

Uninsurable Risks, Bank Defaults and Loan Supply*

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Abstract

We use individual U.S. commercial bank balance sheet information to develop stylized facts about bank behavior in both the cross section and over time. We then build a quantitative model of bank behavior taking as exogenous inputs the aggregate and idiosyncratic components of problem loans, interest rate spreads and deposit shocks, seeking to understand decisions regarding new loans provision, access to wholesale funding and defaults. The model generates highly procyclical loan supply and banks can curtail new lending very aggressively in response to background risk shocks, such as an increase in bad loans. Bank failures, though, are strongly countercyclical. Relative to a baseline recession, in a recession simultaneously accompanied by a temporary freeze in the money market, bank defaults increase by a factor of three and credit supply drops by 2.5 percentage points more.

JEL Classification: E32, E44, G21

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1 Introduction

The recent crisis has made more important the persistent call by some macroeconomists (Goodhart (2010)) to better understand financial intermediation. The role of leverage in the recent crisis and the position of financial institutions as leveraged intermediaries between households and firms has further intensified the urgency behind understanding banking decisions. 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) further illustrate the importance of banking decisions¹ for 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, on the prudential regulation front, the G20 nations have agreed to strengthen capital buffers in the banking system to improve resilience to shocks. They also recognized the need to amend the 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) were 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*

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.

*financial sector and the assessment of how risks evolve over time*².

Efforts by policy makers to rein in bank leverage have recently been endorsed by some senior banking executives.³ But putting limits on leverage is likely to become a contentious issue at the implementation stage given the impact such measures could have on banks' return on equity. Other things being equal, the more cents a bank sets aside as equity, for every dollar it lends out, the lower is the return on equity (*RoE*). For example, the French Banking Federation warned that European financial institutions will be unfairly penalized, compared with US banks, by new capital requirement rules on the agenda at the G20 summit in September 2009.⁴ On the other hand, maintaining a lower level of leverage could increase banks' resilience to shocks and reduce the likelihood of bank failures. Therefore, setting leverage limits at an appropriate level is a balancing act of choosing between lower *current* profits and higher bank safety, namely higher *future* profits. 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 of our main goals is to take a step in that direction by providing a structural, quantitative economic analysis of how US commercial banks determine their leverage levels over time. If one can build an empirically successful quantitative model of banking decisions,

²The Basel Committee on Banking Supervision will also incorporate leverage limits in the Basel framework, supplementing the risk-based measures of capital adequacy. Leverage limits aim to contain the build-up of excessive risk in the banking system that could be a result of a down-right migration of banks in the [leverage, RoE] space.

³See, for example, FT 8 Sep 2009. "Ackermann joins calls for tough capital rules," and FT 9 Sep 2009 "Goldman chief hits at 'useless' banking".

⁴See, FT 17 Sep 2009. "French banks say capital plans 'unfair'".

then counterfactual experiments can be used to inform policy makers of the likely economic outcomes from various policy decisions.

To do so, 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 level of problem loans) and certain balance-sheet items, such as customer deposits and tangible equity. We should emphasize that despite being exogenous (or partly exogenous), these data generating processes are chosen to be consistent with the empirical evidence.⁵ 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 applies to U.S. deposit-taking institutions.

Our empirical approach is 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 but then

⁵Chen (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.

deviate from this approach to build a structural model following Corbae and D’Erasmus (2011 & 2012). We do so because we are interested in providing a setting where policy advice can be readily given through counterfactual, quantitative, experiments. Corbae and D’Erasmus 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. On the other hand, 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. 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.⁶ We make this decision because we think that an individual banks’ model is needed first, before the more complicated holding bank model is developed to match the data.

The quantitative model is successful in replicating the data in some dimensions but not in all dimensions, indicating the need for further work in the area. The structural model does generate the fact that smaller banks tend to rely more on deposits than larger banks, but the deposit to asset ratio is more volatile in the model than in the data. Larger banks are also predicted to be more highly levered than small banks, and the model predicts similar cyclical properties as in the data. Our results show that leveraged banks are more likely to fail in a recession, both in the model and in the data.⁷ The model predicts strongly procyclical loan

⁶Cetorelli and Goldberg (2012) provide evidence of an international lending channel whereby liquidity shocks at home may propagate internationally through internal capital markets and cross-border liquidity transfers among the head office and foreign affiliates of global banks. That follows some early evidence on the international transmission of liquidity shocks via banks by Peek and Rosengren (2000).

⁷Kishan and Opiela (2000) determine that equity is another variable that affects banks’ sensitivity to

growth that is slightly asymmetric (positive spikes tend to happen when the economy exits the recessionary period). We interpret this procyclicality as consistent with the empirical evidence. The model also generates strongly countercyclical default rates, consistent with the data. Overall, we interpret these findings as consistent with quantitative features of the data, and therefore we use the model for counterfactual analysis.

We limit our counterfactuals to analyzing the effect of the money markets and the leverage constraint on bank behavior. We first 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. If money markets freeze, the model predicts a trebling of default rates during the recession. In the second counterfactual we analyze the behavior of the economy by reducing the baseline leverage limit from 20 to 15. The default rate rises slightly for higher leverage limits, but higher leverage limits allow stronger lending growth rates in the economy.

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

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.

95th and 98th percentile and large those above the 98th percentile. There is also a distinction between studying the decisions of bank holding companies versus individual banks. We study the decisions of individual banks even though we view mergers and acquisitions and decisions at the holding bank level as an interesting avenue for future research.⁸ We limit our attention to individual banks and banks that failed over this period because we view this as a useful starting point in building a behavioral banking model. We also consider the bank failures reported by the FDIC for the period 1991Q1-2010Q4. 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 sheets at year-end of the first and last year of our sample period, by bank size. Notice the significant reduction in the number of banks over time, from 12,651 in 1990:Q4 to 6,871 banks by 2010:Q4, while average assets have increased in real terms across all bank sizes. That was mainly a result of regulatory changes that led to substantial consolidation in the U.S. commercial banking.⁹

⁸Holod and Peek (2010) document, for example, the existence of internal capital and secondary loan markets within multibank holding companies. Such internal markets are used to mitigate equity capital constraints – due to minimum regulatory requirements at a bank subsidiary level – and to enhance the efficiency of the loan origination process.

