

Bank Portfolio Choice, Uninsurable Risks and Regulatory Constraints*

Jochen Mankart[†] and Alexander Michaelides[‡] and Spyros Pagratis[§]

21st May 2014

*We would like to thank Javier Suarez, Vania Stavrakeva and seminar participants at workshops at the Central Bank of Austria, Central Bank of Cyprus and the ECB, the EABCN-INET conference in Cambridge, the MFS conference in Cyprus, Lyon and Surrey for helpful comments. All remaining errors are our own.

[†]University of St. Gallen, jochen.mankart@unisg.ch

[‡]Imperial College Business School, University of Cyprus and CEPR, a.michaelides@imperial.ac.uk

[§]Athens University of Economics and Business, spagratis@aueb.gr

Abstract

We use individual U.S. commercial bank balance sheet and income statement information to develop stylized facts about bank portfolio choices in both the cross section and over time. We then estimate the structural parameters of a quantitative model of bank portfolio choices (new loans, liquid investments and endogenous failure) that are made in the presence of undiversifiable background risk (problem loans, interest rate spreads and deposit shocks) and regulatory constraints. The loan portfolio is highly procyclical and banks curtail new lending very aggressively in response to background risk shocks, such as a higher uncertainty in bad loans or deposits. Bank failures are strongly countercyclical and depend positively on leverage. Increasing equity requirements generates higher equity but also results in higher failures because the increase in equity is less than proportional to the increase in the leverage limit, whereas background risk remains the same.

JEL Classification: E32, E44, G21

Key Words: Leverage, Uninsurable Risk, Capital Adequacy, Bank Failures, Quantitative Models, Bank Portfolios.

1 Introduction

The role of leverage in the recent crisis and the position of financial institutions as leveraged intermediaries between households and firms has intensified the urgency behind understanding banking decisions and financial intermediation more broadly. Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999) are seminal examples where leverage interacts with asset prices to generate amplification and persistence over the business cycle, while Gertler and Kiyotaki (2010) and Gertler and Karadi (2010) illustrate the importance of banking decisions¹ in understanding aggregate business cycle dynamics. Adrian and Shin (2010) provide empirical evidence further stressing the importance of leveraged bank balance sheets in the monetary transmission mechanism.

At the same time, the G20 nations have agreed to strengthen capital buffers in the banking system to improve resilience to shocks. They also recognize the need to amend regulatory rules to account for macro-prudential risks across the financial system. In particular, the Financial Stability Board (FSB) and the Bank of International Settlements (BIS) have been delegated to develop quantitative models to monitor and assess the build-up of macro-prudential risks in the financial system. These tools aim to improve the identification and assessment of systemically important components of the financial sector and the assessment of how risks evolve over time, and we aim to take a step in that direction.

Maintaining a lower level of leverage could increase banks' resilience to shocks and reduce

¹Bernanke and Blinder (1988) provide the macro-theoretic foundations of the bank lending channel of monetary policy transmission. Using aggregate data, Bernanke and Blinder (1992), Kashyap et al. (1993 & 1996), Oliner and Rudebusch (1996) provide evidence that supports the existence of the bank-lending channel.

the likelihood of bank failures. But putting limits on leverage is likely to become a contentious issue with most bank executives pointing out that such measures could negatively affect banks' return on equity, and therefore their ability to provide financial intermediation services for the real economy. Therefore, setting leverage limits at an appropriate level is a balancing act of choosing between lower current profits and higher bank safety. However, in order to set appropriate leverage limits for banks, one needs to understand individual bank decisions with regards to loan and dividend policy, and by implication, leverage.

One recent approach to determine the optimal amount of leverage, or equity capital banks should be forced to hold, is Miles, Yang and Marcheggiano (2012). They estimate effectively the elasticity of bank cost of equity with respect to leverage and find that this is very small. As a result, given that more well-capitalized banks are safer, they provide further evidence for the message in Admati and Hellwig (2013) that banks need to hold substantially more capital than the currently prescribed regulation to avoid banking crises. Our approach is different but complementary in that we build a structural, quantitative model of how U.S. commercial banks determine their leverage levels over time. The idea is that if one can build an empirically successful quantitative model of banking decisions, then counterfactual experiments can be used to inform policy debate of the likely economic outcomes from various policy decisions, including forcing banks to hold more equity capital.

To implement this idea, we use a structural model of bank lending behavior, assuming that a bank's objective is to maximize shareholder utility. We assume that leverage adjustments are influenced by perceived profit opportunities, funding conditions and risk perceptions. Such perceptions are driven by exogenous processes for funding costs, asset

quality (such as the loanwrite-off levels) and certain balance-sheet items, such as customer deposits and tangible equity. We should emphasize that despite being exogenous, these data generating processes are chosen to be consistent with the empirical evidence². We also make informed assumptions about retained income ratios (i.e. the proportion of post-tax profits that is retained by banks to augment their capital reserves), as well as the regulatory leverage limits that the Federal Deposit Insurance Corporation (FDIC) applies to U.S. deposit-taking institutions.

We emphasize that our approach is quantitative in nature, with the model being built evaluated by its ability to replicate the cross-sectional and time series evolution of bank balance sheets in the U.S.. The empirical part of the approach is therefore inspired by Kashyap and Stein (2000) who use disaggregated data to show that monetary shocks affect mostly the lending behavior of smaller banks (those with lower liquid asset holdings) due to frictions in the market for uninsured funds. We replicate empirically the substantial heterogeneity in bank balance sheets over time. We condense this heterogeneity into a few broad categories: long term loans and short term liquid assets on the asset side; and long term deposits, short term wholesale liabilities, and equity on the liability side when we build our structural model. We do so because we are interested in providing a setting where policy

²Chen (2010) solves for a firm's optimal capital structure over the business cycle. Using essentially an exogenous stochastic discount factor, the model allows for endogenous financing and default decisions by firms and generates countercyclical default probabilities, default recovery rates and risk premia. That helps explain the large credit spreads and limited use of debt in the capital structure of investment-grade corporates. We take these risk premia as exogenous at this stage of our research and focus on matching quantities.

advice can be readily given through counterfactual, quantitative experiments.

The quantitative model is estimated using a Method of Simulated Moments and is relatively successful in replicating the data in a number of dimensions. In the model smaller banks rely more on deposits than larger banks because smaller banks face a larger cost of accessing the wholesale markets. As a result, larger banks are also more highly levered than smaller banks. Moreover, leveraged banks are more likely to fail in a recession, both in the model and in the data.³ Banks invest in liquid assets along with making loans and the model is estimated to capture the substantial component of liquid assets in the balance sheet. Liquid assets are held as a way to hedge illiquidity risk arising from long-term loan provision and also as a way to smooth background risk (deposit outflow volatility).

In the data, a substantial cross sectional heterogeneity in loan to asset ratios exists (this ranges between 20% and 90%). Given that we split the balance sheet of each bank across broad categories (loans and liquid assets on the asset side), this implies a substantial heterogeneity in liquid asset holdings as well. There is also heterogeneity in the deposit to asset ratios, although the range there is tighter (between 70% and 95%). The model replicates the wide range of cross sectional heterogeneity in loans and liquid assets to total assets through the idiosyncratic risks (deposit and loan write-off shocks) that each bank faces. The tighter deposit to asset ratio is also replicated through a convex funding cost to access the wholesale market.

³Kishan and Opiela (2000) determine that equity is another variable that affects banks' sensitivity to monetary policy shocks. By classifying banks not only by size, but also in terms of leverage ratios, they show that the smallest and least capitalized banks are the most sensitive to monetary contractions. Our results are consistent with this finding.

Empirically, in the time series dimension, the deposit to asset ratio is countercyclical while the loan to asset ratio is procyclical. Leverage and failure rates are also countercyclical. The model predicts similar cyclical properties for these variables. The deposit to asset ratio in the model is countercyclical because banks lower lending and shrink their balance sheets by reducing reliance on wholesale funding markets during recessions. The model also predicts strongly procyclical loan growth that is slightly asymmetric (positive spikes tend to happen when the economy exits the recessionary period). The model also generates strongly countercyclical failure rates, consistent with the data. Moreover, these failure rates are more likely for highly levered firms and are driven by bad loan shocks. Overall, we interpret these findings as consistent with quantitative features of the data, therefore we use the model for counterfactual analysis.

The main counterfactual we focus on is tightening the leverage constraint banks face. Specifically, the leverage limit is reduced from 20 to 15 in an attempt to evaluate the costs (lower financial intermediation) versus the benefits (lower failures) from this regulatory change. This lowering of the leverage constraint increases bank equity since banks are forced to accumulate more capital. However, it also increases significantly the failure rate, a result that goes against conventional wisdom that higher equity should make banks safer. This is because banks endogenously move closer to the constraint and a lower leverage limit makes it more likely for them to hit the constraint given the same level of risks they face. But, consistent with prior intuition, higher equity requirements lower loan issuance. Moreover, the negative loan supply effects of tighter leverage limits are much more pronounced for smaller than for larger banks underlying the need for models that take cross-sectional heterogeneity

into account. We also undertake a second counterfactual to capture money market freezes. Specifically, we compare two recessions: one with a temporary (one quarter) freeze in the money market and another recession without any change in the operation of the money markets. This has surprisingly little effect. Banks simply lower their holdings of liquid assets during the crisis period so that lending and bank survival hardly decline.

In terms of related literature, De Nicolo, Gamba and Lucchetta (2014) and Repullo and Suarez (2013) also model banks' capital buffers in response to aggregate shocks to analyze the effects of capital requirements in a general equilibrium model. We differ by studying the portfolio choices of banks, as well as their failure decisions, in a model that allows for risk aversion and cross-sectional heterogeneity, but our model remains partial equilibrium in nature. Corbae and D'Erasmus (2011 and 2012) also build a dynamic model of banking to investigate optimal capital requirements. Unlike our setting, they use a general equilibrium model featuring strategic interaction among a dominant big bank and a competitive fringe. We emphasize more the maturity transformation role of banks with loans having a larger duration, while banks can decide simultaneously on new loans, dividends and money market borrowing or security investments, thereby emphasizing more the portfolio choices banks make. We should emphasize that we focus on individual banking decisions and not holding bank ones, even though this might not be a trivial assumption either theoretically or empirically.⁴ We make this decision because individual bank data allow for greater hetero-

⁴Holod and Peek (2010) find evidence of internal capital and secondary loan markets within multi-bank holding companies that mitigate equity capital constraints and enhance the efficiency of the loan origination process. Cetorelli and Goldberg (2012) also show that internal capital markets and cross-border liquidity transfers among head offices and foreign affiliates of global banks lead to liquidity shocks at home propagating

geneity, while, in the time dimension, bank holding company data are plagued with reporting seasonalities.

2 Data

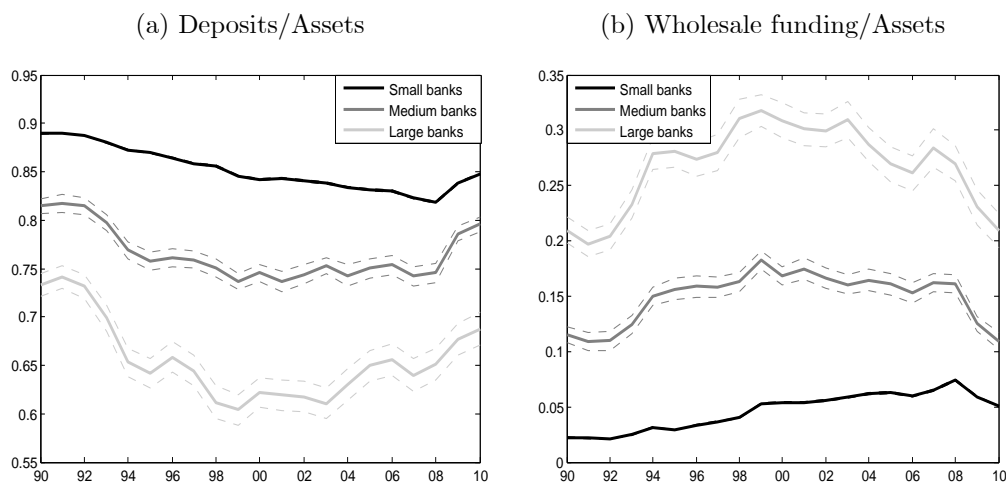
We consider a sample of individual bank data from the Reports of Condition and Income (Call Reports) for the period 1990:Q1-2010:Q4. For every quarter, we categorize banks in three size categories (small, medium and large). Small banks are those below the 95th percentile of the distribution of total assets in the given quarter, medium those between the 95th and 98th percentile and large those above the 98th percentile. We also consider the bank failures reported by the FDIC for the same period. A more detailed description of our sample is discussed in the Data Appendix.

2.1 Cross Sectional Statistics

Table 1 shows descriptive statistics for bank balance sheet compositions at year-end of the first and last year of our sample period, sorted by bank size. The significant reduction in the number of banks over time was mainly a result of regulatory changes that led to substantial consolidation in U.S. commercial banking.⁵ We abstract from endogeneizing mergers in our internationally.

⁵According to Calomiris and Ramirez (2004), branch banking restrictions and protectionism towards unit banks (i.e. one-town, one-bank) led to a plethora of small U.S. commercial banks over the last century. But in the early 1990s protectionism was relaxed, especially following the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994. That spurred a wave of mergers and acquisitions that reduced significantly the number of U.S. commercial banks. Calomiris and Ramirez (2004) provide some key facts

Figure 1: Evolution of deposit and wholesale funding of U.S. commercial banks as a proportion of total assets



model.

