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A DYNAMIC MODEL OF BANKING WITH UNINSURABLE RISKS AND REGULATORY CONSTRAINTS†

Abstract

We estimate the structural parameters of a quantitative banking model featuring maturity transformation and endogenous failures in the presence of undiversifiable background risk and regulatory constraints. Pervasive balance sheet cross-sectional heterogeneity can be rationalized with idiosyncratic shocks and differential access to wholesale funding markets. Moreover, loans are highly procyclical, bank failures strongly countercyclical and increasing in leverage. Tightening capital requirements increases precautionary equity but results in higher failures because equity rises proportionately less than the capital ratio requirement change. The endogenous fall in the expected return on equity lowers the incentive to further increase precautionary equity.

JEL Classification: E32, E44 and G21
Keywords: bank failures, bank leverage, capital requirements and uninsurable risks

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1 Introduction

Policy makers recognize the importance of developing quantitative models to assess both microprudential and macroprudential risks in the financial system. These tools aim to improve the identification and assessment of systemically important risks from high leverage,[1] credit growth,[2] or money market freezes.[3] Moreover, quantitative structural models can be used in real time to perform counterfactual experiments and complement the tools available to regulators before making policy decisions. For instance, in October 2011 European political leaders agreed that Eurozone banks should increase their core-tier I capital ratios to 9% by the end of June 2012 to improve investor confidence in the banking system. A quantitative model that can assess the range of possible outcomes would be useful for policy analysis.

Given the need for such applied, quantitative models, we construct a structural model of bank lending behavior, assuming that a bank's objective is to maximize shareholder utility. Banks in our dynamic model perform a maturity transformation function as in Diamond and Dybvig (1983). They transform short term deposits into long term loans. Moreover, loans are risky so that loan losses may lead to equity capital shortfalls, in conjunction with a debt overhang problem discussed in Duffie (2010) that prevents banks from raising external equity

[1] 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 decisions 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.

[2] Bernanke 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), Oliner and Rudebusch (1996) provide evidence that supports the existence of the bank-lending channel.

[3] Brunnermeier (2009) discusses the freeze of money markets during the recent recession in the U.S..

capital in a crisis situation.[4] Banks also face different background risks (in deposit liquidity, funding conditions, asset quality and profit opportunities) in an incomplete markets setup in the spirit of Allen and Gale (2004). Despite being exogenous, the data generating processes for background risks are calibrated using microeconomic bank balance sheet and profit and loss data and are therefore consistent with the empirical evidence.

The theoretical model generates substantial heterogeneity given the undiversifiable aggregate and idiosyncratic risks that banks face. This heterogeneity is intended to replicate empirical regularities like the ones emphasized in, for instance, Kashyap and Stein (2000) and Berger and Bouwman (2013), who use disaggregated data to understand the differential behavior between small and large banks. We complement their approach by building a quantitative structural model to replicate the cross-sectional and time series evolution of commercial bank balance sheets in the U.S.. The quantitative model is estimated using a Method of Simulated Moments (see, for example, Hennessy and Whited (2005)) and replicates the data in a number of dimensions.

There is substantial cross sectional heterogeneity in the loan to asset ratio. In the data this ratio is 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. 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, and the endogenous decisions

[4] Banks' limited access to equity markets could also arise due to adverse selection problems a la Myers and Majluf (1994) and the information sensitivity of equity issuance. That problem might be particularly acute in a situation where a bank faces an equity shortfall due to loan losses, in which case information sensitivities may prevent the bank from accessing external equity capital from private investors.

in response to these risks. In the data, there also exists heterogeneity in the deposit to asset ratio, although that range is tighter (between 70% and 95%) than in the loan to asset ratio. The tighter deposit to asset ratio is replicated through a convex funding cost to access the wholesale market. Smaller banks are estimated to face a higher cost in accessing the wholesale market than larger banks and therefore rely more heavily on deposits to finance the asset side of their balance sheet. As a result, larger banks are 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.[5] Banks invest in liquid assets along with making loans and the model replicates 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 loans and also as a way to smooth background risk (deposit outflow volatility and loan write-off shocks).

Empirically, in the time series dimension the deposit to asset ratio, leverage and failure rates are all countercyclical, while the loan to asset ratio is procyclical. 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). This peak of loan growth at the onset of booms leads to a further increase in the leverage ratio in the first few periods of a boom. However, over the course of the boom, banks retain part of their higher earnings and replenish their

[5] Kishan 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.

equity stock. Thus, overall leverage is countercyclical.

The model also generates strongly countercyclical failure rates, consistent with the data. These failure rates are driven by loan write-off shocks. The model is consistent with the empirical results in Berger and Bouwman (2013) in that failed banks, regardless of size, tend to have higher (lower) average leverage (equity capital) than banks that survive. Given the motive for smoothing dividends through the concave utility function, the model also generates a smooth dividend to profits and dividend to equity ratio, both consistent with empirical observation.

We interpret these findings as consistent with quantitative features of the data. We therefore use the model to analyze the effect of changing capital requirements, a major issue of policy concern. Maintaining a higher level of capital (lower leverage) could increase banks' resilience to shocks and reduce the likelihood of bank failures.[6] On the other hand, imposing tighter leverage limits can increase the likelihood of bank failures if banks do not increase their equity holdings sufficiently because, for any given amount of equity, a tighter limit is more likely to be breached than a looser limit. Thus, more stringent capital requirements can potentially reduce banks' financial flexibility and therefore might increase the likelihood of failure.[7] Therefore, setting capital requirements at an appropriate level is a balancing act, as shown by Van den Heuvel (2008) and De Nicolo, Gamba and Lucchetta (2014), even though most studies favor the idea that higher capital and the probability of survival tend to be positively correlated (Freixas and Rochet (2008)).

[6] Higher equity capital might mechanically increase an individual bank's survival probability, while higher equity capital can also alleviate other frictions thereby increasing the likelihood of survival (see Allen, Carletti and Marquez (2011) and Mehran and Thakor (2011)).

[7] For instance, Koehn and Santomero (1980) and Besanko and Kanatas (1996).

In the model banks respond to higher capital requirements by accumulating more equity. Banks also lower loan issuance consistent with the empirical findings in Aiyar et. al. (2014). However, the average failure rate is significantly increased, a surprising result given conventional wisdom that higher equity should make banks safer (Miles, Yang and Marcheggiano (2012), Admati and Hellwig (2013)). What is the intuition behind this result? There are two countervailing forces when the capital ratio requirement is increased. On one hand, we have the standard effect that a tighter constraint increases precautionary equity. On the other hand, however, the increase in equity needs to be more than the change from the old capital ratio requirement to the new one. It turns out that, because of risk aversion, the increase in precautionary equity is less than the required change in capital ratios. Banks therefore move closer to the new constraint, making it more likely for them to hit the constraint and fail.

Why is the increase in equity less than the required increase in capital? The answer comes from the behavior of savings in portfolio choice models where the expected rate of return is endogenous and depends on the asset allocation decision of households. In intertemporal portfolio choice models, Campbell and Viceira (1999) and Gomes and Michaelides (2005) show that savings can rise or fall as the elasticity of intertemporal substitution changes depending on the expected rate of return on stocks. With low risk aversion, a higher proportion of financial wealth is invested in the stock market and therefore the expected rate of return is higher (relative to the high risk aversion case). The (endogenous) difference between the expected rate of return and the discount rate can affect the response of saving to changes in the intertemporal elasticity of substitution. In a similar fashion, a tighter capital ratio

leads to a fall in the expected return on equity as loans get reduced and equity rises more than profits. A lower expected return on equity makes the banker relatively more impatient and therefore lowers the incentive to accumulate more equity. Moreover, the strength of the attenuating effect of the fall in the expected return on equity is amplified by leverage. In our model, as in the data, leverage is higher for larger banks. Therefore, larger banks respond more strongly to higher capital ratio requirements; they lower loan supply more than smaller banks and their failure rate also increases by more than the failure rate of smaller banks.

The result that failures rise when the capital ratio requirement is increased is surprising but is robust to changes in model parameters (discount rate, loan returns, and risk aversion). Whether this result continues to hold in general equilibrium settings is an interesting topic for future research. We note the recent study by Gale (2010), however, who uses general equilibrium arguments to question conventional wisdom that higher capital requirements reduce failures. We show that even in a partial equilibrium model this conventional wisdom can be questioned.

One important difference from the related literature is that we estimate preference parameters. In particular, we find a significantly positive coefficient of relative risk aversion while previous papers typically use risk neutral preferences. Risk aversion is an important factor for the strength of the precautionary equity motive. De Nicolo, Gamba and Lucchetta (2014) also model banks' capital buffers in response to aggregate shocks and analyze the effects of capital requirements. In addition to the differences in preferences, we also have a richer balance sheet structure where wholesale funding and liquid securities coexist in the bank's balance sheet with substantial cross-sectional heterogeneity arising from background

risks and bank choices. Repullo and Suarez (2013) analyze capital regulation in a general equilibrium model. We differ by having different preferences and emphasizing the maturity transformation role for banks and banks' portfolio choices, albeit in a partial equilibrium setting. Corbae and D'Erasmo (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 longer duration, while banks can decide simultaneously on new loans, liquid security holdings, wholesale borrowing and dividends, thereby focusing on the portfolio choices banks make.

The rest of the paper is organized as follows. Section 2 discusses the data to be replicated, and section 3 the theoretical model. Section 4 shows the estimation results and section 5 compares the model with the data and discusses the model's implications. Section 6 examines the effect of tighter leverage limits and section 7 concludes.

