

Capital Requirements in a Quantitative Model of Banking Industry Dynamics*

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Abstract

We develop a model of banking industry dynamics to study the quantitative impact of capital requirements on bank risk taking, commercial bank failure, and market structure. We propose a market structure where big banks with market power interact with small, competitive fringe banks. Banks face idiosyncratic funding shocks as well as aggregate shocks to the fraction of performing loans in their portfolio. A nontrivial size distribution of banks arises out of endogenous entry and exit, as well as banks' buffer stock of net worth. We test the model using business cycle properties and the bank lending channel across banks of different sizes. We then conduct a series of counterfactuals (including countercyclical requirements and size contingent (e.g. SIFI) requirements). We find that regulatory policies can have an important impact on market structure itself.

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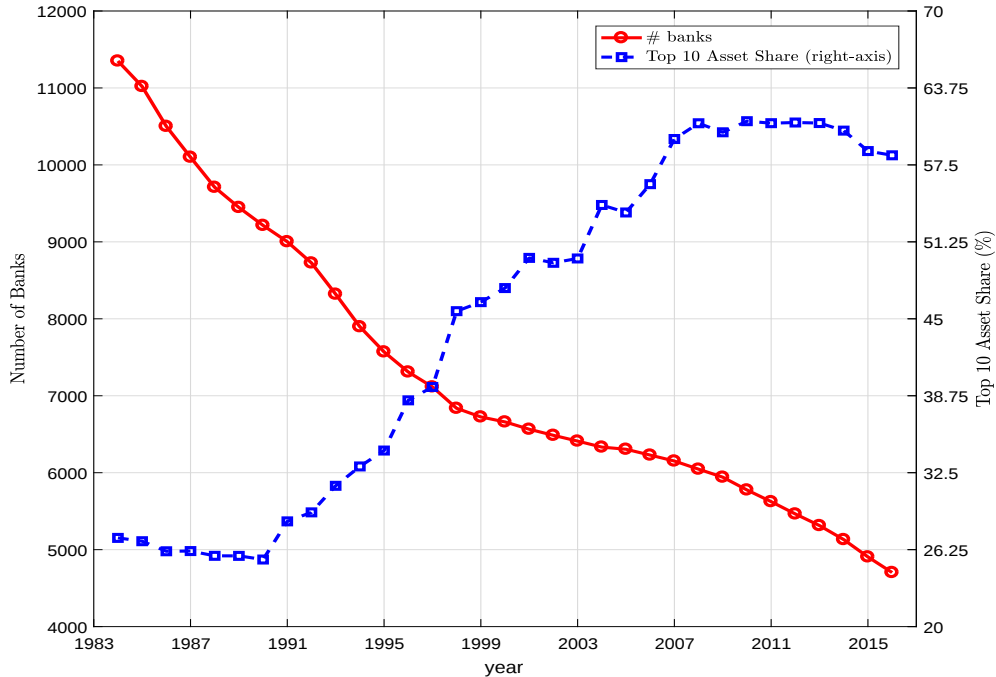
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1 Introduction

The banking literature has focused on two main functions of bank capital. First, because of limited liability and deposit insurance, banks have an incentive to engage in risk shifting. Requiring banks to hold a minimum ratio of capital to assets constrains the banks' ability to take risk. Second, bank capital acts like a buffer that may offset losses and save its charter value. In this paper we develop a quantitative model of banking industry dynamics with imperfect competition and an endogenous size distribution of banks to answer the following question: How much does an increase in capital requirements affect failure rates, interest rates, and market shares of large and small banks?

As Figure 1 makes clear, the number of commercial banks in the U.S. has fallen from over 11,000 in 1984 to under 5000 in 2016 while the asset market share of the top 10 banks has grown from 27.2% in 1984 to 58.3% in 2016. Rising market shares of big banks motivates us to consider a model of the banking industry which allows for imperfect competition. Furthermore, it allows us to understand how regulatory policy may actually affect market structure as well as consider how market structure influences risk taking behavior which regulators are attempting to mitigate.

Figure 1: Number of Banks and Bank Concentration



Note: Number of Banks refers to the number of bank holding companies. Top 10 Asset share refers to the share of total assets in the hands of the top 10 banks in the asset distribution.

In an earlier paper (Corbae and D’Erasmus [18]), we endogenized market structure, but limited the asset side of the bank balance sheet to loans and the liabilities side to deposits and equity. While loans and deposits are clearly the largest components of each side of the balance sheet of U.S. banks, this simplification does not admit ways for banks to insure themselves at a cost through precautionary holdings of lower risk, highly liquid securities like T-bills.

In this paper, we extend the portfolio of bank assets in the above direction. Further we assume that banks are randomly matched with depositors and that these matches follow a Markov process that is independently distributed across banks. Thus, we add fluctuations in deposits (which we term “funding shocks”) to the model of the first paper.

We assume banks have limited liability. At the end of the period, banks may choose to exit in the event of cash shortfalls if their charter value is not sufficiently valuable. If a bank’s charter value is sufficiently valuable, banks can use their stock of net securities as a buffer or issue seasoned equity. Thus, the extension allows us to consider banks undertaking precautionary savings in the face of idiosyncratic shocks as in a household income fluctuations problem, but with a strategic twist, since here, big banks have loan market power.

We “test” our model along two dimensions. First, we look at the untargeted business cycle implications of the model and compare them with those from the data to show that the model predictions are in line with the empirical evidence. Second, we “test” the model via a policy experiment that considers the effects of “monetary” policy changes on the bank balance sheet and lending decisions. In an important paper, Kashyap and Stein [36] studied whether the impact of Fed policy on lending behavior is stronger for banks with less liquid balance sheets (where balance sheet strength is measured as the ratio of securities plus federal funds sold to total assets). The mechanism they test relies on the idea that (p. 410) “banks with large values of this ratio should be better able to buffer their lending activity against shocks in the availability of external finance, by drawing on their stock of liquid assets.” One of their measures of monetary policy is the federal funds rate. They find strong evidence of an effect for small banks (those in the bottom 95% of the distribution). In this section, we conduct a similar exercise by running a set of two stage regressions on a pseudo panel of banks from our model and find that the results are qualitatively consistent with the empirical evidence presented in Kashyap and Stein [36].

A benefit of our structural framework is that we can conduct policy counterfactuals. We study a rise in level of capital requirements from 4% under Basel II to 8.5% (corresponding to a minimum risk weighted capital requirement of 6% plus a 2.5% capital buffer) motivated by changes recommended by Basel III. FDIC Rules and Regulations (Part 325) establishes the criteria and standards to calculate capital requirements and adequacy (see DSC Risk Management Manual of Examination Policies, FDIC, Capital (12-04)).¹

We find that a rise in capital requirements from 4% to 8.5% leads to a reduction in exit rates of small banks and a more concentrated industry. In order to meet the increased capital requirements, big banks lower their loan supply. The higher capital requirements result in a lower value for the bank and consequently the mass of fringe banks decreases. These two effects account for the reduction in loan supply and consequently a rise in loan interest rates

¹See a full description in BIS [13].

. The lower exit rate causes taxes (relative to output) used to pay for deposit insurance to drop in half. On the other hand, higher interest rates result in a higher default frequency as well as a lower aggregate level of intermediated output.

To understand the interaction between regulatory policy and market structure, we also conduct a counterfactual where we increase the entry cost for dominant banks to a level that prevents their entry. Since our benchmark model with dominant and fringe banks nests an environment with only perfect competition, we can use this counterfactual to understand the role of imperfect competition on the banking sector. We find that capital buffers are much larger in the benchmark economy than in the one with only competitive banks. The reason is that the environment with dominant banks is riskier (a higher default frequency and volatility of all aggregates). We document that strategic loan supply by dominant banks results in an important source of amplification of shocks. We also find, as one would expect, that in a perfectly competitive industry the loan interest rate is lower than in the benchmark, resulting in lower default frequencies and higher intermediated output. Finally, we find that certain cyclical properties are quite different between an imperfectly competitive model and one with perfect competition. For instance, markups are countercyclical in the imperfectly competitive model (as they are in the data), while they are procyclical in the model with perfect competition.

In order to determine the case for any capital requirement at all, we assess the implications of removing capital requirements entirely. As expected, both big and small banks hold a lower buffer of capital but it is still non-zero since they provide a buffer to maintain the bank's charter value. Interestingly, the big bank strategically lowers loan supply in order to raise interest rates and profitability. Higher profitability raises entry rates by fringe banks.

Basel III also calls for banks to maintain a “countercyclical” capital buffer of up to 2.5% of risk-based Tier 1 capital. As explained in BIS [13] the aim of the “countercyclical” buffer is to use a buffer of capital to protect the banking sector from periods of excess aggregate credit growth and potential future losses. According to Basel III, a buffer of 2.5% will be in place only during periods of credit expansion.² we run a counterfactual where the capital requirement increases by 2.5% during periods of economic expansion, so the capital requirement fluctuates between 8.5% and 11%.

Another proposal in Basel III calls for large, systemically important financial institutions (SIFI) to face a higher capital requirement than small banks. We run a counterfactual where the capital requirement is 2% higher on big banks than small banks.³

Finally, we examine how the imposition of liquidity requirements affects market structure.

1.1 Related Literature

Our paper is related to the literature studying the impact of financial regulation in quantitative structural models of banking. The first strand of literature studies dynamic bank

²BIS [12] establishes that credit/GDP is a reference point in taking buffer decisions but suggests examples of other variables that may be useful indicators such as asset prices, spreads and real GDP growth.

³The SIFI surcharge is 2.5% for Citi and JP Morgan, 2% for BoA HSBC, Deutsche and HSBC, 1.5% for Wells Fargo, Goldman, Barclays and 1% for other large banks.

decision problems. For example, De Nicolo et al. [21] show an inverted U-shaped relationship between capital requirements and bank lending. On the other hand, since they study only a decision problem, they do not consider the impact of such policies on loan interest rates and the equilibrium bank size distribution.

The second strand of literature studies dynamic general equilibrium models with a representative bank under perfect competition in loan and deposit markets. Van Den Heuvel [46] was one of the first to study the welfare impact of capital requirements with perfect competition.⁴ In these papers, constant returns and perfect competition imply that there is an indeterminate distribution of bank sizes, so they do not make predictions for how regulation affects banking industry market structure. Others with perfect competition assume idiosyncratic shocks which can generate an endogenous size distribution of banks.⁵ In such models, big banks have no impact on lending or deposit rates and the failure of an individual big bank has no market impact (since it is of measure zero).

Diamond's [20] delegated monitoring model provides a foundation for the existence of large banks due to economies of scale in monitoring. There are numerous empirical papers documenting the existence of scale economies in banking such as Berger and Mester [11].⁶ Following deregulation of the banking industry in the 1990s, there was a wave of bank mergers to take advantage of scale economies resulting in loan (deposit) market concentration of the top 10 going from 29.8% (25.8%) in 1984 to 54.7% (57.3%) in 2016.

