - \mu\frac{(\psi-z)^2}{2}
\end{aligned}
$$

$$= \underbrace{\frac{1+A}{2}\left[\frac{2}{n(n+1)} - n\underline{s}^{n-1} + \frac{2n^2+n-2}{n}\underline{s}^n - \frac{n^2+2n-1}{n+1}\underline{s}^{n+1}\right]}_{\equiv \gamma_L}\psi - \mu\frac{(\psi-z)^2}{2}$$

A lender's return to information γ_L captures the effects of competition and the tightness of credit standards on a lender's share of the surplus from information.

An interior solution to a lender's problem satisfies a first order condition that balances the surplus from efficient lending, which lenders internalize at the rate γ_L, the effect of information on the return to information,[66] and the acquisition cost

$$0 = \gamma_L + \frac{\partial \gamma_L}{\partial \psi}\psi - \mu(\psi - z) \tag{1.30}$$

It is possible to have a boundary solution at the upper bound $\psi_{max} = 2\lambda_b$. If $B < \lambda_b$ it is also possible to have a boundary solution at the lower bound $\psi_{min} = z$ since a lender may have to make a large enough investment in information to have a positive probability of competing in the auction.

1.B.5 Calculation for equation (1.18)

This section shows

$$\frac{\partial \psi}{\partial z} \geqslant 0$$

Note that

$$\frac{\partial \psi}{\partial z} = -\frac{\partial^2 \pi_L / \partial z \partial \psi}{\partial^2 \pi_L / \partial \psi^2} > 0$$

where $\frac{\partial^2 \pi_L}{\partial \psi^2} < 0$ is the second order condition that holds at an interior optimum and $\frac{\partial^2 \pi_L}{\partial z \partial \psi} = \mu \geqslant 0$ represents how transparency reduces the marginal information acquisition cost.

To see how transparency affects acquired information η, note that

$$\frac{\partial \eta}{\partial z} = \frac{\partial \psi}{\partial z} - 1$$

[66]The effect of the information level on the return to information can be decomposed as $\frac{\partial \gamma_L}{\partial \psi} = \frac{\partial \gamma_L}{\partial \underline{s}}\frac{\partial \underline{s}}{\partial \psi}$. The factor $\frac{\partial \underline{s}}{\partial \psi} \leqslant 0$ represents how information increases the probability that a lender receives a sufficiently strong signal of the firm's creditworthiness to compete in the auction. Then $\frac{\partial \gamma_L}{\partial \underline{s}}$ represents how the probability of competing affects a lender's return to information, which has a positive direct effect for a lender but also a negative effect by intensifying the degree of competition with other lenders.

Since

$$\frac{\partial \psi}{\partial z} = \frac{\mu}{\mu - \frac{\partial^2 \gamma_L \psi}{\partial \psi^2}}$$

it's straightforward to see that $\frac{\partial \eta}{\partial z}$ has the same sign as

$$\frac{\partial^2 \gamma_L \psi}{\partial \psi^2} = \frac{\partial^2 \gamma_L}{\partial \underline{s}^2} \left(\frac{\partial \underline{s}}{\partial \psi} \right)^2 + \frac{\partial \gamma_L}{\partial \underline{s}} \frac{\partial^2 \underline{s}}{\partial \psi^2}$$

Note that $\frac{\partial \gamma_L}{\partial \underline{s}}$ represents how the probability of competing affects a lender's return to acquiring information, which has a positive direct effect for a lender but also a negative effect by intensifying the degree of competition with other lenders. Because of these competing effects, $\frac{\partial \eta}{\partial z}$ cannot generically be signed. It it is positive at the parameters that are calibrated in Section 1.5.1.

1.B.6 Calculation for equation (1.19)

This section shows

$$\lim_{n \to \infty} \psi = z$$

Let $a = \frac{2(\lambda_b - B)}{\psi}$ so that we can write $\underline{s} = \frac{n+a}{n+1}$. If $a \geqslant 1$ then $\bar{s} = 1$, which implies $\gamma_L = 0$ and $\frac{\partial \gamma_L}{\partial \psi} = 0$, and therefore by (1.30) we have $\psi = z$. If $a < 1$, the return to information can be written

$$\gamma_L = \frac{2}{n(n+1)} - \left(\frac{n+a}{n+1} \right)^n \frac{a^2 n^3 + 2a^2 n^2 - a^2 n - a n^3 - 4an^2 + 3an + 2a + 4n^2 + 2n}{n(n+1)^2 (a+n)}$$

which converges to 0 as n goes to infinity. Also, it straightforward to see that $\lim_{n \to \infty} \frac{\partial \gamma_L}{\partial \psi} = 0$. Therefore by (1.30) we have $\lim_{n \to \infty} \psi = z$.

1.B.7 Calculation for $\frac{\partial \psi}{\partial n}$

This section decomposes $\frac{\partial \psi}{\partial n}$. Note that

$$\frac{\partial \psi}{\partial n} = -\frac{\partial^2 \pi_L / \partial n \partial \psi}{\partial^2 \pi_L / \partial \psi^2}$$

where $\frac{\partial^2 \pi_L}{\partial \psi^2} < 0$ is the second order condition that holds at an interior optimum and

$$\frac{\partial^2 \pi_L}{\partial n \partial \psi} = \frac{d\gamma_L}{dn} + \psi \frac{d}{dn}\left(\frac{\partial \gamma_L}{\partial \psi}\right)$$

The first term

$$\frac{d\gamma_L}{dn} = \frac{\partial \gamma_L}{\partial n} + \frac{\partial \gamma_L}{\partial \underline{s}}\frac{\partial \underline{s}}{\partial n}$$

represents how competition from other lenders affects a lender's return to information. In particular, the term $\frac{\partial \gamma_L}{\partial n}$, which corresponds the direct effect emphasized in the main text, captures how the number of lenders affects the probability of obtaining the most optimistic signal and the expected profit margin conditional on having the most optimistic signal. The term

$$\frac{\partial \underline{s}}{\partial n} = \frac{1-\underline{s}}{n+1} \geqslant 0 \tag{1.31}$$

represents how increasing the number of lenders increases the degree of bid shading, which in turn decreases the probability that a lender competes in the auction. Then $\frac{\partial \gamma_L}{\partial \underline{s}}$ represents how the probability of competing affects a lender's return to acquiring information, which has a positive direct effect for a lender but also a negative effect by intensifying the degree of competition with other lenders.

The term $\psi \frac{d}{dn}\left(\frac{\partial \gamma_L}{\partial \psi}\right)$ represents how the number of lenders affects the impact of the information level on the return to information.

1.B.8 Calculation for $\frac{\partial \psi}{\partial B}$

This section decomposes $\frac{\partial \psi}{\partial B}$. Note that

$$\frac{\partial \psi}{\partial B} = -\frac{\partial^2 \pi_L / \partial B \partial \psi}{\partial^2 \pi_L / \partial \psi^2}$$

where $\frac{\partial^2 \pi_L}{\partial \psi^2} < 0$ is the second order condition that holds at an interior optimum and

$$\frac{\partial^2 \pi_L}{\partial B \partial \psi} = \frac{\partial \gamma_L}{\partial B} + \psi \frac{\partial^2 \gamma_L}{\partial B \partial \psi}$$

The first term $\frac{\partial \gamma_L}{\partial B} = \frac{\partial \gamma_L}{\partial \underline{s}}\frac{\partial \underline{s}}{\partial B}$ represents how tightening credit standards decreases the probability of competing in the auction ($\frac{\partial \underline{s}}{\partial B} \leqslant 0$ is shown in equation (1.12)). Then $\frac{\partial \gamma_L}{\partial \underline{s}}$ represents how the probability of competing affects a lender's return to acquiring information, which has a positive direct effect for a lender but also a negative effect by intensifying the degree of competition with other lenders.

The second term
$$\psi\frac{\partial^2\gamma_L}{\partial B\partial\psi} = \psi\left(\frac{\partial^2\gamma_L}{\partial B\partial\underline{s}}\frac{\partial\underline{s}}{\partial\psi} + \frac{\partial\gamma_L}{\partial\underline{s}}\frac{\partial^2\underline{s}}{\partial B\partial\psi}\right)$$
represents how tightening credit standards affects the impact of a lender's information level on the return to information. The effect of information in mitigating tight credit standards increases in the level of tightness ($\frac{\partial^2\underline{s}}{\partial\psi\partial B} \geqslant 0$ follows from (1.13)), but the total effect on the incentive to acquire information also depends on how this affects the degree of competition among the lenders.

1.B.9 Calculation for equation (1.20)

First I compute a firm's profits as a function of primitives. Note that the distribution for the second to highest signal conditional on being a good firm can be written as

$$\begin{aligned}
f_{n-1:n}(s|g;\psi) &= n(n-1)f(s|g;\psi)F(s|g;\psi)^{n-2}(1-F(s|g;\psi)) \\
&\underset{\psi\approx 0}{\approx} n(n-1)\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)s^{n-2}\left(1+(n-2)\frac{1}{2}(s-1)\frac{\psi}{\lambda_g}\right)\left(1-s-\frac{1}{2}(s^2-s)\frac{\psi}{\lambda_g}\right) \\
&\underset{\psi\approx 0}{\approx} \underbrace{n(n-1)s^{n-2}(1-s)}_{=f_{n-1:n}(s)} \\
&\quad + \psi \underbrace{n(n-1)s^{n-2}\left[(1-s)\left(\left(s-\frac{1}{2}\right)+(n-2)\frac{1}{2}(s-1)\right)-\frac{1}{2}(s^2-s)\right]\frac{1}{\lambda_g}}_{\equiv h(s)} \\
&= f_{n-1:n}(s)+\psi h(s) \qquad (1.32)
\end{aligned}$$

For a finite number of relationship lenders, a firm's expected profits can be expressed as

$$\pi_F = E\left[(A-\min\{\underline{R}(D(s_{n-1:n},s_{n-1};\psi,n)),A\})\,1_{\{s_{n:n}\geqslant\underline{s}\}}|g;\psi\right] + 0 * Pr(s_{n:n}<\underline{s}|g;\psi) \qquad (1.33)$$
$$= APr(s_{n-1:n}\geqslant\underline{s}|g;\psi) - \int_{\underline{s}}^{1}\underline{R}(D(s,s;\psi,n))f_{n-1:n}(s|g;\psi)ds \qquad (1.34)$$

Substituting the zero profits interest rate (see equation (1.15)) associated with the posterior risk (see equation (1.9)) and approximating at $\psi \approx 0$ obtains

$$\begin{aligned}
\pi_F &= APr\left(s_{n-1:n} \geqslant \underline{s}|g;\psi\right) - \int_{\underline{s}}^{1} \left(A + \frac{1+A}{\lambda_g}\frac{1}{2}(n-(n+2)s)\psi\right) f_{n-1:n}(s|g;\psi)ds \\
&= -\int_{\underline{s}}^{1} \left[\frac{1+A}{\lambda_g}\frac{1}{2}(n-(n+2)s)\psi\right] f_{n-1:n}(s|g;\psi)ds \\
&\underset{(1.32)}{=} -\int_{\underline{s}}^{1} \frac{1+A}{\lambda_g}\frac{1}{2}(n-(n+2)s)\psi\left(f_{n-1:n-1}(s)+\psi h(s)\right)ds \\
&\underset{\psi\approx 0}{\approx} -\int_{\underline{s}}^{1} \frac{1+A}{\lambda_g}\frac{1}{2}(n-(n+2)s)\psi f_{n-1:n-1}(s)ds \\
&= \underbrace{-\frac{1+A}{\lambda_g}\frac{1}{2}\left[\frac{2}{n+1} - n^2\underline{s}^{n-1} + 2(n+1)(n-1)\underline{s}^{n} - \frac{n(n-1)(n+2)}{n+1}\underline{s}^{n+1}\right]}_{\equiv \gamma_F}\psi
\end{aligned} \tag{1.35}$$

A firm's return to information $\gamma_F \geqslant 0$ captures the effect of competition and the tightness of credit standards on its share of the surplus from information. In particular, a greater number of lenders increases the probability of finding a lender that is willing to lend and limits the ability of a lender to charge a mark-up over its zero-profits interest rate.[67]

Regarding n as a continuous concentration index rather than a literal integer, an interior solution to a firm's problem satisfies a first order condition that balances the effect of the number of lenders on a firm's return to information and the incentive for lenders to acquire information

$$0 = \frac{d\gamma_F}{dn}\psi + \gamma_F\frac{\partial\psi}{\partial n} \tag{1.36}$$

Alternatively, the firm may prefer to issue bonds, which corresponds to $n = \infty$ and $B = \lambda_b$. To compute the expected profit in that case, note that the firm's return to information

[67]Note that the number of lenders also affects the return to information through the intensity of bid shading and information acquisition incentive of lenders. These channels are captured by the second term in $\frac{d\gamma_F}{dn} = \frac{\partial\gamma_F}{\partial n} + \frac{\partial\gamma_F}{\partial\underline{s}}\frac{d\underline{s}}{dn}$, which can be further decomposed as $\frac{d\underline{s}}{dn} = \frac{\partial\underline{s}}{\partial n} + \frac{\partial\underline{s}}{\partial\psi}\frac{\partial\psi}{\partial n}$.

can be expressed as

$$\gamma_F = -\frac{1+A}{\lambda_g}\frac{1}{2}\left[\frac{2}{n+1} - \underline{s}^n \frac{n^2+5n+2}{(n+1)^2}\right]$$

Note that

$$\begin{aligned}\lim_{n\to\infty} \underline{s}^n &= \left(\frac{n}{n+1}\right)^n \\ &= \lim_{n\to\infty}\left(1+\frac{1}{n}\right)^{-n} \\ &= e^{-1}\end{aligned}$$

Then it is easy to see that

$$\lim_{n\to\infty} \gamma_F = \frac{1+A}{\lambda_g}\frac{1}{2}e^{-1}$$

and therefore

$$\begin{aligned}\lim_{n\to\infty} \pi_F &= \lim_{n\to\infty} \gamma_F * \lim_{n\to\infty} \psi \\ &= \frac{1+A}{\lambda_g}\frac{1}{2}e^{-1}z\end{aligned}$$

1.B.10 Calculation for $\frac{\partial n}{\partial z}$

This section decomposes $\frac{\partial n}{\partial z}$. First note the marginal effect of increasing the number of lenders can be expressed as

$$\frac{\partial \pi_F}{\partial n} = \frac{d\gamma_F}{dn}\psi + \gamma_F \frac{\partial \psi}{\partial n}$$

where, assuming a typical case in which $\frac{d\gamma_F}{dn} \geqslant 0$ and $\frac{\partial \psi}{\partial n} \leqslant 0$, the first term represents the benefits of increasing the number of lenders in terms of increasing the firm's bargaining power and the second term represents the cost in terms of reducing the acquisition of information.

Then note that

$$\frac{\partial n}{\partial z} = -\frac{\partial^2 \pi_F / \partial z \partial n}{\partial^2 \pi_F / \partial n^2}$$

where $\frac{\partial^2 \pi_F}{\partial n^2} < 0$ is the second order condition that holds at an interior optimum and

$$\begin{aligned}\frac{\partial^2 \pi_F}{\partial z \partial n} &= \frac{\partial}{\partial z}\left(\frac{d\gamma_F}{dn}\psi + \gamma_F \frac{\partial \psi}{\partial n}\right) \\ &= \frac{\partial}{\partial z}\left(\frac{d\gamma_F}{dn}\right)\psi + \frac{d\gamma_F}{dn}\frac{\partial \psi}{\partial z} + \frac{\partial \gamma_F}{\partial z}\frac{\partial \psi}{\partial n} + \gamma_F \frac{\partial^2 \psi}{\partial z \partial n}\end{aligned}$$

The second term $\frac{d\gamma_F}{dn}\frac{\partial \psi}{\partial z} \geqslant 0$, which corresponds to the effect emphasized in the main text, represents how transparency, by increasing the total information level ($\frac{\partial \psi}{\partial z} \geqslant 0$ follows from Appendix 1.B.5), increases the marginal benefit of increasing the firm's return to information.

The first term

$$\frac{\partial}{\partial z}\left(\frac{d\gamma_F}{dn}\right)\psi = \frac{\partial \psi}{\partial z}\frac{\partial}{\partial \psi}\left(\frac{d\gamma_F}{dn}\right)\psi$$

represents how transparency, by increasing the information level ($\frac{\partial \psi}{\partial z} \geqslant 0$ follows from Appendix 1.B.5), affects the impact of the number of lenders on the firm's return to information.

The third term

$$\frac{\partial \gamma_F}{\partial z}\frac{\partial \psi}{\partial n} = \frac{\partial \gamma_F}{\partial \psi}\frac{\partial \psi}{\partial z}\frac{\partial \psi}{\partial n}$$

represents how transparency, by increasing the total information level ($\frac{\partial \psi}{\partial z} \geqslant 0$ follows from Appendix 1.B.5), affects the firm's return to information, which in turn affects the firm's sensitivity to the effect of the number of lenders on information acquisition.

The fourth term $\gamma_F \frac{\partial^2 \psi}{\partial z \partial n}$ represents how transparency affects the sensitivity of a lender's incentive to acquire information to the number of lenders.

1.B.11 Calculation for $\frac{\partial \pi_F}{\partial B}$

This section decomposes $\frac{\partial \pi_F}{\partial B}$. The marginal effect can be expressed as

$$\frac{\partial \pi_F}{\partial B} = \frac{\partial \gamma_F}{\partial B}\psi + \gamma_F \frac{\partial \psi}{\partial B}$$

The first term $\frac{\partial \gamma_F}{\partial B}\psi = \frac{\partial \gamma_F}{\partial \underline{s}}\frac{\partial \underline{s}}{\partial B}\psi$, which corresponds to the direct effect emphasized in the main text, represents how tightening credit standards decreases the probability of lender participation ($\frac{\partial \underline{s}}{\partial B} \leqslant 0$ follows from equation (1.12)). This in turn affects the firm's return to information by $\frac{\partial \gamma_F}{\partial \underline{s}}$, which is intuitively negative at the calibrated parameters.

The second term $\gamma_F \frac{\partial \psi}{\partial B}$ represents how tightening credit standards affects the incentive of lenders to acquire more information.

1.B.12 Calculation for $\frac{\partial n}{\partial B}$

This section decomposes $\frac{\partial n}{\partial B}$. First note the marginal effect of increasing the number of lenders can be expressed as

$$\begin{aligned}\frac{\partial \pi_F}{\partial n} &= \frac{d\gamma_F}{dn}\psi + \gamma_F \frac{\partial \psi}{\partial n} \\ &= \left(\frac{\partial \gamma_F}{\partial n} + \frac{\partial \gamma_F}{\partial \underline{s}}\frac{d\underline{s}}{dn}\right)\psi + \gamma_F \frac{\partial \psi}{\partial n}\end{aligned}$$

where, assuming a typical case in which $\frac{d\gamma_F}{dn} \geqslant 0$ and $\frac{\partial \psi}{\partial n} \leqslant 0$, the first term represents the benefits of increasing the number of lenders in terms of increasing the firm's bargaining power and the second term represents the cost in terms of reducing the acquisition of soft information.

Then note that

$$\frac{\partial n}{\partial B} = -\frac{\partial^2 \pi_F / \partial B \partial n}{\partial^2 \pi_F / \partial n^2}$$

where $\frac{\partial^2 \pi_F}{\partial n^2} < 0$ is the second order condition that holds at an interior optimum and

$$\begin{aligned}\frac{\partial^2 \pi_F}{\partial B \partial n} &= \left(\frac{\partial^2 \gamma_F}{\partial B \partial n} + \frac{\partial^2 \gamma_F}{\partial B \partial \underline{s}}\frac{d\underline{s}}{dn}\right)\psi \\ &\quad + \frac{\partial \gamma_F}{\partial \underline{s}}\frac{\partial}{\partial B}\left(\frac{d\underline{s}}{dn}\right)\psi \\ &\quad + \frac{d\gamma_F}{dn}\frac{\partial \psi}{\partial B} \\ &\quad + \frac{\partial}{\partial B}\left(\gamma_F \frac{\partial \psi}{\partial n}\right)\end{aligned}$$

The second line

$$\begin{aligned}\frac{\partial \gamma_F}{\partial \underline{s}}\frac{\partial}{\partial B}\left(\frac{d\underline{s}}{dn}\right)\psi &= \frac{\partial \gamma_F}{\partial \underline{s}}\frac{\partial}{dB}\left(\frac{\partial \underline{s}}{\partial n} + \frac{\partial \underline{s}}{\partial \psi}\frac{\partial \psi}{\partial n}\right)\psi \\ &= \frac{\partial \gamma_F}{\partial \underline{s}}\left(\frac{\partial^2 \underline{s}}{\partial B \partial n} + \frac{\partial^2 \underline{s}}{\partial B \partial \psi}\frac{\partial \psi}{\partial n} + \frac{\partial \underline{s}}{\partial \psi}\frac{\partial^2 \psi}{\partial B \partial n}\right)\psi\end{aligned}$$

represents how tightening credit standards affects the sensitivity of the probability that a lender competes in the auction to the number of lenders. In particular, the term $\frac{\partial^2 \underline{s}}{\partial B \partial \psi} \geqslant 0$ (see equation (1.13)), which corresponds to the effect emphasized in the main text, represents how tightening credit standards increases the effect of information in increasing the probability of lender participation. Assuming a typical case in which $\frac{\partial \psi}{\partial n} < 0$ and $\frac{\partial \gamma_F}{\partial \underline{s}} < 0$, this decreases the marginal benefit of increasing the number of lenders.

The first line represents how tightening credit standards affects the sensitivity of the firm's return to information to the number of lenders. For example, it can capture an insurance motive in which, for a given level of information acquisition, firms have an incentive to establish more lending relationships to increase the probability that at least one lender would be willing to lend.

The third line represents how tightening credit standards affects the level of information acquired by lenders, which in turn affects the marginal benefit of increasing the firm's return to information.

The fourth line represents how tightening credit standards affects the firm's sensitivity to how the number of lenders affects the information level acquired by its lenders.

1.B.13 Calculation for equivalence of surplus decompositions

This section shows

$$\lambda_g \pi_F + n\pi_L = A\lambda_g - A\lambda_g(1 - P_g) - \lambda_b P_b - n\mu \frac{(\psi - z)^2}{2}$$

I show that both can be expressed as

$$S = \frac{1+A}{2}\underline{s}^n(1-s)n\psi - n\mu\frac{(\psi - z)^2}{2}$$

It is straightforward to see that the distributional decomposition is equal to this by substituting the profit functions with their expressions in (1.17) and (1.20).

For the losses decomposition, first note that the normalization in equation (1.4) implies

$$A\lambda_g = (1+A)\lambda_g\lambda_b = \lambda_b$$

and therefore, using the expressions for the probabilities from Section 1.E, it can be expressed as

$$
\begin{aligned}
S^{loss} &= (1+A)\lambda_g\lambda_b\left[P_g - P_b\right] - n\mu\frac{(\psi-z)^2}{2} \\
&\underset{(1.39,1.40)}{=} (1+A)\lambda_g\lambda_b\left[1-\underline{s}^n\left(1-\frac{n}{2}(1-\underline{s})\frac{\psi}{\lambda_g}\right)-\left(1-\underline{s}^n\left(1+\frac{n}{2}(1-\underline{s})\frac{\psi}{\lambda_b}\right)\right)\right]-n\mu\frac{(\psi-z)^2}{2} \\
&= \frac{1+A}{2}\underline{s}^n(1-\underline{s})n\psi - n\mu\frac{(\psi-z)^2}{2}
\end{aligned}
$$

1.C Generality of the distribution system

Up to a first order approximation in ψ, the distribution system defined by equations (1.5) and (1.6) can be assumed without loss of generality conditional on the following set of intuitive properties: the predictive distribution does not depend on the information level, the conditional distributions converge to the predictive distribution when the information level is equal to zero, and the first order effect of information on the conditional pdf for a good signal is given by the probability of receiving as high a signal under the predictive distribution.

To show this, consider a distribution system with conditional pdfs $f(s|\theta;\psi)$ and predictive distribution

$$
f(s) = \lambda_b f(s|b;\psi) + \lambda_g f(s|g;\psi) \tag{1.37}
$$

Since the conditional distributions converge to the predictive distribution when the information level is equal to zero, a first order approximation obtains

$$
f(s|\theta;\psi) = f(s) + \psi\frac{\partial f(s|\theta;\psi)}{\partial\psi}
$$

Differentiating (1.37) obtains

$$
\lambda_b\frac{\partial f(s|b;\psi)}{\partial\psi} = -\lambda_g\frac{\partial f(s|g;\psi)}{\partial\psi}
$$

Let

$$
\begin{aligned}
h(s) &= \lambda_g\frac{\partial f(s|g;\psi)}{\partial\psi}f(s)^{-1} \\
&= -\lambda_b\frac{\partial f(s|b;\psi)}{\partial\psi}f(s)^{-1}
\end{aligned}
$$

Then the conditional distributions can be written

$$f(s|b;\psi) = f(s)\left(1 - h(s)\frac{\psi}{\lambda_b}\right)$$
$$f(s|g;\psi) = f(s)\left(1 + h(s)\frac{\psi}{\lambda_g}\right)$$

The assumption that the first order effect of information on the conditional pdf for a good signal is given by the probability of receiving as high a signal under the predictive distribution is captured by choosing

$$h(s) = F(s) - \frac{1}{2}$$

Intuitively, $h(s)$ is equal to $F(s)$ plus a translation by $-\frac{1}{2}$ to ensure that the pdf integrates to 1. Finally, note that the implied distribution system

$$f(s|b;\psi) = f(s)\left(1 - \left(F(s) - \frac{1}{2}\right)\frac{\psi}{\lambda_b}\right)$$
$$f(s|g;\psi) = f(s)\left(1 + \left(F(s) - \frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)$$

yields the same results as the distribution system with a uniform predictive distribution since all the relevant quantities are computed using integrals that are equivalent via a change in variables.

1.D Modeling information acquisition as a Nash equilibrium

This section models the information acquisition of lenders as a symmetric Nash equilibrium. It first generalizes the new loan application phase to account for the possibility that lenders have different information levels. It then similarly generalizes the net information rents of a lender. Finally, it shows that calibrating the version of the model with the Nash equilibrium exhibits a worse fit to the data compared to the version of the model with the coordinated equilibrium but that the comparative statics are qualitatively similar.

1.D.1 New loan application

This section shows how the auction in the loan application phase (as originally described in Section 1.4.3) changes as a result of allowing lenders to consider acquiring different levels of information.

Consider a deviation from a symmetric equilibrium in which lenders have the information level ψ'. In particular, suppose that a lender deviates to information level ψ but that the other lenders acquire information at level ψ' and expect all the other lenders to acquire information at level ψ'. Applying the logic from Milgrom (1981), I determine that the deviating player's bid is based on the minimum posterior risk of default that it could have conditional on winning the auction with the signal that it receives.

