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CAPITAL REQUIREMENTS IN A QUANTITATIVE MODEL OF BANKING INDUSTRY DYNAMICS

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Capital Requirements in a Quantitative Model of Banking Industry Dynamics
Dean Corbae and Pablo D'Erasmo
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ABSTRACT

We develop a model of banking industry dynamics to study the quantitative impact of capital requirements on equilibrium bank risk taking, commercial bank failure, interest rates on loans, 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 in addition to aggregate shocks to the fraction of performing loans in their portfolio. A nontrivial bank size distribution arises out of endogenous entry and exit, as well as banks' buffer stock of net worth. We show the model predictions are consistent with untargeted business cycle properties, the bank lending channel, and empirical studies of the role of concentration on financial stability. We then conduct a series of counterfactuals (including countercyclical and size contingent (e.g. SIFI) capital requirements). We find that regulatory policies can have an important impact on market structure in the banking industry which, along with selection effects, can generate changes in allocative efficiency.

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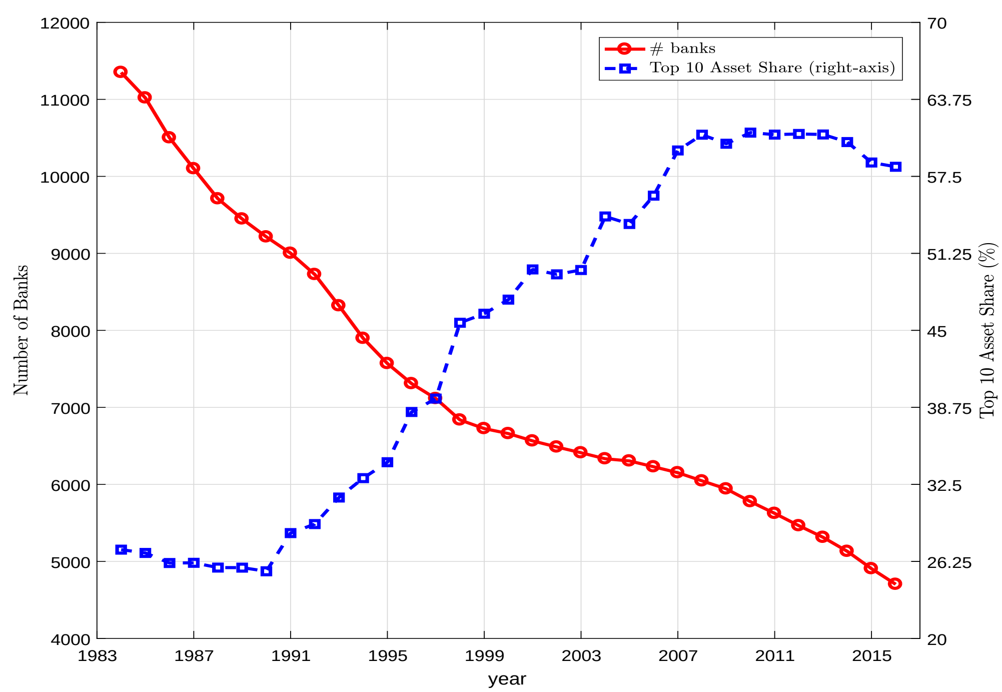
1 Introduction

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 that allows for imperfect competition. Furthermore, it allows us to understand how regulatory policy may affect market structure as well as consider how market structure influences risk taking behavior that 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'Erasmo [23]), 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 assets like cash and securities such as T-bills.

In this paper, we still work with an endogenous market structure but 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 and other sources of funds (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" the model by showing its predictions are qualitatively consistent with untargeted data moments and empirical studies. First, in Subsection 6.2, we show the model's business cycle predictions are qualitatively consistent with untargeted data correlations. Second, in Subsection 6.3 we show the model's predictions for lending across banks of different sizes in response to a rise in the cost of external funding are qualititatively consistent with the predictions from an important set of papers by Kashyap and Stein ([46],[47]). Kashyap and Stein 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 (see [46] 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 an analogous exercise by running a similar regression on panel data generated by our model and find that the results are qualitatively consistent with the empirical evidence presented in Kashyap and Stein [46]. Third, in Subsection 6.4 we show the model's predictions are qualitatively consistent with the large empirical literature on the competition-stability tradeoff along the lines of Beck, et. al. [11], Berger, et. al. [12], and Jiang, et. al. [44]. Our model generates endogenous changes in market structure that are correlated with cyclical changes in financial stability and intermediated output.

A benefit of our structural framework is that we can conduct policy counterfactuals. In Subsection 7.1 we study a rise in level of capital requirements from 4% under Basel II to 8.5% (corresponding to the required minimum risk weighted capital requirement of 6% plus a 2.5% capital conservation 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% actually leads to an increase in long run exit rates of small banks from the model's long run benchmark of 2.31% to 5.48% and a more concentrated industry. In the short run, big banks decide to strategically gain loan market share financed by issuing more equity, cutting dividends, shifting out of securities, and retaining more earnings. This results in a short run loss of market share of fringe banks of 22% and a long run loss of 5%. Most of these changes in fringe banks market share are explained by a drop in the number (measure) of fringe banks in the economy but the intensive margin also responds negatively. The increase in exit rates by small banks can be explained by a drop in their profitability. The high equity issuance costs that these banks face forces them to shift towards securities (i.e., reduce lending) in order to achieve higher capital ratios. This change in portfolio composition leads to lower profits (and charter values) and an increase in the likelihood of exit.

The net effect of higher big bank lending and lower small bank lending is a decrease in aggregate lending of over 16% in the short run and nearly 1% in the long run. This leads to an increase in interest rates on loans of 142 basis points in the short run but only a modest 6 basis points in the long run. Higher interest rates lead to lower intermediated output (16% in the short run and only 1% in the long run), but lower costs of funding failed banks relative to output in the long run (-12%). While we do not model explicitly the behavior of the non-bank sector (sometimes called the "shadow banking" sector), borrowers in the model have access to an outside option that determines the commercial banking sector loan demand. This margin of adjustment captures the effect of regulation on the size of the regulated banking sector.