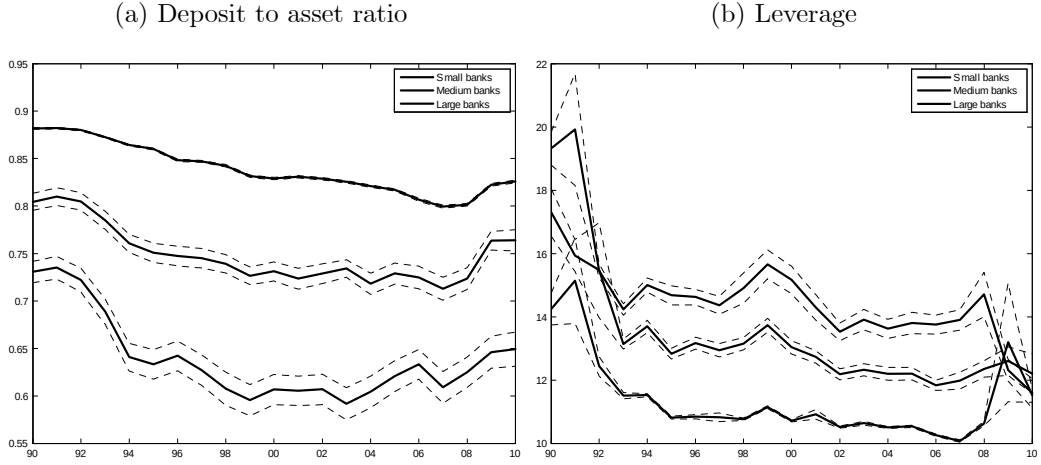
⁹According to Calomiris and Ramírez (2004), branch banking restrictions and protectionism towards unit banks (i.e. one-town, one-bank) led to a plethora of small U.S. commercial banks over the last century. But in the early 1990s protectionism was relaxed, especially following the Riegle-Neal Interstate 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 Ramírez (2004) provide some key facts

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%
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%
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	10%	9%	10%

Figure 1: Evolution of deposit to asset ratio and leverage of U.S. commercial banks



Deposits (normalized by total assets) are the major item on the liability side of all commercial banks. Nevertheless, the deposit to asset ratio varies by bank size. We find that small banks rely more on deposits than large banks. Moreover, comparing 1990:Q4 with 2010:Q4 we see that the importance of deposits has declined throughout this period for all bank sizes. 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 (bootstrap standard-error confidence intervals are shown with dotted lines).

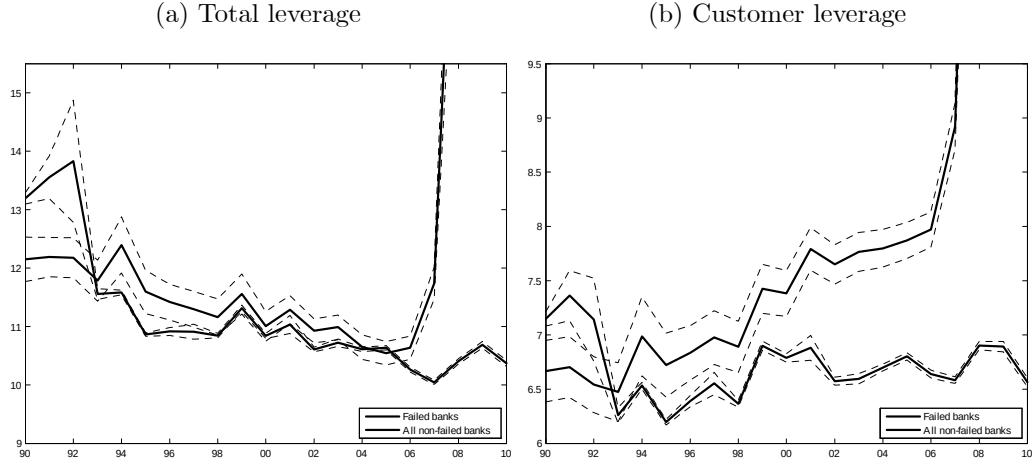
Larger banks also seem to have more access to other funding sources like the Fed Funds and other money market funding. In 1990 (2010) the sum of Fed Funds borrowed, subordinated debt and other non-deposit liabilities as a fraction of total assets rises monotonically from 0.03 (0.05) for banks in the bottom 95th percentile to 0.21 (0.22) for banks in the top 5th percentile. For some excellent reviews, see also Berger, Kashyap, and Scalise (1995), Calomiris and Karceski (1998) and Calomiris (2000).

largest percentile. This is probably driven by the fact that larger banks have more easily access to non-deposit funding sources. Smaller banks compensate for this risk by holding more liquid assets, mainly cash and securities. Adding cash and other liquid assets such as FF lent, reverse repos and securities, we find an almost monotonic drop in 1990 (2010) from 0.43 (0.32) in the bottom 95th percentile to 0.31 (0.29) in the top percentile.

Another variable of interest in the recent crisis is the level of leverage by bank size and over time. We use two definitions of leverage: customer leverage (defined as loans divided by tangible equity) and total leverage (defined as total tangible assets divided by tangible equity). Tangible equity equals total assets minus total liabilities minus intangible assets, such as goodwill. The next figure reports total leverage over time for banks with different sizes. As can be seen from Figure 1b, smaller banks tend, on average, to have a lower level of leverage than larger banks. During crisis periods, on the other hand, the ordering might get reversed.

We are also interested in the characteristics of banks that default at some point in time. We construct a panel of banks that defaulted between 2008-2010 and we track over time some of their balance sheet characteristics. A stark difference between banks that default and banks that do not is their leverage ratio. Figure 2 shows that for banks that eventually fail, customer leverage increases substantially in the years before their failure. This holds true for both: total leverage (Figure 2a) and customer (Figure 2b), even though total leverage tends to go up for banks closer to the recession.

Figure 2: Leverage of banks that failed and did not fail during crises 2008-2010



2.2 Time Series Statistics

To generate the observed cross sectional heterogeneity, banks in our model will face uninsurable idiosyncratic shocks coming either from deposit growth or bad loans. 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 problem loans and we will use the data to constrain the data generating processes that will be possible. 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 and non-deposit funding. The exogenous processes will be taken to be as close as possible to their empirical counterparts.

Specifically, for deposit growth we posit the following model, where D denotes deposits:

$$\Delta \ln D_{it+1} = \ln G_{Dt+1} + \ln G_{Dit} \quad (1)$$

implying a decomposition between an aggregate component ($\ln G_t$) and an orthogonal component capturing idiosyncratic shocks ($\ln G_{Dit}$). The data generating process for the idiosyncratic shocks is assumed to be a linear dynamic panel data model that is estimated using Blundell-Bond system GMM. The aggregate component of the process can be isolated by taking the cross sectional sum of individual deposits across all banks for every year. The log of the resulting aggregate deposit series (D_{t+1}/D_t) equals $\ln G_{t+1}$ and we can determine its time series process by fitting an ARMA process on the twenty annual observations we have data for this variable.

Because we will repeat this process for all growth rate series, it is useful to go through it once. We will be assuming that the data generating processes for our variables can be decomposed in two orthogonal parts, an aggregate and an idiosyncratic one. Therefore, $D_{it+1} = A_{t+1}f(I_{it+1})$ where A denotes an aggregate shock and $f(I)$ is a function of the idiosyncratic shock. The aggregate growth rate for deposits can be computed as

$$\frac{\sum_i D_{it+1}}{\sum_i D_{it}} = \frac{\sum_i A_{t+1}f(I_{it+1})}{\sum_i A_t f(I_{it})} = \frac{A_{t+1} \sum_i f(I_{it+1})}{A_t \sum_i f(I_{it})} = \frac{A_{t+1}}{A_t} \quad (2)$$

since the cross sectional sums of the idiosyncratic shocks cancel out (by a law of large numbers argument).

