A Dynamic Model of Heterogeneous Banks with Uninsurable Risks and Capital Requirements*

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Abstract

We estimate the structural parameters of a quantitative banking model featuring maturity transformation, financial frictions and endogenous failures with undiversifiable background risks and capital requirements. Tighter risk-weighted capital requirements reduce loan supply since banks substitute high risk-weighted loans with low risk-weighted liquid assets. This leads to an endogenous fall in the expected return on equity, causing banks to hold less equity in excess of capital requirements and fail more often. Tighter leverage requirements, on the other hand, increase lending because high-yielding loans start dominating low risk-weighted liquid assets, leaving the expected return on equity, and therefore, bank failures relatively unchanged.

JEL Classification: E44, G21, G38

Key Words: Banking, Uninsurable Risk, Capital Requirements, Bank Failures.

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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 inform policy making.

Given the need for such applied, quantitative models, we construct a dynamic structural model of bank lending behavior and capital structure choices with the following features. Banks transform short-term liabilities into long-term loans (a maturity transformation function) and premature liquidation of loans is costly, in the spirit of Diamond and Dybvig (1983), Gorton and Pennacchi (1990), Diamond and Rajan (2001), and Holmström and Tirole (1998). One key departure from Modigliani-Miller (MM) arises because banks are run by managers maximizing bank charter value, defined as the utility from consuming current and future dividends accruing to shareholders for as long as the bank remains a going concern. Another departure from MM is the existence of deposit insurance, implying that depositors do not respond to bank riskiness. Banks also operate in an incomplete markets setup in the spirit of Allen and Gale (2004) and face uninsurable background risks in funding conditions and asset quality. Banks raise equity capital only internally through retained earnings while

[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.

we abstract from seasoned equity issuance.[4]

In such an environment the limited liability option of bank shareholders may lead to incentives to shift risks to creditors and to the deposit insurance fund. Especially for banks whose charter value is low, excessive risk taking in good times could lead to high losses when the cycle turns, as documented in Beltratti and Stulz (2012) and Fahlenbrach and Stulz (2011).[5] Bank capital regulation exists to contain excessive risk-taking and limit potential losses to the deposit insurance fund.[6]

Using U.S. individual commercial bank data, we first establish empirical regularities similar to the ones emphasized in, for instance, Kashyap and Stein (2000) and Berger and Bouwman (2013), who also use disaggregated data to understand bank behavior. We complement their approach by building a quantitative structural model to replicate the cross-sectional and the time series evolution of bank financial statements. We consider a relatively rich balance sheet structure where illiquid loans and liquid assets are funded by short-term insured deposits, unsecured wholesale funds and equity.

To perform counterfactual experiments, the quantitative model is estimated using a Method of Simulated Moments, as in Hennessy and Whited (2005). The model replicates the wide range of cross-sectional heterogeneity in bank financial ratios through the endo-

[4]Banks' limited access to equity markets could be due to a debt overhang problem as in Myers (1977) and Hanson, Kashyap and Stein (2011). It could also be due to adverse selection problems à 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 as discussed in Duffie (2010).

[5]Fahlenbrach and Stulz (2011) also find evidence that better alignment of incentives between bank managers and shareholders implies worse performance during the crisis, supporting the idea of risk-shifting moral hazard due to limited liability.

[6]Jimenez, Ongena, Peydro and Saurina (2014) also show that banks with less "capital in the game" are susceptible to excessive risk-taking.

genous response to idiosyncratic risks emanating from deposit flows and loan write-offs, as well as the motive to hedge liquidity risk arising from maturity transformation. Consistent with the data, smaller banks are estimated to face a higher cost of accessing the wholesale funding market and therefore rely more heavily on deposit funding. Small banks also are also estimated to have a more concave objective function associated with more severe financial frictions (Hennessy and Whited (2007)). Larger banks, on the other hand, are more highly levered due to the additional flexibility provided by easier access to wholesale funding.

Loan growth is strongly procyclical and peaks at the onset of expansions leading to an increase in leverage during the first few quarters of an expansion, consistent with Adrian and Shin (2010, 2014). However, over the course of the expansion, banks retain part of their higher earnings to replenish their equity, leading to a reduction in leverage, as in He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014). During recessions, banks curtail new lending and shrink their balance sheets, reducing reliance on wholesale funding. The model also generates strongly countercyclical bank failures induced by a deterioration in asset quality and the associated reduction in the bank charter value. Consistent with the empirical results in Berger and Bouwman (2013), banks that fail tend to have higher (lower) average leverage (equity capital) than surviving banks, regardless of size.

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. We assume that regulatory intervention takes the form of a prudential limit on bank leverage (henceforth, the leverage requirement), measured as the ratio of total assets to equity. In addition to the leverage constraint, banks face regulatory restrictions with respect to the ratio of risk-weighted assets to equity (henceforth, the capital adequacy requirement), a proxy for Tier 1 capital ratio.

Tighter capital requirements could increase bank resilience to shocks and reduce the likelihood of bank failure.[7] On the other hand, tighter capital requirements reduce financial flexibility. Lower flexibility might increase the likelihood of bank failure by either reducing bank charter value or increasing the likelihood of breaching a tighter limit, or both.[8] Therefore, setting capital requirements at an appropriate level is a balancing act, as shown by Freixas and Rochet (2008), Van den Heuvel (2008) and De Nicolo, Gamba and Lucchetta (2014).

In the model, banks respond to tighter capital adequacy requirements by accumulating more equity and lowering loan issuance consistent with the empirical findings in Aiyar et al. (2014) and Behn et al. (2015). When capital adequacy requirements get too tight, bank charter value and equity buffers relative to the regulatory minimum fall, leading to an increase in bank failures.[9] However, for a given capital adequacy requirement, a tighter leverage restriction induces banks to increase lending, in line with Miles, Yang and Marcheggiano (2012) and Admati and Hellwig (2013), while bank failures remain relatively unchanged.

What is the intuition behind the differential impact of tightening the two constraints? At the optimum, banks are indifferent between holding an extra unit of higher-yielding (yet high risk-weighted) loans or low risk-weighted (yet lower-yielding) liquid assets. A tighter

[7] 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)).

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

[9] Gale (2010) uses general equilibrium arguments to question the same conventional wisdom that higher capital requirements reduce failures. We show that even in a partial equilibrium model this conventional wisdom can be questioned.

capital adequacy ratio induces a substitution of high risk-weighted loans with liquid assets, leading to an endogenous fall in the expected return on assets. Banks also respond to the tighter constraint by increasing equity. As a result, a tighter capital adequacy ratio lowers the expected return on equity, thereby weakening bank incentives to accumulate equity. Therefore, banks increase equity by less than the increase in the capital requirement, making failure more likely.[10]

On the other hand, by tightening the leverage constraint – which does not discriminate between the two types of assets – the capital adequacy constraint becomes less important. As a result, loans start dominating liquid assets, since lower risk weights matter less for bank asset choices, leading to an increase in loan supply. Tighter leverage requirements keep the expected return on equity relatively intact because the induced asset reallocation towards loans increases profitability, counteracting the increase in equity. Therefore, banks increase equity in proportion to the tighter constraint, leading to relatively unchanged failure rates, especially for large banks.

Our findings complement the recent literature emphasizing the link between asset and liability structure. In the presence of uncertain but relatively "sleepy" deposits and differential (by bank size) costs of accessing wholesale funding markets, banks lever up and invest in illiquid long-term loans and liquid assets to maximize their charter value while managing background risks (DeAngelo and Stulz (2015) and Hanson, Shleifer, Stein and

[10]This behavior shares similarities with savings decisions 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 (positive or negative) response of saving to changes in the intertemporal elasticity of substitution.

Vishny (2015)).

We depart from the previous literature (for example, Van den Heuvel (2007), De Nicolo, Gamba and Lucchetta (2014)) by analyzing a richer balance sheet structure. In our model, wholesale funding and liquid assets coexist, with substantial cross-sectional heterogeneity arising from background risks and bank choices. Repullo and Suarez (2013) analyze capital regulation in a dynamic model where precautionary equity buffers arise from asymmetric information stemming from relationship lending and associated costly equity issuance. We differ by generating precautionary equity buffers through the presence of background idiosyncratic risks. Corbae and D'Erasmo (2011 and 2012) build a dynamic model of banking to investigate optimal capital requirements in a general equilibrium model featuring strategic interaction between a dominant big bank and a competitive fringe. We differ by emphasizing the maturity transformation role of banks and by analyzing the implications of a richer balance sheet structure.

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 changing capital requirements 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. Following Kashyap and Stein (2000), we categorize banks in three size categories (small, medium and large) for every quarter. 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 and variable definitions is given in the Data Appendix.

2.1 Cross-sectional Statistics

Table 1 shows descriptive statistics for bank balance sheet compositions at the end of 2010, sorted by bank size.[11] Deposits are the major item on the liability side of all commercial banks. Smaller banks rely more on deposits (85 percent of total assets) than the largest banks (68 percent). Larger banks tend to have more access to alternative funding sources like Fed funds, repos and other instruments in the wholesale funding market. Figure 1 confirms that these differences persist and are both economically and statistically different across bank sizes over the 1990-2010 period. We use these differences in deposit and wholesale funding reliance as a defining variation between large and small banks in the structural model.