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 a 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 Federal Deposit Insurance Corporation (FDIC) for the same period. Bank failure occurs when either the FDIC closes down a bank or assists in the

re-organization of the bank. 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 last year of our sample period, sorted by bank size.[8]

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 which shows 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 instruments in the wholesale funding market. 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 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 are more important for the largest banks relative to the smallest banks throughout

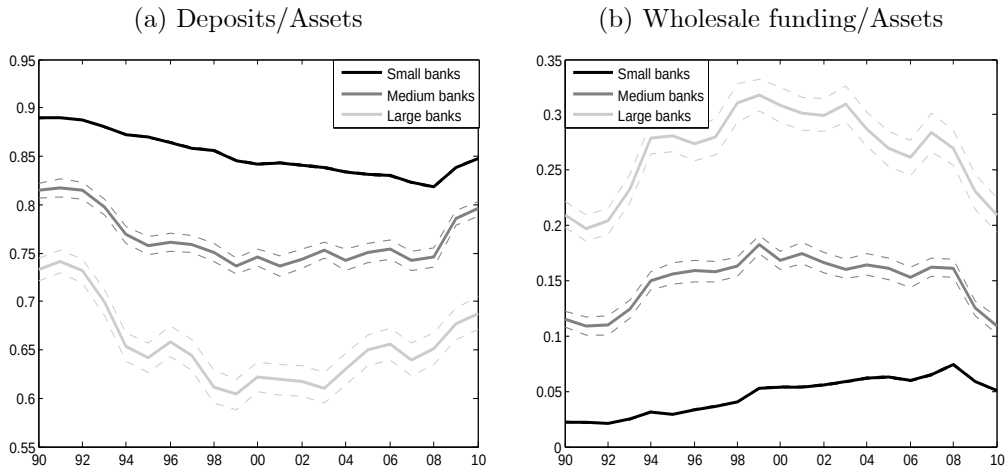
[8] The significant reduction in the number of banks over our sample period was mainly a result of regulatory changes that led to substantial consolidation in U.S. commercial banking. According to Calomiris and Ramirez (2004), branch banking restrictions and protectionism towards unit banks (i.e. one-town, 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 and references on the subject. For some excellent reviews, see also Berger, Kashyap, and Scalise (1995), Calomiris and Karceski (2000) and Calomiris (2000). We abstract from endogeneizing mergers in our model.

Table 1: Balance sheets of U.S. commercial banks by bank size in 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	10%	9%	10%

This table shows some summary balance sheets of U.S. commercial banks in 2010, by size class. Small banks are those below the 95th percentile of total assets. Medium banks are those in the 96th-98th percentile. Large banks belong to the top two percentiles.

Figure 1: Evolution of deposit and wholesale funding of U.S. commercial banks



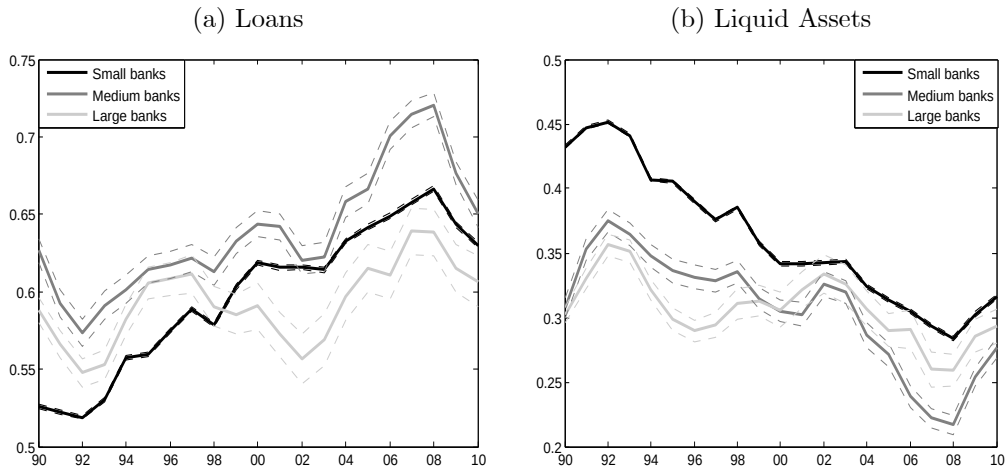
This figure shows the evolution of the liabilities as a proportion of total assets of U.S. commercial banks in the period 1990-2010 by bank size. Panel (a) shows the deposit to asset ratio while panel (b) shows the wholsale funding to asset ratio. Deposits consist of transaction and non-transaction deposits. Wholesale fundings consists of Fed funds borrowed, repos and other liabilities. Small banks are those below the 95th percentile of total assets. Medium banks are those in the 96th-98th percentile. Large banks belong to the top two percentiles.

this period. There seems to be an increase in accessing the wholesale funding market from the largest banks during the period between 1992 and 2007 and a reduction back to around 20% of the balance sheet in 2010. 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 longer maturities. There is an upward trend in the proportion of loans in the balance sheet across all bank sizes between 1992 and 2007, with the trend briefly interrupted during the short 2001 recession. The average loan to asset ratio is around 60% for both small and large banks.

The largest remaining part of the asset side of the balance sheet is liquid assets which

Figure 2: Evolution of loan and liquid assets of U.S. commercial banks



This figure shows the evolution of assets as a proportion of total assets of U.S. commercial banks in the period 1990-2010 by bank size. Panel (a) shows the loan to total asset ratio while panel (b) shows the liquid asset to total asset ratio. Loans consist of real estate, commercial, industrial, farmer loans and loans to individuals. Liquid assets are cash, reverse repos, Fed funds lent and securities. Small banks are those below the 95th percentile of total assets. Medium banks are those in the 96th-98th percentile. Large banks belong to the top two percentiles.

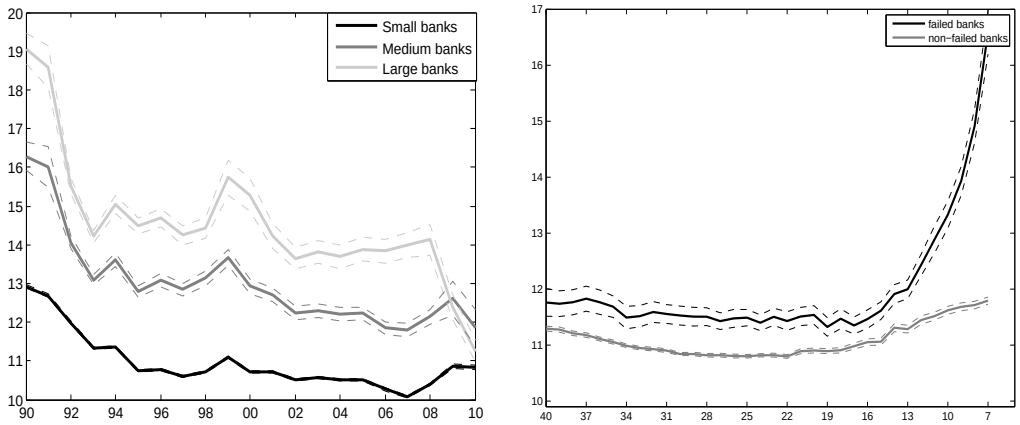
comprise cash, Fed funds lent, reverse repos and securities. At the beginning of the period, which is right after the savings and loans crisis, smaller banks hold significantly more liquid assets as a proportion of total assets relative to larger banks. However, these differences across size classes become less pronounced over time as smaller banks increase their loan to asset ratio faster than larger banks do. Nevertheless, liquid assets as a proportion of total assets, remain higher on average for smaller banks throughout the sample period, consistent with Kashyap and Stein (2000).

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.[9] Figure 3a reports total leverage over time for banks of different sizes.

[9] Tangible equity equals total assets minus total liabilities minus intangible assets, such as goodwill.

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

(a) Leverage by size (b) Leverage of failed and non-failed banks



Panel (a) shows the evolution of leverage of U.S. commercial banks in the period 1990-2010 by bank size. Small banks are those below the 95th percentile of total assets. Medium banks are those in the 96th-98th percentile. Large banks belong to the top two percentiles. Panel (b) shows leverage of failed banks (FDIC regulatory-assigned bank failures) and non-failed banks during the period 1990-2010. The x-axis is the time-to-failure measured in quarters. The leverage of non-failed banks is the average of non-failed peer groups of banks that failed with a given time-to-failure.

Smaller banks are consistently less levered than large banks with the exception of the recent crisis.[10]

We are also interested in the characteristics of banks that fail or receive FDIC assistance (hereafter called failed banks). Those banks may have taken more risks and run higher leverage than non-failed banks. Figure 3b shows average leverage of failed banks (FDIC regulatory-assigned bank failures) and non-failed banks over the 10-year period prior to failure. That is for bank failures occurring between 1990 and 2010, where the x-axis is the time-to-failure in quarters. For banks that eventually fail, leverage is consistently higher over time relative to non-failed banks and increases sharply as they approach failure. This figure is consistent with the empirical findings in Berger and Bouwman (2013) who find that

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

higher capital can increase a bank's survival probability.

2.2 Time Series Statistics

Banks in our model face uninsurable idiosyncratic shocks coming from deposit growth, loan write-offs and different asset returns. At the same time banks will be exposed to aggregate uncertainty which generates cyclical fluctuations.[11] We will use the data to constrain the data generating processes of the model's exogenous variables. 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, liquid assets, wholesale funding, dividends and failure rates. This section shows estimation results for the relevant variables. In particular, we show that there is a large amount of heterogeneity across banks and over time.

2.2.1 Uninsurable Risk

To capture uninsurable risk from deposit growth, loan write-offs and returns on different assets, we examine the time-series statistical properties of these processes individually for each bank. We concentrate on the first and second moment and the persistence of these risks, conditional on a boom or recession state. Given our approach, that relies on computing individual statistics per bank over a twenty year period (84 quarters) and the fact that we condition on booms and recessions as well, we cannot perform a vector autoregression for all

[11] We count as a recession the two quarters before the start, and the six quarters after the end, of the NBER-dated recessions. There are two reasons for doing this. First, this allows us to extend the sample given the short recessions in this period. Second, loan write-off rates in the data start picking up before the official NBER recession dates and continue after well after the end of the official recession end date.

these variables at the individual bank level. A panel VAR would be an alternative approach but we prefer to emphasize the rich heterogeneity that exists at the individual bank level that can be generate substantial heterogeneity in behavior in response to regulatory changes.

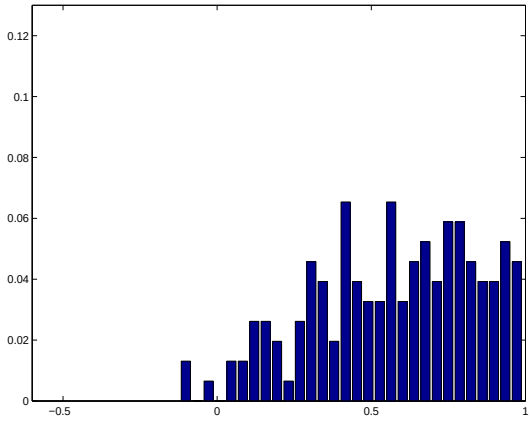
We focus on four main variables: real deposit growth, loan write-offs (defined as current loan charge-offs over end of last period total loans), and the spreads of loan and liquid asset returns over transaction deposit rates. All these variables combine information that exists in either balance sheet or profit and loss accounts or both. Loan returns are defined as loan interest income (which includes income from all customer loans) divided by lagged loans, and liquid asset returns are defined as interest income on Fed funds sold and reverse repos plus gains or losses on securities over the period divided by the stock of lagged liquid assets. Deposit rates are defined as interest expense on transaction deposits divided by lagged transaction deposits. In the analysis that follows we report statistics both unconditionally but also conditional on a boom or a recession and for both large and small banks.

