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Toshiaki Ogawa

Discussion Paper No. 2020-E-5

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IMES Discussion Paper Series 2020-E-5
March 2020

Liquidity Management of Heterogeneous Banks during the Great Recession

Toshiaki Ogawa*

Abstract

I construct a dynamic stochastic general equilibrium model to investigate how the liquidity management of different size banks responds to liquidity and loan demand shocks. My investigation shows the following. Compared with small banks, large banks tend to be net borrowers and thus more exposed to liquidity risk. In response to negative liquidity shocks, large banks decrease their credit supply while small ones increase theirs. In response to negative loan demand shocks, both large and small banks decrease their credit supply. Connecting these implications with the panel data, I argue that negative liquidity shocks served as the main driver of the Great Recession initially, and negative demand shocks did so later, and that demand shocks accounted for two thirds of the greatest fall in aggregate loans during the recession.

Keywords: Great Recession; Bank liquidity management; Occasionally binding constraints; Heterogeneous bank model; General equilibrium model
JEL classification: E00, G01, G18, G20, G21

* Deputy Director and Economist, Institute for Monetary and Economic Studies, Bank of Japan (E-mail: toshiaki.ogawa@boj.or.jp)

This paper is the main chapter of my PhD thesis, undertaken at the University of Wisconsin-Madison. I am grateful to the members of my dissertation committee, Kenneth West, Enghin Atalay, Oliver Levine, and especially my main advisor, Dean Corbae for invaluable guidance. I would like to thank Saleem Bahaj, Keshav Dogra, Nobuhiko Kiyotaki, May Rostom, Francesco Zanetti, and staff at the Bank of Japan for their helpful comments. I also appreciate the comments of seminar participants at the University of Wisconsin-Madison, Hitotsubashi University, 31st AFBC, and 5th Annual CIGS End of Year Macroeconomics Conference. All remaining errors are my own. Views expressed in this paper are those of the author and do not necessarily reflect the official views of the Bank of Japan.

1 Introduction

The financial crisis of 2007-2008 and the subsequent Great Recession (henceforth, GR) caused a large contraction in bank lending. It is unclear whether this contraction was driven by the demand side (i.e., because firms decreased investment) or the supply side (i.e., because banks decreased their credit supply). Understanding which factor was dominant is important because it guides policy responses to future crises. For example, if the supply side was completely responsible for the contraction, it may be better for policymakers to focus on the financial sector in order to prevent the next crisis. In this paper, I construct a structural model where heterogeneously-sized banks are engaged in dynamic liquidity management.[1] I then use cross-sectional variations in banks' lending behavior to investigate whether the demand side or supply side dominated during the GR.

The contributions of this paper to the literature on banking are twofold. First, I construct a dynamic stochastic general equilibrium model that describes heterogeneous-sized banks' liquidity management. By calibrating the model, I show that, in the stationary equilibrium, while small banks are net lenders, large banks are net borrowers, as they must raise funds in the market because their deposits are insufficient to fully finance their loans.[2] The capital requirement is occasionally binding, but many banks hold more capital than required. In particular, small banks have larger capital buffers than large banks because they have stronger precautionary motives than large banks.

Second, I identify the reasons for the aggregate loan contraction during the GR. Specifically, I introduce two types of unanticipated shocks, namely productivity shocks (loan demand side) and liquidity shocks (loan supply side), and identify a specific combination of those shocks that can replicate differences by size in banks' lending

[1] In this paper, a bank's size is determined by its amount of total assets, as is common in banking literature. Throughout this paper (in both the empirical part and the model part), I define a "small bank" as a bank whose assets are in 0th-20th percentile, a "medium bank" as one with assets in the 20th-80th percentile, and a "large bank" as one with assets in the 80th-100th percentile. Notice that this definition is different from that in the previous banking literature, where large banks are in the top 10 or top 1% banks by asset size (Corbae and D'Erasmo (2019), Corbae et al. (2011), and Kashyap and Stein (2000)).

[2] This explanation is consistent with the FDIC Banking Review (Bradley and Shibut (2006)). "When deposits lagged behind loan growth in the 1990s, some bankers argued that there was a funding crisis. And indeed, managing bank liquidity is not as easy as it once was. However, calling it a crisis gives short shrift to the funding options available to banks. Now both small and large banks regularly use wholesale sources and rate-sensitive deposits as part of their funding strategy. By wholesale sources, we mean borrowings (such as federal funds, repurchase agreements, and Federal Home Loan Bank [FHLB] advances) as well as brokered deposits."

and fund-raising activities during the GR. In my model, negative productivity shocks push down demand for bank loans, regardless of the size of lender banks. Liquidity shocks, by contrast, come up with a difference in lending activity between large and small banks. Large banks reduce the amount of loans they make, while small ones increase their loans. This is because of the difference between large and small banks in the exposure of their debt finance to liquidity risk. To finance loans, large banks depend on market finance more than small banks, as mentioned above. Banks that raise funds in the market are exposed to liquidity risk more than banks that collect deposits. Consequently, my model shows that the difference in their lending activities is caused by liquidity shocks, and that an averaged change in large and small banks' loans is driven by productivity shocks.

Connecting these implications with the panel data, I estimate the following. First, the liquidity of the financial market declined rapidly after the fall of Lehman Brothers. Second, this was followed by a gradual decline in demand for loans. Third, the initial sharp decline in liquidity accompanied a significant contraction in lending by market-dependent large banks. On the other hand, the liquidity decline benefited small banks that relied mainly on stable funding such as deposits, because they were able to substitute for financially distressed large banks in the loan market by using their rich capital cushion.[3] As a result, small banks performed relatively well between 2009 and 2010, even though aggregate loan demand declined. Finally, 67 percent of the greatest drop in aggregate loans was due to decreased loan demand. These findings are in line with the results of previous studies that attempt to identify the driving forces of the GR by using aggregate data (e.g., Christiano et al. (2015), Negro et al. (2017), and Bianchi and Bigio (2017)).

To the best of my knowledge, this paper is the first to identify the shocks that caused the GR by considering cross-sectional differences in banks' behavior. Considering cross-sectional differences has two advantages, as follows.

Firstly, heterogeneity itself is important to understanding the macroeconomic implications. A growing body of recent literature has studied how the conventional representative-agent shortcut can generate misleading macroeconomic implications for the household sector (e.g., Kaplan and Violante (2014, 2018), Kaplan et al. (2018),

[3] As empirical evidence that shows financially distressed banks were substituted by healthy banks in the financial crisis, Jensen and Johannesen (2017) investigate the impact of the credit supply channel on household consumption in Denmark. They estimate around half of the decrease in lending by financially distressed banks was neutralized by their customers borrowing more from other healthy banks.

Ahn et al. (2018), Heathcote et al. (2009), and Guerrieri and Lorenzoni (2017)).[4] When considering the banking sector, some empirical studies indicate that banks respond to macroeconomic or policy shocks differently, depending on the composition of their balance sheets (e.g., Kashyap and Stein (2000) and Hosono (2006)). Moreover, Cornett et al. (2011) and Berrospide (2012) study how banks contracted their credit supply differently, depending on their liquidity positions during the financial crisis. The more binding borrowing constraints, or liquidity constraints, are for banks, the more seriously banks contracted their credit supply. These empirical facts would suggest that macroeconomic implications derived using a representative model for the banking sector may be misleading, similar to the above-mentioned case of the household sector.

The second advantage of considering the cross-sectional differences in banks' lending behaviors is that it enables analyses without using loan rates. When we attempt to decompose changes in bank loans into the supply and demand factors by using only aggregate data, we need to use the loan rates for the decomposition. However, loan rates are not determined purely by the balance between demand and supply of the loan. They include many types of spreads. Furthermore, as is epitomized in the "flight to quality", the quality, or the riskiness, of borrowers changes counter-cyclically. Changes in loan rates mainly reflect changes in the quality of borrowers (Bernanke et al. (1994) and Lang and Nakamura (1995)). Using cross-sectional differences for the decomposition enables us to avoid the problem of the associated estimation errors.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 reviews some empirical facts. Sections 4 constructs a dynamic general equilibrium model. Section 5 presents a calibration of the model for the U.S. economy. Section 6 shows static and dynamic analyses of the model, describes the GR as a combination of liquidity and productivity shocks, and provides a counterfactual analysis. Section 7 concludes.

[4]In these studies, some households are unable to smooth their consumption due to uninsurable income shocks, combined with borrowing constraints. As a result, those households tend to have high marginal propensities of consume (MPCs). These studies argue that those agents who are liquidity constrained, or have high MPCs, play an important role in business cycle effects and macroeconomic responses to policies (e.g., monetary policy). This position is empirically supported by, e.g., Mian et al. (2013), and Mian and Sufi (2015).

2 Literature

This paper contributes mainly to two strands of the literature. The first strand documents the empirical evidence of credit contraction during the financial crisis. Cornett et al. (2011) and Berrospide (2012) investigate the liquidity management strategies of U.S. commercial banks during the crisis. Cornett et al. (2011) find that large banks performed worse than small banks because the former encountered the crisis with more risk exposures than the latter (e.g., lower capital, greater reliance on wholesale funds, and larger illiquid assets). Ivashina and Scharfstein (2010) show for U.S. banks that the more the banks' liability depended on deposits, the less they reduced making syndicated loans. These findings can be replicated by my model showing that large banks take more liquidity risk (greater reliance on market borrowing) in the stationary equilibrium, and that they contract their lending more than small ones when liquidity shocks occur.

In this strand, there is mixed evidence for the main driver of the financial crisis. Some experts attribute it to the deterioration of financial intermediation, while others attribute it to the drop in demand. Duchin et al. (2010) find that the decline in corporate investment was the greatest for firms that had low cash reserves or high net short-term debt. This would be a typical consequence of negative supply shocks to bank credit. Dewally and Shao (2014) find that firms that relied on bank credit were unable to increase the leverage as much as other firms did during the crisis, and firms with established lending relationships were able to increase it significantly more than those without such relationships. By contrast, Mian and Sufi (2015) and Kahle and Stulz (2013) argue that a demand shock was the main driver of the financial crisis. My model suggests that an initial contraction in credit supply was likely to be followed by a gradual drop in credit demand. Finally, my estimation is that demand shocks accounted for 67 percent of the greatest drop in aggregate loans during the GR.

The second strand is the theoretical literature on bank liquidity management. My research is closely related to Bianchi and Bigio (2017) in the sense that they also construct a general equilibrium model with a financial sector to identify what kind of shocks can explain the financial crisis. Notably, my approach is different from theirs in that banks' response to negative shocks in a crisis can differ by bank size; that is, the banks in my model are formulated to differ in the structure of liability by size.[5]

[5] In identifying shocks, Bianchi and Bigio (2017) ignore such cross-sectional differences and resort simply to aggregate data. They conclude that interbank market freezing may have been important at

My model is also close to Corbae et al. (2016) and De Nicolò et al. (2014) in that banks' liquidity management is formulated to be responsive over time to shocks to both their assets and their liabilities. These banks have two types of assets: liquid assets, such as cash and securities, and illiquid assets, such as loans. A constant fraction of loans matures every period, and the banks pay a liquidation cost if loans are liquidated before they mature. Since bank deposits are liquid, the banks face a maturity mismatch between their assets and liabilities. They must manage this mismatch dynamically. In this sense, those banks' liquidity management can be seen as an infinite-time version of that in Diamond and Dybvig (1983). Meanwhile, an important difference between my model and those of Corbae et al. (2016) and De Nicolò et al. (2014), is that my model is a general equilibrium model while theirs are partial equilibrium models (i.e., they focus solely on banks' decision rules).

Finally, my model is also related to Gomes (2001), Hopenhayn and Rogerson (1993), Katagiri (2014), Corbae and D'Erasmo (2019), and Cooley and Quadrini (2001) because, in line with these studies, it considers the entry and exit of heterogeneous firms.

3 Empirical Facts

In this section, I review some empirical facts about the financial crisis and GR. These facts are well documented in previous studies that investigate the liquidity management of U.S. commercial banks during the crisis (e.g., Cornett et al. (2011), Berrospide (2012)).

As in Negro et al. (2017) and Christiano et al. (2015), I focus on a period after Lehman Brothers went bankrupt in September 2008, when bank loans began to drop.[6] The data I use in this section begin in the third quarter of 2008, unless otherwise stated. Section 5 details the data used. Specifically, I mention two facts, as follows.

- **Fact 1.** *Large banks contracted their loans more than small banks. Small banks initially maintained their credit supplies.*

the beginning of the crisis, which was followed by a persistent decline in demand. This conclusion is supported by my model too, as shown later.

[6] Chari et al. (2008) point out that the data show bank lending did not decline until at least 2008Q3, even though the financial crisis started in 2007. Cohen-Cole et al. (2008) and Ivashina and Scharfstein (2010) argue that the environment for new lending actually became weaker after 2007Q2-Q3. However, drawdowns of existing credit line increased significantly, and outstanding loans also increased as a result.

- **Fact 2.** *Large banks experienced the financial crisis with much more liquidity risk exposures than small banks. During the crisis, large banks increased their net liquidity positions more than small banks did.*

Figure 1 shows the growth rates of loans by bank size.[7,8] As verified in Cornett et al. (2011) and Berrospide (2012), large banks depended on market borrowing, such as repo transactions and interbank transactions, and therefore contracted their loans more than small banks, which depended on stable funding, such as deposits. In fact, small banks actually maintained their loans during the financial crisis (between 2009 and 2010).

Figure 2 shows how the ratios of repo- and net liquidity-to-total assets changed by bank size after the financial crisis. Figure 2a shows that when the financial crisis started, large banks relied on the repo market for their funding (for the top 5% of banks, about 8% of total assets were financed by repos) while small banks hardly used repo transactions. As the crisis progressed, large banks reduced their reliance on the repo market dramatically.