For the deviating agent, the posterior risk of default conditional on winning the auction with signal s and inferring from the equilibrium interest rate that the highest signal among the $n-1$ competing lenders is equal to t becomes[68]

$$D(s,t;\psi,\psi',n) = \lambda_b + \left(\frac{1}{2} - s\right)\psi + \frac{1}{2}\left(-1 + n(1-t)\right)\psi'$$

Then the tightness of credit standards imposes the following threshold for the deviating lender's signal[69]

$$\underline{s}(\psi,\psi') = \frac{\psi + (n-1)\psi'}{2\psi + (n-1)\psi'} + \frac{2(\lambda_b - B)}{2\psi + (n-1)\psi'}$$

If the deviating lender is willing to finance the firm, then it bids the zero-profits interest rate $\underline{R}(D)$ (see equation (1.15)) based on the posterior risk $D(s,\bar{s};\psi,\psi',n)$, where $\bar{s}(s;\psi,\psi')$ is the greatest signal among the the $n-1$ competing lenders at which the deviating lender wins the auction. Note that $\bar{s}$ is determined by equating the bid of the deviating lender and the bid of one of the other lenders if it were to draw $\bar{s}$

$$\underline{R}(D(s,\bar{s};\psi,\psi',n)) = \underline{R}(D(\bar{s},\bar{s};\psi',\psi',n))$$

This determines

$$\bar{s}(s;\psi,\psi') = \begin{cases} \frac{1}{2} + \left(s - \frac{1}{2}\right)\frac{\psi}{\psi'} & s \in \left(\frac{1}{2}, \frac{1}{2} + \frac{1}{2}\frac{\psi'}{\psi}\right) \\ 1 & s \in \left(\frac{1}{2} + \frac{1}{2}\frac{\psi'}{\psi}, 1\right] \end{cases}$$

[68] The calculation is analogous to Appendix 1.B.1.

[69] The calculation is analogous to Appendix 1.B.2.

1.D.2 A lender's information acquisition

This section shows how the net information rents of a lender (as originally described in Section 1.4.4) changes as a result of allowing the deviating lender to consider acquiring a different level of information compared to the other lenders.

Let t denote the maximum signal among the $n-1$ competing lenders. The deviating lender's net information rents can be expressed as

$$\pi_L = \lambda_g E\left[(\min\{\underline{R}(D(t,t;\psi,\psi',n)),A\} - \underline{R}(D(s,t;\psi,\psi',n)))\,1_{\{s\geqslant\bar{s}\cap s\geqslant\underline{s}(\psi,\psi')\}}|g;\psi\right] - \mu\frac{(\psi-z)^2}{2} \tag{1.38}$$

The formula for π_L as a function of primitives in this setting is complex and offers less lucid guidance for intuition compared to the version of the model with the coordinated equilibrium. Calculations are available upon request.

1.D.3 Calibration

This section shows that calibrating the version of the model with the Nash equilibrium exhibits a worse fit to the data compared to the version of the model with the coordinated equilibrium.

Table 1.12 presents the calibrated parameters and Table 1.13 compares the empirical and model-generated values for the observables. The model with the coordinated with the equilibrium is preferred because it achieves a better fit to the data, it is simpler, and it is consistent with the fact that banks appear to coordinate on the prime interest rate.

Table 1.12: Calibrated parameters (Nash equilibrium version)

This table presents the calibrated parameter values.

Parameter	Value
Information cost (μ)	3.000
Fraction of bad firms (λ_b)	0.040
Pre-tightening looseness (B_{loose})	0.034
Post-tightening looseness (B_{tight})	0.032

Table 1.13: Comparison of empirical and model-generated variables (Nash equilibrium version)

This table presents the empirical and model-generated values for a set of targeted variables.

Variable	Empirical	Model
Pre-tightening levels		
Access to credit	0.561	0.346
Number of lenders	1.741	1.939
Default rate	0.047	0.029
Interest rate spread (%)	3.184	3.920
Tightening-induced difference		
Access to credit	–0.200	–0.157
Number of lenders	–0.053	–0.048
Default rate	–0.002	–0.002
Interest rate spread (%)	–0.087	0.022

1.D.4 Screening efficiency

This section shows that the comparative statics of the model with the Nash equilibrium are qualitatively similar to the model with the coordinated equilibrium.

Table 1.14 shows how the surplus from lending and its components in the losses decomposition vary with the loosenes of credit standards. Similar to the model with the coordinated equilibrium, the adjustment of lending relationships substantially mitigates the losses due to tightening credit standards. Table 1.15 shows how the components of the distributional decomposition of the surplus vary with the looseness of credit standards and again shows that most of the results are qualitatively similar. One difference is that tightening lending relationships can actually result in a lower interest rate if the negative direct effect of decreasing the number of relationship lenders on the equilibrium interest rate is smaller than the positive effect due to the increased acquisition of information.

Finally, Figure 1-9 shows that effect of firm transparency is also qualitatively similar to the version of the model with the coordinated equilibrium.

1.E Formal definition of calibration variables

This section formally defines the calibration variables within the model.

The *number of lenders* is an explicit feature of the model.

Table 1.14: Losses decomposition of surplus from lending (Nash equilibrium version)

This table presents the surplus and its decomposition in the losses distribution at four different states: loose credit, tight credit with no adjustment by any agents, tight credit with adjustment of only information ψ by lenders, and tight credit with adjustment of both information by lenders ψ and relationship lenders n by firms. Values have been multiplied by 100.

	Surplus	Perfect info.	Missed good loans	Bad loans	Info. costs
Loose credit	0.128	4.000	2.602	1.010	0.260
Tight credit: no adjustment	0.068	4.000	2.915	0.757	0.260
Tight credit: lenders adjust	0.072	4.000	2.849	0.791	0.289
Tight credit: full adjustment	0.084	4.000	2.803	0.810	0.304

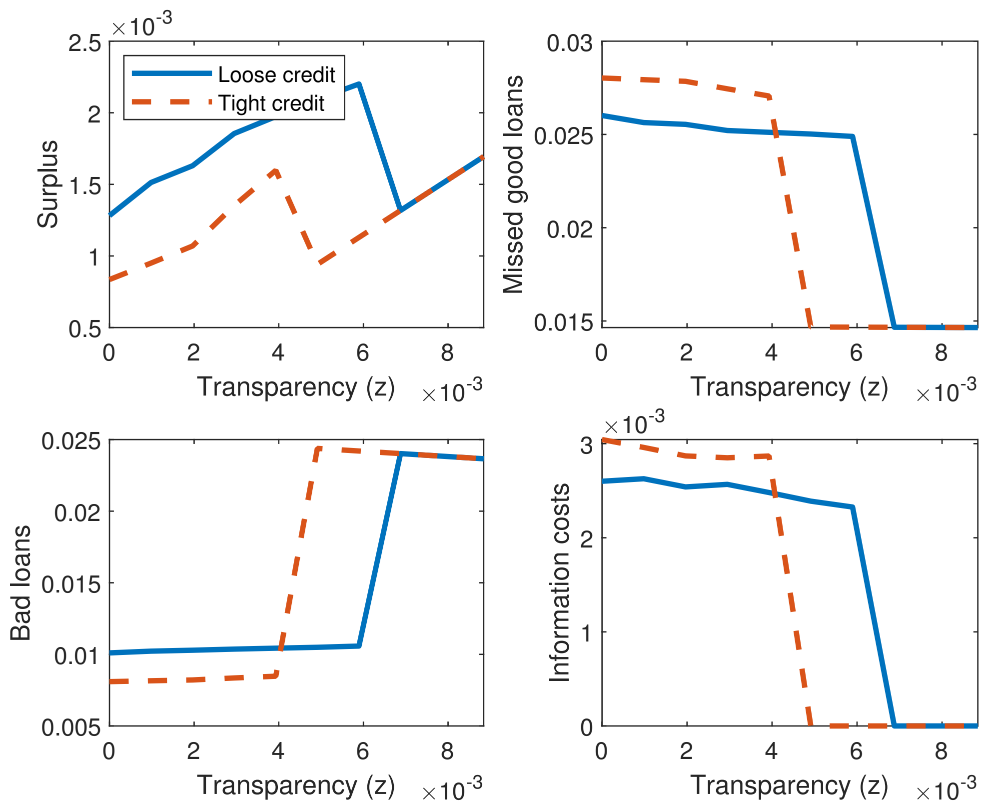
Table 1.15: Distributional decomposition of surplus from lending

This table presents the surplus and its decomposition in the losses distribution at four different states: loose credit, tight credit with no adjustment by any agents, tight credit with adjustment of only information ψ by lenders, and tight credit with adjustment of both information by lenders ψ and relationship lenders n by firms. Access to credit is and the interest rate spread are reported as a percentage, and values for the other columns have been multiplied by 100.

	Surplus	Firm profits	Lender profits	Access to credit	Interest rate spread
Loose credit	0.128	0.082	0.046	34.573	3.920
Tight credit: no adjustment	0.068	0.051	0.018	26.796	3.970
Tight credit: lenders adjust	0.072	0.060	0.012	28.426	3.947
Tight credit: full adjustment	0.084	0.064	0.020	29.548	3.941

Figure 1-9: Effect of transparency on surplus from lending (Nash equilibrium version)

This figure shows how the surplus from lending S and its components in the losses decomposition vary with transparency z for different levels of the looseness of credit standards B.



The *access to credit* is the fraction of firms that obtain credit. To compute this, first note that

$$\begin{aligned} f_{n:n}(s|g;\psi) &= nf(s|g;\psi)F(s|g;\psi)^{n-1} \\ &= n\left(1+\left(s-\frac{1}{2}\right)\frac{\psi}{\lambda_g}\right)\left(s^{n-1}+(n-1)s^{n-2}\frac{1}{2}(s^2-s)\frac{\psi}{\lambda_g}\right) \\ &\underset{\psi\approx 0}{\approx} ns^{n-1}\left[1+\left(\frac{n+1}{2}s-\frac{n}{2}\right)\frac{\psi}{\lambda_g}\right] \end{aligned}$$

The fraction of good firms that do not obtain credit is then

$$\begin{aligned} R_g &= \int_0^{\underline{s}} f_{n:n}(s|g;\psi)ds \\ &\underset{(1.27)}{=} \underline{s}^n\left[1-\frac{n}{2}(1-\underline{s})\frac{\psi}{\lambda_g}\right] \end{aligned} \tag{1.39}$$

Similarly, the fraction of bad firms that do not obtain credit is

$$R_b = \underline{s}^n\left[1+\frac{n}{2}(1-\underline{s})\frac{\psi}{\lambda_b}\right] \tag{1.40}$$

The fraction of firms that do not obtain credit is then

$$\begin{aligned} R &= \lambda_g R_g + \lambda_b R_b \\ &= \underline{s}^n \end{aligned}$$

The fraction of firms that obtain credit is then

$$access = 1-\underline{s}^n$$

The *default rate* is the fraction of the firms receiving credit that are bad

$$\begin{aligned} default &= \frac{\lambda_b P_b}{\lambda_b P_b + \lambda_g P_g} \\ &= \lambda_b + \frac{n}{2}(1-\underline{s})\psi \end{aligned}$$

The *average interest rate spread* is the expected net interest charged conditional on receiving credit

$$spread = \frac{\int_{\underline{s}}^{1} \underline{R}(D(s,s;\psi,n)) f_{n-1:n}(s) ds}{access}$$

where $f_{n-1:n}(s)$ is defined as in Appendix 1.B.9. This is converted as a percentage by multiplying by 100.

Chapter 2

The Effect of Liquidity Regulation on U.S. Bank Risk-Taking: Evidence from Non-Performing Loans and CDS Spreads*

2.1 Introduction

The liquidity stress observed during the 2008 financial crisis has led to increased attention on liquidity regulations. A prominent recent example is the liquidity coverage ratio (LCR), which has been effective in the US since January 2015. The LCR requires a subset of banks to hold a certain percentage of high quality liquid assets, such as cash and Treasury securities, against their 30-day net cash outflows. A notable historical precedent is the reserve requirement (RR), which existed in the US from the 1800s until 2020. The RR is similar to the LCR in that it required banks to hold a certain percentage of reserves, consisting of cash and deposits with the central bank, relative to their net transaction accounts, consisting of demand deposits and other liquid liabilities. Both of these liquidity regulations have been associated with increased holdings of liquid assets (see Figure 2-1).[1] How does increasing bank liquidity in turn affect financial stability? Recent studies

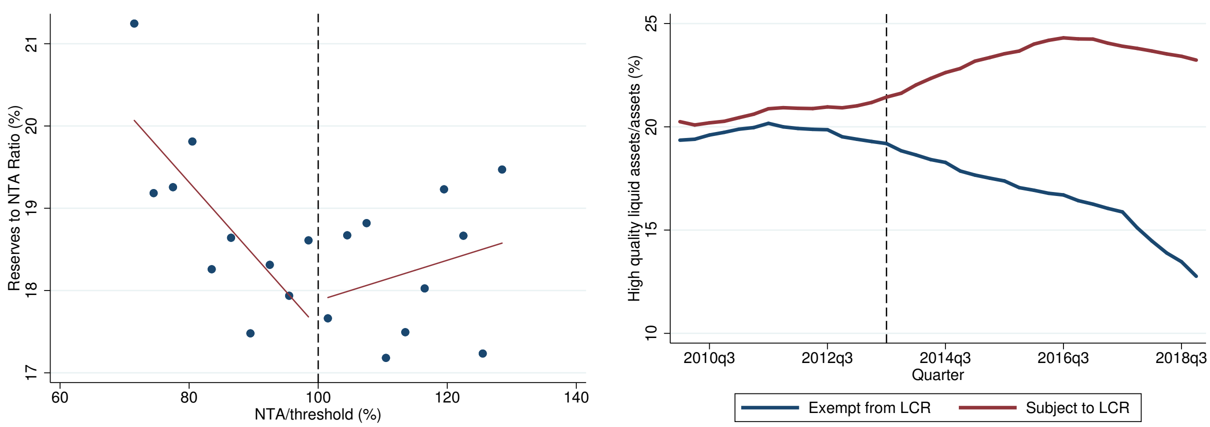
*Joint with Ali Kakhbod. We thank Daron Acemoglu, Ricardo Caballero, Andrey Malenko, Stephen Morris, Alp Simsek, David Thesmar, and Rob Townsend for very helpful and constructive comments.

[1]Figure 2-1a shows that banks hold more reserves when they are subject to higher marginal RR rates, and Figure 2-1b shows that bank holding companies (BHCs) that were subject to the LCR increased holdings of high quality liquid assets after the proposal of the LCR compared to BHCs that were exempt from the LCR.

Figure 2-1: The effect of liquidity regulations on liquid asset holdings.

Figure (a) presents a binned scatterplot relating the percentage of reserves to net transaction accounts to the percentage of net transaction accounts to a threshold at which marginal the reserve requirement rate exhibited a discontinuous jump. The figure also presents predicted values from estimating a linear regression for the subsamples on either side of the threshold. This figure uses Call Reports data from 1993Q1 to 2018Q4 for observations exhibiting a less than 30% deviation of net transaction accounts relative to the threshold. See Section 2.4 for more details. Figure (b) shows the mean ratio of high quality liquid assets to total assets for a balanced sample of bank holding companies (BHCs), split between BHCs that were required to satisfy the liquidity coverage ratio (LCR) and those that were exempt from the LCR. The series have been smoothed using a moving average to reduce seasonal fluctuations. The dashed line indicates the proposal date for the LCR at approximately 2013Q3. The figure uses FR Y-9C data from 2010Q1 to 2018Q4. See Section 2.5 for more details.

(a) (b)



have provided evidence that liquidity regulations are associated with fewer banks failures (Curfman and Kandrac (2018)) and reduced fire-sale risk (Roberts, Sarkar and Shachar (2018)). However, less is known about how liquidity regulations affect the incentive for banks to take risk with their remaining ineligible assets. Understanding the interactions between liquidity risk and credit risk is important for assessing the total effect of liquidity regulations on financial stability.

This paper introduces a model to illustrate channels by which regulations that require banks to hold liquid assets can either increase or decrease the incentive for banks to take risk with their remaining assets. In the model, a risk neutral bank acquires funding from depositors, maintains a required fraction of liquid assets, such as cash, and chooses the riskiness of its remaining long-term assets, such as loans.[2] Before the long-term assets

[2]Liquid assets in the model can be interpreted more broadly to include reserves and certain types of securities, similar to Berger and Bouwman (2009). Both the LCR and the RR require banks to hold a sufficient stock of liquid assets, although they assign different weights to the various types of liquid assets and have a different method of computing the liabilities that these assets must be held against. See Section 2.4.1 and 2.5.1 for more details about the policies.

mature, the bank may experience liquidity stress, which means that a fraction of its depositors withdraw their investment. The bank can respond to liquidity stress by either paying out of its liquid asset stock or, if necessary, selling its long-term assets in debt market to generate funds. On the one hand, limited liability and deposit insurance create an incentive for the bank to invest in risky long-term assets in order to maximize the option value of its net return.[3] On the other hand, risky assets sell at a lower price in the debt market, which makes them less suitable for coping with liquidity stress. This trade-off determines whether the bank invests in risky or safe long-term assets.

The model illustrates that the effect of tightening liquidity requirements on the bank's incentive to invest in risky long-term assets qualitatively depends on its capacity to respond to liquidity stress. The bank has a low capacity to respond to liquidity stress if it owns few liquid assets and can only sell its long-term assets at a low price. In that case, liquidity stress can cause the bank to default. The bank can reduce the probability of default due to liquidity stress by investing in safe long-term assets, because they can be liquidated at a higher price in the debt market compared to risky assets. Tightening liquidity requirements improves the bank's profitability in states where it faces liquidity stress and but does not default. It therefore increases the profitability of safe assets relative to risky assets in states where the bank faces liquidity stress, which in turn increases the incentive to invest in safe assets ex-ante.

By contrast, the bank has a high capacity to respond to liquidity stress if it has a large stock of liquid assets or if the price of long-term debt is high. In that case, the bank can adequately respond to liquidity stress without defaulting, even if it invests in risky long-term assets. Tightening liquidity requirements decreases the extent to which the bank needs to sell its long-term assets in the debt market to respond to liquidity stress. This in turn mitigates the relative disadvantage of investing in risky assets, which is their lower price in the debt market. Hence, tightening liquidity requirements increases the incentive to invest in risky assets.

The result from the model that liquidity regulations can either increase or decrease the incentive to take risk motivates an empirical analysis to determine whether either effect dominates in practice. We first focus on a sharply identified setting in the context of the RR. In recent decades, the RR has primarily been used in the implementation of monetary policy (Feinman (1993)). However, the RR can also be understood as a liquidity regulation with a similar form as the LCR since both policies require banks to hold liquid assets against their liquid liabilities. Using quarterly Call Reports data, we exploit a

[3]Risky assets in the model can be interpreted, for example, as loans with a relatively high probability of default.

discontinuous jump in marginal RR rates at a threshold in the volume of net transaction accounts. Implementing a regression kink design comparing banks that are marginally on either side of this threshold, we find that RR rates were associated with increased holdings of reserves but were not associated with changes in the ratio of non-performing loans to total loans, a measure of the riskiness of a bank's loan portfolio.

We also estimate the effects of the LCR using a difference-in-differences specification. Specifically, we exploit the fact that the LCR only applies to a subset of bank holding companies (BHCs) based on their size and foreign exposures. Using data from quarterly FR Y-9C filings by BHCs, we find that the proposal of the LCR in 2013 was associated with increased holdings of high quality liquid assets but was not associated with changes in non-performing loans ratios. We also do not find that the LCR was significantly associated with changes in jumps of credit default swap (CDS) spreads during the COVID-19 crisis compared to the global financial crisis, which suggests a limited effect of the LCR on overall bank risk during crises.

2.2 Literature Review

This paper addresses prior work that examines two important causes of bank failures. First, the liquidity risk associated with banks' maturity transformation role makes them vulnerable to runs (Diamond and Dybvig (1983)). Second, banks can also fail due to the credit risk associated with their investments. In particular, banks may have an incentive to take excessive risk or "gamble for resurrection" because the equityholders reap the rewards if it pays off while creditors or insurers absorb the losses if it fails (Hellmann, Murdock and Stiglitz (2000)). A bank's incentive to take risk is inversely related to its "charter value" or expected profits stream (Keeley (1990)). This paper combines these strands of the literature by illustrating how regulations that mitigate a bank's liquidity risk can increase the potential profits it could lose by investing the illiquid portion of its portfolio in risky assets.[4]

This paper is also related to the literature on financial crises. In this literature, crises

[4]This paper also relates more generally to a vast literature on banking. See, for example, work on banking failures and crises (Caballero (2010), Caballero and Krishnamurthy (2008), Ashcraft (2005)), contagion (Acemoglu, Ozdaglar and Tahbaz-Salehi (2015)), shadow banking (Gennaioli, Shleifer and Vishny (2013)), loan supply effects of monetary policy and bank financing constraints (Kashyap, Stein and Wilcox (1993), Paravisini (2008)), the effects of banking regulations on credit supply and risky lending (Di Maggio and Kermani (2017), Di Maggio, Kermani and Korgaonkar (2019)), corporate governance (Ivashina et al. (2009)), the role of supervisory policies on bank lending and external financing (Beck, Demirguc-Kunt and Levine (2006)), and monopoly banking with uncertainty (Prisman, Slovin and Sushka (1986)).

are usually explained as being caused by either panics or weak fundamentals (Goldstein (2012)). The basic idea underlying this literature is that decision-makers transmit shocks by changing their exposure to risks. This literature is vast. For example, among others, bank runs associated with deteriorations in fundamentals are analyzed in Jacklin and Bhattacharya (1988) and Allen and Gale (1998), while self-fulfilling crises caused by panics among bank depositors are considered in Bryant (1980), Diamond and Dybvig (1983), and Ahnert and Kakhbod (2017). We depart from this literature by analyzing how regulations that mitigate liquidity risk during crises affect banks' exposure to other kinds of risk. In particular, we empirically identify how the RR and the LCR affect a bank's attitude toward credit risk in its loan portfolio.

This paper is also related to a discussion of the tradeoffs associated with liquidity regulations. Perotti and Suarez (2011) show that taxes can be used as a liquidity regulation to correct for fire sale externalities in short-term funding markets. Diamond and Kashyap (2016) show that liquidity regulations with a structure like the LCR can correct for inefficient investment in liquid assets owing to depositors' incomplete information about a bank's resilience to liquidity stress. Allen and Gale (2017) surveys the literature and concludes that it has not converged on a paradigm for understanding the role of liquidity regulations. This paper contributes to this literature by illustrating how the effectiveness of liquidity regulations in supporting financial stability depends on how they also affect the degree to which banks take risk with their ineligible assets.

This paper also contributes to an empirical literature looking at the effects of liquidity regulations on banks. This paper is specifically related to work on the RR that explores its institutional structure and historical uses (Feinman (1993)), its effectiveness in mitigating liquidity stress (Carlson (2015)), and its effects on other bank characteristics (Curfman and Kandrac (2018)). It is also related to work that examines the effect of recent liquidity regulations. Banerjee and Mio (2018) show that the Individual Liquidity Guidance, a precursor to the LCR in the UK, led banks to decrease lending to financial firms, but they do not find evidence that it reduced the amount of lending to non-financial firms. Bonner and Eijffinger (2016) show that a precursor of the LCR in the Netherlands was associated with higher long-term interbank lending rates. In the US, Roberts, Sarkar and Shachar (2018) show that the LCR in the US has been associated with reduced liquidity creation, while Sundaresan and Xiao (2019) provide evidence that the LCR led banks to acquire liquidity by borrowing more from the Federal Home Loan Banks.

2.3 Model

This section introduces a model of bank risk-taking in the presence of liquidity risk and liquidity requirements. It illustrates channels by which tightening liquidity requirements can either increase or decrease the incentive for banks to invest the remaining illiquid part of their portfolios in risky assets. It also shows that the risk-motivating effect is more likely to dominate when the capacity to respond to liquidity stress is high. Finally, it demonstrates how these incentives affect the optimal level of liquidity requirements from the perspective of a government that seeks to minimize deposit insurance payouts.

2.3.1 Environment

As an overview of the model, there are three dates $t = 0, 1, 2$. At date $t = 0$, a limited liability commercial bank acquires funding, allocates liquid assets to meet liquidity requirements, and chooses whether to invest the remainder of its portfolio in risky or safe long-term assets. At date $t = 1$, a liquidity shock may occur, in which case a fraction of depositors withdraw early. The bank can repay these depositors by paying out of its liquid assets and, if necessary, by selling a fraction of its illiquid investments on the long-term debt market to generate additional funds. If the bank cannot fully repay the early depositors, then it defaults in period 1, which corresponds to experiencing a run. At date $t = 2$, the bank's investment yields a return. The bank then repays the late depositors and keeps the remainder as a profit. If the return is insufficient to fully repay the late depositors, then the bank defaults. If the bank defaults in either period, then the bank is liquidated and its assets are redistributed to the depositors.

More specifically, at date $t = 0$, the bank acquires funding from a mass 1 of depositors that each invests 1 unit in the bank. The depositors are protected by deposit insurance. Because depositing in the bank is riskless, the bank pays the short-term gross interest rate R_{st} on deposits withdrawn in period 2. Deposits withdrawn in period 1 are returned without interest.[5] For simplicity, there is no other source of bank funding.

The bank invests in a combination of liquid and illiquid assets. Liquidity regulations require the bank to hold a fraction l of liquid assets, which maintain their value (or generate a gross return of 1), in period 1 and generate a return in period 2 that is equal to the

[5]See Section 2.3.5 for an extension of the model in which the bank can also pay interest on deposits that are withdrawn in period 1.

short-term interest rate R_{st}.[6] The bank can invest the remainder of its funds in long-term assets that are either safe ($i = s$) or risky ($i = r$).[7] The long-term assets generate a return $\tilde{\mu}_i$. In particular, safe assets generate a riskless return of μ while risky assets generate a return of either 2μ or 0, each with probability 1/2. Note that the two types of assets generate the same expected return μ, but the risky assets exhibit greater volatility.

At date $t = 1$, a liquidity shock occurs with probability q. In that case, a fraction λ of depositors withdraw their investment with no interest. Banks can pay depositors from their liquid asset stock.[8] If the bank has insufficient liquid assets to pay the early depositors, it can sell a fraction of its illiquid assets on the long-term debt market. The bank faces a perfectly elastic demand for its long-term. Safe assets sell at the price $p_s = p$, while risky assets sell at the lower price $p_r = \delta p$, where $\delta \in (0,1)$ to reflect a risk-averse market.

The equity value of the bank is then equal to

$$V = \underbrace{(1-q)}_{\text{normal times}} \mathbb{E}_{\tilde{\mu}_i}\left[\underbrace{\tilde{\mu}_i(1-l)}_{\text{ret. on long-term assets}} + \underbrace{lR_{st}}_{\text{ret. on liquid}} - \underbrace{R_{st}}_{\text{return to dep.}}\right]^+$$
$$+ \underbrace{q}_{\text{liquidity stress}} \mathbb{E}_{\tilde{\mu}_i}\left[\underbrace{\tilde{\mu}_i\left(1-l-\frac{\lambda-l}{p_i}\mathbf{1}_{\lambda>l}\right)}_{\text{ret. on long-term assets}} + \underbrace{(l-\lambda)R_{st}\mathbf{1}_{l>\lambda}}_{\text{ret. on liquid}} - \underbrace{(1-\lambda)R_{st}}_{\text{return to late dep.}}\right]^+$$

where $[A]^+ = \max\{A, 0\}$ and $\mathbf{1}_A$ is an indicator function that is equal to 1 when A holds and is 0 otherwise. Taking the expectation over the return of the long-term assets, the first term averages over states in which there is no liquidity shock, or normal times. In those states, the bank accrues the remainder of the return from its liquid and illiquid assets after paying off the depositors. The payoff is restricted to be nonnegative due to limited liability.