Deposits (normalized by total assets) are the major item on the liability side of all commercial banks, see also Figure 1. Nevertheless, the deposit to asset ratio varies by bank size, with smaller banks relying more on deposits. Moreover, the importance of deposits has declined over time for all bank sizes until 2008. Both stylized facts can be seen in Figure 1a that graphs the mean deposit to asset ratio sorted by bank size over the period 1990-2010 (bootstrapped standard error confidence intervals are shown with dotted lines).

Larger banks tend to have more access to alternative funding sources like the Fed funds, repos and other money market instruments in the wholesale funding market. In 1990 (2010) the sum of Fed funds borrowed, subordinated debt and other non-deposit liabilities as a

and references on the subject. For some excellent reviews, see also Berger, Kashyap, and Scalise (1995), Calomiris and Karceski (2000) and Calomiris (2000).

Table 1: Balance sheets of U.S. commercial banks by bank size

(a) 1990

size percentile	<95th	95 - 98	>98- 99
Number of banks	12022	376	253
Mean assets (2010 \$million)	128	1701	14500
Median assets (2010 \$million)	75	1518	7795
Frac. total system as.	26%	11%	63%
Fraction of tangible asset			
Cash	7%	7%	10%
Securities	29%	20%	17%
Fed funds lent & rev. repo	7%	4%	4%
Loans to customers	53%	63%	59%
Real estate loans	27%	35%	27%
C&I loans	10%	13%	18%
Loans to individuals	10%	14%	14%
Farmer loans	6%	1%	0%
Other tangible assets	4%	7%	11%
Total Deposits	89%	81%	73%
Transaction deposits	23%	19%	20%
Non-transaction deposits	65%	62%	53%
Fed funds borrowed & repo	1%	6%	10%
Other liabilities	2%	6%	11%
Tangible equity	9%	7%	6%

(b) 2010

size percentile	<95th	95 - 98	>98- 99	
Number of banks	6528	206	137	
Mean assets (2010 \$million)	238	2715	72000	
Median assets (2010 \$million)	141	2424	13600	
Frac. total system as.	13%	5%	82%	
Fraction of tangible asset				
Cash	9%	7%	7%	
Securities	21%	21%	20%	
Fed funds lent & rev. repo	2%	1%	2%	
Loans to customers	62%	64%	61%	
Real estate loans	45%	49%	38%	
C&I loans	9%	10%	11%	
Loans to individuals	4%	5%	11%	
Farmer loans	4%	0%	0%	
Other tangible assets	5%	7%	10%	
Total Deposits	85%	79%	68%	
Transaction deposits	22%	10%	7%	
Non-transaction deposits	63%	70%	61%	
Fed funds borrowed & repo	1%	4%	6%	
Other liabilities	4%	7%	16%	
Tangible equity	11	10%	9%	10%

fraction of total assets rises monotonically from 3% (5%) for banks in the bottom 95th percentile to 21% (22%) for banks in the largest percentile. Figure 1b reveals that the wholesale funding markets have become more important over time for small and medium sized banks up to the financial crisis. For large banks the share of this funding source started already to decline before the crisis. However, even at the peak the share of these funds did not exceed 7% for small banks. We use these stark differences in access to the wholesale funding market as a defining variation between big and small banks in the structural model.

Figure 2 shows the evolution of the asset side of the bank balance sheets. The biggest components are loans which are relatively illiquid because they are contractual obligations with long term maturities. Liquid assets which comprise cash, Fed funds lent, reverse repos and securities make up a significant fraction too, however. At the beginning of the period smaller banks hold significantly more liquid assets and less loans. However, these differences across size classes become less pronounced over time as smaller banks increase their loan to asset ratio faster than larger banks do. These trends are also reflected in the proportion of liquid assets in the balance sheet with substantial changes from 1992 (right after the 1991 recession) to 2008 (the financial crisis).

Another variable of interest in the recent crisis is the level of leverage by bank size and over time, and this is shown in Figure 3. Leverage is defined as total tangible assets divided by tangible equity.⁶ Figure 3a reports total leverage over time for banks with different sizes. It shows that smaller banks tend, on average, to have a lower level of leverage than larger banks. During the recent crisis period, on the other hand, the ordering is affected.⁷

⁶Tangible equity equals total assets minus total liabilities minus intangible assets, such as goodwill.

⁷This might reflect special government programs under TARP (Troubled Assets Relief Program) mainly affecting larger banks.

Figure 2: Evolution of loan and liquid assets of U.S. commercial banks as a proportion of total assets

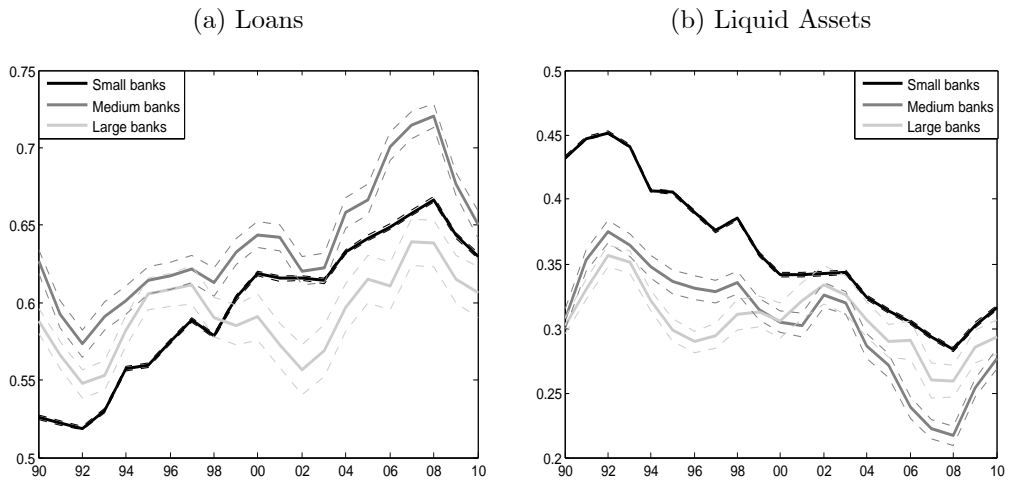
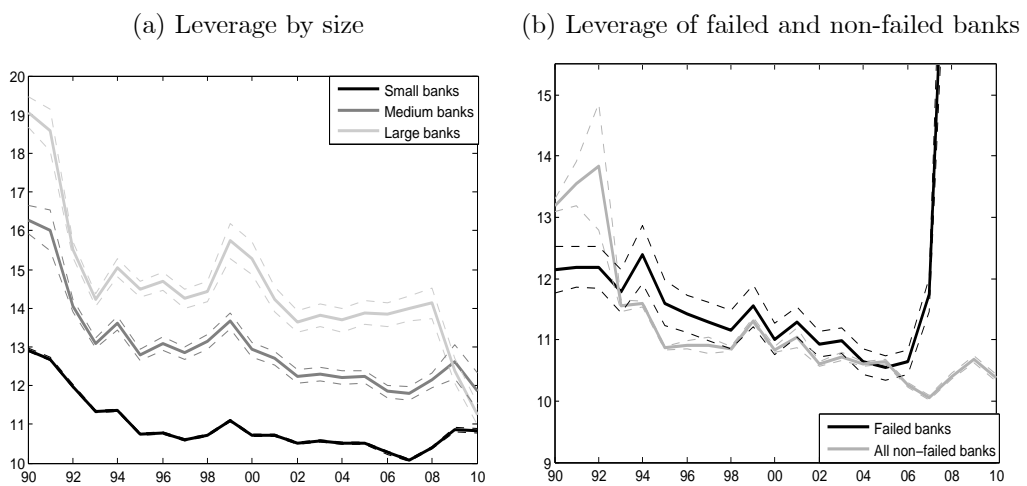


Figure 3: Leverage by size and leverage of failed vs. non-failed banks



We are also interested in the characteristics of banks that fail or receive FDIC assistance (hereafter called failed banks) at some point in time. We construct a panel of failed banks between 2008-2010 and we track over time some of their balance sheet characteristics. A stark difference between banks that fail or receive assistance and banks that do not is their leverage ratio. Figure 3b shows that for banks that eventually fail, leverage increases sharply before their failure.

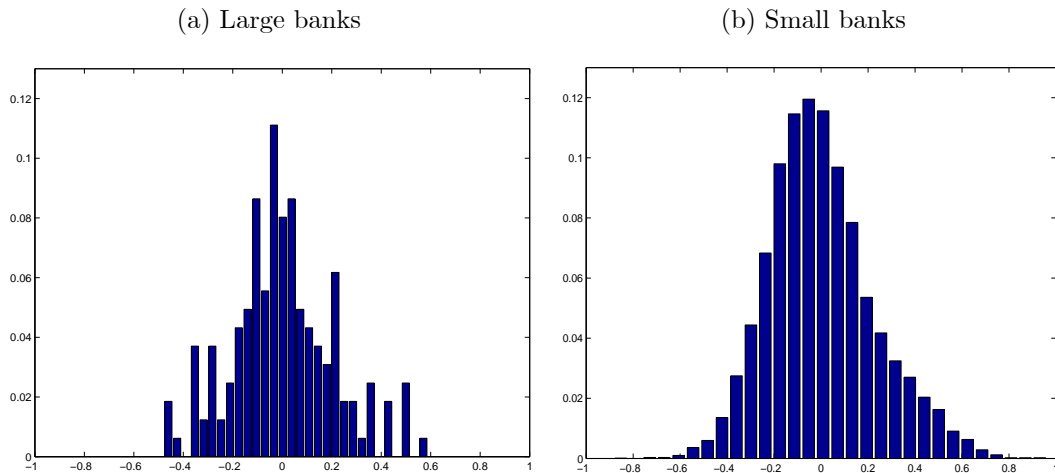
2.2 Time Series Statistics

Banks in our model will face uninsurable idiosyncratic shocks coming either from deposit growth or loan write-offs. At the same time banks will be exposed to aggregate uncertainty to generate cyclical fluctuations. There are two main exogenous variables in the model: deposits and loan write-offs and we will use the data to constrain their data generating processes. Given the non-stationary nature of deposits, we work with deposit growth. The idea will be to use these processes as inputs to the theoretical model and then examine the ability of the model to explain the endogenous variables of interest: new loans and asset growth, tangible equity, wholesale funding and failure rates. The exogenous processes will be taken to be as close as possible to their empirical counterparts.

2.2.1 Uninsurable Risk

To capture uninsurable liquidity risk from deposit growth and loan write-offs, we run for each bank-type an AR(1) time series regression if there are more than 35 consecutive observations. This is done both unconditionally but also conditional on a boom or a recession,

Figure 4: AR(1) coefficients of deposit growth rates



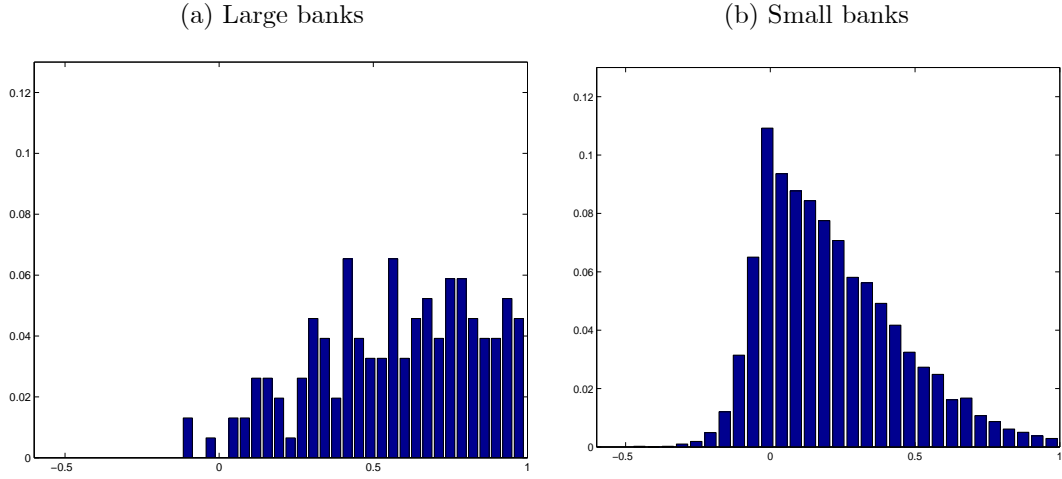
for both large and small banks. The histograms for the AR(1) coefficients for deposit growth can be found in figure 4 and show that an AR(1) coefficient for zero cannot be rejected.

The loan write-off process is already normalized by the stock of outstanding loans and is therefore likely to be (and turns out to be) stationary. We also consider loan write-offs in booms and recessions. We follow the same procedure as for the deposit growth process and find that the histograms show strong positive persistence for large banks and a milder persistence for small banks, as shown in figure 5.

Table 2 shows that idiosyncratic bad loans behave very differently in booms and recessions. Due to this asymmetry, we model the bad loan process as state dependent. We estimate two different AR(1) processes, one for boom periods and one for recession periods. During a recession, the bad loan process is significantly worse for banks. The mean is around 50% higher, while the standard deviation and the persistence also increase significantly.