I define the net liquidity position as

$$\begin{aligned}\text{net liquidity position} = &\underbrace{\text{securities}+\text{federal funds sold }+\text{reverse repo}}_{\text{liquid assets}}\\ &-\underbrace{\{\text{federal funds purchased}+\text{repo}+\text{trading liabilities}+\text{subordinated notes}+\text{other borrowed money}\}}_{\text{liquid liabilities}}. \end{aligned} \tag{1}$$

I divide this net liquidity position by total assets.[9] Figure 2b plots the mean of all size groups. Banks experienced the crisis with different liquidity positions, depending on their size. On average, small banks had a positive liquidity position, or they were net lenders, while large banks had a negative liquidity position, or they were net borrowers. After the crisis began, the average large bank dramatically increased its net liquidity position. This means that they borrowed less from the market, as shown above, and

[7] Here I use "total loans and leases (rcfd1400)" in call reports instead of "commercial and industrial loans (rcfd1600)" because I use "total loans and leases (rcfd1400)" for model calibration. Almost the same pattern can be seen regardless of the series used for loans.

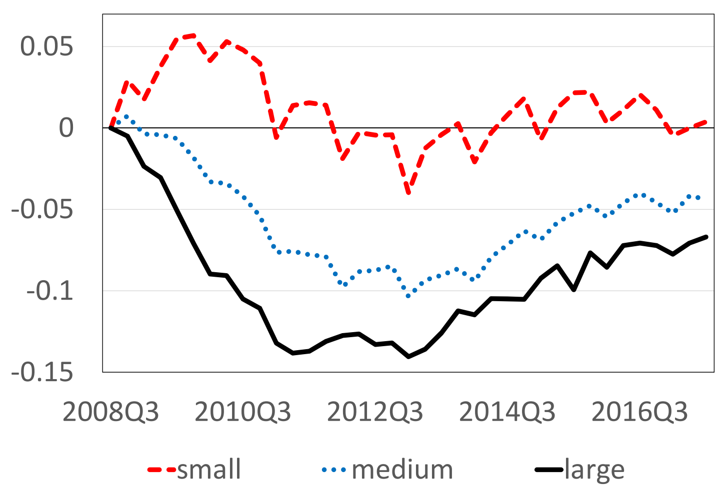
[8] I use the HP filter with parameter 1600 to detrend the growth rates and plot the means for each size group.

[9] The Federal Reserve started to pay interest on banks' reserves in October 2008. This policy increased banks' cash holdings. To exclude the impact of this policy, the above-defined liquidity assets does not include the central bank reserves, in line with Kashyap and Stein (2000).

increased their accumulation of liquid assets. On the other hand, the average small bank did not change its liquidity position to the same degree. These facts are consistent with the finding of Cornett et al. (2011) that large banks were more dependent on market borrowing, or took more liquidity risk, and this is why they reduced their lending more than small banks during the crisis.

These facts jointly indicate that the financial crisis occurred in the financial market (Gorton and Metrick (2012a), Gorton and Metrick (2012b), and Brunnermeier (2009)). Large banks depended heavily on the financial market for their funding and therefore contracted their lending more than small banks, whose funding depended on more stable deposits (Berrospide (2012), Cornett et al. (2011), and Ivashina and Scharfstein (2010)).

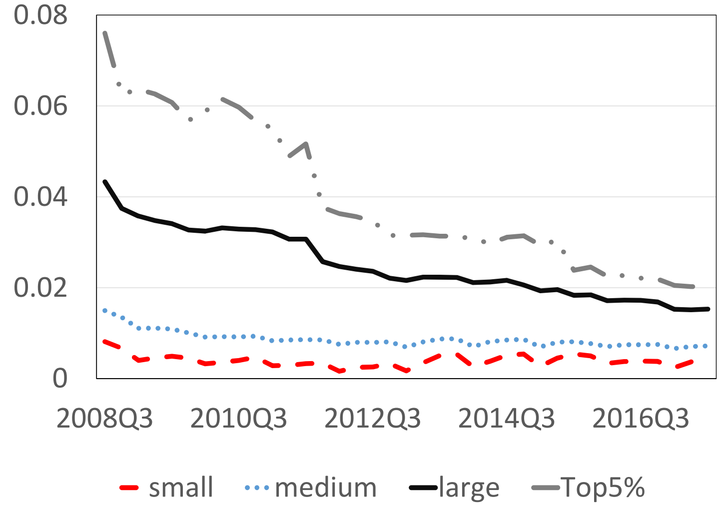
Figure 1: Growth of loans for each size group



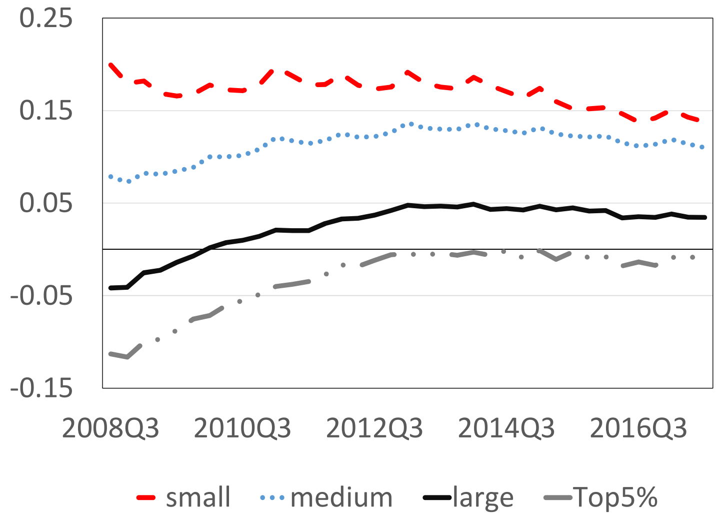
Note: Source: Call Reports. The amount of loans corresponds to total loans (rcfd 1400) in Call Reports. Banks are divided into 3 size groups according to their amount of assets at 2008Q3. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. The mean of growth from 2008Q3 is plotted for each size group after the trend is extracted using the HP (1600) filter.

Figure 2: Repo-to-total assets ratio and liquidity-to-total assets ratio for each size group

(a) Repo-to-total assets ratio



(b) Liquidity-to-total assets ratio



Note: Source: Call Reports. Banks are divided into 3 size groups according to their amount of assets at the initial period. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. In addition to these groups, I show the data for the top 5% of banks. Net liquidity position is defined as $\text{net liquidity position} = \text{securities}+\text{federal funds sold} + \text{reverse repo} - \{\text{federal funds purchase}+\text{repo}+\text{trading liabilities}+\text{subordinated notes}+\text{other borrowed money}\}$. In Figure 2a, I plot (repo + federal funds purchased)/assets for each size goup. The mean of each variable is plotted for each size group.

4 Model

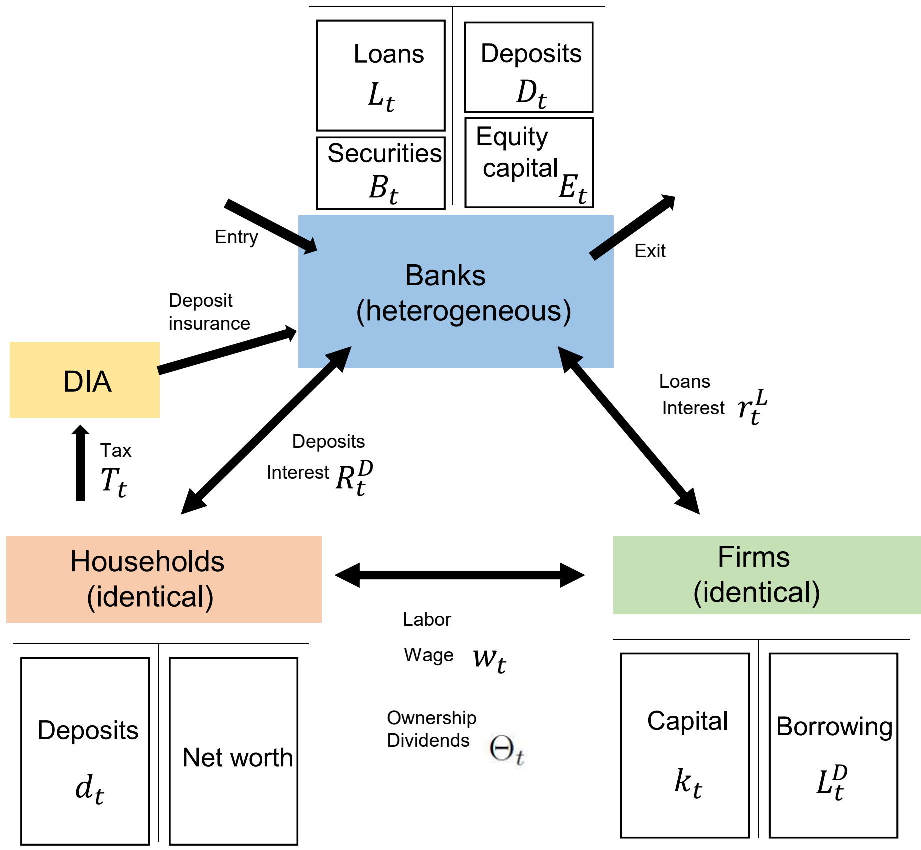
In this section, I construct a general equilibrium model with a banking sector. I extend the partial equilibrium model of Corbae et al. (2016) and De Nicolò et al. (2014) to a general equilibrium setting with households and productive firms. I introduce two types of idiosyncratic shocks to banks, namely deposit funding shocks and monitoring technology shocks. There is no aggregate uncertainty in the economy.

4.1 Preliminaries

Time is discrete, indexed by t and infinite. The economy is populated by four types of agents: households, firms, a deposit insurance agency (DIA),[10] and banks. All agents behave competitively, and prices adjust to clear the relevant markets in equilibrium. Firms are owned by households and produce consumption goods by using labor as the input. Households supply labor to firms and provide deposits to banks. Banks make loans to firms. Households cannot provide funds directly to firms because that requires monitoring and screening technologies which only banks have. Banks choose entry and exit endogenously and can default on deposits when they exit. When they default, the DIA repays the deposits to households using a lump-sum tax levied on households. Thanks to this deposit insurance, households do not care whether their banks default or not. Figure 3 summarizes the model.

[10] The governmental organization which provides deposit insurance. In the U.S., this corresponds to the Federal Deposit Insurance Corporation (FDIC).

Figure 3: Summary of model structure



4.2 Households

A continuum of identical households (measure one) are infinitely-lived and risk neutral. They value consumption c_t and disvalue working l_t. They can have deposits d_t in the banks which pay an interest rate R_{t-1}^D. Deposits are fully guaranteed by the DIA, so households receive R_{t-1}^D per dollar, whether the bank defaults or not. Furthermore, households own productive firms, so they obtain ownership dividends Θ_t. The household's budget constraint is as follows:

$$c_t + d_{t+1} = w_t l_t + R_{t-1}^D d_t + \Theta_t - T_t \tag{2}$$

where w_t is the wage for labor and T_t is a lump-sum tax for deposit insurance. Households solve the following recursive problem subject to their budget constraint.

$$\Omega(d_t) = \max_{\{c_t, l_t, d_{t+1} \geq 0\}} c_t - \frac{l_t^{1+\nu}}{1+\nu} + \beta^D \Omega(d_{t+1}) \tag{3}$$

where β^D is the households discount factor and ν is the inverse of the Frisch elasticity. This problem is deterministic in a stationary equilibrium.

The first-order condition for labor supply leads to

$$w_t^{\frac{1}{\nu}} = l_t. \tag{4}$$

The optimal choice of consumption and deposits is described by

$$\{c, d\} = \begin{cases} c_t = y_t, d_{t+1} = 0 & \text{if } R_t^D < \dfrac{1}{\beta^D} \\ c_t \in [0, y_t], d_{t+1} = y_t - c_t & \text{if } R_t^D = \dfrac{1}{\beta^D} \\ c_t = 0, d_{t+1} = y_t & \text{if } R_t^D > \dfrac{1}{\beta^D} \end{cases} \tag{5}$$

where y_t is defined as $y_t = w_t^{\frac{1+\nu}{\nu}} + R_{t-1}^D d_t + \Theta_t - T_t$. In the following, I assume the economy is in the second case, $R_t^D = \frac{1}{\beta^D}$, so that households are indifferent between consuming and saving.

4.3 Firms

There is a continuum of identical firms (measure one) that are owned by households. As in Gertler et al. (2012), firms rely exclusively on banks to obtain funds. The production technology of firms is $f_t(k_t, l_t) = A_t k_t^\alpha l_t^{1-\alpha}$ where k_t is productive capital, l_t is labor input, and A_t is productivity. At the end of period $t-1$, they costlessly adjust the amount of borrowing from banks L_t^D and the amount of productive capital k_t,[11] which is inputted to production in period t. Because the production function has constant returns to scale and borrowing adjustment is frictionless, their problem is static. Firms maximize dividends Θ_t (which are always zero in equilibrium) as follows:

$$\Theta_t \equiv \max_{\{k_t, l_t, L_t^D\}} A_t k_t^\alpha l_t^{1-\alpha} - \underbrace{r_{t-1}^L L_t^D}_{\text{interest to bank}} - \underbrace{w_t l_t}_{\text{payroll to worker}} - \underbrace{\delta_k k_t}_{\text{capital depreciation}}$$

[11] Firms can increase and decrease the amount of borrowing L_t^D without any costs. This is why there are no parameters associated with loan maturity in the firm's problem. On the other hand, banks pay liquidation costs when they reduce the amount of loan L_t faster than at rate δ (maturity rate). Since our main focus is on the liquidity management of banks, I use relatively simple assumptions for firms.

subject to the resource constraint

$$k_t \leq L_t^D$$

where δ_k is the capital depreciation rate.[12] Solving the firms' problem using equation (4) leads to the solution

$$\begin{aligned} L_t^D(r_{r-1}^L) = k_t(r_{r-1}^L) &= \left[\frac{\alpha(1-\alpha)^{\frac{1-\alpha}{\nu+\alpha}} A_t^{\frac{1+\nu}{\nu+\alpha}}}{\delta_k + r_{t-1}^L}\right]^{\frac{\nu+\alpha}{\nu(1-\alpha)}} \\ l_t(r_{r-1}^L) &= \left[A_t(1-\alpha)L_t^D(r_{r-1}^L)^\alpha\right]^{\frac{1}{\nu+\alpha}} \\ \Theta_t &= 0. \end{aligned} \tag{6}$$

Equation (6) is interpreted as the loan demand function.