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 run for each bank type an AR(1) time series regression if there are more than 35 consecutive observations for a particular bank. We find that the histograms show strong positive persistence for large banks and a milder persistence for small banks, as shown in Figure 4. The figures illustrate the large amount of heterogeneity that exists in the data. For brevity, we do not show the histograms for deposit growth rates. But these show a similar degree of heterogeneity.

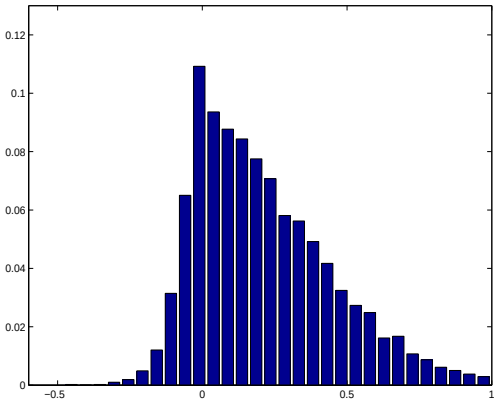
Table 2 reports the results for the mean, standard deviation and persistence across different variables of interest, both unconditionally and conditioning on a recession and for

Figure 4: AR(1) of loan write-off process

(a) Large banks



(b) Small banks



This figure shows the histogram of individual banks' AR(1) coefficients of loan write-offs for small and large banks in the period 1990-2010. For each bank in the dataset we run an AR(1) time series regression if it has more than 35 consecutive observations. Panel (a) shows large banks which are defined as the top two percentiles in the total asset distribution. Panel (b) shows small banks which are all banks the 98th percentile in the total asset distribution

both small and large banks. This table illustrates that there are substantial differences both across banks (small versus large) and also over the business cycle (booms versus recessions). Starting with the idiosyncratic component of the loans' write-off process, we observe that the persistence is higher for larger than smaller banks but does not significantly change between booms and recessions. Deposit growth tends to be higher in recessions than in booms, probably due to a flight to the safety deposits offer. The standard deviation of loan write-offs is also higher in recessions and is higher for larger banks. The median persistence of real deposit growth is zero over both states and bank sizes. Moreover, even after conditioning the aggregate state of the economy, individual bank heterogeneity remains pervasive.

Table 2: Time varying aggregate parameters

Parameter (all in % except AR(1))	Small banks			Large banks		
	Uncon	*recession*	*boom*	Uncon	*recession*	*boom*
Loan write-offs: mean	0.10	0.13	0.08	0.31	0.37	0.22
Loan write-offs: AR(1)	0.21	0.20	0.14	0.72	0.70	0.51
Loan write-offs: st. deviation	0.17	0.20	0.10	0.24	0.28	0.14
Deposit growth: mean	0.81	0.65	0.90	1.63	1.60	1.64
Deposit growth: AR(1)	-0.01	-0.01	-0.01	0.03	0.03	0.03
Deposit growth: st. deviation	3.71	3.50	3.48	5.64	5.31	5.41

This table shows the estimation results for the mean, standard deviation and persistence across different variables of interest. Small banks are those below the 98th percentile in the distribution of total assets and large are those above the 98th percentile. Uncon is the unconditional statistic, whereas recession and boom denote the statistics conditional on being in a recession or a boom respectively. All statistics are computed at the individual level over time and then averaged across banks.

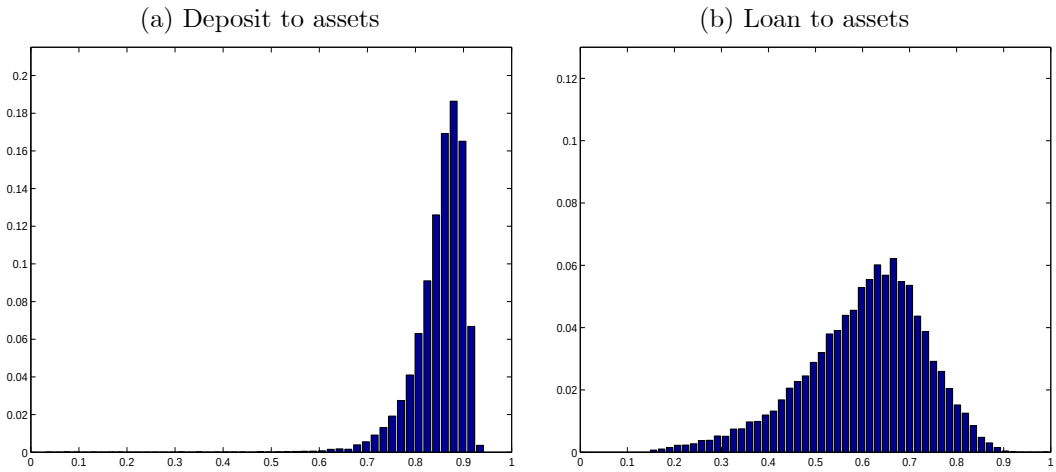
2.2.2 Balance Sheet Distributions

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 20 observations. We then produce histograms for these moments that can be either unconditional or conditional on a boom or conditional on a recession.

Figure 5 shows the distribution of the deposit to asset ratio and the loan to asset ratio for small banks.[12] Loans are the most important component on the asset side of the balance sheet. Figure 5b shows a pretty wide dispersion of this ratio across small banks, ranging from 15% to 90%, with a mean equal to 60%. Figure 5a 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%. An empirically successful model should be able to replicate this

[12] The corresponding graphic for large banks looks similar.

Figure 5: Distribution of deposit to asset and loan to asset ratios



This figure shows the distribution of the deposit to asset ratio (a) and the loan to asset ratio (b) of small (below the 98th percentile) U.S. commercial banks in the period 1990-2010.

heterogeneity in the data.

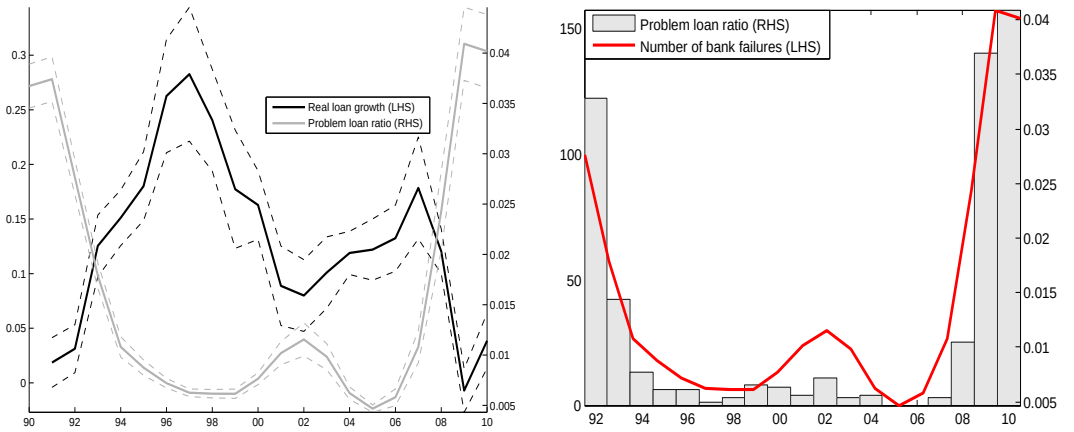
2.2.3 Cyclical Properties

Figure 6 shows the behavior of loan growth, the evolution of problem loans and the resulting bank failures over the sample period. Figure 6a 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 6b 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% (0.08%)

Figure 6: Cyclical properties of loan growth, problem loans and bank failures

(a) Loan growth and problem loans (b) Aggregate problem loans and bank failures



This figure shows the distribution of the cyclical behavior of loan growth, the problem loan ratio and bank failures for U.S. commercial banks in the period 1990-2010.

for small (big) banks, which rises in recessions to 0.17% (0.18%) and falls in booms to 0.01% (0.01%).

2.3 Summary

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. Moreover, a large heterogeneity exists in the cross section on items that are either on the bank's balance sheet (deposit and loan to asset ratios, for instance) but also in their profit and loss statements (loan write-offs and profits). 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 next build a structural model to replicate these stylized facts.

Table 3: Bank balance sheet in the model

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	

This table represents the balance sheet of the banks in our model. There are illiquid loans and liquid assets on the asset side while the liability side consists of deposits, short term wholesale market funds and equity.

3 The Model

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 have limited liability. We consider interest income from relatively illiquid loans and liquid assets as the key driver of decisions by commercial banks. 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,[13] 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 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 real return on 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. This screening cost is assumed to be convex in new loans either because bank resources get stretched over more projects or because the quality of additional projects is declining. 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 (the 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.

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

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 with both aggregate and idiosyncratic components that are specified in the calibration section.

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, follows 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. 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 important 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 1 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 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

$$E_{t+1} = E_t + \Pi_{t+1} - X_t \tag{1}$$

3.1.4 Capital Ratio Requirement

Banks are subject to regulatory constraints regarding their capital ratio, namely a minimum ratio between bank equity and 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. *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.

The leverage constraint (the inverse of the capital ratio requirement) is captured by parameter λ which gives the maximum ratio of assets to equity that the bank must respect:

$$\frac{L_t + N_t + S_t}{E_t - X_t} \leq \lambda \tag{2}$$

The numerator in (2) represents total assets after new loans and securities have been

chosen. The denominator denotes equity after dividends have been paid out.

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:

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

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). In the data set we analyze, it is indeed the case that dividends to equity (assets) are smoother than profits to equity (assets) and this becomes one of the endogenous moments that the model can match.[14]

3.1.6 Profits

The profits of bank i attributable to shareholders are[15]

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

[14] Dividends need to always be positive in this world due to the concavity of the utility function but can be set very close to zero, if needed.