The differences in deposit growth rates are less pronounced; with the exception of the

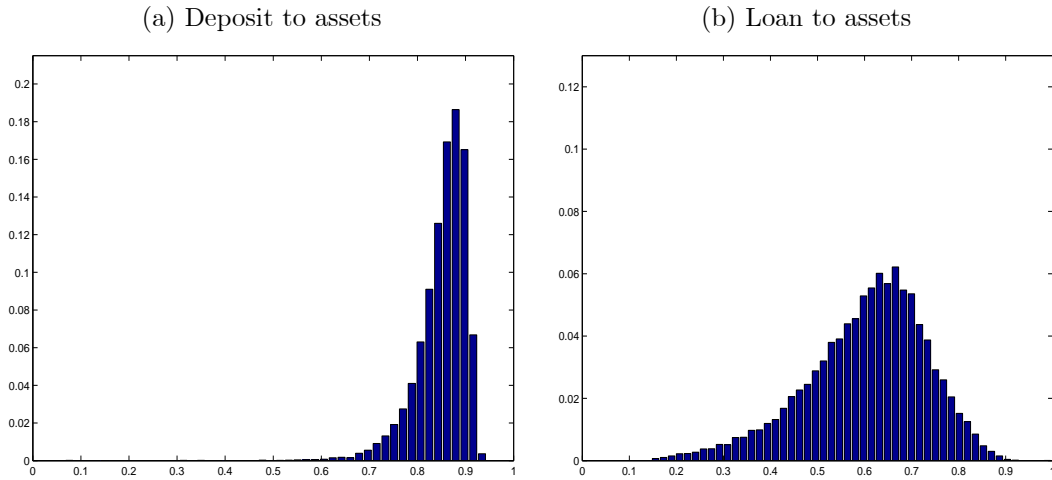
Figure 5: AR(1) of loan write-off process



Parameter	Small banks		Big banks	
	<i>recession</i>	<i>boom</i>	<i>recession</i>	<i>boom</i>
problem loans: mean	0.15	0.10	0.34	0.26
problem loans AR(1)	0.25	0.15	0.75	0.66
problem loans: std	0.23	0.14	0.26	0.14
deposit growth rate: mean	0.010	0.006	0.012	0.013
deposit growth rate: std	0.047	0.045	0.063	0.070

Table 2: Time varying aggregate parameters

Figure 6: Distribution of deposit to asset and loan to asset ratios



mean growth rate of small banks, which is lower in booms than in recessions. The mean growth rate of big banks is similar across booms and recessions and is always higher than the growth rate of small banks.

2.2.2 Moment Distributions

We compute the mean and the variance of key balance sheet and income statement items for each bank over time, provided that the bank has at least 10 observations. We then produce histograms for these moments that can be either unconditional or conditional on a boom or conditional on a recession.

Figure 6 shows the distribution of the deposit to asset ratio and the loan to asset ratio for small banks.⁸ Loans are the most important component on the asset side of the balance sheet. Figure 6b shows a pretty wide dispersion of this ratio across small banks, ranging

⁸The corresponding graphic for large banks can be found in the appendix, see Figure 23.

from 15% to 90%, with a mean around 65%.

Figure 6a shows that the dispersion of the deposit to asset ratio, in contrast, is much smaller. Most of these banks have a deposit to asset ratio around 85%.⁹

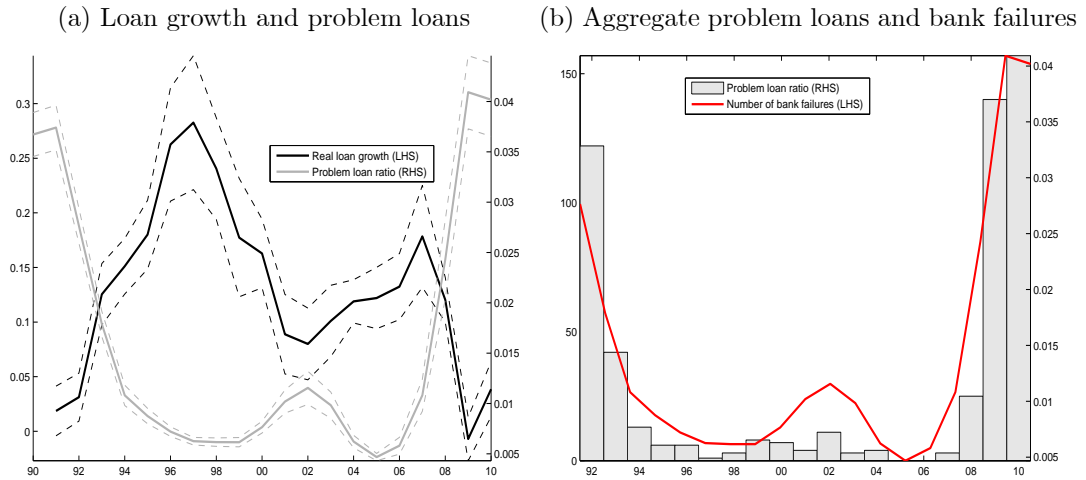
2.2.3 Cyclical Properties

Figure (7) shows the behavior of loan growth, the evolution of problem loans and the resulting bank failures over the sample period. Figure (11a) shows that loan growth rates are procyclical whereas problem loans are countercyclical. Problem loans are high at the beginning and at the end of the sample, coinciding with recession periods. The first period reflects the savings and loans (S&L) crisis and the second period the recent financial crises starting in 2007.

Figure (11b) shows the business cycle behavior of aggregate problem loans and bank failures. Not surprisingly, these two series are highly correlated and strongly countercyclical. Banks do fail over the business cycle in a countercyclical way and the possibility of banks failing will be an important ingredient in our model. The unconditional failure rate is 0.05% (0.07%) for small (big) banks, which rises in recessions to 0.17% (0.18%) and falls in booms to 0.01% (0.01%).

⁹The other two ratios: the wholesale funding to asset ratio and securities to asset ratio can be found in section 5.2, where we report the model equivalents of all these ratios.

Figure 7: Cyclical properties of loan growth, problem loans and bank failures



3 The Model

In the previous section, we have established that in the cross section, larger banks tend to rely less on deposits and more on wholesale funding and they tend to be more levered. Moreover, banks that fail tend to have more levered balance sheets before eventual failure. In the time series, real loan growth is procyclical as it falls in recessions, whereas problem loans and failures are countercyclical as they tend to increase during recessions. We want our structural model to replicate all these facts.

3.1 The model environment

We consider a discrete-time infinite horizon model. We assume that banks are run by managers whose incentives are fully aligned with those of bank shareholders. Therefore, banks maximize the present discounted value of utility of their existing shareholders and

assets		liabilities	
loans L_t	r_{Lt}	deposits D_t	r_{Dt}
liquid assets S_t	r_{St}	wholesale funding F_t	r_{Ft}
		equity E_t	

Table 3: Bank balance sheet in the model

have limited liability. We consider interest income from relatively illiquid loans and liquid assets as the key driver of decisions by commercial banks. This modeling choice is justified by the fact that net interest income is the main source of income across U.S. commercial banks.¹⁰ Banks in our model have the following stylized balance sheet: their liabilities consist of deposits, wholesale funding (equivalent in the data to the sum of Federal Funds borrowed, subordinated debt and other non-deposit liabilities) and equity. Their assets consist of loans and liquid assets (securities). A stylized balance sheet is shown in table 3, which also reports the real rate of return on each asset and liability.

3.1.1 The Asset Side of the Balance Sheet

Consistent with the maturity transformation role of banks,¹¹ we assume that loans (L_t) are long term and these loans are funded through deposits, wholesale funding and equity capital. Both deposits and wholesale funding are assumed to be of shorter maturity than customer loans. Such a maturity mismatch gives rise to funding liquidity risk. To capture this risk we assume that a fraction of outstanding loans (ϑ) gets repaid every period. This generates an exogenous deleveraging process, which we calibrate to our data. At the same

¹⁰For instance, the median net interest income has remained above 70% of total operating revenue during the relevant period.

¹¹We omit using an i -subscript for banks but all bank-specific variables must be understood to have an i -subscript.

time, in every period the bank issues (endogenously) new long term loans (N_t) to customers.

The income from customer lending is the interest income from long term loans. The interest rate earned on outstanding customer loans equals $(r_{Lt} - w_t)$ where r_{Lt} is the weighted average of the 30 year U.S. mortgage rate and the loan rate for business loans, and w_t measures the loans that banks have to write-off every period. Issuing new loans requires banks to assess and screen their clients though. This screening cost is assumed to be convex in new loans. This occurs either because bank resources get stretched over more projects or because the quality of additional projects is declining.¹² The specific functional form is discussed in Section 4.2.

Loan write-offs follow a process with both aggregate and idiosyncratic components. We model this by assuming (consistent with the data) that the idiosyncratic first and second moments depend on the aggregate state (state of the economy). Empirically, there is more uncertainty during recessions than booms in the loan write-off process. Therefore, loan write-offs have a higher mean and a higher variance during recessions than during booms. We calibrate these moments to what we calculate from our data set.

Instead of investing in long term loans, banks can also invest in short term liquid assets (S_t denoting securities). The return on these liquid assets r_{St} is stochastic and we assume that it has only an aggregate component.

¹²At this stage, we ignore corporate taxation (T_C), even though we may consider adding this later by recognizing the tax-shield role of interest expenses.

3.1.2 The Liability Side of the Balance Sheet

The main liability of most commercial banks are customer deposits D_t . We assume that the deposit growth rate, similar to loan write-offs, follow a process where the mean and variance of the idiosyncratic shocks depend on the aggregate state. Conditional on the aggregate state, the growth rate of deposits is i.i.d. over time, and can be well approximated by a log-normal distribution.

$$\log(G_{D_t}) \sim N(\mu_{D_j}, \sigma_{D_j}^2)$$

where j refers to a boom or a recession. This is consistent with the idea that there is higher uncertainty in recessions than in booms. We use the empirical counterparts to determine specific values for the means and variances.

A second source of external funds for banks is the wholesale funding market where banks can borrow short term (wholesale funding, F_t). However, as discussed in the data section, there is an interesting difference between small and large banks in their reliance on short-term borrowing from the wholesale market. For most small banks, wholesale funding is a small fraction of their overall liabilities even in recent years, as shown in Table 1a and Figure 1b. To capture this difference in the model we specify a size-dependent net cost function (over the interest rate cost) of accessing the wholesale market. We assume a convex function to reflect that higher short term borrowing implies that more risk is borne by lenders, thereby justifying a higher external finance premium to access this market. The weight on this risk premium is higher for small banks that do not have access to the wholesale funding market to the same degree as larger banks. The specific functional form is discussed in Section 4.2.

3.1.3 Equity

Equity is defined as assets minus liabilities. Equity is the sum of past earnings (positive or negative), reduced by the amount of dividends the bank has paid to shareholders. At any period t , the bank has the option to pay out dividends ($X_t > 0$). If, in addition, we denote by Π_{t+1} the bank profits at time $t + 1$, then the amount of equity at the beginning of next period is given by

$$E_{t+1} = E_t + \Pi_{t+1} - X_t \quad (1)$$

3.1.4 Regulatory Leverage Limit

Banks are subject to regulatory constraints regarding their capital adequacy ratios, namely a minimum ratio between measures of bank capital and measures of bank assets. We consider an exogenously specified leverage ceiling that regulators set and banks must respect. Leverage is defined as the ratio of total assets (total loans plus liquid assets) to equity.¹³ *Ceteris paribus*, the higher the profitability of the bank in a given period, the higher its retained income and therefore equity, and the less likely it is to breach its regulatory leverage limit in the future. This gives the bank the incentive to extend more lending to customers to boost its return on equity or to pay out dividends to its owners, and these are the two key endogenous decisions studied by the model.

The leverage constraint is captured by parameter λ which gives the maximum ratio of

¹³Our model has only equity whereas in the data there is the distinction between tangible and non-tangible equity. All our empirical results use only tangible equity since this measure is closer to what regulators consider as loss-absorbing capital.

assets to equity that the bank must respect:

$$\frac{L_t + N_t + S_t}{E_t - X_t} \leq \lambda \quad (2)$$

We also experiment with a risk-weighted capital constraint that treats riskier loans differently from liquid risky assets. Specifically, we assign a risk weight equal to 60% on L_t and a risk weight equal to 10% on S_t , which is consistent with Basel II capital adequacy rules and also experiment with a more radical setting where the weight on liquid assets drops to 0%, i.e. studying the extreme case where S_t disappears from (2).

3.1.5 Objective function

Banks discount the future with a constant discount factor β . They maximize the present discounted value of a concave function of dividends:

$$V = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{X_t^{1-\gamma}}{1-\gamma} \quad (3)$$

where \mathbb{E}_0 denotes the conditional expectation given information at time 0. Bankers are risk averse: $\gamma > 0$ is the coefficient of relative risk aversion. The concavity from risk aversion captures the idea that banks (like other firms) might want to smooth dividends over time, as suggested by empirical evidence in Acharya, Le and Shin (2013). Dividends need to always be positive in this world due to the concavity of the utility function.