The second term averages over states in which a liquidity shock occurs. If the bank's liquid assets are insufficient to repay the early depositors, or $\lambda > l$, then the bank must

[6] Liquid assets can be interpreted to include cash, reserves, and some types of securities, similar to Berger and Bouwman (2009). See Section 2.3.5 for an extension of the model in which the return on liquid assets can be different from 1 in period 1 and different from R_{st} in period 2.

[7] The long-term assets can be interpreted as loans.

[8] For simplicity, there are no penalties for using liquid assets to respond to liquidity stress. To consider the effect of penalties, see Section 2.3.5 for an extension of the model that allows for variation in the return on liquid assets in period 1. In particular, a penalty can be represented by decreasing this return.

sell a fraction of its long-term assets in the debt market to generate additional funds. The bank can default in period 1 if selling all of its illiquid assets does not generate enough funds to pay the early depositors:

$$p_i(1-l)+l<\lambda$$

If the bank can generate enough funds to avoid a run, then it maintains $1-l-\frac{\lambda-l}{p_i}$ units of long-term assets. The bank can also default in period 2 if the return from its residual holdings of long-term assets is insufficient to repay the late depositors:

$$\tilde{\mu}_i\left(1-l-\frac{\lambda-l}{p_i}\right)<(1-\lambda)R_{st}$$

If the return is sufficient to repay the late depositors, then the bank accrues the remainder as a profit.

Figure 2-2 summarizes the determination of the bank's equity value.

We assume $q<\delta p$, and $\mu>\max\left\{R_{st},\frac{1-q}{1-\frac{q}{p}}R_{st},\frac{1}{2}\frac{1-q}{1-\frac{q}{\delta p}}R_{st}\right\}$ to ensure that it is not profitable for the bank to hold more than the required level of liquid assets.

Proposition 2.1. *If $q<\delta p$ and $\mu>\max\left\{R_{st},\frac{1-q}{1-\frac{q}{p}}R_{st},\frac{1}{2}\frac{1-q}{1-\frac{q}{\delta p}}R_{st}\right\}$, then the bank never wants to hold more than the required level of liquid assets.*

Proof. See Appendix. ▪

The intuition is that holding liquid assets has the benefit of improving the bank's performance in the liquidity stress state, but it also has an opportunity cost associated with reducing the bank's investment in higher-yield long-term assets. Assuming a high expected return on long-term assets μ and a low probability of the liquidity shock state q ensures that the cost always exceeds the benefit in expectation.

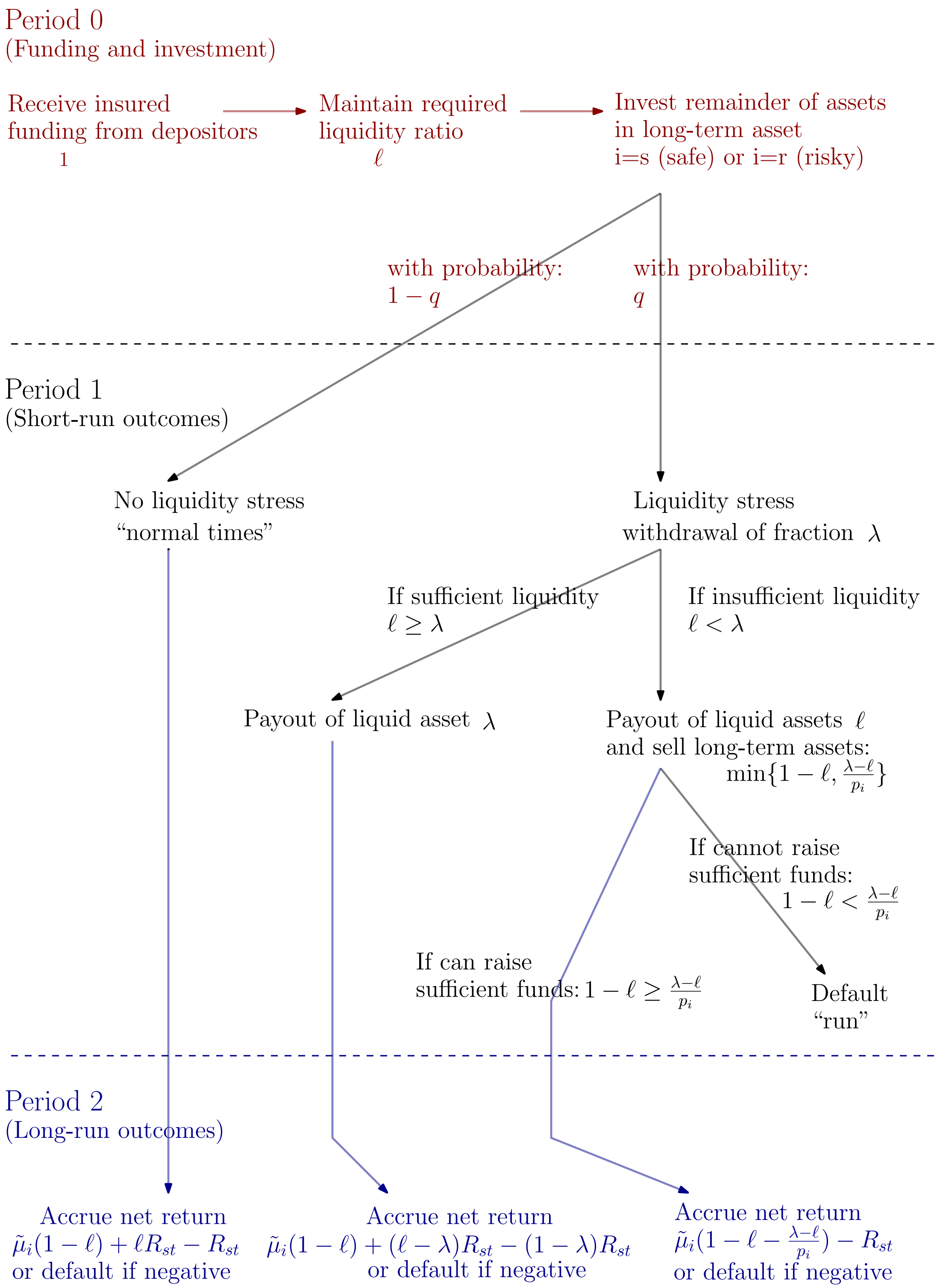
We also assume $p<1$ to ensure that holding liquid assets increases the bank's capacity to respond to liquidity stress.

Proposition 2.2. *If $p<1$, then holding liquid assets increases the probability that the bank does not default due to liquidity stress.*

Proof. See Appendix. ▪

The intuition is as follows. On the one hand, holding greater liquid assets can improve the bank's performance in the liquidity shock state because it decreases the amount of

Figure 2-2: The sequence of events in the model.



long-term assets it needs to liquidate. On the other hand, it can also reduce the bank's ability to generate a large enough return to pay the late depositors since it decreases the bank's investment higher-yield in long-term assets. Restricting to $p < 1$ ensures that this benefit always exceeds the cost.

The parametric restrictions $q < \delta p$, $\mu > \max\left\{\frac{1-q}{1-\frac{q}{p}}R_{st}, \frac{1}{2}\frac{1-q}{1-\frac{q}{\delta p}}R_{st}\right\}$, and $p < 1$ are assumed for the rest of the analysis.[9]

2.3.2 Characterization of bank risk-taking

The bank chooses to invest the illiquid portion of its portfolio in either risky assets or safe assets in order to maximize its expected profits. Risky assets achieve a higher expected net return in normal times because of limited liability, whereas safe assets achieve a higher expected net return when there is a liquidity shock because they can be sold for a higher price in the debt market. The incentive to invest in risky assets is decreasing in the expected return μ. This is because banks that invest in risky assets accrue a smaller fraction of this expected return in the liquidity shock state. As a result, the bank's asset choice can be summarized by a threshold μ^* in the expected return, which can be interpreted as the propensity to take risk.

Lemma 2.1. *The bank's asset choice can be summarized by a threshold μ^* such that it invests in safe assets if $\mu > \mu^*$ and invests in risky assets if $\mu < \mu^*$.*

Proof. See Appendix. ∎

This result is analogous to a classical idea from the financial stability literature that a bank's franchise value, or the profits it would expect to accrue as long as it remained solvent, can decrease its incentive to take risk (Keeley (1990)). The channel is based on bank equityholders' risk-shifting incentive (Jensen and Meckling (1976)). For a bank with limited liability, the payoff for the equityholders is like a call option on the value of the bank with a strike price corresponding to its debt payment. A standard result from options theory is that the value of an option increases in the volatility of the underlying asset (McDonald (2008)). By analogy, the equity value of a bank increases in the risk of its assets. Moreover, this risk-taking incentive is larger when the value is near the strike price, which in the analogy corresponds to a bank with low profitability.

[9] Note that it is not necessary to explicitly assume $\mu > R_{st}$ since $\mu > \frac{1-q}{1-\frac{q}{p}}$ and $p < 1$ imply $\mu > R_{st}$.

2.3.3 The effect of liquidity regulations on bank risk-taking

Requiring banks to hold a greater fraction of liquid assets can either increase or decrease the incentive to invest the illiquid portion of their portfolios in risky assets. Tightening liquidity requirements is more likely to induce greater risk-taking when banks have a greater capacity to respond to liquidity stress, such as when the liquidity requirements are already tight.

Proposition 2.3. *There exists a threshold $l^*(p)$ such that μ^* is decreasing in l for $l < l^*(p)$ and μ^* is increasing in l for $l > l^*(p)$. The threshold $l^*(p)$ corresponds to the minimal level of liquidity at which the bank can survive liquidity stress if it invests in risky assets.*

Proof. See Appendix. ∎

Corollary 2.1. *The threshold $l^*(p)$ can also be interpreted as the level of liquidity that minimizes the propensity to take risk.*

Figure 2-3 illustrates this result graphically. The intuition is as follows. If the bank holds few liquid assets, then a liquidity shock can cause it to default. In particular, if $l < l^*(p)$, liquidity stress causes the bank to default if it holds risky assets, but it may not cause the bank to default if it holds safe assets due to their higher liquidation value. As a result, if the bank holds risky assets, then marginally tightening liquidity requirements has no effect on the bank's equity value in the liquidity shock state. However, if the bank holds safe assets, then tightening liquidity requirements increases the bank's performance in the liquidity shock state. Therefore, tightening liquidity requirements increases the expected return of safe assets relative to risky assets, which decreases the incentive to invest in risky assets ex-ante.[10]

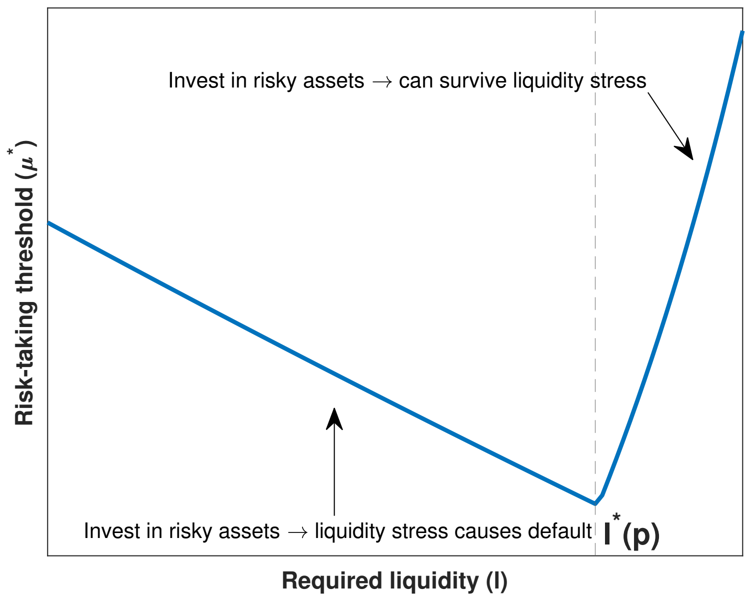
By contrast, if the bank has a high capacity to respond to liquidity stress, or $l > l^*(p)$, then tightening liquidity requirements increases the incentive to take risk. In particular, the bank can adequately respond to liquidity stress without defaulting, even if it invests in risky assets. In that case, tightening liquidity requirements increases the bank's equity value in the liquidity shock state relatively more if it holds risky assets. This is because it increases the extent to which the bank can respond to liquidity stress by using its own

[10]Note that this follows from assuming that the debt price satisfies $p < 1$ as in Proposition 2.2. This assumption implies that paying out liquid assets is a more efficient way to respond to liquidity stress than selling long-term assets in the debt market. By contrast, if the price p is sufficiently high, then liquidity requirements can decrease the return of safe assets in the liquidity shock state since holding liquid assets becomes less efficient than selling in the debt market. In that case, increasing the fraction of liquid assets always increases the incentive to take risk.

liquidity buffer rather than by liquidating its long-term assets. This mitigates the disadvantage of risky assets, which is their lower price in the debt market. This in turn increases the incentive to invest in risky assets.

Figure 2-3: Bank asset choice and liquidity requirements.

This figure plots the risk-taking threshold in the mean return μ^* as a function of the bank's required fraction of liquid assets.



By similar reasoning, tightening liquidity requirements is also more likely to induce greater risk-taking when the long-term debt price is high.

Proposition 2.4. *Increasing the price for long-term debt increases the range for l on which risk-taking increases in the tightness of liquidity requirements:* $\frac{dl^*(p)}{dp} < 0$.

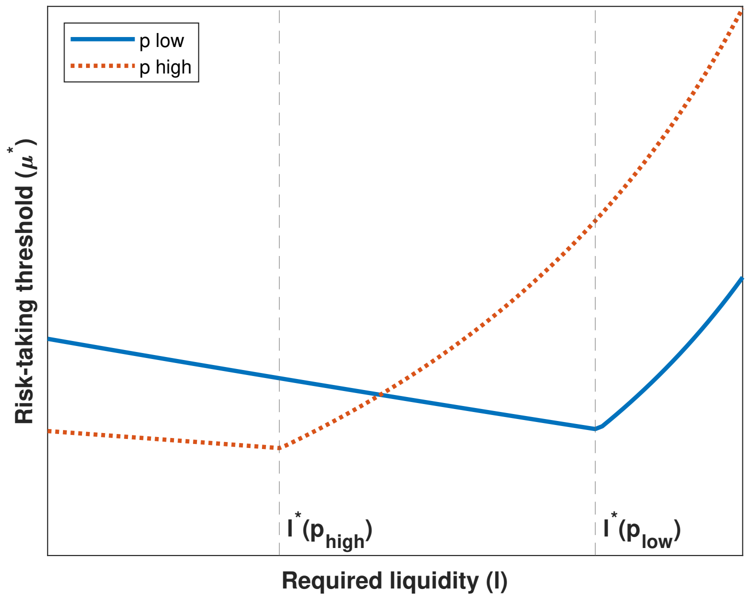
Proof. See Appendix. ∎

Figure 2-4 illustrates this result graphically. The intuition is that increasing the long-term debt price increases the bank's capacity to respond to liquidity stress, as it reduces the fraction of the bank's long-term assets that must be sold to generate sufficient funds to pay the early depositors. This in turn decreases the probability that the bank will default. The bank therefore becomes less dependent on maintaining a buffer of liquid assets to avoid default. This induces a decrease in the threshold $l^*(p)$ at which the bank can survive liquidity stress even if it invests in risky assets.[11]

[11]Incidentally, the figure also shows that increasing the price p decreases the propensity to take risk for l in the region where the bank defaults if it invests in risky assets for both the high and low price. It also

Figure 2-4: Bank asset choice and long-term debt market price.

This figure compares the risk-taking threshold in the mean return μ^* for different long-term debt market prices.



2.3.4 Optimal liquidity regulation

This section illustrates the optimal level of liquidity requirements from the perspective of a government that seeks to minimize deposit insurance payouts.

The government insures against a bank's failure to repay but does not insure against a depositor's own liquidity risk. Specifically, the government insures depositors at a gross return of R_{st} for late withdrawals and a return of 1 for early withdrawals. The total payout for depositors is then given by $T = (1 - \lambda q)R_{st} + q\lambda$. If the expected payout from banks is equal to B, then the government must pay the difference $G = T - B$. Suppose there is a mass 1 of banks whose expected return μ is distributed with cdf F.

Proposition 2.5. *The optimal level of liquidity that minimizes the government's expenditure, denoted by l^G, is at least as great as the level $l^*(p)$ that minimizes the fraction of banks that invest in risky assets.*

Proof. See Appendix. ■

shows that increasing the price increases the propensity to take risk for l in the region where the bank can survive liquidity stress for both the high and low price. The intuition and proof are closely analogous to the effect of tightening liquidity requirements (Proposition 2.3), as both liquidity requirements and a high liquidation value of long-term assets increase the bank's capacity to respond to liquidity stress.

The intuition is as follows. Tightening liquidity requirements increases the amount that the bank can pay back to depositors if liquidity stress causes it to default. If liquidity is lower than $l^*(p)$, then tightening liquidity requirements also decreases the incentive for banks to invest in risky assets (Proposition 2.3). Both of these effects decrease government expenditure, which implies that the government's optimal liquidity level must be at least as great as the threshold $l^*(p)$. If liquidity is higher than this level, then tightening liquidity requirements instead intensifies the incentive for banks to invest in risky assets. The government then faces a tradeoff in which liquidity requirements increase the resilience of banks to liquidity stress but also increases their incentive to take risk with their remaining illiquid assets.

Figure 2-5a shows the government expenditure for the case of a homogenous mass of banks with expected return μ. Government expenditure is positive when the banks invest in risky assets (which occurs when $\mu < \mu^*$) and zero when the banks invest in safe assets (which occurs when $\mu > \mu^*$). Therefore any liquidity level that induces the banks to invest in safe assets is optimal for the government. Note additionally that, conditional on the banks investing in risky assets, government expenditure is decreasing in the level of the liquidity requirement. This reflects the fact that liquidity increases the capacity of the banks to respond to liquidity stress. However, government expenditure is still positive since liquidity does not eliminate the risk associated with the return on the banks' long-term assets.

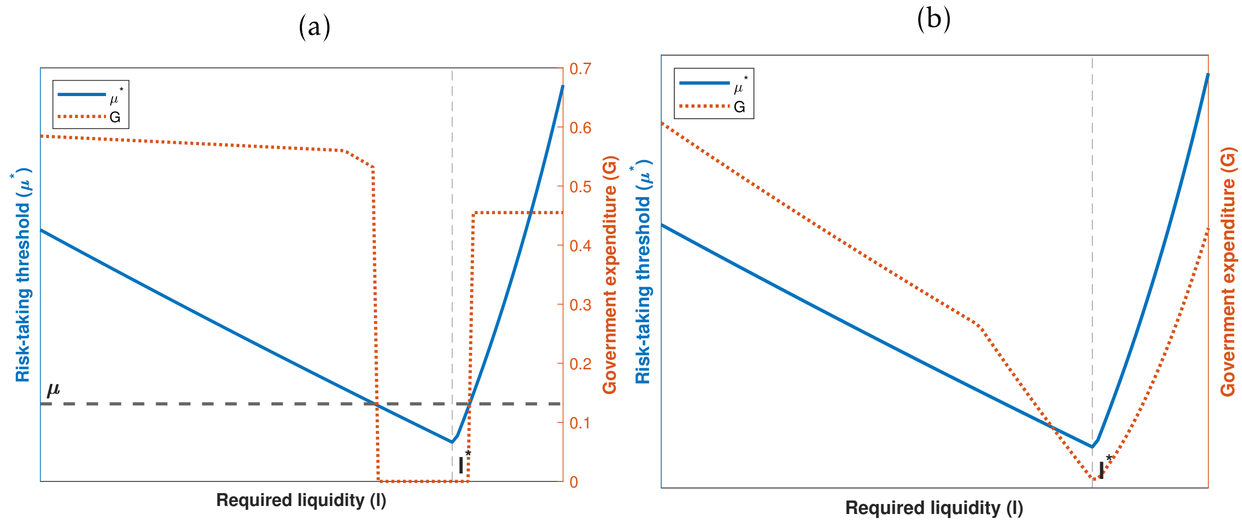
Figure 2-5b shows government expenditure for the case of a mass of banks whose expected return is uniformly distributed. The optimal liquidity level that minimizes government's expenditure is approximately equal to the level $l^*(p)$ that minimizes the fraction of banks that invest in risky assets. This indicates that, for this example, the cost of liquidity requirements associated with encouraging more banks to invest in risky assets outweighs the benefit from increasing the resilience to liquidity stress for the banks that would have already chosen to invest in risky assets.

2.3.5 Extensions

The results of the model are robust to various extensions, including generalizing the return of the depositors who withdraw in period 1, the return on liquid assets in period 1, the return on liquid assets in period 2, and the fraction of the bank's assets that depositors can recover if the bank defaults. See Appendix Section 2.A for further elaboration.

Figure 2-5: Government expenditure

Panel (a) depicts government expenditure for a single bank with expected return μ. Panel (b) depicts government expenditure for a mass of banks with a uniformly distributed return.



2.4 The effect of the reserve requirement on banks

The result from the model that liquidity can either increase or decrease the incentive for banks to invest the remaining illiquid portion of their portfolios in risky assets (Proposition 2.3) motivates an empirical analysis to determine whether either effect dominates in practice. This section empirically examines the effect of the reserve requirement (RR) on banks. Using Call Reports data, we implement a regression discontinuity design that exploits the progressive structure of the RR in the US. We find evidence that RR rates are associated with increased holdings of reserves, but we do not find evidence that RR rates are associated with changes in risk-taking.

2.4.1 Setting: the reserve requirement

The RR required banks to hold a fraction of net transaction accounts (NTA), which includes demand deposits and other short-term liabilities[12] net of amounts due from other depository institutions and cash items in the process of collection, as liquid reserves, which includes either vault cash or deposits with the Federal Reserve. In recent decades, the RR was primarily used as a means to facilitate the implementation of monetary pol-

[12]This specifically includes automatic transfer service (ATS) accounts, NOW accounts, share draft accounts, telephone or preauthorized transfer accounts, ineligible bankers acceptances, and obligations issued by affiliates maturing in seven days or less.

icy.[13] However, the RR also functioned like a liquidity requirement with a structure that is comparable to more recent liquidity regulations like the LCR.

The most recent RR regime started in the early 1980s with the Monetary Control Act and the Garn-St. Germain Act. From 1982 until 2020, all commercial banks were subject to a progressive RR rate characterized by two thresholds in the volume of NTA. For example, in 2019, the first $16.3 million of NTA was called the "exemption amount" and did not require any reserves. The next $107.9 million was called the "low reserve tranche" and required reserves to be held at 3%. The remaining NTA required reserves to be held at 10%. Note that RR rates have been modified three times since 1980: in 1990 the RR rate on nonpersonal time deposits and Eurocurrency liabilities was reduced from 3% to 0%, in 1992 the maximal RR rate on NTA was reduced from 12% from 10%, and in 2020 the reserve requirement was eliminated.

The thresholds mechanically adjusted each year based on a formula involving banking system aggregates. In particular, the exemption amount threshold adjusted by 80% of the previous year's growth in aggregate reservable liabilities if the growth rate was positive, otherwise it did not adjust.[14] The low reserve tranche upper threshold adjusted by 80% of the previous year's positive or negative net growth of aggregate NTA.

2.4.2 Data: Call Reports

This exercise uses data from filings of the Consolidated Report on Condition and Income, otherwise known as the Call Reports. All US insured commercial banks are required by the Federal Deposit Insurance Corporation to file on a quarterly basis. Our baseline sample covers the period from 1993Q1 to 2018Q4, during which time marginal RR rates were constant except for yearly adjustments of the thresholds. Note that the results for many of the RR exercises are reported for the full sample period as well as for the subsample restricting to years before 2008. We distinguish this subsample due to substantial changes that occurred during the financial crisis, including a substantial increase in reserves and the introduction of interest on reserves. We examine the effect of the discontinuous jump in marginal RR at the low reserve tranche upper threshold.

Table 2.1 presents summary statistics for the characteristics used in the analysis. The marginal RR rate is determined using an approximation of NTA that can be computed using the Call Reports data.[15] The remaining characteristics correspond to the CAMELS

[13] See Feinman (1993) for background information on the structure and historical uses of the RR.

[14] Reservable liabilities include NTA, nonpersonal time deposits, and Eurocurrency liabilities.

[15] Specifically, we compute NTA as total transaction accounts minus, where available, cash deposits in

risk raking system, including the capital to assets ratio (C), the ratio of non-performing loans as a measure of asset quality and risk-taking and (A), non-interest expenses to assets as a measure of managerial efficiency (M), return on assets as a measure of earnings (E), an approximation of reserves to NTA as a measure of liquidity (L),[16] and the absolute difference between short-term assets and liabilities as a measure of sensitivity to market risk (S). Non-categorical variables are winsorized at 1% in each year.

2.4.3 Specification: regression kink design

We estimate the following baseline regression kink design (RKD) specification based on the change in marginal RR rates at the low reserve tranche upper threshold:

$$Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta (D_{it} * \Delta NTA_{it}) + \epsilon_{it} \tag{2.1}$$

where Y_{it} is the dependent variable (the reserves to NTA ratio as a measure of liquidity or the non-performing loans ratio as a measure of risk-taking) for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's NTA and low reserve tranche upper threshold, and D_{it} indicates whether a bank's NTA exceeded the threshold. The regression kink estimate is obtained by dividing δ, which corresponds to the change in the slope of the dependent variable at the threshold, by the change in the marginal RR rate 10%-3%=7%. T-statistics computed using bank-clustered standard errors are reported in parentheses. This specification is implemented with a bandwidth of 30% and a rectangular kernel. In some estimations we also include a set of lagged controls that includes bank size and proxies for indicators from the CAMELS risk rating system (excluding the dependent variable) as well as time fixed effects. Note that the control variables and fixed effects are included to reduce sampling variation, although they are not necessary for identification in a RKD.