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

where the first two terms are the interest income on performing loans where we assume that new loans do not experience any losses; the third term reflects income from holding liquid assets, the fourth term is the cost from servicing deposits, the fifth term is the cost of issuing new loans and the sixth term is the cost of accessing the wholesale funding market. The final term is the non-interest expense associated with operating the bank and is modelled as proportional to deposits. This term includes various costs to operate a bank (operating expenses) and also the FDIC insurance surcharge to fund deposit insurance.

We could introduce corporate taxation in the model, but prefer to leave it out for three reasons. First, we would like to determine whether a model without a tax shield can replicate the observed leverage in the banking sector. Second, the tax-shield benefit from interest expenses can be quite low in this sector given the low observed deposit interest rates in the last ten years. Last, to the extent that the value of the tax shield is fairly constant over this period, adding a tax shield would most likely affect only the estimate of our operating expense cost.

3.1.7 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 constant amount of consumption C^D and a level of utility equal to V^D.[16] 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

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

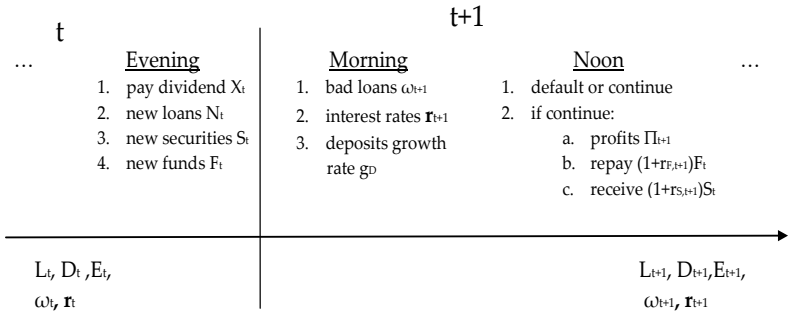
the deposits of the failed bank but which starts at a good idiosyncratic state, i.e. low loan losses.

3.2 Timing

Figure 7 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), 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 loan write-offs) are realized: the bank learns the various rates of return $\mathbf{r}_{t+1}$;, deposit withdrawals, how many loans are repaid and how many have to be written off (w_{t+1}).

The bank decides whether to continue or exit at that stage. 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 exogenous shock realization in the current period and are therefore equal to D_{t+1} after the shock realizes. 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}).

Figure 7: Timing in the model



3.3 Value functions

A banker who has exited in the past cannot become a banker again. This banker enjoys an exogenous constant level of consumption C^D yielding utility V^D.[17]

A banker who has not exited in the past solves the following continuation problem that takes into account that exit is possible in the future

$$V^C\left(L_t, D_t, E_t; w_t, \mathbf{r}_t\right) = \max_{X_t, S_t, F_t, N_t} \left\{ \frac{(X_t)^{1-\gamma}}{1-\gamma} + \right. \tag{5}$$

$$\left. \mathbb{E}_t\left[\beta V\left(L_{t+1}, D_{t+1}, E_{t+1}; w_{t+1}, \mathbf{r}_{t+1}\right)\right]\right\}$$

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

where the last term is defined as the upper envelope

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

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

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

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.

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 based on our estimates for small and big banks, respectively. Lastly, we show the results from the Method of Simulated Moments estimation of the remaining six 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. Both assumptions are common in the investment literature (see, for example, Abel and Eberly (1994)).

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

$$g_N\left(N_t, D_t\right) = \phi_N n_t^2 D_t$$

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

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

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

4.3 Calibrated parameters

The model features aggregate and idiosyncratic uncertainty. In general, we estimate the stochastic processes generating these variables from the data discussed in section 2. Since we estimate the idiosyncratic stochastic processes as depending on the aggregate state but we have only a a relatively short time series, we use two aggregate states only. 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 8 quarters on average and booms that last for 20 quarters on average. The deposit interest rate depends on the aggregate state only, whereas conditional on the aggregate state and bank size, idiosyncratic uncertainty has different properties (the variance of the shocks is different for example).

Idiosyncratic uncertainty (or background risk) is captured by four different variables: loan write-offs, the deposit growth rate, the loan spread, and the spread on liquid assets. As discussed in section 2.3 (Table 2), idiosyncratic write-offs behave very differently in booms and recessions. Due to this asymmetry, we model the loan write-off process as state dependent. During a recession, the write-off process is significantly worse for banks. The mean is around 50% higher, while the standard deviation and the persistence also increase signific-

antly. We use the means, standard deviation and persistence from Table 2 as inputs in the structural model. Note that these are conditional on a boom or a recession and are also conditional on bank size (small versus large).

One non-trivial choice is the benchmark value for the leverage limit. Since the U.S. has not implemented the Basel II accord, we do not use a risk-based measure. Moreover, there is no clear quantitative rule for leverage either. However, in reality, leverage limits that trigger FDIC intervention are set on a case by case basis, based on the general risk profile of the bank. We consider 33 as a reasonable proxy for the leverage limit because in our data sample, we find that only 0.37% of all bank quarter observations have a leverage above that limit.

4.4 Estimated parameters

There are six parameters left to be estimated: the discount factor β, the curvature of the utility function γ, the flow cost of operating the bank c, the new loans screening cost parameter ϕ_N, the external finance premium for accessing wholesale funding ϕ_F, and the value of consumption after failure c^D. We estimate the model separately for small and large 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 4 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)

Table 4: Model and Data Moments

Moments	Large banks		Small banks	
	model	data	model	data
Mean default rate (in %)	0.085	0.084	0.049	0.05
Mean loans/assets	0.692	0.665	0.650	0.622
Mean deposits/assets	0.559	0.633	0.888	0.857
Mean equity/assets	0.057	0.072	0.075	0.099
Mean profit/equity	0.049	0.063	0.019	0.037
Mean dividends/equity	0.037	0.028	0.011	0.013
Std. loans/assets	0.13	0.076	0.083	0.082
Std. deposits/assets	0.077	0.086	0.049	0.035
Std. equity/assets	0.015	0.013	0.022	0.014
Std. profit/equity	0.037	0.048	0.027	0.024
Std dividends/equity	0.029	0.034	0.012	0.016

This table shows the result of the method of simulated moments estimations of our benchmark model and the corresponding data moments for small and large banks separately. Both have a quarterly frequency. Both the mean of each variable and the standard deviation is over time. The sample is all U.S. commercial banks in the period 1990-2010. Small banks are those below the 95th percentile of total assets. Large banks belong to the top two percentiles.

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 underpredicts equity holdings, i.e. the bankers in our model have a weaker precautionary motive than what is observed in the data. The model also underpredicts the profit to equity ratio for both big and small banks. This might be due to the omission of all taxes. On the other hand, the model is closer in terms of the dividend to asset ratio which determines bank owners' utility. Most of the second moments of the balance sheet variables are slightly overpredicted but the model generates low volatility in the dividend process, as in the data.

Table 5 shows the estimated parameters. Most of the estimated parameters for large and small banks are similar. One important exception is the weight on the convex cost of

Table 5: Estimated parameters using the Method of Simulated Moments.

Parameter	Large banks	Small banks
Discount factor β	0.987 (0.002)	0.980 (0.002)
CRRA γ	1.421 (0.030)	1.618 (0.050)
Operating cost c	0.012 (0.002)	0.010 (0.001)
Screening cost new loans ϕ_N	0.524 (0.02)	1.116 (0.04)
Risk premium wholesale funding ϕ_F	0.006 (0.001)	0.083 (0.005)
Consumption after bank failure c^D	0.0002 (0.0001)	0.0001 (0.0001)

This table shows the results of the method of simulated moments estimations of our benchmark model. We estimate the small and large banks separately. The standard errors of the estimated parameters are shown in parenthesis.

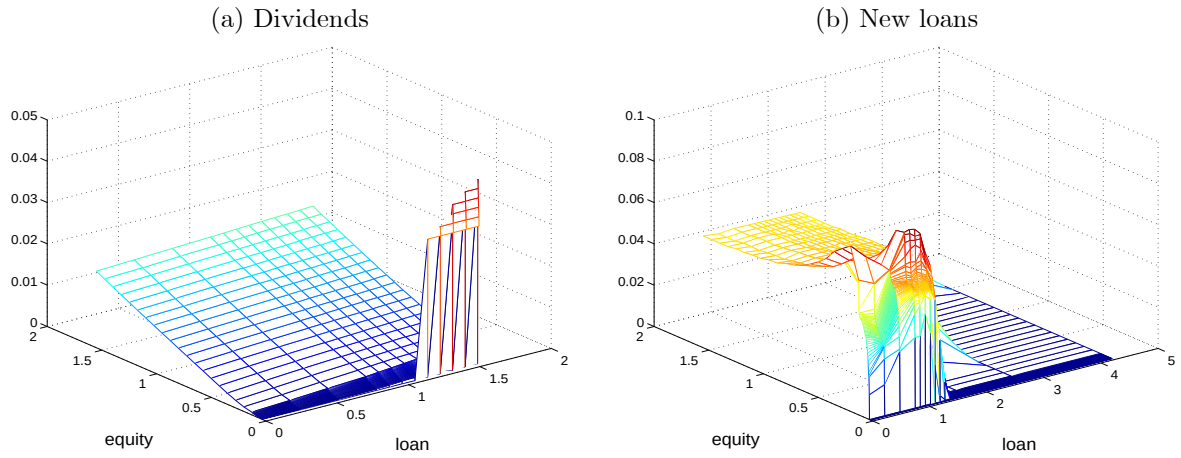
accessing wholesale funding markets. The estimated ϕ_F is more than ten times lower for large than small banks, allowing larger banks to access wholesale funding markets. This leads to a significantly lower share of deposits in total assets for large banks, as can be seen in the third row in Table 4. Moreover, better access to this alternative funding source also allows big banks to operate with lower equity.

The rate of time preference is similar across the two types of banks. Both show a significant degree of risk aversion which is explained by the low volatility of the dividend process in the data. However, large banks are somewhat less risk averse than small banks.

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.

Figure 8: Policy functions with low idiosyncratic loan losses during a boom



This figure shows policy functions of the model for small banks in a boom when they experience low loan write-offs. Panel (a) shows normalized dividends, while panel (b) shows normalized new loan issuance.

5.1 Policy functions

Having normalized the model by deposits, we are left with two continuous state variables: (normalized) loans and (normalized) 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 loan write-offs. All the policy functions shown are for a small 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 0.04 and loans exceeding 1.32 will be closed down immediately. In the graphs, this region is at the very right end of the loan state.