3.1.6 Entry and exit

Exit is endogenous in this model. We assume that following bank failure, bankers pursue another career (outside banking) that we do not endogenize. The outside option yields a

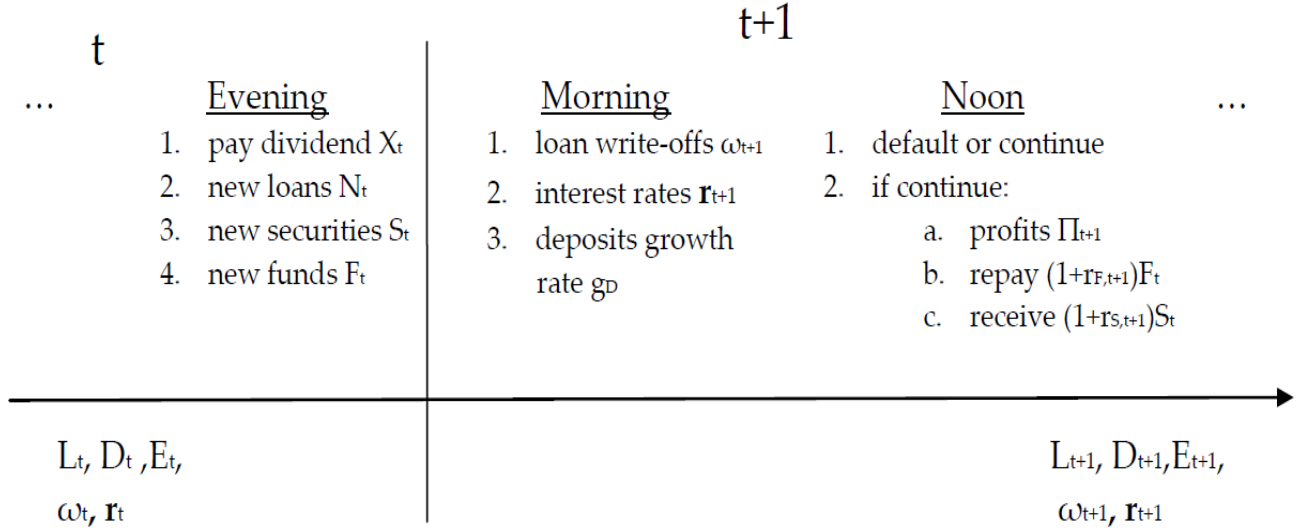


Figure 8: Timing of the model

constant amount of consumption C^D and a level of utility equal to V^D .¹⁴ Since the banker takes this continuation value into account when making decisions, exit is endogenous. In the simulation, whenever a bank exits, we exogenously add another bank that takes over the deposits of the failed bank but which starts at a good idiosyncratic state, i.e. low loan losses.

3.2 Timing

Figure 8 shows the timing of the model for a bank that continues in period t with a stock of loans L_t , deposits D_t , and equity E_t . Since the various interest rates \mathbf{r}_t and the idiosyncratic loan write-off process w_{it} are persistent, these are state variables in the bank's problem as well. At the end of period t , decisions about new loans (N_t), dividends (X_t),

¹⁴We have to assume that a failed banker can consume after exiting, otherwise no banker would ever choose to fail given the concave utility function.

liquid assets (S_t) and wholesale funding (F_t) are made. At this stage the leverage constraint must be respected. At the beginning of the next period the exogenous shocks (returns, deposit shocks and problem loans) are realized: the bank learns the various rates of return \mathbf{r}_{t+1} ; deposit withdrawals and how many loans are repaid and how many loans have to be written off (w_{t+1}).

The profits of bank i attributable to shareholders are¹⁵

$$\Pi_{i,t+1} = (r_{L,t+1} - w_{i,t+1})(L_{it} + N_{it}) + r_{S,t+1}S_{it} - r_{D,t+1}D_{i,t} - g(N_{it}) - g(F_{it}) - cD_{i,t} \quad (4)$$

where the first term is the interest income on performing loans; the second term reflects income from holding liquid assets, the third term is the cost from servicing deposits, the fourth term is the cost of issuing new loans, the fifth term is the cost of accessing the wholesale funding market and the final term is the non-interest expense associated with operating the bank.

The bank decides whether to continue or fail at that stage. If the bank fails, it exits the market forever. If it continues, it repays wholesale funds and receives the payment on the liquid assets. These cash-flows, the flow profits and the new dividend payment X_{t+1} determine the equity E_{t+1} at the end of period $t + 1$. Deposits depend only on the initial value D_t and the shock realization in the current period and are therefore equal to D_{t+1} . The stock of loans L_{t+1} is the sum of the old loan stock and the new loans made in period t , adjusted for the exogenous repayment fraction ϑ and the fraction of loans the bank has to write-off (w_{t+1}).

¹⁵We introduce the i subscript to make the distinction between aggregate and idiosyncratic variables.

3.3 Value functions

A banker who has failed in the past cannot become a banker again. This banker enjoys an exogenous constant level of consumption C^D yielding utility V^D .¹⁶

A banker who has not failed in the past solves the following continuation problem that takes into account the fact that failure is possible in the future

$$V^C(L_t, D_t, E_t; w_t, \mathbf{r}_t) = \max_{X_t, S_t, F_t, N_t} \left\{ \frac{(X_t)^{1-\gamma}}{1-\gamma} + \mathbb{E}_t[\beta V(L_{t+1}, D_{t+1}, E_{t+1}; w_{t+1}, \mathbf{r}_{t+1})] \right\} \quad (5)$$

where the last term is defined as the upper envelope

$$V(L_t, D_t, E_t; w_t, \mathbf{r}_t) = \max[V^D, V^C(L_t, D_t, E_t; w_t, \mathbf{r}_t)] \quad (6)$$

subject to the equity evolution equation (1), the leverage constraint (2), the profit evolution (4) and the evolution of the loan stock

$$L_{t+1} = (1 - \vartheta - w_{t+1})(L_t + N_t). \quad (7)$$

The first decision of the bank is to decide whether to continue operating. If the bank continues its operations, it chooses the optimal level of pay-out to shareholders X_t , how many new loans N_t to issue, how many liquid assets S_t to buy and how much funding F_t to borrow on the wholesale market. If it ceases operations, it is liquidated.

¹⁶Specifically, the value V^D is given by the formula $V^D = \frac{1}{1-\beta} \frac{(C^D)^{1-\gamma}}{1-\gamma}$.

4 Estimation

In this section, we first discuss the normalization that is necessary to make the model stationary. Second, we specify the two cost functions. Third, we present the exogenous parameters which are either common across both banks or are based on estimates for small and big banks, respectively. Lastly, we show the results from the Method of Simulated Moments estimation of the remaining four parameters that involves one estimation for small, and one for big banks.

4.1 Normalization

The estimated process of deposits contains a unit root. To render the model stationary, we normalize all variables by deposits, e.g. equity E_t is transformed into $e_t \equiv \frac{E_t}{D_t}$. For this transformation to work, all components of the profit function have to be homogenous of degree one in deposits. Details of these transformations are in the solution appendix in Section 10.1.

4.2 Cost functions

The functional forms for the cost functions are chosen to satisfy different objectives. First, to limit the volatility of new loans and wholesale funding, we choose the cost of screening new loans and the cost of accessing the wholesale funding market to have a convex component. Second, to be able to normalize the model by deposits, these functions have to be homogenous of degree one in deposits.

We assume a convex screening cost in the ratio of new loans to deposits. To capture that

the screening cost rises with the scale of the bank, we multiply it by deposits. Thus, the resulting cost function is

$$g(N_t, D_t) = \phi_N n_t^2 D_t$$

where $n_t \equiv \frac{N_t}{D_t}$ is the normalized variable, generating a Hayashi-type convex cost function.

A similar reasoning leads to the following cost of accessing the wholesale funding market

$$g(F_t, D_t) = r_{Dt} F_t + \phi_F f_t^2 D_t$$

where the first term is the interest rate cost and the second term reflects the convex risk premium. The external finance premium is increasing in the bank's reliance on the wholesale funding market.

4.3 Calibrated parameters

We will eventually estimate four parameters. Given the complexity associated with solving and estimating the model, we also have to choose certain other parameters exogenously. We discuss these choices now, and these choices come either from economic intuition or data.

Table 4 reports the calibrated parameters that are the same for both small and large banks. The model period is one quarter. Therefore, we set the discount factor β to 0.98 and the risk aversion to 2. The FDIC has imposed an informal (unweighted) leverage limit of 20 which we use in the baseline model. Note that the unweighted leverage limit is significantly more stringent than the risk-weighted one. Later, we investigate the effects of changing these limits or the risk weights.

The model features aggregate and idiosyncratic uncertainty. In general, we estimate the

Parameter	value	
discount factor (β)	0.98	
risk aversion (γ)	2	
leverage limit (λ^l)	20	
	<i>recession</i>	<i>boom</i>
return on liquid assets $r_{S,t}$ (in %)	0.08	0.41
return on loans $r_{L,t}$ (in %)	0.94	1.32
return on deposits $r_{D,t}$ (in %)	-0.39	-0.39

Table 4: Fixed parameters

stochastic processes generating these variables from the data discussed in section 2. There are four aggregate persistent variables: the deposit interest rate, the returns on liquid assets, the loan spread, and the aggregate component of the bad loan process. In order to keep the state space tractable, we assume that all aggregate variables follow the same two-state persistent process. We label the bad aggregate state a recession and the good one a boom. We choose the transition probabilities to obtain recessions that last for 2 years on average and booms that last for 5 years on average.

The values for the aggregate variables are based on the data discussed previously. The rate on liquid assets is higher during booms than during recessions. The loan rate is procyclical as well. Note however, the loan spread as measured over the return on liquid assets is only mildly procyclical. The rate banks have to pay their depositors is acyclical and always negative.¹⁷

As discussed in section 2.3, see Table 2, idiosyncratic bad loans behave very differently in booms and recessions. Due to this asymmetry, we model the bad loan process as state dependent. During a recession, the bad loan process is significantly worse for banks. The

¹⁷The nominal rate was never negative. But inflation was in most periods higher than this nominal rate.

mean is around 50% higher, while the standard deviation and the persistence also increase significantly. The difference in the deposit growth rate is somewhat smaller.

One key economic role of the banking sector is maturity transformation. As explained in section 2, the fraction of loans repaid in each quarter is rather low. It is 8% for small and 6% for large banks.

4.4 Estimated parameters

There are four parameters left that have to be estimated: the flow cost of operating the bank c , the new loans screening cost parameter ϕ_N , the external finance risk premium for accessing wholesale funding ϕ_F , and the value of consumption after failure c^D . We estimate the model separately for small and big banks by the Method of Simulated Moments using eleven moment conditions. We use the standard deviation of the chosen moments in the cross-section to weight the moment conditions and minimize their squared differences from their simulated counterparts.

Table 5 shows the estimated moments for big and small banks in columns 2 and 4, respectively. Their corresponding data counterparts are in columns 3 and 5. Overall, the model matches the moments reasonably well but the OID (Overidentifying restrictions test) rejects the model, implying that further work is needed to match the data. In terms of specific results, the mean failure rate is matched. Similarly, the means of the loan to asset and the deposit to asset ratio are fairly well matched too. The model overpredicts equity holdings, i.e. the bankers in our model have a stronger precautionary motive than what observed in the data. This could come from preference parameters, they might be too patient or too

Table 5: Estimated and data moments

<i>Moments</i>	Big banks		Small banks	
	<u>model</u>	<u>data</u>	<u>model</u>	<u>data</u>
mean default rate (in %)	0.07	0.07	0.05	0.05
mean loans/assets	0.580	0.599	0.602	0.604
mean deposits/assets	0.628	0.667	0.824	0.850
mean equity/assets	0.110	0.077	0.131	0.102
mean profit/equity	0.055	0.046	0.043	0.031
mean dividends/profits	1.067	0.678	1.167	0.527
std. loans/assets	0.126	0.068	0.088	0.080
std. deposits/assets	0.082	0.065	0.083	0.038
std. equity/assets	0.039	0.013	0.040	0.020
std. profit/equity	0.022	0.059	0.017	0.031
std dividends/profits	0.830	0.990	1.21	0.806

risk averse. The model overpredicts the dividend to profit ratio significantly. This might be due to the omission of all taxes. The second moments of the balance sheet variables are overpredicted.

Table 6 shows the estimated parameters. The estimated parameters for big and small banks are rather similar with the exception of the weight on the convex cost of accessing wholesale funding markets. As shown in section 2.1 the crucial difference between small and big banks is the differential access to the wholesale funding market. Thus, the result that the estimated ϕ_F is eight times lower for big than small banks is reasonable. This leads to a significantly lower share of deposits in total assets for the big banks, as can be seen in the third row in Table 5. Moreover, better access to this alternative funding source also allows big banks to operate with lower equity, despite the fact that we assume the same preferences across banks.

Parameter	Big banks	Small banks
operating cost c	0.006	0.0065
screening cost new loans ϕ_N	0.740	0.771
risk premium wholesale funding ϕ_F	0.008	0.063
consumption after bank failure c^D	0.002	0.0018

Table 6: Calibrated parameters

5 Results

We first present individual policy functions to enhance our intuition about the economics behind the model and then proceed with analyzing the implications of the model through simulations.