Another proposal in Basel III calls for large, systemically important financial institutions (SIFI) to face a higher capital requirement than small banks. In Subsection 7.2 we run a counterfactual where the capital requirement is 2% higher on big banks than small banks.[2] 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 [17] 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.[3] Implementation in the U.S. restricted the application of the countercyclical capital buffer only to large banks. In Subsection 7.3 we run a counterfactual where the capital requirement for big banks increases by 2.5% during periods of economic expansion, so the capital requirement for these banks fluctuates between 8.5% and 11% (it is constant at 8.5% for all other banks).

In order to determine the case for any capital requirement at all, in Subsection 7.4 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

[1] See a full description in BIS [17].

[2] The 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.

[3] BIS [16] 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.

supply in order to raise interest rates and profitability. Higher profitability raises entry rates by fringe banks.

In Subsection 7.5 we examine how the imposition of liquidity requirements affects market structure. Basel III requires bank to hold enough high quality liquid assets to sustain significant losses (stress) for at least one month. We implement this by requiring that banks hold safe assets to cover at least 8% of its expected outflows in the worst case scenario. We also study a counterfactual that analyzes the interaction between liquidity and capital requirements in Subsection 7.6. Interestingly, we find that capital requirements and liquidity requirements have large complementary effects. When both policies are implemented together, the probability of a banking crisis declines to one third of its original value. This change is considerably larger than the sum of the changes that can be attained by implementing each policy in isolation.

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 in Subsection 7.7.

In Subsection 7.8 we examine the implications of policy changes for allocative efficiency in the banking industry. We use an analogue of the Olley and Pakes [55] decomposition to assess how the costs of operating banks varies with policy. We find that there can be increases in allocative efficiency arising from selection effects induced by the alternative policies. Specifically, a large fraction (40% on average) of the decline in loan-weighted costs can be explained by an increase in allocative efficiency.

We complete the paper in subsection 7.9 by analyzing the welfare effects of rising capital and liquidity requirements. Assessing welfare gains and losses using consumption equivalents, we find large short-term losses but modest long-term gains for households associated with the counterfactuals we undertake in the previous sections.

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 decision problems. For example, De Nicolo et al. [28] 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 [63] 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

[4] Among others, see Aliaga-Diaz and Olivero [3], Begenau [9], Bianchi and Bigio [10], Clerc, et. al. [21].

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 technically the failure of an individual big bank has no market impact (since it is of measure zero).

Diamond's [27] 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 Hannan [14] or Berger and Mester [15].[6] Following deregulation of the banking industry in the 1990s, there was a wave of bank mergers which took 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 [18]. In those models, there is an exogenous number of banks that are Cournot competitors either in the loan and/or deposit market. Martinez-Miera and Repullo [50] also consider a dynamic model of Cournot competition, but do not endogenize the number of banks. 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 [33] augmented with a competitive fringe as in Gowrisankaran and Holmes [39]. 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, Clark, and Wang [2], and Egan, Hortascu, and Matvos [34]). We focus on loan markets since in the recent financial crisis, aggregate bank risk weighted asset accumulation (including loans) grew at an annual 8.5% rate in 2006 while they shrank at a -4.3% rate in 2009 at the same time that aggregate bank borrowings (including deposits) grew at an annual 10.9% rate in 2006 while they shrank at a -0.4% rate in 2009. 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.[7]

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 distribution 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 [43] adapted to this environment. This entails approximating the distribution of banks by a finite number of moments.[8]

[5] For example, see Rios-Rull et. al [60] and Nguyen [54].

[6] For a more recent paper, see Wheelock and Wilson [64].

[7] Repullo [58] was an important early paper to study the role of capital requirements in a model with imperfect competition in the banking sector.

[8] Appendix A-1 states the algorithm we use to compute an approximate Markov perfect industry equilib-

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 [23], 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 baseline model. Subsections 6.2 to 6.4 assess the model's ability to qualitatively match certain untargeted empirical facts: business cycle moments, the bank lending channel, and the correlation between bank concentration and fragility. Section 7 conducts our policy counterfactuals and present the allocative efficiency and welfare results.

2 Banking Data Facts

In our previous paper [23], 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.[9] 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 by failure 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, $H = 40$).[10] Loan returns, margins, markups, delinquency rates, and charge-offs are countercyclical.[11]

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 "big"

rium.

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

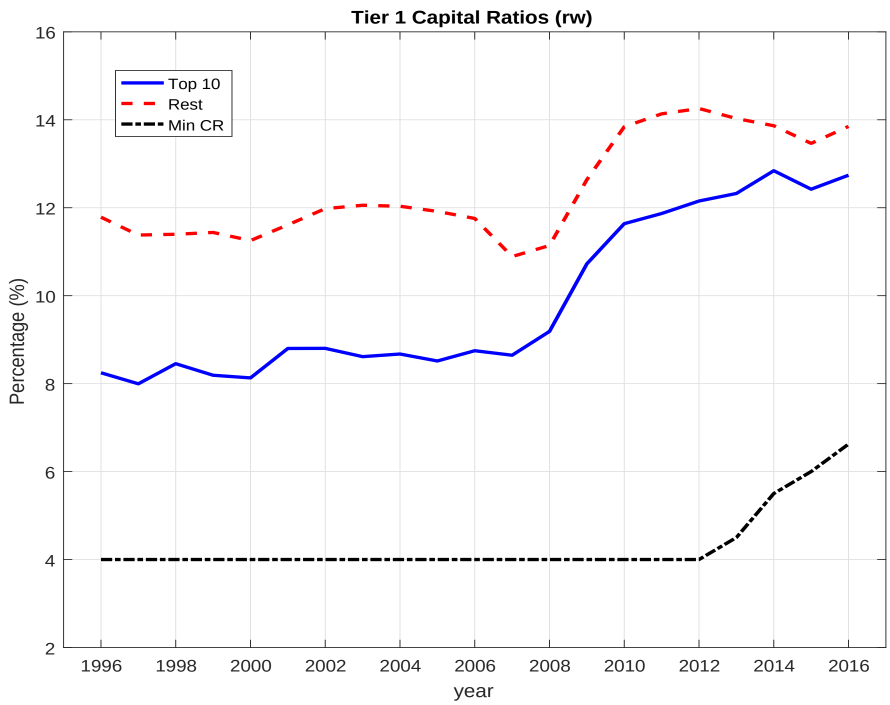
[10]See Section 5 and the Appendix A-3 for a description on how the interest margin, markup, the Lerner Index and $H-$statistic are computed as well a description of the data.