The problem loans process is already normalized by the stock of outstanding loans and is therefore likely to be (and turns out to be) stationary. We consider problem loans to be all

idiosyncratic and to follow different processes in booms and recession. We estimate AR(1) processes for the logit transform of the problem loan ratio in booms and recessions where recession periods are defined as NBER recessions, including the two periods that precede and six periods that follow the recession period.

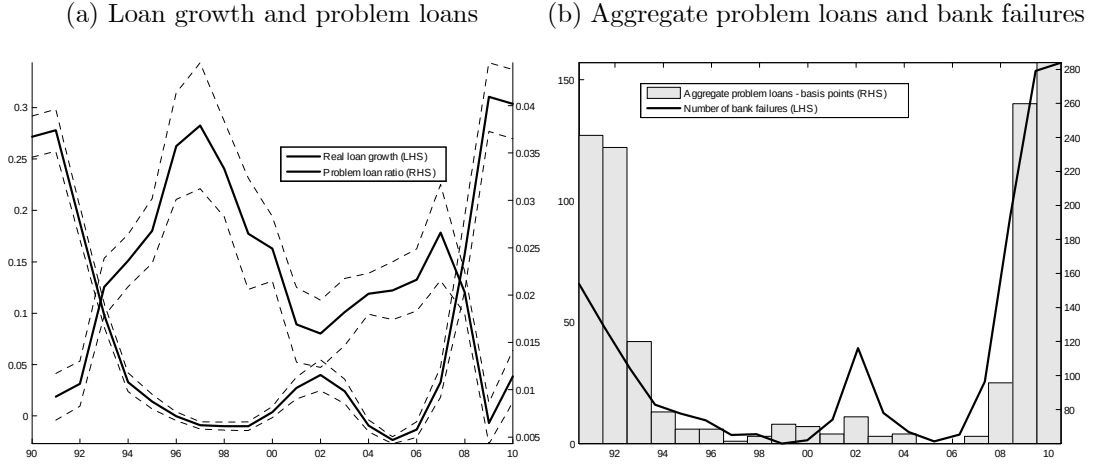
Cyclical properties

Figure 3 shows the behavior of loan growth, the evolution of problem loans and the resulting bank failures over the sample period. Figure 3a 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. The first period reflects the savings and loans (S&L) crisis and the second period the recent financial crises starting in 2007. Figure 3b 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.

3 The Model

In the previous section, we have established certain robust stylized facts in the cross section and time series dimensions which we want our structural model to replicate. In the cross section, larger banks tend to rely less on deposits and more on money market funding and they tend to be more levered. Moreover, defaulting banks tend to have more levered balance sheets before default eventually takes place. In the time series, real loan growth is procyclical as it falls in recessions, whereas problem loans and defaults are countercyclical

Figure 3: Cyclical properties of loan growth, problem loans and bank failures



as they tend to increase during recessions.

3.1 The model environment

We consider a discrete-time infinite horizon model. Banks maximize the present discounted value of utility of their owners and have limited liability. We consider interest income as the key driver of decisions by commercial banks, abstracting from other sources of revenue, such as trading and fee income. This modeling choice is justified by the fact that net interest income is the main source of income across US commercial banks¹⁰. Banks in our model have the following stylized balance sheet: their liabilities consist of deposits, non-deposit liabilities (equivalent in the data to the sum of Federal Funds borrowed, subordinated debt and other liabilities) and equity. Their assets consist of loans and securities. A stylized balance sheet

¹⁰For instance, the median net interest income has remained above 70% of total operating revenue during the whole sample period 1993-2008.

assets		liabilities	
loans L_t	r_t^L	deposits D_t	r_t^D
securities S_t	r_t^S	non-deposit liabilities F_t	r_t^F
		equity X_t	

Table 2: Bank balance sheet in the model

is shown in table 2

3.1.1 Loans

Consistent with the maturity transformation role of banks, we assume that customer loans (L) are long term and these loans are funded through deposits, money market funding and equity capital. Both deposits and money market funding are assumed to be of shorter maturity than customer loans. Such a maturity mismatch gives rise to funding liquidity risk. A fraction of outstanding loans get repaid (an exogenous de-leveraging process) every period. We capture this by assuming that an exogenous fraction ϑ of outstanding loans gets repaid every period. 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 $(r_L - w)$ where r_L is the weighted average of the 30 year US mortgage rate and the loan rate for business loans; and w measures the loans that banks have to write-off every year.¹¹

In the data, we proxy write-offs with problem loans, namely non-performing and restructured loans.¹² Problem loans follow a random process where the idiosyncratic shock process

¹¹At 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.

¹²We approximate write offs with the amount of problem loans. Hence, we assume that loss given default

depends on the aggregate state. There is more uncertainty during recessions than during booms. Therefore, problem loans have a higher mean and a higher variance during recessions than during booms.

3.1.2 Deposits

The main liability of most commercial banks are customer deposits D_{it} . We assume that they grow at a time-varying exogenous rate g_t with an aggregate and an idiosyncratic component.

$$D_{it+1} = D_{it}G_{Dt}G_{Dit}$$

In the data both aggregate and idiosyncratic components are i.i.d. over time, and are well approximated, if we assume that the growth rate of deposits is log normally distributed, by:

$$\log(G_{Dt}) \sim N(0, \sigma_D^2)$$

$$\log(G_{Dit}) \sim N(0, \sigma_{Di}^2)$$

We use the empirical counterparts to determine specific values for variances.

3.1.3 Securities

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

 (LGD) of such loans is 100%. We could also consider alternative LGDs, such as the LGD under the foundation approach of Basel II. Under the foundation approach, senior unsecured claims on corporates, sovereigns and bank are assigned a minimum 45% LGD. All subordinated claims on corporates, sovereigns and banks are assigned a minimum 75% LGD.

3.1.4 Non-Deposit Liabilities

A second source of external funds for banks is the debt market where banks can borrow short term (non-deposit liabilities, $F_{i,t}$). The cost of short term external funds includes a fixed cost component. This captures the fact that only big banks can borrow significant amounts. For most small banks, non-deposit liabilities are a small fraction of their overall liabilities even in 2012, as shown in Table 1a. The fixed cost however is state dependent and is smaller in recessions than in booms.