Given high concentration in the banking industry, another branch of the literature considers imperfect competition in loan and/or deposit markets. Our dynamic banking industry model builds upon the static framework of Allen and Gale [5] and Boyd and DeNicolo [14]. In those models, there is an exogenous number of banks that are Cournot competitors either in the loan and/or deposit market.⁷ Given both aggregate productivity and idiosyncratic funding shocks, we endogenize the number of banks by considering dynamic entry and exit decisions and apply a version of the Markov perfect equilibrium concept in Ericson and Pakes [26] augmented with a competitive fringe as in Gowrisankaran and Holmes [32]. While ours is the first quantitative structural model to focus on imperfect competition in loan markets, there is also an important set of papers analyzing imperfect competition in the deposit market (see for example Aguirregabiria, et. al. [2], Drechsler, et. al. [24], and Egan, et. al. [27]). Besides imperfect competition, our framework deviates from the frictionless Modigliani-Miller paradigm by including government deposit insurance and limited liability generating a moral hazard problem for banks, bankruptcy and equity issuance costs, as well as agency conflicts between the manager and shareholders. Regulation in this environment can help mitigate bank risk taking.⁸

The computation of this model is a nontrivial task. In an environment with aggregate shocks, all equilibrium objects, such as value functions and prices, are a function of the dis-

⁴Among others, see Aliaga-Diaz and Olivero [3], Begenau [8], Bianchi and Bigio [9], Clerc, et. al. [16].

⁵For example, see Rios-Rull, Nguyen [40]

⁶For a more recent paper, see Wheelock and Wilson [47].

⁷Martinez-Miera and Repullo [38] also consider a dynamic model, but do not endogenize the number of banks.

⁸Repullo [42] was an important early paper to study the role of capital requirements in a model with imperfect competition in the banking sector.

tribution of banks. Interestingly, even if we did not include aggregate shocks, idiosyncratic shocks to large banks do not wash out in the aggregate. The distribution of banks is an infinite dimensional object and it is computationally infeasible to include it as a state variable. Thus, we solve the model using an extension of the algorithm proposed by Ifrach and Weintraub [28] adapted to this environment. This entails approximating the distribution of banks by a finite number of moments.⁹

1.2 Roadmap

The paper is organized as follows. While we have documented a large number of banking facts relevant to the current paper in our previous work [18], Section 2 documents a new set of banking data facts relevant to this paper. Section 3 lays out a simple model environment to study bank risk taking and loan market competition. Section 4 describes a Markov perfect equilibrium of that environment. Section 5 discusses how the preference and technology parameters are chosen and Section 6 provides results for the simple model. Section 7.1 presents the first test of the model, its business cycle implications and Section 7.2 the second test, where we analyze the impact of easier “monetary policy” (lower borrowing terms) on bank lending behavior. Section 8 conducts our policy counterfactuals.

2 Banking Data Facts

In our previous paper [18], we documented the following facts for the U.S. using data from the Consolidated Report of Condition and Income (known as Call Reports) that insured banks submit to the Federal Reserve each quarter.¹⁰ Entry is procyclical and exit by failure is countercyclical (correlation with detrended GDP is equal to 0.61 and -0.16 , respectively for the period 1984-2016). Almost all entry and exit is by small banks (defined as banks in the bottom 99% of the asset distribution). Loans and deposits are procyclical (correlation with detrended GDP is equal to 0.44 and 0.18, respectively for the same period). As evident from Figure 1, bank concentration has been rising. There is evidence of imperfect competition: The interest margin is 4.6%; markups exceed 50%; the Lerner Index exceeds 30%; and the Rosse-Panzar H statistic (a measure of the sensitivity of interest rates to changes in costs) is significantly lower than the perfect competition number of 100% (specifically, $H = 40$). Loan returns, margins, markups, delinquency rates, and charge-offs are countercyclical.¹¹

⁹An appendix to this paper states the algorithm we use to compute an approximate Markov perfect industry equilibrium.

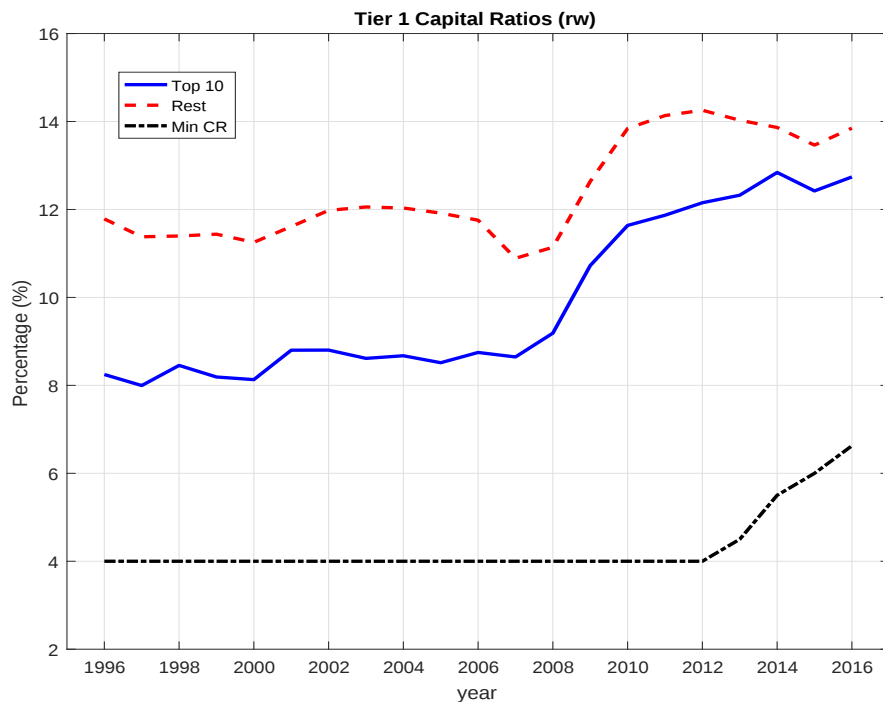
¹⁰Balance Sheet and Income Statements items can be found at <https://cdr.ffiec.gov/public/>. We use group commercial banks to the Bank Holding Company Level.

¹¹The countercyclicality of margins and markups is important. Building a model consistent with this is a novel part of our previous paper [18]. The endogenous mechanism in our papers works as follows. During a downturn, there is exit by smaller banks. This generates less competition among existing banks, which raises the interest rate on loans. But since loan demand is inversely related to the interest rate, the ensuing increase in interest rates (barring government intervention) lowers loan demand even more, thereby amplifying the downturn. In this way our model provides a novel mechanism - imperfect loan market competition - to produce endogenous loan amplification in the banking sector.

Since we are interested in the effects of capital and liquidity requirements on bank behavior and loan rates, we organize the data in order to understand differences in capital holdings across banks of different sizes. We refer to the Top 10 banks in the asset distribution as “large” banks and we refer as “small” banks the rest.¹²

Figure 2 presents the evolution of the ratios of Tier 1 capital-to-assets ratio and Tier 1 capital-to-risk-weighted-assets Ratio for the 10 largest banks and the remaining banks when sorted by assets.

Figure 2: Average Bank Capital by Size



Note: Tier 1 Capital (rw) refers to Risk-weighted Tier 1 Capital Ratio. Averages are computed as asset-weighted averages. Min CR refers to minimum capital requirement (risk-weighted) plus capital conservation buffer for banks with less than 50 billion in assets (all of these banks included in the “Rest” group). Banks with more than 50 billion are required to hold additional capital since 2013. Source: Consolidated Report of Condition and Income.

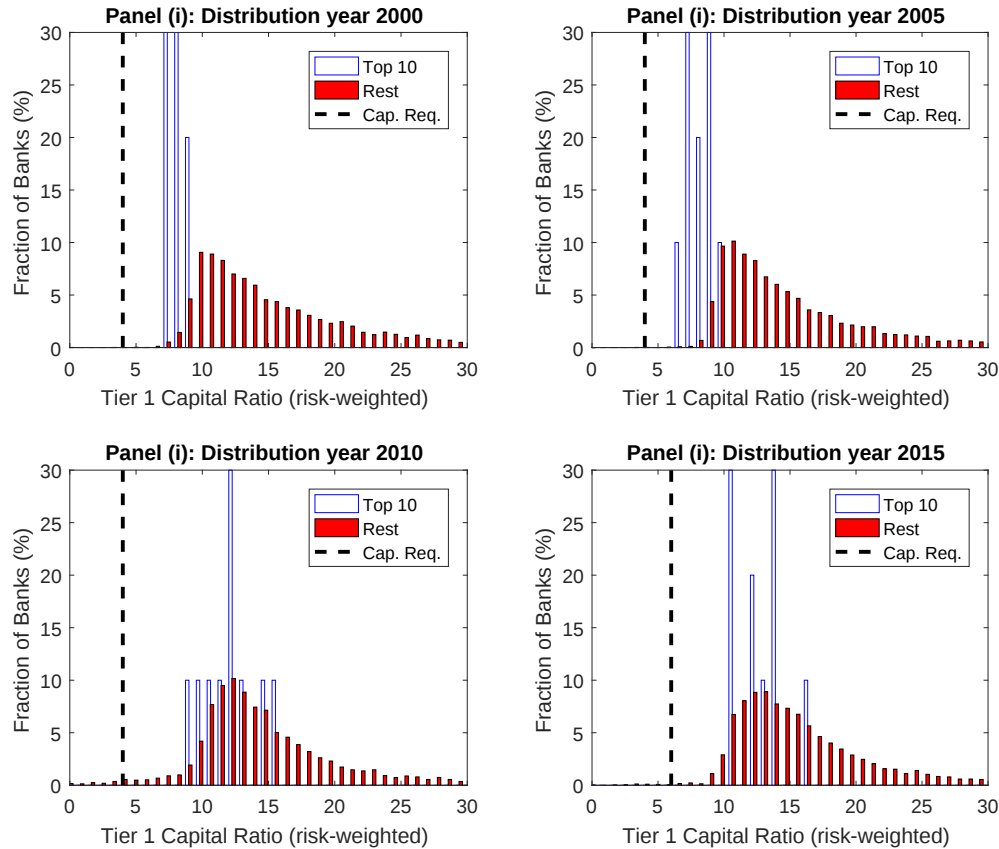
In all periods, risk-weighted capital ratios are lower for large banking institutions than those for small banks.¹³ The fact that capital ratios are above what regulation defines as well capitalized suggests a precautionary motive.

¹²The group of Top 10 banks contains all the U.S. banks that were classified as global systemically important banks (G-SIBs) as of December of 2016.

¹³Capital ratios based on total assets (as opposed to risk-weighted assets) present a similar pattern.

While 2 presents the cross-sectional average for big (Top 10) and small (rest) banks across time, the average masks the fact that some banks spend time at the constraint (and even violate the constraint). Figure 3 plots the histogram of all banks across several years (2000, 2005, 2010 and 2015).