To achieve identification, the RKD mitigates potential confounding due to systematic differences between banks whose NTA are smaller or larger than the threshold. The identification assumption is that, for a bank near the threshold, its position on either side of the threshold is as good as randomly assigned. This assumption is supported if banks cannot perfectly manipulate their treatment status, which is evidenced by a smooth density in the assignment variable (Card et al. (2015)). This is plausible since considerations other than the RR are also likely to determine a bank's level of NTA, such as the activi-

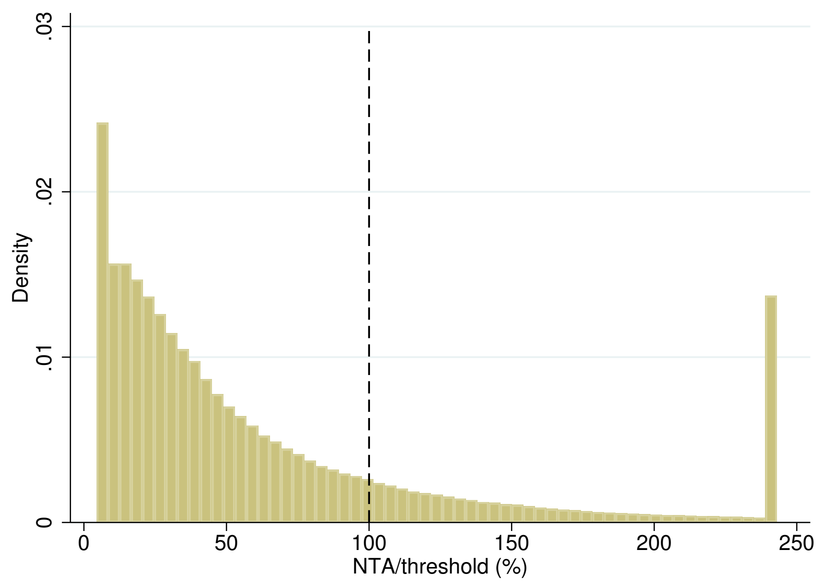
the process of collection and unposted debits, balances due from depository institutions in the US, and balances due from banks in foreign countries and foreign central banks.

[16]Specifically, we compute reserves as currency and coin plus balances due from Federal Reserve Banks.

ties of depositors or the bank's incentive to respond to market conditions. Additionally, Figure 2-6 plots the pooled distribution of banks by the ratio of NTA to the low reserve tranche upper threshold. The fact that there is no visible bunching around the threshold suggests that banks do not manipulate their volume of NTA to affect their RR rates. We also implement the density estimation and discontinuity test proposed in Cattaneo, Jansson and Ma (2019) and do not find statistically significant evidence of assignment manipulation at the 5% significance level.

Figure 2-6: Distribution of NTA.

This figure plots the pooled distribution of banks by the ratio of NTA to the low reserve tranche upper threshold. The sample is winsorized at 5%.



To further assess the identification assumption, we show that the treatment and control samples are balanced with respect to lagged covariates. In particular, Online Appendix Section 2.F shows binned scatter plots for the logarithm of assets, capital ratio, non-interest expenses to assets ratio, return on assets, and sensitivity to market risk. It also shows the predicted values from estimating linear regressions for the subsample of observations within a 30% deviation within the threshold over the whole sample period. The coefficient δ from estimating the regression in equation (2.1) is insignificant for all of these characteristics except the sensitivity to market risk.

2.4.4 Results

Table 2.2 shows the results from estimating equation (2.1) within a bandwidth of 30% around the low reserve tranche upper threshold using the reserves to NTA ratio as the dependent variable. Column (1) reports the coefficient on the treatment indicator when estimating the regression on the full sample period without the controls and time fixed effects, column (2) includes the controls and fixed effects, and columns (3) and (4) report the corresponding results from on a subsample restricting to years before 2008. The estimated effect is positive and significant, indicating that a 1% increase in RR rates is associated with a 1.6 basis point increase in the reserves to NTA ratio. This is consistent with Figure 2-1a, which shows a corresponding binned scatterplot corresponding to the estimation in column (1).

By contrast, Table 2.3 and Figure 2-10 show that the RR is not significantly associated with non-performing loans.

2.5 The effect of the liquidity coverage ratio on banks

This section empirically examines the effects of the liquidity coverage ratio (LCR) on the extent to which banks take risk with their illiquid assets. We implement a difference-in-differences design exploiting the introduction of the LCR for a subset of bank holding companies (BHCs) in 2015. We find that the LCR was associated with increased liquidity, but we do not find that it was associated with significant variation in non-performing loans. Finally, we do not find that the LCR was associated with a significant change in credit default swap (CDS) jumps during the COVID-19 crisis compared to the global financial crisis.

2.5.1 Setting: liquidity coverage ratio

The LCR was introduced at Basel III in December 2010 in response to the observed liquidity stress during the 2008 financial crisis. The LCR requires BHCs to hold a certain percentage of high quality liquid assets (HQLA) relative to net cash outflows over a 30-day stress period. The following assets contribute to HQLA: excess reserves, Treasury securities, government agency debt and MBS, and sovereign debt with zero risk-weights contribute without any discount, government-sponsored agency (GSE) debt, GSE MBS, and sovereign debt with risk-weights less than 20% contribute at a 15% discount, and investment-grade (IG) debt by non-financial corporations, IG municipal debt, and equities contribute at a 50% discount. Net cash outflows associated with a bank's liabilities are computed based on their maturity, stability, whether they are insured, whether they are foreign or domestic, and whether they are retail or wholesale. See Hong, Huang and Wu (2014) or Roberts, Sarkar and Shachar (2018) for more details about the computation of high quality liquid assets and net cash outflows.

The US implementation of the LCR was proposed in October 2013, finalized in September 2014, and phased-in from January 2015 to January 2017. It applies to BHCs with total assets exceeding $250 billion or on-balance sheet foreign exposure exceeding $10 billion. A modified LCR of 70% applies to BHCs with assets between $50 billion and $250 billion.

2.5.2 Data: FR Y-9C

This exercise uses data from quarterly FR Y-9C filings by BHCs. We construct a balanced sample for the period from 2010Q1 until 2018Q4.

Table 2.4 presents summary statistics for various bank characteristics, including an indicator for whether a bank is subject to either the 70% LCR or the 100% LCR as well as characteristics corresponding to the CAMELS risk rating system. The CAMELS characteristics are similar to the ones described in Section 2.4.2 except that liquidity is represented by the ratio of HQLA to total assets to match the LCR. HQLA is computed using the LCR weights for the different asset categories. Similar to Roberts, Sarkar and Shachar (2018), HQLA is approximated using the FR Y-9C data as follows: cash assets, federal funds sold, treasury securities, and agency debt and MBS contribute without discount, GSE debt and MBS contribute at a 15% discount, and municipal securities and equity securities contribute at a 50% discount. Non-categorical variables are winsorized at 1% in each year.

2.5.3 Specification: difference-in-differences

We estimate the following difference-in-differences specification:

$$Y_{it} = \beta LCR_i \times post2013Q3_t + \gamma controls_{it-1} + \psi_i + \phi_t + \epsilon_{it} \tag{2.2}$$

where Y_{it} is one of the outcome variables (the liquid assets ratio as a measure of liquidity or the non-performing loans ratio as a measure of risk-taking) for bank i in quarter t, LCR_i is an indicator for whether a bank was subject to either the 100% or 70% LCR at the implementation date of 2015Q1, $post2013Q3_t$ is an indicator for quarters greater than or equal to the proposal date of 2013Q3, $controls_{it-1}$ is a set of lagged control variables,

ψ_i represent bank fixed effects, and ϕ_t represent time fixed effects. We consider the LCR to be effective as of the proposal date to account for the possibility that BHCs would attempt to smoothly transition to compliance with the LCR by its implementation date. The set of controls includes the logarithm of total assets and proxies for indicators from the CAMELS risk rating system, as described in Section 2.5.2. The controls are lagged by one quarter to mitigate endogeneity, and we exclude the dependent variable from the controls. T-statistics computed using bank-clustered standard errors are reported in parentheses.

The difference-in-differences methodology mitigates potential confounding due to aggregate trends or systematic differences between treated and untreated banks. The coefficient β represents the degree to which banks subject to the LCR changed from before to after the introduction of the LCR relative to other banks. The identification assumption is that the treated and untreated groups would have experienced parallel trends in the absence of the policy intervention. To assess the relative trend between the two groups before and after the introduction of the LCR in 2015, we also estimate a version of this regression with yearly treatment effects

$$Y_{it} = \sum_{t \neq 2013Q3} \beta_t LCR_i \times \phi_t + \gamma controls_{it-1} + \psi_i + \phi_t + \epsilon_{it} \tag{2.3}$$

where LCR_i is the indicator for whether a bank was subject to the 100% LCR or the 70% LCR, the coefficients β_t represent the differential trend of the treatment group compared to the control group over the sample period, and the other variables are the same as above.

Figure 2-11 presents the coefficients β_t from estimating equation (2.3) for the set of dependent variables. The results for the HQLA ratio are generally consistent with the parallel trends assumption, as the yearly effects associated with the relative trend of the treatment group are generally evenly distributed around zero in the period before the introduction of the stress tests. The results for the non-performing loans ratio are consistent with the parallel trends assumption starting in 2012Q1, although there are fluctuations in the relative trend from 2010Q1 to 2012Q1.

To further address endogeneity concerns, Table 2.5 compares the treatment and control groups with respect to the control variables in the period before the introduction of the LCR. It shows the mean for each variable and group in the period preceding the LCR. It also shows the t-statistic on the coefficient η from estimating the regression

$$Y_{it} = \eta LCR_i + \phi_t + \epsilon_{it}$$

where Y_{it} represents one of the control variables from equation (2.2). The two groups exhibit a statistically significant difference in total assets, which is unsurprising since eligibility for the LCR depends on a threshold in total assets. The only other characteristic for which the two groups exhibit a statistically significant difference is the capital ratio. The similarity between the two groups with respect to the majority of characteristics reduces the concern that systematic differences between the two groups that are correlated with the timing of the LCR could confound the results.

2.5.4 Results

Table 2.6 presents the coefficients from estimating equation (2.2) using an indicator for banks subject to the 100% LCR, an indicator for banks subject to the 70% LCR on a subsample omitting banks that were subject to the 100% LCR, and an indicator for banks subject to either the 100% LCR or the 70% LCR. The coefficient for banks subject to either version of the LCR is positive and significant, indicating that the LCR was associated with a relative increase in the liquid assets ratio of around 3.4%. The results for the 100% LCR and the 70% LCR are similar.

By contrast, Table 2.7 indicates that the LCR was not significantly associated with risk-taking.

2.5.5 CDS spreads

This section considers the effect of the LCR on overall bank risk as measured by increases in credit default swap (CDS) spreads during crises. A CDS is like an insurance contract in which the purchaser pays a premium, which is called the CDS spread, in return for a payoff conditional on a credit event, such as default, of a reference entity. CDS spreads are therefore positively associated with the credit risk of the reference entity (Augustin et al. (2014), Sarin and Summers (2016)).

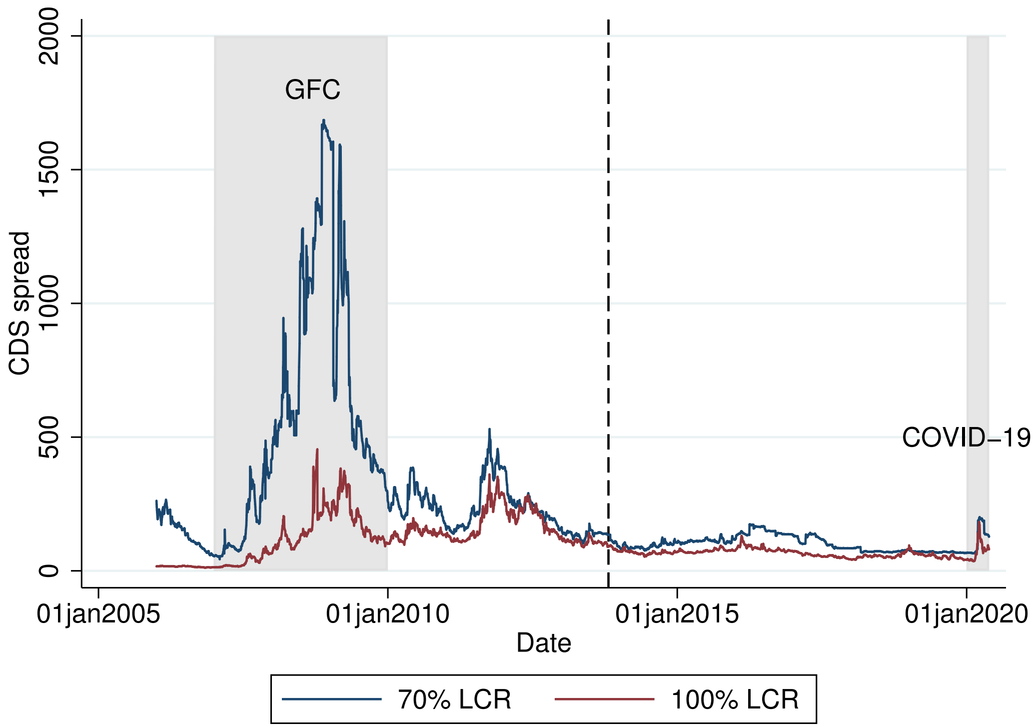
Figure 2-7 shows the mean CDS spread for a balanced subsample of BHCs for which we could obtain CDS spread data from Bloomberg and Refinitiv's Datastream database. The figure compares the mean CDS spread for 6 BHCs that were subject to the 100% LCR and 2 BHCs that were subject to the 70% LCR.[17] The figure indicates that CDS spreads for both groups of banks exhibited a larger increase during the global financial crisis, which occurred before the introduction of the LCR, compared to the COVID-19 crisis,

[17] Note that CDS data is not available for this sample period for any banks that are not subject to either the 100% LCR or the 70% LCR.

which occurred after the introduction of the LCR. Figure 2-8 and Figure 2-9 additionally show how the distribution of the CDS jumps during the two crises changed for the two groups of BHCs.

Figure 2-7: CDS spreads

This figure shows the mean CDS spread for a balanced subsample of BHCs for which we could obtain CDS spread data from Bloomberg and Refinitiv's Datastream database. The figure compares the mean CDS spread for 6 BHCs that were subject to the 100% LCR and 2 BHCs that were subject to the 70% LCR.



There are many factors that could have affected the relative magnitudes of CDS spread responses between these two crises, including the nature of the shock, the magnitude of the shock, policy responses, and ex-ante regulations. To better isolate the effect of liquidity regulations, we implement a difference-in-differences design by comparing the two groups, which have differential exposure to the LCR, with respect to the change in CDS spread jumps between the two crises. In particular, we estimate the specification

$$Y_{it} = Post_t + \beta LCR_i \times Post_t + \psi_i + \epsilon_{it}$$

where Y_{it} is the difference between the maximum and the minimum of the CDS spread in period t, LCR_i is an indicator for whether a bank was subject to the 100% LCR as of the implementation date of 2015Q1, $Post_t$ is an indicator that equals 1 for the COVID-19

Figure 2-8: CDS spread jumps (density)

This figure shows the density of CDS spread jumps for BHCs subject to the 100% LCR and BHCs subject to the 70% LCR for the global financial crisis and the COVID-19 crisis.

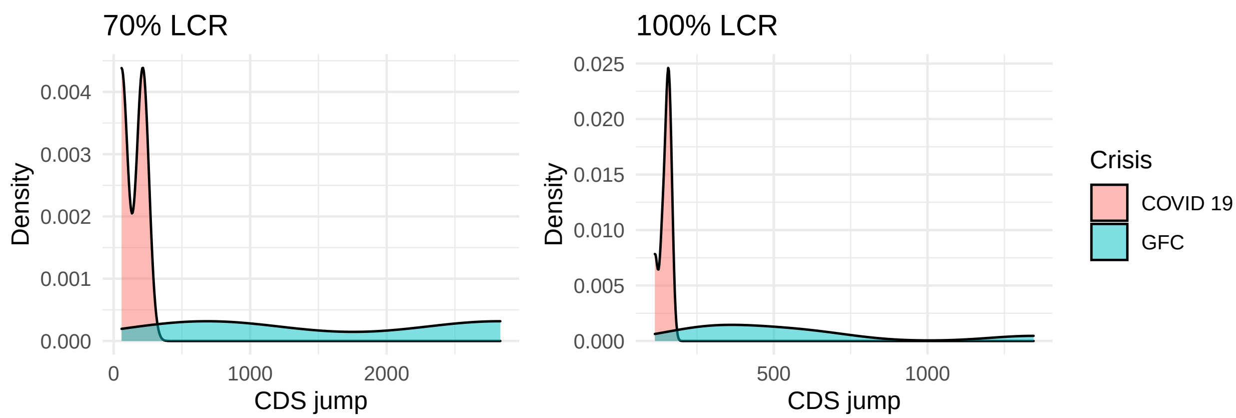
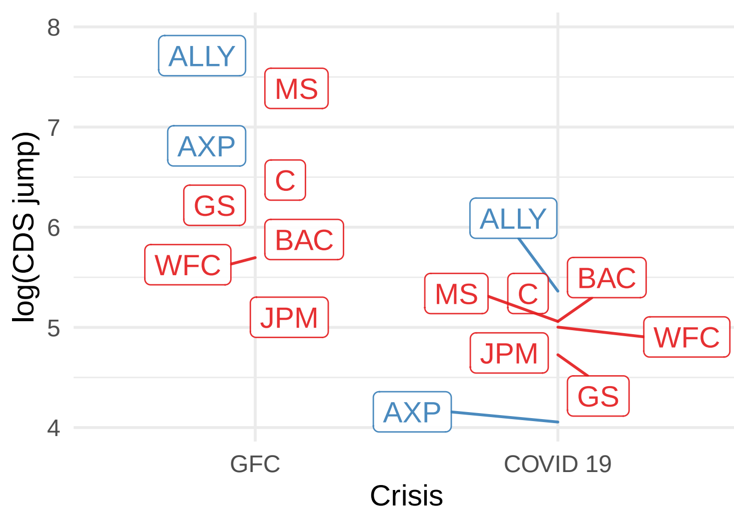


Figure 2-9: CDS spread jumps (by bank)

This figure shows the CDS spread jumps (in log scale, for visibility) for BHCs subject to the 100% LCR (red) and banks subject to the 70% LCR (blue) for the global financial crisis and the COVID-19 crisis. The BHCs in our sample are identified by stock ticker.



crisis (corresponding to dates in 2020) and 0 for the global financial crisis (corresponding to dates in 2007-2009), and ψ_i represent bank fixed effects. T-statistics with standard errors are clustered by bank.

Table 2.8 presents the results. The LCR is not significantly associated with changes in CDS spreads during crises.

2.6 Conclusion

This paper introduces a model to illustrate channels by which liquidity requirements can either increase or decrease the incentive for banks to take risk with their illiquid assets, such as loans. On the one hand, improving resilience to liquidity stress increases the expected losses from risky lending. On the other hand, holding more liquid assets decreases the need for banks to liquidate their long-term assets to generate funds in times of liquidity stress, which can in turn increase the incentive to invest in risky assets with lower liquidation values. The latter effect is more likely to dominate when banks have a high capacity to respond to liquidity stress, such as when the price for long-term debt is high. By illustrating channels by liquidity risk interacts with credit risk, our analysis sheds light on the potential side effects of liquidity regulation on financial stability.

This paper also empirically assesses how the reserve requirement (RR) and the liquidity coverage ratio (LCR) have affected liquidity and risk-taking for US banks. We show using a regression discontinuity design that the RR did not appear to significantly affect bank risk-taking as measured by the non-performing loans ratio. We also show using a difference-in-differences methodology that the LCR also did not significantly affect the non-performing loans ratio or jumps in CDS spreads during crises.

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Appendices for Chapter 2

2.A Extensions

This section describes parametric restrictions under which the main theoretical results of the model are preserved in an extension that generalizes the return of the depositors who withdraw in period 1, the return on liquid assets in period 1, the return on liquid assets in period 2, and the fraction of the bank's assets that depositors can recover if the bank defaults. In the generalized model, denote the return of depositors who withdraw in period t by $R_{d,t}$, the return on liquid assets in period t by $R_{l,t}$, the recovery rate as $w \in [0,1]$. Note that in the baseline model we have $R_{d,1} = 1$, $R_{l,1} = 1$, $R_{l,2} = R_{d,2} = R_{st}$, and $w = 1$.

We maintain analogous parametric restrictions as in the original model (see Section 2.3.1): $qR_{l,1} < \delta p$, $p < R_{l,1}$, and $\mu > \max\left\{\frac{1-q}{1-\frac{R_l q}{p}} R_{l,2}, \frac{1}{2}\frac{1-q}{1-\frac{R_l q}{\delta p}} R_{l,2}\right\}$.[18] We also introduce the following additional restrictions: $R_{l,1} \geqslant R_{d,1} \geqslant lR_{l,1}$, $R_{l,2} \geqslant R_{d,2} \geqslant lR_{l,2}$, and $\frac{R_{d,2}}{R_{l,2}} \geqslant \frac{R_{d,1}}{R_{l,1}}$. The following elaborates on the intuition behind why these additional restrictions are important for maintaining the main results of the model.[19]

Proposition 2.6. *The bank never wants to hold more than the required level of liquid assets.*

Proof. See Appendix. ∎

The intuition for this result is the same as in Proposition 2.1 and does not involve the additional restrictions.

Proposition 2.7. *Holding liquid assets reduces the probability that a liquidity shock causes the bank to default.*

[18]Note that the last two assumptions also imply $\mu > R_{l,2}$.

[19]Many of these assumptions are also intuitively natural: $R_{l,t} \geqslant R_{d,t}$ for $t = 1,2$ could be interpreted to represent the bank's superior expertise with respect to investing in liquid assets compared to depositors, and $R_{d,t} \geqslant lR_{l,t}$ for $t = 1,2$ could be interpreted to represent the idea that banks are sufficiently invested in long-term investments such as loans that they require a positive return on these assets to avoid default.

Proof. See Appendix. ▪

This result uses the assumptions $R_{l,1} \geqslant R_{d,1}$ and $R_{l,2} \geqslant R_{d,2}$. These assumptions ensure that the bank cannot default from liquidity stress if it maintains enough liquid assets to pay all the early depositors. In particular, $R_{l,1} \geqslant R_{d,1}$ implies that the bank does not need to maintain a large fraction of liquid assets in order to meet the liquidity demand in period 1, and $R_{l,2} \geqslant R_{d,2}$ implies that the return the bank pays to the late depositors is not too large compared to its own return on assets.

Proposition 2.8. *The bank's asset choice can be summarized by a threshold μ^* such that it invests in safe assets if $\mu > \mu^*$ and invests in risky assets if $\mu < \mu^*$. Moreover, there is a threshold $l^*(p)$ such that μ^* is decreasing in l for $l < l^*(p)$ and μ^* is increasing in l for $l > l^*(p)$.*

Proof. See Appendix. ▪

This result uses the assumptions $R_{d,1} \geqslant lR_{l,1}$ and $R_{d,2} \geqslant lR_{l,2}$, which ensure that the bank pays a net cost on the liquid part of its portfolio (i.e. liquid assets and deposits). This in turn provides an incentive to invest the remaining illiquid assets in risky assets since they have a higher net return in period 2 due to limited liability. The result that μ^* is increasing for $l > l^*(p)$ also uses the assumption $\frac{R_{d,2}}{R_{l,2}} \geqslant \frac{R_{d,1}}{R_{l,1}}$. In particular, increasing liquid assets increases the incentive to take risk by mitigating the disadvantage of risky assets associated with having a lower price on the debt market in period 1. However, it also mitigates the advantage of risky assets associated having a higher net return in period 2 due to limited liability. This assumption ensures that the period 2 advantage of risky assets is large compared to the period 1 disadvantage, which in turn implies that the proportional effect from increasing liquidity requirements is smaller.

Proposition 2.9. *Increasing the price for long-term debt increases the range for l on which risk-taking increases in the tightness of liquidity requirements: $\frac{dl^*(p)}{dp} < 0$.*

Proof. The proof is closely analogous to the proof of Proposition 2.4. ▪

The intuition for this result is the same as in Proposition 2.4 and does not involve the additional restrictions.

Proposition 2.10. *The optimal level of liquidity that minimizes the government's expenditure, l^G, is at least as great as the level $l^*(p)$ that minimizes the fraction of banks that invest in risky assets.*

Proof. See Appendix. ▪

The intuition for this result is the same as in Proposition 2.5 and does not involve the additional restrictions.

2.B Omitted Proofs

2.B.1 Proof of Proposition 2.1

Proposition 2.1. *If $q < \delta p$ and $\mu > \max\left\{R_{st}, \frac{1-q}{1-\frac{q}{p}}R_{st}, \frac{1}{2}\frac{1-q}{1-\frac{q}{\delta p}}R_{st}\right\}$, then the bank never wants to hold more than the required level of liquid assets.*

Suppose the bank invests in risky assets. If the bank defaults in the liquidity stress state, then the expected value is

$$V_r^d = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{st} - R_{st}] > 0$$

Note that this is positive since $\mu > R_{st}$, which in turn follows from assuming $p < 1$ and $\mu > \frac{1-q}{1-\frac{q}{p}}R_{st}$. Then we have

$$\frac{dV_r^d}{dl} = \frac{1}{2}(1-q)[-2\mu + R_{st}] < 0$$

since $\mu > R_{st}$. If the bank can remain solvent in the face of liquidity stress, then the expected value is

$$\begin{aligned} V_r^s = &\frac{1}{2}(1-q)\left[2\mu(1-l) + lR_{st} - R_{st}\right] \\ &+ \frac{1}{2}q\left[2\mu\left(1 - l - \frac{\lambda - l}{\delta p}\mathbf{1}_{\lambda > l}\right) + (l-\lambda)R_{st}\mathbf{1}_{l>\lambda} - (1-\lambda)R_{st}\right] \end{aligned}$$

Note that

$$\begin{aligned} \frac{dV_r^s}{dl} &= \frac{1}{2}(1-q)[-2\mu + R_{st}] - q\mu + q\mu\frac{1}{\delta p}\mathbf{1}_{\lambda>l} + \frac{1}{2}qR_{st}\mathbf{1}_{l>\lambda} \\ &= \left[-\mu\left(1 - \frac{q}{\delta p}\right) + \frac{1}{2}(1-q)R_{st}\right]\mathbf{1}_{\lambda>l} \\ &\quad + \frac{1}{2}[-2\mu + R_{st}]\mathbf{1}_{l>\lambda} < 0 \end{aligned}$$

since $q < \delta p$ and $\mu > \frac{1}{2}\frac{1-q}{1-\frac{q}{\delta p}}R_{st}$.

Suppose the bank invests in safe assets. If liquidity stress causes the bank to default in either period, then the expected value is

$$V_s^d = (1-q)[\mu(1-l) + lR_{st} - R_{st}] > 0$$

Note that

$$\frac{dV_s^d}{dl} = (1-q)[-\mu + R_{st}] < 0$$

since $\mu > R_{st}$. If the bank can remain solvent in the face of liquidity stress, then the expected value is

$$\begin{aligned} V_s^s = &(1-q)[\mu(1-l) + lR_{st} - R_{st}] \\ &+ q\left[\mu\left(1 - l - \frac{\lambda - l}{p}\mathbf{1}_{\lambda > l}\right) + (l-\lambda)R_{st}\mathbf{1}_{l>\lambda} - (1-\lambda)R_{st}\right] \end{aligned}$$

Note that

$$\begin{aligned} \frac{dV_s^s}{dl} &= (1-q)[-\mu + R_{st}] - q\mu + q\mu\frac{1}{p}\mathbf{1}_{\lambda > l} + qR_{st}\mathbf{1}_{l>\lambda} \\ &= \left[-\mu\left(1 - \frac{q}{p}\right) + (1-q)R_{st}\right]\mathbf{1}_{\lambda > l} \\ &\quad + [-\mu + R_{st}]\mathbf{1}_{l>\lambda} < 0 \end{aligned}$$

since $q < \delta p$ (which also implies $q < \delta p < p$) and $\mu > \frac{1-q}{1-\frac{q}{p}} R_{st}$.