Figure 8a shows the dividend policy function which has three implications. The first one

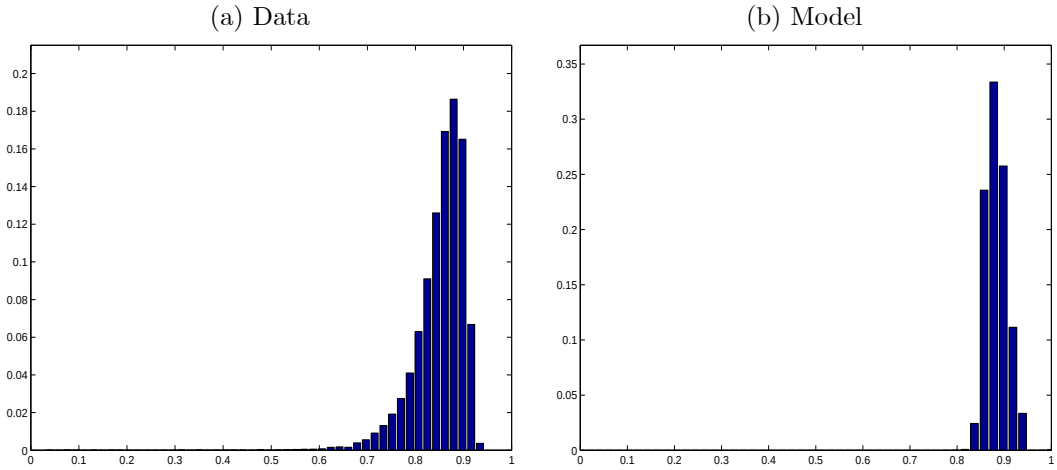
[18] To be precise, the policy functions are for a small bank in a boom but with low idiosyncratic bad loans. The policy functions in other states and for small banks look similar.

is standard. For a low amount of loans, 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 expands its loan exposure. This incurs screening costs for issuing new loans. 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 8b shows the issuance of new loans. For each level of equity there is a desired level of loans. Nevertheless, due to the convex loan issuance cost, banks do not reach this desired level of loans in one step. From the simulations we know that the relevant region is the one with equity less than 0.25, and new loans are monotonically increasing in equity in this region. At high levels of equity, banks prefer to invest in liquid assets. Buying liquid assets does not incur any adjustment cost, therefore the investment in liquid assets is monotonic in initial equity.

To take stock, given a particular state, banks have a desired balance sheet structure. 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 optimal allocation. When the states change, the policy functions change in expected ways. If the

Figure 9: Distribution of deposit to asset ratios



This figure shows the distribution of deposit to asset ratios of small banks in the data (a) and in the model (b). The data are for U.S. commercial banks in the period 1990-2010. Panel (b) shows the results of simulating 100,000 banks for 2,000 periods where only the last 500 periods are used. Details can be found in the appendix.

idiosyncratic persistent loan write-offs 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.

5.2 Cross section

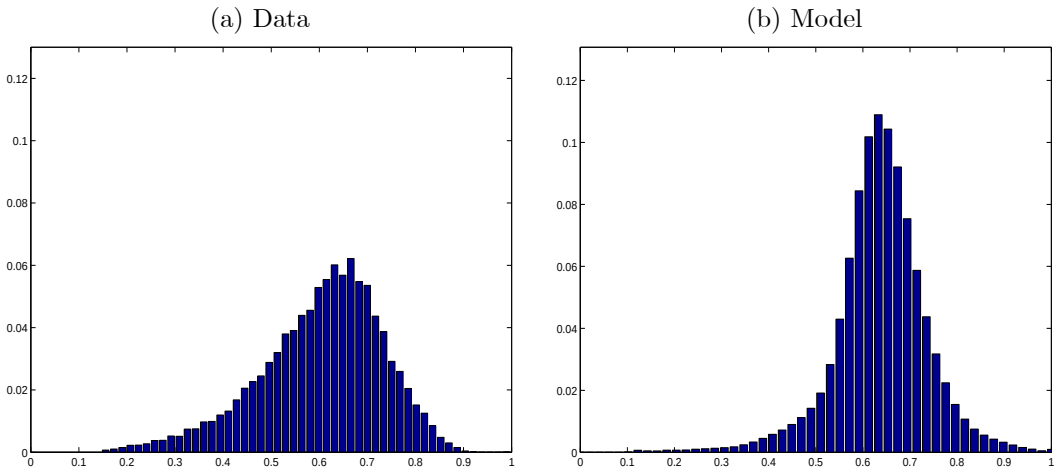
In this section, we provide further empirical evidence for heterogeneity and compare the model outcomes to their data counterparts.[19] The results here are the outcome of simulating the model for small banks.[20] Figures 9 to 11 show histograms of the respective variable; the data (simulations) are depicted on the left (right) hand side of each figure.

Figure 9 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

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

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

Figure 10: Distribution of loan to asset ratios



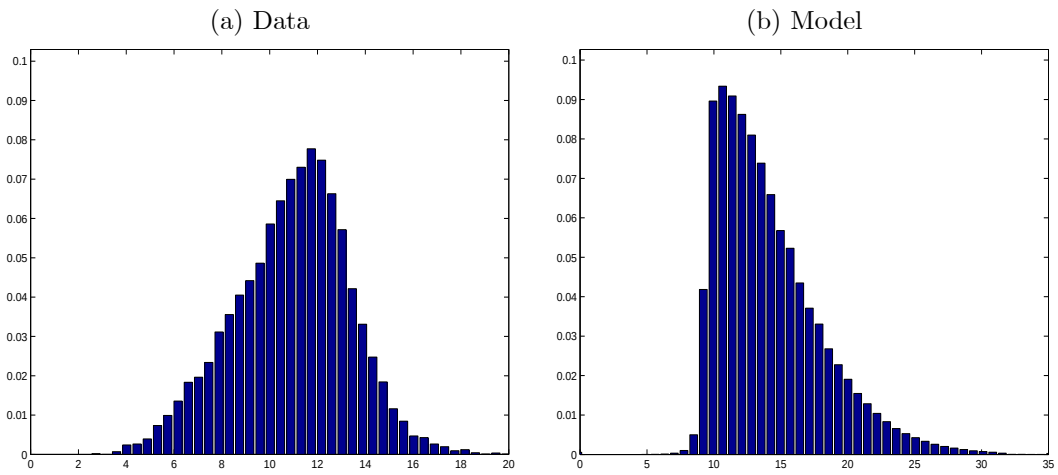
This figure shows the distribution of loan to asset ratios of small banks in the data (a) and in the model (b). The data are for U.S. commercial banks in the period 1990-2010. Panel (b) shows the results of simulating 100,000 banks for 2,000 periods where only the last 500 periods are used. Details can be found in the appendix.

70 and 90 percent. The model replicates this distribution relatively well, even though the model distribution is somewhat more symmetric than the data.

Figure 10 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 the model produces thinner tails.

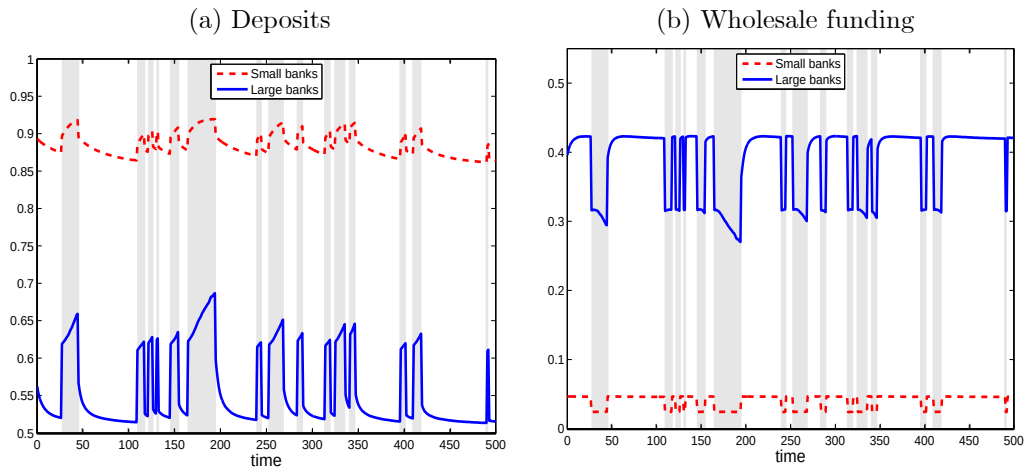
Figure 11 shows the distributions of leverage. Leverage in the data is distributed symmetrically around its mean. The model dispersion is somewhat wider and is not as symmetric as in the data. The mean in the model is higher since equity holdings (which are the inverse of leverage) are lower, as was shown in the estimation section.

Figure 11: Distribution of leverage ratios



This figure shows the distribution of leverage ratios of small banks in the data (a) and in the model (b). The data are for U.S. commercial banks in the period 1990-2010. Panel (b) shows the results of simulating 100,000 banks for 2,000 periods where only the last 500 periods are used. Details can be found in the appendix.

Figure 12: Evolution of the share of deposits and wholesale funding in the model



This figure shows the evolution of the deposit to asset ratio (a) and the wholesale funding to asset ratio (b) for small and large banks in the model. These ratios are the results of simulating 100,000 small and large banks independently for 2,000 periods where only the last 500 periods are shown. Grey areas depict recessions. Details of the simulation can be found in the appendix.