Figure 3: Distributions of Risk-Weighted Bank Capital

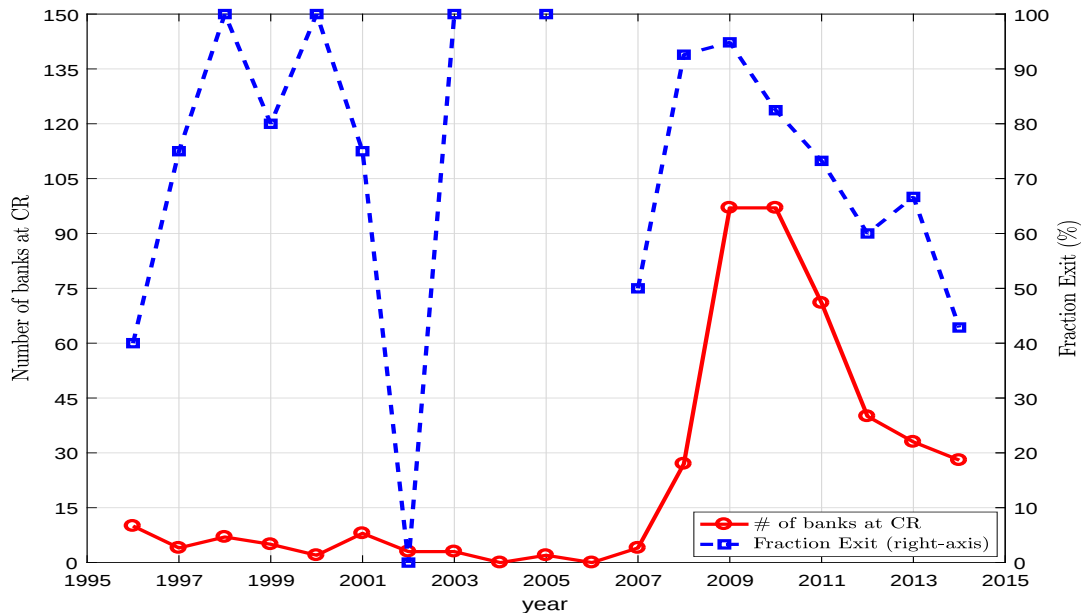


Note: Tier 1 Capital (rw) refers to Risk-weighted Tier 1 Capital Ratio. Cap. Req. refers to minimum capital requirement (risk-weighted) plus capital conservation buffer for banks with less than 50 billion in assets (all of these banks included in the “Rest” group). Banks with more than 50 billion are required to hold additional capital since 2013. Source: Consolidated Report of Condition and Income.

The figure makes clear that large institutions have consistently lower levels of capital than other banks. That is, the capital buffer for large banks is smaller for the Top 10 banks than for the other banks. Government assistance, private injection of equity and changes in capital regulation have induced shifts in the distribution of capital. Moreover, during the crisis, a considerable number of banks failed, merged with other institutions under distress or received government assistance. The bottom panels of 3 (years 2010 and 2015) show that it is possible to find banks close or below the minimum required. Many of these banks end

up failing. To analyze the relationship between bank failure and capital ratios, Figure 4 shows the number banks that are at or below the minimum risk-weighted capital required and the fraction of those that exit (via failure or merger the the corresponding year or the year after).

Figure 4: Distributions of Bank Capital



Note: Tier 1 Capital (rw) refers to Risk-weighted Tier 1 Capital Ratio. Cap. Req. refers to minimum capital requirement (risk-weighted) plus capital conservation buffer for banks with less than 50 billion in assets (all of these banks included in the “Rest” group). Banks with more than 50 billion are required to hold additional capital since 2013. Source: Consolidated Report of Condition and Income.

Figure 4 makes evident that most banks with capital ratios close to the minimum required exit the industry. The average fraction of banks that exit conditional on being close to the minimum required is well above 70 percent.

3 Environment

Each period, banks intermediate between a unit mass of ex-ante identical entrepreneurs who have a profitable project which needs to be funded (the potential borrowers) and a mass $N > 1$ of identical households (the potential depositors).

3.1 Entrepreneurs

Infinitely lived, risk neutral entrepreneurs demand bank loans in order to fund a new project each period. We assume a sufficiently low discount factor β_E such that entrepreneurs choose not to use retained earnings to finance their projects, instead choosing to eat their earnings and fund projects which generate returns in the following period using one period loans that require monitoring. Specifically, a project requires one unit of investment in period t and returns next period:

$$\begin{cases} 1 + z_{t+1}R_t & \text{with prob } p(R_t, z_{t+1}) \\ 1 - \lambda & \text{with prob } [1 - p(R_t, z_{t+1})] \end{cases} \quad (1)$$

in the successful and unsuccessful states, respectively. That is, borrower gross returns are given by $1 + z_{t+1}R_t$ in the successful state and by $1 - \lambda$ in the unsuccessful state. The success of a borrower's project, which occurs with probability $p(R_t, z_{t+1})$, is independent across borrowers and time *conditional* on the borrower's choice of technology $R_t \geq 0$ and an aggregate technology shock at the beginning of the following period denoted z_{t+1} (i.e. there is one period time-to-build). The aggregate technology shock $z_t \in Z$ evolves as a Markov process $F(z', z) = \text{prob}(z_{t+1} = z' | z_t = z)$.

When the borrower makes his choice of technology R_t , the aggregate shock z_{t+1} has not been realized. As for the likelihood of success or failure, a borrower who chooses to run a project with higher returns has more risk of failure and there is less failure in good times. Specifically, $p(R_t, z_{t+1})$ is assumed to be decreasing in R_t and increasing in z_{t+1} . While borrowers are ex-ante identical, they are ex-post heterogeneous owing to the realizations of the shocks to the return on their project. We envision borrowers either as firms choosing a technology that might not succeed or households choosing a house that might appreciate or depreciate.

There is limited liability on the part of the borrower. If r_t^L is the interest rate on a bank loan that the borrower faces, the borrower receives $\max\{z_{t+1}R_t - r_t^L, 0\}$ in the successful state and 0 in the failure state. Specifically, in the unsuccessful state he receives $1 - \lambda$ which must be relinquished to the lender. Table 1 summarizes the risk-return tradeoff that the borrower faces if the cross-sectional distribution of banks is μ_t .

Table 1: Borrower's Problem

Borrower Chooses R_t	Receive	Pay	Probability
Success	$1 + z_{t+1}R_t$	$1 + r^L(\mu_t, z_t)$	$p(R_t, z_{t+1})$
Failure	$1 - \lambda$	$1 - \lambda$	$1 - p(R_t, z_{t+1})$

Borrowers have an outside option (reservation utility) $\omega_t \in [\underline{\omega}, \bar{\omega}]$ drawn at the beginning of the period from distribution function $\Omega(\omega_t)$. These draws are i.i.d. over time. We think of this outside option as an alternative source of external finance to the bank loan.

Both R_t and ω_t are private information to the entrepreneur, as well as the history of past borrowing and repayment by the entrepreneur. Success or failure is also private information to the entrepreneur unless the loan is monitored by the lender. With one period loans, since reporting failure (and hence repayment of $1 - \lambda < 1 + r_t^L$) is a dominant strategy in the absence of monitoring, loans must be monitored. Monitoring is costly as in Diamond [20].

3.2 Households

Infinitely lived, risk neutral households with discount factor β are endowed with $1/N$ units of the good. We assume households are sufficiently patient such that they choose to exercise their savings opportunities. In particular, households have access to a risk-free storage technology yielding $1 + \bar{r}$ with $\bar{r} \geq 0$ between any two periods. They can also choose to supply their endowment to a bank or to an individual borrower. If the household deposited its endowment with a bank, it receives r_t^D whether the bank succeeds or fails since we assume deposit insurance. Households can also hold a fraction of the portfolio of bank stocks yielding dividends (claims to bank cash flows) and can inject equity to banks. They also pay lump-sum taxes τ_t used to cover deposit insurance for failing banks. Finally, if a household was to match directly with an entrepreneur (i.e. directly fund an entrepreneur's project), it must compete with bank loans. Hence, the household could not expect to receive more than the bank lending rate r^L in successful states and must pay a monitoring cost. Since households can purchase claims to bank cash flows, and banks can more efficiently minimize costly monitoring along the lines of Diamond [20], there is no benefit to matching directly with borrowers.

3.3 Banks

As in Diamond [20], banks exist in our environment to pool risk and economize on monitoring costs. We assume there are two types of banks: $\theta \in \{b, f\}$ for big and small - what we call "fringe" - banks, respectively. Unlike our earlier paper [18] where there are multiple big banks, to keep the analysis simple, we assume there is a representative big bank if it is active. If active, the big bank is a Stackelberg leader in the loan market, each period choosing a level of loans before fringe banks make their choice of loan supply. Consistent with the assumption of Cournot competition, the dominant bank understands that its choice of loan supply will influence the interest rate on loans. A fringe bank takes the interest rate as given when choosing its loan supply. We assume there is a representative big bank.¹⁴

At the beginning of each period t after the realization of the aggregate shock z_t , the cash flows for bank i of type θ that are realized from its previous lending (denoted $\ell_{\theta,t}^i$), liquid assets (cash and securities, denoted $A_{\theta,t}^i$), and deposits (denoted $d_{\theta,t}^i$) augment existing equity to give beginning of period net worth $n_{\theta,t}^i$. At that point, a bank can choose to exit. If the bank chooses not to exit, the incumbent is randomly matched with a set of potential depositors $\delta_{\theta,t}$. An incumbent bank then chooses a quantity $d_{\theta,t+1}^i$ of deposits to accept up to

¹⁴Our previous paper [18] considers the more complex case of multiple dominant banks.

the capacity constraint $\delta_{\theta,t}$ (i.e., $d_{\theta,t+1}^i \leq \delta_{\theta,t}$ where $\delta_{\theta,t} \in \{\delta_{\theta}^1, \dots, \delta_{\theta}^n\} \subseteq \mathbb{R}_+$).¹⁵ The capacity constraint evolves according to a Markov process given by $G_{\theta}(\delta_{\theta,t+1}, \delta_{\theta,t})$ with realizations which are i.i.d across banks. The value of $\delta_{\theta,t}$ for a new entrant is drawn from the probability distribution $G_{\theta}^e(\delta_{\theta,t})$. Differences in the volatility of funding inflows we find in the data between big and small banks provide a reason why banks of different sizes hold different size capital buffers.

Along with possible equity injections (denoted $e_{\theta,t}^i \in \mathbb{R}_+$), an incumbent bank allocates its net worth and deposits to its asset portfolio and pays dividends (denoted $\mathcal{D}_{\theta,t}^i \in \mathbb{R}_+$). We assume liquid assets have a return equal to r_t^A . The incumbent bank's portfolio and dividend policy must satisfy the following constraint

$$n_{\theta,t}^i + d_{\theta,t+1}^i + e_{\theta,t}^i \geq \ell_{\theta,t+1}^i + A_{\theta,t+1}^i + \mathcal{D}_{\theta,t}^i + \zeta_{\theta}(e_{\theta,t}^i, z_t) + \kappa_{\theta}^i + c_{\theta}^i(\ell_{\theta,t+1}^i) \quad (2)$$

where $\zeta_{\theta}(e_{\theta,t}^i, z_t)$ denotes aggregate state dependent equity issuance costs and $[\kappa_{\theta}^i + c_{\theta}^i(\ell_{\theta,t+1}^i)]$ represents non-interest expenses (including monitoring costs which are a function of loans issued).¹⁶ We assume that $\zeta_{\theta}(0, z_t) = 0$ and $\zeta_{\theta}(e_{\theta,t}^i, z_t)$ is an increasing function of $e_{\theta,t}^i$ and decreasing in z_t (i.e. external financing costs are increasing in the amount of equity issued and less costly in good times). Since the bank's objective is increasing in dividends $\mathcal{D}_{\theta,t}^i$, (2) will hold as an equality constraint.

In Corbae and D'Erasmus [18] we document differences in bank cost structure across size. We assume that banks pay non-interest expenses on their loans (as in the delegated monitoring model of Diamond [20]) that differ across banks of different sizes, which we denote $c_{\theta}^i(\ell_{\theta,t+1}^i)$. Further, as in the data we assume a fixed cost κ_{θ}^i .