2.B.2 Proof of Proposition 2.2

Proposition 2.2. *If $p < 1$, then holding liquid assets increases the probability that the bank does not default due to liquidity stress.*

First, we derive conditions under which the bank defaults in period 1, which can also be interpreted as a run:

- If the bank invests in risky assets, it experiences a run if $l < \zeta_r \equiv \frac{\lambda - \delta p}{1-\delta p}$
- If the bank invests in safe assets, it experiences a run if $l < \zeta_s \equiv \frac{\lambda - p}{1-p}$

Clearly, increasing l always reduces the probability of default in period 1.

Second, we derive conditions under which the bank can repay the early depositors but then defaults in period 2. If the bank invests in risky assets and the assets generate a positive return, then the bank's payoff in the liquidity shock state is

$$2\mu\left(1-l-\frac{\lambda-l}{\delta p}\mathbf{1}_{\lambda>l}\right)+(l-\lambda)\mathbf{1}_{l>\lambda}R_{st}-(1-\lambda)R_{st}$$

The threshold for μ at which the bank defaults is

$$\gamma_r=\frac{R_{st}(1-\lambda-(l-\lambda)\mathbf{1}_{l>\lambda})}{2\left(1-l-\frac{\lambda-l}{\delta p}\mathbf{1}_{\lambda>l}\right)}$$

Similarly, the threshold corresponding to the case where the bank invests in safe assets is

$$\gamma_s=\frac{R_{st}(1-\lambda-(l-\lambda)\mathbf{1}_{l>\lambda})}{1-l-\frac{\lambda-l}{p}\mathbf{1}_{\lambda>l}}$$

Whether or not liquidity stress causes the bank to default is inversely related to γ_i. If $l>\lambda$, then $\frac{d\gamma_i}{dl}=0$ for $i=r,s$. If $\lambda\geqslant l$, then the assumption $p<1$ (which also implies $\delta p<p<1$) implies

$$\frac{d\gamma_r}{dl}=-\frac{R_{st}(1-\lambda)}{2\left(1-l-\frac{\lambda-l}{\delta p}\right)^2}\left(\frac{1}{\delta p}-1\right)<0$$
$$\frac{d\gamma_s}{dl}=-\frac{R_{st}(1-\lambda)}{\left(1-l-\frac{\lambda-l}{p}\right)^2}\left(\frac{1}{p}-1\right)<0$$

2.B.3 Proof of Lemma 2.1

Lemma 2.1. *The bank's asset choice can be summarized by a threshold μ^* such that it invests in safe assets if $\mu>\mu^*$ and invests in risky assets if $\mu<\mu^*$.*

Determining conditions under which the bank experiences a run or defaults

The proof uses the default thresholds ζ_i and γ_i defined in the proof of Proposition 2.2.

The rest of the proof considers cases corresponding to the solvency of the bank after investing in either type of asset. In each case, we derive a threshold in the expected return μ^* such that it invests in safe assets if $\mu>\mu^*$ and invests in risky assets if $\mu<\mu^*$. In enumerating the cases, note that $\zeta_s<\zeta_r$, which illustrates that if liquidity stress causes a invested in safe assets to default in period 1 then it also causes a bank invested in risky assets to default in period 1. Note also that if $l > \lambda$ then $l > \zeta_i$ and $\mu > \gamma_i$ for $i = r, s$,[20] which illustrates that a bank cannot default from liquidity stress if it can pay all the early depositors using its liquid assets. The cases are therefore as follows.

Case 1: liquidity stress causes the bank to default if it invests in either type of asset
This case occurs when liquidity stress causes the bank to default in period 1 with either type of asset ($l < \zeta_s, \zeta_r$), liquidity stress causes the bank to default in period 1 if it invests in risky assets and to default in period 2 if it invests in safe assets ($\zeta_s < l < \zeta_r$ and $\mu < \gamma_s$), or liquidity stress causes a bank to default in period 2 if it invests in either type of asset ($\zeta_s, \zeta_r < l$ and $\mu < \gamma_s, \gamma_r$).

The expected value from investing in either type of asset can be written as

$$V_r^d = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{st} - R_{st}]$$
$$V_s^d = (1-q)[\mu(1-l) + lR_{st} - R_{st}]$$

Note that the two types of assets generate the same expected return but risky assets have a lower expected cost due to limited liability.

Define the relative value of risky assets by $\Delta V^{d,d} \equiv V_r^d - V_s^d$. Then

$$\Delta V = \frac{1}{2}(1-q)[R_{st} - lR_{st}] > 0$$

The fact that $\Delta V^{d,d}$ is positive in case 1 implies that the bank prefers risky assets for all values of μ, which implies $\mu^* = \infty$. The intuition is that risky assets achieve a higher net return in normal times since they generate the same expected return but have a lower cost due to limited liability.

Case 2: liquidity stress causes the bank to default only if it invests in safe assets
This case occurs when $\zeta_s, \zeta_r < l$ and $\gamma_r < \mu < \gamma_s$.

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$V_r^s = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{st} - R_{st}] + \frac{1}{2}q\left[2\mu\left(1 - l - \frac{\lambda - l}{\delta p}\right) - (1-\lambda)R_{st}\right]$$

[20] In particular, note that the baseline assumptions in Section 2.3.1 imply $\mu > R_{st}$, and it's straightforward to show that in this case we have $\gamma_r = \frac{R_{st}}{2}$ and $\gamma_s = R_{st}$.

$$V_s^d = (1-q)[\mu(1-l) + lR_{st} - R_{st}]$$
$$\Delta V^{s,d} = \frac{1}{2}(1-q)[R_{st} - lR_{st}] + \frac{1}{2}q\left[2\mu\left(1-l-\frac{\lambda-l}{\delta p}\right) - (1-\lambda)R_{st}\right] > 0$$

The fact that $\Delta V^{s,d}$ is positive in case 2 implies that the bank prefers risky assets for all values of μ, which implies $\mu^* = \infty$. This is because, as shown in case 1, risky assets always outperform in normal times, and in case 2 they also outperform in times of liquidity stress since only risk assets can generate a high enough return to potentially repay the late depositors.

Case 3: liquidity stress causes the bank to default only if it invests in risky assets
This case occurs when liquidity stress does not cause the bank to default if it invests in safe assets and but it does cause the bank to default if it invests in risky assets either in period 1 ($\zeta_s < l < \zeta_r$ and $\gamma_s < \mu$) or in period 2 ($\zeta_s, \zeta_r < l$ and $\gamma_s < \mu < \gamma_r$).

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$V_r^d = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{st} - R_{st}]$$
$$V_s^s = (1-q)[\mu(1-l) + lR_{st} - R_{st}] + q\left[\mu\left(1-l-\frac{\lambda-l}{p}\right) - (1-\lambda)R_{st}\right]$$
$$\Delta V^{d,s} = \frac{1}{2}(1-q)[R_{st} - lR_{st}] + q(1-\lambda)R_{st} - \mu q\left(1-l-\frac{\lambda-l}{p}\right)$$

Note that $\Delta V^{d,s}$ is decreasing in μ, which reflects the fact that the bank can only acquire any fraction of the return in the liquidity stress state if it invests in safe assets. This determines the threshold μ^* for case 3 as

$$\mu^* = \frac{\frac{1}{2}(1-q)[R_{st} - lR_{st}] + q(1-\lambda)R_{st}}{q\left(1-l-\frac{\lambda-l}{p}\right)}$$

Case 4: the bank can remain solvent in the face of liquidity stress with either type of asset by selling on long-term debt markets
This case occurs when $\zeta_s, \zeta_r < l < \lambda$ and $\gamma_r, \gamma_s < \mu$. Note that the condition that the bank must sell on long-term debt markets to respond to liquidity stress implies $\lambda > l$.

The expected value from investing in either type of asset, the relative value of risky assets, and the propensity to take risk can be written as

$$\begin{aligned}
V_r^s &= \frac{1}{2}(1-q)[2\mu(1-l)+lR_{st}-R_{st}] + \frac{1}{2}q\left[2\mu\left(1-l-\frac{\lambda-l}{\delta p}\right)-(1-\lambda)R_{st}\right] \\
V_s^s &= (1-q)[\mu(1-l)+lR_{st}-R_{st}] + q\left[\mu\left(1-l-\frac{\lambda-l}{p}\right)-(1-\lambda)R_{st}\right] \\
\Delta V^{s,s} &= \frac{1}{2}R_{st}\left[(1-q)(1-l)+q(1-\lambda)\right] - \mu q\frac{(1-\delta)(\lambda-l)}{p\delta} \\
\mu^* &= \frac{\frac{1}{2}R_{st}\left[(1-q)(1-l)+q(1-\lambda)\right]}{\frac{q(1-\delta)(\lambda-l)}{p\delta}}
\end{aligned}$$

Case 5: the bank can respond to liquidity stress without selling on long-term debt markets

This case occurs when the bank has excess liquid assets or $\lambda < l$.

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$\begin{aligned}
V_r^e &= \frac{1}{2}(1-q)[2\mu(1-l)+lR_{st}-R_{st}] + \frac{1}{2}q[2\mu(1-l)+(l-\lambda)R_{st}-(1-\lambda)R_{st}] \\
V_s^e &= (1-q)[\mu(1-l)+lR_{st}-R_{st}] + q[\mu(1-l)+(l-\lambda)R_{st}-(1-\lambda)R_{st}] \\
\Delta V^{e,e} &= \frac{1}{2}(1-q)[R_{st}-lR_{st}] + \frac{1}{2}q[(1-\lambda)R_{st}-(l-\lambda)R_{st}] > 0
\end{aligned}$$

The fact that $\Delta V^{e,e}$ is positive in case 5 implies that the bank prefers risky assets for all values of μ, which implies $\mu^* = \infty$. This is because risky assets outperform in both normal times and times of liquidity stress since they generate the same expected return but have a lower cost due to limited liability. Since the bank does not have to sell on the long-term debt markets, the disadvantage of risky assets in the liquidity stress state due to having a lower price is completely avoided.

2.B.4 Proof of Proposition 2.3

Proposition 2.3. *There exists a threshold $l^*(p)$ such that μ^* is decreasing in l for $l < l^*(p)$ and μ^* is increasing in l for $l > l^*(p)$. The threshold $l^*(p)$ corresponds to the minimal level of liquidity at which the bank can survive liquidity stress if it invests in risky assets.*

Consider the effect of liquidity requirements l on the propensity to take risk μ^* when

μ^* occurs in each of cases introduced in the proof of Lemma 2.1. Note that the cases depend on the thresholds ζ_i and γ_i, which are defined in the proof of Proposition 2.2.

Case 1: liquidity stress causes the bank to default if it invests in either type of asset ($l < \zeta_s, \zeta_r$, or $\zeta_s < l < \zeta_r$ and $\mu^* < \gamma_s$, or $\zeta_s, \zeta_r < l$ and $\mu^* < \gamma_s, \gamma_r$)

In this case, the bank always prefers risky assets and $\mu^* = \infty$.

Case 2: liquidity stress causes the bank to default only if it invests in safe assets ($\zeta_s, \zeta_r < l$ and $\gamma_r < \mu^* < \gamma_s$)

Note that case 2 requires $\gamma_r < \mu^* < \gamma_s$, but the proof of Lemma 2.1 shows that $\mu^* = \infty$ in case 2. Therefore μ^* never occurs in case 2.

Case 3: liquidity stress causes the bank to default only if it invests in risky assets ($\zeta_s < l < \zeta_r$ and $\gamma_s < \mu^*$, or $\zeta_s, \zeta_r < l$ and $\gamma_s < \mu^* < \gamma_r$)

Using the assumption that $p < 1$, in this case the effect of tightening liquidity requirements on the propensity to take risk is negative:

$$\frac{d\mu^*}{dl} = -\frac{\frac{1}{2}(1-q)R_{st}\left(1-l-\frac{\lambda-l}{p}\right)+\left(\frac{1}{p}-1\right)\left[\frac{1}{2}(1-q)[R_{st}-lR_{st}]+q(1-\lambda)R_{st}\right]}{q\left(1-l-\frac{\lambda-l}{p}\right)^2} < 0$$

Case 4: the bank can remain solvent in the face of liquidity stress with either type of asset by selling on long-term debt markets ($\zeta_s, \zeta_r < l < \lambda$ and $\gamma_r, \gamma_s < \mu^*$)

In this case, the effect of tightening liquidity requirements on the propensity to take risk is positive:

$$\frac{d\mu^*}{dl} = \frac{\frac{1}{2}R_{st}(1-\lambda)}{\frac{q(1-\delta)(\lambda-l)^2}{p\delta}} > 0$$

Case 5: the bank can respond to liquidity stress without selling on long-term debt markets ($\lambda < l$)

In this case, the bank always prefers risky assets and $\mu^* = \infty$.

Summary

If l is low enough such that case 1 occurs, then $\mu^* = \infty$. By Proposition 2.2, the probability that liquidity stress causes the bank to default decreases in l. Thus, as l increases, μ^* eventually occurs in case 3, in which case $\frac{d\mu^*}{dl} < 0$. As l increases further, μ^* eventually occurs in case 4, in which case $\frac{d\mu^*}{dl} > 0$. As l increases further such that case 5 occurs, then $\mu^* = \infty$. Therefore $l^*(p)$ is the threshold between case 3 and case 4, which can also be written as the solution to $\mu^*(l;p) = \gamma_r(l;p)$.

2.B.5 Proof of Proposition 2.4

Proposition 2.4. *Increasing the price for long-term debt increases the range for l on which risk-taking increases in the tightness of liquidity requirements: $\frac{dl^*(p)}{dp} < 0$.*

Recall from the proof of Proposition 2.3 that $l^*(p)$ is the solution to $\mu^*(l,p) = \gamma_r(l,p)$. Let

$$F(l,p) \equiv \mu^*(l,p) - \gamma_r(l,p)$$

Consider μ^* as computed in case 4. By Proposition 2.3 we have $\frac{d\mu^*}{dl} > 0$, and by Proposition 2.2 we have $\frac{d\gamma_r}{dl} < 0$, which together imply $\frac{dF}{dl} > 0$. It is also straightforward to check that $\frac{d\mu^*}{dp} > 0$ and $\frac{d\gamma_r}{dp} < 0$ and therefore $\frac{dF}{dp} > 0$. By the implicit function theorem, we have

$$\frac{dl^*(p)}{dp} = -\frac{dF/dp}{dF/dl} < 0$$

2.B.6 Proof of Proposition 2.5

Proposition 2.5. *The optimal level of liquidity that minimizes the government's expenditure, denoted by l^G, is at least as great as the level $l^*(p)$ that minimizes the fraction of banks that invest in risky assets.*

We first compute the government's expected insurance payout G assuming there is an individual bank with expected return μ. Note that the total payout for depositors is given by $T = (1 - \lambda q)R_{st} + q\lambda$. If the expected payout from banks is equal to B, then the government must pay the difference $G = T - B$. We compute government expenditure G for a set of cases depending on l and μ that correspond to the ones introduced in the proof of Lemma 2.1. Note that the cases depend on the thresholds ζ_i and γ_i, which are defined in the proof of Proposition 2.2.

Case 1: liquidity stress causes the bank to default if it invests in either type of asset
There are three subcases depending on whether liquidity stress causes a bank invested in either type of asset to default in period 1 or period 2. In the subcases below, the bank always prefers risky assets. Therefore, it suffices to compute the government expenditure

assuming the bank chooses risky assets.

Case 1A: liquidity stress causes the bank to default in period 1 with either type of asset ($l < \zeta_s, \zeta_r$)

In this case, for a bank invested in risky assets the expected repayment to depositors is

$$B_{D1} = \frac{1}{2}(1-q)R_{st} + q[l + \delta p(1-l)]$$

Then denote the government's expenditure in this case by

$$G_{D1} = T - B_{D1} = (1-\lambda q)R_{st} + q\lambda - \left[\frac{1}{2}(1-q)R_{st} + q[l + \delta p(1-l)]\right]$$

Case 1B: liquidity stress causes the bank to default in period 1 if it invests in risky assets and to default in period 2 if it invests in safe assets ($\zeta_s < l < \zeta_r$ and $\mu < \gamma_s$)

In this case, the bank invests in risky assets and the associated government expenditure is G_{D1}.

Case 1C: liquidity stress causes a bank to default in period 2 if it invests in either type of asset ($\zeta_s, \zeta_r < l$ and $\mu < \gamma_s, \gamma_r$)

In this case, for a bank invested in risky assets the expected repayment to depositors is

$$B_{D2} = \frac{1}{2}(1-q)R_{st} + q\lambda + \frac{1}{2}q2\mu\left(1 - l - \frac{\lambda - l}{\delta p}\right)$$

Then denote the government's expenditure in this case by

$$G_{D2} = T - B_{D2} = (1-\lambda q)R_{st} + q\lambda - \left[\frac{1}{2}(1-q)R_{st} + q\lambda + \frac{1}{2}q2\mu\left(1 - l - \frac{\lambda - l}{\delta p}\right)\right]$$

Case 2: liquidity stress causes the bank to default only if it invests in safe assets ($\zeta_s, \zeta_r < l$ and $\gamma_r < \mu < \gamma_s$)

In this case, the bank always prefers risky assets. Therefore, it suffices to compute the government expenditure assuming the bank chooses risky assets. Assuming the bank can remain solvent in the face of liquidity stress if it invests in risky assets, the expected repayment to depositors is

$$B_{ND} = \frac{1}{2}(1-q)R_{st} + \frac{1}{2}q(1-\lambda)R_{st} + q\lambda$$

Denote the government's expenditure in this case by

$$G_{ND} = T - B_{ND} = (1-\lambda q)R_{st} + q\lambda - \left[\frac{1}{2}(1-q)R_{st} + \frac{1}{2}q(1-\lambda)R_{st} + q\lambda\right]$$

Case 3: liquidity stress causes the bank to default only if it invests in risky assets

There are two subcases depending on whether liquidity stress causes a bank invested in risky assets to default in period 1 or period 2. In either subcase, the bank prefers safe assets if $\mu > \mu^*$ and prefers risky assets if $\mu < \mu^*$, where μ^* is computed in the proof of Lemma 2.1. If the bank invests in safe assets and can remain solvent in the face of liquidity stress, then the expected repayment to depositors is equal to T and government expenditure is equal to zero. The government expenditure for a bank choosing risky assets depends on the subcase.

Case 3A: liquidity stress causes the bank to default in period 1 if it invests in risky assets ($\zeta_s < l < \zeta_r$ and $\gamma_s < \mu$)

By similar reasoning as in Case 1A, the government expenditure assuming the bank invests in risky assets is given by G_{D1}.

Case 3B: liquidity stress causes the bank to default in period 2 if it invests in risky assets ($\zeta_s, \zeta_r < l$ and $\gamma_s < \mu < \gamma_r$)

By similar reasoning as in Case 1B, the government expenditure assuming the bank invests in risky assets is given by G_{D2}.

Case 4: the bank can remain solvent in the face of liquidity stress with either type of asset by selling on long-term debt markets ($\zeta_s, \zeta_r < l < \lambda$ and $\gamma_r, \gamma_s < \mu$)

In this case, the bank prefers safe assets if $\mu > \mu^*$ and prefers risky assets if $\mu < \mu^*$. As argued in Case 3, if the bank invests in safe assets, then government expenditure is equal to zero. If the bank invests in risky assets and can remain solvent in the face of liquidity stress, then the expected government expenditure is equal to G_{ND}.

Case 5: the bank can respond to liquidity stress without selling on long-term debt markets ($\lambda < l$)

In this case, the bank always prefers risky assets. Since the bank can remain solvent in the face of liquidity stress, the expected government expenditure is equal to G_{ND}.

Aggregating over banks
Consider now that there is a mass of banks where the expected return is distributed according to the cdf F. We compute the government expenditure G averaged across the distribution of banks for a set of cases depending on l and the propensity to take risk μ^*.

- Case 1
  - Case 1A ($l < \zeta_s, \zeta_r$): $G = G_{D1}$
  - Case 1B ($\zeta_s < l < \zeta_r$ and $\mu^* < \gamma_s$): μ^* cannot occur in this case since being in Case 1 implies $\mu^* = \infty$
  - Case 1C ($\zeta_s, \zeta_r < l$ and $\mu^* < \gamma_s, \gamma_r$): μ^* cannot occur in this case since being in Case 1 implies $\mu^* = \infty$
- Case 2 ($\zeta_s, \zeta_r < l$ and $\gamma_r < \mu^* < \gamma_s$): μ^* cannot occur in this case since being in Case 2 implies $\mu^* = \infty$
- Case 3
  - Case 3A ($\zeta_s < l < \zeta_r$ and $\gamma_s < \mu^*$): $G = \int_{\mu_{min}}^{\mu^*} G_{D1} f(\mu) d\mu$
  - Case 3B ($\zeta_s, \zeta_r < l$ and $\gamma_s < \mu^* < \gamma_r$): $G = \int_{\mu_{min}}^{\mu^*} G_{D2} f(\mu) d\mu$
- Case 4 ($\zeta_s, \zeta_r < l < \lambda$ and $\gamma_r, \gamma_s < \mu^*$): $G = \int_{\mu_{min}}^{\gamma_r} G_{D2} f(\mu) d\mu + \int_{\gamma_r}^{\mu^*} G_{ND} f(\mu) d\mu$
- Case 5: ($\lambda < l$): $G = G_{ND}$

Government's preferred liquidity level
It's straightforward to see that $G_{D1} \geqslant G_{D2}$ always holds. It's also clear that $G_{D2} \geqslant G_{ND}$ in cases where the government has to pay G_{D2}. Therefore the minimum government expenditure level occurs in either case 4 or case 5, which implies $l \geqslant l^*(p)$.

2.C Proofs for the extended model

2.C.1 Proof of Proposition 2.6

Proposition 2.6. *The bank never wants to hold more than the required level of liquid assets.*

Using similar notation as in the proof of Proposition 2.1, we have

$$
\begin{aligned}
V_r^d &= \frac{1}{2}(1-q)[2\mu(1-l)+lR_{l,2}-R_{d,2}] \\
V_r^s &= \frac{1}{2}(1-q)[2\mu(1-l)+lR_{l,2}-R_{d,2}] \\
&\quad + \frac{1}{2}q\left[2\mu\left(1-l-\frac{R_{d,1}\lambda-R_{l,1}l}{\delta p}\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l}\right)+(R_{l,1}l-R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}}\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda}-(1-\lambda)R_{d,2}\right] \\
V_s^d &= (1-q)[\mu(1-l)+lR_{l,2}-R_{d,2}] \\
V_s^s &= (1-q)[\mu(1-l)+lR_{l,2}-R_{d,2}] \\
&\quad + q\left[\mu\left(1-l-\frac{R_{d,1}\lambda-R_{l,1}l}{p}\right)\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l}+(R_{l,1}l-R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}}\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda}-(1-\lambda)R_{d,2}\right]
\end{aligned}
$$

By similar reasoning as in the proof of Proposition 2.1, we can see that the assumptions $qR_{l,1}<\delta p$, $p<R_{l,1}$, and $\mu>\max\left\{\frac{1-q}{1-\frac{R_{l,1}q}{p}}R_{l,2}, \frac{1}{2}\frac{1-q}{1-\frac{R_{l,1}q}{\delta p}}R_{l,2}\right\}$ imply

$$
\begin{aligned}
\frac{dV_r^d}{dl} &= \frac{1}{2}(1-q)[-2\mu+R_{l,2}]<0 \\
\frac{dV_r^s}{dl} &= \frac{1}{2}(1-q)[-2\mu+R_{l,2}]-q\mu+q\mu\frac{R_{l,1}}{\delta p}\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l}+\frac{1}{2}qR_{l,2}\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda} \\
&= \left[-\mu\left(1-\frac{qR_{l,1}}{\delta p}\right)+\frac{1}{2}(1-q)R_{l,2}\right]\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l} \\
&\quad + \frac{1}{2}[-2\mu+R_{l,2}]\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda}<0 \\
\frac{dV_s^d}{dl} &= (1-q)[-\mu+R_{l,2}]<0 \\
\frac{dV_s^s}{dl} &= (1-q)[-\mu+R_{l,2}]-q\mu+q\mu\frac{R_{l,1}}{p}\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l}+qR_{l,2}\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda} \\
&= \left[-\mu\left(1-\frac{qR_{l,1}}{p}\right)+(1-q)R_{l,2}\right]\mathbf{1}_{R_{d,1}\lambda>R_{l,1}l} \\
&\quad + [-\mu+R_{l,2}]\mathbf{1}_{R_{l,1}l>R_{d,1}\lambda}<0
\end{aligned}
$$

2.C.2 Proof of Proposition 2.7

Proposition 2.7. *Holding liquid assets reduces the probability that a liquidity shock causes the bank to default.*

Using similar notation as in the proof of Proposition 2.2, the thresholds determining whether liquidity stress causes a bank to default or not can be written as

$$\zeta_r = \frac{R_{d,1}\lambda - p\delta}{R_{l,1} - p\delta}$$
$$\zeta_s = \frac{R_{d,1}\lambda - p}{R_{l,1} - p}$$
$$\gamma_r = \frac{R_{d,2}(1-\lambda) - (R_{l,1}l - R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}}\mathbf{1}_{R_{l,1}l > R_{d,1}\lambda}}{2\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\mathbf{1}_{R_{d,1}\lambda > R_{l,1}l}\right)}$$
$$\gamma_s = \frac{R_{d,2}(1-\lambda) - (R_{l,1}l - R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}}\mathbf{1}_{R_{l,1}l > R_{d,1}\lambda}}{1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\mathbf{1}_{R_{d,1}\lambda > R_{l,1}l}}$$

Clearly, increasing l always reduces the probability of default in period 1. As for the period 2 default thresholds, if $R_{l,1}l \geqslant R_{d,1}\lambda$, then the assumptions $R_{l,1} \geqslant R_{d,1}$ and $R_{l,2} \geqslant R_{d,2}$ implies[21]

$$\frac{d\gamma_r}{dl} = -\frac{(1-\lambda)(R_{l,2} - R_{d,2}) + \lambda\frac{R_{l,2}}{R_{l,1}}(R_{l,1} - R_{d,1})}{2(1-l)^2} \leqslant 0$$
$$\frac{d\gamma_s}{dl} = -\frac{(1-\lambda)(R_{l,2} - R_{d,2}) + \lambda\frac{R_{l,2}}{R_{l,1}}(R_{l,1} - R_{d,1})}{(1-l)^2} \leqslant 0$$

If $R_{l,1}l \leqslant R_{d,1}\lambda$, then the assumption $R_{l,1} > p$ (which also implies $R_{l,1} > p > \delta p$) implies

$$\frac{d\gamma_r}{dl} = -\frac{R_{d,2}(1-\lambda)}{2\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\right)^2}\left(\frac{R_{l,1}}{\delta p} - 1\right) < 0$$
$$\frac{d\gamma_s}{dl} = -\frac{R_{d,2}(1-\lambda)}{\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right)^2}\left(\frac{R_{l,1}}{p} - 1\right) < 0$$

2.C.3 Proof of Proposition 2.8

Proposition 2.8. *The bank's asset choice can be summarized by a threshold μ^* such that it invests in safe assets if $\mu > \mu^*$ and invests in risky assets if $\mu < \mu^*$. Moreover, there is a threshold $l^*(p)$ such that μ^* is decreasing in l for $l < l^*(p)$ and μ^* is increasing in l for $l > l^*(p)$.*

The proof follows cases analogous to those introduced in the proof of Lemma 2.1. The proof uses the thresholds ζ_i and γ_i defined in the proof of Proposition 2.7.