Figure 2 shows the evolution of the asset side of the balance sheets. The biggest components are loans that represent around 60% of total assets for both small and large banks. The

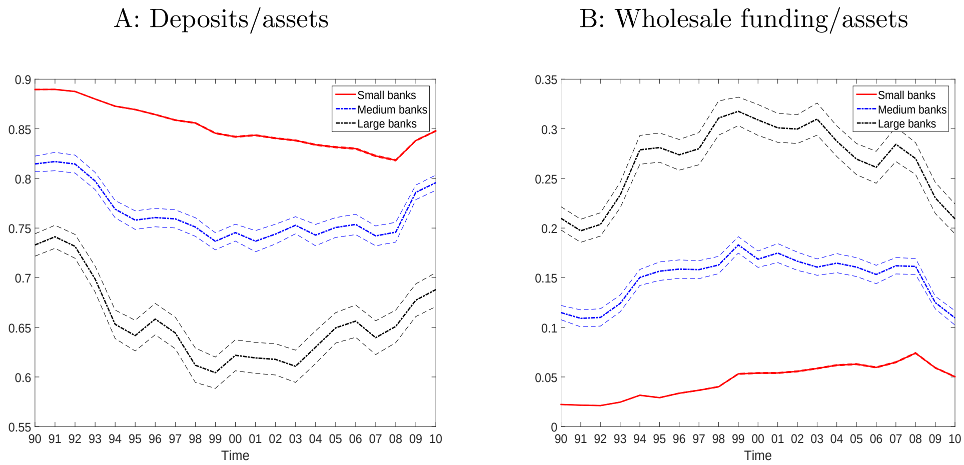
[11] The significant reduction in the number of banks over the sample period was mainly a result of regulatory changes that led to substantial consolidation in U.S. commercial banking. According to Calomiris and Ramirez (2004), branch banking restrictions and protectionism towards unit banks (i.e. one-town, one-bank) led to a plethora of small U.S. commercial banks over the last century. 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	95th - 98th	>98th
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 summary statistics and balance sheet information of U.S. commercial banks in the last quarter of 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 95th-98th percentile. Large banks belong to the top two percentiles.

largest remaining asset class is liquid assets, which comprise cash, Fed funds lent, reverse repos and securities. Liquid assets, as a proportion of total assets, remain higher on average for small banks throughout the sample period, consistent with Kashyap and Stein (2000).

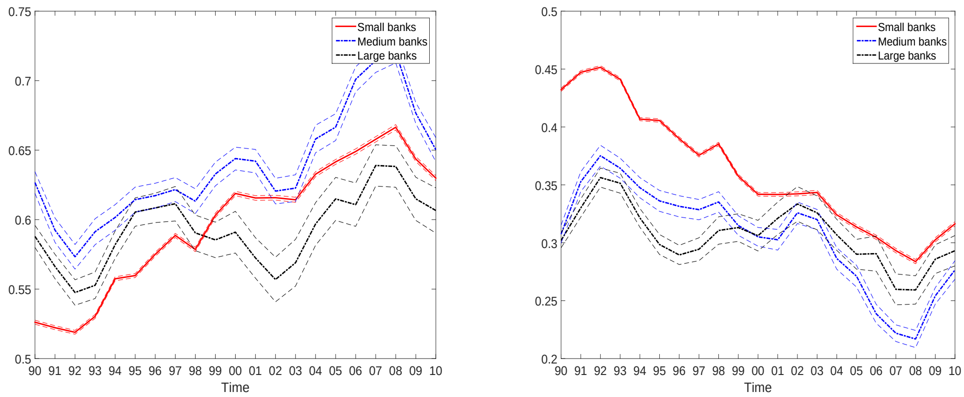
Another variable of interest is bank leverage (tangible assets divided by tangible equity),[12] shown in Figure 3. Small banks are consistently less leveraged than large banks with the exception of the recent crisis (Figure 3A).[13] Figure 3B shows the average leverage of failed and non-failed banks over the 10-year period prior to failure, where the x-axis is the time to failure in quarters. For banks that eventually fail, leverage is consistently higher prior to failure relative to non-failed banks, and increases sharply as they approach failure, consistent

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

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

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

A: Loans/assets B: Liquid assets/(total) assets



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 95th-98th percentile. Large banks belong to the top two percentiles.

with the empirical findings in Berger and Bouwman (2013).

2.2 Aggregate and Idiosyncratic Uncertainty

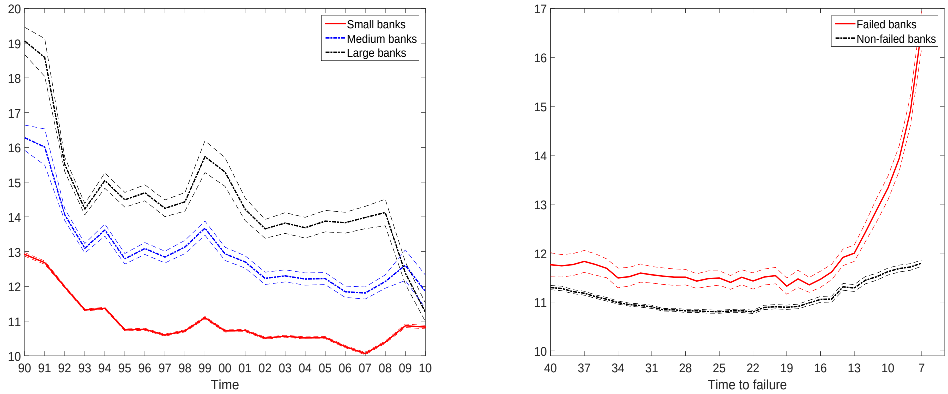
We use the data to constrain the data generating processes of the exogenous uncertainty banks face. Banks in the model are subject to aggregate uncertainty and uninsurable idiosyncratic shocks stemming from deposit growth and loan write-offs. The idea will be to use these processes as empirically relevant exogenous inputs to the structural model.

2.2.1 Uninsurable risks

To capture uninsurable risks from deposit growth and loan write-offs, we examine the time-series statistical properties of these processes individually for each bank over a twenty-

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 95th-98th percentile. Large banks belong to the top two percentiles. Panel B shows the 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.

year period (84 quarters). We concentrate on the first and second moments and the persistence of these risks, conditional on an expansion or a recession state,[14] and on bank size.

Table 2 reports statistics for loan write-offs, deposit growth and bank failure rates. In unreported tests we reject the hypothesis that log deposits follow a stationary process. We therefore analyze the behavior of the growth rate in individual bank deposits and find that the persistence of real deposit growth is around zero over both states (expansions and recessions) and bank sizes (small and large). Moreover, even after conditioning on the aggregate state of the economy, individual bank heterogeneity remains pervasive, as illustrated by the large standard deviation of deposit growth rates.

[14] 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 well after the official recession end date.

Table 2: Time-series statistics of key variables.

Parameter (% except AR(1))	Small banks			Large banks		
	Uncon	Rec	Exp	Uncon	Rec	Exp
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: s.d.	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: s.d.	3.71	3.50	3.48	5.64	5.31	5.41
Deposit rate	-0.46	-0.34	-0.51	-0.55	-0.48	-0.58
Loan spread	1.83	1.72	1.87	1.84	1.68	1.89
Liquid asset spread	0.81	0.42	0.92	0.96	0.56	1.07
Bank failure rate	0.05	0.17	0.01	0.08	0.18	0.01

This table shows the estimation results for the mean, standard deviation and persistence across different variables of interest that capture bank heterogeneity. It also shows expected real rates of return on deposits as well as loan and liquid asset spreads relative to the deposit rate. Small banks are those below the 95th percentile in the distribution of total assets and large are those above the 98th percentile. Uncon is the unconditional statistic, whereas Rec and Exp denote the statistics conditional on being in a recession, or an expansion, respectively. All statistics are computed at the individual level over time and then averaged across banks at a quarterly frequency (not annualized), and deposit growth is deseasonalized as described in the data appendix.

On the other hand, the idiosyncratic component of the loan write-off process follows a stationary process and we observe that the persistence is higher for large (0.72) than for small banks (0.21). Moreover, the persistence is slightly higher in recessions than in expansions. The standard deviation of loan write-offs is also higher in recessions and is higher for larger banks.

2.2.2 Rates and loan growth

For each bank we use the profit and loss statements from individual Call Reports to derive expected real rates of return on deposits, and liquid asset and loan spreads (relative to the deposit rate). We find that loan growth is procyclical: the contemporaneous correlation between average loan growth and loan write-offs (proxying for recessions) is -0.75 and statistically significant. Table 2 also reports mean loan and liquid asset spreads and the countercyclical behavior of bank failures.

2.3 Summary

In the cross-section, there is a significant degree of heterogeneity. Larger banks rely less on deposits, more on wholesale funding and tend to be more leveraged. Moreover, banks that fail tend to have more leveraged balance sheets ahead of failure. Further cross-sectional heterogeneity exists within each size class with respect to the loan write-off process and deposit growth rate. In the time series, real loan growth is procyclical, whereas loan write-offs and bank failures are countercyclical. We next build a structural model to replicate quantitatively these stylized facts.

3 The Model

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 shareholder utility and have limited liability.

Banks invest in illiquid loans (L) and liquid assets (S) and fund their assets through insured deposits (D), uninsured wholesale funding (F) and equity capital (E). We consider interest income from relatively illiquid loans and liquid assets as the key driver of decisions by commercial banks. A stylized balance sheet is shown in Table 3, which also reports the real rate of return on each asset and liability class.

The continuous state variables are balance sheet variables: loans (L_t), deposits (D_t),

Table 3: Bank balance sheet in the model

Assets		*Liabilities*	
Loans L_t	r_{Lt+1}	Deposits D_t	r_{Dt+1}
Liquid assets S_t	r_{St+1}	Wholesale funding F_t	r_{Ft+1}
		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 with associated rates of return.

and equity (E_t); the various returns ($\mathbf{r}_t$)[15] and loan write-offs (w_t). 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 and the adjustment costs for new loans ($g_N(N_t, D_t)$) are incurred. At this stage, regulatory capital requirements must be respected and the balance sheet constraint holds:

$$L_t + N_t + S_t = D_t + F_t + E_t - X_t - g_N(N_t, D_t) \tag{1}$$

At the beginning of the next period the exogenous shocks (returns, deposit shocks and loan write-offs) are realized. The bank decides whether to continue or exit at that stage based on a constant outside option that is specified in Section 3.5.

3.1 Asset Side of the Balance Sheet

Consistent with the maturity transformation role of banks,[16] we assume that loans (L_t) are long-term and funded through deposits, wholesale funding and equity capital. To capture the extent of maturity mismatch, we assume that a fraction of outstanding loans (ϑ) gets repaid every period. This generates an exogenous deleveraging process, which we calibrate

[15] In bold to denote a vector of returns.

[16] We suppress the i-subscript for banks, but all bank-specific variables must be understood to have an i-subscript.

to the data. At the same time, in every period the bank issues new loans (N_t) which can be negative, capturing the possibility of premature liquidation taking place at an additional cost proportional to N_t.