Let $\pi_{\theta,t+1}^i$ denote the net cash flow of bank i of type θ after the realization of the next period's aggregate shock associated with its current lending and borrowing decisions given by

$$\pi_{\theta,t+1}^i = \left\{ p(R_t, z_{t+1}) r_t^L - (1 - p(R_t, z_{t+1})) \lambda \right\} \ell_{\theta,t+1}^i + r_t^A A_{\theta,t+1}^i - r_t^D d_{\theta,t+1}^i. \quad (3)$$

The first two terms represent the gross return the bank receives from successful and unsuccessful loan projects, respectively, the third term represents returns on securities, and the fourth represents interest expenses (payments on deposits).

The capital requirement for bank i of type θ after loan, deposit, asset and dividend payment decisions have been made can be written

$$\ell_{\theta,t+1}^i + A_{\theta,t+1}^i - d_{\theta,t+1}^i \geq \varphi_{\theta,t}(w_{\theta,t}^{\ell} \ell_{\theta,t+1}^i + w_{\theta,t}^A A_{\theta,t+1}^i) \quad (4)$$

where $\varphi_{\theta,t}$ is the capital requirement and $(w_{\theta,t}^{\ell}, w_{\theta,t}^A)$ are risk weights associated with loans and liquid assets, respectively. We will typically take $w_{\theta,t}^{\ell} = 1$. Given $w_{\theta,t}^{\ell} > w_{\theta,t}^A$, liquid assets help relax the capital requirement constraint, but may also lower bank profitability and

¹⁵Anticipating a "recursive" formulation of the bank decision problem, certain state variables chosen in period t but paying off in period $t + 1$ will be denoted x_{t+1} (e.g. deposits d_{t+1}).

¹⁶This "reduced form" approach to modeling equity issuance is similar to Cooley and Quadrini [17], Gomes [31], and Hennessey and Whited [34],

solvency. This creates room for a precautionary motive for liquid assets and the possibility that banks hold capital equity above the level required by the regulatory authority.

Another policy proposal is associated with bank liquidity requirements. Basel III [7] proposed that the liquidity coverage ratio, which is the stock of high-quality liquid assets (which include government securities) divided by total net cash outflows over the next 30 calendar days, should exceed 100%. In the context of a model period being one year, this would amount to a critical value of 1/12 or roughly 8%. This is also close to the figure for reserve requirements that is bank-size dependent, anywhere from zero to 10%. Since reserves now pay interest, bank liquidity requirements are similar in nature to current reserve requirement policy in our model. For the model, we assume

$$\gamma_{\theta,t} d_{\theta,t+1}^i \leq A_{\theta,t}^i, \quad (5)$$

where $\gamma_{\theta,t}$ denotes the (possibly) size and state dependent liquidity requirement.¹⁷

Beginning-of-next-period net worth is then given by

$$\begin{aligned} n_{\theta,t+1}^i &= \pi_{\theta,t+1}^i + \ell_{\theta,t+1}^i + A_{\theta,t+1}^i - d_{\theta,t+1}^i \\ &= \pi_{\theta,t+1}^i + n_{\theta,t}^i + e_{\theta,t}^i - \mathcal{D}_{\theta,t}^i - \zeta_{\theta}(e_{\theta,t}^i, z_t) - \kappa_{\theta}^i - c_{\theta}^i(\ell_{\theta,t+1}^i) \end{aligned} \quad (6)$$

where the second inequality follows from (2) with equality. The law of motion for net worth in (6) makes clear that retained earnings augment net worth and dividend payouts lower net worth.

There is limited liability on the part of banks. This imposes a lower bound equal to zero in the event the bank exits. In the context of our model, limited liability implies that, upon exit, shareholders get:

$$\max \left\{ n_{\theta,t+1}^i - \xi \ell_{\theta,t+1}^i, 0 \right\}, \quad (7)$$

where $\xi \in [0, 1]$ measures liquidation costs in the event of exit.

The objective function of the bank is to maximize the expected present discounted value of future dividends net of equity injections using the manager's discount factor which can depart from the households' discount factor β by the factor $\gamma \in (0, 1]$:

$$E_t \left[\sum_{s=0}^{\infty} (\gamma\beta)^s (\mathcal{D}_{\theta,t+s}^i - e_{\theta,t+s}^i) \right] \quad (8)$$

We introduce the possibility of agency problems through managerial myopia when $\gamma < 1$ along the lines of Acharya and Thakor [1].¹⁸

Entry costs for the creation of banks are denoted by $\Upsilon_b \geq \Upsilon_f \geq 0$. Every period a large number of potential entrants make the decision of whether or not to enter the market after

¹⁷Notice that an increase in $A_{\theta,t+1}^i$ and decrease in $d_{\theta,t+1}^i$ help to satisfy both the risk weighted capital requirement in (4) and the liquidity coverage ration in (5).

¹⁸There are many papers on managerial myopia providing a foundation for such behavior. See for instance, Stein [44] who provides a signalling argument or Minnick and Rosenthal [39] who provide a compensation argument.

the realization of z_t and incumbent exit but before the realization of δ_t shocks. Entry costs correspond to the initial injection of equity into the bank subject to equity finance costs $\zeta_\theta(\Upsilon_\theta + n_{e,\theta,t}^i, z_t)$ where $n_{e,\theta,t}^i$ is the entrant's initial equity injection.

3.4 Information

There is asymmetric information on the part of borrowers and lenders. Only borrowers know the riskiness of the project they choose (R_t) and their outside option (ω_t). All other information (e.g., project success or failure provided the loan is monitored) is observable.

3.5 Timing

At the beginning of period t ,

1. Aggregate shock z_t is realized which induces $n_{\theta,t}^i$ for incumbent banks and project returns for entrepreneurs.
2. Incumbents decide whether to exit and potential entrants decide whether to enter which requires an initial equity injection in stage 3.
3. Funding shocks δ_t - the mass of potential depositors the bank is matched with - are realized and borrowers draw ω_t .
 - The dominant bank chooses how many loans to extend, how many deposits to accept given depositors' choices, how many assets to hold, how many dividends to pay, and equity injections $(\ell_{b,t+1}^i, d_{b,t+1}^i, A_{b,t+1}^i, \mathcal{D}_{b,t}^i, e_{b,t}^i)$.
 - Each fringe bank observes the total loan supply of the dominant bank ($\ell_{b,t+1}^i$) and all other fringe banks (that jointly determine the loan interest rate r_t^L) and simultaneously decide how many loans to extend, how many deposits to accept, how many assets to hold, how many dividends to pay, and equity injections $(\ell_{f,t+1}^i, d_{f,t+1}^i, A_{f,t+1}^i, \mathcal{D}_{f,t}^i, e_{f,t}^i)$.
 - Borrowers choose whether or not to undertake a project requiring bank funding and, if so, a level of technology R_t .
 - Households pay taxes τ_t to fund deposit insurance, choose to store or deposit at a bank, how many stocks to hold, equity injections, and consume.

4 Industry Equilibrium

This section presents the equilibrium of the model. We start by describing the household problem (which determines the supply of deposits and seasoned equity to banks) and the entrepreneur problem (which determines the demand for bank loans) followed by the bank problem.

4.1 Household's Problem

The problem of a representative household is

$$\max_{\{C_t, a_{h,t+1}, d_{h,t+1}, \{S_{\theta,t+1}^i\}_{\forall i}\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t C_t \right] \quad (9)$$

subject to

$$\begin{aligned} & C_t + a_{h,t+1} + d_{h,t+1} + \sum_{\theta} \int [P_{\theta,t}^i + \mathbf{1}_{\{e_{\theta,t}^i=1\}}(\Upsilon_{\theta} + n_{\theta,t}^i)] S_{\theta,t+1}^i di \\ &= \frac{1}{N} + \sum_{\theta} \int (\mathcal{D}_{\theta,t}^i - e_{\theta,t}^i + P_{\theta,t}^i) S_{\theta,t}^i di + (1 + \bar{r})a_{h,t} + (1 + r_t^d)d_{h,t} - \tau_t. \end{aligned} \quad (10)$$

where $P_{\theta,t}^i$ and $S_{\theta,t+1}^i$ are the after dividend stock price and stock holding of bank i of type θ , respectively. Given exit and entry decision rules, in cases in which a firm has exited, $P_{\theta,t}^i = 0$ on the right-hand side of the budget constraint, and, in cases in which a firm has entered, $P_{\theta,t}^i > 0$ on the left hand side of the budget constraint.

The first order condition for $S_{\theta,t+1}^i$ is:

$$P_{\theta,t}^i = \beta E_{z_{t+1}|z_t} [\mathcal{D}_{\theta,t+1}^i - e_{\theta,t+1}^i + P_{\theta,t+1}^i], \forall i. \quad (11)$$

We will derive the expression for the equilibrium price of a share after we present the bank's problem.

If banks offer the same interest rates on deposits as households can receive from their storage opportunity (i.e. $r_{t+1}^D = \bar{r}$), then a household would be indifferent between matching with a bank and using the autarkic storage technology. In that case, any household who is matched with a bank would be willing to deposit at the insured bank. Furthermore, the first order condition for saving in the form of deposits or storage technology implies $\beta(1 + \bar{r}) = 1$.

4.2 Entrepreneur's Problem

Every period, given $\{r_t^L, z_t, \omega_t\}$, entrepreneurs choose whether or not to operate the technology ($\iota_t \in \{0, 1\}$) and if they do, they choose the type of technology to operate R_t , whether to use retained earnings $I_{t+1} \in [0, 1]$ to internally finance the project, how much to save $a_{E,t+1} \in \mathbb{R}_+$ to maximize the expected discounted utility of consumption. Therefore,

$$\max_{\{C_{E,t}, a_{E,t+1}, I_{t+1}, \iota_t \in \{0, 1\}, R_t\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t C_{E,t} \right] \quad (12)$$

subject to

$$C_{E,t} + a_{E,t+1} + I_{t+1} = \iota_t(\omega_t + I_t) + (1 - \iota_t)\pi_E(I_t, R_t, z_{t+1}) + (1 + \bar{r})a_{E,t} \quad (13)$$

where

$$\pi_E(I_t, R_t, z_{t+1}) = \begin{cases} \max\{0, z_{t+1}R_t - r_t^L + (1 + r^L)I_t\} & \text{with prob } p(R_t, z_{t+1}) \\ \max\{0, -\lambda - r^L + (1 + r^L)I_t\} & \text{with prob } 1 - p(R_t, z_{t+1}) \end{cases}$$

where $C_{E,t} \in \mathbb{R}_+$ is the entrepreneur's consumption.

If m_t is the multiplier on the non-negativity constraint on $a_{E,t+1} \geq 0$, the first order condition for $a_{E,t+1}$ is given by

$$m_t = \beta^E(1 + \bar{r}) - 1. \quad (14)$$

Since we assume a sufficiently impatient entrepreneur (i.e. $\beta^E(1 + \bar{r}) < 1$), then $a_{E,t+1} = 0$. Similarly, the entrepreneur chooses not to use retained earnings to fund the project (i.e. $I_{t+1} = 0$ provided $\beta_E(1 + r_t^L) < 1$ (i.e. the bank loan is not too costly relative to current consumption).