[21] One can also check using these assumptions that $\gamma_i \leqslant R_{l,2}$, and hence there is no risk of default since we have also assumed $\mu > R_{l,2}$.

Case 1: liquidity stress causes the bank to default if it invests in either type of asset ($l < \zeta_s, \zeta_r$, or $\zeta_s < l < \zeta_r$ and $\mu^* < \gamma_s$, or $\zeta_s, \zeta_r < l$ and $\mu^* < \gamma_s, \gamma_r$)

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$\begin{aligned} V_r^d &= \frac{1}{2}(1-q)[2\mu(1-l) + lR_{l,2} - R_{d,2}] \\ V_s^d &= (1-q)[\mu(1-l) + lR_{l,2} - R_{d,2}] \\ \Delta V^{d,d} &= \frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] > 0 \end{aligned}$$

Note that the last inequality uses the assumption $R_{d,2} \geqslant lR_{l,2}$. The fact that $\Delta V^{d,d} > 0$ implies that risky assets are always preferred in this case, so $\mu^* = \infty$.

Case 2: liquidity stress causes the bank to default only if it invests in safe assets ($\zeta_s, \zeta_r < l$ and $\gamma_r < \mu^* < \gamma_s$)

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$\begin{aligned} V_r^s &= \frac{1}{2}(1-q)[2\mu(1-l) + lR_{l,2} - R_{d,2}] + \frac{1}{2}q\left[2\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\right) - (1-\lambda)R_{d,2}\right] \\ V_s^d &= (1-q)[\mu(1-l) + lR_{l,2} - R_{d,2}] \\ \Delta V^{s,d} &= \frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] + \frac{1}{2}q\left[2\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\right) - (1-\lambda)R_{d,2}\right] > 0 \end{aligned}$$

Note that the last inequality uses the assumption $R_{d,2} \geqslant lR_{l,2}$. The fact that $\Delta V^{s,d} > 0$ implies that risky assets are always preferred in this case, so $\mu^* = \infty$.

Case 3: liquidity stress causes the bank to default only if it invests in risky assets ($\zeta_s < l < \zeta_r$ and $\gamma_s < \mu^*$, or $\zeta_s, \zeta_r < l$ and $\gamma_s < \mu^* < \gamma_r$)

The expected value from investing in either type of asset, the relative value of risky assets, and the propensity to take risk can be written as

$$\begin{aligned} V_r^d &= \frac{1}{2}(1-q)[2\mu(1-l) + lR_{l,2} - R_{d,2}] \\ V_s^s &= (1-q)[\mu(1-l) + lR_{l,2} - R_{d,2}] + q\left[\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right) - (1-\lambda)R_{d,2}\right] \end{aligned}$$

$$\Delta V^{d,s} = \frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] + q(1-\lambda)R_{d,2} - \mu q\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right)$$

$$\mu^* = \frac{\frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] + q(1-\lambda)R_{d,2}}{q\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right)}$$

Using the assumptions $R_{l,1} > p$ and $R_{d,2} \geqslant lR_{l,2}$, we have that the effect of tightening liquidity requirements on the propensity to take risk is negative:

$$\frac{d\mu^*}{dl} = -\frac{\frac{1}{2}(1-q)R_{l,2}\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right) + \left(\frac{R_{l,1}}{p} - 1\right)\left[\frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] + q(1-\lambda)R_{d,2}\right]}{q\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right)^2} < 0$$

Case 4: the bank can remain solvent in the face of liquidity stress with either type of asset by selling on long-term debt markets ($\zeta_s, \zeta_r < l < \frac{R_{d,1}}{R_{l,1}}\lambda$ **and** $\gamma_r, \gamma_s < \mu^*$)

The expected value from investing in either type of asset, the relative value of risky assets, and the propensity to take risk can be written as

$$V_r^s = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{l,2} - R_{d,2}] + \frac{1}{2}q\left[2\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\right) - (1-\lambda)R_{d,2}\right]$$

$$V_s^s = (1-q)[\mu(1-l) + lR_{l,2} - R_{d,2}] + q\left[\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{p}\right) - (1-\lambda)R_{d,2}\right]$$

$$\Delta V^{s,s} = \frac{1}{2}(1-q)(R_{d,2} - lR_{l,2}) + \frac{1}{2}q(1-\lambda)R_{d,2} - \mu q\frac{(1-\delta)(R_{d,1}\lambda - R_{l,1}l)}{p\delta}$$

$$\mu^* = \frac{1}{2}\frac{(1-q)(R_{d,2} - lR_{l,2}) + q(1-\lambda)R_{d,2}}{\frac{q(1-\delta)(R_{d,1}\lambda - R_{l,1}l)}{p\delta}}$$

In this case, under the assumption that $\frac{R_{d,2}}{R_{l,2}} \geqslant \frac{R_{d,1}}{R_{l,1}}$, the effect of tightening liquidity requirements on the propensity to take risk is positive:

$$\frac{d\mu^*}{dl} = \frac{1}{2}\frac{(1-q\lambda)R_{l,1}R_{d,2} - \lambda(1-q)R_{l,2}R_{d,1}}{\frac{q(1-\delta)\left(R_{d,1}\lambda - R_{l,1}l\right)^2}{p\delta}} > 0$$

Case 5: the bank can respond to liquidity stress without selling on long-term debt markets $\left(\frac{R_{d,1}}{R_{l,1}}\lambda < l\right)$

The expected value from investing in either type of asset and the relative value of risky assets can be written as

$$V_r^e = \frac{1}{2}(1-q)[2\mu(1-l) + lR_{l,2} - R_{d,2}] + \frac{1}{2}q\left[2\mu(1-l) + (R_{l,1}l - R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}} - (1-\lambda)R_{d,2}\right]$$

$$V_s^e = (1-q)[\mu(1-l) + lR_{l,2} - R_{d,2}] + q\left[\mu(1-l) + (R_{l,1}l - R_{d,1}\lambda)\frac{R_{l,2}}{R_{l,1}} - (1-\lambda)R_{d,2}\right]$$

$$\Delta V^{e,e} = \frac{1}{2}(1-q)[R_{d,2} - lR_{l,2}] + \frac{1}{2}q\left[(1-\lambda)(R_{d,2} - lR_{l,2}) + \lambda\frac{R_{l,2}}{R_{l,1}}(R_{d,1} - lR_{l,1})\right] > 0$$

Note that $\Delta V^{e,e} > 0$ follows from assuming $R_{d,2} \geqslant lR_{l,2}$ and $R_{d,1} \geqslant lR_{l,1}$. The fact that ΔV is positive implies that the bank always prefers risky assets in this case, so $\mu^* = \infty$.

Summary

The reasoning is similar to Proposition 2.3: $l^*(p)$ is the threshold between case 3 and case 4, which can also be written as the solution to $\mu^*(l;p) = \gamma_r(l;p)$.

2.C.4 Proof of Proposition 2.10

Proposition 2.10. *The optimal level of liquidity that minimizes the government's expenditure, l^G, is at least as great as the level $l^*(p)$ that minimizes the fraction of banks that invest in risky assets.*

We follow the structure of the proof of Proposition 2.5. It's straightforward to check that the government's expenditure in each case is the same function of G_{D1}, G_{D2}, and G_{ND} as in the proof of Proposition 2.5, except that we now have

$$G_{D1} = T - B_{D1} = (1-\lambda q)R_{d,2} + qR_{d,1}\lambda - \left[\frac{1}{2}(1-q)R_{d,2} + wq[R_{l,1}l + \delta p(1-l)]\right]$$

$$G_{D2} = T - B_{D2} = (1-\lambda q)R_{d,2} + qR_{d,1}\lambda - \left[\frac{1}{2}(1-q)R_{d,2} + q\lambda R_{d,1} + \frac{1}{2}wq2\mu\left(1 - l - \frac{R_{d,1}\lambda - R_{l,1}l}{\delta p}\right)\right]$$

$$G_{ND} = T - B_{ND} = (1-\lambda q)R_{d,2} + qR_{d,1}\lambda - \left[\frac{1}{2}(1-q)R_{d,2} + \frac{1}{2}q(1-\lambda)R_{d,2} + q\lambda R_{d,1}\right]$$

It's straightforward to see that $G_{D1} \geqslant G_{D2}$ always holds. It's also clear that $G_{D2} \geqslant G_{ND}$ for cases in which the government pays G_{D2}. Therefore the minimum government expenditure level occurs in either case 4 or case 5, which implies $l \geqslant l^*(p)$.

2.D Tables

2.D.1 Reserve requirement tables

Table 2.1: Summary statistics for the reserve requirement exercise

This table presents summary statistics for the sample of bank-quarter observations obtained from the Call Reports during the period 1993Q1-2018Q4 and omitting banks for which the deviation between net transactions accounts and the low reserve tranche upper threshold exceeds 30%.

	N	Mean	SD	P25	P75
Marginal RR (%)	64564	5.90	3.45	3.00	10.00
Log assets	64564	12.73	0.75	12.14	13.16
Equity/assets (%) (C)	64564	9.77	3.12	7.93	10.88
NPLs/loans (%) (A)	64564	1.36	1.90	0.32	1.60
Non-interest expenses/assets (%) (M)	64564	1.07	0.65	0.73	1.23
Net income/assets (%) (E)	64564	1.01	1.01	0.71	1.43
Reserves/assets (%) (L)	64564	18.65	45.90	4.35	14.95
Sensitivity to market risk (%) (S)	64564	14.55	9.18	6.60	21.19

Table 2.2: The effect of the reserve requirement on the reserves to NTA ratio

This table presents results from estimating variations of the regression $Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta(D_{it} * \Delta NTA_{it}) + \gamma controls_{it-1} + \phi_t + \epsilon_{it}$ where Y_{it} is the reserves to NTA ratio for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's net transaction accounts and low reserve tranche upper threshold, D_{it} indicates whether a bank's net transaction accounts exceeded the threshold, $controls_{it-1}$ is a set of lagged controls that includes bank size and proxies for indicators from the CAMELS risk rating system (as described in Section 2.4.2) excluding the dependent variable, and ϕ_t represents time fixed effects. T-statistics computed using bank-clustered standard errors are reported in parentheses. The specification is estimated on a subset of banks exhibiting a deviation from the low reserve tranche threshold that is less than 30%. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) reports $\delta/(10-3)$ when estimating the regression on the full sample period without the controls and time fixed effects, column (2) includes the controls and fixed effects, and columns (3) and (4) report the corresponding results from on a subsample restricting to years before 2008.

	(1) Base	(2) + ctrls + FE	(3) pre-2008	(4) + ctrls + FE
RKD estimate	0.016**	0.029***	0.003*	0.005***
	(2.07)	(4.01)	(1.82)	(3.25)
Observations	64564	64564	42633	42633
R^2	0.000	0.263	0.000	0.244
Controls	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes

Table 2.3: The effect of the reserve requirement on the non-performing loans ratio

This table presents results from estimating variations of the regression $Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta(D_{it} * \Delta NTA_{it}) + \gamma controls_{it-1} + \phi_t + \epsilon_{it}$ where Y_{it} is the non-performing loans ratio for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's net transaction accounts and low reserve tranche upper threshold, D_{it} indicates whether a bank's net transaction accounts exceeded the threshold, $controls_{it-1}$ is a set of lagged controls that includes bank size and proxies for indicators from the CAMELS risk rating system (as described in Section 2.4.2) excluding the dependent variable, and ϕ_t represents time fixed effects. T-statistics computed using bank-clustered standard errors are reported in parentheses. The specification is estimated on a subset of banks exhibiting a deviation from the low reserve tranche threshold that is less than 30%. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Column (1) reports $\delta/(10-3)$ when estimating the regression on the full sample period without the controls and time fixed effects, column (2) includes the controls and fixed effects, and columns (3) and (4) report the corresponding results from on a subsample restricting to years before 2008.

	(1) Base	(2) + ctrls + FE	(3) pre-2008	(4) + ctrls + FE
RKD estimate	0.000	-0.000	0.000	0.000
	(0.39)	(-0.09)	(0.18)	(0.02)
Observations	64564	61780	42633	40844
R^2	0.000	0.318	0.001	0.121
Controls	No	Yes	No	Yes
Quarter FE	No	Yes	No	Yes

2.D.2 Liquidity coverage ratio tables

Table 2.4: Summary statistics

	N	Mean	SD	P25	P75
LCR indicator	10243	0.11	0.31	0.00	0.00
Log assets	10243	15.42	1.56	14.40	16.07
Tier 1 capital/assets (%) (C)	10243	9.80	2.63	8.43	10.54
NPLs/loans (%) (A)	10243	1.81	2.15	0.58	2.15
Non-interest expenses/assets (%) (M)	10243	1.05	0.78	0.72	1.12
Net income/assets (%) (E)	10243	0.92	0.93	0.65	1.20
Total liquid assets/assets (%) (L)	10243	17.78	9.80	10.90	22.10
Sensitivity to market risk (%) (S)	10243	5.50	6.35	1.60	6.84

Table 2.5: Comparison of observables

This table presents the means of characteristics for bank holding companies (BHCs) that were subject to the 100% LCR or the 70% LCR compared to banks that were exempt from the LCR during the period 2010Q1-2013Q2. It also presents the t-statistic for the coefficient η from estimating the regression $Y_{it} = \eta LCR_i + \phi_t + \epsilon_{it}$ and computing bank-clustered standard errors for each characteristic Y_{it}.

	LCR-exempt	LCR	T-statistic
Log assets	14.83	18.82	32.157
Tier 1 capital/assets	9.715	8.395	-3.233
NPLs/loans	2.851	3.309	1.289
Non-interest expenses/assets	1.087	1.407	1.79
Net income/assets	0.717	0.706	-.095
Liquid assets/assets	19.22	20.66	.607
Sensitivity to market risk	5.918	8.775	1.757

Table 2.6: Effect of liquidity coverage ratio on the liquidity ratio

This table presents results from estimating the regression $Y_{it} = \beta LCR_i \times post2013Q3_t + \gamma controls_{it-1} + \psi_i + \phi_t + \epsilon_{it}$ where Y_{it} is the liquidity ratio, LCR_i is an indicator for whether a bank was subject to either the 100% LCR or the 70% LCR (Column (1)), only the 100% LCR (Column (2)), or only the 70% LCR (Column (3)) as of the implementation date of 2015Q1, $post2013Q3_t$ is an indicator for quarters greater than or equal to 2013Q3, $controls_{it-1}$ is a set of controls that includes bank size and indicators from the CAMELS risk rating system (as described in section 2.5.3) excluding the dependent variable, ψ_i represent bank fixed effects, ϕ_t represent time fixed effects. Column (3) excludes banks subject to the 100% LCR. T-statistics computed using bank-clustered standard errors are reported in parentheses. T-statistics with standard errors are clustered by bank. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Either LCR	(2) 100% LCR	(3) 70% LCR
LCR x Post	3.402***	4.422***	2.446***
	(4.70)	(3.77)	(3.37)
Observations	10237	10237	9747
R^2	0.863	0.863	0.837
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Table 2.7: Effect of liquidity coverage ratio on the non-performing loans ratio.

This table presents results from estimating the regression $Y_{it} = \beta LCR_i \times post2013Q3_t + \gamma controls_{it-1} + \psi_i + \phi_t + \epsilon_{it}$ where Y_{it} is the non-performing loans ratio, LCR_i is an indicator for whether a bank was subject to either the 100% LCR or the 70% LCR (Column (1)), only the 100% LCR (Column (2)), or only the 70% LCR (Column (3)) as of the implementation date of 2015Q1, $post2013Q3_t$ is an indicator for quarters greater than or equal to 2013Q3, $controls_{it-1}$ is a set of controls that includes bank size and indicators from the CAMELS risk rating system (as described in section 2.5.3) excluding the dependent variable, ψ_i represent bank fixed effects, ϕ_t represent time fixed effects. Column (3) excludes banks subject to the 100% LCR. T-statistics computed using bank-clustered standard errors are reported in parentheses. T-statistics with standard errors are clustered by bank. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Either LCR	(2) 100% LCR	(3) 70% LCR
LCR x Post	-0.181	-0.369	-0.043
	(-0.60)	(-0.61)	(-0.23)
Observations	10237	10237	9747
R^2	0.695	0.695	0.697
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Table 2.8: Effect of liquidity coverage ratio on the CDS spread

This table presents results from estimating the regression $Y_{it} = Post_t + \beta LCR_i \times Post_t + \psi_i + \epsilon_{it}$ where Y_{it} is the difference between the maximum and the minimum of the CDS spread in period t, LCR_i is an indicator for whether a bank was subject to the 100% LCR as of the implementation date of 2015Q1, $Post_t$ is an indicator that equals 1 for the COVID-19 crisis (dates in 2020) and 0 for the global financial crisis (dates in 2007-2009), ψ_i represent bank fixed effects. T-statistics computed using bank-clustered standard errors are reported in parentheses. T-statistics with standard errors are clustered by bank. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1)
	100% LCR
LCR x Post	1193.293
	(1.44)
Observations	16
R^2	0.809
Bank FE	Yes

2.E Omitted figures

Figure 2-10: The effect of the reserve requirement on the non-performing loans ratio

This figure presents a binned scatterplot relating the non-performing loans ratio to the percentage of net transaction accounts to the low reserve tranche threshold for observations within a 30% deviation of the low reserve tranche threshold. The figure also presents predicted values from estimating the following specification: $Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta(D_{it} * \Delta NTA_{it}) + \epsilon_{it}$, where Y_{it} is the dependent variable for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's net transaction accounts and low reserve tranche upper threshold, and D_{it} indicates whether a bank's net transaction accounts exceeded the threshold.

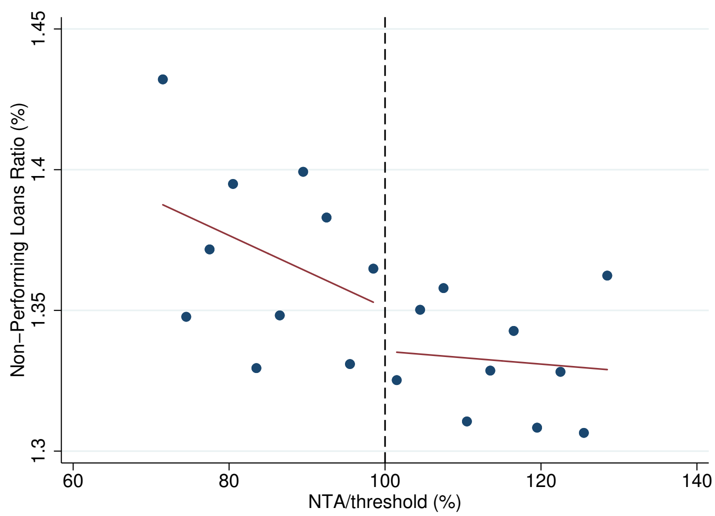
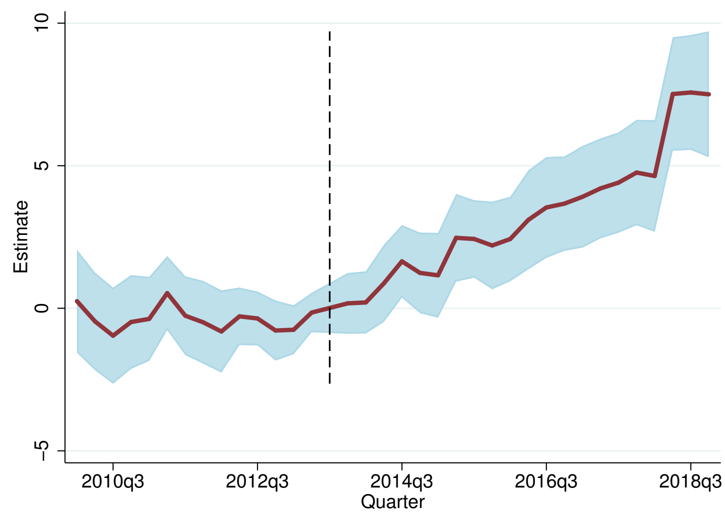


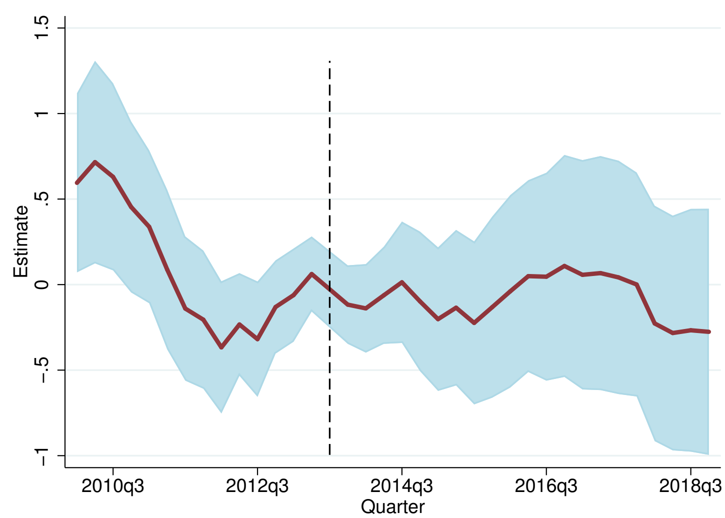
Figure 2-11: The effect of the liquidity ratio (quarterly effects)

This figure presents the coefficients β_t from estimating the regression $\Delta Y_{it} = \sum_{t \neq 2013Q4} \beta_t LCR_i \times \phi_t + \gamma controls_{it-1} + \psi_i + \phi_t + \epsilon_{it}$ where Y_{it} is the dependent variable for bank i in quarter t, LCR_i is an indicator for whether a bank was subject to the 100% LCR or the 70% LCR at the implementation date of 2015Q1, $controls_{it-1}$ is a set of controls that includes bank size and indicators from the CAMELS risk rating system (as described in Section 2.4.2) excluding the dependent variable, ψ_i represents bank fixed effects, and ϕ_t represents time fixed effects. 95% confidence intervals are computed using bank-clustered standard errors. The dashed line indicates the LCR proposal date of 2013Q3.

(a) Liquidity ratio



(b) Non-performing loans

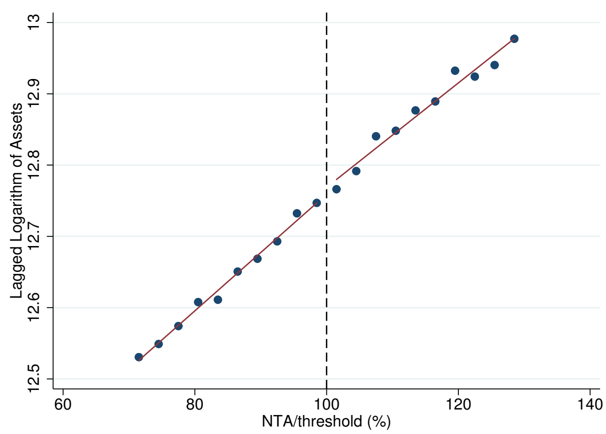


2.F The reserve requirement and other bank characteristics

Figure 2-12: The effect of the reserve requirement on predetermined covariates

This figure presents a binned scatterplot relating the lag of each dependent variable to the percentage of net transaction accounts to the low reserve tranche threshold for observations within a 30% deviation of the low reserve tranche threshold. The figure also presents predicted values from estimating the following specification: $Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta(D_{it} * \Delta NTA_{it}) + \epsilon_{it}$, where Y_{it} is the lag of a characteristic for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's net transaction accounts and low reserve tranche upper threshold, and D_{it} indicates whether a bank's net transaction accounts exceeded the threshold.

(a) [Log assets



(b) Capital ratio

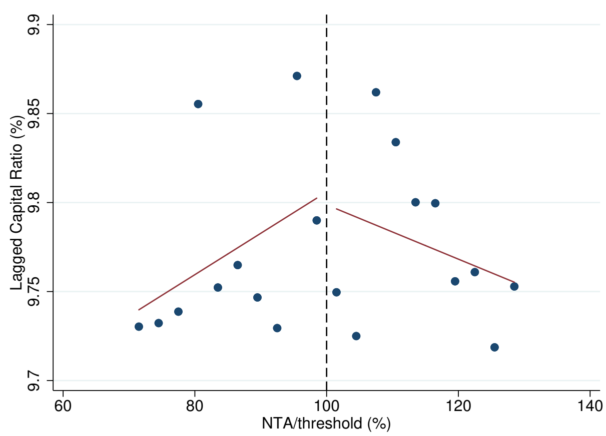
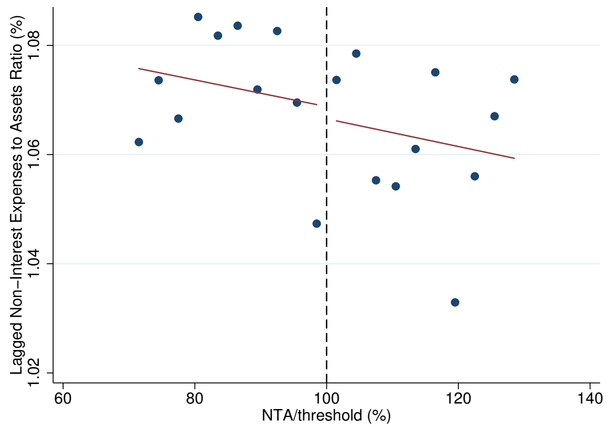
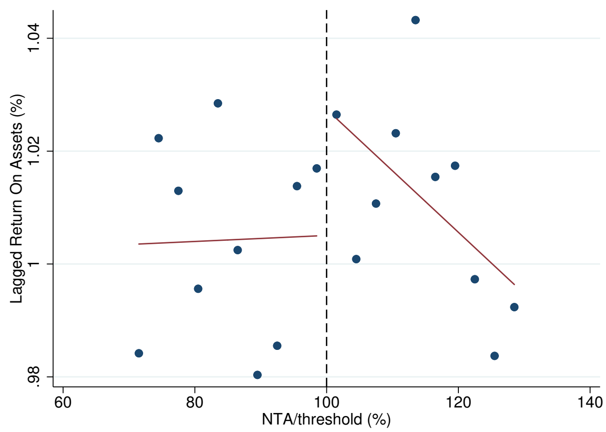


Figure 2-12: The effect of the reserve requirement (continued)

(c) Non-interest expense ratio



(d) Return on assets



(e) Sensitivity to market risk

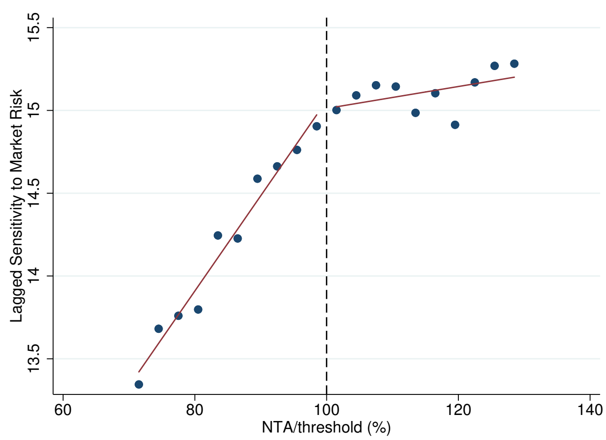


Table 2.9: The effect of reserve requirements on predetermined covariates

This table presents results from estimating variations of the regression $Y_{it} = \alpha \Delta NTA_{it} + \beta D_{it} + \delta(D_{it} * \Delta NTA_{it}) + \gamma controls_{it-1} + \phi_t + \epsilon_{it}$ where Y_{it} is the lag of the indicated dependent variable for bank i in year t, ΔNTA_{it} is the percentage deviation between a bank's net transaction accounts and low reserve tranche upper threshold, D_{it} indicates whether a bank's net transaction accounts exceeded the threshold. T-statistics computed using bank-clustered standard errors are reported in parentheses. The specification is estimated on a subset of banks exhibiting a deviation from the low reserve tranche threshold that is less than 30%. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Each column reports $\delta/(10-3)$.