The interest earned on outstanding loans equals ($r_{Lt} - w_t$) where r_{Lt} is the real return on loans and w_t measures the proportion of loans that are written off. The evolution of loans is given by:

$$L_{t+1} = (1 - \vartheta - w_{t+1}) L_t + N_t. \tag{2}$$

Banks are identical ex ante but heterogeneous ex post in that they face undiversifiable background risks. One source of risk is the persistent loan write-off process whose moments depend on the state of the business cycle (b):

$$w_{t+1} = \mu_b + \rho_b w_t + \sigma_{b\varepsilon}\varepsilon_{t+1} \tag{3}$$

where $\varepsilon_{t+1} \sim N(0,1)$. The business cycle follows a two-state Markov process (expansion or recession). Consistent with the data, loan write-offs have a higher mean (μ_b), persistence (ρ_b) and variance of the shocks ($\sigma^2_{b\varepsilon}$) during recessions than during expansions, reflecting the fact that uncertainty rises during recessions.

To avoid a very volatile loan process, we assume adjustment costs for new loans. 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 are stretched over more projects or because the quality of additional projects declines. We also assume that the cost function is homogeneous of degree one in deposits because the model is non-stationary in deposits.[17] Thus, the resulting cost function is

$$g_N(N_t, D_t) = \mathcal{I}_{N_t>0}\phi_N \frac{N_t^2}{D_t} + (1 - \mathcal{I}_{N_t>0})\psi\phi_N \frac{N_t^2}{D_t} \tag{4}$$

where $\mathcal{I}_{N_t>0}$ is an indicator function that is one when new loans are positive, ϕ_N determines the intensity of the cost, and $\psi > 1$ captures costly loan liquidation.

In addition to investing in loans, banks can also invest in liquid assets that are always non-negative. The return on liquid assets (r_{St}) is stochastic and varies with the business cycle.

3.2 Liability Side of the Balance Sheet

Equity is accumulated retained earnings over time, after dividends (X_t) and loan adjustment costs ($g_N(N_t, D_t)$) have been paid. Corporate taxes (τ) are paid on positive profits Π_{t+1} generating after-tax profits $(1-\tau)\Pi_{t+1}$. Negative profits on the other hand are not taxed:

$$E_{t+1} = E_t + (1-\tau)\Pi_{t+1}\mathcal{I}_{\Pi_{t+1}>0} + \Pi_{t+1}(1 - \mathcal{I}_{\Pi_{t+1}>0}) - X_t - g_N(N_t, D_t) \tag{5}$$

where $\mathcal{I}_{\Pi_{t+1}>0}$ is an indicator function that is one when profits are positive. The main liability class is deposits (D_t). Funding risk through deposit flows is the second background risk that generates ex post heterogeneity. Conditional on the aggregate state, the idiosyncratic deposit

[17] This assumption is common in the investment literature (Abel and Eberly (1994)).

growth rate follows an i.i.d. process whose mean and variance depend on the state of the business cycle (b), consistent with the data:

$$\log\left(\frac{D_{it+1}}{D_{it}}\right) \sim N(\mu_{bD}, \sigma^2_{bD}). \tag{6}$$

In addition to equity and deposit funding, banks also finance their assets through unsecured wholesale funding (F_t). We assume that the cost of accessing wholesale funding decreases with equity but increases with higher exposure to the wholesale funding market to capture counterparty risk. Similar to the new loans issuance specification, we assume a convex function that scales up with deposits:

$$g_F(F_t, D_t, E_t) = r_{Ft+1}F_t + \phi_F\frac{F_t^2}{D_t} - \phi_E\frac{E_t^2}{D_t}. \tag{7}$$

3.3 Profits

The profits attributable to shareholders are

$$\Pi_{t+1} = (r_{L,t+1} - w_{t+1})L_t + r_{L,t+1}N_t\mathcal{I}_{N_t>0} + r_{S,t+1}S_t - r_{D,t+1}D_t - g_F(F_t, D_t, E_t) - cD_t \tag{8}$$

where $(r_{L,t+1} - w_{t+1})L_t$ is the interest income on existing loans, net of write-offs. We assume that if new loans are positive ($\mathcal{I}_{n_t>0}$) they earn interest income without experiencing any immediate loss ($r_{L,t+1}N_t\mathcal{I}_{n_t>0}$). The next term ($r_{S,t+1}S_t$) reflects income from holding liquid assets, and we subtract the cost from servicing deposits ($r_{D,t+1}D_t$). The cost of accessing the wholesale funding market is denoted by $g_F(F_t, D_t, E_t)$ and the non-interest expense associated with operating the bank is proportional to deposits (cD_t). This term captures various operating expenses, including overhead costs and the FDIC surcharge to fund deposit insurance.

3.4 Capital Requirements

Banks are subject to two regulatory capital requirements. The first is the capital adequacy constraint, which consists of a maximum ratio of risk-weighted assets to equity, captured by parameter λ_w:

$$\frac{\omega_L(L_t + N_t) + \omega_S S_t}{E_t - X_t - g_N\left(N_t, D_t\right)} \leq \lambda_w. \tag{9}$$

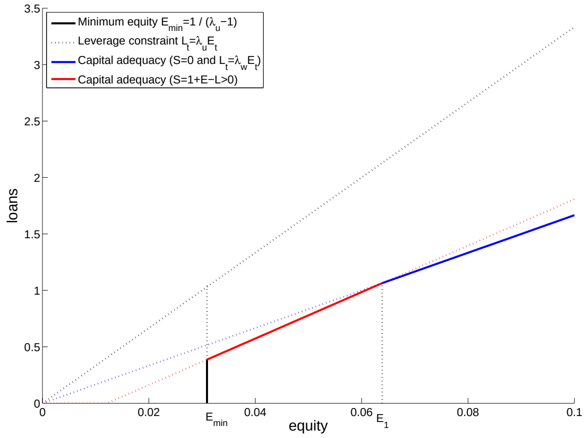
The numerator in (9) represents risk-weighted assets after new loans (N_t) and liquid assets (S_t) have been chosen. The denominator is equity (E_t) after dividends (X_t) and loan adjustment costs (g_N). The risk weight on loans ω_L is higher than the risk weight on liquid assets ω_S in line with the standardized approach of Basel II and FDIC regulations.

The second regulatory capital requirement consists of a plain (unweighted) leverage ratio of total assets (loans plus liquid assets) to equity. This leverage requirement is consistent with FDIC regulations and is captured by λ_u:

$$\frac{L_t + N_t + S_t}{E_t - X_t - g_N\left(N_t, D_t\right)} \leq \lambda_u. \tag{10}$$

Normalizing deposits to one, Figure (4) shows the regions where a bank remains a going concern and therefore how the two capital requirements can constrain loan choices as a

Figure 4: The two regulatory capital requirements



The figure shows how the two capital requirements can constrain loan choices as a function of equity. Normalizing deposits to one, the binding leverage constraint implies minimum equity $E_{min} = 1/(\lambda_u - 1)$. The maximum allowed loans increase linearly with equity with slope λ_u. The binding capital adequacy constraint with no liquid assets corresponds to the line with the lowest slope λ_w starting from the origin. For low levels of loans, liquid assets are included in the balance sheet $S = 1 + E - L$, the capital adequacy constraint shifts to the right of the origin and increases with a steeper slope $(\lambda_w - \omega_S)/(\omega_L - \omega_S)$. Only combinations of equity and loans below and to the right of the solid lines satisfy all constraints.

function of equity. The combination of loans and equity where both constraints are satisfied are to the right of the solid lines. For a given level of deposits, the leverage constraint implies a minimum equity level $E_{\min} = \frac{1}{\lambda_u - 1}$ below which a bank fails (vertical line at $E_{\min}$). For equity levels between $E_{\min}$ and E_1 liquid assets are positive and the capital adequacy constraint dominates. For equity levels higher than E_1, liquid assets hit the binding constraint at zero and the slope of the capital adequacy constraint flattens since the bank only holds loans.

Figure (4) shows that both constraints affect bank decisions but their relative importance changes depending on the state space. The minimum equity requirement is crucial for banks with low equity, whereas the capital adequacy constraint matters at higher levels of equity. However, even if a bank starts at an equity level where the capital adequacy constraint matters more, loan losses during bad times might deplete equity to a point where the minimum equity level becomes more relevant.

3.5 Entry and Exit

In the model a bank enters each period with a given level of equity. If equity is low enough that even with zero dividends any of the two regulatory capital requirements is violated, the bank is closed down by the regulators. A second type of failure occurs if, to meet its capital requirements, the bank has to pay out such low dividends that the banker prefers to exit and get an outside option. Such an outside option is defined as a constant flow of consumption C^D yielding a level of utility V^D.[18] However, if equity is high enough, the bank is able to pay out a sufficient amount of dividends and continue its operations for another period. In the simulation, whenever a bank exits we exogenously add another bank that takes over the deposits of the failed bank, starting at a good idiosyncratic state, i.e. low loan losses.

3.6 Objective and Value Functions

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

$$V = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{{X_t}^{1-\gamma}}{1-\gamma} \tag{11}$$

where $\mathbb{E}_0$ denotes the conditional expectation given information at time 0. Following Hennessy and Whited (2007), the objective function is concave to capture the magnitude of

[18]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 value V^D is given by $V^D = \frac{1}{1-\beta}\frac{(C^D)^{1-\gamma}}{1-\gamma}$.

financial frictions, such as bankruptcy costs or dividend taxes. This concavity also captures the idea that banks (like other firms) smooth dividends over time, as suggested by empirical evidence in Acharya, Le and Shin (2013).

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:

$$V^C\left(L_t, D_t, E_t; w_t, \mathbf{r}_t\right) = \max_{X_t, S_t, F_t, N_t} \left\{ \frac{\left(X_t\right)^{1-\gamma}}{1-\gamma} + \right. \tag{12}$$

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

where the last term is defined as the upper envelope:

$$V\left(L_t, D_t, E_t; w_t, \mathbf{r}_t\right) = \max[V^D, V^C\left(L_t, D_t, E_t; w_t, \mathbf{r}_t\right)] \tag{13}$$

subject to the balance sheet constraint (1), the evolution of the loan stock (2), the equity evolution equation (5), profits (8) and the regulatory capital constraints (9) and (10).

The bank first decides whether to continue operating or to exit. If the bank continues, it chooses optimally the level of dividends X_t, the amount of new loans N_t, how much liquid assets S_t to hold and the level of wholesale funding F_t.

4 Estimation

In this section we first discuss the normalization needed to make the model stationary. Then we discuss the calibration choices. Lastly, we show the results from the Method of

Simulated Moments estimation.