If the entrepreneur undertakes the project, then an application of the envelope theorem implies

$$\frac{\partial E_{z_{t+1}|z_t} \pi_E(I_t, R_t, z_{t+1})}{\partial r_t^L} = -E_{z_{t+1}|z_t} [p(R_t, z_{t+1})] < 0. \quad (15)$$

Thus, participating borrowers are worse off the higher the borrowing rates are. This has implications for the demand for loans determined by the participation constraint. In particular, since the demand for loans is given by

$$L^d(r_t^L, z_t) = \int_0^{\bar{\omega}} \mathbf{1}_{\{\omega_t \leq E_{z_{t+1}|z_t} \pi_E(0, R_t, z_{t+1})\}} d\Omega(\omega_t), \quad (16)$$

where $\mathbf{1}_{\{\cdot\}}$ is an indicator function that takes the value one if the argument $\{\cdot\}$ is true and zero otherwise. In that case, (15) implies $\frac{\partial L^d(r_t^L, z_t)}{\partial r_t^L} < 0$. That is, the loan demand curve is downward sloping.

4.3 Incumbent Bank Problem

We will study equilibria which do not depend on the name i of the bank, only relevant state variables. Since we will use recursive methods to solve a bank's decision problem, let any variable $x_{\theta,t}$ be denoted x_θ and $x_{\theta,t+1}$ be denoted x'_θ . Further, we denote the cross-sectional distribution of banks or "industry state" by

$$\mu = \{\mu_b(n, \delta), \mu_f(n, \delta)\}, \quad (17)$$

where each element of μ is a measure $\mu_\theta(n, \delta)$ corresponding to *active* banks of type θ over matched deposits δ and net worth n at stage 3 in period t of our timing.¹⁹ The law of motion for the industry state is denoted $\mu' = H(z, \mu, z', M'_e)$ where $M'_e = \{M'_{e,b}, M'_{e,f}\}$ denotes the vector of entrants of each type and the transition function H is defined explicitly below.

¹⁹It should be understood that μ_b is a counting measure.

After being matched with δ_θ potential depositors, an incumbent bank of type θ chooses loans ℓ'_θ , deposits d'_θ , and asset holdings A'_θ in order to maximize expected discounted dividends net of equity injections. We assume Cournot competition in the loan market. Following the realization of z , banks can choose to exit setting $x_\theta = 1$ or choose to remain $x_\theta = 0$.

Let σ_{-i} denote the industry state dependent balance sheet, exit, and entry strategies of all other banks. Given the Cournot assumption, the big bank takes into account that it affects the loan interest rate and its loan supply affects the total supply of loans by fringe banks. Differentiating the bank profit function π'_θ defined in (3) with respect to ℓ_θ we obtain

$$\frac{d\pi'_\theta}{d\ell'_\theta} = \underbrace{[pr^L - (1-p)\lambda - c'_\theta]}_{(+)\text{ or }(-)} + \ell'_\theta \left[\underbrace{p}_{(+)} + \underbrace{\frac{\partial p}{\partial R} \frac{\partial R}{\partial r^L} (r^L + \lambda)}_{(-)} \right] \underbrace{\frac{dr^L}{d\ell'_\theta}}_{(-)}. \quad (18)$$

The first bracket represents the marginal change in profits from extending an extra unit of loans. The second bracket corresponds to the marginal change in profits due to a bank's influence on the interest rate it faces. This term depends on the bank's market power; for big banks $\frac{dr^L}{d\ell'_b} < 0$ while for fringe banks $\frac{dr^L}{d\ell'_f} = 0$. Note that a change in interest rates also endogenously affects the fraction of delinquent loans faced by banks; given limited liability entrepreneurs take on more risk when their financing costs rise.

Let the total supply of loans by fringe banks as a function of the aggregate state $\{z, \mu\}$ and the big bank's choice of loans ℓ'_b be given by

$$L_f(z, \mu, \ell'_b) = \int \ell'_f(n, \delta; z, \mu, \ell'_b) \mu_f(dn, d\delta). \quad (19)$$

The loan supply of fringe banks is a function of the big bank's loan supply ℓ'_b because fringe banks move after the big bank.

The value of an incumbent bank in period t (at stage 3) consistent with the manager's choice over $\{\{\ell'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta\} \geq 0, d_\theta \in [0, \delta_\theta], x'_\theta \in \{0, 1\}\}$ is given by

$$V_\theta(n_\theta, \delta_\theta; z, \mu, \cdot) = \max_{\{\ell'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta\} \geq 0, d_\theta \in [0, \delta_\theta]} \left\{ \mathcal{D}_\theta - e_\theta \right. \\ \left. + \gamma \beta E_{z'|z} \left[\max_{x'_\theta \in \{0, 1\}} \left\{ (1 - x'_\theta) E_{\delta'_\theta | \delta_\theta} V_\theta(n'_\theta, \delta'_\theta; z', \mu', \cdot) + x'_\theta V_\theta^x(n'_\theta, \ell'_\theta) \right\} \right] \right\} \quad (20)$$

s.t.

$$\ell'_\theta + A'_\theta - d'_\theta \geq \varphi_{\theta, z}(w_\theta^\ell \ell'_\theta + w_{\theta, z}^A A'_\theta) \quad (21)$$

$$\gamma_{\theta, z} d'_\theta \leq A'_\theta \quad (22)$$

$$n_\theta + d'_\theta + e_\theta \geq \ell'_\theta + A'_\theta + \mathcal{D}_\theta + \zeta_\theta(e_\theta, z) + [\kappa_\theta + c_\theta(\ell'_\theta)] \quad (23)$$

$$n'_\theta = \pi'_\theta + e_\theta + n_\theta - \mathcal{D}_\theta - \zeta_\theta(e_\theta, z) - [\kappa_\theta + c_\theta(\ell'_\theta)] \quad (24)$$

$$L^d(r^L, z) = \ell'_\theta + L_f(z, \mu, \ell'_b) \quad (25)$$

$$\mu' = H(z, \mu, z', M'_e), \quad (26)$$

where

$$V_{\theta}^x(n'_{\theta}, \ell'_i) = \max \{0, n'_{\theta} - \xi_{\theta} \ell'_i\} \quad (27)$$

where $V_{\theta}^x(n'_{\theta}, \ell'_i)$ is the liquidation value of the bank for given n'_b and ℓ'_b . The lower bound on the exit value in (27) is associated with limited liability. The value function in (20) is defined over individual states $\{n_{\theta}, \delta_{\theta}\}$, aggregate states $\{z, \mu\}$, and $\{\cdot\}$ which is empty if $\theta = b$ and is ℓ'_b if $\theta = f$ (consistent with the Stackelberg game in the loan market). Equations (21) to (24) are the capital requirement, liquidity coverage ratio, balance sheet constraint, and law of motion for net worth, respectively. Equation (25) is the market-clearing condition which is included since the dominant bank must take into account its impact on prices. Changes in ℓ'_b affect the equilibrium interest rate through its direct effect on the aggregate loan supply (first term) but also through the effect on the loan supply of fringe banks (second term). For any given μ , $L_f(z, \mu, \ell'_b)$ can be thought of as a “reaction function” of fringe banks to the loan supply decision of the dominant bank. Equation (26) corresponds to the evolution of the aggregate state to be defined below. The solution to the problem of the big bank provides big bank decision rules $\ell'_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)$, $A'_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)$, $\mathcal{D}_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)$, $e_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)$ and $x'_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot, z')$ as well as value functions.

Now that we presented the problem of an incumbent bank, we can show how the price of a bank's shares and the value of a bank are related. After normalizing the number of shares of each bank to N , the price of a share of a non-exiting bank of type θ in state $(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)$ after dividends have been paid and equity injected is defined by

$$P_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) \equiv V_{\theta}^*(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - (\mathcal{D}_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - e_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)) \quad (28)$$

where the value of a continuing bank to the household using the manager's decision rules is defined by

$$V_{\theta}^*(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) \equiv \left\{ \mathcal{D}_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - e_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) + \beta E_{z', \delta'_{\theta} | z, \delta_{\theta}} V_{\theta}^*(n'_{\theta}, \delta'_{\theta}; z', \mu', \cdot) \right\} \quad (29)$$

Thus, substituting (28) into the household's first order condition for its stock choice in equation (11) implies

$$\begin{aligned} P_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) &= \beta E_{z', \delta'_{\theta} | z, \delta_{\theta}} [\mathcal{D}_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - e_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) + P'_{\theta}(n'_{\theta}, \delta'_{\theta}; z', \mu', \cdot)] \iff \\ V_{\theta}^*(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - (\mathcal{D}_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot) - e_{\theta}(n_{\theta}, \delta_{\theta}; z, \mu, \cdot)) &= \beta E_{z', \delta'_{\theta} | z, \delta_{\theta}} [V_{\theta}^*(n'_{\theta}, \delta'_{\theta}; z', \mu', \cdot)] \end{aligned} \quad (30)$$

But (30) can be re-arranged to be identical to the value of a continuing bank defined in (20) when managers' and households' preferences are aligned (i.e. when $\rho = 1$) while $V_{\theta}(\cdot) < V_{\theta}^*(\cdot)$ otherwise.

4.4 Bank Entry

Next we turn to the value of entry. Both the industry state μ and the incumbent value function above in (20) are defined for stage 3 in period t of our timing. However, the entry decision is at stage 2 after exit but before the current mass of entrants $M_{e,\theta}$ is known (so

that μ is not yet fully defined at that stage). Hence, we will define the entry value function in terms of stage 2 of period $t + 1$. In particular, the value of entry net of entry costs for banks of type θ in stage 2 of period $t + 1$ in aggregate state z' if there were $M'_{e,\theta}$ entrants at stage 2 of period $t + 1$ is then given by

$$V_\theta^e(z, \mu, z', M'_{e,\theta}) \equiv \max_{n'_{e,\theta}} \left\{ - (n'_{e,\theta} + \Upsilon_\theta)(1 + \zeta_\theta(n'_{e,\theta} + \Upsilon_\theta, z')) \right. \\ \left. + E_{\delta'|\theta} V_\theta(n'_{e,\theta}, \delta'_\theta, z', H(z, \mu, z', M'_{e,\theta})) \right\}. \quad (31)$$

Potential entrants will decide to enter if $V_\theta^e(z, \mu, z', M'_{e,\theta}) \geq 0$. The argmax of equation (31) for those firms that enter defines the initial equity injection of banks. The mass of entrants is determined endogenously in equilibrium. Free entry implies that

$$V_\theta^e(z, \mu, z', M'_{e,\theta}) \times M'_{e,\theta} = 0. \quad (32)$$

That is, in equilibrium, either the value of entry is zero, the number of entrants is zero, or both.

4.5 Evolution of the Cross-Sectional Bank Size Distribution

The distribution of banks evolves according to $\mu' = H(z, \mu, z', M'_e)$ where each component is given by:

$$\mu'_\theta(n'_\theta, \delta'_\theta) = \int \sum_{\delta_\theta} (1 - x'_\theta(n_\theta, \delta_\theta; z, \mu, \cdot, z')) \mathbf{1}_{\{n'_\theta = n'_\theta(n_\theta, \delta_\theta, z, \mu, \cdot, z')\}} G_\theta(\delta'_\theta, \delta_\theta) d\mu_\theta(n_\theta, \delta_\theta) \quad (33) \\ + M'_{e,\theta} \mathbf{1}_{\{n'_\theta = n'_{e,\theta}(z, \mu, z', M'_{e,\theta})\}} G_{e,\theta}(\delta'_\theta),$$

where (33) makes clear how the law of motion for the distribution of banks is affected by entry and exit decisions.