5.3 Time series behavior

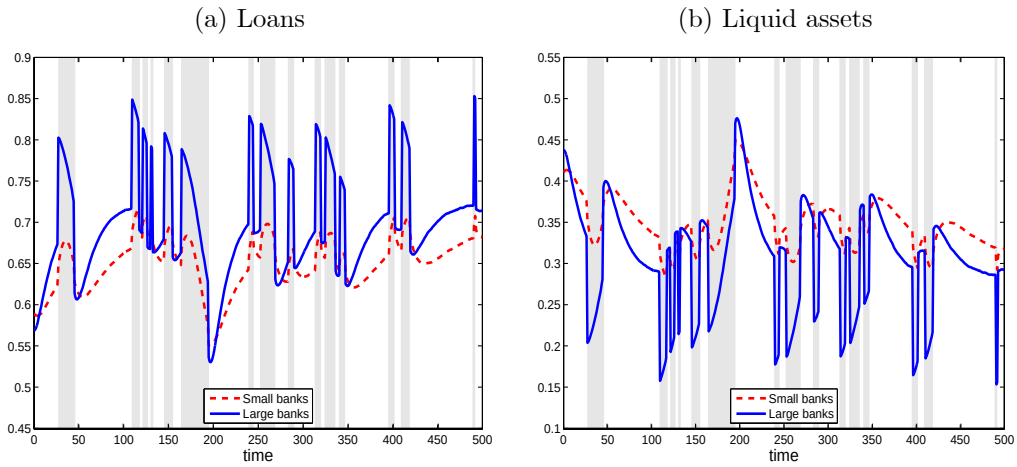
Figures 12 to 15 provide a more detailed view of the model's time series behavior.[21] Figure 12a shows the deposit to asset ratio in the model over time for big and small banks and Figure 12b shows the wholesale funds to total assets ratio. Consistent with the data, small banks rely significantly more on deposits to fund their operations, while large banks rely more on wholesale funds. However, even for large banks deposits are the main funding source. During recessions, when expected asset returns fall, banks reduce their borrowing in the wholesale 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 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 smaller number of recessions.

Figure 13 shows the asset side of the balance sheet. As a proportion of the total balance sheet, small banks invest less (more) in loans (securities) than large banks. The fact that small banks hold more liquid assets is consistent with the evidence in Kashyap and Stein (2000).

The evolution of the fraction of loans in total assets is more complex. The issuance of new loans is strongly procyclical. During a boom, loan write-offs are low and banks issue more new loans. This increases the loan to asset ratio. The opposite happens during a recession, when the share of liquid assets in the balance sheet increases. The evolution of

[21] The shaded areas denote model recessions.

Figure 13: Evolution of the share of loans and liquid assets in the model



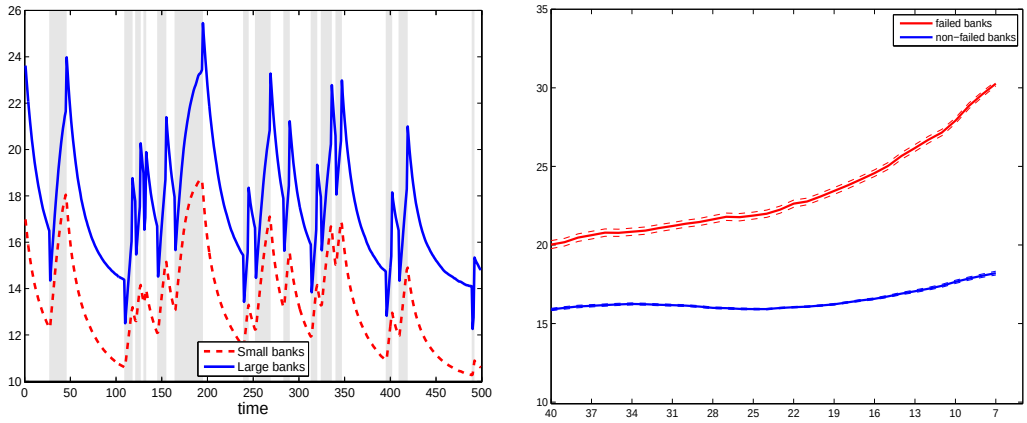
This figure shows the evolution of the loan to asset ratio (a) and the liquid asset to total asset ratio (b) for small and large banks in the model. These ratios are the results of simulating 100,000 small and large banks independently for 2,000 periods where only the last 500 periods are shown. Grey areas depict recessions. Details of the simulation procedure can be found in the appendix.

loans and liquid assets at the turning points of the business cycle is different. At the onset of the recession the share of loans jumps up and then declines during the recession. The explanation is that banks want to lower their entire balance sheet during a recession. Banks can reduce their liquid assets immediately at the onset of a recession. Loans are more illiquid, however, and therefore it takes time until outstanding loans are reduced. This implies that the loan to asset ratio takes a few quarters to fall below the level it had before the recession. This effect is more pronounced for large than for small banks because large banks fund their activities to a greater degree with wholesale funds which can be cut back quickly.

Figure 14a shows the leverage ratio of the banks in the model. Consistent with the data, see Figure 3a, big banks are more levered than small banks. Since small banks have less access to the wholesale funding market, they rely more on deposit and equity funding. Thus, on average, they hold significantly more precautionary equity. This increase in equity funding

Figure 14: Leverage by size and of failed and non-failed banks in the model

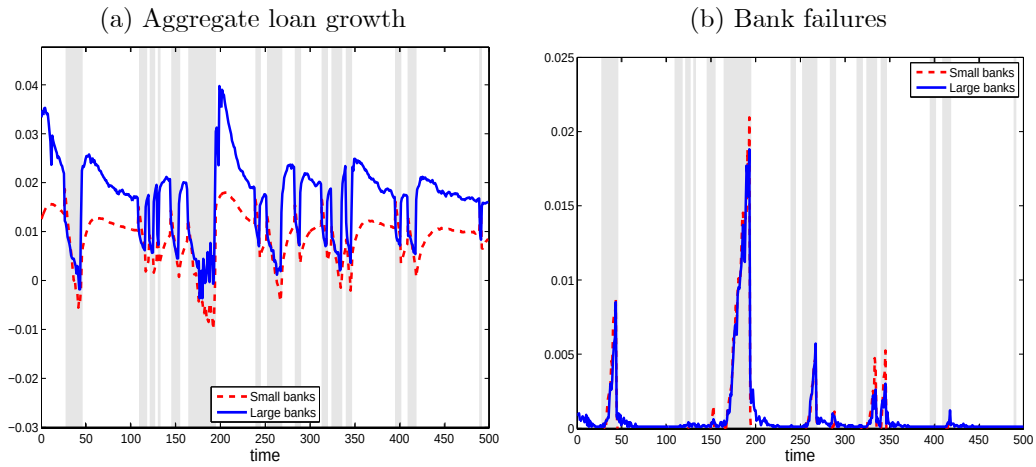
(a) Leverage (b) Leverage of failed and non-failed banks



This figure shows the evolution of leverage ratios for small and large banks in the model in panel (a). These ratios are the results of simulating 100,000 small and large banks independently for 2,000 periods where only the last 500 periods are shown. Grey areas depict recessions. Panel (b) shows the evolution of leverage of failed banks and their non-failed peer groups. The x-axis measures the time-to-failure in quarters. Details of the simulation can be found in the appendix.

translates into a lower leverage ratio. Leverage is countercyclical for big and small banks. Banks use the profits to build up equity during good times through retained earnings. During recessions, equity declines and leverage increases because profits are lower. Since banks want to smooth dividends, 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 wholesale borrowing quickly, the share of equity in total assets actually rises, and therefore leverage falls at the onset of a recession. However, the reduced profits deplete equity quickly and it takes less than a year until the leverage level rises above its level at the end of the boom. The maximum leverage occurs, however, in the first period of the boom when banks have little equity left after the recession but start lending aggressively again.

Figure 15: Cyclical properties of loan growth and bank failures



Panel (a) of this figure shows aggregate loan growth for small and large banks in the model. Loan growth is defined as the log difference of the outstanding stock of loans. The simulations are for 100,000 small and large banks independently for 2,000 periods where only the last 500 periods are shown. Panel (b) shows the evolution of bank failure rates. Grey areas depict recessions. Details of the simulation can be found in the appendix.

Figure 14b is the model counterpart to Figure 3b. It shows the average leverage for banks that fail and a corresponding peer group. Leverage rises significantly for those banks that fail. This increase is more gradual than in the data, see Figure 3b. Thus, an increase in leverage is an indicator for subsequent vulnerability. This is consistent with the evidence in Berger and Bouwman (2013).

Figure 15 is the model counterpart to Figure 6 in the data section. Figure 15a shows that aggregate loan growth in the model is strongly procyclical. Loan growth is positive during booms and declines during recessions. Loan growth declines throughout recessions as banks delever. As soon as aggregate conditions improve, banks start lending aggressively to replenish their loan book. This makes loan growth highly procyclical. This increase in loans at the onset of a boom explains why leverage reaches its maximum at that point in time.

Figure 15b also shows that failures are strongly countercyclical. 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 up to two percent, as bank equity gets more depleted. In contrast, there are almost no failures in good times. The only exception is big banks directly after a long recession. At that point, they have not yet replenished their equity holding sufficiently and idiosyncratic loan losses may generate some defaults.ummary

Overall, the model captures the empirical evidence reasonably well both in the cross section and in the time series dimension and can therefore be used for counterfactual analysis.

6 Changing capital requirements

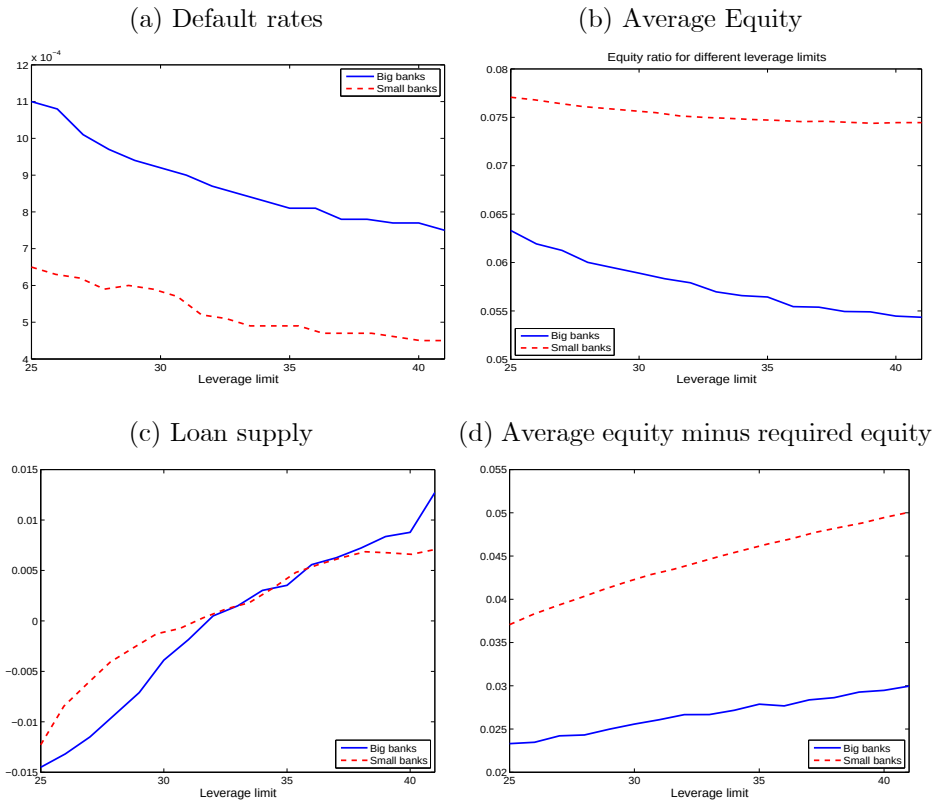
One important policy change is the move towards tighter capital requirements. In this section we show the consequences of such a policy by comparing results across steady states. We show the baseline results in subsection 6.1 and in subsection 6.2 we show that our results are robust to several changes.