3.1.5 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 ($X_{i,t}^N > 0$). If, in addition, we denote by Π_t the bank profits at time t then, the amount of equity at the beginning of next period is given by

$$X_{i,t+1} = X_{i,t} + \Pi_{i,t} - X_{i,t}^N \quad (3)$$

To keep things tractable we treat dividends as a stock repurchase which is equivalent to a negative equity issuance.¹³

3.1.6 Regulatory Leverage Limit

Banks are subject to capital adequacy rules, namely a minimum ratio between a measure of capital and a measure of assets. We consider an exogenously specified leverage ceiling that

¹³Note that dividend payment ($X_{i,t}^N > 0$) enters negatively since it subtracts from next period's equity.

regulators set and banks must respect. Leverage is defined as the ratio of total assets (total loans plus securities) to equity.¹⁴ *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. But, if the bank faces a significant fall in profitability, or a loss (e.g. due to an idiosyncratic or general macroeconomic shock) then, breaching its regulatory leverage limit becomes more likely in future periods. Banks then have an incentive to curtail new lending and de-leverage. Addressing the issue of regulatory leverage constraints in the model is important, given the current debate on the need to tighten regulatory capital and leverage rules for banks in order to prevent them from taking on excessive risks. On the one hand, tighter leverage limits could potentially increase bank safety. On the other hand, tighter leverage limits could force banks to rein in lending at times when they would otherwise wish to expand their balance sheets. That could adversely impact credit conditions and economic recovery.

The leverage constraint is captured by parameter λ which gives the maximum ratio of assets to equity that the bank must respect.

$$\frac{L_{i,t} + S_{i,t}}{X_{i,t}} \leq \lambda \quad (4)$$

¹⁴Our 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 is a measure that is less susceptible to accounting rules and interpretation.

3.1.7 Objective function

Banks discount the future with a time-varying stochastic discount factor $\beta(t)$. They maximize the present discounted value of a concave function of dividends:

$$V = \sum_{t=0}^{\infty} \beta(t) \frac{X_{i,t}^{1-\rho}}{1-\rho} \quad (5)$$

Banks are risk averse and $\rho > 0$ 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.

3.1.8 Entry and exit

Exit is endogenous in this model. We assume that a banker who exists through default or liquidation pursues another career (outside banking) which we do not endogenize. In that case he enjoys a constant amount of consumption which yields him a level of utility W^D .¹⁵ He obtains W^D whenever he is forced to exit by the regulator or when he chooses to exist. Since he takes this continuation value into account when making his decisions, exit is endogenous. Due to the partial equilibrium nature of our model, we do not model entry endogenously. 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.¹⁶

¹⁵We have to assume that a failed banker can consume after exiting, otherwise no banker would ever choose to default given his concave utility function.

¹⁶It is very likely that this would also be the case if we had endogenous entry.

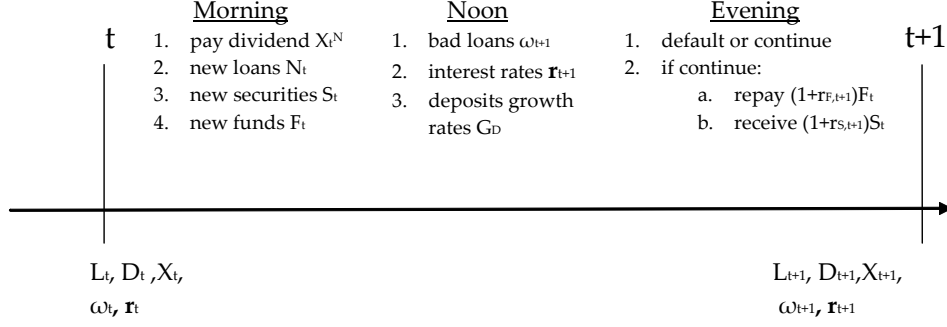


Figure 4: Time Line in Model

3.2 Timing

Figure 4 shows the timing of the model.¹⁷ A bank enters period t with a stock of loans $L_{i,t}$, deposits $D_{i,t}$, and equity $X_{i,t}$. Since the various interest rates r and the bad loan process w_i are persistent, these are state variables in the bank's problem as well. In the beginning of the period, decisions about new loans ($N_{i,t+1}$), dividends or equity injections ($X_{i,t+1}^N$), securities $S_{i,t+1}$ and short term debt $F_{i,t+1}$ are made. At this stage the leverage constraint must be respected. Then the exogenous shocks (returns and problem loans) are realized: the bank learns the various rates of return r_{t+1} ; how many loans are repaid and how many loans it has to write off $w_{i,t+1}$.

Profits of bank i evolve as follows

$$\Pi_{i,t} = (r_{L,t+1} - w_{i,t+1})(L_{i,t} + N_{i,t}) + r_{S,t+1}S_{i,t} - r_{D,t+1}D_{i,t} - g(r_{F,t+1})F_{i,t} \quad (6)$$

where the first term is the interest income on performing loans; the second term reflects

¹⁷The individual specific i subscripts is suppressed in the graph for readability.

income from holding securities, the third term is the cost from servicing deposits and the final term the cost from servicing non-deposit liabilities.

3.3 Value functions

A banker who has defaulted in the past cannot become a banker again. This banker enjoys a constant level of consumption $\overline{C^D}$ yielding utility W^D .¹⁸

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

$$W^C(L_t, D_t, X_t; w_t, \mathbf{r}_t, \mathbf{g}_t) = \max_{X_t^N, S_t, F_t, N_t} \left\{ \frac{(X_t^N)^{1-\rho}}{1-\rho} + E_t [\beta_t V(L_{t+1}, D_{t+1}, X_{t+1}; w_{t+1}, \mathbf{r}_{t+1}, \mathbf{g}_{t+1})] \right\} \quad (7)$$

where the last term is defined as the upper envelope

$$V(L_t, D_t, X_t; w_t, \mathbf{r}_t, \mathbf{g}_t) = \max[W^D, W^C(\cdot)] \quad (8)$$

There are the following 5 constraints:

$$X_{t+1} = X_t + \Pi_t - X_t^N \quad (9)$$

where flow profits are

$$\Pi_t = (r_{L,t+1} - w_{t+1})(L_t + N_t) + r_{S,t+1}S_t - r_{D,t+1}D_t - g(r_{F,t+1})F_t \quad (10)$$

$$L_{t+1} = (1 - \vartheta - w_t)L_t + N_t \quad (11)$$

¹⁸From now on subscript i is suppressed.

$$\frac{L_t + N_t + S_t}{X_t + X_t^N} < \lambda$$

The first decision of the bank is decide whether to continue operating. If it ceases operations, all depositors are repaid either through the liquidation proceeds or the FDIC. The other creditors who have lent F_t are unsecured and only receive a repayment if the liquidation receipts are sufficient.

If the bank continues its operations it chooses the optimal level of pay-out to shareholders X_t^N so that equity at the beginning of next period is given by (3). It also decides on how many new loans N_{t+1} to issue, how many securities S_{t+1} to buy and many funds F_{t+1} to borrow on the money market. The new loans add to the existing loans so that at the beginning of the next period, the bank's loans are given by

$$L_{t+1} = \tilde{L}_t + N_{t+1} \tag{12}$$

4 Calibration

4.1 Fixed parameters

The model period is one quarter. Therefore, we set the discount factor β to 0.98. Risk aversion is set to 2. The (unweighted) leverage limit in the baseline model is set to 20 which is according with US practise. Later, we investigate the effects of lowering this limit. 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. We set it to 0.05.