4.6 Funding Deposit Insurance

In this section, we continue to use the same timing convention used in the previous section. Across all states (z, μ, z') , taxes must cover deposit insurance in the event of bank failure. Let post-liquidation net transfers be given by

$$\Delta'_\theta(n_\theta, \delta_\theta, z, \mu, z') = (1 + r^D)d'_\theta - \left\{ p(R, z')(1 + r^L) + (1 - p(R, z'))(1 - \lambda) - \xi_\theta \right\} \ell'_\theta - (1 + r^a)A'_\theta$$

where $\xi \leq 1$ is the post-liquidation value of the bank's loan portfolio. Then aggregate taxes are given by

$$\tau'(z, \mu, z') \cdot N = \sum_\theta \left[\int \sum_{\delta_\theta} x'_\theta \max\{0, \Delta'_\theta(n_\theta, \delta_\theta, z, \mu, z')\} d\mu_\theta(n_\theta, \delta_\theta) \right]. \quad (34)$$

4.7 Definition of Equilibrium

Given policy parameters $(r^a, \varphi_{\theta,z}, w_{\theta,z}^\ell, w_{\theta,z}^A, \gamma_{\theta,z})$, a pure strategy Markov Perfect Industry Equilibrium (MPIE) is a set of functions $\{a'_E, I', \iota, R\}$ describing entrepreneur (financing) behavior, $\{a'_h, d'_h, S'_\theta\}$ describing household (saving) behavior, $\{V_\theta, \ell'_\theta, d'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta, x'_\theta, V_\theta^e\}$ describing bank balance sheet, dividend, exit and entry behavior, a cross-sectional distribution of banks μ , a function describing the mass of entrants M_θ^e , a loan interest rate $r^L(\mu, z)$, a deposit interest rate r^D , stock prices P_θ , and a tax function τ_z such that:

1. Given r^L and $\bar{r}$, $\{a'_E, I', \iota, R\}$ are consistent with entrepreneur optimization (12)-(13) inducing an aggregate loan demand function $L^d(r^L, z)$ in (16).
2. Given $r^D = \bar{r}$ and P_θ , $\{a'_h, d'_h, S'_\theta\}$ are consistent with household optimization (9)-(10) inducing a deposit matching process.
3. Given the loan demand function and deposit matching process, $\{V_\theta, \ell'_\theta, d'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta, x'_\theta\}$ are consistent with bank optimization (20)-(26) inducing an aggregate loan supply function $\ell'_b + L_f(z, \mu, \ell'_b)$ where L_f is defined in (19).
4. The entry asset decision rules are consistent with bank optimization (31) and the free-entry condition is satisfied (32).
5. The law of motion for the industry state induces a sequence of cross-sectional distributions that are consistent with entry, exit, and asset decision rules in (33).
6. The interest rate $r^L(\mu, z)$ is such that the loan market clears. That is,

$$L^d(r^L, z) = \ell'_b + L_f(z, \mu, \ell'_b).$$

7. Stock prices satisfy (28).
8. Across all states (z, μ, z') , taxes cover deposit insurance transfers in (34).

5 Calibration

A model period is one year. We use several sources to calibrate the model. Our main source for bank level variables (and aggregates derived from it) is the Consolidated Report of Condition and Income for Commercial Banks (regularly called “call reports”).²⁰ We aggregate commercial bank level information to the Bank Holding Company Level.²¹ We also use the TFP series for the U.S. Business Sector, produced by John Fernald [?] and data provided by the Federal Deposit Insurance Corporation to identify bank failures and losses

²⁰Source: FDIC, Call and Thrift Financial Reports, Balance Sheet and Income Statement (<http://www2.fdic.gov/hsob/SelectRpt.asp?EntryTyp=10>).

²¹Appendix ?? provides information on how this is done and also a description of the variables used in the paper.

in the event of failure. Our calibration strategy involves setting a set of parameters directly from the data and a second set using Simulated Method of Moments (SMM).

We begin with the parameterization of the four stochastic processes: $F(z', z)$, $G^\theta(\delta', \delta)$, $p(R, z')$, and $\Omega(\omega)$. To calibrate the stochastic process for aggregate technology shocks $F(z', z)$, we detrend the sequence of TFP using the H-P filter and estimate the following equation:

$$\log(z_t) = \rho_z \log(z_{t-1}) + u_t^z,$$

with $u_t \sim N(0, \sigma_{u^z})$. Once parameters ρ_z and σ_{u^z} are estimated, we discretize the process using the Tauchen [45] method. We set the number of grid points to four, that is $z_t \in Z = \{z_1, z_2, z_3, z_4\}$. We choose the grid in order to capture the infrequent crisis states we observe in the data. In particular, we choose z_3 to match the mean of the process normalized to 1 (i.e. $z_3 = 1$), select z_2 and z_4 so they are at 1.5 standard deviations from z_3 and set the value of z_1 to be at 2.75 standard deviations from the mean to be consistent with the observed TFP levels during the 1982 recession and the last financial crisis (years 2008/2009).

Moments from the call report data are computed using the period that goes from 1984 to 2007.²² This period does not include the 1982 recession or the last financial crisis, so we filter the model data accordingly when computing the moments used to estimate the parameters. That is, when performing the estimation exercise, moments from the model are computed using samples of 24 years that do not include observations with $z = z_1$.²³

We identify “big” banks with the top 10 banks (when sorted by assets) and the fringe banks with the rest.²⁴ As in Pakes and McGuire [41] we restrict the number of big banks by setting the entry cost to a prohibitively high number if the number of incumbents after entry and exit exceeds a given number. In our application, there will be at most one representative big bank and an infinite mass of potential fringe entrant banks.

The solution to our problem implies that the deposit capacity constraint binds in all states, so we can approximate the constraint using information on deposits from our panel of commercial banks in the U.S. In particular, after controlling for firm and year fixed effects as well as a time trend, we estimate the following autoregressive process for log-deposits for bank i of type θ in period t :

$$\log(\delta_{\theta,t}^i) = (1 - \rho_\theta^d)k_\theta^0 + \rho_\theta^d \log(\delta_{\theta,t-1}^i) + u_{\theta,t}^i, \quad (35)$$

where $\delta_{\theta,t}^i$ is the sum of deposits and other borrowings in period t for bank i , and $u_{\theta,t}^i$ is iid and distributed $N(0, \sigma_{\theta,u}^2)$. Since this is a dynamic model we use the method proposed by Arellano and Bond [6]. To keep the state space workable, we again apply the method

²²There was an overhaul of the data in 1984. Starting in this year makes the construction of a consistent time series possible for most variables in our sample. Moreover, the last financial crisis and subsequent government intervention makes the data since 2008 not suitable for a calibration exercise. Our Data Appendix provides a detailed description of all variables used in the paper and their construction.

²³All averages from the call report data correspond to asset-weighted averages. That is, the average of variable x in year t equals $\hat{x} = \sum_{i=1}^{N_t} w_t^i x_t^i$ where w_t^i is the ratio of assets of bank i in year t to total assets in year t and x_{it} is the observation of variable x for bank i in year t .

²⁴The group of Top 10 banks contains all the U.S. banks that were classified as global systemically important banks (G-SIBs) as of December of 2016.

proposed by Tauchen [45] to obtain a finite state Markov representation $G^\theta(\delta', \delta)$ to the autoregressive process in (35). To apply Tauchen's method, we use the estimated values of $\rho_b^d = 0.41$ and $\rho_f^d = 0.88$, and $\sigma_{b,u} = 0.11$ and $\sigma_{f,u} = 0.15$ from (35). Since we work with a normalization in the model (i.e., $z_3 = 1$), the mean k_θ^0 in (35) is not directly relevant. Instead, we include the mean of the finite state Markov process, denoted μ_θ^d , as one of the parameters to be estimated via SMM. From these estimates, we can construct the variance of deposits for big and small banks (i.e. $\sigma_{b,d} = \frac{\sigma_{b,u}}{(1-(\rho_b^d)^2)^{1/2}} = 0.124$ and $\sigma_{f,d} = \frac{\sigma_{f,u}}{(1-(\rho_f^d)^2)^{1/2}} = 0.322$). Thus, big banks have less volatile funding inflows, which is one factor explaining why they hold a smaller capital buffer.

We parameterize the stochastic process for the borrower's project as follows. For each borrower, let $y = \alpha z' - bR^\psi + \varepsilon_e$, where ε_e is iid (across agents and time) and drawn from $N(0, \sigma_\varepsilon^2)$. We define success to be the event that $y > 0$, so in states with higher z or higher ε_e success is more likely. Then

$$\begin{aligned} p(R, z') &= 1 - \Pr(y \leq 0 | R, z') \\ &= 1 - \Pr(\varepsilon_e \leq -\alpha z' + bR^\psi) \\ &= \Phi(\alpha z' - bR^\psi), \end{aligned} \quad (36)$$

where $\Phi(x)$ is a normal cumulative distribution function with zero mean and variance σ_ε^2 . The stochastic process for the borrower outside option, $\Omega(\omega)$, is simply taken to be the uniform distribution $[0, \bar{\omega}]$.

We estimate the marginal cost of producing a loan $c_\theta(\ell'_\theta)$ and the fixed cost κ_θ following the empirical literature on banking (see, for example, Berger et. al. [10]).²⁵ The marginal cost is derived from an estimate of marginal net expenses that is defined to be marginal non-interest expenses net of marginal non-interest income. Marginal non-interest expenses are derived from the following trans-log cost function:

$$\begin{aligned} \log(T_t^i) &= g_1 \log(w_t^i) + h_1 \log(\ell_{\theta,t}^i) + g_2 \log(q_t^i) + g_3 \log(w_t^i)^2 \\ &\quad + h_2 [\log(\ell_t^i)]^2 + g_4 \log(q_t^i)^2 + h_3 \log(\ell_t^i) \log(q_t^i) + h_4 \log(\ell_t^i) \log(w_t^i) \\ &\quad + g_5 \log(q_t^i) \log(w_t^i) + \sum_{j=1,2} g_6^j t^j + g_{8,t} + g_9^i + \epsilon_t^i, \end{aligned} \quad (37)$$

where $T_{\theta,t}^i$ is total expenses minus the cost of deposits, the cost of federal funds purchased, and expenses on premises and fixed assets, g_9^i is a bank fixed effect, w_t^i corresponds to input prices (labor expenses), ℓ_t^i corresponds to real loans (one of the two bank i 's outputs), q_t^i represents securities (the second bank output), the t regressor refers to a time trend, and $k_{8,t}$ refers to time fixed effects. We estimate this equation by panel fixed effects with robust standard errors clustered by bank. Non-interest marginal expenses are then computed as:

$$\frac{\partial T_t^i}{\partial \ell_t^i} = \frac{T_t^i}{\ell_t^i} \left[h_1 + 2h_2 \log(\ell_t^i) + h_3 \log(q_{it}) + h_4 \log(w_t^i) \right]. \quad (38)$$

The estimated (asset-weighted) average of marginal non-interest expenses is reported in the second column of Table 2. Marginal non-interest income is estimated using an equation

²⁵The marginal cost estimated is also used to compute our measure of Markups and the Lerner Index.

similar to the one used for marginal non-interest expenses (without input prices) where the left hand side corresponds to total non-interest income. The estimated (asset-weighted) average of marginal non-interest income is reported in the first column of Table 2. Net marginal expenses are computed as the difference between marginal non-interest expenses and marginal non-interest income. The estimated (asset-weighted) average of net marginal non-interest expenses is reported in the third column of Table 2. The fixed cost κ^θ is estimated as the total cost on expenses of premises and fixed assets. The estimated (asset-weighted) average fixed cost (scaled by loans) is reported in the fourth column of Table 2.