6.1 Main experiment

We solve the model for different values of the leverage limit, leaving all other parameters at their benchmark ($\lambda = 33$) values. The simulation uses exactly the same shock sequence in every experiment. Fig 16 shows the effect of changing the leverage limit from 25 to 42, which corresponds to a minimum capital requirement that declines from 4% to 2.4%.

Figure 16a shows our main result: a tightening of the leverage constraint (intended to make the banking system safer) leads to more failures. This is despite the fact that a tighter constraint has the desired effect of increasing average equity holdings for small and,

Figure 16: Effects of changing the regulatory leverage limit



This figure shows the result of changing the leverage limit for small and large banks. All results are based on solving and simulating the model for the changed leverage parameter while keeping all other parameters at their estimated values. Details of the solution and simulationn procedure can be found in the appendix. Panel (a) shows the default rates, panel (b) mean holdings of equity, panel (c) aggregate loan supply and panel (d) the mean distance to the frontier which is computed as mean equity minus the minimum capital ratio.

in particular for big banks, as shown in Figure 16b. 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.

Figure 16d shows average equity relative to the required equity (capital) ratio. This is defined as mean equity minus the minimum equity level, which measures the distance to the regulatory frontier. This is declining with the leverage limit, showing that the increase in

equity holdings is less than the increase in the required capital. Figure 16c compares the differences in average loan supply relative to the baseline case. The figure shows that loan supply falls (rises) more for larger banks than for smaller banks when the leverage constraints falls (rises). This is consistent with the idea that larger banks take on more leverage than smaller banks and therefore they react more than smaller banks to changes in the capital ratio requirement.

Banks do not increase their equity holding by more than the required increase because the rate of return on equity falls endogenously with any increase in equity. In our incomplete markets model, bank owners are relatively impatient and make their equity accumulation decisions by comparing the difference between the expected return on equity and the discount rate. By holding more equity and making fewer loans due to the tighter capital constraint, their expected return on equity falls. This depresses their incentive to hold precautionary equity. This effect is more pronounced for big banks which are much closer to the constraint in the baseline setting, are more leveraged and react more strongly than small banks, see Figure 16b. Therefore, the effect on their loan supply and their failure rate is also stronger than for small banks, despite having better access to wholesale funding markets which helps them cushion shocks better. The intuition behind this result is almost identical to the intuition given in Campbell and Viceira (1999) and Gomes and Michaelides (2005) on how saving responds to higher elasticities of intertemporal substitution for different measures of risk aversion. For higher risk aversion coefficients there is a lower portfolio allocation to stocks, generating a lower expected return. Saving therefore responds differently to changing elasticities of intertemporal substitution depending on the expected rate of return and

therefore the risk aversion coefficient. The same intuition applies here since the constraint affects the expected return on equity (or average profits to equity) in two ways. First, the lower loan supply reduces profits. Second, the higher precautionary equity implies a lower average return on equity.

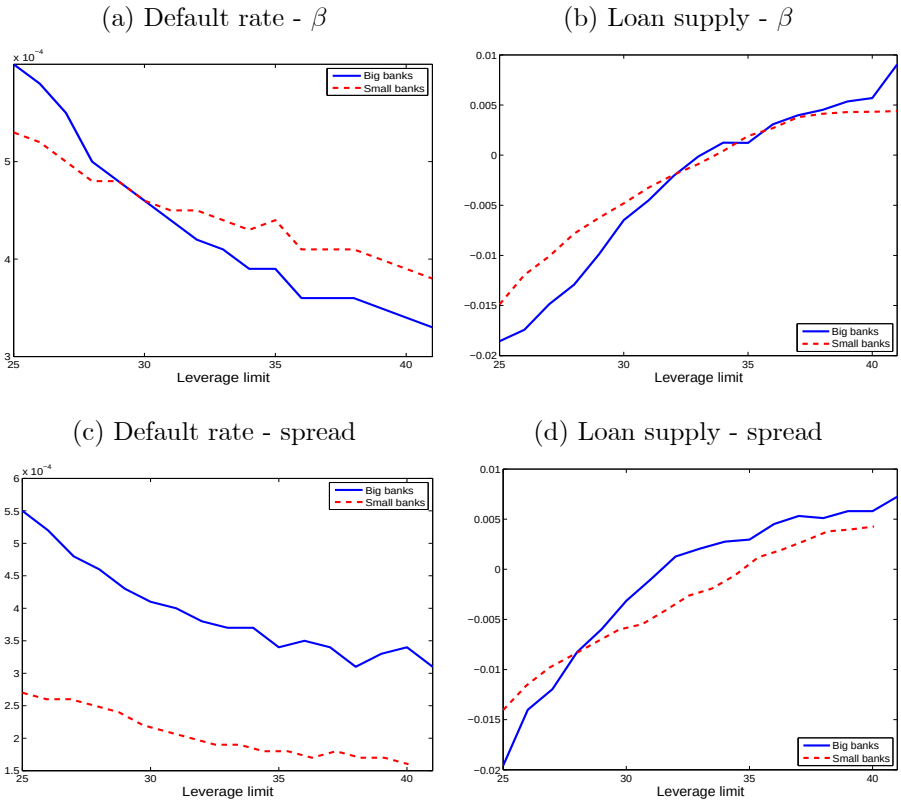
Note however, one important motivation for tighter leverage limits are the fiscal costs of bank bail-outs. Even though we do not model bail-outs directly, we can use our model to assess its implications. Bail-out costs depend on two quantities: first the failure rate and second the bailout costs conditional 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 16b. Thus, banks will have more equity capital left in the case of a failure which lowers the cost of third parties.

6.2 Robustness and discussion

In this section we first show that our results are robust to small perturbations in the estimated parameters. Then, we discuss some broader issues. In our robustness experiments, we change one parameter at a time, while keeping all other parameters at their respective baseline values. For brevity, we report only the effects on the default rate (left column) and on loan supply (right column) in Figure 17.

The first line shows the policy experiment when the discount factor β is increased by 0.2%. As in the baseline case, failures increase while loan supply decreases when the leverage constraint is tightened. This is also true in the second robustness check where we have increased the loan spread by 0.2%. Note that the effect is always bigger for larger banks

Figure 17: Robustness



This figure shows the result of perturbing the estimated parameters. All results are based on solving and simulating the model for the perturbed parameter while keeping all other parameters at their estimated values. Details of the solution and simulationn procedure can be found in the appendix. Panel (a) and (b) show the results for a higher discount factor. Panels (c) and (d) show the results of an increased loan spread.

because the return on equity changes more for them. Thus our results are robust towards small changes in our estimated parameters.[22]

One might worry that general equilibrium effects might overturn our result. In particular, the fall in loan supply might, in a general equilibrium setting, lead to an increase in the return on loans which would make banks more profitable and therefore might lead to less frequent defaults. However, the fall in loan supply is relatively small, never more than two percent. Therefore it is unlikely that a price effect will be big enough to increase the endogenous rate of return on equity. Of course, an extension to a full general equilibrium model is an important next step.

It is also unlikely that a different specification of the cost of wholesale borrowing would change the result. In our model, this cost is increasing in the amount of borrowing but is not derived from an endogenous zero profit condition on the side of the lenders. With a tighter leverage limit, bank failure becomes more likely, which would increase the cost of wholesale funds. Moreover, our result obtains for both small and big banks despite the difference in their reliance on wholesale borrowing.

Another simplification in our model is that we assume a constant outside option. If the value of the outside option was increasing in the amount of equity at the time of failure, our results would be strengthened because banks would opt to fail at higher equity levels.

7 Conclusion

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 estimate the

[22] We have also changed the coefficient of relative risk aversion to 1.1 with similar findings.

structural parameters of a quantitative banking model that includes choices of new loans, liquid investments and failure and are made in the presence of undiversifiable background risk (loan write-offs, interest rate spreads and deposit shocks) and regulatory constraints. The model replicates many features of the data and can therefore provide a useful approximation of reality to perform counterfactual experiments. We show that a tighter leverage limit can counter-intuitively lead to more bank failures since banks might not increase their equity holdings by a sufficient amount in response to tighter capital requirements. This is because the endogenous rate of return on equity falls, which, in an incomplete markets setting lowers the incentive to hold precautionary equity. Future work can extend the model to a general equilibrium environment to determine whether the results continue to hold. In addition, introducing a central bank as a lender of last resort and investigating the implications of different recapitalization mechanisms for various stakeholders and public policy is another interesting research avenue.

8 References

Abel, Andrew and Janice Eberly, 1994, "A Unified Model of Investment under Uncertainty," American Economic Review, 85: 1369-84.

Acharya, Viral V., Hanh Le and Hyun Song Shin, 2013, "Bank Capital and Dividend Exter-nalities," working paper.

Adda, Jerome and Russell Cooper, 2003, Dynamic Economics, MIT Press.

Admati, Anat and Martin Hellwig, 2013, The Bankers' New Clothes, Princeton University Press.

Adrian, Tobias and Hyun Song Shin, 2010, "Liquidity and Leverage," Journal of Financial Intermediation, 19(3), 418-437.

Aiyar, Shekhar, Charles W. Kalomiris, John Hooley, Yevgeniya Korniyenko and Tomasz Wieladek, 2014, "The international transmission of bank capital requirements: Evidence from the U.K." Journal of Financial Economics, 113, 368-382.

Allen, Franklin and Douglas Gale, 2004, "Financial Intermediaries and Markets," Econometrica, 72: 1023-61.

Allen, Franklin, Elena Carletti and Robert Marquez, 2011, "Credit Market Competition and Capital Regulation," Review of Financial Studies, 24, 983-1018.