4.1 Normalization

The estimated process for deposits contains a unit root. To render the model stationary, we normalize all variables by deposits (D_t). For example, equity (E_t) is transformed into $e_t \equiv \frac{E_t}{D_t}$. For this transformation to work, all profit and cost functions have to be homogenous of degree one in deposits. Details of these transformations are shown in the solution appendix.

4.2 Calibration

The model features aggregate and idiosyncratic uncertainty. We choose the transition probabilities for the aggregate state to obtain recessions that last for eight quarters on average and expansions that last for 20 quarters on average. Idiosyncratic uncertainty depends on the aggregate state and is captured by two different variables: loan write-offs and the deposit growth rate. We use the estimated moments (means and standard deviations) and the persistence parameters reported in Table 2 as exogenous inputs. Note that these are conditional on an expansion or a recession and are also conditional on bank size (small versus large). Table 2 also shows the expected real return on deposits and loan and liquid asset spreads. The fraction of loans (ϑ) that are repaid every quarter is 6% (8%) for large (small) banks. The corporate tax rate (τ) is set to 15%.

Regarding capital requirements, the FDIC initiates an enforcement action when a bank is deemed to be undercapitalized, significantly undercapitalized, or critically undercapitalized. The extent of undercapitalization is determined by the (risk-weighted) capital adequacy requirement and the (unweighted) leverage requirement. Once a bank is deemed to belong in any of the three categories, an enforcement action is initiated and the bank faces restrictions on dividend payouts, and asset growth and also needs to submit a capital restoration plan. Given the breadth and complexity of possible enforcement actions, we make the simplifying assumption that a bank fails if it is deemed significantly undercapitalized. The FDIC rules and regulations (that hold over most of our sample period) define as significantly undercapitalized banks those with a risk-weighted capital ratio less than 6.0% and (inverse) leverage ratio less than 3.0%.[19] These numbers imply that their model counterparts are $\lambda_w = 16.66$ and $\lambda_u = 33.33$. The risk weights for the capital adequacy requirement are $\omega_L = 1$ for loans and $\omega_S = 0.2$ for liquid assets.

4.3 Baseline Results

There are seven 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, the reduction in cost from accessing wholesale funding when bank equity is higher ϕ_E, 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 11 moment conditions. We use the standard deviations 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 parameters and Table 5 shows the estimated moments

[19] More details can be found at https://www.fdic.gov/regulations/laws/rules/2000-4500.html#fdic2000part325103.

and their empirical counterparts for both large and small banks. One important difference between large and small banks is the cost of accessing wholesale funding; the estimated ϕ_F is almost ten times lower for large than small banks. This leads to a significantly lower role of deposits as a funding source for large banks (Table 5).

Table 4: Estimated parameters using the Method of Simulated Moments.

Parameter	Large banks	Small banks
Premium accessing wholesale funding ϕ_F	0.0092 (0.0023)	0.081 (0.00293)
Discount accessing wholesale funding ϕ_E	0.07 (0.0036)	0.007 (0.0014)
Discount factor β	0.975 (0.0041)	0.986 (0.0115)
CRRA γ	1.31 (0.0042)	1.89 (0.0056)
Consumption after bank failure c^D	2e-5 (3.8e-4)	4e-5 (8.4e-4)
Operating cost c	0.011 (0.0023)	0.0096 (0.0012)
Screening cost new loans ϕ_N	0.63 (0.0037)	0.90 (0.0035)

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.

Large banks have a higher rate of time preference and a less concave objective function than small banks generating a higher standard deviation of dividends to equity. A smaller degree of concavity in the objective function of large banks is interpreted as large banks facing less severe financial frictions compared to small banks. The mean failure rate is matched mainly through the consumption after failure parameter. Similarly, the mean loan to asset ratio is matched by the cost of screening new loans.

For both large and small banks the model underpredicts mean equity holdings, slightly underpredicts the mean profit to equity ratio but matches the mean dividend to equity ratio. The model also closely matches second moments of key ratios with the exception of the standard deviations of the loan to asset ratio and the dividend to equity ratio.

Table 5: Model and Data Moments.

	Large banks		Small banks	
Moments	model	data	model	data
Mean failure rate (in %)	0.092	0.084	0.051	0.050
Mean loans/assets	0.704	0.665	0.626	0.622
Mean deposits/assets	0.638	0.633	0.891	0.857
Mean equity/assets	0.065	0.072	0.067	0.099
Mean profit/equity	0.055	0.063	0.029	0.037
Mean dividends/equity	0.029	0.028	0.012	0.013
Std. loans/assets	0.100	0.076	0.050	0.082
Std. deposits/assets	0.062	0.086	0.021	0.035
Std. equity/assets	0.013	0.013	0.015	0.014
Std. profit/equity	0.035	0.048	0.024	0.024
Std. dividends/equity	0.011	0.034	0.007	0.016

This table shows the results of the method of simulated moments estimations of our benchmark model and the corresponding data moments for small and large banks separately at a quarterly frequency. 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.

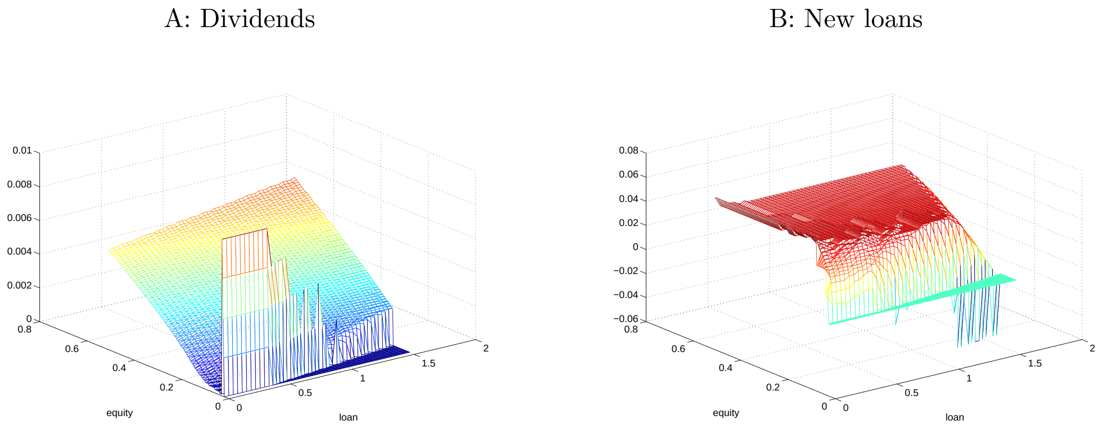
5 Discussion of Results

We first present individual bank policy functions and a typical time path of a bank to enhance our intuition about the economics behind the model, and then proceed with analyzing the implications of the model for the cross-section and for aggregate fluctuations.

5.1 Policy Functions and the Life of a Bank

Having normalized the model by deposits, we are left with two continuous state variables: (normalized) loans and (normalized) equity. Figure 5A shows the dividend policy function conditional on the low loan losses idiosyncratic state during a boom. Dividends are monotonically increasing in equity due to a wealth effect for most parts of the state space. For low levels of equity and low levels of loans, bankers exhibit risk-shifting behavior by expropriating value from other stakeholders and consuming excessive dividends. The bank

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



This figure shows policy functions of the model for large banks in a boom when they experience low loan write-offs. Panel A shows normalized dividends, while Panel B shows normalized new loan issuance.

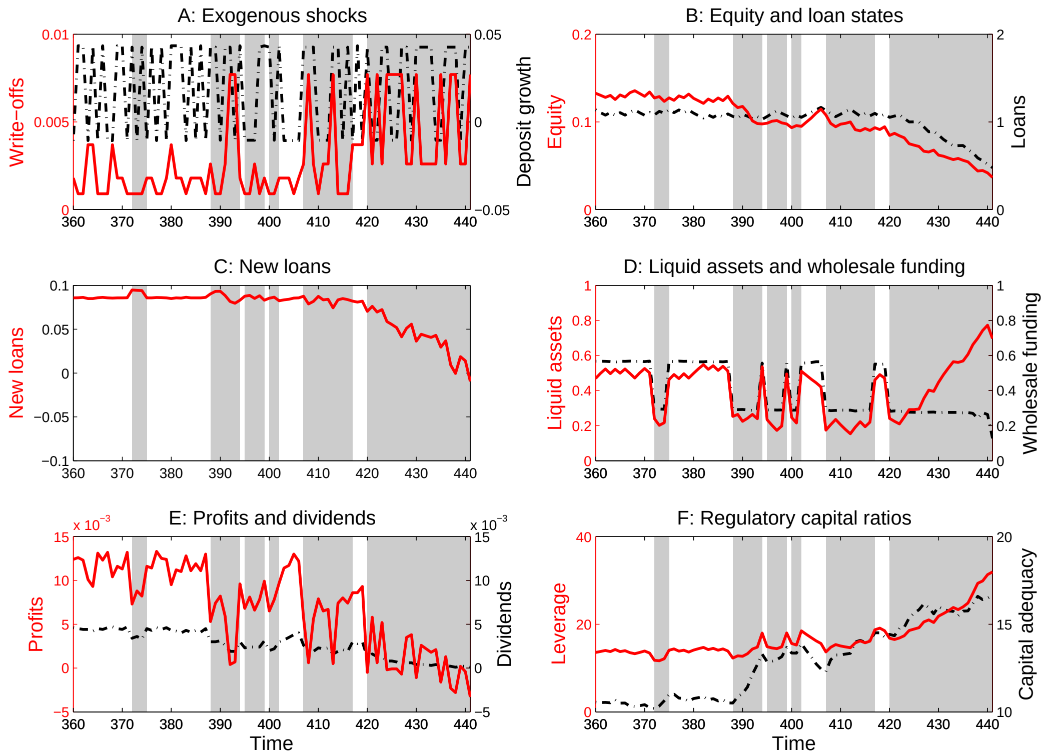
moves close to the regulatory capital constraints but does not violate them. Depending on the shock realizations next period, the bank might either survive or fail. For low levels of equity and high loan levels, the constraints are violated and the bank fails, in which case dividends are zero.

Figure 5B shows new loan issuance. New loans are monotonically increasing in equity and decreasing in the stock of loans for most parts of the state space. As in the dividend policy function, there are two distinct regions for low values of initial equity: at low levels of existing loans, the bank curtails new lending and at higher levels it starts liquidating loans.