[11]The countercyclicality of margins and markups is important. Building a model consistent with this is a novel part of our previous paper Corbae and D'Erasmo [23]. 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 business cycle amplification arising from the banking sector.

banks and we refer to the remaining banks as "small" or "fringe".[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.

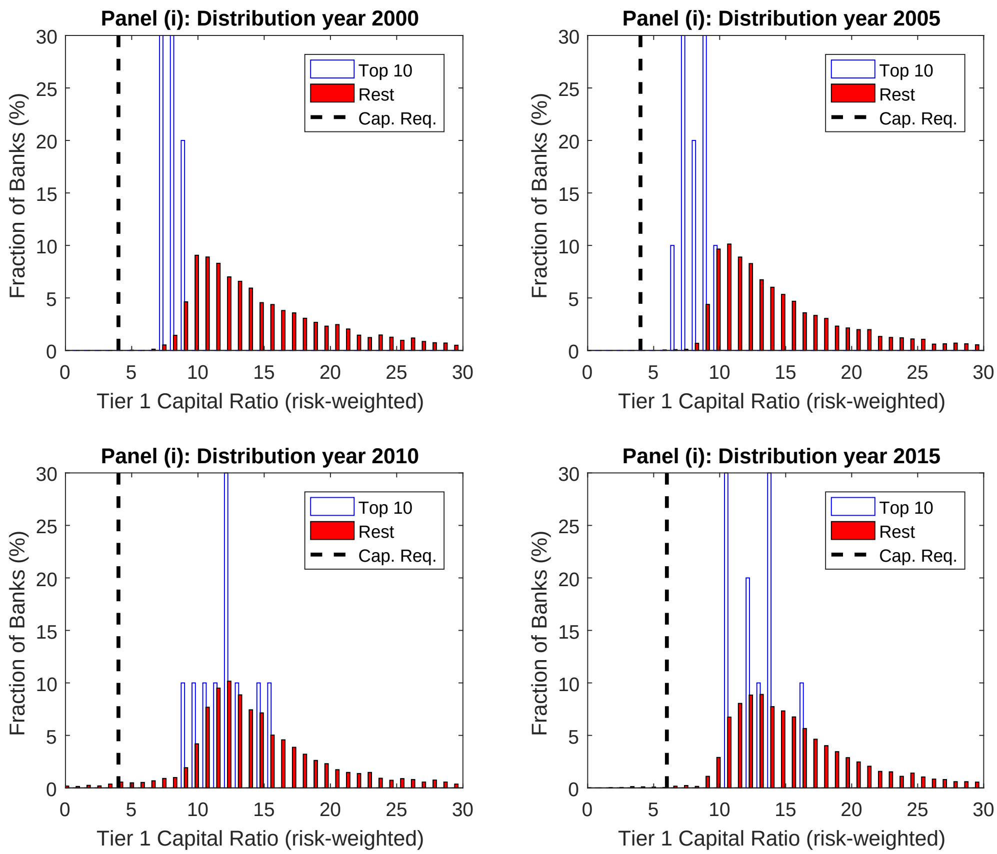
In all periods, risk-weighted capital ratios are lower for large banking institutions than those for small banks.[13] The fact that capital ratios are above what regulation defines as well capitalized suggests a buffer stock motive which we model.

While Figure 2 presents the cross-sectional average for big and small 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).

[12]All the banks in the group of Top 10 banks were classified as global systemically important banks (G-SIBs) as of December of 2016.

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

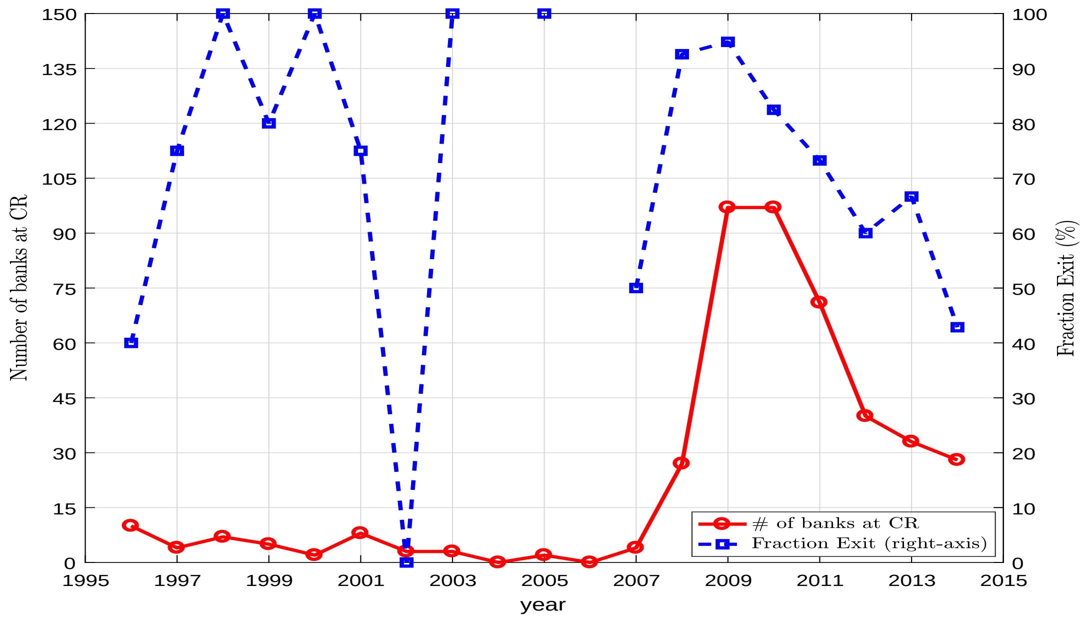
Figure 3: Distributions of Risk-Weighted Bank Capital



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 are 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 Figure 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 corresponding year or the year after).

Figure 4: Bank Capital and Failure



Note: # of banks at CR refers to the number of banks with capital ratios no larger than 0.5% than the minimum required. Fraction Exit refers to the fraction of banks within the group of banks with capital ratios no larger than 0.5% that fail during that given year or the following. The line for the Fraction Exit is missing during periods where there are no banks with capital ratios at or below the minimum required. Source: Consolidated Report of Condition and Income.