5.1 Policy functions

To understand the workings of the model, we first present the policy functions. Having normalized the model by deposits, we are left with two continuous state variables: normalized loans and equity. Due to the persistence in the aggregate state and idiosyncratic loan losses, there are two additional discrete state variables, an aggregate state that can be a boom or a recession and idiosyncratic problem loans can be either high or low. All the policy functions shown are for a big bank and are for the same aggregate and idiosyncratic state.¹⁸ All policy functions share the feature that the leverage constraint becomes binding if loans exceed equity by the allowed multiple. For instance, all banks with equity equal to 0.06, but loans that exceed 1.2 will be closed down immediately. In the graphs, this region is at the very right end of the loan state.

¹⁸To be precise, the policy functions are for a big bank in a recession but with low idiosyncratic bad loans. The policy functions in other states and for small banks look similar.

Figure 9: Policy functions with low idiosyncratic loan losses during a boom

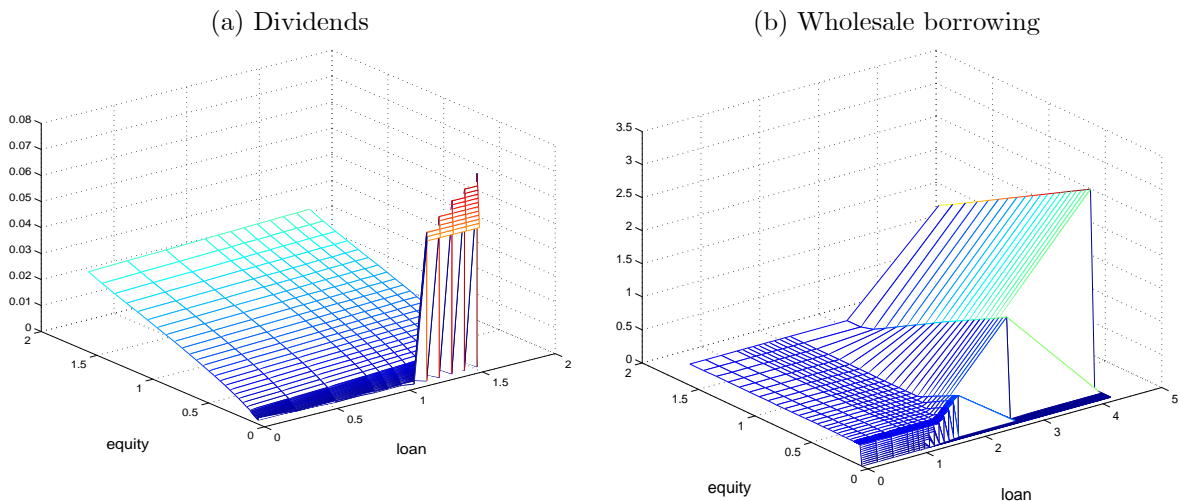


Figure 9a shows the dividend policy function which has three noteworthy implications. The first one is standard. For a low amount of loans and sufficiently high equity (so that a bank is not closed down), dividends are monotonically increasing in equity. This happens because equity is the measure of the banker's wealth and a richer banker can consume more. Second, there is a small hump in the direction of loans, keeping equity fixed. For low levels of loans, the bank wants to expand its loan exposure. This, however, incurs screening costs for issuing new loans which the bank has to pay and which subtracts from available equity. When the bank is already close to its desired level of loan holdings, it does not have to pay this cost and can therefore enjoy higher dividends. The third region is for low levels of equity and high levels of loans. In this region, banks, at first, pay out low amounts of dividends since they get close to the leverage constraint. When equity is so low that banks could pay out only a very small dividend to stay in business and therefore not violate the leverage constraint, they pay out all remaining equity as a dividend and close the bank.

Figure 10: Policy functions with low idiosyncratic loan losses during a boom

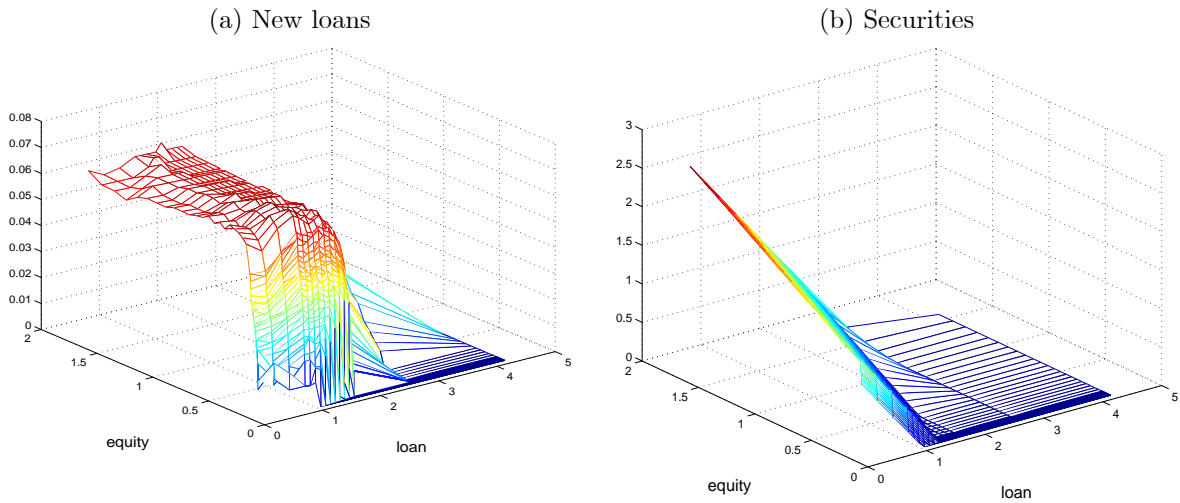
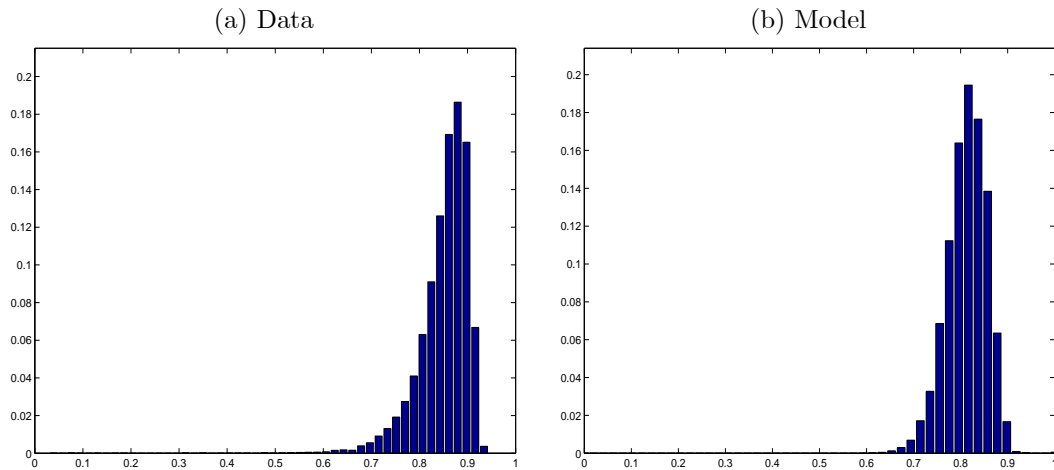


Figure 9b shows the wholesale borrowing of these banks. Due to the convex cost, there is an optimal level for this borrowing. In most parts of the state space, banks borrow this amount. The area where borrowing is higher is the one where banks do not have sufficient deposits and equity to fund their outstanding loan book. Thus, to fund their loans, they need to borrow on the wholesale market, and they borrow more the less initial equity they have.

Figure 10a shows the issuance of new loans. At low initial loan levels and with sufficient equity, banks can reach their desired level of loan holdings. However, due to the convex loan issuance cost, banks do not go to this desired level of loan holdings in one step. Thus, as equity increases, new loans increase monotonically to a desired level given a low level of initial loans. At higher levels of equity, banks prefer to invest in liquid assets, see Figure 10b. Buying liquid assets does not incur any adjustment cost, therefore the investment in liquid assets policy function is monotonic over the entire state space. It is increasing in equity and

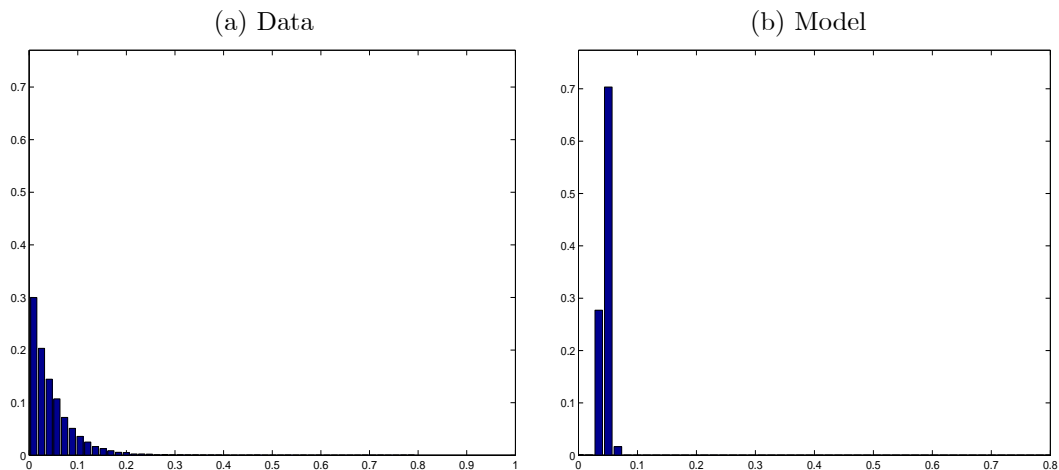
Figure 11: Distribution of deposit to asset ratios



declining in loans. The latter comes from the fact that more old loans mean that there is already more of the alternative asset in the balance sheet.

To take stock, given a particular state, banks have a desired balance sheet structure, i.e. an optimal portfolio. Due to the direct adjustment costs for issuing new loans and for borrowing in the wholesale market and the dividend smoothing motive, it takes time until they reach that state. When the states change, the policy functions change in the expected way. If the idiosyncratic persistent bad loans increase, banks issue less new loans and instead invest more in liquid assets. If the aggregate state changes to a boom, they expand their overall balance sheet by borrowing more in the wholesale market. The resulting cyclical pattern is shown in Section 5.3.

Figure 12: Distribution of wholesale funding to asset ratios



5.2 Cross section

In this section, we provide further empirical evidence for heterogeneity and compare the model outcomes to their data counterparts.¹⁹ The results here are the outcome of simulating the model for the small banks.²⁰ Figures 11 to 14 all show histograms of the respective variable; the data (simulations) are depicted on the left hand side (right hand side) of each figure.

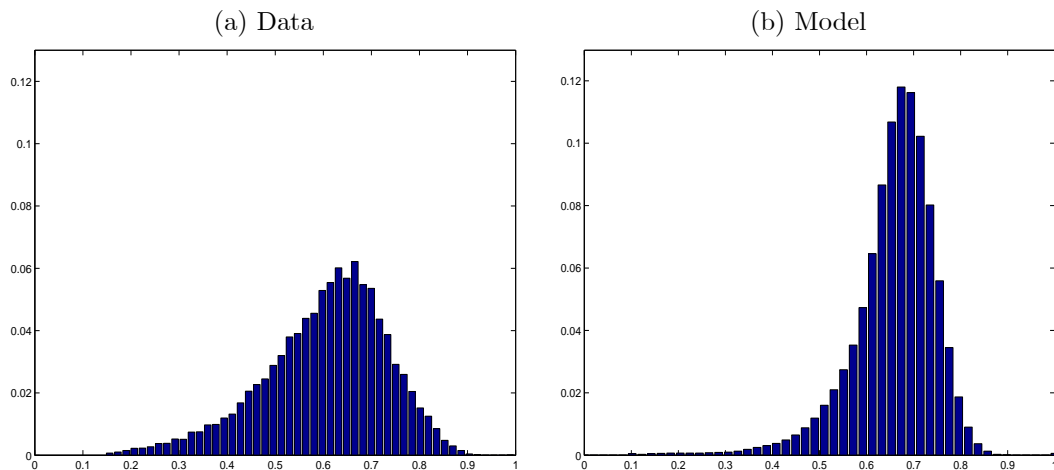
Figure 11 shows the distribution of the unconditional average deposit to asset ratios in the data and in the model simulation, respectively. For most banks, this ratio is between 70 and 90 percent. The model replicates this distribution very well, even though the model distribution is somewhat more symmetric than the data.

Figure 12 shows the distribution of wholesale borrowing. While the distribution in the data is smoothly right-skewed, the model is more symmetric. Moreover, the model misses

¹⁹Details for the simulation procedure can be found in the computational appendix in Section 10.1

²⁰The results for big banks are similar and skipped for brevity.