The final column of Table 2 presents our estimate of average costs for big and small banks. We find a statistically significant lower average cost for big banks than small banks. This is consistent with increasing returns as in the delegated monitoring model of Diamond [20].

Table 2: Banks' Cost Structure

Moment (%)	Mg Non-Int Inc. $c_\theta^{inc}(\ell'_\theta)$	Mg Non-Int Exp. $c_\theta^{exp}(\ell'_\theta)$	Mg Net Exp. $c_\theta(\ell'_\theta)$	Fixed Cost $\kappa_\theta/\ell_\theta$	Avg. Cost
Top 10 Banks	4.07 [†]	4.72 [†]	0.65 [†]	0.84	1.49 [†]
Fringe Banks	2.12	3.69	1.57	0.75	2.32

Note: [†] denotes statistically significant difference between the Top 10 and the rest. Mg Non-Int Inc. refers to marginal non interest income, Mg Non-Int exp. to marginal non interest expenses. Mg Net Exp. corresponds to net marginal expense and it is calculated as marginal non-interest expense minus marginal non-interest income. Fixed cost κ^θ is scaled by loans. Data correspond to commercial banks in the U.S. Source: FDIC, Call and Thrift Financial Reports.

We parameterize the cost function in the model as $c_\theta(\ell'_\theta) = c_{\theta,0}\ell'_\theta + c_{\theta,1}(\ell'_\theta)^2$. We incorporate the estimated average marginal net expenses to our SMM procedure to help pin down the parameters of this function. We also use the estimates of the fourth column of Table 2 to pin down the fixed operating costs in the model.

To calibrate $\bar{r} = r^D$ we target the average cost of funds computed as the ratio of interest expense on deposits and federal funds purchased over total deposits plus federal funds purchased.²⁶ Similarly, we calibrate r^a to the ratio of interest income from safe securities over the total safe securities (net of marginal not interest expenses on securities). The parameter λ is set to 0.406 to be consistent with the average charge-off rate that equals 0.7457% in the data at the observed default frequency of 1.835%. The liquidation value of the loan portfolio $(1 - \xi_\theta)$ is estimated using data from the FDIC. We set $\xi_b = \xi_f = 0.1965$. The equity issuance cost function is parameterized as follows: $\zeta_\theta(e, z) = (\zeta_{\theta,0}e + \zeta_{\theta,1}e^2)(\frac{z_4}{z})^{\zeta_z}$.

In our benchmark parameterization, we use values associated with regulation in place before Basel III and the recent financial crisis. Thus we set the minimum level of the bank

²⁶The nominal interest rate is converted to a real interest rate by using the CPI.

equity risk-weighted capital ratio for both types of banks to 4%. That is, $\varphi_{b,z} = \varphi_{f,z} = 0.04$ for all z and $w_{\theta,z}^A = 0$ for all θ and z .

We are left with 21 parameters to estimate via simulated method of moments (SMM):

$$\{\alpha, b, \sigma_\varepsilon, \psi, \bar{\omega}, \gamma, \mu_b^d, \mu_f^d, c_{b,0}, c_{b,1}, c_{f,0}, c_{f,1}, \kappa_b, \kappa_f, \zeta_{b,0}, \zeta_{b,1}, \zeta_{f,0}, \zeta_{f,1}, \zeta_z, \Upsilon_f, \Upsilon_b\}.$$

To pin down these parameters, except for two data moments, we use the data for commercial banks described in Section 2 and in our companion paper. One of the extra moments is the average real equity return (12.94%) as reported by Diebold and Yilmaz [23] is added to help identify parameters associated with the borrower's return $pz'R^*$. The other moment is the elasticity of loan demand (-1.40) as estimated by Bassett, Chosak, Driscoll and Zakrajsek (2013).

The set of targets from commercial bank data includes the interest margin (4.69%) that is defined as the difference between the interest income from loans minus the cost of deposits, the standard deviation of the interest margin (0.339%), the loan default frequency (1.835%), marginal net expenses and fixed cost by bank size (as reported in Table 2), equity issuance over assets by bank size (0.02% and 0.11% for big and fringe banks, respectively), and the frequency of equity issuance (9.86% and 9.59%), the bank failure and entry rate (1.02% and 1.35%, respectively), the dividend to asset ratio by bank size (0.62% and 0.66% for big and fringe banks, respectively), and the frequency of dividend payments (96.11% and 85.38% for big and fringe banks, respectively).

While the balance sheet in our model is fairly rich and considers the most important pieces of its empirical counterpart such as loans, cash and securities, deposits and equity, in order to connect the model's balance sheet with the one in the data that contains several additional items, we proceed as follows. We identify loans in the model with the reported value for risk-weighted assets. The ratio of risk-weighted assets to total assets (loans to assets in the model) by bank size implies the ratio of cash and securities to assets (since loans plus cash and securities equals total assets in the model). One of the main counterfactuals in the paper evaluates changes in capital regulation, so we target the risk-weighted Tier 1 capital ratio by bank size (equity to loans in the model). Once the risk-weighted capital ratio is obtained, the ratio of equity to total assets and the ratio of deposits to total assets can be derived (since deposits is the only other liability in the model, thus effectively representing the ratio of deposits plus other borrowings and other liabilities to assets). Table 3 presents the balance sheet of the banks in the data.

Table 3: Banks' Balance Sheet by Size

<i>Assets</i>	Top 10	Fringe
Cash/Securities	21.75	24.90
Loans (risk-weighted assets)	78.25	75.10
<i>Liabilities</i>		
Deposits/Borrowings	93.36	91.27
Equity	6.64	8.73
Capital Ratio (risk-weighted)	8.48	11.62

Note: All variables except capital ratio (risk-weighted) are reported as the ratio to total assets. Data correspond to commercial banks in the U.S. Source: FDIC, Call and Thrift Financial Reports.

We include as targets the loans to assets ratio and the capital ratio (risk-weighted). We also use as targets the ratio of deposits to total output (56.20%) as well as measures of concentration such as the deposit market share of fringe banks (60.99%), and the loan market share of fringe banks (61.87%). While we do not use them as targets, we provide information on how the model behave in terms of loan returns (4.53%), markup and the Lerner index. The markup is derived using the cost estimates presented above. In particular, the markup is defined as follows

$$Markup = \frac{p}{c} - 1$$

where p denotes a measure of price and c a measure of marginal cost. We estimate p as the ratio of interest income from loans to loans plus marginal non-interest income (as reported in column 1 of Table 2) and c as the ratio of interest expenses from deposits and fed funds over deposits and fed funds plus marginal non-interest expenses (as reported in column 2 of Table 2). Similarly, the Lerner index is computed as $Lerner = 1 - \frac{c}{p}$. The average markup is 46.27% and the average Lerner is 30.32%,

We use the following definitions to connect the model to the data.

Definition Model Moments

Aggregate loan supply	$L^s(z, \mu) = \ell'_b + L^f(z, \mu, \ell'_b)$
Aggregate Output	$L^s(z, \mu) \left\{ p(z, \mu, z')(1 + z'R) + (1 - p(z, \mu, z'))(1 - \lambda) \right\}$
Entry Rate	$\sum_{\theta} M'_{e,\theta} / \sum_{\theta} \int d\mu_{\theta}(n_{\theta}, \delta_{\theta})$
Default Frequency	$1 - p(R^*, z')$
Borrower Return	$p(R^*, z')(z'R^*)$
Loan Return	$p(R^*, z')r^L(z, \mu) - (1 - p(R^*, z'))\lambda$
Loan Charge-off Rate	$(1 - p(R^*, z'))\lambda$
Interest Margin	$p(R^*, z')r^L(z, \mu) - r^d$
Loan market share fringe banks	$L^f(z, \mu, \ell'_b) / L^s(z, \mu)$
Deposit market share fringe banks	$\int d'_f d\mu_f(n_f, \delta_f) / [\sum_{\theta} \int d'_{\theta} d\mu_{\theta}(n_{\theta}, \delta_{\theta})]$
Risk- Weighted Capital Ratio	$(\ell'_{\theta} + A'_{\theta} - d'_{\theta}) / \ell'_{\theta}$
Loans to Asset Ratio	$\ell'_{\theta} / (\ell'_{\theta} + A'_{\theta})$
Equity to Asset Ratio	$(\ell'_{\theta} + A'_{\theta} - d'_{\theta}) / (\ell'_{\theta} + A'_{\theta})$
Securities to Assets Ratio	$A'_{\theta} / (\ell'_{\theta} + A'_{\theta})$
Markup	$[p(R^*(\mu, z), z')r^L(\mu, z) + c_{\theta}^{inc}(\ell'_{\theta})] / [r^d + c_{\theta}^{exp}(\ell'_{\theta})] - 1$

Table 4 shows the calibrated parameters.

Table 4: Model Parameters

Parameter		Value	Target
Autocorrel. z	ρ_z	0.256	TFP US (Fernald/SanFran Fed)
Std. Dev. Error (%)	σ_{uz}	0.87	TFP US (Fernald/SanFran Fed)
Crisis state	z_c	0.976	TFP US (Fernald/SanFran Fed)
Deposit interest rate (%)	$\bar{r} = r^d$	0.659	Int. expense
Securities Return (%)	r^a	1.28	Return Safe Securities
Charge-off rate	λ	0.41	Charge off rate
Autocorrel. Deposits	ρ_b^d	0.410	Deposit Process Bottom Fringe
Std. dev. error b bank	$\sigma_{b,u}^d$	0.070	Deposit Process Bottom Fringe
Autocorrel. Deposits	ρ_f^d	0.876	Deposit Process Bottom Fringe
Std. dev. error f bank	$\sigma_{f,u}^d$	0.156	Deposit Process Bottom Fringe
Salvage value	ξ	0.1965	Recovery Failures (FDIC)
Capital requirement b bank	φ_b	0.04	Basel II Capital Regulation
Capital requirement f bank	φ_f	0.04	Basel II Capital Regulation
Weight agg. shock	α	5.093	Std. dev. net-int. margin (%)
Success prob. param.	b	26.474	Borrower Return (%)
Volatility borrower's dist.	σ_ϵ	0.106	Default freq. (%)
Success prob. param.	ψ	0.873	Net Interest Margin (%)
Max. reservation value	$\bar{\omega}$	0.466	Elasticity loan demand
Discount Factor Manager	γ	0.96	Loans to asset ratio fringe
Avg. deposits f banks	μ_f^d	0.082	Deposits to output ratio
Avg. deposits b bank	μ_b^d	0.096	Deposit mkt share fringe (%)
Cost function b bank	$c_{b,0}$	0.001	Net non-int exp. Top 10 (%)
Cost function b bank	$c_{b,1}$	0.015	Capital ratio (risk-weighted) top 10
Cost function f bank	$c_{f,0}$	0.002	Net non-int exp. Fringe (%)
Cost function f bank	$c_{f,1}$	0.024	Capital ratio (risk-weighted) fringe
Fixed cost b bank	κ_b	0.0009	Fixed cost over loans top 10 (%)
Fixed cost f banks	κ_f	0.0027	Fixed cost over loans fringe (%)
Equity Issuance Cost b bank	$\zeta_{b,0}$	0.050	Equity Issuance over Assets Top 10 (%)
Equity Issuance Cost b bank	$\zeta_{b,1}$	0.100	Frequency of Equity Issuance Top 10 (%)
Equity Issuance Cost f bank	$\zeta_{f,0}$	0.150	Equity Issuance over Assets Fringe (%)
Equity Issuance Cost f bank	$\zeta_{f,1}$	0.50	Frequency of Equity Issuance Fringe (%)
Equity Issuance Cost	ζ_z	2.00	Loans to asset ratio Top 10
Entry Cost f banks	Υ_f	0.008	Bank failure rate (%)
Entry Cost b bank	Υ_b	0.150	Bank entry rate (%)
			Loan mkt share fringe (%)

Table 5 provides the moments generated by the model for the above parameter values relative to the data. Once again we note that the calibration is preliminary and so several

model moments are relatively far from their targets.