Having solved for the policy functions, Figure 6 shows the behavior of an individual large bank that eventually fails.[20] Panel A reports the exogenous simulated loan write-off and deposit shocks. In reaction to this substantial idiosyncratic uncertainty, the bank accumulates an equity buffer above the regulatory capital requirements (Panel B)

[20]The shaded areas denote model recessions.

Figure 6: Life of a bank that eventually fails



This figure shows the behavior of a large bank that eventually fails. Panel A shows the exogenous shocks and Panel B the endogenous equity and loan states. Bank choices are shown in Panels C-E. Liquid asset holdings and wholesale funding are strongly procyclical and dividends are smoother than profits. Panel F shows the evolution of regulatory capital ratios as the bank approaches failure. In the run-up to bank failure, loan write-offs (Panel A) gradually deplete equity (Panel B). The bank also engages in costly loan liquidation (Panel C), while it increases its liquid asset holdings (Panel D). Loan liquidation depletes equity further, causing the bank to hit the leverage constraint (Panel F) and eventually fail.

Panel C shows that loan issuance falls when write-offs are high. Liquid asset holdings and wholesale funding are procyclical (Panel D). Both profits and dividends also fall in recessions, but dividends are significantly smoother than profits (Panel E).

In the final recession starting in period 420, the bank fails. At the beginning of this recession, the bank experiences a few periods of low or negative profits which deplete equity, but the share of loans has not yet fallen significantly. In period 425 the bank has risk-weighted assets of around 16 times equity, which is close to the capital adequacy constraint. But the unweighted leverage ratio is around 20, still far from its constraint.

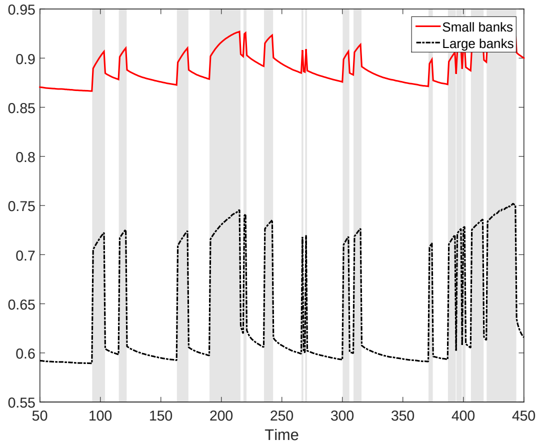
To observe the capital adequacy requirement, the bank issues less new loans and substitutes into liquid assets that carry a lower risk weight. Since loan write-offs remain elevated, equity is gradually depleted. In the run-up to failure, the bank engages in costly liquidation of loans and increases liquid assets. This behavior is driven by the capital adequacy requirement, since loans have a five times higher risk weight than liquid assets. However, costly loan liquidation depletes equity further. Thus, ultimately in period 442 the bank violates the leverage requirement and fails. This interaction between the two regulatory capital requirements is typical for failures in the model and demonstrates the importance of studying them jointly.

5.2 Time Series Behavior: Small versus Large Banks

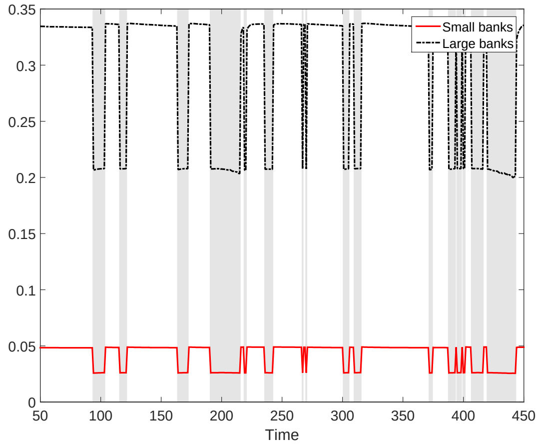
Figures 7 to 10 provide a more detailed view of the model's time series behavior. Figure 7A (Figure 7B) compares the deposit (wholesale funds) to asset ratio for large and small banks over time. Consistent with the data, small banks rely significantly more on deposit

Figure 7: Evolution of the share of deposits and wholesale funding in the model

A: Deposits



B: Wholesale funding

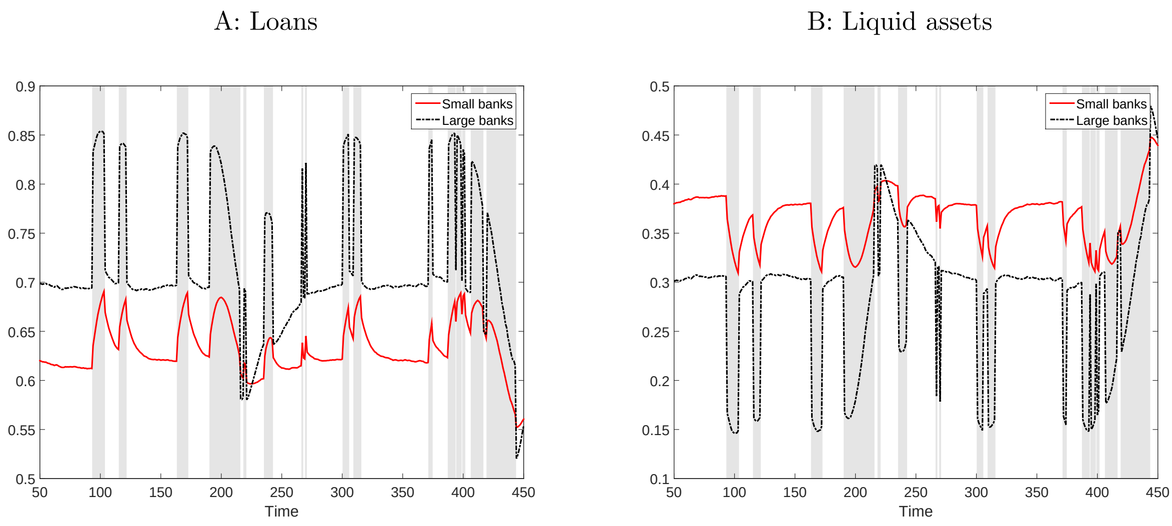


This figure shows the evolution of the deposit to asset ratio (Panel A) and the wholesale funding to asset ratio (Panel B) for small and large banks in the model. These ratios are the results of simulating 100,000 small and large banks independently for 2,000 periods of which only the last 500 periods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

funding, while large banks rely more on wholesale funds. Nevertheless, even for large banks, deposits remain the main funding source. During recessions, banks shrink total assets and reduce wholesale borrowing. As a result, the relative importance of deposits as a funding source increases. This cyclical pattern is consistent with Figure 1.

Figure 8 shows the asset side of the balance sheet. Small banks hold more liquid assets than large banks. This is consistent with the idea of precautionary liquidity buffers in Kashyap and Stein (2000), given that small banks face higher costs of accessing wholesale funding. At the onset of the recession, banks shrink their balance sheet by initially reducing liquid assets, given that loan liquidation is costly. Therefore, the share of loans initially jumps, before declining deeper into the recession. This effect is more pronounced for large banks because they rely more on wholesale funding, which can be cut back quickly. A slower

Figure 8: Evolution of the share of loans and liquid assets in the model



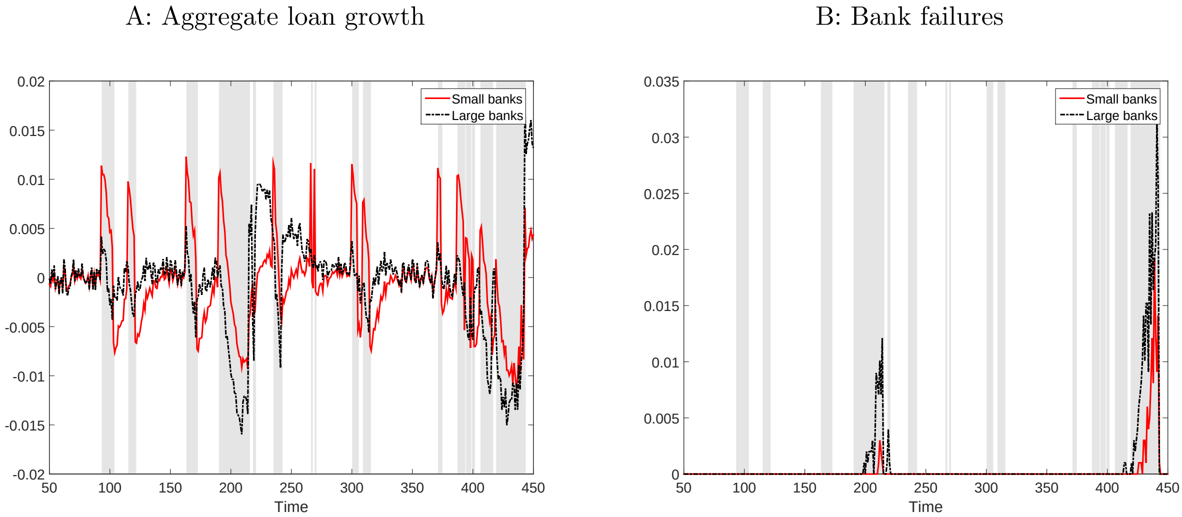
This figure shows the evolution of the loan to asset ratio (Panel A) and the liquid asset to total asset ratio (Panel B) for small and large banks in the model. These ratios are the results of simulating 100,000 small and large banks independently for 2,000 periods of which only the last 500 periods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

reduction in loans arising from a more stable funding source (deposits) during a recession is consistent with the empirical findings in Ivashina and Scharfstein (2010) and Dagher and Kazimov (2015).

Figure 9A shows that aggregate loan growth is strongly procyclical. Figure 9B shows that failures are 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 by up to three percent.

Figure 10A shows that, consistent with the data, large banks are more leveraged 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 translates into a lower leverage ratio.