Figure 13: Distribution of loan to asset ratios



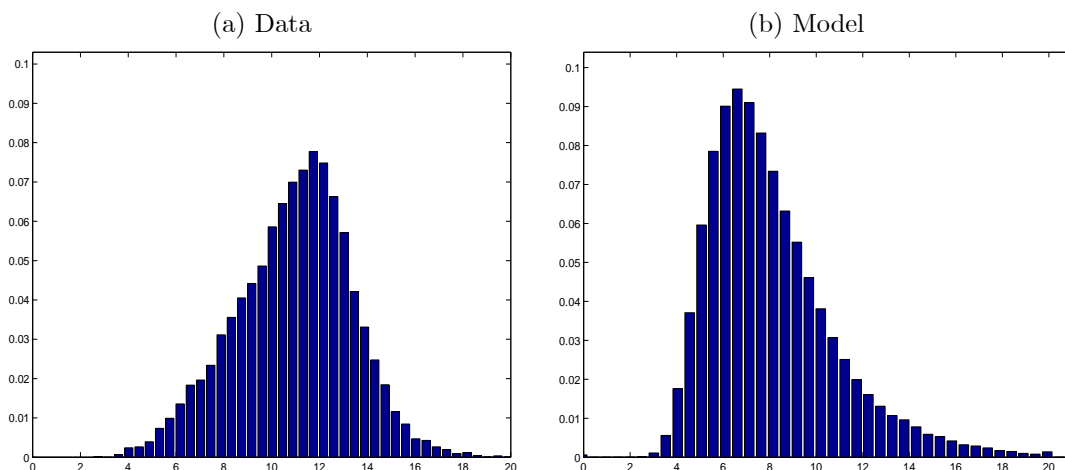
the large mass of the distribution at $F = 0$.²¹ These model results can be understood from the policy function for wholesale borrowing, Figure 9b. Banks have a preferred value for this borrowing which does not vary much with the state. This explains the concentrated distribution in the model.

Figure 13 shows the distribution of loan to asset ratios. This ratio is a lot more dispersed than, for example, the deposit to assets ratio. This wide dispersion, even when we focus on small banks, shows that heterogeneity is an important feature of the data. The model captures this wide dispersion reasonably well, even though its mass is closer to the mean than the data.

The distributions for liquid assets (not shown) are similarly well captured. Lastly, Figure 14 shows the distributions of leverage. Leverage in the data is distributed symmetrically around its mean. The model dispersion is somewhat wider and in particular is skewed to

²¹We experiment with a fixed cost in the model. This generates a mass at zero. However, the shape of the distribution still differs significantly from the data. We leave this issue for future research.

Figure 14: Distribution of leverage ratios



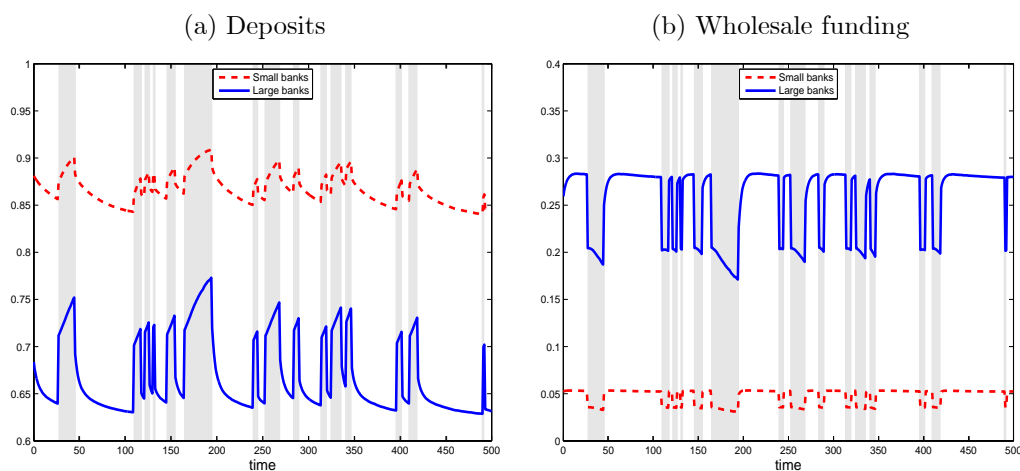
the left and not as symmetrical as in the data. The mean in the model is lower since equity holdings (which are the inverse of leverage) are higher, as was shown in the estimation section.

5.3 Time series behavior

Figures (15) to (18) provide a more detailed view on the time series behavior of the model.²² The corresponding figures in the data are Figures (1) to (7). Figure (15a) shows the deposit to asset ratio in the model over time for big and small banks and Figure (15b) shows the wholesale funds to total assets ratio. Consistent with the data, small banks rely significantly more on deposits to fund their operations, while large banks rely on wholesale funds to a significant extent. However, even for large banks deposits are the main funding source. During recessions, when the perceived return on assets falls, the deposit to asset ratio rises for both big and small banks because banks reduce their borrowing in the wholesale

²²The shaded areas denote model recessions.

Figure 15: Evolution of deposit to asset ratio and wholesale funding to asset ratio in the model

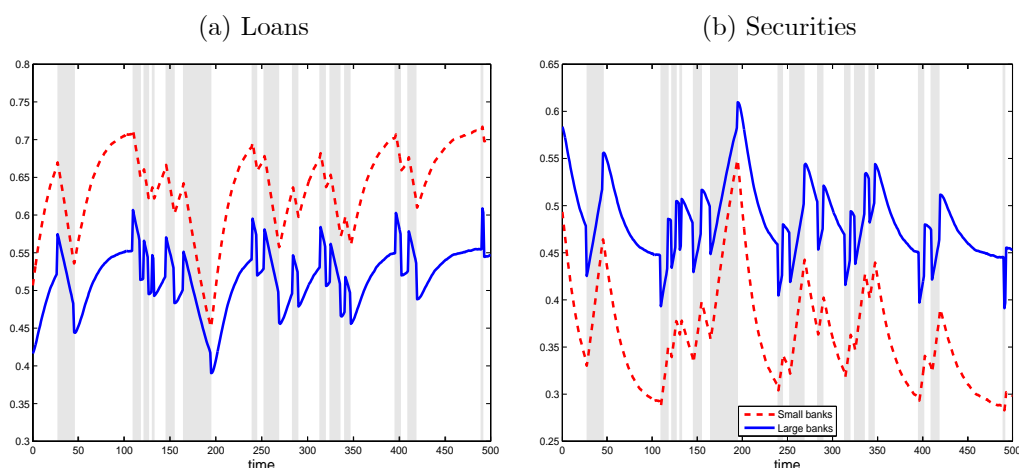


funding markets. Because equity is a small component of the balance sheet, reduced borrowing in wholesale funding markets translates into a relative increase in the share of deposits in the total balance sheet during recessions. Thus, even though deposits grow more slowly in recessions than in a boom, and total assets shrink in a recession, the relative importance of deposits in the balance sheet increases. This cyclical pattern seems consistent with the evidence in Figure 1, even though the empirical counterparts are based on a limited number of recessions and should therefore be treated with caution.

Figure (16) shows the asset side of the balance sheet. As a proportion of the total balance sheet, small banks invest more (less) in loans (securities) than large banks because smaller banks face less uncertainty for loan write-offs and lower deposit growth uncertainty than larger banks.

Moreover, the fraction of loans in total assets is strongly procyclical for both types of banks and arises because loan write-offs are very countercyclical. However, the evolution

Figure 16: Evolution of loan to asset ratio and securities to asset ratio in the model



of loans and liquid assets at the onset and during the recession is not the same across the two bank sizes. For large banks, at the onset of the recession the share of loans jumps up and then declines during the recession, a behavior that is different from smaller banks. The explanation is that large banks also invest less in liquid assets during recessions. Thus, they want to reduce their holdings of both liquid assets and loans. Banks can reduce their liquid assets immediately at the onset of a recession. Loans are illiquid, however, since only a small fraction gets repaid every period. Thus it takes some time until banks deleverage by reducing their loans, which means that the loan to asset ratio takes a few quarters to fall below the level it had just before the recession. This effect is more pronounced for big than for small banks because big banks fund their activities to a larger degree with wholesale funds which can be quickly cut back. For small banks it takes only a few quarters until the loan to asset ratio is back to its original level, while for big banks it takes significantly longer. For example, in the long recession in periods 165-194, it takes 10 quarters until the

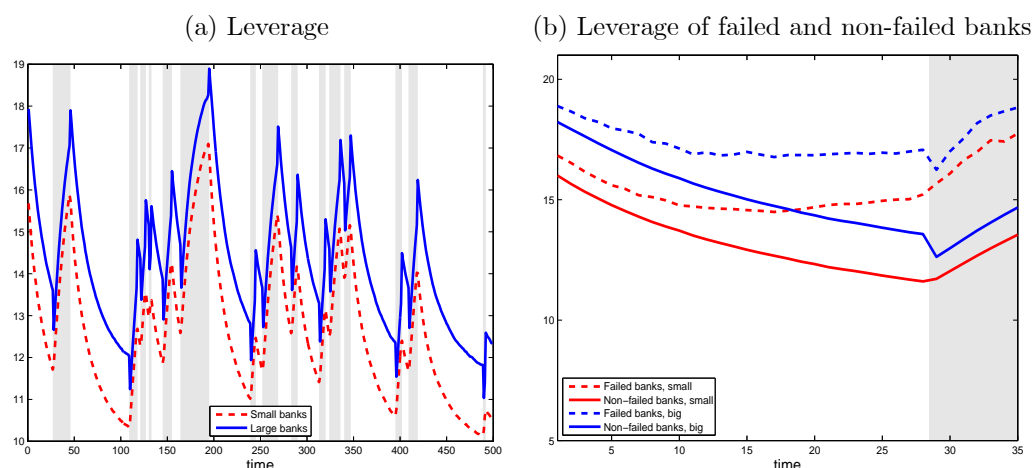
loan to asset ratio falls below its initial value for the big banks.

Figure 17a shows the leverage ratio of the banks in the model. Consistent with the data, see Figure 3a, big banks are more highly levered than small banks. Since small banks have less access to the wholesale funding market, they rely more on deposit and equity funding. This increase in equity funding translates into a lower leverage ratio. Leverage is countercyclical for big and small banks. They use the profits to build up equity during good times through retaining some of their earnings. This is similar to the role of precautionary savings in the consumer literature. During recessions, equity declines and leverage increases because profits are lower. Since banks want to smooth dividends to some degree, they do not lower dividend payments as much as profits fall. Again, there is a non-monotonicity at the onset of a recession for big banks. Since they are able to cut their liquid assets and liquid liabilities quickly, the share of equity in total assets actually rises, and so leverage falls, at the onset of a recession. However, the reduced profits deplete equity rather fast so that it takes less than a year until the leverage level rises above its initial level.

Figure 17b is the model counterpart to Figure 3b. It shows the leverage for banks that ultimately fail and those that survive in a model recession. Leverage rises significantly for those banks that ultimately fail. The different evolution is similar for big and small banks. Thus, an increase in leverage is an indicator for successive vulnerability. This is consistent with the evidence in Berger and Udell (2013).

Figure 18 is the model counterpart to Figure 7 in the data section. Figure 18a shows that aggregate loan growth in the model is strongly procyclical. Loan growth hardly differs between big and small banks. It is positive during booms and declines during recessions. While

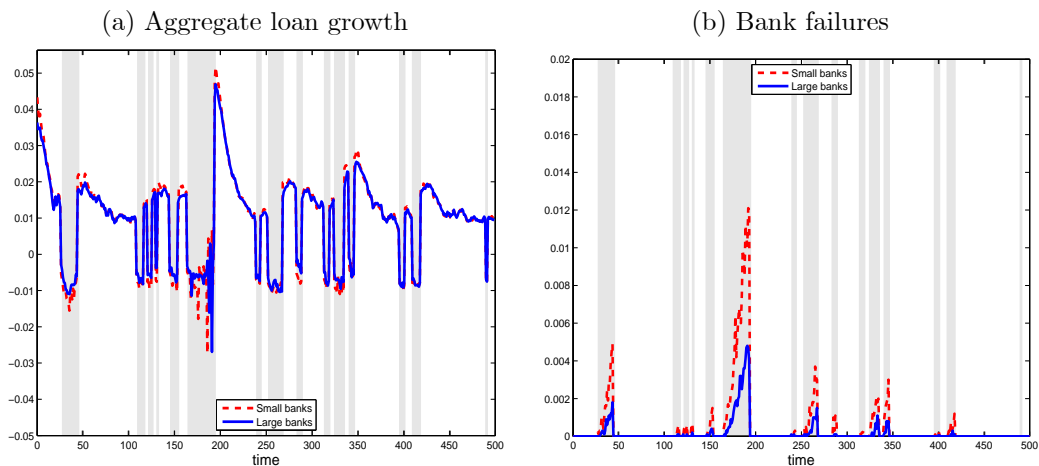
Figure 17: Leverage by size and leverage of failed vs. non-failed banks in the model



loan growth is fairly stable during recessions, meaning that banks delever continuously, it is somewhat different in booms. As explained above, at the beginning of a boom, banks have invested a relatively small share of their assets in loans, therefore as soon as aggregate conditions improve, they start lending more to replenish their loan book. This makes loans very procyclical. Note that they do this despite the convex cost function for new loans. Thus, at the beginning of the boom, they are willing to incur these high costs because the benefits of increasing their loan exposure are high enough.

Figure 18b shows that failures are higher for small than for big banks. This feature is not consistent with the data. The reason is that big banks have cheaper access to wholesale funding markets which enables them to deal better with shocks. Figure 18b also shows that failures are strongly countercyclical. There are almost no failures in good times. The intensity of failures increases strongly with the length of a recession. In short recessions there are only few failures, while in long recessions the failure rate rises above one percent.

Figure 18: Cyclical properties of loan growth and bank failures



The reason is that the equity stock of banks gets more and more depleted during recessions. This is confirmed in Figure 17a where leverage is at its highest level at the end of the longest recession.