Figure 4 makes clear 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 Households

Infinitely lived, risk neutral households with discount factor β are endowed with $1/N$ units of the good each period. We assume households are sufficiently patient such that they choose to exercise their savings opportunities. In particular, households have access to an exogenous risk-free storage technology yielding $1+\overline{r}$ between any two periods with $\overline{r} \geq 0$ and $\beta(1+\overline{r}) = 1$. They can also choose to supply their endowment to a bank or to an individual borrower. If matched with a bank, a household who deposits its endowment there receives r_t^D whether the bank succeeds or fails since we assume deposit insurance. Households can hold a fraction of the portfolio of bank stocks yielding dividends (claims to bank cash flows) and can inject equity to banks. They pay lump-sum taxes/transfers τ_t which include a lump-sum tax τ_t^D used to cover deposit insurance for failing banks, and a tax (transfer if negative) for government sales and service of securities τ_t^A. 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 [27], there is no benefit to matching directly with entrepreneurs.

3.2 Entrepreneurs

Infinitely lived, risk neutral entrepreneurs demand bank loans in order to fund a new project each period. Specifically, a project requires one unit of investment in period t and returns next period:

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

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 $F(z', z) = prob(z_{t+1} = z' | z_t = z)$.

The entrepreneur can save $a_{E,t+1} \in \mathbb{R}_+$ with return $\overline{r}$ (that is also accessible to households) and can choose whether to retain earnings $I_{t+1} \in [0, 1]$ in order to finance investment. We assume that the entrepreneur is sufficiently impatient that she would not choose to undertake any of these alternatives. That is, the discount factor β_E is sufficiently low 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.

When the borrower makes her 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}. Thus, the technology exhibits a risk-return trade-off. 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 and the aggregate state is z_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) $\omega_t \in [\underline{\omega}, \overline{\omega}]$ 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 (which provides the rationale for short term bank loans). As in Bernanke and Gertler [13], 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 [27].

3.3 Banks

As in Diamond [27], 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 (Corbae and D'Erasmo [23]) where there are multiple big banks, to keep the analysis simple, we assume there is a representative big bank if it is active (as in Gowrisankaran and Holmes [39]). 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 a Cournot framework, the dominant bank understands that its choice of loan supply will influence the interest rate on loans given the best response of fringe banks. A fringe bank takes the interest rate as given when choosing its loan supply.

At the beginning of each period t after the realization of the aggregate shock z_t, the net cash flows (denoted $\pi^i_{\theta,t}$) for bank i of type θ are realized from its previous lending (denoted $\ell^i_{\theta,t}$), liquid assets (cash and securities, denoted $A^i_{\theta,t}$), and deposits (denoted $d^i_{\theta,t}$) augment existing equity to give beginning of period equity (or net worth) $n^i_{\theta,t}$. 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 household depositors $\delta_{\theta,t}$. An incumbent bank then chooses a quantity $d^i_{\theta,t+1}$ of deposits to accept up to the capacity constraint $\delta_{\theta,t}$ (i.e., $d^i_{\theta,t+1} \leq \delta_{\theta,t}$

where $\delta_{\theta,t} \in \{\delta^1_\theta, \ldots, \delta^n_\theta\} \subseteq \mathbb{R}_+$) at interest rate $r^{D,i}_{\theta,t}$ that it offers each potential depositor.[14] The capacity constraint evolves according to an exogenously given 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 $G^e_\theta(\delta_{\theta,t})$. 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. Since the household can always store at rate $\overline{r}$, we know $r^{D,i}_{\theta,t} \geq \overline{r}$.

Along with possible seasoned equity injections (denoted $e^i_{\theta,t} \in \mathbb{R}_+$), an incumbent bank allocates its net worth and deposits to its asset portfolio and pays dividends (denoted $\mathcal{D}^i_{\theta,t} \in \mathbb{R}_+$). We assume liquid assets (e.g. U.S. treasuries) have a return equal to r^A_t, which the government takes as given. The incumbent bank's portfolio and dividend policy must satisfy the following constraint

$$n^i_{\theta,t} + e^i_{\theta,t} + d^i_{\theta,t+1} \geq \ell^i_{\theta,t+1} + A^i_{\theta,t+1} + \mathcal{D}^i_{\theta,t} + \zeta_\theta(e^i_{\theta,t}, z_t) + \kappa^i_\theta + c^i_\theta\left(\ell^i_{\theta,t+1}\right) \tag{2}$$

where $\zeta_\theta(e^i_{\theta,t}, z_t)$ denotes aggregate state dependent equity issuance costs and $[\kappa^i_\theta + c^i_\theta\left(\ell^i_{\theta,t+1}\right)]$ represents non-interest expenses (including monitoring costs which are a function of loans issued). We assume that $\zeta_\theta(0, z_t) = 0$ and $\zeta_\theta(e^i_{\theta,t}, z_t)$ is an increasing function of $e^i_{\theta,t}$ and decreasing in z_t (i.e. external financing costs are increasing in the amount of equity issued and less costly in good times).[15] Since the bank's objective is increasing in dividends $\mathcal{D}^i_{\theta,t}$, (2) will hold as an equality constraint.

In Corbae and D'Erasmo [23], 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 [27]) that differ across banks of different sizes, which we denote $c^i_\theta\left(\ell^i_{\theta,t+1}\right)$. Further, as in the data we assume a fixed cost κ^i_θ.

Let $\pi^i_{\theta,t+1}$ 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

$$\pi^i_{\theta,t+1} = \Big\{p(R_t, z_{t+1})r^L_t - (1 - p(R_t, z_{t+1}))\lambda\Big\}\ell^i_{\theta,t+1} + r^A_t A^i_{\theta,t+1} - r^D_t d^i_{\theta,t+1}. \tag{3}$$

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).

Beginning-of-next-period equity (or net worth) is then given by

$$\begin{aligned} n^i_{\theta,t+1} &= \ell^i_{\theta,t+1} + A^i_{\theta,t+1} + \pi^i_{\theta,t+1} - d^i_{\theta,t+1} && \text{(4a)} \\ &= n^i_{\theta,t} + e^i_{\theta,t} + \pi^i_{\theta,t+1} - \mathcal{D}^i_{\theta,t} - \zeta_\theta(e^i_{\theta,t}, z_t) - \kappa^i_\theta - c^i_\theta\left(\ell^i_{\theta,t+1}\right)] && \text{(4b)} \end{aligned}$$

where the second inequality follows from (2) with equality. Equation (4a) is the bank balance sheet identity where equity and deposits equal loans, securities and bank net cash. The law

[14] Anticipating 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 y_{t+1} (e.g. deposits d_{t+1}).