	(1)	(2)	(3)	(4)	(5)
	Log assets	Capital	Expenses	ROA	Sensitivity
Treatment x (NTA - threshold)	-0.000	-0.001	-0.000	-0.000	-0.007***
	(-0.60)	(-0.79)	(-0.38)	(-0.79)	(-3.25)
Observations	64564	64564	64564	64564	64564
R^2	0.034	0.000	0.000	0.000	0.004
Controls	No	No	No	No	No
Quarter FE	No	No	No	No	No

Chapter 3

Why Did Public Banks Lend More During the Global Financial Crisis?*

3.1 Introduction

There are numerous perspectives on the value of state-owned or public banks. Public banks can help resolve credit market inefficiencies (Eslava and Freixas (2016)), reduce the procyclicality of credit (Micco and Panizza (2006), Brei and Schclarek (2013), Cull and Martínez Pería (2013), and Bertay, Demirgüç-Kunt and Huizinga (2015)), support projects with positive externalities (e.g., lending to small and medium-sized enterprises as highlighted by Behr, Foos and Norden (2017) and Ogura (2018)), and extend financial networks to a greater fraction of the population (Anson et al. (2013)). However, they can also be sensitive to political influences (Dinç (2005), Carvalho (2014)), inefficient (Micco and Panizza (2006), Coleman and Feler (2015)), and associated with slower growth and financial development (La Porta, Lopez-de Silanes and Shleifer (2002)).

During the Global Financial Crisis (GFC), public banks experienced little contraction in lending compared to domestic private banks in some countries (see Figure 3-1 as well as Brei and Schclarek (2013), Cull and Martínez Pería (2013), and Bertay, Demirgüç-Kunt and Huizinga (2015)), which suggests that they can also help stabilize the economy by

*Joint with Eugenio Cerutti. This chapter is a revised version of IMF WP/20/84. Reprinted with permission. We thank Giovanni Dell'Ariccia, Thomas Helbling, Samuel Mann, Sole Martinez-Peria, Mahvash Qureshi, Brett Rayner, Miguel Segoviano, Rob Townsend, and participants of an IMF Research Seminar. Moshan Bilal provided excellent research assistance during the developing of the quarterly bank level dataset. All errors are ours. The opinions expressed herein are solely the responsibility of the authors and should not be interpreted as reflecting those of the IMF, its Executive Board, or IMF management.

avoiding a credit crunch.[1] However, data limitations have hindered a thorough assessment of what led public banks to maintain lending during the GFC. In particular, all cross-country studies use annual data, which is unsuitable for detecting short-lived depositor behavior as well as the fast-changing features of the GFC. Previously used datasets also lack sufficiently detailed balance-sheet breakdowns, such as measures of the funding from the public sector.

This paper studies how public banks in emerging markets (EMs) maintained lending during the GFC. We consider three hypotheses:

1. Public banks lent more because they exhibited sounder fundamentals that enabled them to take greater risks.

2. Public banks lent more because they benefitted from funding advantages, such as safe haven perceptions of depositors or special access to government funding.

3. Public banks lent more because they pursued an objective of helping stabilize the economy during the crisis.

We address these questions using a novel dataset consisting of quarterly balance sheet information provided by the central banks from a diverse sample of 25 EM countries during the period 2006Q1-2010Q4. We focus on EMs during the financial crisis in order to avoid reverse causality bias arising from channels in which public banks have been associated with financial instability (Caprio and Martinez Peria (2000)). In particular, reverse causality bias is unlikely in this context because the financial crisis originated in advanced economies and spread to EMs as an external shock.[2]

We find evidence suggesting that public banks lent more because they pursued an objective of helping to stabilize the economy during the GFC rather than because they possessed different characteristics that were better suited to support loans. In particular, we find that public bank lending during the crisis cannot be explained by sounder fundamentals or advantages in obtaining funding from the public sector. Public banks attracted more deposits at the peak of the crisis in 2008Q4, but not enough to explain the difference in lending compared to domestic private banks. The additional lending

[1]Some country specific studies have also highlighted similar results. For example, Coleman and Feler (2015) shows that localities in Brazil with a high share of public banks received more loans and experienced better employment outcomes relative to localities with a low share of government banks. Similarly, in the case of Turkey, Önder and Özyıldırım (2013) show that credit provided by public banks during the crisis has a significant and positive effect on local growth.

[2]Moreover, based on Laeven and Valencia (2018), none of the 25 countries included in our sample experienced a systemic banking crisis during this period.

growth that exceeds growth in funding corresponds to public banks' willingness to shift the composition of assets, particularly from liquid assets to a higher concentration of loans. Moreover, our analysis using both standard linear regressions and semiparametric distribution regressions (Chernozhukov, Fernández-Val and Melly (2013)) suggests that this countercyclical behavior was only prevalent during the GFC, not before and after the GFC.

Our contribution to the literature is threefold. First, this paper contributes to a literature on the behavior of public banks over the business cycle and during crises. Several papers have documented that lending by public banks is less procyclical compared to that of private banks, and many have considered potential explanations for this behavior of public banks using annual data. The results in Micco and Panizza (2006) do not support the view that this is attributable to misaligned incentives or lazy management. Brei and Schclarek (2013) do not find evidence that public banks acquire more deposits or equity during crises. Bertay, Demirgüç-Kunt and Huizinga (2015) find that public banks have more stable funding and rates of non-performing loans, which could contribute to the relative countercyclicality of public bank lending independently of the occurrence of a financial crisis. Duprey (2015) additionally shows that public banks in medium to-high income countries rely less on vulnerable funding like short-term and wholesale liabilities. We show that public banks lent relatively more during the GFC because they pursued an objective of helping to stabilize the economy, rather than because they had superior fundamentals or access to public or depositors' funding. Moreover, we highlight that the documented relative countercyclicality of public bank lending was not present in EMs before the GFC, as we show that this conclusion reflects mean estimates that do not characterize the behavior of typical banks.

Second, we also contribute to the wider discussion concerning the merits of public banks. On the one hand, public banks can help support projects that private banks might find unprofitable (Eslava and Freixas (2016), Brei and Schclarek (2015)).[3] On the other hand, they also have been associated with inefficiencies (Dinç (2005), Micco and Panizza (2006), La Porta, Lopez-de Silanes and Shleifer (2002)). Our results offer some positive evidence on the long-term effects of using public banks as an instrument to support lending during crises. We do not find evidence that public banks experienced higher non-performing loans ratios after the GFC, suggesting that public bank lending during

[3] Assunção, Mityakov and Townsend (2020) find mixed evidence regarding the degree to which public banks pursue this role in practice: in particular, they find evidence that the Bank for Agriculture and Agricultural Cooperatives in Thailand yields some profitable opportunities to private banks while generally giving greater attention to relatively poor and isolated areas, yet it also does not target the poorest areas.

the GFC was not inefficient or unduly risky. More generally, our analysis of the behavior of public banks during the GFC is in line with one of the three theoretical hypotheses of the model in Brei and Schclarek (2015): in the event of a crisis, public banks might be more willing than private banks to tolerate risky lending with the objective of counteracting the negative spillovers of the financial shock to the real economy.[4] We find that many public banks achieved this objective by shifting their asset composition from liquid instruments to more loans.

Finally, our paper also offers new evidence on the behavior of depositors during periods of financial instability. In particular, if depositors believe that public banks are more likely to be bailed out, then they may transfer their funds to public banks in a flight to safety. Brei and Schclarek (2013) do not find that public banks attract more deposits during crises, but their annual data is unsuitable for detecting short-lived movements in deposits. Other studies with higher frequency data have reported that public banks sometimes attract more deposits during crises (McCandless, Gabrielli and Rouillet (2003), D'Amato, Grubisic and Powell (1997), Adler and Cerutti (2015)), but these papers only consider Argentina and Uruguay. We find that public banks on average were indeed able to attract more deposits during the GFC across our sample of EM countries, but not enough to explain the difference in lending compared to private banks.

We approach the question of why public banks lent more during the GFC using quarterly data for a diverse set of countries. The paper continues as follows. Section 3.2 describes the data. Section 3.3 introduces the empirical methodology. Section 3.4 presents the results. Section 3.5 concludes.

3.2 Data

This paper introduces a novel bank-level dataset consisting of quarterly balance sheet information obtained from the central banks of 25 emerging market (EM) countries during the period 2006Q1-2010Q4. During the data compilation of the IMF Bank contagion module, which is based on BIS and annual bank level data (see Cerutti, Claessens and McGuire (2014) for a description), we noted that several EM countries published quarterly balance sheet data either online or in print form. Our sample of 25 countries is based on those countries for which we were able to obtain the data from the central banks or

[4] This behavior of public banks could be explained by different factors related to their state-owned enterprise (SOE) condition. As highlighted in IMF (2020), SOEs may benefit from preferential debt and equity financing, special tax and regulatory provisions, privileged market position and access to information, and rescues from bankruptcy.

supervisory agencies. Table 3.1 describes the variables, and Table 3.2 provides summary statistics. All non-categorical variables are winsorized at 5% in each quarter.

This dataset possesses several advantages relative to the datasets used in the literature. First, the quarterly frequency of the dataset facilitates a more precise analysis of potentially short-lived phenomena during the different phases of the crisis. Second, several countries in the sample report detailed balance sheet items that are not included in other studies, such as deposits from the central bank and other funds from the state. Third, the dataset includes every bank operating in the countries included in the sample, whereas commonly used databases such as Bureau van Dijk's Banscope have incomplete coverage.[5]

A potential caveat is that countries use different conventions to report some of the accounting items. We exercised care in ensuring that the definitions of accounting items are comparable across countries, and the use of country fixed effects in our regression analysis likely mitigates any residual discrepancies. Another caveat is that the data on state funds primarily reflects regular balance sheet items, such as deposits from the central bank, whereas state support during the crisis might have also occurred through unusual transactions that may not be reflected in this data.

We determine the ownership type of a bank as follows. A bank is classified as foreign if it is a branch office of a foreign-owned bank or majority-owned by foreign shareholders, otherwise it is domestic. To determine whether a bank is foreign-owned, we first consulted information included with the account filings data, which was supplemented using the database associated with Claessens and Van Horen (2015), the database associated with the IMF Bank Contagion Module, ownership history information provided by Bankscope, and online searches. To determine whether a domestic bank is publicly owned, we first consulted indications included with the account filings data, which was supplemented using ownership information provided by Bankscope and online searches.

The initial dataset consists of 1062 firms, which includes commercial banks as well as investment banks, savings banks, development banks, specialty banks such as real estate banks, and other financial entities. This paper focuses on commercial banks, whose operations primarily consist of taking customer deposits and issuing loans to individuals and non-financial firms. To obtain the subsample of commercial banks, we apply a "de facto" rule that excludes banks whose average loans to assets ratio or deposits to non-equity liabilities ratio is less than 10% over the sample period.[6] The final sample includes

[5]Bankscope covers an average of approximately 86.43% of total banking system assets relative to our dataset.

[6]We use a "de facto" rule because a bank's official designation may not be sufficiently descriptive of

877 banks, of which 96 are public banks.

Table 3.3 describes the asset share of public banks as of 2008Q4. There is notable variation ranging from 0% in Honduras, Jamaica, and Nicaragua to 73.56% in Belarus. The average across all countries is equal to 18.40%. Latin American and Caribbean countries exhibit the lowest share of public banks at 11.61%, Eastern European and Central Asian countries exhibit an average share of 28.24%, and East Asian countries exhibit the highest share of public banks at 37.41%.

3.3 Empirical methodology

This paper focuses on the behavior of public banks before, during, and after the global financial crisis, which is associated with the period 2008Q4-2009Q1. We estimate an OLS regression model of the form

$$\begin{aligned}\Delta log(loans)_{ijt} = {} & \beta Public_{ijt} + \eta Public_{ijt} \times GFC_t \\ & + \mu Foreign_{ijt} + \phi Foreign_{ijt} \times GFC_t \\ & + \gamma X_{ijt-1} + \alpha_{jt} + \epsilon_{ijt}\end{aligned} \tag{3.1}$$

where $\Delta log(loans)_{ijt}$ is loans growth for bank i in country j at quarter t, $Public_{ijt}$ is an indicator for whether a bank is publicly owned,[7], $Foreign_{ijt}$ is an indicator for whether a bank is foreign-owned, GFC_t is an indicator for whether a quarter occurs during the crisis period 2008Q4-2009Q1, α_{jt} is an indicator for each country-quarter to control for demand for credit, and $X_{ij,t-1}$ is a set of control variables representing bank fundamentals, which includes the share of total banking system assets, the ratio of equity to assets, the ratio of liquid assets, and the ratio of non-deposit liabilities to total liabilities. It also includes the ratio of non-performing loans (NPL) to total loans in some specifications. Bank fundamentals are lagged by one quarter to mitigate reverse causality bias. Standard errors are clustered by country-quarter.

its operational model. For example, some development banks primarily lend to other banks as second tier institutions while others primarily lend to individuals and non-financial corporations, and some primarily obtain funding through international agencies or directly from the state while others take deposits (Eslava and Freixas (2016)). The de facto rule is intended to retain the development banks that operate like commercial banks. A caveat is that banks that operate like commercial banks according to this de facto rule but that are not formally commercial banks may still differ in other respects, such as regulatory requirements. The results are qualitatively robust to also excluding banks that are explicitly designated as second tier institutions, development banks, or otherwise distinct from typical commercial banks.

[7] Note that $Public_{ijt}$ is subscripted by quarter since a small number of banks transition into or out of public ownership.

The coefficient β on the public ownership indicator captures the average difference, conditional on the covariates, in loans growth between public and domestic private banks during non-crisis quarters, and the coefficient η on the interaction with the crisis dummy indicates the difference in lending between the two types of banks during the crisis relative to non-crisis quarters. We include corresponding indicators for foreign banks so that the coefficients associated with the public ownership indicator capture the difference between domestic public banks and domestic private banks.

The following fundamentals are included as controls in the regressions. The asset share of a bank relative to the total banking assets of a country captures multiple determinants of loans growth. A high asset share could be associated with lower loans growth since large banks are often more mature in the firm life cycle and less focused on growth. However, larger banks are also more likely to be bailed-out, which could allow them to take greater risks.

The ratio of equity to assets captures bankruptcy risk. A high capital ratio provides a buffer that allows a bank to avoid bankruptcy in the face of unexpected asset write-downs, which could provide flexibility for expanding credit. Additionally, many countries require banks to maintain a capital ratio above a regulatory lower limit. To the extent that issuing new equity is relatively costly, banks operating near the limit may be constrained from issuing new loans.

The ratio of liquid assets, particularly cash and securities, to total assets captures risks arising from banks' maturity transformation role. A higher liquidity ratio ensures that a bank can pay withdrawals of short-term liabilities without having to liquidate its long-term assets, which may in turn increase the capacity for issuing new loans.

The ratio of non-deposit or wholesale liabilities to total liabilities captures risks associated with the composition of a bank's funding. To the extent that wholesale funds can be relatively unstable during a crisis, we predict a negative association between wholesale ratio and loans growth during the crisis.

The NPL ratio measures the quality of a bank's loan portfolio. Delinquent loans can worsen liquidity risks because they do not yield interest payments, and they can worsen bankruptcy risks because they are more likely to be written-off from total assets. Both of these effects are likely to be negatively associated with loans growth.[8]

[8]Since the ratio of non-performing loans is relatively slow-moving, we supplement our primary quarterly dataset with annual data from Bankscope in order to increase the number of observations. We interpolate by matching annual observations to quarters in the same year.

3.4 Results

This section reports the results from testing the hypotheses introduced in Section 3.1 to explain why public banks lent more during the crisis relative to private banks.

3.4.1 Hypothesis 1: sounder fundamentals

Hypothesis 1 states that public banks lent more during the crisis because they exhibited sounder fundamentals that enabled them to take greater risks. To investigate this hypothesis, Table 3.4 compares the mean of bank-level averages of fundamentals during the periods before, during, and after the crisis for domestic private and domestic public banks. Before and during the crisis, public banks were significantly larger and exhibited a greater asset share of liquid assets, both of which could have increased their capacity to issue loans during the crisis.[9] If the difference in lending between public and private banks during the crisis was solely attributable to such differences in fundamentals, then the estimate for the interaction $Public_{ijt}$ x GFC_t would yield an estimate that is equal to zero when bank fundamentals are included as controls.

Table 3.5 presents the results from estimating equation (3.1). As a benchmark, column (1) includes only country-quarter fixed effects. The coefficient on $Public_{ijt}$ x GFC_t is positive and significant at 1%, indicating that public banks increased lending by approximately 5% more than private banks during the crisis conditional on only country-quarter effects. Column (2) includes the control variables. The conditional effect of public ownership remains positive, significant, and of similar magnitude compared to column (1), which suggests that the difference in loans growth between public and private banks cannot be solely attributed to differences in fundamentals. The coefficients on the fundamentals are generally consistent with the predictions in Section 3.3. Column (3) estimates a similar regression on an alternative set of bank control variables that includes the NPL ratio, which is only available for a subset of countries. The coefficient on $Public_{ijt}$ x GFC_t remains positive and significant.

Finally, we investigate to what extent the relative increase in public bank lending during the crisis was a result of exhibiting different sensitivities to fundamentals. In particular, we estimate a model where all of the control variables in the baseline regression are interacted with indicators for the crisis, public ownership, and their interaction. The effect of public ownership in this model depends on the values of the fundamentals, which

[9]Private and public banks exhibit similar ratios of cash to assets, but public banks have a higher asset share of securities.

generates a distribution of effects over the sample. The average public ownership effect during the crisis is equal to 4.2% and significant at 5%. The coefficients are displayed in Table 3.6. The coefficient on $Public_{ijt}$ x GFC_t is positive and signficant at 5%, whereas most of the interactions with the fundamentals are insignificant. This further supports the interpretation that the relative increase in public bank lending during the crisis cannot be attributed to differences in fundamentals, even after allowing for the possibility that public ownership or the crisis changed the way that banks responded to fundamentals.

3.4.2 Hypothesis 2: funding advantages

Hypothesis 2 states that public banks lent more because they benefitted from funding advantages specifically related to their ownership status, such as safe haven perceptions of depositors or special access to government funds. In this section, we first show that public banks attracted more deposits during the peak of the crisis, which is consistent with a flight to safety in which depositors migrated to banks that they perceived as safer. If depositors migrated to public banks because they had stronger fundamentals, then regressing deposits growth on $Public_{ijt}$ x GFC_t would yield an estimate that is equal to zero when including fundamentals as controls. By contrast, a positive estimate would suggest that depositors believed that public banks were more likely to be bailed out.

Column (1) of Table 3.7 presents the estimation results after running the regression specified in equation (3.1) except with deposits growth as the dependent variable. Public banks acquired about 2.4% more deposits than domestic private banks during the crisis conditional on fundamentals and country-quarter effects. The effect is most prevalent at the peak of the crisis in 2008Q4: the coefficient in a regression that replaces the indicator for the GFC by an indicator for 2008Q4 is 4.9% and significant at 10% (column 2), whereas the coefficient for a similar exercise except using an indicator for 2009Q1 is only 1.3% and insignificant (column 3).

To capture the pass-through effect of deposits on loan growth, we estimate the regression with loans growth as the dependent variable except also including deposits growth and its interaction with the crisis as regressors. The results in column (4) indicate that deposits growth strongly predicts lending in general (e.g. a 1% increase in deposits increases lending by about 0.25%), but it does not explain the increased lending of public banks during the crisis since the coefficient on $Public_{ijt}$ x GFC_t remains significant and large. So, even though public banks attracted more deposits during the peak of the GFC, this is not enough to explain their increased lending.

Another possibility is that public banks might have lent more due to receiving greater funding support from the state. To test this hypothesis, Table 3.8 column (1) show the results from estimating the regression with state funds growth as the dependent variable.[10] The coefficient on $Public_{ijt}$ x GFC_t is insignificant and does not suggest that public banks obtained more state funds during the crisis. Note that the number of observations is reduced in a regression involving the growth rate of state funds since it is restricted to the subsample of observations where the level of state funds is greater than zero. To incorporate cases where state funds increased from zero, column (2) estimates a similar regression except using the quarterly difference in state funds as the dependent variable.[11] In this specification, the coefficient on the public ownership dummy is positive and significant, indicating that public banks exhibited greater growth in public liabilities during the non-crisis years. However, the coefficient on the interaction is insignificant, which suggests that public banks did not obtain significantly more state funds during the crisis.

Finally, since public banks did not acquire significantly more funding from deposits or state support during the crisis compared to private banks, another possibility is that they were more willing to invest in loans rather than safer liquid assets. To test this hypothesis, Table 3.8 column (3) runs the regression with the growth in the share of liquid assets as the dependent variable. The negative and significant coefficient on $Public_{ijt}$ x GFC_t indicates that private banks stocked up on liquid assets during the crisis to a greater extent than public banks. This suggests that public banks might have possessed a unique business model that led them to prioritize lending over mitigating liquidity risk.

3.4.3 Hypothesis 3: stabilization motives

Hypothesis 3 states that public banks lent more during the crisis because they pursued an objective to help stabilize the economy.[12] This section considers two ways in which this might have occurred. First, public banks may follow a different business model that

[10] As described in Section 3.2, state funds includes deposits from the central bank and other liabilities associated with the public sector.

[11] Note that even when using this specification there are still fewer observations compared to the regressions involving other dependent variables. This is because only a subset of countries reports state funds.

[12] Another interpretation is that public banks pursued a unique business model that effectively led them to play a stabilizing role. For example, public banks may have had higher tolerance for risk due to relatively strong expectations of government guarantees, although the results from Table 3.8 suggests that public banks did not benefit from greater realized state support. Additionally, if expectations of government guarantees drove public bank lending during the crisis, then it should have also motivated higher lending by private banks with relatively strong expectations of bail-outs, such as large banks that might be considered "too big to fail." Table 3.6 shows that the interaction of asset share with the GFC is positive but insignificant.

causes them to generally operate in a relatively countercyclical manner during normal times, which could give them greater capacity to also operate in a countercyclical manner during crises. Second, public banks may have expanded lending during the crisis as an ad hoc measure to avoid a credit crunch.

To assess the procyclicality of public banks around the time of the crisis, Table 3.9 presents the estimates from a similar regression as equation (3.1) that is estimated separately on the subsamples before, during, and after the crisis. Column (1) indicates that public banks were on average less procyclical compared to private banks before the crisis. Column (2) indicates that public banks were also less procyclical during the crisis, but the magnitude of the estimate on the public ownership dummy is notably larger compared to before the crisis. This comparison suggests that the degree of countercyclicality that public banks exhibited during the crisis was unique and may have been intentionally motivated to avoid a credit crunch.

The insignificant estimate in column (3) suggests that public banks failed to wind-down lending after expanding during the crisis. This finding is consistent with case studies of individual countries. For example, World Bank (2013) finds that after Brazil used its public banks to stabilize credit supply during the crisis, the share of loans by public banks continued to expand for several subsequent years, suggesting a failure to behave relative countercyclically compared to private banks during the recovery.[13]

The above considerations about the relative countercyclicality of public banks before and during the GFC are based on regression results that estimate mean difference between public and private banks, which might not adequately compare the behavior of a typical banks from the two groups due to the influence of outliers. To better assess the procyclicality of public bank lending, we also employ the semiparametric distribution regression methodology introduced in Chernozhukov, Fernández-Val and Melly (2013) to estimate cross-sectional models of loans growth for periods before, during, and after the GFC (2007Q1-2007Q4, 2008Q4-2009Q1, and 2010Q1-2010Q4, respectively). In each period, we estimate the distribution of loans growth over the period for public banks, the distribution of loans growth for private banks, and a counterfactual distribution of loans growth for public banks as if lending for public banks were determined from their characteristics, such as fundamentals and country-quarter effects, in the same way as lending is determined for private banks.[14]

[13]Note that our results are qualitatively similar if Brazil is excluded.

[14]This exercise can be interpreted as a distributional version of a Oaxaca-Blinder decomposition, where the difference between the observed distributions of the two groups is split between the difference in characteristics and the difference in the way that characteristics determine the dependent variable (Oaxaca

Figure 3-2 presents the results of this exercise for the three periods. During the crisis, the distribution of loans growth for public banks is uniformly greater across all quantiles compared to the counterfactual distribution, which reinforces the interpretation that public bank lending cannot be attributed to differences in characteristics. By contrast, before the crisis the distributions are similar except for the fast-growing banks with loans growth above the 80th percentile. Similarly, in 2010 public banks lent as much or more compared to private banks except among the fastest-growing banks. Thus, although fewer public banks expanded very rapidly during non-crisis times, the typical public bank was not less procyclical than the typical private bank. This result suggests that the countercyclical behavior of public banks was unique to the crisis rather than a regular characteristic of public banks.

Consistent with these findings from the distribution regression analysis, column (1) of Table 3.10 shows that the negative effect of public ownership in the linear regression estimated on the period before the GFC diminishes dramatically and becomes insignificant in the period before the GFC if we omit the top 20% of the observations by country, quarter, and ownership type. The remaining columns show that the effect of public ownership during other periods is not significantly affected by omitting these observations.

3.4.4 Long-term implications

This sections considers the long-term consequences of public banks' relatively countercyclical lending during the crisis. The unique degree of countercyclicality exhibited by public banks during the crisis suggests that they may have maintained lending as an emergency financial stabilization policy. Since such a motivation could prioritize lending more over lending well, it could have increased public banks' willingness to write risky loans that would more likely become non-performing loans (NPLs).

We investigate this hypothesis using a difference-in-difference specification. We use annual data from Bankscope in order to study the change in the non-performing loans ratio after 2010, the last year in our primary dataset.[15] The dataset for this exercise consists of two bank-level cross-sections: the pre-crisis period corresponds to 2008Q3, which is the last year quarter before the crisis, and the post-crisis period corresponds to the mean during 2012-2015. We estimate a difference-in-differences specification

$$NPL_{ijt} = Post_t + Public_{ijt} + Post_t \times Public_{ijt} + \alpha_j + \epsilon_{ijt} \tag{3.2}$$

(1973), Blinder (1973)).