Figure 9: Cyclical properties of loan growth and bank failures

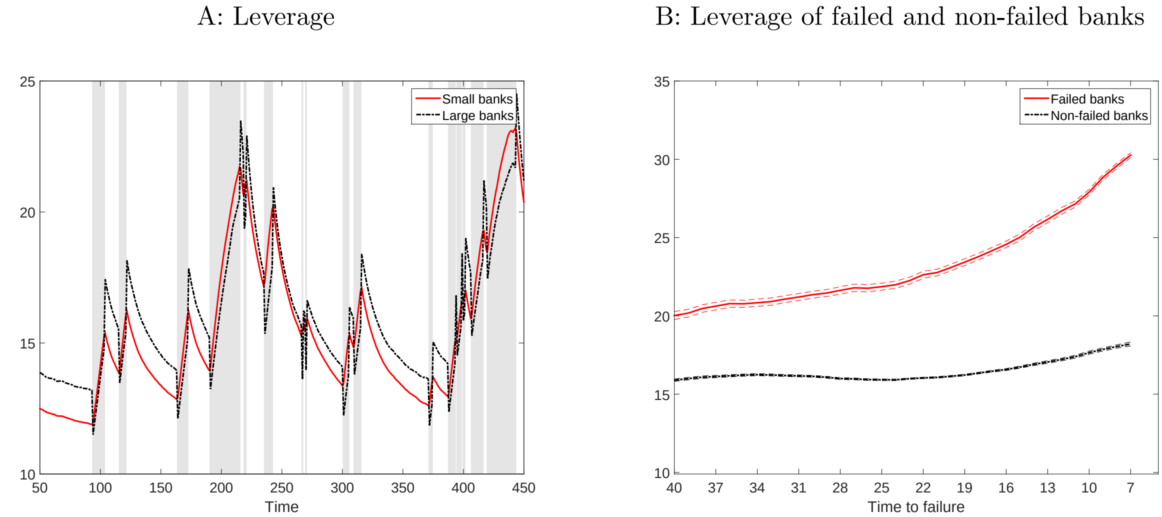


Panel A of this figure shows aggregate loan growth for small and large banks in the model. Loan growth is defined as the log difference of the outstanding stock of loans. The simulations are for 100,000 small and large banks independently for 2,000 periods of which only the last 500 periods are shown.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

To the extent that large banks have better access to wholesale funding than small banks, they use higher leverage to take advantage of profit opportunities, consistent with De Angelo and Stulz (2015). Banks use retained earnings to build up equity during good times. During recessions, equity declines and leverage increases because profits fall. Since banks want to smooth dividends, they do not lower dividend payouts as much as profits. At the onset of a recession, large banks reduce wholesale borrowing quickly leading to a rise in equity relative to total assets and a fall in leverage. Such leverage procyclicality is consistent with Adrian and Shin (2010, 2014). Deeper into the recession, loan losses eat into bank equity, making leverage countercyclical. This longer-run behavior is consistent with He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014).

Figure 10B is the model counterpart to Figure 3B; it shows the average leverage of

Figure 10: Leverage by size and of failed and non-failed banks in the model



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 of which 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 group. The x-axis measures the time-to-failure in quarters. Details of the simulation can be found in the appendix.

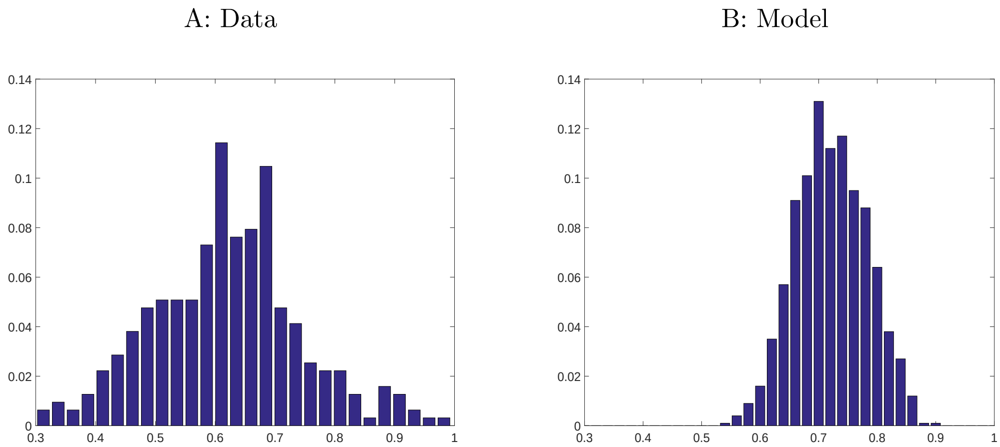
failed and non-failed banks over a ten-year period prior to failure. Leverage of failed banks is consistently higher than of surviving banks and increases significantly towards failure. Thus, an increase in leverage is an indicator for subsequent vulnerability, consistent with the evidence in Berger and Bouwman (2013).

5.3 Cross-section

In this section, we compare model outcomes to their data counterparts focusing on cross-sectional heterogeneity. The results here are the outcome of simulating the model for large banks.[21] Figure 11 shows the distribution of mean loan to asset ratios across banks. The model produces significant heterogeneity despite banks being ex ante identical and facing

[21]The cross-sectional results for small banks are similar and skipped for brevity.

Figure 11: Distribution of loan to asset ratios



This figure shows the distribution of loan to asset ratios of large banks in the data (Panel A) and in the model (Panel 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 of which only 80 periods are used for comparability with the data. Details can be found in the appendix.

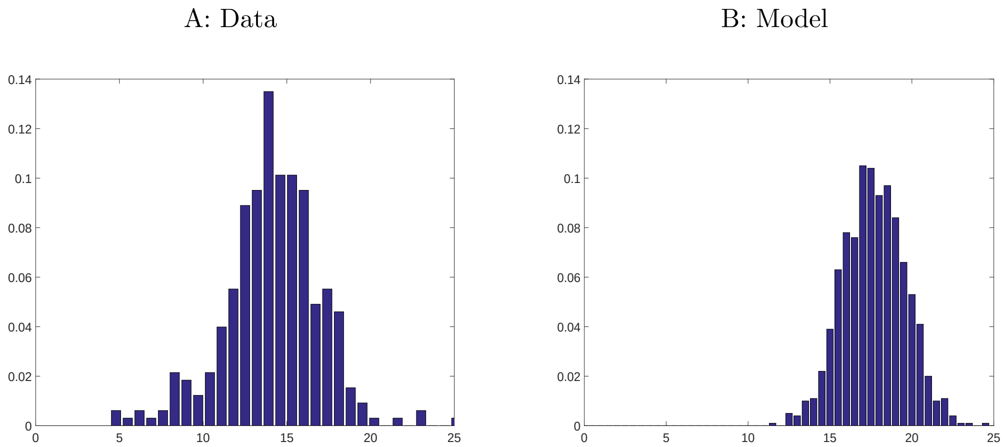
only two sources of idiosyncratic uncertainty. Nevertheless, the model distribution is not as wide as in the data.

Figure 12 shows the distributions of mean leverage across banks. This is important since bank failures are ultimately driven by high leverage. Mean leverage in the data and the model are symmetrically distributed. As in the case of the mean loan to asset ratio, the model dispersion is not as wide as in the data.

6 Counterfactual Experiments

Part of the appeal in building a structural quantitative model lies in the ability to perform realistic counterfactual experiments. The presence of both capital adequacy and leverage constraints affects loan choices differently. Figure 13 illustrates how the feasible loan set

Figure 12: Distribution of leverage ratios

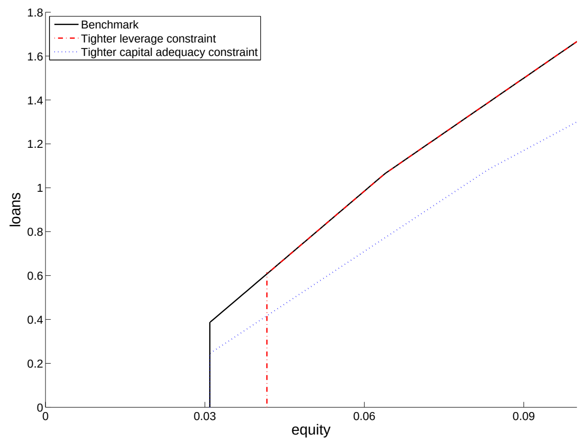


This figure shows the distribution of leverage ratios of large banks in the data (Panel A) and in the model (Panel B). The data are for U.S. commercial banks in the period 1990-2010. Panel B shows the results of simulating 100,000 banks for 2,000 periods of which only 80 periods are used for comparability with the data. Details can be found in the appendix.

changes as each constraint is separately tightened. The black (solid) line is the baseline situation: the vertical segment is at the minimum equity level implied by the binding leverage limit and the upward-sloping segment is the binding capital adequacy constraint. Tightening the capital adequacy constraint shifts down the upward-sloping segment, leaving unchanged the vertical segment at the minimum equity level. Tightening the leverage limit shifts the minimum equity level to the right but leaves the upward-sloping segment unchanged. Therefore, changes in the capital adequacy constraint affect banks over a wider equity space than changes in the leverage constraint, implying that banks may respond differently to changes in different constraints.

We perform two experiments and compare the results across stochastic steady states. The first experiment analyzes the implications for different risk-weighted capital adequacy constraints (λ_w) between 13 and 20 (baseline is 16.66, which corresponds to a 6% Tier 1

Figure 13: Changes in the regulatory capital requirements



This figure shows the capital requirements at the beginning of a period for a bank that has exogenous deposits D=1. The capital requirements are shown for the benchmark values, a tighter capital adequacy constraint and a tighter leverage constraint. See Figure 4 for a detailed derivation of the benchmark case.

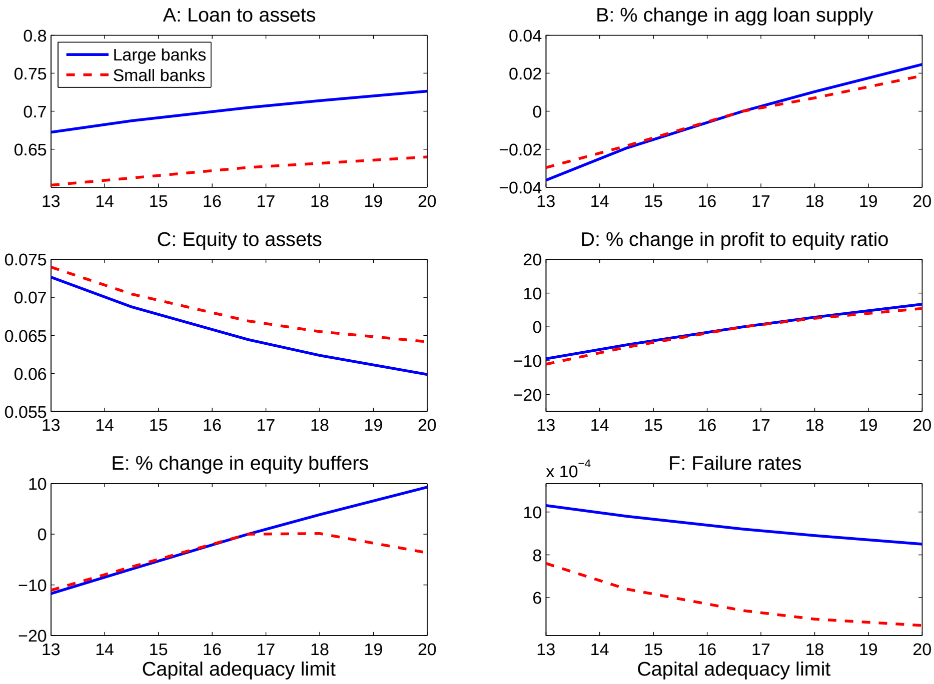
capital ratio). The second experiment analyzes what happens when the unweighted leverage requirement (λ_u) changes from 25 to 41 (baseline is 33.33, which corresponds to a 3% leverage ratio under Basel III).