[15] This "reduced form" approach to modeling equity issuance is similar to Cooley and Quadrini [22], Gomes [38], and Hennesy and Whited [41].

of motion for net worth in (4b) makes clear that retained earnings augment net worth and dividend payouts lower net worth.

Using the definition of equity in (4a), when making loan, securities, and deposit decisions, bank i of type θ faces a constraint that they expect to have sufficient equity at the beginning of next period to meet its risk weighted capital requirement:

$$\begin{aligned} E_t[n^i_{\theta,t+1}] = \quad & \ell^i_{\theta,t+1} + A^i_{\theta,t+1} + E_t[\pi^i_{\theta,t+1}] - d^i_{\theta,t+1} \\ & \geq \varphi_{\theta,t}(w^\ell_{\theta,t}\ell^i_{\theta,t+1} + w^A_{\theta,t}(A^i_{\theta,t+1} + E_t[\pi^i_{\theta,t+1}])) \end{aligned} \tag{5}$$

where $\varphi_{\theta,t}$ is the capital requirement and $\left(w^\ell_{\theta,t}, w^A_{\theta,t}\right)$ are risk weights associated with loans and liquid assets, respectively. We will typically take $w^\ell_{\theta,t} = 1$. Given $w^\ell_{\theta,t} > w^A_{\theta,t}$, liquid assets help relax the capital requirement constraint, but may also lower bank profitability and 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% under a stress scenario. 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%. For the model, we implement a liquidity requirement as:

$$\varrho_{\theta,t} d^i_{\theta,t+1} \leq A^i_{\theta,t+1} + \pi^i_{\theta,t+1}(z_C), \tag{6}$$

where $\varrho_{\theta,t}$ denotes the (possibly) size and state dependent liquidity requirement and cash $\pi^i_{\theta,t+1}(z_C)$ is evaluated in a stress scenario.[16]

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:

$$\max\left\{ n^i_{\theta,t+1} - \xi \ell^i_{\theta,t+1}, 0 \right\}, \tag{7}$$

where $\xi \in [0,1]$ measures liquidation costs of an insolvent loan portfolio 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 $\gamma \in (0,1]$:

$$E_t\left[\sum_{s=0}^{\infty} (\gamma\beta)^s \left(\mathcal{D}^i_{\theta,t+s} - e^i_{\theta,t+s}\right)\right] \tag{8}$$

We introduce the possibility of agency problems through managerial myopia when $\gamma < 1$ along the lines of Acharya and Thakor [1].[17] Since asset markets are incomplete and banks

[16] Notice that an increase in $A^i_{\theta,t+1}$ and decrease in $d^i_{\theta,t+1}$ help to satisfy both the risk weighted capital requirement in (5) and the liquidity coverage ratio in (6).

[17] There are many papers on managerial myopia providing a foundation for such behavior. See for instance, Stein [61] who provides a signalling argument or Minnick and Rosenthal [53] who provide a compensation argument.

face a minimum capital requirement constraint together with equity issuance costs (which in place derive in a concave value function), in order to obtain a well defined distribution of banks, we need a condition that guarantees that $\gamma\beta(1+r_t^A) < 1$, a standard assumption in models with incomplete markets. Since we assumed $\beta(1+\bar{r}) = 1$ to keep the household decision problem bounded, we assume $\frac{1+\bar{r}}{1+r^A} > \gamma$ which assures a bounded distribution over bank net worth.

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 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 $\zeta_\theta(\Upsilon_\theta + n^i_{e,\theta,t}, z_t)$ where $n^i_{e,\theta,t}$ is the entrant's initial equity injection.

3.4 Information

There is asymmetric information on the part of borrowers and lenders (banks and households). Only borrowers know the riskiness of the project they choose (R_t) and their outside option (ω_t). Project success or failure is unobservable unless the project is monitored. All other information is observable.

3.5 Timing

At the beginning of period t,

1. Aggregate shock z_t is realized which induces $n^i_{\theta,t}$ 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 $(\ell^i_{b,t+1}, d^i_{b,t+1}, A^i_{b,t+1}, \mathcal{D}^i_{b,t}, e^i_{b,t})$.
    - Each fringe bank observes the total loan supply of the dominant bank ($\ell^i_{b,t+1}$) and all other fringe banks (that jointly determine the loan interest rate r^L_t) 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 $(\ell^i_{f,t+1}, d^i_{f,t+1}, A^i_{f,t+1}, \mathcal{D}^i_{f,t}, e^i_{f,t})$.
    - Borrowers choose whether or not to undertake a project requiring bank funding and, if so, a level of technology R_t.
    - Households pay taxes/transfers $\tau_t = \tau^D_t + \tau^A_t$ to fund deposit insurance (τ^D_t) and service government securities (τ^A_t), 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

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

subject to

$$\begin{aligned} & C_t + a_{h,t+1} + d_{h,t+1} + \sum_{\theta} \int [P^i_{\theta,t} + \mathbf{1}_{\{e^i_{\theta,t}=1\}} (\Upsilon_\theta + n^i_{\theta,t})] S^i_{\theta,t+1} di \\ = \; & \frac{1}{N} + \sum_{\theta} \int (\mathcal{D}^i_{\theta,t} - e^i_{\theta,t} + P^i_{\theta,t}) S^i_{\theta,t} di + (1+\overline{r}) a_{h,t} + (1 + r^D_t) d_{h,t} - \tau_t. \end{aligned} \tag{10}$$

where $P^i_{\theta,t}$ and $S^i_{\theta,t+1}$ are the post-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, $P^i_{\theta,t} = 0$ on the right-hand side of the budget constraint, and, in cases in which a firm has entered, $P^i_{\theta,t} > 0$ on the left hand side of the budget constraint.

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

$$P^i_{\theta,t} = \beta E_{z_{t+1}|z_t} \left[\mathcal{D}^i_{\theta,t+1} - e^i_{\theta,t+1} + P^i_{\theta,t+1} \right], \forall i. \tag{11}$$

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. $r^D_{t+1} = \overline{r}$), 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 $\beta(1+\overline{r}) = 1$, which we assume parametrically.