4.4 Banks

4.4.1 The Banks' Environment

At the beginning of period t, there are two endogenous state variables, namely, illiquid loans $L_t \geq 0$ and liquid assets (i.e., securities such as Treasury bills) B_t. The loans are illiquid and have an exogenous maturity $\frac{1}{\delta}$ so that, in each period, a constant fraction δ of loans L_t matures. Hence, the law of motion of L_t is $L_{t+1} = L_t(1-\delta) + I_{t+1}$, where I_t is the investment in new loans if it is positive, or the amount of cash obtained by liquidating loans if it is negative.[13] I do not restrict the sign of B_t, which means it is the net position in securities, thereby allowing the bank to either borrow from the financial market[14] ($B_t < 0$) or lend ($B_t \geq 0$) at the same risk-free rate.[15]

In addition, there are two exogenous states: deposit funding $D_t \in D = [0, \bar{D}]$ and monitoring technology $Z_t \in Z = (0, \bar{Z}]$. These two types of exogenous state variables follow a bivariate Markov process with transition matrix $P(s_t|s_{t+1})$, where the vector

[12]We assume that loan interest rates are floating. This is reflected by the fact that the contemporaneous interest rate r_{t-1}^L applies to all loans outstanding L_t^D. According to Ippolito et al. (2018), the vast majority of corporate loans from banks feature floating interest rates.

[13]This is similar to Corbae et al. (2016) and De Nicolò et al. (2014).

[14]This includes federal funds purchased and repurchase agreements (repos).

[15]This is similar to De Nicolò et al. (2014) and Hennessy and Whited (2005).

of idiosyncratic shocks is $s_t = (D_t, Z_t) \in D \times Z = S$. Equity capital at the beginning of the period is given by

$$E_t \equiv L_t + B_t - D_t \geq 0. \tag{7}$$

The idiosyncratic shocks $s_{t+1} = (D_{t+1}, Z_{t+1})$ occur at the beginning of the period t.[16]

Cash flow π_{t+1} and interest income e_{t+1} are expressed by

$$\pi_{t+1} = \pi(L_t, B_t; s_t, s_{t+1}) = (\delta + r^L_{t-1})L_t - \frac{L_t^2}{Z_t} + (1+r_f)B_t - r^d_{t-1}D_t + (D_{t+1} - D_t) - \Upsilon \tag{8}$$

$$e_{t+1} = e(L_t, B_t; s_t) = r^L_{t-1}L_t - \frac{L_t^2}{Z_t} + r_f B_t - r^d_{t-1}D_t - \Upsilon. \tag{9}$$

In equation (8), the first term is matured loans plus interest returns. The second term captures convex non-interest expenses of loan providence such as screening and monitoring costs, as in Corbae et al. (2016). The larger Z_t is, the smaller these costs are, which means the bank has good monitoring technology.[17] When $B_t \geq 0$, securities mature with risk-free return r_f. When $B_t < 0$, the bank pays capital and interest cost to market borrowing in the previous period.[18] The deposit rate $r^d_{t-1}(\equiv R^D_{t-1} - 1)$ is paid on deposits D_t and $(D_{t+1} - D_t)$ captures deposit outflow. Finally, Υ is the fixed cost of operating in the loan market.

After the cash flow π_{t+1} is realized, banks can choose exit or stay. If they exit, they can default on deposits, in which case deposit holders are protected by deposit insurance. If they stay, they choose new loans and liquid assets (L_{t+1}, B_{t+1}). When cash flow is negative $\pi_{t+1} < 0$, the bank is in financial distress. In this situation, banks in financial distress can choose to either (a) liquidate loans, (b) borrow in the financial market, or (c) recapitalize (i.e., issue equity), all of which are costly to the bank. Each option is described below.

(a) Liquidate loans

[16] I use time scripts $t+1$ for variables other than prices (r^L, r^d) after s_{t+1} is realized.

[17] This is similar to Boissay et al. (2016) in the sense that banks' heterogeneity is generated by shocks to loan management skill, and high skilled banks borrow from low skilled banks to finance their loans through the interbank market.

[18] In this paper, we assume risk-free interest return r_f is exogenously given rather than endogenously determined by market clearing of the liquid asset market. This is justified by assuming in reality this type of short-term risk-free interest rate is controlled by central banks.

The law of motion for loans is

$$L_{t+1} = L_t(1-\delta) + I_{t+1}$$

where I_{t+1} are new loans made at period t. New loans I_{t+1} yield interest return after period $t+1$. The banks can reduce loan exposure faster than at rate δ, which corresponds to the case where $I_{t+1} < 0$, above. In this case, it must pay liquidation costs for disinvestment

$$\Psi(L_t, L_{t+1}) = \frac{\Psi_L}{2}\frac{(I_{t+1})^2}{L_t(1-\delta)}\mathbb{I}\{I_{t+1} < 0\}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function and Ψ_L is the cost coefficient.[19]

(b) Borrow in the financial market

If $B_{t+1} < 0$, the amount of debt issued by the bank must be fully collateralized. Hence, the collateral constraint

$$\underbrace{\phi_t}_{\text{pledgeability}} \cdot \left[\underbrace{(1+r_t^L)L_{t+1} - \frac{L_{t+1}^2}{Z_{t+1}} - \Psi(L_{t+1}, 0) - \Upsilon}_{\text{earning from loans+liquidation value of loans}}\right] \geq \underbrace{-(1+r^f)B_{t+1}}_{\text{debt repayment}}. \tag{10}$$

must be satisfied.[20] ϕ_t is the fraction of the value of the loans and earnings that can be used as collateral for market finance (pledgeability). In the latter part of this paper, I

[19] Notice that liquidation cost is normalized by L_t. Thanks to this normalization, the liquidation cost is scale free. This means it depends on what fraction of loans they liquidate and not the absolute amount of liquidated loans. The reason why I assume this functional form is because I do not want to distinguish between large and small banks on how easily they liquidate their loans.

[20] In the U.S., when a (insured) bank fails, the FDIC receives the failed bank. The FDIC sells the assets of the failed bank and settles its debts. By law, depositors are paid first, followed by uninsured general creditors, and then stockholders (https://www.fdic.gov/consumers/banking/facts/). Thus, the priority of payments of uninsured market borrowing B_u (as federal funds purchased) and deposits D is $D \succ B_u$. On the other hand, the priority of repos is $B_{repo} \succ D$ since repos change ownership of assets from the bank to the investor (this is well documented in Gorton and Metrick (2012a)). In my data, just before the financial crisis occurred (2008Q2), the total amount of borrowing through repos was larger than total amount of borrowing through federal funds purchased. Further, based on Gorton and Metrick (2012b,a), the financial crisis actually occurred in the repo market. Taking these facts into account, I use the collateral constraints where market borrowing B is prior to deposits D.

define a liquidity shock as a reduction of ϕ_t.

(c) Recapitalize

As a result of the choice of (L_{t+1}, B_{t+1}), the residual cash flow to bankers (i.e, dividend) at the end of period t is

$$\begin{aligned} U_{t+1} &= U(L_t, \pi_{t+1}, L_{t+1}, B_{t+1}) \\ &= \pi_{t+1} - B_{t+1} - \{L_{t+1} - L_t(1-\delta)\} - \Psi(L_t, L_{t+1}). \end{aligned}$$

The first term is realized cash flow. The second term is market borrowing (if negative), or security purchase (if positive). The third and fourth terms are new loan investment if $L_{t+1} - L_t(1-\delta) \geq 0$, and the amount of the liquidated loans minus liquidation cost if $L_{t+1} - L_t(1-\delta) < 0$. $U_{t+1} < 0$ means the bank issues new equity, which is costly, as shown below.

The objective of banks at the beginning of period t is to maximize expected franchise value

$$V(L_t, B_t; \underbrace{D_t, Z_t}_{\equiv s_t}) \equiv E_t \sum_{k=t}^{+\infty} \beta^{k-t} \eta(U_{k+1}) \tag{11}$$

where β is the discount factor of bankers and the function

$$\eta(x) = \begin{cases} x & \text{if } x \geq 0 \\ x(1+\chi) & \text{if } x < 0. \end{cases} \tag{12}$$

reflects the fact that recapitalization (equity issuance) is costly, as in De Nicolò et al. (2014), Corbae and D'Erasmo (2019), and Hennessy and Whited (2005). Using this function, the policy function of dividends (or equity issuance if negative) can be expressed as

$$Div_{t+1} = Div(L_t, \pi_{t+1}, L_{t+1}, B_{t+1}) = \eta(U(L_t, \pi_{t+1}, L_{t+1}, B_{t+1})).$$

Meanwhile, an expectation operator (E_t) is used with respect to the two kinds of shocks (s_t).

Figure 4: Timeline for a bank

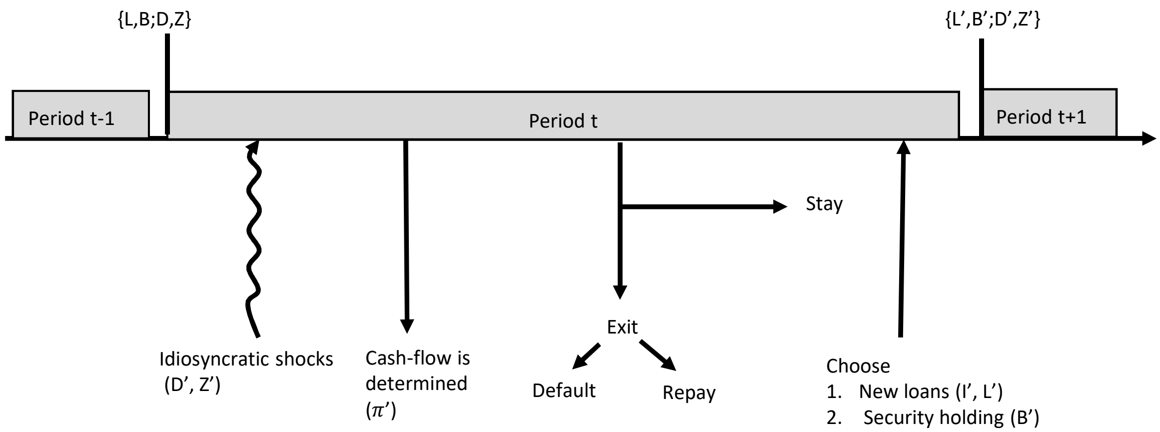


Figure 4 summarizes the timing for banks.

4.4.2 The Bank's Problem

Due to the recursive nature of the bank's problem, we can drop time subscripts. Let $x_t = x$ and $x_{t+1} = x'$. The bank's objective is to maximize expected franchise value (11).

Let the value of banks just after they decide to stay rather than exit be denoted as $W^s(L, \pi'; s')$. Then their problem is expressed recursively by

$$W^s(L, \pi'; s') = \max_{L' \geq 0, B'} \eta(U(L, \pi', L', B')) + \beta V(L', B'; s')$$

subject to

$$(1 - \kappa)L' + B' \geq D' \tag{13}$$

$$\phi \cdot \left[(1 + r^L)L' - \frac{L'^2}{Z'} - \Psi(L', 0) - \Upsilon \right] \geq -(1 + r^f)B' \ \text{ if } B' < 0. \tag{14}$$

Equation (13) is the capital requirement,[21] and equation (14) is the banks collateral constraint introduced in the previous subsection.

When they choose exit, they solve the problem

[21] We assume that banks are required to hold at least κ times the amount of loans L as capital, $E \geq \kappa L$. From definition (7), this condition is reduced to (13).

$$W^o(L,\pi';s') = \max\{\underbrace{0}_{\text{default}}, \underbrace{\pi' - D' + L(1-\delta) - \Psi(L,0)}_{\text{repay}}\}.$$

Thanks to limited liability, they can choose default and obtain zero value. When they repay, they obtain their cash flow minus new deposits, plus the liquidation value of all loans minus the liquidation cost.

Combining these two problems, a bank's value at the beginning of period t is reduced to the following:

$$\begin{aligned} V(L,B;s) &= E_{s'|s}\max\{W^o(L,\pi';s'), W^s(L,\pi';s')\} \\ &= E_{s'|s}\max\{\underbrace{0}_{x=1}, \underbrace{\pi' - D' + L(1-\delta) - \Psi(L,0)}_{x=2}, \\ &\quad \underbrace{W^s(L,\pi';s')}_{x=3}\} \end{aligned}$$

where π' is given in equation (8). I define the exit policy $x(L,B;s,s')$ as

$$x(L,B;s,s') = \begin{cases} 1 & \text{exit after default} \\ 2 & \text{exit after repayment} \\ 3 & \text{stay} \end{cases} \tag{15}$$

and other policies

$$\begin{aligned} L' &= L(L,\pi';s') \\ B' &= B(L,\pi';s') \end{aligned}$$

as the solutions to the above problem.

4.4.3 Entrance of New Banks and Stationary Distribution of Banks

Entry dynamics are similar to Cooley and Quadrini (2001) and Katagiri (2014) in the sense that entrants decide whether or not to enter after they observe their idiosyncratic shocks.[22] There is a continuum of potential entrants of measure M. Entrants draw

[22]This assumption, rather than deciding upon entry before shocks are realized, makes the computation of dynamic analysis conducted later easier to handle. When they decide whether to enter or not before they draw their shocks s'(as in Gomes (2001), Corbae and D'Erasmo (2019), and Hopenhayn

$s' = \{D', Z'\}$ from $\varphi(s')$.[23] Their initial state variables are $\{L, B; D\} = \{0, 0, 0\}$. Let the value just after entry be denoted as $W^e(s')$, which is defined below. They enter if

$$W^e(s') \geq 0. \tag{16}$$

Let the mass of banks in the state $(dL, dB; s)$ at the beginning of period t be denoted as $\zeta_t(dL, dB; s)$. By using the policy functions introduced above, we can trace the law of motion of the distribution $\zeta_t(dL, dB; s)$ as

$$\begin{aligned}\zeta_{t+1}(dL', dB'; s') = \int \sum_s & P(s|s') \cdot \zeta_t(dL, dB; s) \cdot \mathbb{I}\{x(L, B; s, s') = 3\} \\ & \times \mathbb{I}\{dL' \ni L(L, \pi(L, B; s, s'); s')\} \cdot \mathbb{I}\{dB' \ni B(L, \pi(L, B; s, s'); s')\} \\ & + M \cdot \mathbb{I}\{dL' \ni L^e(s')\} \cdot \mathbb{I}\{dB' \ni B^e(s')\} \cdot \mathbb{I}\{W^e(s') \geq 0\}\varphi(s'). \end{aligned} \tag{17}$$

where $\mathbb{I}\{\cdot\}$ is an indicator function. The first term on the right-hand side represents the distribution of incumbent banks, and the second term represents new entrants. $L^e(s')$ and $B^e(s')$ describe the solution of the new entrant's problem

$$\begin{aligned} W^e(s') &= \max_{L' \geq 0, B'} \eta(U(0, \pi' = D' - \kappa, L', B')) + \beta V(L', B'; s') \\ &= \max_{L' \geq 0, B'} \eta(D' - \kappa - B' - L') + \beta V(L', B'; s') \end{aligned}$$

subject to equations (13) and (14). Notice that when banks enter, they hold no loans and securities, so that their initial cash flow is $D' - \kappa$.