6.1 Changing Capital Adequacy Requirements

We solve the model for different values of the capital adequacy constraint, leaving all other parameters, including the leverage limit, constant. The simulation uses exactly the same shock sequence in every experiment. Figure 14 shows the effect of tightening λ_w from 20 to 13 (corresponding to a minimum capital adequacy requirement increase from 5% to 7.7%) for small and large banks.

As the risk-weighted capital constraint is tightened, the average loan to asset ratio for both small and large banks falls (Panel A), because banks substitute from high-yielding,

Figure 14: The effects of changing the risk-weighted capital adequacy constraint



This figure shows the effects of changing the capital adequacy limit between 13 (7.7% minimum risk-weighted equity ratio) to 20 (5% minimum risk-weighted equity ratio). Panel A shows that the loan to asst ratio falls as the constraint is tightened (λ_w is lowered). Panel B shows that this translates into a fall in the aggregate loan supply (expressed relative to the baseline (16.66) calibration). Panel C shows that the equity to asset ratio increases as the constraint is tightened; while Panel D shows that this leads to a fall in the profit to equity ratio (expressed relative to the baseline calibration) Panel E shows that the equity buffer (mean equity minus the tighter of the two constraints) mostly falls as the constraint is tightened, also expressed relative to the baseline calibration. Panel F shows that failure rates increase as the constraint is tightened.

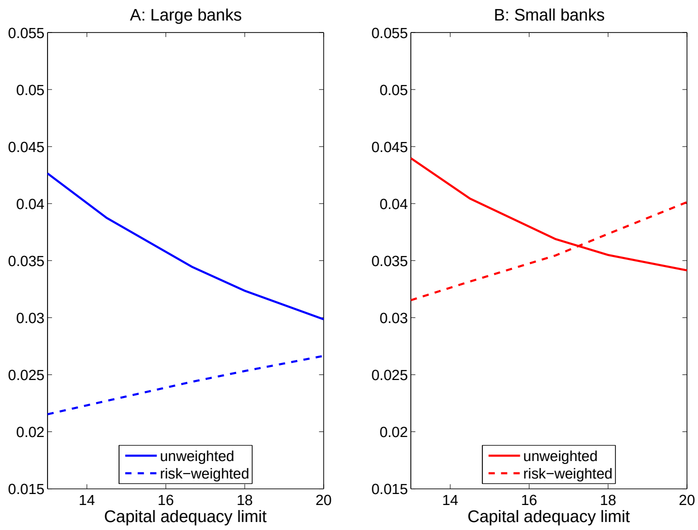
high risk-weighted loans to low-yielding, low risk-weighted liquid assets. Panel B confirms that the decrease in the loan to asset ratio translates into a fall in aggregate loan supply. A tighter capital adequacy constraint also implies a higher equity to asset ratio (Panel C).

Given that loans are reduced and equity increases, the return on equity falls. The numerator of this ratio decreases since banks substitute out of high-yielding loans into low-yielding liquid assets. The denominator rises since banks hold more equity. This implies an unambiguous fall in the profit to equity ratio as the constraint tightens (Panel D). Therefore, equity does not rise as much as the constraint tightens, implying a fall in the equity buffer defined as the distance between equity and the tighter of the two constraints (Panel E). For large banks, equity buffers fall monotonically as the constraint is tightened. However, for small banks, the change in equity buffers is non-monotonic in the constraint.

This difference can be seen in Figure 15, Panel A (B) for large (small) banks. There are two types of equity buffers, one relative to each constraint. Since λ_u is kept constant, mean equity rises as the capital adequacy constraint is tightened, and so does the equity buffer relative to this constraint (solid lines). On the other hand, the equity buffer relative to the risk-weighted constraint falls because the direct effect of tightening the constraint is greater than the endogenous increase in equity. The risk-weighted constraint is uniformly the tighter of the two for large banks, whereas for small banks at around $\lambda_w = 17$ the unweighted leverage constraint becomes more binding. This explains the hump-shaped pattern in Panel E of Figure 14, since this always shows the tighter of the two constraints.

The change in equity buffers explains the change in failure rates in Panel F to a significant degree. The failure rate increases as the risk-weighted constraint is tightened, since the

Figure 15: Mean equity buffers for different values of the risk-weighted capital adequacy constraint

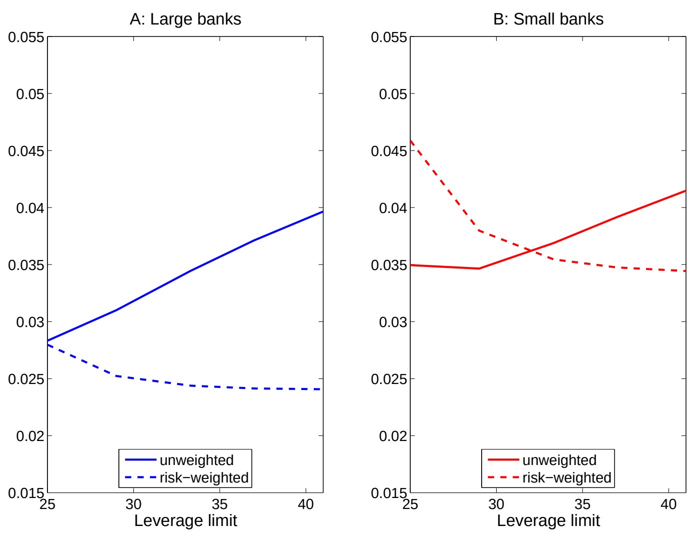


This figure shows mean equity buffers, which are defined as mean equity minus the minimum equity implied by the constraints. The solid line is the mean equity buffer with respect to the unweighted leverage constraint, which is kept constant at its baseline value of 33.33. This equity buffer increases as the constraint is tightened (λ_w is lowered). The broken line is the mean equity buffer with respect to the risk-weighted capital adequacy constraint, which varies between 13 and 20. It falls as the constraint is tightened average bank moves closer to the constraint: the endogenous increase in equity is not as large as the tightening of the constraint. At high values of λ_w, failures and equity buffers of small banks flatten.

6.2 Changing Leverage Requirements

We solve the model for different values of the leverage constraint, leaving all other parameters, including the capital adequacy constraint, constant. For both small and large banks, Figures 16 and 17 show the effect of tightening λ_u from 41 to 25 (corresponding to a minimum requirement that increases from 2.44% to 4%).

Figure 16: Mean equity buffers for different values of the unweighted leverage constraint



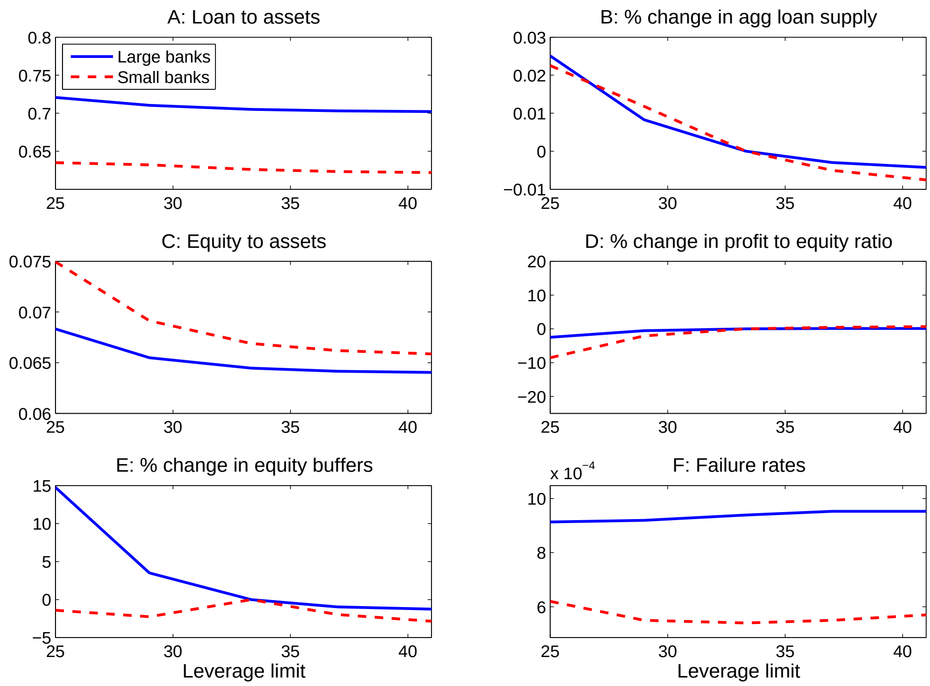
This figure shows mean equity buffers, which are defined as mean equity minus the minimum equity implied by the constraints. The solid line is with respect to the unweighted leverage limit, which varies between 25 and 41. This equity buffer falls as the constraint is tightened (λ_u is lowered). The broken line is the mean equity buffer with respect to the risk-weighted capital adequacy constraint, which is at its baseline value of 16.66. It increases as the constraint is tightened.

Figure 16 is the analogue to Figure 15 and shows equity buffers relative to the two constraints. For large banks the risk-weighted constraint is always more likely to become the binding constraint, whereas for small banks that only happens for $\lambda_u > 32$.