4.2 Entrepreneur's Problem

Every period, given $\{r^L_t, z_t, \omega_t\}$, entrepreneurs choose whether ($\iota_{E,t} = 1$) or not ($\iota_{E,t} = 0$) to operate the technology ($\iota_{E,t} \in \{0, 1\}$) 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,

$$\max_{\{C_{E,t},a_{E,t+1},I_{t+1},\iota_{E,t},R_t\}_{t=0}^{\infty}} E_0\left[\sum_{t=0}^{\infty}\beta_E^t C_{E,t}\right] \tag{12}$$

subject to

$$C_{E,t} + a_{E,t+1} + I_{t+1} = (1-\iota_{E,t})(\omega_t + I_t) + \iota_{E,t}\pi_E(I_t, R_t, z_{t+1}) + (1+\overline{r})a_{E,t} \tag{13}$$

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

$$m_t = 1 - \beta_E(1+\overline{r}). \tag{14}$$

Since we assume a sufficiently impatient entrepreneur (i.e. $\beta_E(1+\overline{r}) < 1$), 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

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

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

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

where $\mathbf{1}_{\{.\}}$ 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 $y_{\theta,t}$ be denoted y_θ and $y_{\theta,t+1}$ be denoted y'_θ. Further, we denote the cross-sectional distribution of banks or "industry state" by

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

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.[18] 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.

After being matched with δ_θ potential depositors and making them a take-it-or-leave-it deposit rate offer r^D_θ, 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. Following the realization of z, banks can choose to exit setting $x_\theta = 1$ or choose to remain $x_\theta = 0$. Given the take-it-or-leave-it deposit rate offer and that the outside storage option for a household is $\overline{r}$, we know in equilibrium $r^D_\theta = \overline{r}$.

Given the Stackelberg assumption, the big bank takes into account that its loan supply affects the loan interest rate and that fringe banks will best respond to its loan supply. Differentiating the bank profit function π'_θ defined in (3) with respect to ℓ_θ we obtain

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

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 (the term $\frac{\partial p}{\partial R}\frac{\partial R}{\partial r^L} < 0$). That is, 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

$$L^s_f(z, \mu, \ell'_b) = \int \ell'_f(n, \delta; z, \mu, \ell'_b)\mu_f(dn, d\delta). \tag{19}$$

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

$$\begin{aligned} \mathcal{V}_\theta(n_\theta, \delta_\theta; z, \mu, \iota) = & \max_{\{\ell'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta\} \geq 0, d'_\theta \in [0, \delta_\theta]} \Big\{\mathcal{D}_\theta - e_\theta \\ & + \gamma\beta E_{z'|z}\left[\max_{x'_\theta \in \{0,1\}} \left\{(1 - x'_\theta)E_{\delta'_\theta|\delta_\theta} V_\theta(n'_\theta, \delta'_\theta; z', \mu') + x'_\theta V^x_\theta(n'_\theta, \ell'_\theta)\right\}\right]\Big\} \end{aligned} \tag{20}$$

[18]It should be understood that μ_b is a counting measure.

s.t.

$$
\begin{aligned}
n_\theta + d'_\theta + e_\theta &\geq \ell'_\theta + A'_\theta + \mathcal{D}_\theta + \zeta_\theta(e_\theta, z) + [\kappa_\theta + c_\theta(\ell'_\theta)] && (21)\\
n'_\theta &= \pi'_\theta + \ell'_\theta + A'_\theta - d'_\theta && (22)\\
E[n'_\theta] &\geq \varphi_{\theta,z}(w^\ell_\theta \ell'_\theta + w^A_{\theta,z}(A'_\theta + E[\pi'_\theta])) && (23)\\
\varrho_{\theta,z} d'_\theta &\leq A'_\theta + \pi'_\theta(z' = z_C) && (24)\\
L^d(r^L, z) &= \ell'_b + L^s_f(z, \mu, \ell'_b) && (25)\\
\mu' &= H(z, \mu, z', M'_e, \ell'_b), && (26)
\end{aligned}
$$

where the value function in (20) is defined over individual states $\{n_\theta, \delta_\theta\}$, aggregate states $\{z, \mu\}$, and ι which is empty if $\theta = b$ and is ℓ'_b if $\theta = f$. This latter variable takes into account that fringe banks take as given the loan supply decision by the big bank in this Stackelberg game (not only on the equilibrium path but any arbitrary value of ℓ'_b). Since $\iota = \emptyset$ for big banks, the continuation value on-the-equilibrium path $V_b(n_\theta, \delta_\theta; z, \mu) = \mathcal{V}_b(n_\theta, \delta_\theta; z, \mu, \emptyset)$. In the case of fringe banks, the continuation value is

$$
V_f(n_f, \delta_f; z, \mu) = \mathcal{V}_f(n_f, \delta_f; z, \mu, \ell'_b(n_b, \delta_b; z, \mu))
$$

(i.e. the value consistent with the equilibrium loan decision of the big bank $\ell'_b(n_b, \delta_b; z, \mu)$). These continuation values capture how changes in ℓ'_b affect the full equilibrium path.[19] Equations (21) to (24) are the bank's budget constraint, balance sheet constraint, capital requirement constraint, and liquidity coverage ratio constraint, respectively. Equation (25) is the market-clearing condition which is included since the dominant bank must take into account its impact on prices. 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. 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). Equation (26) corresponds to the evolution of the aggregate state to be defined below. The liquidation value of the bank for a given n'_θ and ℓ'_θ is

$$
V^x_\theta(n'_\theta, \ell'_\theta) \quad = \quad \max\{0, n'_\theta - \xi_\theta \ell'_\theta\}. \tag{27}
$$

The lower bound on the exit value in (27) is associated with limited liability.

The solution to this problem provides value functions as well as bank decision rules, that when *evaluated* at ι on-the-equilibrium-path (i.e., for fringe banks at $\iota = \ell'_b(n_b, \delta_b; z, \mu)$), can be written as $\ell'_\theta(n_\theta, \delta_\theta; z, \mu)$, $A'_\theta(n_\theta, \delta_\theta; z, \mu)$, $\mathcal{D}_\theta(n_\theta, \delta_\theta; z, \mu)$, $e_\theta(n_\theta, \delta_\theta; z, \mu)$, $d'_\theta(n_\theta, \delta_\theta; z, \mu)$, and $x'_\theta(n_\theta, \delta_\theta; z, \mu, z')$.