A stationary distribution is a distribution ζ^* satisfying $\zeta_{t+1} = \zeta_t = \zeta^*$. Once the stationary distribution ζ^* is derived, the aggregate deposits (D_{tot}), outstanding loans

(1992)), their entry condition becomes that they enter if $\sum_{s'} W^e(s')\varphi(s') \geq 0$. In this case, the equilibrium mass of new entrants M^* and the price (lending rate) r^{L*} are endogenously determined by the market clearing condition of loans and the free entry condition, respectively. When we solve the dynamic problem, we should adjust both the mass of entrant M_t and the lending rate r_t^L to satisfy these conditions, which is computationally costly. On the other hand, when we assume their entry decisions are made after they observe drawing, as in this paper, the mass of *potential* new entrants M is an exogenous parameter (estimated within the model), and the price (lending rate) r^{L*} is endogenously determined by the market clearing condition of loans. In dynamic analysis, we have to adjust only the lending rate r_t^L to satisfy the market clearing condition and adjusted threshold of shocks above which *potential* entrants decide to enter to pin down the mass of *actual* entrants. In this case, we need only satisfy the market clearing condition to solve the problem, which reduces the computational burden.

[23] I assume this distribution is the invariant distribution, which is implied by $P(s|s')$.

(L_{tot}), new loans (I_{tot}), net securities holding (B_{tot}), dividends (Div_{tot}), and lump-sum tax for deposit insurance (T_{tot}) are computed by aggregating each bank's variables using the stationary distribution.

$$
\begin{aligned}
\text{deposits} \quad &: \ D_{tot} = \int \sum_{s} D\zeta^*(dL, dB; s) \\
\text{loans} \quad &: \ L_{tot} = \int \sum_{s} L\zeta^*(dL, dB; s) \\
\text{new loans} \quad &: \ I_{tot} = \int \sum_{s,s'} P(s|s')\mathbb{I}\{x(L, B; s, s') = 3\}\{L(L, \pi(L, B; s, s'); s, s') \\
&\quad - L(1-\delta)\}\zeta^*(dL, dB; s) + M \cdot \sum_{s'} L^e(s')\mathbb{I}\{W^e(s') \geq 0\}\varphi(s') \\
\text{net securities} \quad &: \ B_{tot} = \int \sum_{s} B\zeta^*(dL, dB; s) \\
\text{dividends} \quad &: \ Div_{tot} = \int \sum_{s,s'} P(s|s')\mathbb{I}\{x(L, B; s, s') = 3\}Div(L, \pi(L, B; s, s'), \\
&\quad L(L, \pi(L, B; s, s'); s'), B(L, \pi(L, B; s, s'); s'))\zeta^*(dL, dB; s) \\
&\quad + M \cdot \sum_{s'} Div(0, D' - \kappa, L^e(s'), B^e(s'))\mathbb{I}\{W^e(s') \geq 0\}\varphi(s') \\
\text{lump} - \text{sum tax} \quad &: \ T_{tot} = \int \sum_{s,s'} P(s|s')\mathbb{I}\{x(L, B; s, s') = 1\}\{\Psi(L, 0) - \pi(L, B; s, s') \\
&\quad + D' - L(1-\delta)\}\zeta^*(dL, dB; s)
\end{aligned}
\tag{18}
$$

4.5 Stationary Competitive Equilibrium

Given the capital requirement policy κ, a stationary competitive equilibrium is a set of

(i) bank policy functions $\{x(L, B; s, s'), L(L, \pi'; s'), B(L, \pi'; s')\}$, value functions $\{V(L, B; s), W^o(L, \pi; s'), W^s(L, \pi; s'), W^e(s')\}$, a stationary distribution $\zeta^*(L, B; s)$, aggregate bank variables $\{D^*_{tot}, L^*_{tot}, I^*_{tot}, B^*_{tot}, Div^*_{tot}, T^*_{tot}\}$

(ii) household policy variables $\{c^{h*}, d^{h*}, l^{h*}\}$

(iii) firm policy variables $\{l^{f*}, L^{D*}\}$

(iv) a set of prices $\{w^*, r^{L*}, r^{d*} = \frac{1}{\beta^D} - 1\}$, dividends $\Theta^*(= 0)$, and lump-sum tax T^*

such that

1. Given (iv), (ii) satisfies the household's problem.
2. Given (iv), (iii) satisfies the firm's problem.
3. Given (iv), (i) satisfies the bank's problem.
4. Markets clear

$$d^{h*} = D^*_{tot}$$
$$l^{h*} = l^{f*}$$
$$L^{D*} = L^*_{tot}.$$

5. The budget constraint of the DIA is satisfied $T^* = T^*_{tot}$.

The computational method is described in detail in Appendix A.

5 Calibration

I use panel data constructed from the Call Reports of U.S. commercial banks, which is transformed to a yearly basis (hence, the model period corresponds to a year). The sample period is 1983 to 2008.[24] For the calibration, I drop data for new entrants (the year when they enter) because deposits and loans of these banks move quite differently from those of incumbent banks, and because my interest is mainly incumbent banks.[25] The variables in the model correspond to the following data from the Call Reports (following Kashyap and Stein (2000)).

[24] In regard to the data for capital ratios, I choose sample periods from 1996-2008, during which periods I can obtain data directly from Call Reports.

[25] As a possible extension of this model, we can model two types of banks, new banks and old banks, as follows. Their law of motion of deposits and monitoring technology follow different AR(1) processes, and a new bank becomes an old bank with a certain probability.

Table 1: Correspondence of model variables with Call Report

	Variables in Call Reports
Loans	1983 Total Loans and Leases (RCFD1400)+Lease Financing Receivables (RCFD2165)
	1984- Total Loans and Leases, Gross (RCFD1400)
Deposits	1983- Total Deposits (RCFD2200)
Total Assets	1983- Total Assets (RCFD2170)
Equity Capital	1996- Tier1 Capital (RCFD8274)
Risk-Weighted Assets	1996- Net risk-weighted assets (RFCDA223)
Income	1983- Income before taxes (RIAD4301)
Securities	2001-RCFD0211+RCFD1287+RCFD1289+RCFD1293+RCFD1298+RCFD8496+RCFD8499
Cash	2001-RCFD0081+RCFD0071
Federal funds sold	2001-RCONB987
Reverse repo	2001-RCFDB989
Federal funds purchased	2001-RCONB993
Repo	2001-RCFDB995
Trading liability	2001-RCFD3548
Subordinated notes	2001-RCFD3200
Other borrowed money	2001-RCFD3190

Note: Data in the upper row are for the calibration of the model. Data in the lower row are for calculating the liquidity position defined in (1), and are not used for calibration.

5.1 Dynamics of Deposits and Monitoring Technology Shocks

I assume $\log D_{it}$ and $\log Z_{it}$ follow a bivariate AR(1) process. Let $(\log D_{it}, \log Z_{it})$ be denoted as X_{it}. Then

$$X_{it} = (1-K)\bar{X} + KX_{it-1} + \xi_{it} \tag{19}$$

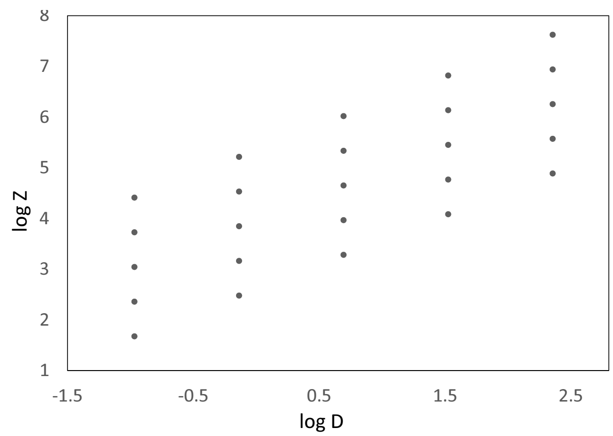
where

$$\bar{X} = \begin{pmatrix} \overline{\log D} \\ \overline{\log Z} \end{pmatrix},\ K = \begin{pmatrix} \kappa_D & 0 \\ 0 & \kappa_Z \end{pmatrix},\ \xi_{it} = \begin{pmatrix} \xi_{it}^D \\ \xi_{it}^Z \end{pmatrix},\ E_t[\xi_{it+1} \cdot \xi'_{it+1}] = \Lambda = \begin{pmatrix} \sigma_D^2 & \rho\sigma_D\sigma_Z \\ \rho\sigma_Z\sigma_D & \sigma_Z^2 \end{pmatrix}.$$

Let Q be a lower triangular matrix such that $\Lambda = QQ'$ (Cholesky decomposition). After some algebra, multiplying equation (19) by Q^{-1} yields

$$Y_{it} = \Pi Y_{it-1} + \varepsilon_{it} \tag{20}$$

Figure 5: Jointly discretized shocks



where

$$\begin{aligned} Y_{it} &= Q^{-1}(X_{it} - \bar{X}) \\ \Pi &= Q^{-1}KQ \\ \varepsilon_{it} &= Q^{-1}\xi_{it} \\ var(\varepsilon_{it}) &= E(Q^{-1}\xi_{it}\xi_{it}^{'}(Q^{-1})^{'}) = I. \end{aligned}$$

I use the discretization strategy of Gospodinov and Lkhagvasuren (2014) for Y_{it} in equation (20).[26] Then we can recover X_{it} by using the relation above. In the following, we discretize $(\log D_{it}, \log Z_{it})$ into 5×5 states. The parameters associated with this process are $(\kappa_D, \kappa_Z, \bar{D}, \bar{Z}, \sigma_D, \sigma_Z, \rho)$ and are calibrated to match the target moments later. The jointly discretized shocks are shown in Figure 5. Deposit funding shocks are on the horizontal axis, and monitoring technology shocks are on the vertical axis. These two shocks jointly move among these 25 states following the Markov transition matrix $P(s|s')$. Banks manage their balance sheets by anticipating these bivariate shocks.

5.2 Calibrated Model Parameters

The model period is one year. The calibrated parameters are shown in Table 2. First, I set the labor share to $\alpha = \frac{1}{3}$ (Bianchi and Bigio (2017)). I set the inverse of the Frisch

[26] I also tried the method of Tauchen (1986) to discretize this bivariate process. I choose the method of Gospodinov and Lkhagvasuren (2014) instead because when the number of discretized states is small, their match on the moments of the original process is more accurate than Tauchen (1986).

elasticity by targeting loan demand elasticity. According to Bassett et al. (2014), an increase of 100 basis points in the loan rate spread lowers the demand of new loans between 1.1-1.7 percent, after controlling for supply factors. I choose $\nu = 2$ by targeting new loan demand elasticity -1.5. I then set the capital depreciation rate to $\delta_k = 0.15$, based on Corbae and D'Erasmo (2017), who estimate it using Compustat.

For the parameters associated with the banking sector, the discount factor for households β^D is chosen so that $\frac{1}{\beta^D} - 1$[27] matches the target deposit rate 0.86%, as in Corbae and D'Erasmo (2019). I set the risk-free rate to $r_f = 0.012$, following Corbae and D'Erasmo (2019). Notice that $r^f > r^d$ means that for banks, deposits are a less costly funding source than market borrowing. This ensures that even though banks can make up for lost deposits with market borrowing if the collateral constraint permits, they would prefer not do so. Next, the banker's discount factor is set to $\beta^b = 0.95$ to target banks' capital cost, as in Corbae and D'Erasmo (2019) and De Nicolò et al. (2014). Loan maturity is set to 5 years ($\delta = 0.2$) as in De Nicolò et al. (2014). The liquidation cost of loans is set to $\frac{\Psi_L}{2} = 0.3$, to match the value of sold banks in Granja et al. (2017). For the capital requirement, I choose $\kappa = 0.08$, based on the U.S. standard of a "well capitalized" bank.[28]

Next, I calibrate the parameters specific to my model. First, as in De Nicolò et al. (2014), I normalize the unconditional average of deposits $\overline{\log D} = \log(2)$. Next, I calibrate (κ_D, σ_D) by directly observing the panel of deposits from the Call Reports. Then, I jointly calibrate the measure of potential new entrants M, the equity issuance cost λ, the fixed cost Υ, and $(\kappa_Z, \overline{\log Z}, \sigma_Z, \rho)$. Even though I cannot observe the monitoring technology Z_{it} directly, it must have a strong relation with the amount of loans L_{it}, so I use moments associated with the amount of loans to calibrate these parameters. I choose seven target moments: the lending rate (r^L in the model), the average capital ratio, the annual bank exit rate,[29] the difference between the unconditional average amount of log-loans and that of log-deposits ($\overline{\log L} - \overline{\log D}$), the annual persistence of log-loans, the annual conditional variance of log-loans, and the intertemporal correlation between log-deposits ($\log D_{it}$) and log-loans ($\log L_{it}$). I estimate the unconditional average of amount of log-loans ($\overline{\log L}$), the annual persistence of log-loans (κ_L), and the annual conditional variance of log-loans (σ_L^2) by

[27] At this stage, we are focusing solely on stationary equilibrium.

[28] Following the Basel Accord, the FDIC categorizes those banks whose capital ratio is ($\frac{\text{Tier 1}}{\text{RWA}} \geq 8\%$) as "well capitalized".