6 Counterfactual policy experiments

In this section we use our structural model of the banking system to perform counterfactual experiments that can provide guidance to policy makers about the possible effects on behavior from changing policy-controlled parameters or how changes in the economic environment can affect behavior.

6.1 Financial crisis

The recent financial crisis has two important elements: first, a wholesale funding market freeze and second, forced sales of liquid assets generating losses for banks. We use our model to assess the implications of such events in our model economy. We model the freeze in the

wholesale funding market as an unexpected loss of non-deposit funding for all banks. Thus, for one (crisis) period, banks are unable to obtain any wholesale funds $F_{i,t}$. Forced sales are modeled as an unexpected drop in the value of liquid assets. We assume however that banks know that normal conditions in the wholesale funding and liquid asset markets will be restored in the following period.²³ This is roughly in line with the events after the Lehman bankruptcy where it took a while for policy makers to respond adequately to the freeze in the wholesale funding market.

6.1.1 Wholesale funding market freeze

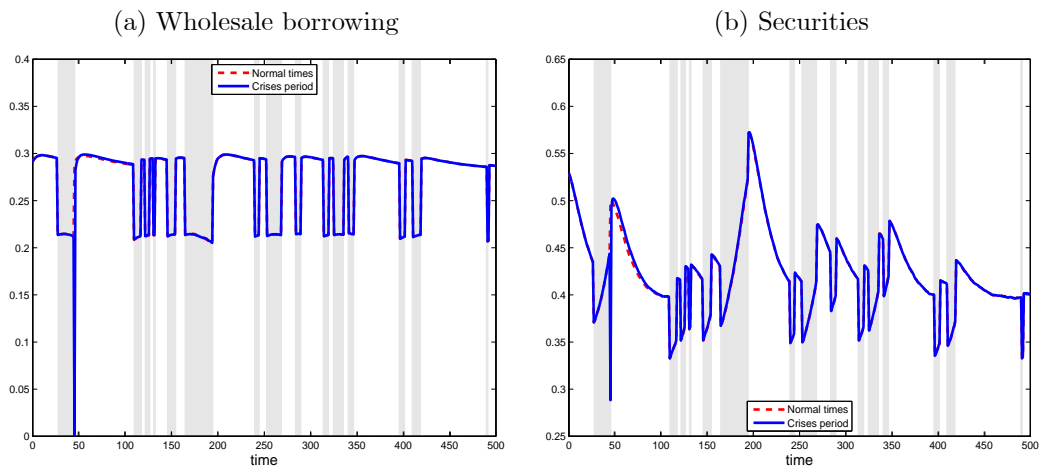
In our model, we assume that at the end of the recession in period 45, banks can not borrow any wholesale funds $F_{i,t}$. This makes all banks that rely on this market, mainly the larger banks, vulnerable to a liquidity crisis.

We implement this by using the regular continuation value functions all the time, also in the crisis period when unexpectedly no bank has access to wholesale funds. We compute new policy functions in this particular period for new loans issued, liquid assets bought and dividends issued. Borrowing in the wholesale market is, by definition, zero in the crisis period. We then simulate the model up to the crisis period as before using the regular policy functions. In the crisis period we use the new policy functions. After the crisis period we use again the normal ones.

Figure (19) shows the results for large banks and is compared to a standard simulation without a freeze in the wholesale funding market. Figure (19a) shows the drop of borrowing in the crisis period. Large banks, however, hold significant amount of liquid assets. Thus, upon

²³Thus, the freeze lasts only for one quarter.

Figure 19: The impact of a money market freeze on borrowing and holding of securities



losing access to short term funds, they lower their investments in short term liquid assets, see Figure 19b. Thus, liquid assets are an important insurance device against problems in funding markets for large banks. However, those large banks that rely extensively on wholesale markets do not survive such a crisis. The failure rate increases from 0.65% to 1.1% for large banks. Small banks (not shown) are a lot less affected because they hardly use the wholesale funding market. Their failure rate does not increase in such a crisis.

6.1.2 Forced sales

We now analyze losses due to forced sales in the crisis period. Fire sale losses are modeled as an unexpected reduction in the return on liquid assets $r_{S,t}$ in the crisis period. As in the previous experiment, normal times resume after the crisis period.

Table 7 shows the failure rate of small and large banks for the same period across four different simulations. Column 2 shows the results in a normal recession without further stress in financial markets. Column 3 shows the effect of a freeze in wholesale funding markets,

	Normal recession	Freeze	Forced sale losses	Freeze & Forced sale losses
Small banks	0.58%	0.58%	3.2%	3.3%
Large banks	0.65%	1.1%	3.5%	3.6%

Table 7: Failure rates in different crisis periods

as discussed previously. The failure rate of large banks increases significantly while small banks are not affected. Column 4 shows the failure rate when there are unexpected losses on the return on liquid assets of 1 percent, i.e. $r_{S,t} = -0.01$.²⁴ The failure rate in this case increases six fold. There is no difference between big and small banks. Both types hold on average around 40% of their total balance sheet as liquid assets. Thus, an unexpected loss on these holdings reduces equity significantly which then triggers failures.

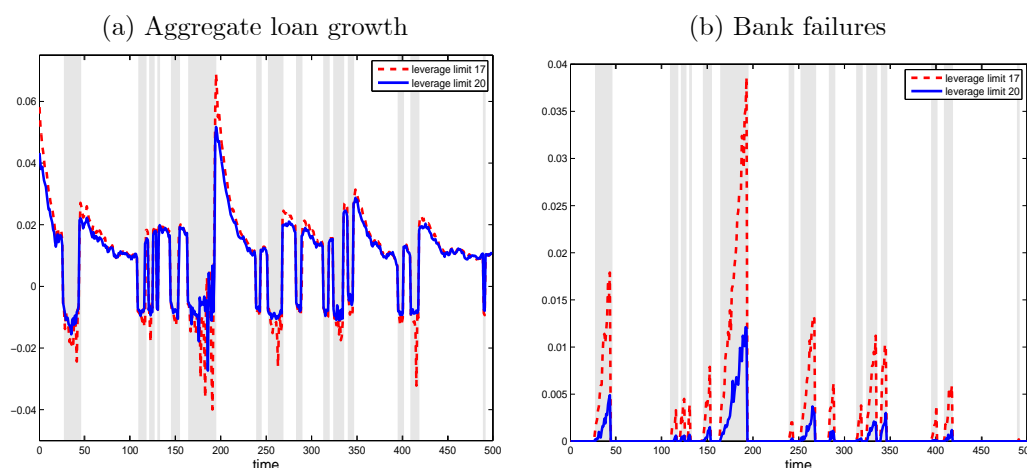
If both types of crises occur in the same period, as has happened during the Lehman crisis, the forced sale losses dominate the overall effect completely, see Column 5. Thus, in our model solvency problems are more important than liquidity problems.

6.2 Tightening leverage constraint

One important policy change currently being implemented is a move towards tighter leverage limits. In this section we show the consequences of such a policy by comparing results across steady states. We solve the model for different values of the leverage limit, leaving all other parameters at their benchmark values. The simulation uses exactly the same shock sequence. Figure (20) shows loan growth rates and failure rates for the benchmark economy with a leverage limit of 20 and a counterfactual economy where the leverage limit is tightened to 17 for small banks. As can be seen in Figure (20a), the average growth

²⁴A quarterly loss of 1% is in line with returns during the Lehman crisis.

Figure 20: Cyclical properties of loan growth and bank failures with different leverage limits



rate of loans is not affected much. However, and in line with, for example, Repullo and Suarez (2013) loan growth becomes more procyclical. In particular, the growth rate during recessions is negatively affected. Figure (20b) shows the impact on the bank failure rate. While this rate is hardly affected during booms, its peaks during recessions increase more than three times. Thus, despite reducing their loan supply somewhat, banks still fail at a much higher rate under a reduced leverage limit.

Figure (21) shows the average equity holding for different leverage limits for big and small banks. It is clear that a tighter leverage constraint leads banks to hold more equity. This effect is very similar for large and small banks. In that sense, a tighter leverage limit leads to safer bank balance sheets. However, a tighter leverage also means that, *ceteris paribus*, a bank with a given balance sheet becomes more likely to breach this lower limit. It is this latter effects that dominates. Therefore a tighter leverage limit leads to an increase in the failure rates, as shown in Figure (22a). Moreover, the increase for small banks is somewhat

Figure 21: Average equity for different leverage limits

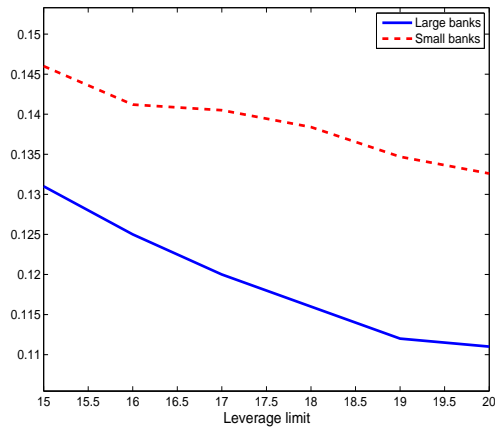
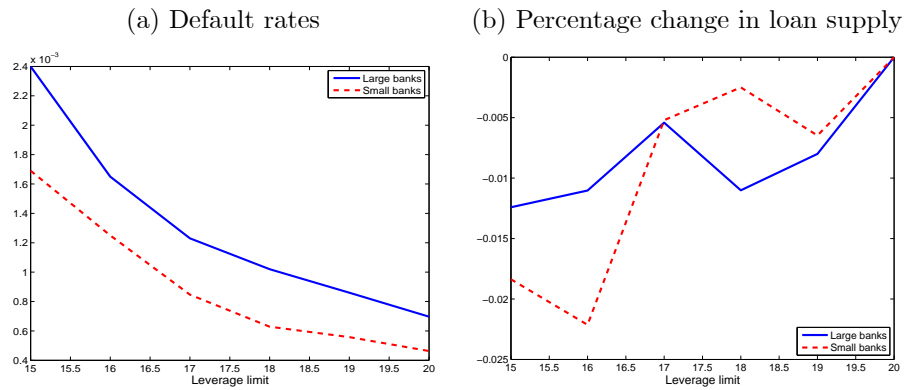


Figure 22: Effects of changing the regulatory leverage limit



larger than for big banks.

This cross-sectional difference is even more pronounced for loan supply, as can be seen in Figure (22b) which shows the percentage change in average loan supply. This effect is mostly negative, even though, there are some non-monotonicities. But again, the effect is much more pronounced for small banks. Lowering the leverage constraint to $\lambda = 15$ leads to a decline in loan supply of about 1.8 percent in the new steady state for small banks but only of about 1.2 percent for big banks. They might increase bank distress and they lower

loan supply, in particular during recessions. And, moreover, this negative effect is stronger for small than for big banks. The reason is that big banks through their better access to the wholesale funding market can easier cope with shocks. Thus, they are less likely to break the leverage constraint and this effect is more pronounced at lower levels.

Note however, one important motivation for tighter leverage limits are the fiscal costs of bank bail-outs. Even though we do not model bail-outs directly, we can use our model to assess its implications. Bail-out costs depend on two quantities: first the failure rate and second the expected loss conditional on failure. We have already seen that a tighter leverage limit increases the frequency of bank failures. However, the second component works in the opposite direction. A tighter leverage limit leads to higher equity holdings, see Figure 21. Thus, it is likely that banks will have more equity capital left in the case of a failure which lowers the cost of third parties.

The partial equilibrium nature of our model does not allow us to make a welfare comparison between the status quo and a tighter leverage limit. Nevertheless, the model does provide instructing results from limiting cases.

7 Conclusion

We use individual U.S. commercial bank balance sheet information to develop stylized facts about bank portfolio choices in both the cross section and over time. We then estimate the structural parameters of a quantitative model of bank portfolio choices (new loans, liquid investments and endogenous failure) that are made in the presence of undiversifiable background risk (problem loans, interest rate spreads and deposit shocks) and regulatory constraints. The model does not replicate all features of the data but can be provide a

useful approximation of reality to perform counterfactual experiments in real time to better understand financial intermediation choices. Future work can extend the model in general equilibrium and introduce a central bank as a lender of last resort, while also investigate the implications of different recapitalization mechanisms.

8 References

Acharya, Viral, Hanh Le and Hyun Song Shin, 2013, “Bank Capital and Dividend Externalities,” working paper.

Adda, J. and R. Cooper, 2003, *Dynamic Economics*, MIT Press.

Admati, A. and M. Hellwig, 2013, *The Bankers’ New Clothes*, Princeton University Press.

Berger, A.N. and Bouwman, C.H.S., 2013, “How does capital affect bank performance during financial crises?” *Journal of Financial Economics* 109 (1), 146-176.

Berger, A. N, Kashyap, A. K. and Scalise, J.M., 1995, “The transformation of the US banking industry: What a long, strange trip it’s been,” in *Brookings Papers on Economic Activity*, 55-218

Bernanke, B. and Blinder, A., 1988, “Credit, Money, and Aggregate Demand,” *American Economic Review*, 78(2), 435-439.

Bernanke, B. and Blinder, A., 1992, “The Federal Funds Rate and the Channels of Monetary Transmission,” *American Economic Review*, 82(4), 901-921.