As the leverage constraint is tightened, Panel A of Figure 17 shows that the loan to asset ratio rises mildly. This is an opposite result relative to what happens when the capital adequacy constraint is tightened in Section 6.1. The risk-weighted constraint becomes the tighter of the two constraints and therefore banks substitute out of loans into liquid assets due to the lower risk weight. This happens despite the fact that the risk-weighted constraint itself is unchanged. Even though the loan to asset ratio increases only mildly, the aggregate loan supply rises significantly as the constraint is tightened (Panel B). Banks raise their equity to asset ratio in response to a tighter leverage constraint (Panel C). Because the loan to asset ratio rises (especially for the large banks), the profit to equity ratio falls only slightly for large banks as the constraint is tightened. For small banks the drop in the profit to equity ratio is larger because they raise relatively more equity in response to a tighter constraint. In contrast to the experiment in Section 6.1 , equity buffers rise for large banks as the leverage constraint tightens. This happens because the endogenous rate of return falls only mildly now, due to the re-allocation into loans. The effect is stronger for large banks since, as shown in Figure 16, for large banks the risk-weighted constraint is the tighter of the two constraints. This effect is also present for small banks but only for values of $\lambda_u > 32$: for smaller values, it is the unweighted leverage constraint that binds more, and this happens because the drop in the endogenous rate of return is higher for smaller banks due to the stronger response of equity to a tighter constraint (Panel D).

Consistent with the rise in equity buffers (Panel E), the failure rate falls uniformly for

Figure 17: The effects of changing the unweighted leverage constraint



This figure shows the effects of changing the unweighted leverage limit between 25 (4% minimum equity ratio) and 41 (2.44% minimum equity ratio). Panel A shows that the loan to asst ratio rises as the constraint is tightened (λ_u is lowered). Panel B shows that this translates into an increase in the aggregate loan supply (expressed relative to the baseline (33.33) calibration. Panel C shows that the equity to asset ratio increases as the constraint is tightened; while Panel D shows that this leads to a small fall in the profit to equity ratio (expressed relative to the baseline calibration) Panel E shows that the equity buffer (mean equity minus the tighter of the two constraints) mostly increases as the constraint is tightened. Panel F shows that the failure rate of large banks falls as the constraint is tightened, whereas it first falls and then rises for small banks.

large banks. For small banks it falls at high values of λ_u (Panel F). But beyond a certain point of tightening the leverage constraint, the failure rate for small banks rises, which is also consistent with the behavior of equity buffers.

6.3 Discussion of Results

The first important result illustrates that the two constraints have opposite effects on loan supply. Tightening the risk-weighted constraint leads to a contraction in loan supply, since loans carry a higher risk weight. On the other hand, tightening the unweighted constraint leads to an increase in loan supply. Banks substitute out of liquid assets into loans, since both asset classes carry the same risk weight but loans offer a higher expected return. In light of our results, a tighter leverage constraint is more beneficial for loan supply to the real economy than a tighter capital adequacy constraint.

The second important result emphasizes the differential effect of the constraints on different sized banks. The capital adequacy constraint is always more important than the leverage constraint for larger banks. This happens because larger banks have a higher (lower) loan (equity) to asset ratio than smaller banks in the model and in the data.

The third important result is that a tightening of the constraints does not necessarily imply a reduction in bank failures. Banks always respond to a tightening with an increase in equity holdings. However, this increase in equity is not always enough to also increase the equity buffer.

If capital adequacy requirements become too tight, bank charter value and equity buffers fall, which makes banks more likely to fail. Equity buffers fall because the return on equity falls endogenously with any increase in equity and a potential change in bank asset structure.[22] In our incomplete markets setup, bankers are relatively impatient and make their equity accumulation decisions by comparing the difference between the expected return on equity and the discount rate. However, by tightening the leverage constraint, failure rates remain relatively unchanged, especially for large banks for which the leverage constraint is less important than the capital adequacy constraint.

An important motivation for tighter regulatory capital requirements are the fiscal costs of bank bail-outs. Even though we do not model bail-outs explicitly, we can use our model to assess their implications. Bail-out costs depend on failure rates and the bail-out costs conditional on failure. We have already seen that tighter regulatory capital requirements may sometimes increase the incidence of bank failures. However, bail-out costs conditional on failure decline since banks hold more equity at the time of failure.

7 Conclusion

We use individual U.S. commercial bank financial statement information to develop stylized facts about bank behavior in both the cross section and over time. We then estimate the structural parameters of a quantitative banking model that includes choices of new loans, liquid investments and failure in the presence of undiversifiable background risks (loan write-

[22] The intuition behind this result is similar 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, potentially lower loan supply reduces profits. Second, the higher precautionary equity implies a lower average return on equity.

offs, interest rate spreads and deposit shocks) and regulatory capital constraints. The model replicates many features of the data and can be used to perform counterfactual experiments.

We find that tighter risk-weighted capital requirements reduce loan supply and increase bank failures because endogenous equity holdings increase by less than capital requirements. On the other hand, tighter leverage requirements increase lending because high-yielding loans start dominating low risk-weighted liquid assets, but bank failure rates remain relatively unchanged. We also find that heterogeneity matters; capital adequacy constraints affect larger banks more strongly than smaller banks. Thus, the two capital requirements interact in a non-trivial way and should therefore be studied jointly.

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9 Data Appendix

The analysis draws on a sample of individual bank data from U.S. Call Reports for the period 1990:Q1-2010:Q4. For every quarter, we categorize banks as small if they are below the 95th percentile of the distribution of total assets, as medium if they are between the 95th and 98th percentile and as large if they are above the 98th percentile.

Our initial dataset is a panel of 890,252 quarterly observations, corresponding to 17,226 different identification numbers of commercial banks. We drop 38,563 observations that have a FDIC identification number equal to zero and 4,313 observations due to missing values. We exclude banks with exceptional growth (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] This removes 25,292 outlier observations and 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 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 (total loans plus quarterly charge-offs). Real deposit growth is calculated by taking the log difference in broad deposits, defined as the sum of

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

transaction and non-transaction deposits. 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 expansions 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.

To derive targeted moments for balance sheet and profit and loss ratios, we first winsorize them at the 1st and 99th percentile of their sample distribution every quarter by size. Moments of ratios are calculated at the individual bank level by considering only banks with at least 20 observations in expansions and equally in recessions, i.e. at least 40 observations in total. We only consider positive tangible equity in all the calculations, and profits are before tax, extraordinary items and other adjustments. For the Method of Simulated Moments estimation we use average moments across banks and for weighting purposes we use the standard deviations around these averages.

A similar approach is used for estimating the average real return on loans, liquid asset returns and deposit 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 6% (8%) for large (small) banks, which assumes a uniform repayment rate over time.

We also consider all bank failures and assistance transactions that occurred during the sample period, altogether 1,292 bank-specific events.[24] From these events we are able to identify 810 failed banks in the data, given that reports often become unavailable some time prior to the effective failure date. This is particularly true for the early part of the sample, where, for example, there are no matching data for 214 and 145 failed banks in the years 1990 and 1991, respectively.

10 Solution Appendix

This section shows the model normalization and outlines the numerical computational approach.

10.1 Normalization

The deposit process contains a unit root but is i.i.d. in growth rates. To make the model stationary, we normalize by deposits. Denote normalized variables as lower case variables, for example $f_t = \frac{F_t}{D_t}$ and the growth rate of deposits with $\Gamma_{t+1} = \frac{D_{t+1}}{D_t}$.

[24] Available at https://www.fdic.gov/bank/individual/failed

The risk-weighted limit (9) becomes

$$\frac{\omega_L \left(l_t + n_t\right) + \omega_S s_t}{e_t - x_t - g_N \left(n_t\right)} \leq \lambda_w. \tag{14}$$

The equity evolution (5) becomes

$$\begin{aligned} e_{t+1} &\equiv \frac{E_{t+1}}{D_{t+1}} = \frac{E_t + (1-\tau)\Pi_{t+1}\mathcal{I}_{\Pi_{t+1}>0} + \Pi_{t+1}(1-\mathcal{I}_{\Pi_{t+1}>0}) - X_t - g_N\left(N_t, D_t\right)}{D_{t+1}} \\ &= \left(e_t - x_t\right)\frac{1}{\Gamma_{t+1}} + (1-\tau)\pi_{t+1}\mathcal{I}_{\Pi_{t+1}>0} + \pi_{t+1}(1-\mathcal{I}_{\Pi_{t+1}>0}) - g_N\left(n_t\right). \end{aligned} \tag{15}$$

All other equations are normalized analogously.

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, and the transition probabilities are chosen to generate expansion 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. Assign values for all exogenous parameters.

2. Construct two grids for the two continuous state variables equity (e) and loans (l).

3. Draw a sequence for all shocks for the simulation.

4. Assign initial starting values for the seven parameters to be estimated.

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

Solution of value function problem

5. Consumption after failure ($\bar{c}$) implies a continuation value after failure v^d.

6. A guess is made for the (normalized) value function $v(l, e; w, b)$

7. The optimization problem is solved for all discrete states: expansion and recession, and nodes for bad loans and for all values on the grids for e and l. At each 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), and s follows from the balance sheet constraint: $s = 1 + f + e - x - l - n$.

   (b) If the candidate (x, n, f) is feasible and obeys the capital requirements, 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 $v(l', e'; w', b')$ or v^d if failure is preferred and the banker pursues a career outside the bank.

   (c) If the candidate (x, n, f) violates any of the regulatory constraints, the regulator takes control of the bank, shareholders are deprived of any dividends and failure utility v^d is assigned.

(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 $v(l', e'; w', b')$ at this node.[25]

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

   (a) If the maximum absolute difference between $\widetilde{v}(l, e; w, b)$ and $v(l, e; w, b)$ at every single node is below the tolerance level, the value function has converged;

   (b) otherwise $v(l, e; w, b)$ at the beginning of step 7 is replaced with $\widetilde{v}(l, e; w, b)$ 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 $N = 10,000$ banks for $T = 2,000$ periods.

11. Each bank starts with some specific initial value for (e_t, l_t), aggregate and idiosyncratic states. The decision rule is then used to compute new loans n_t, dividends x_t, and wholesale borrowing f_t. The shocks $t+1$ are realized, which in turn yield profits π_{t+1}. This yields the new equity level: e_{t+1}. Similarly, loans next period are l_{t+t}.

[25] 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, mean loans and a low loan loss state. Due to the very low number of failures, 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 squared differences between model and data moments are calculated.

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

15. If the criterion function is too high, a new set of values is tried in step 4. For this optimization, we use a standard derivative-free simplex method.