[29] Bank exit is divided into merger and acquisition (M&A), or failure. Since I do not deal with M&A in this model, I only count exit through failure.

$$\log L_{it} = (1-\kappa_L)\overline{\log L} + \kappa_L \log L_{it-1} + \varepsilon^L_{it}$$
$$Var[\varepsilon^L_{it}] = \sigma^2_L.$$

The measure of potential new entrants M influences the total supply of loans and the lending rate through the market clearing condition of loans. The equity issuance cost λ influences banks' precautionary behavior. When $\lambda = 0$, banks can freely recapitalize after they lose deposits, or if they want to increase their loans after their monitoring technology improves. In this case, they have no incentive to hold more capital. On the other hand, when λ is large, they try to hold more capital as a buffer against these shocks. Hence, the equity issuance cost λ has an impact on the average capital ratio. In my model, this parameter is calibrated to $\lambda = 25$.[30] The fixed cost is critical for the exit rate, since it directly reduces the franchise value of banks. Furthermore, the average of the log-monitoring technology $\overline{\log Z}$, the annual persistence of log-monitoring technology κ_Z, and the annual standard deviation of the log-monitoring technology σ_Z impact the unconditional average amount of log-loans ($\overline{\log L}$), the annual persistence of log-loans, and the annual conditional variance of log-loans, respectively. Finally, the intertemporal correlation between log-deposits and the log-monitoring technology ρ impacts intertemporal correlation between log-deposits ($\log D_{it}$), and log-loans ($\log L_{it}$). The consistency between the data and model moments is shown in Table 3.

[30] In Corbae and D'Erasmo (2019) where there are two types of banks (big banks and fringe banks), the equity issuance cost is estimated as 0.05 for big banks and 30 for fringe banks. Taking into account that in my model there exists only one type of bank, this value is reasonable.

Table 2: Calibrated model parameters

Parameters		Values	Target values and sources
Capital share	α	$\frac{1}{3}$	Bianchi and Bigio (2017)
Inverse of the Frisch elasticity	ν	2	New loan demand elasticity -1.5 (Bassett et al. (2014))
Productivity	A	1	A=1 (normalization)
Capital depreciation	δ_k	0.15	Corbae and D'Erasmo (2017)
H.H.'s discount factor	β^D	0.991	Deposits rate 0.0086 (Corbae and D'Erasmo (2019))
Risk-free rate (%)	r_f	0.012	Corbae and D'Erasmo (2019)
Banker's discount factor	β^b	0.95	Cost of capital 5%
			(Corbae and D'Erasmo (2019); De Nicolò et al. (2014))
Annual percentage of reimbursed loan	δ	0.20	De Nicolò et al. (2014)
Liquidation cost	Ψ_L	0.6	Granja et al. (2017)
Pledgeability	ϕ	1.0	assume full pledgeability in steady state
Capital requirement	κ	0.08	Basel Accord
Uncond. average of the log-dep	$\overline{\log D}$	0.69	$\overline{\log D} = \log(2)$ (normalization)
Persistence of the log-dep	κ_D	0.95	Call Reports
Cond. SD of the log-dep	σ_D	0.26	Call Reports
Measure of potential entrants	M	0.0023	Lending rate 7% (Bank prime loan rate)
Equity issuance cost	λ	25	Average capital ratio (Call Reports)
Fixed cost	Υ	0.037	Annual bank's exit rate 0.7 % (FDIC)
Uncond. average of the log-mon tech	$\overline{\log Z}$	4.35	$\overline{\log L} - \overline{\log D} = 0.1$ (Call Reports)
Persistence of the log-mon tech	κ_Z	0.95	Persistence of log-loan 0.96 (Call Reports)
Cond. SD of the log-mon tech	σ_Z	0.35	Uncond. VAR of log-loan 0.90 (Call Reports)
Corr b/w log-dep and log-mon tech	ρ	0.95	Inter-temp. corr b/w log-dep and log-loan
			0.60 (Call Reports)

Table 3: Model and target moments

Target moments	Target values	Model
Interest rate of loan (%)	7% (Bank prime loan rate)	7%
Average capital ratio	0.18 (Call Reports)	0.14
Annual bank exit rate (%)	0.7% (FDIC)	0.7%
Difference b/w av. of log-loan	$\overline{\log L} - \overline{\log D} = 0.1$ (Call Reports)	0.09
and av. of log-dep		
Persistence of log-loan	0.96 (Call Reports)	0.94
Unconditional variance of log-loan	0.90 (Call Reports)	0.95
Inter-temp. correlation between log-deposits and log-loans	0.60 (Call Reports)	0.57

6 Results

In this section, I show the results of analyzing my models. First, I document some characteristics of the model's stationary equilibrium and describe how these match the data. Then, I show how banks respond to unanticipated productivity and liquidity shocks, and how their behavior changes, depending on their size. Finally, I identify the shocks that replicate the observations mentioned in Section 3.

6.1 Stationary Distribution

Figures 6 and 7 show the stationary distributions of bank characteristics in the model and in the data. Except for the average capital ratio, the average amount of loans, and the variance of loans, these distributions were not targets of the calibration in the previous section. Nevertheless, these distributions match the data quite well. Figures 6a and 6b show that while the capital requirement is 8%, many banks have more capital than required. Furthermore, Figures 7c and 7d show the relationship between the capital ratio and the amount of assets. These variables are negatively correlated, which means small banks take greater precautions than large banks. Figure 8 explains the mechanism of banks' precautionary motives graphically. As introduced in the model section, the banker's utility is linear with unit slope in the positive region due to diversification, and with slope $(1+\chi)$ in the negative region due to equity issuance costs χ. Hence, the utility function of bankers becomes a function depicted in the top of Figure 8. As the equity issuance cost χ increases, the function becomes more concave and banks take more precautions by accumulating larger capital buffers. Furthermore, concavity is strongest near the origin. Due to the fixed cost of operation, small banks are more likely to fall into the equity issuance region, which makes them accumulate capital buffers in order to avoid costly equity issuance. The bottom of Figure 8 shows the stationary distribution of dividends (equity issued if negative) normalized by the amount of assets for each size of bank.[31] Small banks are more likely to stay in the region where the concavity of the utility function is strong, which graphically explains why small banks have greater precautionary motives.

The relationship between the liquidity ratio and asset size is shown in Figures 7a

[31] In the model, the amount of assets As is defined as $As \equiv L + B \cdot \mathbb{I}(B > 0)$.

and 7b. The liquidity ratio (LR) is defined as

$$LR = \frac{\text{net liquidity position}}{\text{amount of assets}}.$$

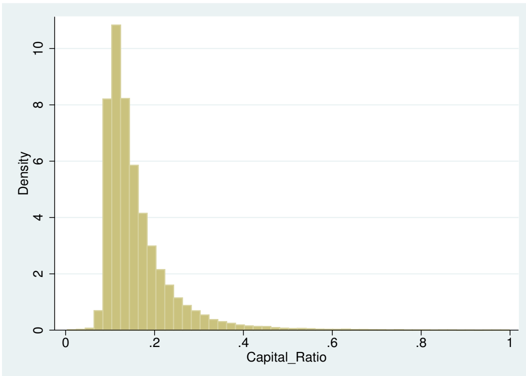
In the data, I define the net liquidity position by (1), but cash is included here.[32] In the model, this value is expressed as $LR = \frac{B}{As(\equiv L+B\cdot\mathbb{I}(B>0))}$.

In the data, LR and the amount of assets have a negative correlation (-0.51). This means that large banks have fewer liquid assets and borrow more from the financial market, while small banks have more liquid assets and do not depend upon the financial market for their funding. The model replicates these characteristics quite well.

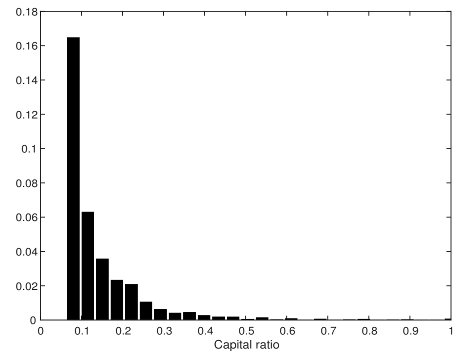
[32] Here, I include cash because I am focusing only on the period before the Federal Reserve started to pay interest on reserves (October 2008).

Figure 6: Stationary distributions

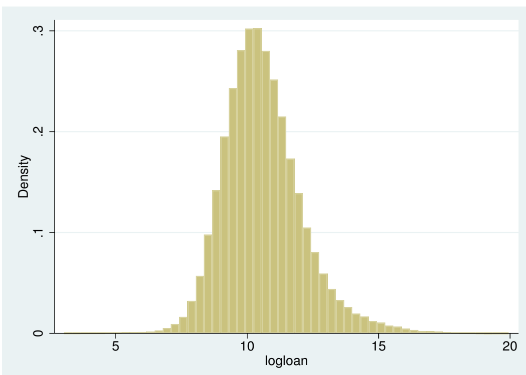
(a) Capital ratio (data)



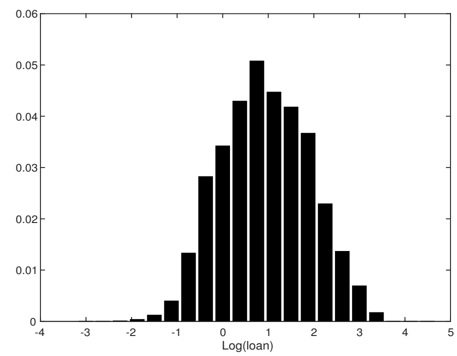
(b) Capital ratio (model)



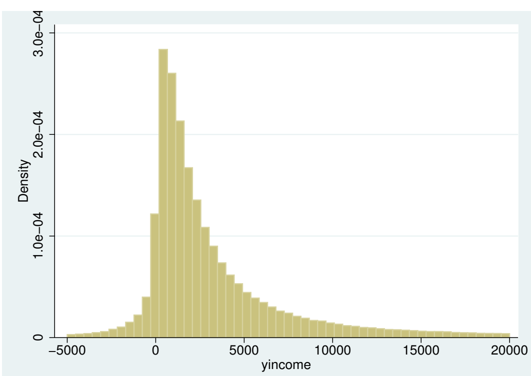
(c) Amount of loans (data)



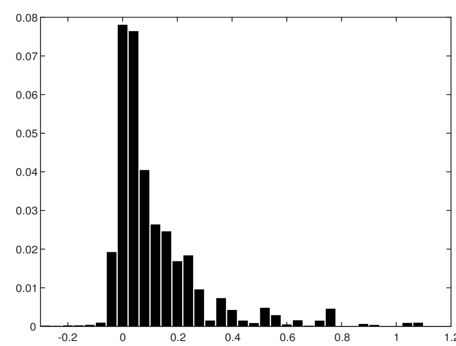
(d) Amount of loans (model)



(e) Income (data)



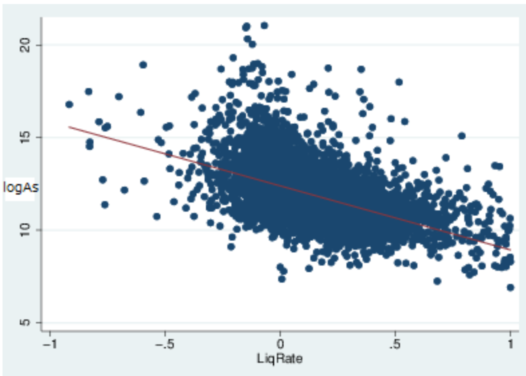
(f) Income (model)



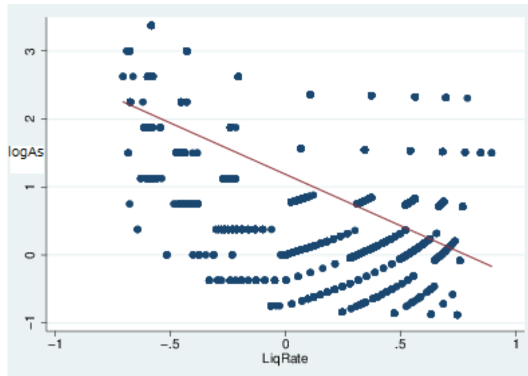
Note: Source: Call Reports (1983-2008).