Calomiris C. and J. Karceski, 2000, “Is the Bank Merger Wave of the 90s Efficient?,” in *Mergers and Productivity*, S. Kaplan, ed., University of Chicago Press, 93-161.

Calomiris C., 2000, “U.S. Bank Deregulation in Historical Perspective,” *Cambridge University Press*.

Cetorelli, N. and Goldberg, L., 2012, “Banking Globalization and Monetary Transmission,” *Journal of Finance*, 67(5), 1811-1842.

Chen, H., 2010, “Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure,” *Journal of Finance*, 65(6), 2171-2212.

Corbae, D. and D’Erasmus, P., 2011, “A Quantitative Model of Banking Industry Dynamics,” Mimeo

Corbae, D. and D’Erasmus, P., 2012, “Capital Requirements in a Quantitative Model of Banking Industry Dynamics,” mimeo.

De Nicolo, G., A. Gamba and M. Lucchetta, 2014, “Microprudential Regulation in a Dynamic Model of Banking,” *The Review of Financial Studies*, in press.

Holod, D. and Peek, J., 2010, “Capital Constraints, Asymmetric Information and Internal Capital Markets in Banking: New Evidence,” *Journal of Money Credit and Banking*, 42(5), 779-905.

Kashyap, A, Stein, J. and Wilcox, D., 1993, “Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance,” *American Economic Review*, 83(1), 78–98.

Kashyap, A. and Stein, J., 2000, “What Do a Million Observations on Banks Say About the Transmission of Monetary Policy?” *American Economic Review* 90(3), 407-428.

Kishan, R. and Opiela, T., 2000, “Bank size, bank capital, and the bank lending channel,” *Journal of Money, Credit and Banking*, 32, 121–141.

Miles, David, Jing Yang and Gilberto Marcheggiano, 2012, “Optimal Bank Capital,” *The Economic Journal*, pp. 1-37.

Oliner, S. and Rudebusch, G., 1996, “Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance: Comment” *American Economic Review*, 86(1), 300–09.

Peek, J., and Rosengren, E., 2000, “Collateral damage: Effects of the Japanese bank crisis on real activity in the United States,” *American Economic Review*, 90, 30-45.

Repullo, Rafael and Javier Suarez, 2013, “The Procyclical Effects of Bank Capital Regulation,” *The Review of Financial Studies*, 26, 452-490.

9 Data Appendix

9.1 Call reports

The analysis draws on a sample of individual bank data from the Reports of Condition and Income (Call Reports) for the period 1990:Q1-2010:Q4. For every quarter, we categorize banks in three size categories: banks of size 1 are those below the 95th percentile of the distribution of total assets in the given quarter, of size 2 those between the 95th and 98th percentile and size 3 those above the 98th percentile.

Our initial dataset is a panel of 834,771 quarterly observations from 18,050 U.S. commercial banks. From these, 35,885 observations are dropped due to having a FDIC identification number equal to zero, reducing the number of banks to 16,670. Moreover, 4,513 observations are dropped due to missing values and 544 due to negative tangible equity. When (real) growth rates are calculated, another 22,157 observations are dropped. Outlier growth rate is defined as any observation below the 0.1th percentile, or above the 99.9th percentile of the sample distribution at a given quarter. Winsorizing with this criterion, 2,373 observations

are dropped due to outlier growth rates in tangible assets and customer loans.²⁵ The final sample is 769,342 observations.

Growth variables are deseasonalised by regressing them on quarterly dummies and obtaining the residuals. Autoregressive coefficients, unconditional standard deviations and means of the idiosyncratic component of reported variables are estimated initially for each bank with at least 40 consecutive observations. There are 8,643 such banks for the problem loan variable, 8,474 for deposit growth, 3,042 for non-deposit funding growth, 8,475 for lending growth, tangible-asset growth and tangible-equity growth.

We have also identified 670 bank failures, which are basically all bank failures reported by the FDIC for the period 1991Q1-2010Q4. For the second half of this period (i.e. 2000Q4-2010Q4), names and FDIC identification numbers of failed banks were obtained from an FDIC list.²⁶ For the first half of the period (i.e. 1990Q1-2000Q3), names of failed banks were obtained from FDIC reports.²⁷ For those banks, we are able to uniquely identify their FDIC identification numbers from Call Reports by matching bank-name, city and state information. From the 670 bank failures reported by the FDIC, it was not possible to identify the FDIC identification numbers in 59 cases. As a result, the number of bank failures considered was reduced to 611. Among those, 19 failed banks had the same FDIC identification number with other banks in Call Reports and were dropped from the sample, reducing the number of bank failures considered to 568.

²⁵Tangible assets equal total assets minus intangible assets, such as goodwill. Tangible equity equals tangible assets minus total liabilities.

²⁶Available at <http://www.fdic.gov/bank/individual/failed/banklist.html>.

²⁷Available at <http://www.fdic.gov/bank/historical/bank/1991/index.html>.

The fraction of loans repaid in each quarter is calculated as the sum of outstanding loans that mature within one year. This is 32% for small and 24% for large banks. We assume a uniform repayment rate and therefore use a quarterly repayment fraction of 8% and 6%, respectively.

9.2 Capital adequacy rules and leverage ratio

Basel II defines different risk weights for different asset classes. The risk weight on government bonds is 0% and on safe financial assets 20%. Banks in our sample hold approximately 50% of their liquid assets in each of these categories. Therefore, we use a risk weight ω^s equal to 10%. The risk weights on residential mortgages are 35%, on commercial real estate 100%, and on personal loans, including small business loans, 75%. Given the average loan portfolio in our sample, we use a risk weight ω^s equal to 65%.

9.3 Rate of returns

The rate of returns on loans is also based on the loan portfolio in our sample. Using data for mortgages and commercial and industrial loans, and using a weight of 60% on mortgages, we get an average real rate (annualized) equal to 5.26% in booms and 3.77% in recessions. The return on liquid assets is based on the real Fed Funds rate since short term bonds and safe short term assets closely follow this rate. The real Fed Funds rate in our sample is equal to 1.66% in booms and 0.31% in recessions.

9.4 Further empirical results

In this section, we report the empirical results we have left out in the main text, which we did to preserve space.

Figure 23: Distribution of deposit to asset and loan to asset ratios; big banks

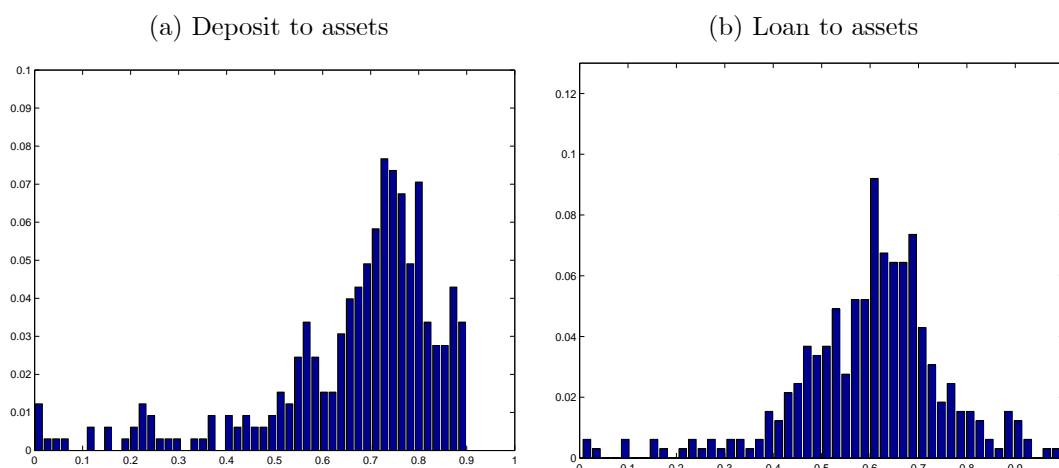


Figure 23 is the equivalent to Figure 6 and shows the deposit to asset ratio and loan to asset ratio of big banks.

The deposit to asset ratio is much more dispersed for big banks, reflecting that some of them rely significantly on wholesale funds. The loan to asset ratio, however, is similar to the small banks. The mean is almost identical and most banks have a ratio between 40% and 80%. The distribution is not as smooth, at least partly, because there are around 35 times less observations for big than small banks.

10 Solution Appendix

This section first shows the normalization of the model and then the computational approach to solve it numerically.

10.1 Normalization

The deposit process contains a unit root but is i.i.d. in growth rates. Therefore we normalize the entire model by deposit growth rates. For this approach to work, all equations have to be homogenous of degree 1. Denote normalized variables as lower case variables, for example $f_t = \frac{F_t}{D_t}$ and the growth rate of deposits with $\Gamma_{t+1} = \frac{D_{t+1}}{D_t}$.

The leverage limit (2) becomes

$$\frac{l_t + n_t + s_t}{e_t - x_t} \leq \lambda. \quad (8)$$

The equity evolution (1) becomes

$$\begin{aligned} e_{t+1} &\equiv \frac{E_{t+1}}{D_{t+1}} = E_t - X_t + \Pi_{t+1} \\ &= (e_t - x_t) \frac{1}{\Gamma_{t+1}} + \pi_{t+1}. \end{aligned} \quad (9)$$

Profits (4) become

$$\pi_{i,t+1} = (r_{L,t+1} - w_{i,t+1})(l_{it} + n_{it}) + r_{S,t+1}s_{it} - r_{D,t+1} - c_M(n_{it}) - g(f_{it}). \quad (10)$$

10.2 Computational appendix

After the normalization there are 2 continuous state variables: normalized equity e_t and normalized loans l_t . The aggregate state is approximated by a two state Markov chain, where the good state is interpreted as a boom, and the bad state as a recession. The transition probabilities are chosen to generate boom and recessions that last, on average, 5 and 2 years, respectively. The state dependent stochastic process for bad loans follows an AR(1) process which is discretized using the procedures described by Adda and Cooper (2003). The numerical solution algorithm is as follows.

1. Values for all exogenous parameters are assigned.
2. Two grids are made for the two continuous state variables equity e and loans l .
3. A sequence for all shocks for the simulation is drawn.
4. Values for the four estimated parameters are assigned.

The remaining computational steps have two components: solution of the value functions and simulation.

Solution of value function problem

5. The value for consumption after failure \bar{c} implies a continuation value after failure V^d
6. A guess is made for the (normalized) value function $v(l, e, w, r, g)$
7. The optimization problem is solved for all discrete states: boom and recession, and nodes for bad loans and for all values on the grids for e and l . At each such node, the bank chooses dividends x , new loans n , liquid assets (securities) s and wholesale borrowing f simultaneously to maximize its life time utility (??). The details for this step are as follows:
 - (a) at each node (e, l) three nested grids are made for (x, n, f) , s follows from the balance sheet constraint that $s = 1 + f + e - x - l - n$.
 - (b) if the candidate for (x, n, f) violates the leverage limit, the bank is closed down and the failure utility level V^d is assigned.
 - (c) if the candidate for (x, n, f) is feasible and obeys the leverage limit, a loop is made over all possible future states and profits in each state are calculated. The

shocks and the choices imply a certain level of profits in each state which leads to a different level of equity and loan (l', e') in the future period. The continuation value is computed in each of these states. This is either $V(l', e', w', r', g')$ or if failure is preferred V^d .

- (d) Since future values of (l', e') will not, in general, lie on the grid, a two-dimensional linear interpolation routine is chosen to obtain the values $V(l', e', w', r', g')$ at this node.²⁸

8. The solution to the optimization problem at each node provides an update value function $\tilde{v}(l, e, w, r, g)$.

- (a) if $\tilde{v}(l, e, w, r, g)$ is close to $v(l, e, w, r, g)$ at every single node, i.e. if the maximum absolute difference is below the tolerance level, the value function has converged;
- (b) otherwise the value function has not converged and $v(l, e, w, r, g)$ at the beginning of step 7 is replaced with $\tilde{v}(l, e, w, r, g)$ and step 7 repeated.

9. After convergence the decision rules for dividends x , new loans n , and wholesale borrowing f are saved for the simulation

Simulation

10. The previously drawn shock sequences and the saved decision rules are used to simulate $N = 100,000$ banks for $T = 2,000$ periods.

²⁸Linear interpolation is chosen because, being a local method, it is more stable than, for example, cubic splines.

11. Each bank starts with some specific initial value for (e_t, l_t) aggregate state and idiosyncratic bad loan state. The decision rule is then used to compute new loans n_t , dividends x_t , wholesale borrowing f_t . The shocks $t + 1$ are realized which in turn yield profits π_{t+1} . This yields new equity $e_{t+1} = e_t + \pi_{t+1} - x_t$. Similarly, the state of loans next period is $l_{t+1} = (1 - \vartheta - w_{t+1})(l_t + n_t)$.
12. A bank that fails during the simulation is replaced by a new one which starts with mean equity and mean loans.²⁹
13. After the simulation is concluded the first 1,500 periods are excluded and all statistics reported are calculated based on the last 500 periods.
14. The criterion function of the estimation is calculated.
 - (a) The squared differences between model and data moments are calculated.
 - (b) These are weighted by the efficient weighting matrix which uses the standard deviations of the empirical moments.
15. If the criterion function is too high, a new set of values is tried in step 4. For this optimization, we use a standard derivative free simplex method.

²⁹However, due to the very low number of defaults, this choice has no influence on aggregate statistics.