Parameter	value
discount factor β	0.98
risk aversion ρ	2
leverage limit λ	20
fraction of loans that is paid off ϑ	0.05

Variable	Quarterly values	
	recession	boom
risk free rate	0.00057	0.0032
securities spread	0.0017	0.0036
loan spread	0.00587	0.0053
bad loans high	0.0063	0.0030
bad loans low	0.00065	.00037

The model features aggregate and idiosyncratic uncertainty. In general, we take the stochastic process for these variables from our estimation in section 2.

There are four aggregate persistent variables: the risk-free interest rate, the loan spread, the Fed 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 processes. We label the bad aggregate state a recession and the good one a boom. We chose 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 risk free rate is higher during booms than during recessions as is the spread on securities. The loan spread is countercyclical.

As discussed in section 2.3, idiosyncratic bad loans behave very differently in booms and recessions. Due to this asymmetry, we model the bad loan process as state dependent. We

estimated two different AR(1) processes, one for boom periods and one for recession periods. We discretize each with two nodes. During a recession bad loans are higher than during a boom. However, as can be seen in the table, the idiosyncratic component dominates the aggregate component. A low idiosyncratic loan loss state during a recession implies less losses than a high idiosyncratic loan loss state during a boom. The transition probabilities are set to match the estimated processes and reflect the persistence of the idiosyncratic bad loan process.

The final stochastic process is for deposit growth. As shown in section 2.3, this can be decomposed into an aggregate and an idiosyncratic component, both of which are not persistent. The mean aggregate deposit growth is set at 0.006 and the standard deviation of aggregate deposit growth is set at 0.0223. The idiosyncratic growth component is 0 with a standard deviation of 0.09.

4.2 Calibrated parameters

The returns on securities are calibrated to match an average share of securities in total assets of 30%. The fixed cost of borrowing on the money market follows the risk free rate. It also entails a fixed convexity parameter to limit the amount a bank borrows which is set at 1.2. The targets for non-deposit funding for are taken from Table 1a and are 5% for small and 20% for large banks.

The model does not obtain all these targets perfectly. In particular, it leads to a share of non-deposit funding by small banks of 10%. The reason is the following: since deposits are non-stationary, we solve the model by normalizing all variables by deposit growth. This

Variable	Quarterly values	
	recession	boom
securities spread	0.0017	0.0036
fixed cost of money market access	0.0005	0.0017
convexity parameter	1.2	1.2
consumption after default	0.0005	0.0005

makes it however difficult to map bank size from the levels model to the normalized model. Consumption after default is chosen to match an unconditional quarterly default rate of 0.12%. The value of 0.005 corresponds to 15% of the average dividend payment.

5 Results

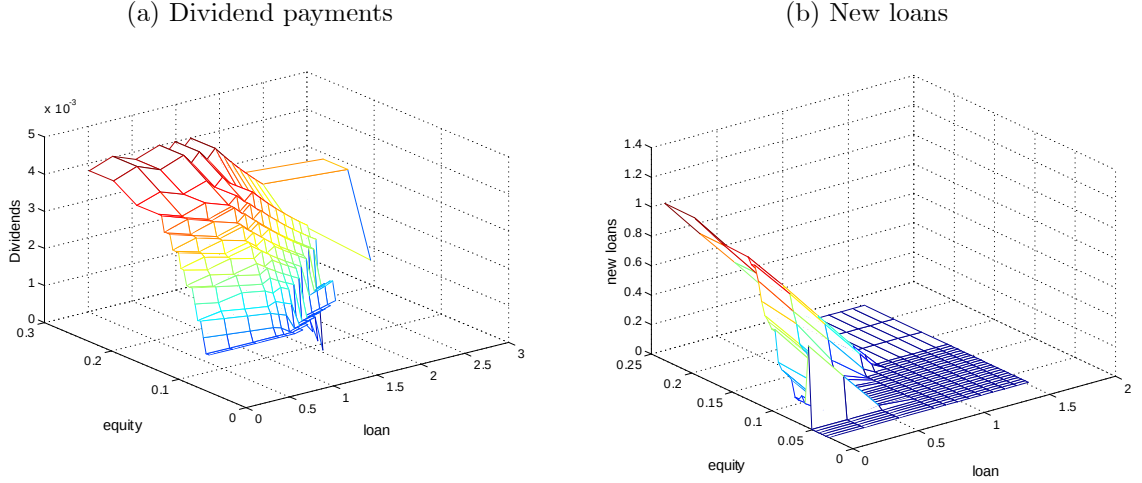
We first present individual policy functions to enhance our intuition about the economics behind the model and then proceed with analyzing the implications of the model through simulations.

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.

Figure 5a shows the dividend policy function of a bank that has low problem loans and where the aggregate economy is in a boom. If we keep loans fixed, e.g. at $l = 1$, we see that as equity is increased, dividends increase. This is intuitive since equity is a measure

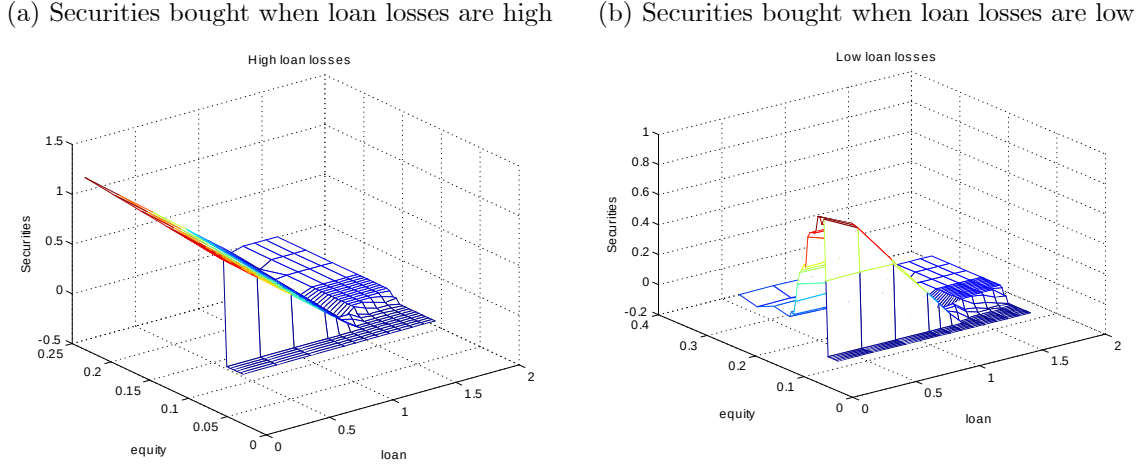
Figure 5: Policy functions with low idiosyncratic loan losses during a boom



of wealth in this model and richer bankers will consume more. If we keep equity fixed, e.g. at $e = 0.2$, we see that as loans are increased, dividends at first remain constant and then decline for loans above 1. This is because with more loans, the leverage constraint is more likely to be binding in the future. For low values of initial loans, the constraint is not binding since with $e = 0.2$ the bank could hold loans up $l = 4$, given the leverage constraint under which the model is solved. Since bankers in the model have a precautionary savings motive, they reduce their dividends before loans reach $l = 4$. Note that the area to the bottom right, where equity is low but loans are high is not feasible since here the leverage constraint is violated. Banks in this region are closed down by the regulator.