Figure 7: Relationship of liquidity ratio and capital ratio to asset size

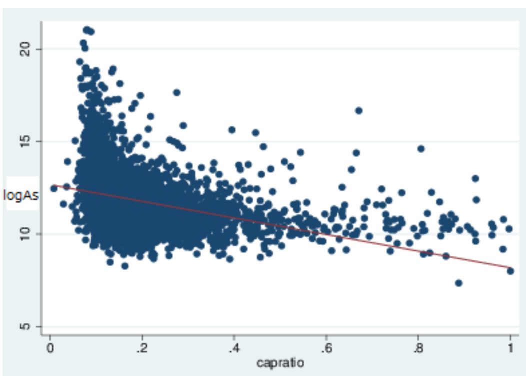
(a) Relationship of liquidity ratio to asset size (data)
Correlation: -0.51



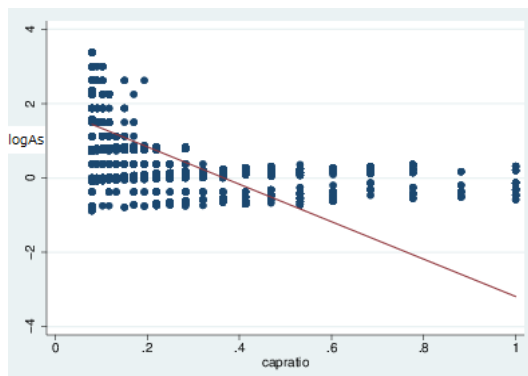
(b) Relationship of liquidity ratio to asset size (model)
Correlation:-0.60



(c) Relationship of capital ratio to asset size (data)
Correlation: -0.34

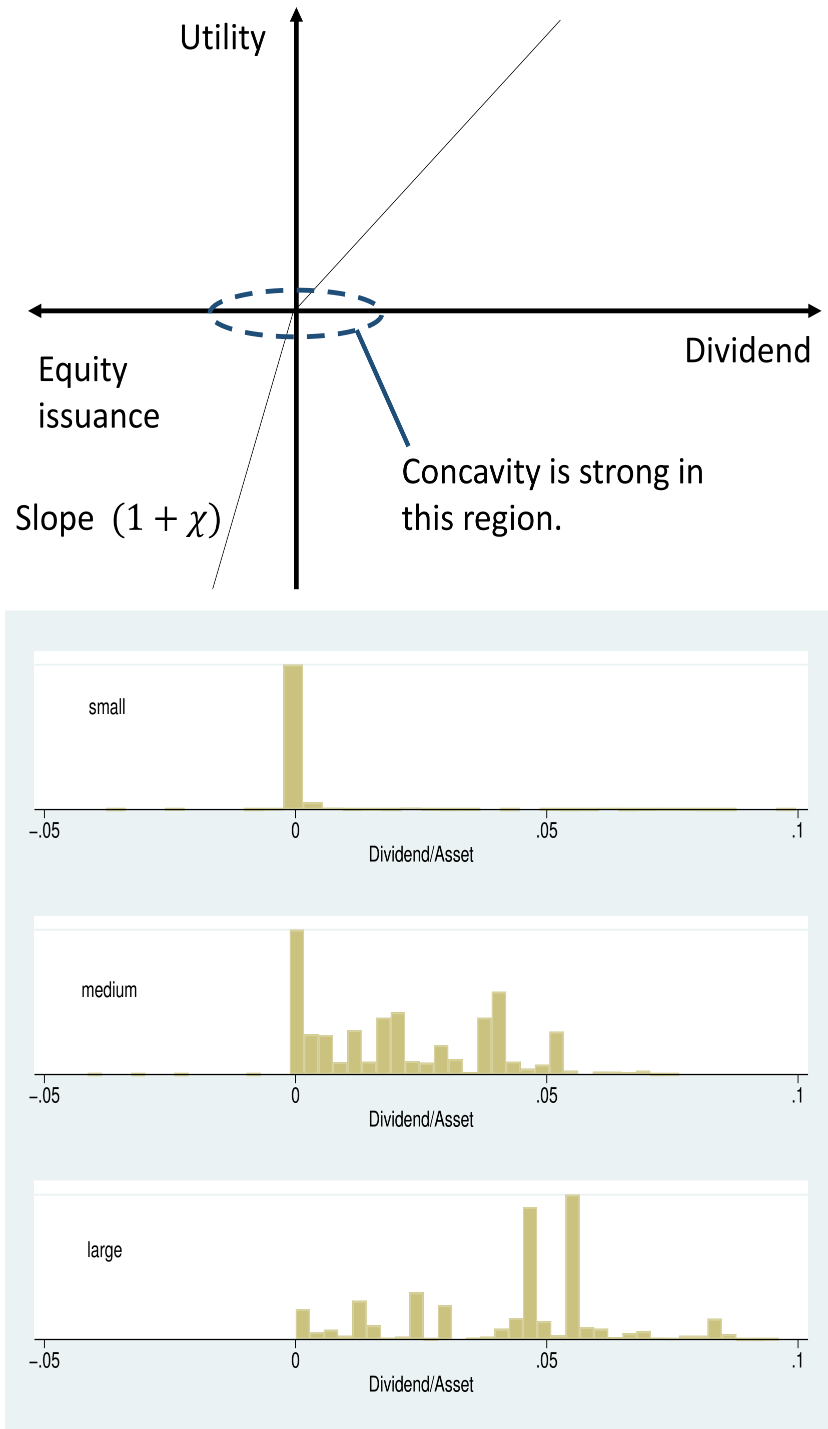


(d) Relationship of capital ratio to asset size (model)
Correlation:-0.61



Note: Source: Call Reports 2008Q2. Liquidity ratio (LR) is defined as $LR = \frac{\text{net liquidity position}}{\text{amount of assets}}$. In the data, I define the net liquidity position by (1), but this time I include cash. In the model this value is expressed as $LR = \frac{B}{As(\equiv L + B \cdot \mathbb{I}(B>0))}$.

Figure 8: Explanation for bank's precautionary motives



Note: The top of the figure shows the utility function of bankers, and the bottom shows the stationary distribution of dividends normalized by the amount of assets for each bank size. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile in assets.

6.2 Dynamic Analysis

In this subsection, I explore how heterogeneously-sized banks respond to two types of shocks in my model. These are unanticipated productivity shocks and liquidity shocks, in line with Guerrieri and Lorenzoni (2017). I also investigate how a combination of these shocks can explain the observations mentioned in Section 3.[33] In doing these analyses, I assume that once the initial shock occurs, agents within the model correctly anticipate the full path of the pledgeability and productivity until the economy recovers to the initial steady state.

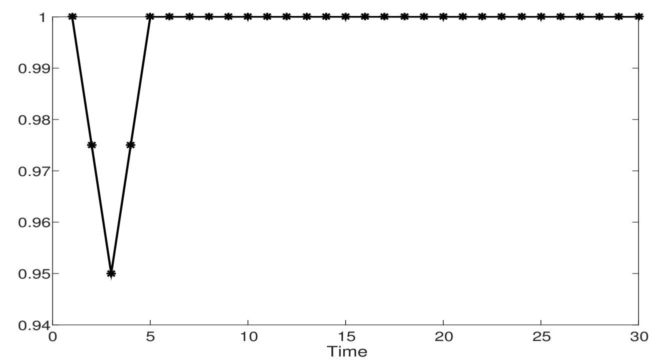
6.2.1 Productivity Shocks

Figure 9 shows how the system responds to the unanticipated productivity shock. Here, the aggregate productivity (A in Section 4) unexpectedly declines to a five percent lower level over two periods, and then returns to the steady state level over two periods as described in Figure 9a. When productivity is low, loan demand is small, so that loan interest rates decline relative to the steady state level, as in Figure 9b. Figure 9c shows how different banks contract their loans in response to productivity shocks, depending on their asset size. As in the empirical counterparts introduced in Section 3, banks are divided into 3 size groups according to their amount of assets in the initial period: small (0-20 percentile), medium (20-80 percentile), and large (80-100 percentile). The mean of each size group is plotted. All banks reduce lending; however, loan contraction is a little larger for small banks. When a negative productivity shock occurs and the interest rate falls, small banks are more likely than large and medium banks to fall into the equity issuance region (i.e., become financially distressed), due to the fixed cost. Since equity issuance is expensive, they choose to liquidate their loans to mitigate this financial stress. Furthermore, the capital of small banks shrinks substantially, causing a slow return to the original steady path. This is why it takes longer for small bank loan growth to recover to its steady state path.

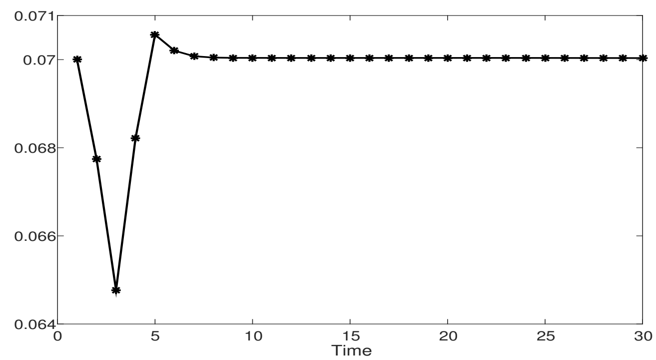
[33]Regarding the sufficiency of the two types of shocks considered here, Bianchi and Bigio (2017) conclude that the disruption in the interbank market (funding shock) and the decline in credit demand were the key driving forces in the crisis, not other kinds of shocks.

Figure 9: Responses to productivity shocks

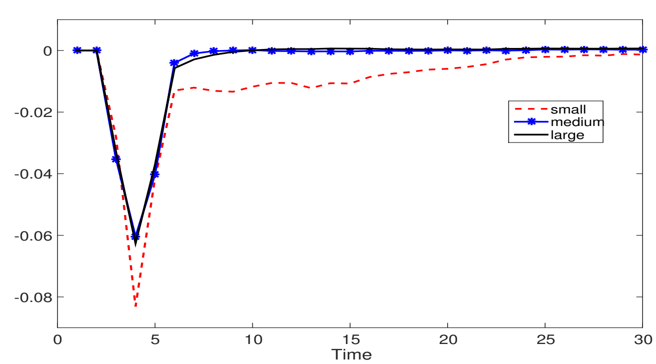
(a) Productivity



(b) Responses of loan interest rate



(c) Responses of loans for each size group



Note: Figure 9c shows deviations from the steady state path. Banks are divided into 3 size groups according to their amount of assets at the initial period. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. The mean of each size group is plotted.

6.2.2 Liquidity Shocks

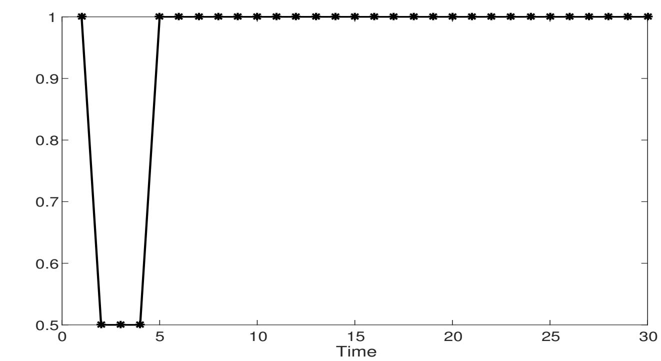
I define unanticipated liquidity shocks as the situation in which banks are unable to borrow from the financial markets. More precisely, I define it as a reduction of pledgeability ϕ in the collateral constraint.[34] Zero pledgeability means banks cannot borrow at all. Figure 10 shows how macroeconomic variables respond to the unanticipated liquidity shock. Here, the pledgeability ϕ unexpectedly declines from $\phi = 1$ to $\phi = 0.5$, stays there for three periods, and then returns to the steady state level as described in Figure 10a. In my model, those banks who borrow from the financial markets are large banks who have a lot of loans. Hence, when a liquidity shock occurs, these market-dependent large banks contract their loans. Since the loan supply decreases while loan demand does not change, the loan interest rate increases as shown in Figure 10b. Small banks that do not use market borrowing increase their loans because the loan interest rate rises. As a result, liquidity shocks cause small banks to substitute for large banks in the loan market, as in Figure 10c.[35] After shocks subside, small banks gradually recover to their steady state path. Since liquidation costs are a quadratic function of liquidated loans, small banks gradually liquidate their increased loans.

[34] This formalization of the liquidity shock is similar to Negro et al. (2017), where the liquidity shock is defined as a shock to the resaleability of assets. The cause of the liquidity shock is beyond the scope of this paper. Gorton and Metrick (2012b,a) and Brunnermeier (2009) explain the mechanism in detail.

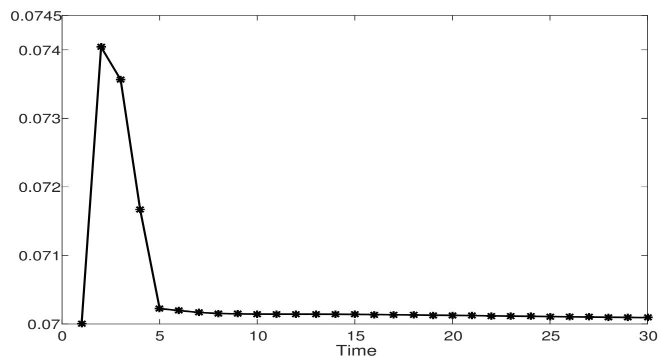
[35] Since loans are reallocated from large banks with high monitoring technologies to small banks with low monitoring technologies, the decline in aggregate lending is proportional to the average decline in monitoring technology. We can interpret this as a misallocation of loans due to tightened collateral constraints. This effect is similar to the misallocation of capital among firms, as discussed in studies by Khan and Thomas (2013) and Moll (2014).

Figure 10: Responses to liquidity shocks

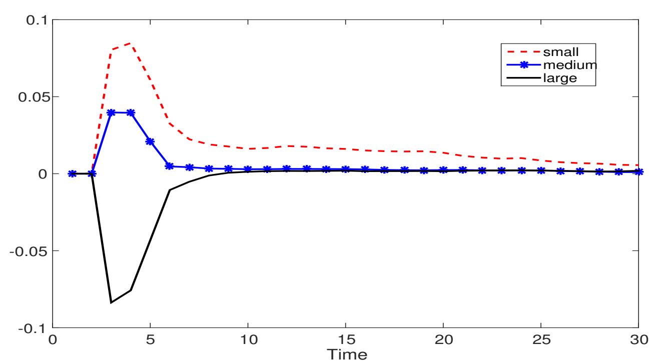
(a) Pledgeability



(b) Responses of loan interest rate



(c) Responses of loans for each size group



Note: Figure 10c plots deviations from the steady state path. Banks are divided into 3 size groups according to their amount of assets at the initial period. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. The mean of each size group is plotted.

6.2.3 Identification and Counterfactual Analysis

In this subsection, I investigate how the two types of shocks introduced in the previous subsections can reproduce the empirical data in the financial crisis and GR. More specifically, I find the combination of shocks (productivity shocks A_t and liquidity shocks ϕ_t) that matches the loan contraction for each size group. During this exercise, I assume that once the initial shock occurs in the third quarter of 2008, agents within the model know the full path of pledgeability and productivity (A_t, ϕ_t) until they recover to the initial level. As described in the previous subsections, negative productivity shocks induce loan contraction of all banks, while liquidity shocks increase loans of small banks and reduce loans of large banks, as summarized in Table 4. Hence, the difference in loan contraction between large and small banks is mainly attributed to the impact of liquidity shocks, and the average reduction is mainly attributed to negative productivity shocks. Using this observation, we can jointly identify both shocks by using cross-sectional loan contraction data. Quantitatively, I choose the combination of shocks (A_t, ϕ_t) to minimize the distance between the data and model result, which is defined as

$$\Xi \equiv \sum_{i=1}^{3} \sum_{t=1}^{10} (LD^i_{2008+t} - LM^i_{2008+t})^2$$

where i is the index of the size group (small, medium, and large), LD^i_{2008+t} is the mean of loan growth of size i banks from the third quarter of 2008, and LM^i_{2008+t} is the model counterpart (deviations from the steady state path). Because (A_t, ϕ_t) has too many potential paths, I impose the following constraint (C) on the recovery processes of (A_t, ϕ_t) in order to reduce the computational burden.