[15]We interpolate by matching annual observations to quarters in the same year.

where NPL_{ijt} is the non-performing loans ratio for bank i in country j at period t, $Public_{ijt}$ is an indicator for whether a bank is publicly owned, $Post_t$ denotes the post-crisis period averaging over 2012-2015, α_j is an indicator for each country. Robust standard errors are reported in parentheses. Foreign banks are excluded.

Table 3.11 presents the results. The estimate indicates that NPLs of public banks did not significantly change relative to private banks. We take care to note that this result is based on *reported* NPLs. However, we do not have reason to believe in our setting that there were discrepancies between reported and actual NPLs that would be correlated with bank ownership status. IMF (2020) also finds no significant performance differences between public and private banks in emerging and developing economies for the decade after the GFC. Nonetheless, the fact that NPL or other performance indicators did not significantly differ does not rule out inefficiencies and low productivity in public banks' lending. Coleman and Feler (2015) highlights that the GFC changed the market shares and power of public banks in Brazil, with public bank lending being politically targeted in the years following the GFC.

3.5 Conclusion

This paper examines several hypotheses to explain what led public banks to lend relatively more compared to private banks during the Global Financial Crisis in a diverse set of countries. Public bank lending during the crisis cannot be explained by sounder fundamentals or advantages in obtaining deposits or funds from the state. Instead, it is more likely that public banks lent more because of different objectives that led them to pursue a stabilizing role during the GFC. Moreover, we also find evidence that their relatively high degree of lending during the crisis did not appear to compromise their stability, as measured by the ratio of non-performing loans.

The role played by public banks during the GFC is not minor from a policy perspective. Helping to avoid a credit crunch can help stabilize the economy during recessions, which is important since hysteresis effects could make GDP losses during a recession partly permanent (Blanchard, Cerutti and Summers (2015)). However, the challenges highlighted in the literature regarding the inefficiencies and political influences in the credit allocation of public banks during normal times could outweigh — if not properly continuously addressed — the potential benefits during crisis times.

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Appendices for Chapter 3

3.A Figures

Figure 3-1: Lending by public and private banks during the crisis

This figure shows the mean quarterly loans growth of domestic private and domestic public banks within a window of the GFC for our sample of banks from 25 emerging market countries, which is described in Section 3.2.

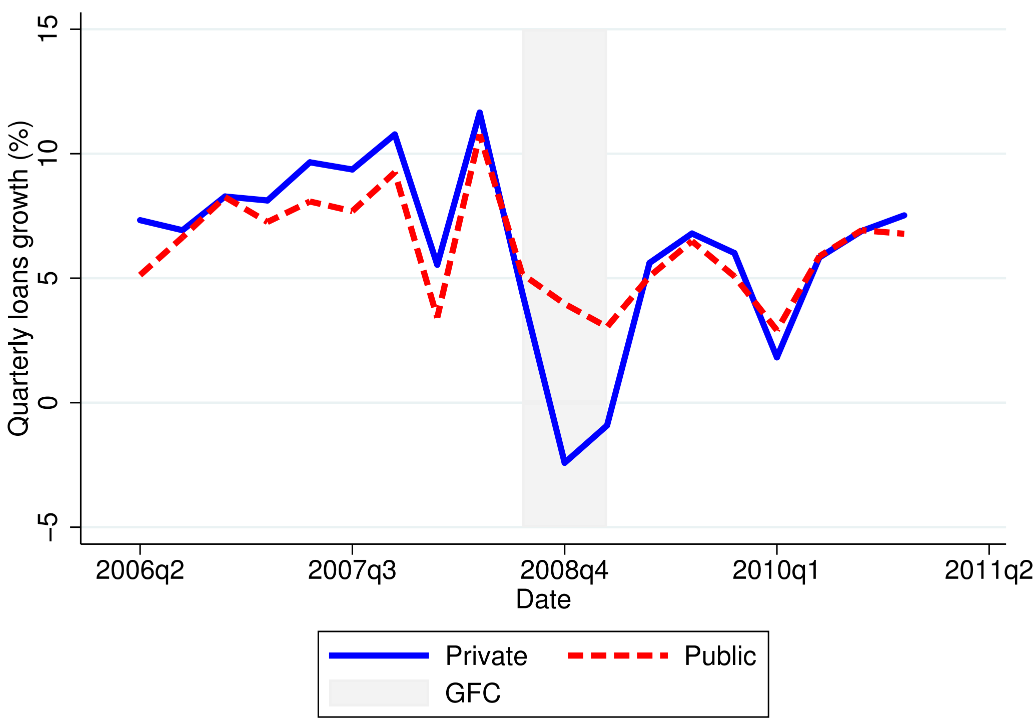


Figure 3-2: Loans growth distribution

These figures show the empirical distribution of loans growth for domestic private banks, the empirical distribution of loans growth for domestic public banks, and a counterfactual distribution estimated using the methodology is Chernozhukov, Fernández-Val and Melly (2013) of loans growth for public banks as if lending for public banks were determined from their characteristics, including fundamentals and country-quarter effects, in the same way as lending is determined for private banks. Panel (a) shows the distributions of loans growth over a period before the crisis (2007Q1-2007Q4), panel (b) corresponds to loans growth over the crisis period (2008Q4-2009Q1), and panel (c) corresponds to loans growth after the crisis period (2010Q1-2010Q4).

(a) Before GFC (2007Q1-2007Q4)

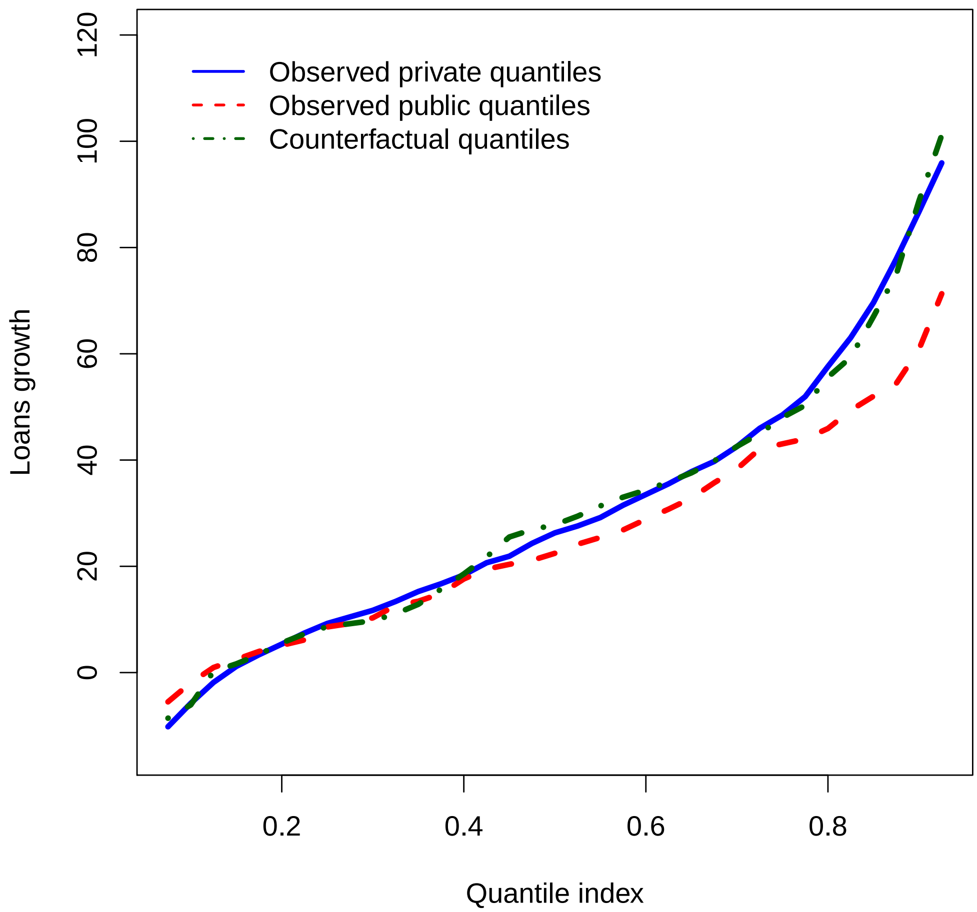


Figure 3-2: Loans growth distribution (cont.)

(b) During GFC (2008Q4-2009Q1)

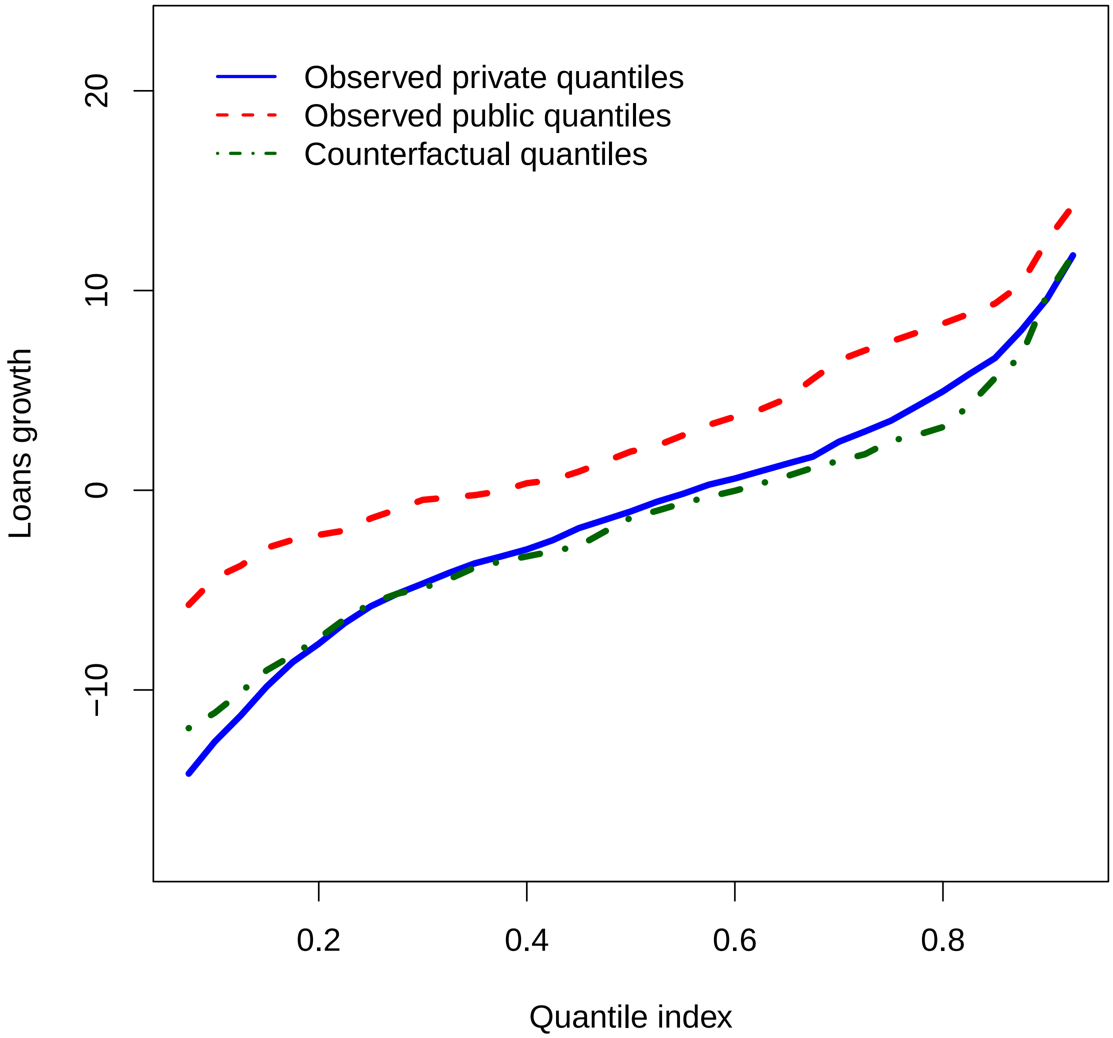
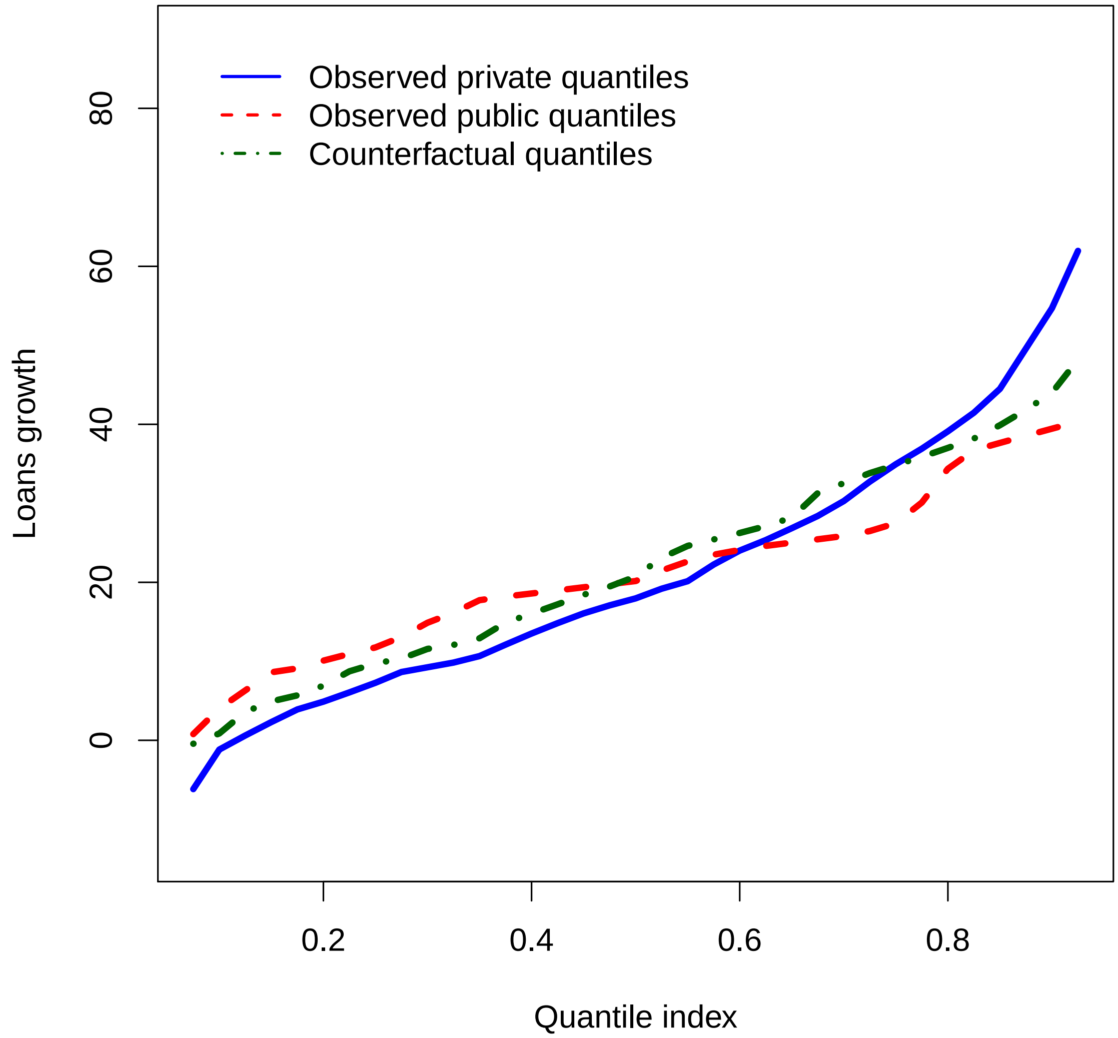


Figure 3-2: Loans growth distribution (cont.)

(c) After GFC (2010Q1-2010Q4)



3.B Tables

Table 3.1: Variable definitions

Variable	Definition	Source
Public	Indicator of public bank	Bankscope, online sources
Foreign	Indicator of foreign bank	Claessens and van Horen (2015), IMF Bank Contagion Module, Bankscope, online sources
Loans growth	Quartlery growth rate of loans (= net loans when available) (%)	Central banks
Deposits growth	Quarterly growth rate of customer deposits (= demand + time + savings deposits, when available) (%)	Central banks
State funds growth	Quarterly growth rate of state funds (= central bank deposits and other public sector liabilities) (%)	Central banks
Asset share	Share of assets in the banking system (%)	Central banks
Capital ratio	Equity divided by assets (%)	Central banks
Liquidity ratio	Liquid assets (= cash + securities) divided by total assets (%)	Central banks
Wholesale ratio	(Non-equity liabilities - customer deposits)/non-equity liabilities (%)	Central banks
Non-performing loans (NPL)	Non-performing loans divided by gross loans (%)	Central banks and Bankscope

Table 3.2: Summary statistics

	N	Mean	SD	SD
Loans growth	14504	6.142	4.370	12.037
Deposits growth	14471	6.091	4.130	14.832
State funds growth	9277	0.054	0.000	0.414
Public	15479	0.111	0.000	0.314
Foreign	15479	0.369	0.000	0.483
Asset share	15479	2.843	0.766	4.270
Capital ratio	15477	15.416	10.963	11.956
Liquidity ratio	15439	28.177	25.358	18.484
Wholesale ratio	15472	32.990	25.889	25.219
Non-performing loans ratio (NPL)	12720	3.016	1.720	3.471

Table 3.3: Public bank share

This table presents the total number of banks, the number of public banks, and the share of bank assets held by public banks in the sample countries as of 2008Q3.

Country name	Total banks	Public banks	Public share
Argentina	62	11	33.891
Belarus	29	4	73.56
Bolivia	11	1	6.856
Brazil	97	12	34.139
Bulgaria	29	1	.782
Chile	21	1	13.375
Colombia	17	1	3.849
Dominican Republic	21	1	35.209
Ecuador	27	5	20.045
El Salvador	12	2	4.162
Guatemala	16	1	.988
Honduras	17	0	0
Indonesia	117	5	36.644
Jamaica	6	0	0
Korea	17	4	31.926
Mexico	32	5	14.02
Nicaragua	7	0	0
Panama	59	2	9.811
Paraguay	15	1	3.205
Peru	14	3	5.753
Serbia	31	5	13.334
Taiwan Province of China	37	9	59.419
Thailand	18	2	21.653
Turkey	26	3	25.304
Venezuela	49	7	12.091

Table 3.4: Fundamentals comparison

This table presents the mean of bank-level averages of fundamentals during the periods before, during, and after the crisis (2006Q1-2008Q3, 2008Q4-2009Q1, and 2009Q2-2010Q4, respectively) for domestic private and public banks as well as the p-value from a difference of means test. All non-categorical variables are winsorized at 5% in each quarter.

	Private	Public	P-Value
Before GFC			
Asset share	2.214	4.616	0
Capital ratio	15.17	13.89	0.313
Liquidity ratio	25.86	35.60	0
Wholesale ratio	28.95	32.90	0.131
NPL ratio	3.210	4.256	0.016
During GFC			
Asset share	2.232	4.906	0
Capital ratio	16.03	14.30	0.255
Liquidity ratio	26.17	33.62	0
Wholesale ratio	31.08	35.58	0.129
NPL ratio	3.422	3.535	0.805
After GFC			
Asset share	2.276	5.292	0
Capital ratio	15.00	13.04	0.132
Liquidity ratio	28.15	33.88	0.004
Wholesale ratio	29.28	36.20	0.010
NPL ratio	3.265	3.801	0.187

Table 3.5: Loans growth regressions

This table presents results from estimating equation (3.1) as described in Section 3.3. T-statistics computed using country-quarter-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) No controls	(2) Baseline	(3) Additional controls
Public	-0.640**	-0.607*	-0.347
	(-2.01)	(-1.91)	(-1.02)
Public × GFC	5.639***	5.605***	5.788***
	(4.59)	(4.71)	(5.50)
Foreign	-0.937***	-1.066***	-1.226***
	(-3.14)	(-3.66)	(-3.75)
Foreign × GFC	3.056***	3.012***	1.981*
	(2.80)	(2.75)	(1.85)
Lag asset share		-0.095***	-0.127***
		(-4.61)	(-6.29)
Lag capital ratio		0.070***	0.085***
		(5.07)	(5.10)
Lag liquidity ratio		0.064***	0.067***
		(6.28)	(6.38)
Lag wholesale ratio		0.001	0.008
		(0.21)	(1.12)
Lag NPL ratio			-0.432***
			(-8.67)
Observations	14504	14464	11890
R^2	0.248	0.259	0.267
Country-quarter FE	Yes	Yes	Yes

Table 3.6: Loans growth regressions with rich interactions

	(1)
	Loans growth
Public	-0.722
	(-0.79)
Public × GFC	6.275**
	(2.35)
Foreign	-1.069***
	(-3.67)
Foreign × GFC	2.758***
	(2.64)
Lag asset share	-0.124***
	(-5.43)
Lag capital ratio	0.074***
	(4.76)
Lag liquidity ratio	0.059***
	(5.09)
Lag wholesale ratio	0.001
	(0.13)
Lag asset share × Public	0.079
	(1.56)
Lag capital ratio × Public	-0.003
	(-0.10)
Lag liquidity ratio × Public	0.012
	(0.67)
Lag wholesale ratio × Public	-0.016
	(-1.40)
Lag asset share × GFC	0.164
	(1.64)
Lag capital ratio × GFC	-0.012
	(-0.27)
Lag liquidity ratio × GFC	0.033
	(0.87)
Lag wholesale ratio × GFC	0.024
	(1.35)

Lag asset share × Public × GFC	-0.193
	(-1.07)
Lag capital ratio × Public × GFC	-0.112
	(-1.08)
Lag liquidity ratio × Public × GFC	0.023
	(0.44)
Lag wholesale ratio × Public × GFC	0.014
	(0.34)
Observations	14464
R^2	0.260
Country-quarter FE	Yes

Table 3.7: Deposits regressions

This table presents results from estimating equation (3.1) as described in Section 3.3 with deposits growth as the dependent variable in columns (1) to (3) and loans growth in column (4). T-statistics computed using country-quarter-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Y=Deposits growth	(2) GFC=2008Q4	(3) GFC=2009Q1	(4) Y=Loans growth
Public	-0.844**	-0.756*	-0.568	-0.408
	(-2.07)	(-1.91)	(-1.35)	(-1.28)
Public × GFC	3.272*	4.866*	1.295	4.716***
	(1.86)	(1.78)	(0.71)	(4.26)
Foreign	-1.355***	-1.276***	-1.006***	-0.718***
	(-4.22)	(-4.12)	(-2.85)	(-2.69)
Foreign × GFC	3.772**	6.095**	1.024	1.975**
	(2.37)	(2.39)	(0.82)	(2.04)
Lag asset share	-0.075**	-0.075**	-0.074**	-0.077***
	(-2.49)	(-2.49)	(-2.47)	(-4.09)
Lag capital ratio	0.133***	0.132***	0.133***	0.038***
	(7.57)	(7.54)	(7.59)	(3.01)
Lag liquidity ratio	-0.042***	-0.042***	-0.042***	0.076***
	(-3.38)	(-3.39)	(-3.35)	(7.57)
Lag wholesale ratio	0.090***	0.090***	0.090***	-0.021***
	(10.46)	(10.46)	(10.46)	(-3.36)
Deposits growth				0.250***
				(22.85)
Observations	14430	14430	14430	14414
R^2	0.220	0.220	0.218	0.334
Country-quarter FE	Yes	Yes	Yes	Yes

Table 3.8: Additional explanations

This table presents results from estimating equation (3.1) as described in Section 3.3 where the dependent variable is the growth in state funds in column (1), the quarterly difference in state funds in column (2), and liquidity ratio growth in column (3). T-statistics computed using country-quarter-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Y=State funds growth	(2) Y=State funds diff	(3) Y=Liquidity growth
Public	-0.757	0.091***	0.860
	(-0.18)	(4.03)	(1.13)
Public × GFC	-39.192	-0.323	-4.719*
	(-1.48)	(-1.24)	(-1.89)
Foreign	-6.784	-0.019*	-0.347
	(-1.27)	(-1.89)	(-0.38)
Foreign × GFC	58.709	-0.047	-3.122
	(0.70)	(-1.04)	(-1.36)
Lag asset share	0.028	0.003**	-0.154***
	(0.06)	(2.17)	(-3.09)
Lag capital ratio	0.054	-0.002**	0.034
	(0.21)	(-2.40)	(1.38)
Lag liquidity ratio	0.005	0.000	-0.385***
	(0.02)	(0.33)	(-11.87)
Lag wholesale ratio	-0.450**	0.000	0.016
	(-2.25)	(0.59)	(1.35)
Observations	2391	9271	14290
R^2	0.367	0.321	0.176
Country-quarter FE	Yes	Yes	Yes

Table 3.9: Loans growth (subsamples)

This table presents results from estimating equation (3.1) as described in Section 3.3 for subsamples corresponding to before, during, and after the global financial crisis. T-statistics computed using country-quarter-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) 2006Q1-2008Q3	(2) 2008Q4-2009Q1	(3) 2009Q2-2010Q4
Public	-1.236***	4.435***	0.354
	(-2.81)	(3.99)	(0.83)
Foreign	-0.786**	1.757*	-1.295***
	(-2.03)	(1.71)	(-3.04)
Lag asset share	-0.125***	0.023	-0.091***
	(-4.13)	(0.28)	(-3.39)
Lag capital ratio	0.095***	0.050	0.045**
	(4.53)	(1.27)	(2.44)
Lag liquidity ratio	0.095***	0.101***	0.007
	(7.31)	(2.74)	(0.52)
Lag wholesale ratio	0.014	0.023	-0.027***
	(1.47)	(1.61)	(-2.98)
Observations	7611	1545	5308
R^2	0.227	0.319	0.193
Country-quarter FE	Yes	Yes	Yes

Table 3.10: Loans growth (subsamples, omitting fast-growing banks)

This table presents results from estimating equation (3.1) as described in Section 3.3 for subsamples corresponding to before, during, and after the global financial crisis and omitting banks with loans growth above the 80th percentile by country, quarter, and ownership type. T-statistics computed using country-quarter-clustered standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) 2006Q1-2008Q3	(2) 2008Q4-2009Q1	(3) 2009Q2-2010Q4
Public	-0.447	4.786***	0.606
	(-1.25)	(3.45)	(1.38)
Foreign	-1.498***	-0.101	-1.853***
	(-5.74)	(-0.13)	(-6.34)
Lag asset share	0.170***	0.228***	0.146***
	(7.44)	(4.63)	(5.94)
Lag capital ratio	-0.104***	-0.091***	-0.093***
	(-8.11)	(-3.64)	(-6.41)
Lag liquidity ratio	-0.020**	-0.005	-0.059***
	(-2.28)	(-0.14)	(-5.77)
Lag wholesale ratio	-0.011*	-0.018	-0.026***
	(-1.90)	(-1.62)	(-3.91)
Observations	5876	1193	4100
R^2	0.349	0.514	0.348
Country-quarter FE	Yes	Yes	Yes

Table 3.11: Long-term effects

This table presents results from estimating equation (3.2) as described in Section 3.4.4. T-statistics computed using heteroscedasticity-robust standard errors are reported in parentheses. * indicates statistical significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	(1) Y = NPL ratio
Post-GFC	0.119
	(0.22)
Public	0.391
	(0.37)
Post-GFC × Public	0.345
	(0.23)
Observations	588
R^2	0.264
Country-quarter FE	Yes