Figure 5b shows the issuance of new loans. Banks with few old loans issue more new loans than banks with the same level of equity but more old loans. Essentially, those banks with no old loans can implement their optimal level of loans. Banks with many old loans, however, have to hold the old loans, since only 7% of old loans are repaid each period. All

Figure 6: Policy functions for securities for two different idiosyncratic loan loss states during a boom

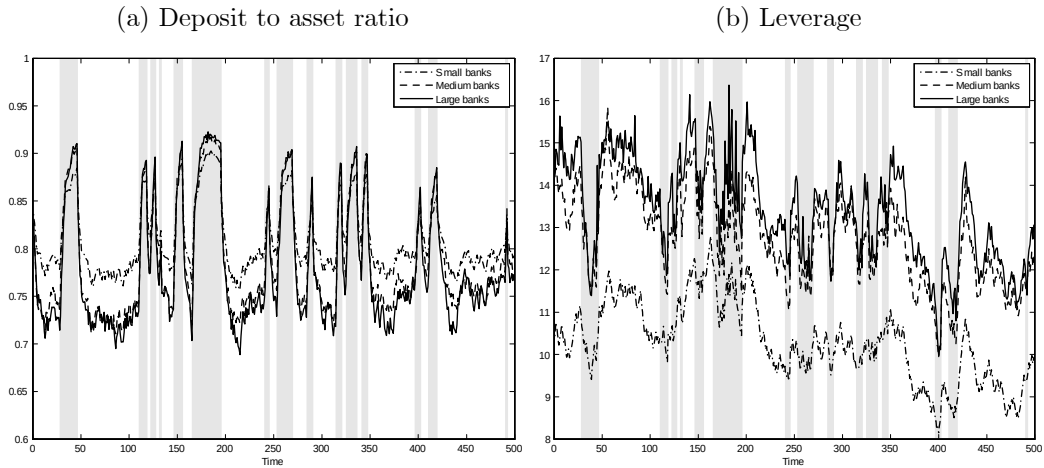


these banks can do is not issue any loans for some periods. This explains the large region with no loan issuances. Conditional on old loans, loan issuance increases with the amount of equity a bank has. This is intuitive because the more equity a bank has the less binding is the leverage limit and the higher is its loss absorbing capacity.

Note, however, one interesting feature. Banks with very little equity $e = 0.05$ give out more new loans than banks with somewhat higher equity, e.g. $e = 0.1$. We interpret this finding as gambling for resurrection. These banks take on a lot of risk by issuing many new loans. If the loan state remains good, they earn a significant profit. If the loan states switches however, they will incur such high losses that they will default. Thus, these banks are locally risk loving.

Figures 6 shows the securities bought during a boom for the two possible values of idiosyncratic problem loans. Securities are liquid assets. Thus, they enjoy a liquidity advantage over loans but their return is lower. Securities bought are declining in the loan state. The

Figure 7: Evolution of deposit to asset ratio and leverage in the model



more a bank has invested in loans, the less it can invest in securities.

If loan losses are high as in Figure 6a, banks do not issue many new loans; in that case they are better off investing in securities. If, in contrast, loan losses are low, banks prefer to issue new loans and do not buy as many securities, as can be seen in Figure 6b.

5.2 Benchmark: Model vs Data

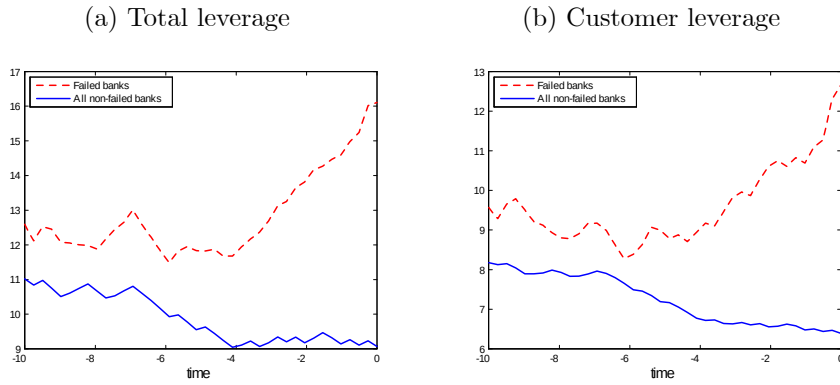
During the simulations, we discard the first 1500 model periods and report results for the next 500 periods, which correspond to 125 years. Figure 7 is the model counterpart to Figure 1 in the data section.

Figure 7a shows the deposit asset ratios in the model over time. The size classification is as in the data section. During recessions the deposit to asset ratio rises because banks reduce their non-deposit borrowing drastically. The ordering during the boom in the model is as in the data. The deposit to asset ratio is less volatile for small than for large banks. That is consistent with Figure 1a. The reason for this behavior is that large banks borrow

on average ten percentage points of their balance sheet more in the money market since they can afford the fixed cost associated with accessing this market more easily. However, during recessions large banks increase their deposit to asset ratio in the model by more than in the data. This is because during a recession more banks are in a bad loan state. These banks curtail new lending as much as possible and therefore lower their borrowing in the money market as much as possible. This reduction in non-deposit funding increases the relative importance of deposits during recessions. Thus, even though deposits grow more slowly and total assets might even shrink, the relative importance of deposit increases.

Figure 7b shows the leverage ratio of the banks. Consistent with data (Figure 1b) big banks are more highly levered than small banks. Medium banks are in between. Small banks have less access to the money market. Therefore, they rely more on deposit and equity funding. This increase in equity funding translates into a lower leverage ratio. The cyclical nature of leverage is complicated. It drops at the onset of recessions, e.g. period 29, and rises a lot at the onset of a boom. During the boom, however, it declines since banks build up more and more equity, as in the data, see Figure 1b. The gradual decline of leverage during a boom is mainly driven by an increase in the value of equity. During a boom, banks use their profits to increase their equity buffer stock. The sharp increase at the beginning of a boom has two reasons: first, equity is low due to the losses experienced by many banks during the preceding recession. Second, banks give out less loans during recessions, therefore their loan books are relatively small at the end of a recession. Thus, when the boom comes, they expand new loans rapidly (see also Figure 9a) but they do not have much equity yet; therefore leverage increases significantly at the beginning of a boom. The drop of leverage at

Figure 8: Leverage of banks that eventually fail in recession starting in period 0



the beginning of a recession is more gradual. The reason for this is that even though banks do not give out many new loans, only 5% of loans are repaid each quarter. Therefore, it takes a while for the value of loans to fall. At the beginning of a recession, banks still have a lot of equity which they built up during the boom. And it takes some time for the loan losses to diminish the value of equity significantly. However, if the recession is long enough, as e.g. in the model periods 29-46 the value of equity will eventually fall by so much that leverage starts increasing again since equity, the denominator falls.