Now that we have 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

[19] More specifically, the recursive formulation captures all possible deviations and its effects on the full equilibrium-path and not only contemporaneous deviations. As the big bank evaluates different values of ℓ'_b it takes into account that this results in contemporaneous changes in the interest rate on loans that feeds directly into the loan and asset decisions of fringe banks, but also into the evolution of the industry (via profitability and entry/exit) that will possibly induce further changes in its loan supply.

of shares of each bank to 1, the price of a share of a non-exiting bank of type θ in state $(n_\theta, \delta_\theta; z, \mu, \iota)$ after dividends have been paid and equity injected is defined by

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

where $V_\theta^*(n_\theta, \delta_\theta; z, \mu, \iota)$ denotes the value of the expected discounted stream of net cash-flows using the household discount factor. Thus, substituting (28) into the household's first order condition for its stock choice in equation (11) yields

$$\begin{aligned} P_\theta(n_\theta, \delta_\theta; z, \mu, \iota) = \beta E_{z',\delta'|z,\delta}\left[\mathcal{D}_\theta(n'_\theta, \delta'_\theta; z', \mu', \iota') - e_\theta(n'_\theta, \delta'_\theta; z', \mu', \iota') + P'_\theta(n'_\theta, \delta'_\theta; z', \mu', \iota')\right] \iff \\ V_\theta^*(n_\theta, \delta_\theta; z, \mu, \iota) - (\mathcal{D}_\theta(n_\theta, \delta_\theta; z, \mu, \iota) - e_\theta(n_\theta, \delta_\theta; z, \mu, \iota)) = \beta E_{z',\delta'|z,\delta}\left[V_\theta^*(n'_\theta, \delta'_\theta; z', \mu', \iota')\right]. \end{aligned} \tag{29}$$

But (29) 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 $\gamma = 1$) while $V_\theta(\cdot) \leq V_\theta^*(\cdot)$ 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

$$\begin{aligned} V_\theta^e(z, \mu, z', M'_{e,\theta}) \equiv \max_{n'_{e,\theta}} \Big\{ & -(n'_{e,\theta} + \Upsilon_\theta)(1 + \zeta_\theta(n'_{e,\theta} + \Upsilon_\theta, z')) \\ & + E_{\delta'|\theta} V_\theta(n'_{e,\theta}, \delta'_\theta, z', H(z, \mu, z', M'_{e,\theta}))\Big\}. \end{aligned} \tag{30}$$

Potential entrants will decide to enter if $V_\theta^e(z, \mu, z', M'_{e,\theta}) \geq 0$. The argmax of equation (30) 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

$$V_\theta^e(z, \mu, z', M'_{e,\theta}) \times M'_{e,\theta} = 0. \tag{31}$$

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:

$$\begin{aligned} \mu'_\theta(n'_\theta, \delta'_\theta) = \int \sum_{\delta_\theta} (1 - x'_\theta(n_\theta, \delta_\theta; z, \mu, \iota, z'))\mathbf{1}_{\{n'_\theta = n'_\theta(n_\theta, \delta_\theta, z, \mu, \iota, z')\}} G_\theta(\delta'_\theta, \delta_\theta) d\mu_\theta(n_\theta, \delta_\theta) \\ + M'_{e,\theta}\mathbf{1}_{\{n'_\theta = n'_{e,\theta}(z, \mu, z', M'_{e,\theta})\}} G_{e,\theta}(\delta_\theta), \end{aligned} \tag{32}$$

where (32) makes clear how the law of motion for the distribution of banks is affected by entry and exit decisions.

4.6 Funding Deposit Insurance and Servicing Securities

In this section, we continue to use the same timing convention used in the previous section. The government collects lump-sum taxes (or pays transfers if negative) denoted τ that cover the cost of deposit insurance τ^D and the net proceeds of issuing securities τ^A.

Across all states (z, μ, z'), τ^D must cover deposit insurance in the event of bank failure. Let post-liquidation net transfers be given by

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

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

$$\tau^{D'}(z, \mu, z') \cdot N = \sum_\theta \left[\int \sum_\delta x'_\theta \max\{0, \Delta'_\theta(n_\theta, \delta_\theta, z, \mu, z')\} d\mu_\theta(n_\theta, \delta_\theta)\right]. \quad (33)$$

Let $\mathcal{A}'$ denote the aggregate demand of securities given by

$$\mathcal{A}'(z, \mu) = \sum_\theta \left[\int \sum_{\delta_\theta} A'(n_\theta, \delta_\theta; z, \mu, \cdot) d\mu_\theta(n_\theta, \delta_\theta)\right].$$

Then, assuming that the government supplies all the securities that the banking sector demands at price r^A (i.e. the supply of domestic securities is perfectly elastic), the tax (transfers if negative) necessary to cover the net proceeds of issuing government securities is given by

$$\tau^{A'}(z, \mu, z') \cdot N = \mathcal{A}'(1 + r^A) - \mathcal{A}''(z', \mu'(z, \mu, z', M'_e(z, \mu, z'))). \quad (34)$$

As a result, the per-capita taxes are

$$\tau'(z, \mu, z') = \tau^{D'}(z, \mu, z') + \tau^{A'}(z, \mu, z'). \quad (35)$$

4.7 Definition of Equilibrium

Given policy parameters $(\overline{r}, \varphi_{\theta,z}, w^\ell_{\theta,z}, w^A_{\theta,z}, \varrho_{\theta,z})$, a pure strategy Markov Perfect Industry Equilibrium (MPIE) is a set of functions $\{a'_E, I', \iota_E, R\}$ describing entrepreneur (financing) behavior, $\{a'_h, d'_h, S'_\theta\}$ describing household (saving) behavior, $\{V_\theta, \ell'_\theta, d'_\theta, A'_\theta, \mathcal{D}_\theta, e_\theta, x'_\theta, V^e_\theta\}$ describing bank balance sheet, dividend, exit and entry behavior, a cross-sectional distribution of banks μ, a function describing the mass of entrants M^e_θ, 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 $\overline{r}$, $\{a'_E, I', \iota_E, R\}$ 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 initial equity injection rule is consistent with entrant bank optimization (30) and the free-entry condition is satisfied (31).

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 (32).

6. The interest rate $r^L(\mu, z)$ is such that the loan market clears. That is,

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

7. Stock prices satisfy (28).

8. Across all states (z, μ, z'), taxes/transfers $\tau'(z, \mu, z')$ cover the cost of deposit insurance in (33) and the net proceeds of government securities issuance in (34).