(C) Once productivity and pledgeability (A_t, ϕ_t) fall to their minimum, they stay there for a few periods and then recover linearly to their initial levels.

Note that this constraint does not restrict the number of years before productivity and pledgeability start to recover, nor how long it takes for them to recover up to the initial level; the model can identify these quantities. The identification problem reduces to choosing (A_t, ϕ_t) that minimize Ξ under (C). The identified shocks are shown in Figure 11a, and how well these combinations match the loan contraction of each size group is shown in Figure 11b. In the model, the amount of loans is evaluated at the beginning of the period, so a shock impacts the amount of loans in the next period. Figure 11a shows that pledgeability dropped faster than productivity. Small banks increased their loans at first (2008Q3-2010Q3) because the negative impact of productivity shocks was weaker than the positive impact of liquidity shocks during these periods.[36] After several periods, the negative impact of productivity shocks overcame the positive impact of liquidity shocks, so the small banks started to decrease their loans (2010Q3-2011Q3). Interestingly, this result is consistent with Bianchi and Bigio (2017), who conclude "interbank market freezing may have been important at the beginning of the crisis, which was followed by a persistent decline in demand." Finally, productivity and pledgeability recover to their initial levels in 2020 and 2025 respectively in my model.

Table 4: Summary of loan response for each size group

	Small	Medium	Large
Negative productivity shock	↓	↓	↓
Liquidity shock	↑	→	↓

For further credibility of the identified shocks, Figure 12 shows how other studies estimate the decline of productivity (this is taken from Christiano et al. (2015)). This figure includes several measures from the Bureau of Labor Statistics (BLS), Penn World Tables, and Fernald (2014), each of which is detrended. (Note that my model lies within the range of these measures.) These measures indicate that the fall in TFP was highly persistent; TFP growth remains lower than it was prior to the GR. My result is consistent with this finding.

Figure 13 plots two types of liquidity ratios over time by bank size. The upper panel (a) shows data-based actual ratios, while the lower panel (b) shows those estimated in my model. Overall, the two ratios change over time in a similar fashion.[37] The level

[36] As empirical evidence that shows financially distressed banks were substituted by healthy banks in the financial crisis, Jensen and Johannesen (2017) investigate the impact of the credit supply channel on household consumption in Denmark. They use data of accounts in Danish banks as well as comprehensive information of individual account holders, and control credit demand shocks by individual-time fixed effects. They estimate around half of the decrease in lending by financially distressed banks was neutralized by their customers borrowing more from other healthy banks.

[37] This can be said less of medium banks. The reason is as follows. Two types of idiosyncratic shocks (deposit funding shocks and monitoring technology shocks) are linearly correlated with each other by assumption, which generates a linear relationship between banks' assets and liquidity ratio (see Figure 7b). However, in reality, the liquidity ratio for medium banks is closer to that of large banks than that of small banks (see Figure 7a). Hence, the response of medium banks to liquidity

of the actual ratios is consistently smaller than that of the model-based ones mainly because, as mentioned in Section 3, central bank reserves are excluded from the former, while such an exclusion is not feasible for the latter.

In both of the panels, the liquidity ratios of small banks dropped around 2009, while those for large banks increased. According to the model, this is because small banks substituted for large banks by shifting their assets from liquid assets to loans. As explained in subsection 6.1, small banks have rich capital buffers simply because they are small and their precautionary motives are large.[38] Small banks could substitute for large banks thanks to their rich capital buffers. Without those capital buffers, small banks would need to either issue new equity (which costs $\lambda \times \kappa = 2$ per unit of loans) or accumulate earnings in order to substitute for large banks. In this case, the substitution for large banks would not have been feasible.

As the crisis progressed, the liquidity ratio of small banks gradually increased. The model shows this was because the impact of productivity shocks became dominant and they shifted their assets from loans to liquid assets. For large banks, the liquidity ratio continued to increase for several years because both liquidity and productivity shocks increased their liquidity ratio by reducing their market borrowing and shifting their assets from loans to liquid assets.

Finally, I investigate the relative importance of productivity and liquidity shocks. A starting point is to compute the reduction of aggregate loans in the case where these two shocks are generated. Let falls in aggregate loans with both of the shocks, without productivity shocks, and without liquidity shocks, be denoted as $\triangle L_t$, $\triangle L_t^{noA}$ and $\triangle L_t^{no\phi}$, respectively. The difference between $\triangle L_t$ and $\triangle L_t^{noA}$ can be attributed to the impact of productivity shocks, and the difference between $\triangle L_t$ and $\triangle L_t^{no\phi}$ can be attributed to the impact of liquidity shocks. Figure 14 shows the results. Without liquidity shocks, aggregate lending falls more slowly than in the case where both of the shocks are generated. At its trough, aggregate lending falls by 6.7 percent from its steady state level. With both of the shocks, aggregate lending declines by 9.3 percent. Hence, 27 percent ($= \frac{9.3-6.7}{9.3}$) of the aggregate loan contraction is caused by liquidity

shocks is closer to that of large banks than that of small banks. Such an association can also be seen in the responses of loan growth (see Figure 11b). One possible way to improve the model is to embed the second-order correlation into the idiosyncratic shocks, which will improve the alignment of the model with the data of medium banks.

[38] Their rich capital buffers are not related to future unanticipated shocks, or liquidity declines taking place in the crisis. These are precautions against deposit funding shocks and monitoring technology shocks.

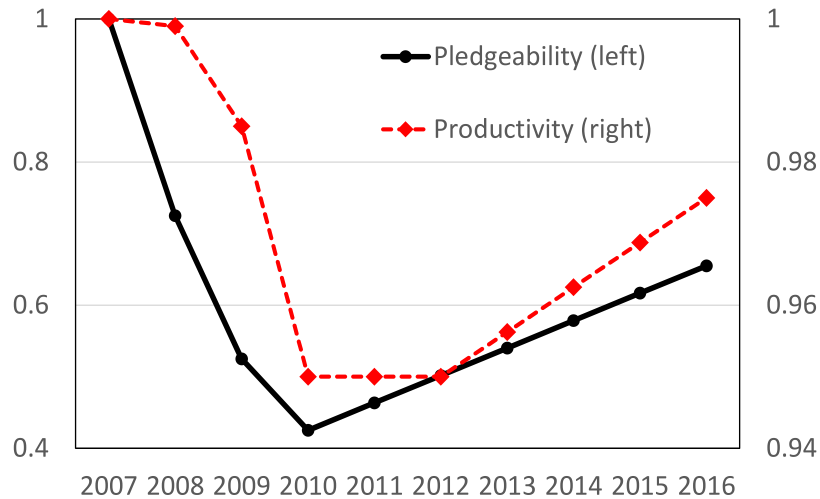
shocks, or the above-identified decline in pledgeability over the period 2008-2010. On the other hand, without productivity shocks, the aggregate loan contraction starts to recover much earlier, and at the bottom it falls by 3.1 percent from the steady state level. Hence, 67 percent ($= \frac{9.3-3.1}{9.3}$) of the aggregate loan contraction is caused by productivity shocks, or the above-identified decline in productivity over the 2008-2012.[39] Thus, my model estimates that during the GR, the decline in productivity (loan demand side) had a larger impact on the aggregate loan contraction than did the decline in liquidity (loan supply side).[40]

[39]By definition, the sum of contributions made by productivity and liquidity shocks will not necessarily be one.

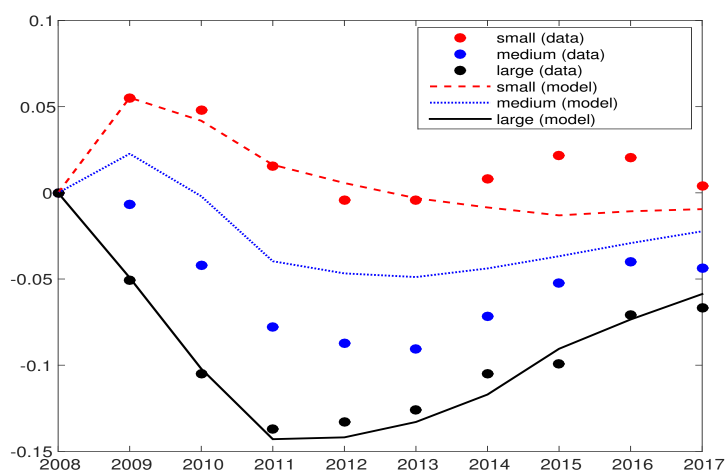
[40]A caveat is that liquidity shocks were never insignificant in the reduction of bank loans in the GR. Liquidity shocks have the potential to affect productivity, as demonstrated by recent endogenous growth models (Shi (2015), Guerron-Quintana and Jinnai (2015)). My model does not consider this possibility.

Figure 11: Results of connecting the model with data

(a) Identified shocks

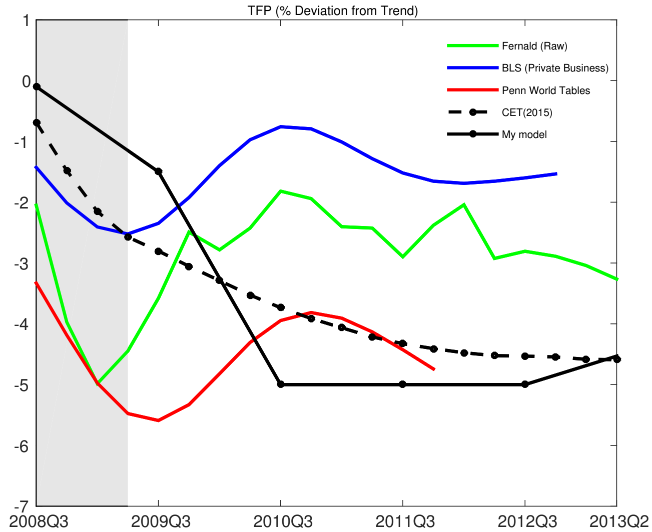


(b) Actual and model-based responses of loans for each size group



Note: Source: Call Reports.
Banks are divided into 3 size groups according to their amount of assets at the initial period. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. For the data, the mean of the detrended loan growth from 2008Q3 is plotted for each size group. For the model, deviations from the steady state path are plotted for each size group.

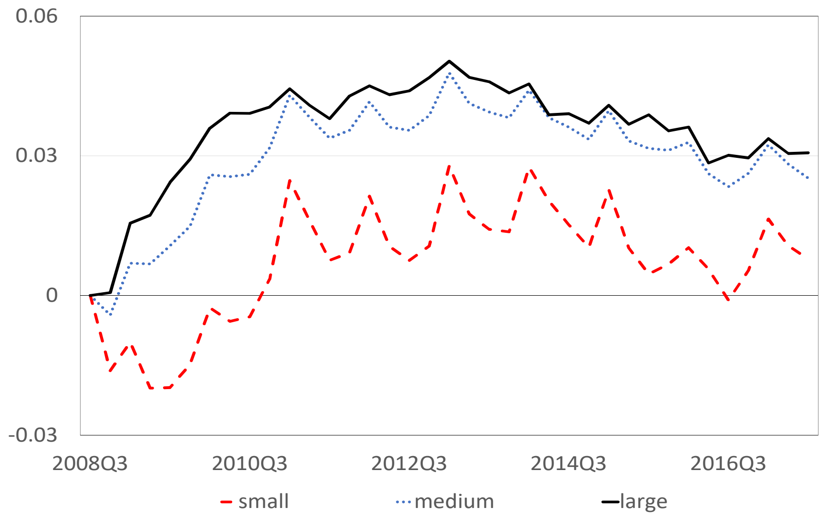
Figure 12: Comparison of productivity with other measures



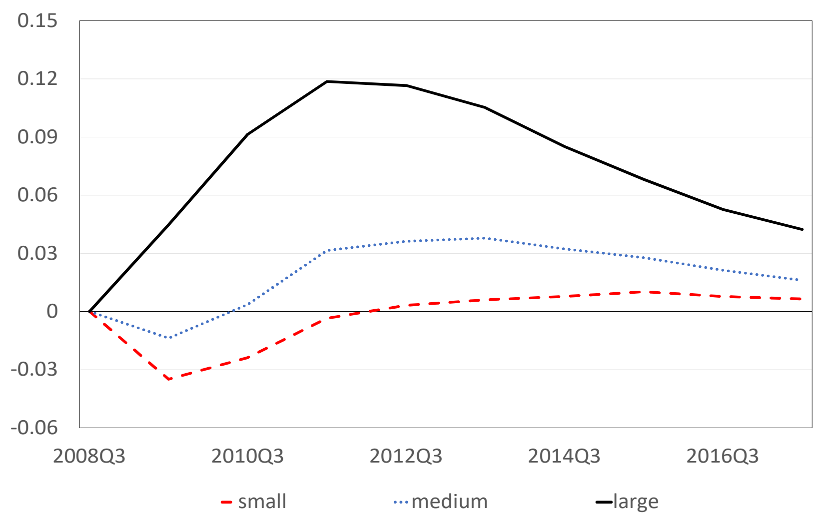
Note: Source: Christiano et al. (2015)

Figure 13: Two types of detrended liquidity ratios

(a) Actual liquidity ratios

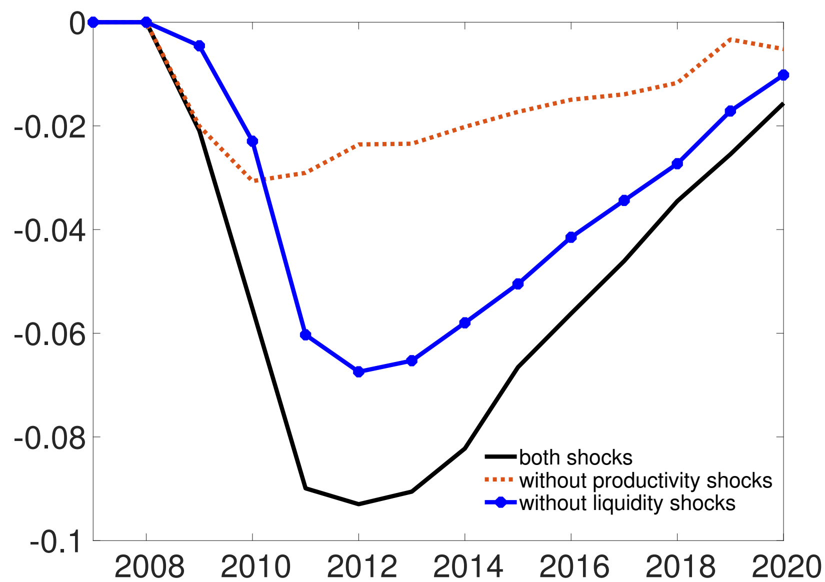


(b) Model-based liquidity ratios



Note: Source: Call Reports.
Banks are divided into 3 size groups according to their amount of assets at the initial period. small: 0-20 percentile, medium: 20-80 percentile, large: 80-100 percentile. For the data, the deviations of the average liquidity ratio from 2008Q3 are plotted for each size group after the trend is extracted using the HP (1600) filter. For the model, deviations from the steady state path are plotted for each size group.