Figure 8 is the model counterpart to Figure 2. It shows the two measures leverage for banks that ultimately fail and those that survive in a model recession which starts in period 0. Total leverage and customer leverage both rise significantly for those banks that ultimately fail. In the data, it is mainly (see Figure 2b) customer leverage that rises for these banks. Banks that are about to fail lower start lowering their investments in securities about 1 year before they ultimately fail.

Figure 9 is the model counterpart to Figure 3 in the data section.

Figure 9: Cyclical properties of loan growth and bank failures

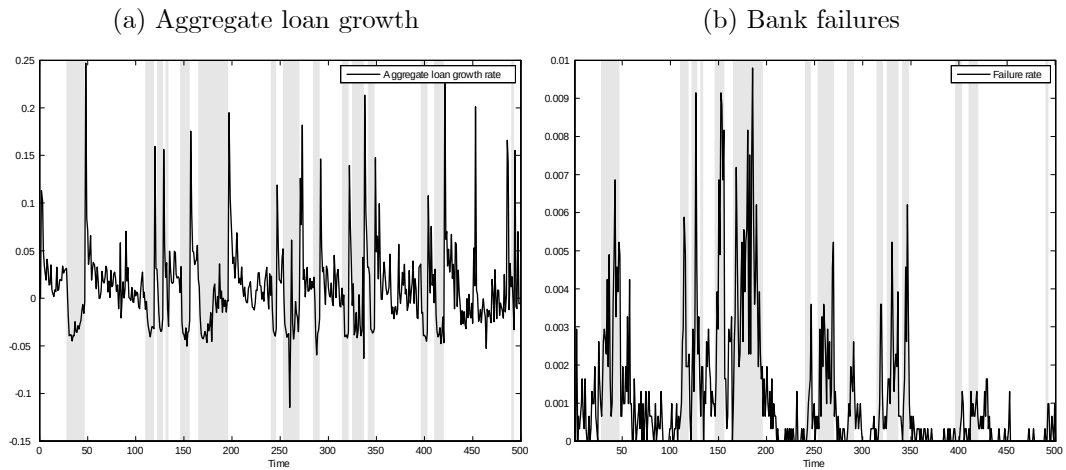


Fig 9a shows that aggregate loan growth in the model is strongly procyclical. Loan growth is positive during booms and declines during recessions. The growth rates are most extreme at the inflection points of the business cycle. At the onset of the recession in period 29, loan growth drops to negative 4.5%. During the recession loan growth climbs back somewhat. But it rises dramatically at the onset of the boom in period 47. During the boom it falls back steadily. 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.

Figure 9b shows that defaults are strongly countercyclical. There is no recession in model periods 50-100 and there is also almost no default. This is similar to the period 1994-2007 in Figure 3a. During the recession in periods 170-180, the failure rate increases a lot and peaks at an (annualized) failure rate of one percent. Bank failures usually are not highest at the onset of a recession because at this point in time most banks still have a large enough

equity cushion. It is only when the recession is long enough and banks have accumulated a lot of losses or the boom phase before was relatively short so that equity holdings at the beginning were short that a significant fraction of banks fails. The former happens around period 40 and the latter around period 180 in Figure 9b.

6 Counterfactual policy experiments

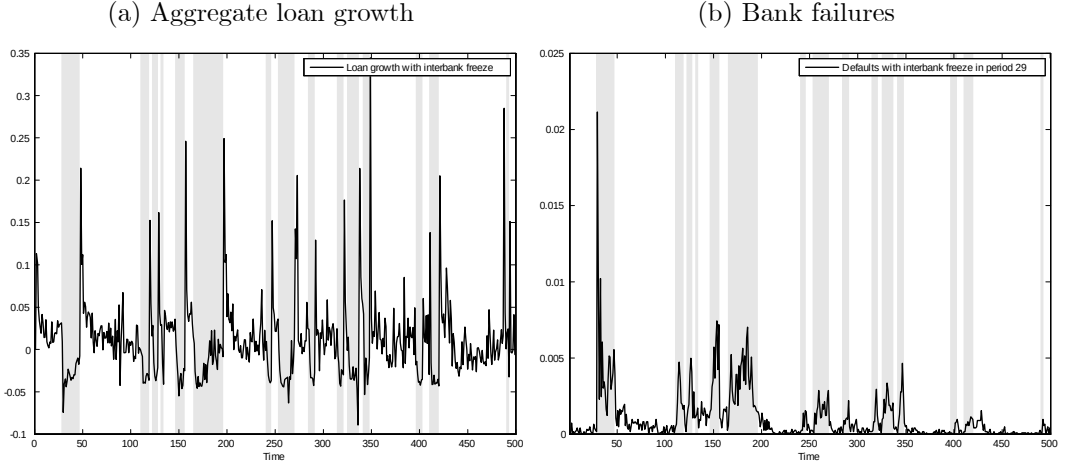
Part of the motivation behind building a structural model of the banking system is to perform counterfactual experiments that can provide guidance to policy makers about the possible effects on behavior from changing policy-controlled parameters or how changes in the economic environment can affect behavior.

6.1 Freeze of the money market

One of the key events of the recent financial crises was the freezing of the money market. We use our structural model to assess the implications of such an event in our model economy. We model the freeze in the money market as an unexpected loss of non-deposit funding (access to the money market) for all banks. Thus, for one (crises) period, banks are unable to obtain any non-deposit funding. We assume however that banks know that normal conditions in the money market will be restored in the following period.¹⁹ 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 money market. In our model, we assume that at the onset of the recession in period 29, banks can not borrow any non-deposit funds. This makes all banks who rely on this market, these are in particular the larger banks, vulnerable to a

¹⁹Recall that one model period is three months.