Berger, Allen N. and Christa Bouwman, 2013, "How does capital affect bank performance during financial crises?" Journal of Financial Economics 109 (1), 146-176.

Berger, Allen N, Anil K. Kashyap and Joseph M. Scalise, 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, Ben S. and Alan S. Blinder, 1988, "Credit, Money, and Aggregate Demand," American Economic Review, 78(2), 435-439.

Bernanke, Ben S. and Alan S. Blinder, 1992, "The Federal Funds Rate and the Channels of Monetary Transmission," American Economic Review, 82(4), 901-921.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist, 1999, "The Financial Accelerator in a Quantitative Business Cycle Framework," in Handbook of Macroeconomics, J. B. Taylor and M. Woodford, ed., Vol. 1A, 1341-1393, North-Holland.

Besanko, David and George Kanatas, 1996, "The Regulation of Bank Capital: Do Capital Standards Promote Bank Safety?" Journal of Financial Intermediation, 5, 160-183.

Brunnermeier, Markus, 2009, "Deciphering the Liquidity and Credit Crunch," Journal of Economic Perspectives, 23, 1, 77-100.

Calomiris, Charles W. and Jason 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, Charles W., 2000, "U.S. Bank Deregulation in Historical Perspective," Cambridge University Press.

Campbell, John Y. and Luis M. Viceira, 1999, "Consumption and Portfolio Decisions When Expected Returns are Time Varying," Quarterly Journal of Economics, 114, 433-495.

Cetorelli, Nicola and Linda Goldberg, 2012, "Banking Globalization and Monetary Transmission," Journal of Finance, 67(5), 1811-1842.

Chen, Hui, 2010, "Macroeconomic Conditions and the Puzzles of Credit Spreads and Ca-pital Structure," Journal of Finance, 65(6), 2171-2212.

Corbae, Dean and Pablo D'Erasmo, 2011, "A Quantitative Model of Banking Industry

Dy-namics," Mimeo

Corbae, Dean and Pablo D'Erasmo, 2012, "Capital Requirements in a Quantitative Model of Banking Industry Dynamics," mimeo.

De Nicolo, Gianni, Andrea Gamba and Marcella Lucchetta, 2014, "Microprudential Regula-tion in a Dynamic Model of Banking," The Review of Financial Studies, 27(7), 2098-2138.

Diamond, Douglas W. and Philip H. Dybvig, 1983, "Bank runs, deposit insurance and li-quidity," Journal of Political Economy, 91(3): 401-419.

Duffie, Darrell, 2010, How Big Banks Fail and What to Do about It, Princeton University Press.

Freixas, Xavier and Jean-Charles Rochet, 2008, Microeconomics of Banking, MIT Press.

Gale, Douglas, 2010, "Capital Regulation and Risk Sharing", International Journal of Central Banking, pp. 187-204.

Gertler, Mark and Peter Karadi, 2011. "A Model of Unconventional Monetary Policy," Jour-nal of Monetary Economics, 58(1), 17.

Gertler, Mark and Nobuhiro Kiyotaki, 2010, "Financial Intermediation and Credit Policy in Business Cycle Analysis," in Handbook of Monetary Economics, B. M. Friedman and M. Woodford, ed., Vol. 3, pages 547-599, North-Holland.

Gomes, Francisco and Alexander Michaelides, 2005. "Optimal Life-Cycle Asset Alloca-tion: Understanding the Empirical Evidence," Journal of Finance, 60(2), 869-904.

Hennessy, Christopher A. and Toni M. Whited, 2005, "Debt Dynamics," Journal of Finance, 60: 1129-65.

Holod, Dmytro and Joe Peek, 2010, "Capital Constraints, Asymmetric Information and In-ternal Capital Markets in Banking: New Evidence," Journal of Money Credit and Banking, 42(5), 779-905.

Kashyap, Anil K., Jeremy C. Stein and David W. Wilcox, 1993, "Monetary Policy and Cre-dit Conditions: Evidence from the Composition of External Finance," American Economic Review, 83(1), 78–98.

Kashyap, Anil K. and Jeremy C. Stein, 2000, "What Do a Million Observations on Banks Say About the Transmission of Monetary Policy?" American Economic Review 90(3), 407-428.

Kiyotaki, Nobuhiro and John Moore, 1997, "Credit Cycles," Journal of Political Economy, 105(2), 211–248.

Kishan, Ruby P. and Timothy P. Opiela, 2000, "Bank size, bank capital, and the bank len-ding channel," Journal of Money, Credit and Banking, 32, 121–141.

Koehn, Michael, and Antony M. Santomero, 1980, "Regulation of Bank Capital and Portfolio Risk," Journal of Finance, 35, 1235-1250.

Mehran, Hamid and Anjan V. Thakor, 2011, "Bank Capital and Value in the Cross Section," Review of Financial Studies, 24(4), 1019-1067.

Miles, David, Jing Yang and Gilberto Marcheggiano, 2012, "Optimal Bank Capital," The Economic Journal, 1-37.

Myers, Stewart and Nicholas Majluf, 1984, "Corporate Financing and Investment Decisions when Firms Have Information that Investors Do Not Have," Journal of Financial Economics, 13, 187-221.

Oliner, Stephen D. and Glenn D. Rudebusch, 1996, "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance: Comment," American Economic Review, 86(1), 300–309.

Peek, Joe, and Eric S. Rosengren, 2000, "Collateral Damage: Effects of the Japanese bank crisis on real activity in the United States," American Economic Review, 90(1), 30-45.

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

Van den Heuvel, S. J., 2008, "The Welfare Cost of Bank Capital Requirements," Journal of Monetary Economics, 55: 298-320.

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 1989: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 890,252 quarterly observations corresponding to 17,226 different identification numbers of U.S. commercial banks. We drop 38,563 observations that have zero FDIC identification number and 4,313 observations due to missing values. We exclude the effect of exceptional growth in bank size (e.g. due to mergers and acquisitions or winding down of bank activities) by winsorizing at the 1st and 99th percentile of the sample

distribution of growth rates in customer loans and tangible assets at every quarter.[23] By this criterion we drop 25,292 outlier observations and also 22,647 observations due to missing values in growth rates. The final sample is a panel of 799,437 quarterly observations from 16,564 uniquely identified U.S. commercial banks.

The loan write-off ratio (the analog of w in the model) is calculated by dividing quarterly loan charge-offs by lagged gross loans, where the latter is defined as total loans plus quarterly charge-offs. Real deposit growth is calculated by taking the log difference in broad deposits, where the latter is defined as the sum of transaction and non-transaction deposits. In order to avoid the impact of outliers when estimating the exogenous processes for loan write-offs and real deposit growth, we winsorize their sample distributions at the 1st and 99th percentile every quarter, by bank size. The autoregressive processes for loan write-offs and deposit growth are estimated at the individual bank level, considering only banks with at least 35 observations in booms and 35 observations in recessions, i.e. at least 70 observations in total. For deposit growth in particular, the autoregressive process is estimated taking into account seasonal effects at a bank level by adding quarterly dummies. The model parameters that we consider for the autoregressive processes are the averages of the estimated ones across banks by size, after winsorizing them at the 1st and 99th percentile of their estimated sample distribution.

We also calculate first and second moments of balance sheet and profit and loss variables that we target for estimating the model using a Method of Simulated Moments. With respect to balance sheet variables, we consider the ratios of broad deposits, wholesale funding, liquid assets and tangible equity over tangible total assets, as well as the ratios of tangible total

[23] Tangible assets equal total assets minus intangible assets, such as goodwill.

assets and total loans over tangible equity, if the latter is strictly positive.[24] Regarding profit and loss variables, we consider the ratios of quarterly profits (before tax, extraordinary items and other adjustments) and dividends over tangible equity. In order to derive targeted moments for these ratios, we first winsorize the ratios at the 1st and 99th percentile of their sample distribution every quarter, by bank size. Moments of ratios are calculated at an individual bank level by considering only banks with at least 20 observations in booms and equally in recessions, i.e. at least 40 observations in total. For the Method of Simulated Moments estimation we use average moments across banks, as well as the standard deviations around these averages for weighting purposes.

The same approach as for targeted moments of ratios is used for estimating average real return on loans, liquid-asset returns and deposits rates from individual bank data. For loan returns we use the ratio of quarterly interest income on loans over lagged loans. For liquid-asset returns we use the ratio of quarterly interest income on Fed funds sold and reverse repo plus gains or losses on securities over lagged liquid assets. For deposit rates we use the ratio of quarterly interest expense on deposits over lagged deposits.

To calculate the fraction of loans that are repaid every quarter (the analog of ϑ in the model), we use one fourth of the ratio of loans that mature in less than 1 year divided by total loans outstanding. The resulting average estimate is 7% which assumes both a uniform repayment rate over time and that banks cannot take action to scale down their existing loans before maturity, e.g. by outright loan sales, or securitization. It also assumes no difference in the ability of small and large banks to delever, e.g. due to different access to loan sales and securitization technology.

[24] Tangible equity equals tangible assets minus total liabilities.

We have also identify 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.[25] For the first half of the period (i.e. 1990Q1-2000Q3), names of failed banks were obtained manually from FDIC reports.[26] 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 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 equatioans 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 $\Gamma_{t+1} = \frac{D_{t+1}}{D_t}$.

[25] Available at http://www.fdic.gov/bank/individual/failed/banklist.html.
[26] Available at http://www.fdic.gov/bank/historical/bank/1991/index.html.

The leverage limit (2) becomes

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

The equity evolution (1) becomes

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

Profits (4) become

$$\pi_{i,t+1} = \frac{(r_{L,t+1} - w_{i,t+1})l_{it} + n_{it} + r_{S,t+1}s_{it} - r_{D,t+1} - g_N(n_{it}) - g_F(f_{it}) - c}{\Gamma_{t+1}}. \tag{10}$$

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 six 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 the normalized value function. 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 prefered 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.[27]

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

   (a) if $\widetilde{v}(l, e, w, r, g)$ 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 $\widetilde{v}(l, e, w, r, g)$ 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.

11. Each bank startes 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 $l_{t+1} = (1 - \vartheta - w_{t+1}) l_t + n_t$.

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

12. A bank that fails during the simulation is replaced by a new one which starts with mean equity and mean loans. However, due to the very low number of defaults, this choice has no influence on aggregate statistics.

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 squarred differences betwenn model and data moments are calculated.

    (b) These are weighted by the efficient weighting matrix which uses the standard deviations of the empirical moements.

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.