Table 5: Target Model and Data Moments

Moment (%)	Data	Model
Std. dev. net-int. margin	0.34	0.22
Borrower Return	12.94	14.11
Default freq.	1.84	1.89
Net Interest Margin	4.69	6.57
Elasticity loan demand	-1.40	-1.05
Loans to asset ratio fringe	75.10	98.16
Deposits to output ratio	56.20	71.68
Deposit mkt share fringe	60.99	30.14
Net non-int exp. Top 10	0.65	0.78
Capital ratio (risk-weighted) top 10	8.48	5.47
Net non-int exp. Fringe	1.57	1.51
Capital ratio (risk-weighted) fringe	11.62	16.70
Fixed cost over loans top 10	0.84	0.98
Fixed cost over loans fringe	0.75	2.81
Equity Issuance over Assets Top 10	0.02	0.01
Frequency of Equity Issuance Top 10	9.86	0.86
Equity Issuance over Assets Fringe	0.11	0.07
Frequency of Equity Issuance Fringe	9.59	4.31
Loans to asset ratio Top 10	78.25	94.87
Bank failure rate	1.02	2.01
Bank entry rate	1.35	2.04
Loan mkt share fringe	61.87	34.27

Table 6 presents a set of moments that were not used as targets and can be used as additional tests of the model.

Table 6: Additional Model and Data Moments

Moment (%)	Data	Model
<i>Averages</i>		
Dividends to asset ratio fringe	0.62	4.02
Dividends to asset ratio Top 10	0.66	2.04
Frequency of Div payment Top 10	96.11	99.24
Frequency of Div payment Fringe	85.38	74.99
Securities to Asset Ratio Top 10	21.75	5.13
Securities to Asset Ratio fringe	24.90	1.84
Dep/Asset ratio Top 10	93.05	94.81
Dep/Asset ratio fringe	90.76	83.60
Avg Markup	46.27	64.27
Avg Lerner Index	30.32	39.12
Avg Loan Return	4.53	6.25
Equity to Asset Ratio Top 10	6.64	5.19
Equity to Asset Ratio fringe	8.73	16.40
<i>Business Cycle Correlations</i>		
Loan Interest rate	-0.23	-0.08
Default Frequency	-0.65	-0.31
Charge-off rate	-0.72	-0.31
Price Cost Margin	-0.31	-0.66
Markup	-0.33	-0.67

6 Tests of the Model

To be added

7 Counterfactuals

To be added

References

- [1] Acharya, V. and A. Thakor (2016) “The dark side of liquidity creation: Leverage and systemic Risk,” *Journal of Financial Intermediation*, vol. 28, 4-21.
- [2] Aguirregabiria, V., R. Clark, and H. Wang (2016) “Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the Riegle-Neal Act,” *Rand Journal of Economics*, vol. 47, 529-572.
- [3] Aliaga Diaz, R. and M., Olivero (2011) “Do Bank Capital Requirements Amplify Business Cycles? Bridging the Gap between Theory and Empirics,” *Macroeconomic Dynamics*, doi:10.1017/S1365100510000623, 1-38.
- [4] Allen, F., E. Carletti and R. Marquez (2011) “Credit Market Competition and Capital Regulation”, *Review of Financial Studies*, 24, p. 983-1018.
- [5] Allen, F. and D. Gale (2004) “Competition and Financial Stability ”, *Journal of Money, Credit, and Banking*, 36, p. 453-80.
- [6] Arellano, Manuel and Bond, Stephen, (1991) “ Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies*, 58(2), p. 277-97.
- [7] Basel Committee on Banking Supervision (2010) “Basel III: International framework for liquidity risk measurement, standards, and monitoring”, *Bank for International Settlements*.
- [8] Begenau, J. (2016) “Capital Requirements, Risk Choice, and Liquidity Provision in a Business Cycle Model”, mimeo.
- [9] Bianchi, J. and S. Bigio (2017) “Banks, Liquidity Management and Monetary Policy”, mimeo.
- [10] Berger, A. L. Klapper and R. Turk-Ariss (2008) “Banking competition and financial stability,” *Journal of Financial Services Research*, pp. 99-118.
- [11] Berger, A. and L. Mester (1997) “Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions?” *Journal of Banking and Finance*, vol. 21, pp. 895-947.
- [12] BIS (2010) “Guidance for national authorities operating the countercyclical capital buffer,” Basel Committee on Banking Supervision.
- [13] BIS (2011) “Basel III: A global regulatory framework for more resilient banks and banking systems,” Basel Committee on Banking Supervision.
- [14] Boyd, J. and G. De Nicolo (2005) “The Theory of Bank Risk-Taking and Competition Revisited”, *Journal of Finance*, 60, p. 1329-43.

- [15] Cociuba, S., M. Shukayev, and A. Ueberfeldt (2011) “Do Low Interest Rates Sow the Seeds of Financial Crises?”, mimeo.
- [16] Clerc, L, A. Derviz, C. Mendicino, S. Moyen, K. Nikolov, L. Stracca, J. Suarez, A. Vardoulakis (2015) “Capital Regulation in a Macroeconomic Model with Three Layers of Default”, *International Journal of Central Banking*, vol. 11, p. 9-63.
- [17] Cooley, T. and V. Quadrini (2001) “Financial Markets and Firm Dynamics”, *American Economic Review*, vol. 91, pp. 1286-1310.
- [18] Corbae, D. and P. D’Erasmus (2011) “A Quantitative Model of Banking Industry Dynamics”, mimeo.
- [19] Corbae, D. and P. D’Erasmus (2015) “Foreign Competition and Banking Industry Dynamics: An Application to Mexico”, *International Monetary Fund Economic Review*, vol. 63, pp. 830-867.
- [20] Diamond, D. (1984) “Financial Intermediation and Delegated Monitoring”, *Review of Economic Studies*, 51, p. 393-414.
- [21] De Nicro, G., A. Gamba, M. Lucchetta (2014) “Microprudential Regulation in a Dynamic Model of Banking”, *Review of Financial Studies*, vol. 27, pp. 2097-2138.
- [22] Diamond, D. and P. Dybvig (1983) “Bank Runs, Deposit Insurance, and Liquidity”, *Journal of Political Economy*, 91, p. 401-19.
- [23] Diebold F. and K. Yilmaz (2009) “Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets,” *Economic Journal*, 119(534), 158-171.
- [24] Drechsler, I., A Savov, and P. Schnabl (2017) “The deposits channel of monetary policy”, *Quarterly Journal of Economics*, vol. 132, pp. 1819-1876.
- [25] Estrella, A. (2004) “The Cyclical Behavior of Optimal Bank Capital,” *Journal of Banking and Finance*, 28, p. 1469-1498.
- [26] Ericson, R. and A. Pakes (1995) “Markov-Perfect Industry Dynamics: A Framework for Empirical Work”, *Review of Economic Studies*, 62, p. 53-82.
- [27] Egan, M., A. Hortascu, and G. Matvos (2017) “Deposit Competition and Financial Fragility: Evidence from the US Banking Sector”, *American Economic Review*, 107, p. 169-216.
- [28] Ifrach, B. and G. Weintraub (2017) “A Framework for Dynamic Oligopoly in Concentrated Industries”, *Review of Economic Studies*, 84, p. 11061150.
- [29] Gale, D. and O. Ozgur (2010) “Are Bank Capital Ratios too High or too Low? Incomplete Markets and Optimal Capital Structure“, *Journal of the European Economic Association*, 3(2-3), p. 690-700.

- [30] Gertler, M. and N. Kiyotaki (2009) “Financial Intermediation and Credit Policy in Business Cycle Analysis”, mimeo.
- [31] Gomes, J. (2001) “Financing Investment”, *American Economic Review*, 91, p. 1263-1285.
- [32] Gowrisankaran, G. and T. Holmes (2004) “Mergers and the Evolution of Industry Concentration: Results from the Dominant-Firm Model,” *RAND Journal of Economics*, 35(3), p. 561-582.
- [33] Granja, J., G. Matvos, and A. Seru (2017) “Selling Failed Banks,” *Journal of Finance*, 72, p. 1723-1784.
- [34] Hennessy, C. and T. Whited (2007) “How Costly is External Financing? Evidence from a Structural Estimation ”, *Journal of Finance*, vol. 62, p. 1705-1745.
- [35] Jimenez, G., S. Ongena, J.L. Peydro, and J. Saurina (2011) “Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? ”, forthcoming *Econometrica*.
- [36] Kashyap A. and J. Stein (2000) “What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?” *American Economic Review*, vol. 90(3), p. 407-428.
- [37] Krusell P. and Anthony Smith (1998) “Income and Wealth Heterogeneity in the Macroeconomy,” *Journal of Political Economy*, 106(5), 867-896.
- [38] Martinez-Miera, D. and R. Repullo (2010) “Does Competition Reduce the Risk of Bank Failure?,” *Review of Financial Studies*, 23, p. 3638-3664.
- [39] Minnick, K. and L. Rosenthal (2014) “Stealth compensation: Do CEOs increase their pay by influencing dividend policy,” *Journal of Corporate Finance*, 25, p. 435-454.
- [40] Nguyen, T. (2013) “Bank Capital Requirements: A Quantitative Analysis,” , mimeo.
- [41] Pakes, A. and P. McGuire (1994) “Computing Markov Perfect Nash Equilibrium: Numerical Implications of a Dynamic Differentiated Goods Model”, *RAND Journal of Economics*, 25, p. 555-589.
- [42] Repullo, R. (1986) “Capital requirements, market power, and risk-taking in banking,” *Journal of Financial Intermediation*, vol. 13, p. 156-182.
- [43] Repullo, R. and J. Suarez (2012) “The Procyclical Effects of Bank Capital Regulation,” CEPR Discussion Papers 8897.
- [44] Stein, J. (1988) “Takeover Threats and Managerial Myopia,” *Journal of Political Economy*, vol. 96, p. 61-80.

- [45] Tauchen, G. (1986) “Finite state markov-chain approximations to univariate and vector autoregressions,” *Economics Letters*, 20(2), p. 177-181.
- [46] Van Den Heuvel, S. (2008) “The Welfare Cost of Bank Capital Requirements” *Journal of Monetary Economics*, 55, p. 298-320.
- [47] Wheelock, D. and P. Wilson (2017) “The Evolution of Scale Economies in U.S. Banking,” Federal Reserve Bank of St. Louis Working paper 2015-021C.
- [48] Zhu, H. (2008) “Capital Regulation and Banks’ Financial Decisions,” *International Journal of Central Banking*, 4, p. 165-211.