Figure 10: Cyclical properties of loan growth, problem loans and bank failures

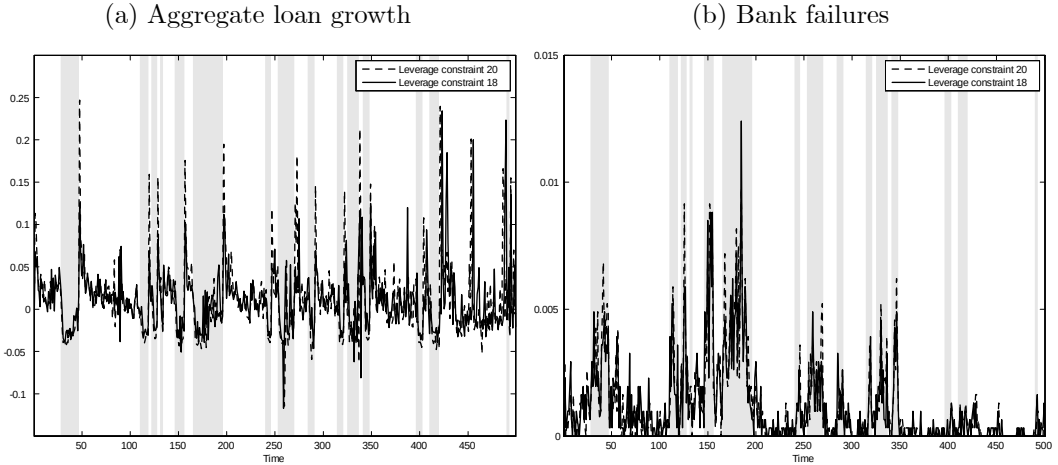


liquidity crises.

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

Figure 10 shows the results and is compared to Figure 9 which shows a recession without a freeze in the money market. Figure 10b shows that the bank failure rate more than trebles in this case compared to the situation before when there was only the onset of the recession but the money market remained active, see Figure 9b. In contrast to the normal pattern when the highest bankruptcy rate in a recession is usually towards the end of the recession

Figure 11: Cyclical properties of loan growth and bank failures with different leverage limits



when banks have experienced loss for an extended period of time, this time the peak in defaults is right at the time of the money market freeze. This is, of course, not surprising since banks did not expect this and therefore react much more strongly. The effect on the real economy is similarly drastic. Loan growth shrinks from negative 4.5% to negative 7.0% in Figure 10a. Thus, the freezing of the money market has a direct negative effect on loan supply in the model economy.²⁰ However, this strong effect at the onset of the recession happens also when the money market is not affected.

6.2 Tightening leverage constraint

One important policy change currently being implemented are 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 para-

²⁰The two series in Figure 10 are not identical to the corresponding series in Figure 9 after the crises because more banks fail in the crises period and these are replaced by new banks. The new banks differ from the old banks which they replace, in particular all new banks start with low loan losses. The aggregate behaviour, however, is unchanged.

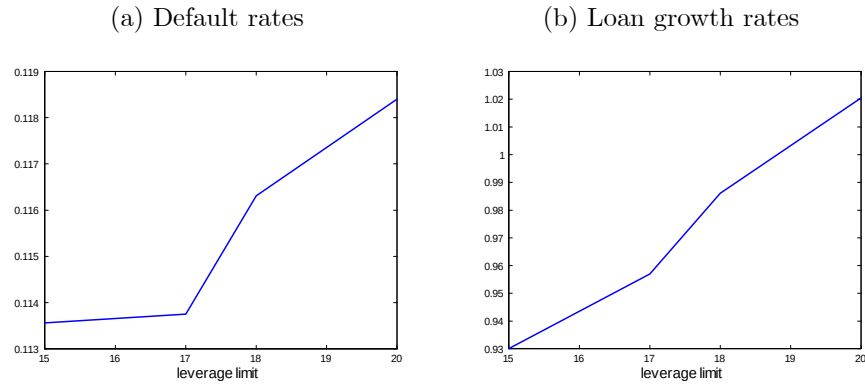
meters at their benchmark values. The simulation uses exactly the same shock sequence. Figure 11 shows loan growth rates and default rates for the benchmark economy with a leverage limit of 20 and a counterfactual economy where the leverage limit is tightened by ten percent to 18. As can be seen in the Figure 11a, the cyclicalities of loan growth is hardly affected. The bank failure rate peaks at a slightly lower level for the tighter leverage limit in Figure 11b.

To investigate the effect of tighter leverage limits (lower λ), we reduce the limit from the baseline $\lambda = 20$ to $\lambda = 15$. Figure 12a shows that the default rate declines, albeit only slowly, when the leverage limit is tightened. In the benchmark case the default rate is 0.118% p.a. on average, while it is 0.114% for $\lambda = 15$. This negative relationship while expected is not necessarily obvious since any given shock makes, everything else equal, a bank more likely to violate this tighter limit. However, the precautionary motive is strong enough in our economy so that banks become less risky, i.e. they accumulate more precautionary equity and therefore default less often.

There are at least two possible explanation for this decline in the failure rate. On the one hand banks might give out less loans and invest ore heavily in more secure and liquid securities. On the other hand, banks might hold more equity for precautionary motives. Figure 12b shows that indeed the average loan growth rate declines when the leverage limit is tightened. It falls from 1.02% p.a. on average for $\lambda = 20$ to 0.93% p.a. for $\lambda = 15$. Thus, while a tighter leverage limit reduces the failure rate, doing this is costly because it lowers credit supply to the real economy.

Another important motivation for tighter leverage limits are the fiscal costs of bank bail-

Figure 12: Effects of changing the regulatory leverage limit



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 default rate and second the expected loss conditional on default. We have already seen that a tighter leverage limit indeed lowers the frequency of bank failures. The second component can be assessed indirectly with the leverage of the defaulting banks. The lower their leverage, the more equity they have relative to their loans at the moment of failure.

Figure 13 shows the evolution of leverage for banks that fail at the onset of a recession. As can be seen, the effect of tightening the leverage limit is not monotonic. However, for a significantly tighter limit, $\lambda = 15$, leverage is a lot lower before but also at the moment of failure. This implies that the losses which have to be incurred by e.g. the deposit insurance institution or the fiscal authority if the bank is recapitalized are significantly reduced.

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. However, it seems unlikely that the only slightly lower frequency of bank failures and their lower cost outweigh the negative

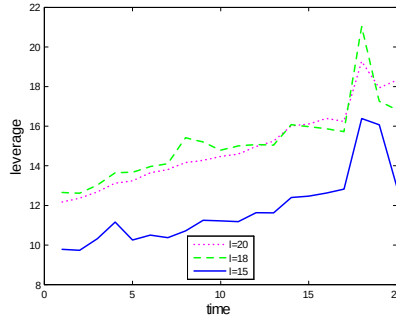


Figure 13: Evolution of leverage of banks which fail for different leverage limits

effect of lower credit supply. A full analysis is left for future research, though.

7 Conclusion

We show results of a very first parametrization and simulation. TBW.

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TBC

9 Data Appendix

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, 544 due to negative tangible equity, 2,373 due to outlier growth rates in tangible assets and customer loans.²¹ 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. When (real) growth rates are calculated, 22,157 observations are dropped and the sample is further reduced to 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

²¹Tangible assets equal total assets minus intangible assets, such as goodwill. Tangible equity equals tangible assets minus total liabilities.

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.²² For the first half of the period (i.e. 1990Q1-2000Q3), names of failed banks were obtained from FDIC reports.²³ 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.

10 Numerical Solution Appendix

TBW

²² Available at <http://www.fdic.gov/bank/individual/failed/banklist.html>.

²³ Available at <http://www.fdic.gov/bank/historical/bank/1991/index.html>.