Figure 14: Aggregate loan contractions by case in response to counterfactual shocks



7 Conclusion

In this paper, I construct a dynamic stochastic general equilibrium model that describes banks' heterogeneous liquidity management. Based on this model, I succeed in replicating important observations from the financial crisis and the GR. In the stationary equilibrium of the calibrated model, (i) large banks raise funds in the market to finance their loans because the amount of deposits they hold is not enough to finance their loans, while small banks hold liquid assets rather than borrowing; (ii) capital requirements are occasionally binding, and many banks have more capital than required. Small banks are more cautious than large banks, so they have larger capital buffers.

My model benefits from the ability to analyze the differences in banks' responses to shocks in terms of their relative size. This paper's application of the model is very specific. That is, I show the mechanics whereby such differences propagated loan demand and liquidity shocks and had a substantial effect on the real economy, as in the GR. I also argue that the dominant driver of the reduction in aggregate loans during the GR was the decline in loan demand rather than a decline in loan supply. My model estimates that 67 percent in the greatest drop of aggregate loans is explained by the decline in loan demand.

Additional applications may prove fruitful. One example is to analyze the effect of banking regulations based on bank size. This could have relevance for the “too big to fail” problem: anticipating a bailout by the government, banks tend to increase their assets and take risks beyond socially optimal levels. My model could also be useful in examining the implications of size-dependent policy interventions for banks’ balance sheet management and default decisions, as well as the implications for social welfare.

References

Ahn, SeHyoun, Greg Kaplan, Benjamin Moll, Thomas Winberry, and Christian Wolf, "When inequality matters for macro and macro matters for inequality," *NBER Macroeconomics Annual*, 2018, *32* (1), pp. 1–75.

Bassett, William F, Mary Beth Chosak, John C Driscoll, and Egon Zakrajšek, "Changes in bank lending standards and the macroeconomy," *Journal of Monetary Economics*, 2014, *62*, pp. 23–40.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist, "The financial accelerator and the flight to quality," *National Bureau of Economic Research Working Paper*, 1994.

Berrospide, Jose M, "Bank liquidity hoarding and the financial crisis: an empirical evaluation," *Board of Governors of the Federal Reserve System Working Paper*, 2012.

Bianchi, Javier and Saki Bigio, "Banks, liquidity management and monetary policy," *National Bureau of Economic Research Working Paper*, 2017.

Boissay, Frédéric, Fabrice Collard, and Frank Smets, "Booms and banking crises," *Journal of Political Economy*, 2016, *124* (2), pp. 489–538.

Bradley, Christine M and Lynn Shibut, "The liability structure of FDIC-insured institutions: changes and implications," *FDIC, Banking Review Series*, 2006, *18.*

Brunnermeier, Markus K, "Deciphering the liquidity and credit crunch 2007–2008," *Journal of Economic Perspectives*, 2009, *23* (1), pp. 77–100.

Chari, Varadarajan V, Lawrence Christiano, Patrick J Kehoe et al., "Facts and Myths about the Financial Crisis of 2008," *Federal Reserve Bank of Minneapolis Working Paper*, 2008, *666.*

Christiano, Lawrence J, Martin S Eichenbaum, and Mathias Trabandt, "Understanding the great recession," *American Economic Journal: Macroeconomics*, 2015, *7* (1), pp. 110–67.

Cohen-Cole, Ethan, Burcu Duygan-Bump, José Fillat, and Judit Montoriol-Garriga, "Looking Behind the Aggregates: A Reply to 'Facts and Myths about the

Financial Crisis of 2008',” *FRB of Boston Quantitative Analysis Unit Working Paper*, 2008.

Conesa, Juan C and Dirk Krueger, “Social security reform with heterogeneous agents,” *Review of Economic Dynamics*, 1999, *2* (4), pp. 757–795.

Cooley, Thomas F and Vincenzo Quadrini, “Financial markets and firm dynamics,” *American Economic Review*, 2001, pp. 1286–1310.

Corbae, Dean and Pablo D'Erasmo, “Reorganization or liquidation: Bankruptcy choice and firm dynamics,” *National Bureau of Economic Research Working Paper*, 2017.

_ and _ , “Capital requirements in a quantitative model of banking industry dynamics,” *National Bureau of Economic Research Working Paper*, 2019.

_ , _ et al., “A quantitative model of banking industry dynamics,” *University of Wisconsin, Madison Working Paper*, 2011.

_ , _ , Sigurd Galaasen, Alfonso Irarrazabal, and Thomas Siemsen, “Stress Testing in a Structural Model of Bank Behavior,” *Society for Economic Dynamics Meeting Paper*, 2016.

Cornett, Marcia Millon, Jamie John McNutt, Philip E Strahan, and Hassan Tehranian, “Liquidity risk management and credit supply in the financial crisis,” *Journal of Financial Economics*, 2011, *101* (2), pp. 297–312.

Dewally, Michaël and Yingying Shao, “Liquidity crisis, relationship lending and corporate finance,” *Journal of Banking & Finance*, 2014, *39*, pp. 223–239.

Diamond, Douglas W and Philip H Dybvig, “Bank runs, deposit insurance, and liquidity,” *Journal of Political Economy*, 1983, *91* (3), pp. 401–419.

Duchin, Ran, Oguzhan Ozbas, and Berk A Sensoy, “Costly external finance, corporate investment, and the subprime mortgage credit crisis,” *Journal of Financial Economics*, 2010, *97* (3), pp. 418–435.

Fernald, John, “A quarterly, utilization-adjusted series on total factor productivity,” *Federal Reserve Bank of San Francisco Working Paper*, 2014.

Gertler, Mark, Nobuhiro Kiyotaki, and Albert Queralto, "Financial crises, bank risk exposure and government financial policy," *Journal of Monetary Economics*, 2012, *59(S)*, S17–S34.

Gomes, Joao F, "Financing investment," *American Economic Review*, 2001, pp. 1263–1285.

Gorton, Gary and Andrew Metrick, "Securitized banking and the run on repo," *Journal of Financial Economics*, 2012, *104* (3), pp. 425–451.

Gorton, Gary B and Andrew Metrick, "Who ran on repo?," *National Bureau of Economic Research Working Paper*, 2012.

Gospodinov, Nikolay and Damba Lkhagvasuren, "A Moment-Matching Method For Approximating Vector Autoregressive Processes By Finite-State Markov Chains," *Journal of Applied Econometrics*, 2014, *29* (5), pp. 843–859.

Granja, Joao, Gregor Matvos, and Amit Seru, "Selling failed banks," *The Journal of Finance*, 2017, *72* (4), pp. 1723–1784.

Guerrieri, Veronica and Guido Lorenzoni, "Credit crises, precautionary savings, and the liquidity trap," *The Quarterly Journal of Economics*, 2017, *132* (3), pp. 1427–1467.

Guerron-Quintana, Pablo A and Ryo Jinnai, "Liquidity Shocks and Asset Prices," *Federal Reserve Bank of Philadelphia Working Paper*, 2015.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L Violante, "Quantitative macroeconomics with heterogeneous households," *Annu. Rev. Econ.*, 2009, *1* (1), pp. 319–354.

Hennessy, Christopher A and Toni M Whited, "Debt dynamics," *The Journal of Finance*, 2005, *60* (3), pp. 1129–1165.

Hopenhayn, Hugo A, "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica: Journal of the Econometric Society*, 1992, pp. 1127–1150.

Hopenhayn, Hugo and Richard Rogerson, "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of Political Economy*, 1993, *101* (5), pp. 915–938.

Hosono, Kaoru, "The transmission mechanism of monetary policy in Japan: Evidence from banks' balance sheets," *Journal of the Japanese and International Economies*, 2006, *20* (3), pp. 380–405.

Ippolito, Filippo, Ali K Ozdagli, and Ander Perez-Orive, "The transmission of monetary policy through bank lending: The floating rate channel," *Journal of Monetary Economics*, 2018, *95*, pp. 49–71.

Ivashina, Victoria and David Scharfstein, "Bank lending during the financial crisis of 2008," *Journal of Financial Economics*, 2010, *97* (3), pp. 319–338.

Jensen, Thais Lærkholm and Niels Johannesen, "The consumption effects of the 2007–2008 financial crisis: Evidence from households in denmark," *American Economic Review*, 2017, *107* (11), pp. 3386–3414.

Kahle, Kathleen M and René M Stulz, "Access to capital, investment, and the financial crisis," *Journal of Financial Economics*, 2013, *110* (2), pp. 280–299.

Kaplan, Greg and Giovanni L Violante, "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 2014, *82* (4), pp. 1199–1239.

_ and _ , "Microeconomic heterogeneity and macroeconomic shocks," *Journal of Economic Perspectives*, 2018, *32* (3), pp. 167–94.

_ , Benjamin Moll, and Giovanni L Violante, "Monetary policy according to HANK," *American Economic Review*, 2018, *108* (3), pp. 697–743.

Kashyap, Anil K and Jeremy C Stein, "What do a million observations on banks say about the transmission of monetary policy?," *American Economic Review*, 2000, pp. 407–428.

Katagiri, Mitsuru, "A macroeconomic approach to corporate capital structure," *Journal of Monetary Economics*, 2014, *66*, pp. 79–94.

Khan, Aubhik and Julia K Thomas, "Credit shocks and aggregate fluctuations in an economy with production heterogeneity," *Journal of Political Economy*, 2013, *121* (6), pp. 1055–1107.

Kitao, Sagiri, "Entrepreneurship, taxation and capital investment," *Review of Economic Dynamics*, 2008, *11* (1), pp. 44–69.

Lang, William W and Leonard I Nakamura, "'Flight to quality' in banking and economic activity," *Journal of Monetary Economics*, 1995, *36* (1), pp. 145–164.

Mian, Atif and Amir Sufi, *House of debt: How they (and you) caused the Great Recession, and how we can prevent it from happening again*, University of Chicago Press, 2015.

_ **, Kamalesh Rao, and Amir Sufi**, "Household balance sheets, consumption, and the economic slump," *The Quarterly Journal of Economics*, 2013, *128* (4), pp. 1687–1726.

Moll, Benjamin, "Productivity losses from financial frictions: Can self-financing undo capital misallocation?," *American Economic Review*, 2014, *104* (10), pp. 3186–3221.

Negro, Marco Del, Gauti Eggertsson, Andrea Ferrero, and Nobuhiro Kiyotaki, "The great escape? A quantitative evaluation of the Fed's liquidity facilities," *American Economic Review*, 2017, *107* (3), pp. 824–857.

Nicolò, Gianni De, Andrea Gamba, and Marcella Lucchetta, "Microprudential regulation in a dynamic model of banking," *Review of Financial Studies*, 2014, *27* (7), pp. 2097–2138.

Shi, Shouyong, "Liquidity, assets and business cycles," *Journal of Monetary Economics*, 2015, *70*, pp. 116–132.

Tauchen, George, "Finite state markov-chain approximations to univariate and vector autoregressions," *Economics Letters*, 1986, *20* (2), pp. 177–181.

Appendix

A Computation

In this section, I describe the method of computation in detail.

A.1 Stationary Competitive Equilibrium

In this subsection, I explain the algorithm for computing the stationary equilibrium. I set the lending rate to $r^{L*} = 0.07$ in the baseline model. The basic algorithm to compute the stationary equilibrium is as follows.

1. Solve the Bellman equations for incumbent banks and new banks under $r^{L*} = 0.07$.
2. Guess an initial mass of potential new entrants M_0.
3. Calculate the stationary distribution implied by policies (from step 1) and M_0.
4. Using the bank's policies (from step 1) and the stationary distribution (from step 3), calculate the equilibrium aggregate supply of loans L_{tot} by equation (18).
5. The demand for loans is calculated by equation (6).
6. Update the measure of new entrants M so that the loan market clears.
7. Using the stationary distribution implied by M (from step 6) and the bank's policies (from step 1), calculate the other equilibrium variables.

A.2 Dynamic Analysis

In this subsection, I explain the computational algorithm for the dynamic analysis in Section 6.2. The algorithm is similar to that in Kitao (2008) and Conesa and Krueger (1999). I assume that the economy is in the initial steady state (computed in A.1) and the unexpected shocks (A_t, ϕ_t) occur to the economy in period $t = 2$. The economy makes a transition back to the initial steady state in period $t = T$. I choose T large enough so that the transition path is not affected by increasing T.

1. Guess the path of lending rate $r_t^L(2 \leq t \leq T)$.
2. Use the value function of the final steady state for the period $t = T$ and solve the bank's problem (for both incumbents and new entrants) backwards from $t = T - 1$ to $t = 2$.
3. Using the bank's policies (from step 2) and the initial distribution $\zeta_2(dL, dB; s) = \zeta^*(dL, dB; s)$, calculate the transition path of the distribution $\zeta_t(dL, dB; s)(3 \leq t \leq T)$ by equation (17).
4. Compute the path of aggregate loan supply $L_t^{tot}(2 \leq t \leq T)$.
5. The path of loans demand $L_t^D(2 \leq t \leq T)$ is calculated by using equation (6).
6. Check if the loan market clears $(L_t^{tot} = L_t^D(2 \leq t \leq T))$. If not, go back to step 1 and adjust the equilibrium lending rate until the loan market clears.