5 Calibration

In order to avoid having a low probability event like the financial crisis play a disproportionate role in our analysis, our calibration strategy is to estimate model parameters using annual data from 1984 to 2007. To account for the possibility of a financial crisis, we add a crisis state to our shock process that is consistent with data from 1984 to 2016. Thus, banks in our model make decisions recognizing a crisis may occur. To accomplish this strategy, we simulate panels of 24 model periods and drop those panels which include a crisis when estimating the parameters. Having explained the strategy, we now go into further detail.

We use several data sources to calibrate the model. A model period is one year. 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. We also use the TFP series for the U.S. Business Sector, produced by John Fernald [35] and data provided by the Federal Deposit Insurance Corporation to identify bank failures and losses 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

[20]Source: FDIC, Call and Thrift Financial Reports, Balance Sheet and Income Statement (http://www2.fdic.gov/hsob/SelectRpt.asp?EntryTyp=10). See Appendix A-3 for a full description of the variables used in the paper.

$F(z', z)$, 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 [62] method. We set the number of grid points to four, that is $z_t \in Z = \{z_C, z_B, z_M, z_G\}$ (for "crisis", "bad", "median", "good"). We choose the grid in order to capture the infrequent crisis states we observe in the data. In particular, we choose z_M to match the mean of the process normalized to 1 (i.e. $z_M = 1$), select z_B ("bad times") and z_G ("good times") so they are at 1.5 standard deviations from z_M and set the value of z_C ("crisis" state) to be at 2.75 standard deviations below the mean to be consistent with the observed TFP levels during the 1982 recession and the last financial crisis (years 2008/2009).

As discussed above, moments from the call report data are computed beginning in 1984 (due to an overhaul of the data in that year) and end in 2007 (due to the unconventional government intervention since 2008 which is not part of our model). When performing the estimation exercise, moments from the model are computed using samples of 24 years that do not include observations with the crisis state $z = z_1$.[21]

We identify "big" banks with the top 10 banks (when sorted by assets) and the fringe banks with the rest.[22] As in Pakes and McGuire [56] 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 a continuum of potential fringe entrant banks.

The solution to our problem implies that the deposit capacity constraint binds in all states (since $r^A > \overline{r}$), 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:

$$\log(\delta_{\theta,t}^i) = (1 - \rho_\theta^d) k_\theta^0 + \rho_\theta^d \log(\delta_{\theta,t-1}^i) + u_{\theta,t}^i, \tag{36}$$

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 $N(0, \sigma_{\theta,u}^2)$.[23] 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 proposed by Tauchen [62] to obtain a finite state Markov representation $G^\theta(\delta', \delta)$ to the autoregressive process in (36). 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 (36). Since we work with a normalization in the model (i.e., $z_3 = 1$), the mean k_θ^0 in (36) is not directly relevant. Instead, we include the mean of the finite state Markov process, denoted μ_θ^d, as one of the parameters

[21] All 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.

[22] The 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.

[23] One could enrich this specification to include a jump process which would be a reduced form way to model random mergers that discretely increase the size of the bank.

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, consistent with big banks having a geographically diversified pool of funding (see Liang and Rhoades [49] and Aguirregabiria et. al [2]), big banks have less volatile funding inflows, which is one important factor explaining why they hold a smaller capital buffer in our model.

We parameterize the stochastic process for the borrower's project as follows. For each borrower, let $s = \alpha z' - bR^{\psi} + \varepsilon_e$, 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 $s > 0$, so in states with higher z or higher ε_e success is more likely. Then

$$\begin{aligned} p(R, z') &= 1 - \Pr(s \le 0 | R, z') \\ &= 1 - \Pr\left(\varepsilon_e \le -\alpha z' + bR^{\psi}\right) \\ &= \Phi\left(\alpha z' - bR^{\psi}\right), \end{aligned} \tag{37}$$

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 $[0, \overline{\omega}]$. We set the value of N (the mass of households) to $N = 4.882$. This value is consistent with a fraction of entrepreneurs in the total population ($\frac{1}{1+N}$) equal to 17% that corresponds to the value reported in Quadrini [57].

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. [12]).[24] 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:

$$\begin{aligned} \log(NIE_t^i) \;=\; & g_1 \log(w_t^i) + h_1 \log(\ell_{\theta,t}^i) + g_2 \log(q_t^i) + g_3 \log(w_t^i)^2 \\ & + h_2[\log(\ell_t^i)]^2 + g_4 \log(q_t^i)^2 + h_3 \log(\ell_t^i)\log(q_t^i) + h_4 \log(\ell_t^i)\log(W_t^i) \\ & + g_5 \log(q_t^i)\log(W_t^i) + \sum_{j=1,2} g_6^j t^j + g_{8,t} + g_9^i + \epsilon_t^i, \end{aligned} \tag{38}$$

where $NIE_{\theta,t}^i$ is Non-interest expenses (calculated as total expenses minus the interest expense on deposits, the interest expense on 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 safe 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.[25] Non-interest marginal expenses are then computed as:

$$\text{Mg Non-Int Exp.} \equiv \frac{\partial NIE_t^i}{\partial \ell_t^i} = \frac{NIE_t^i}{\ell_t^i}\Big[h_1 + 2h_2 \log(\ell_t^i) + h_3 \log(q_{it}) + h_4 \log(w_t^i)\Big]. \tag{39}$$

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

[25]We eliminate bank-year observations in which the bank organization is involved in a merger or the bank is flagged as being an entrant or a failing bank. We only use banks with three or more observations in the sample.

The estimated (asset-weighted) average of marginal non-interest expenses is reported in the second column of Table 2. Marginal non-interest income (Mg Non-Int Inc.) is estimated using an equation similar to equation (38) (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 (Mg Net Exp.) 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 [27] and with empirical evidence on increasing returns as in, among others, Berger and Mester [15].

Table 2: Banks' Cost Structure

Moment (%)	Mg Non-Int Inc.	Mg Non-Int Exp.	Mg Net Exp. $c_\theta(\ell'_\theta)$	Fixed Cost $\kappa_\theta/\ell_\theta$	Avg. Cost
Top 10 Banks	$4.07^\dagger$	$4.72^\dagger$	$0.65^\dagger$	0.84	$1.49^\dagger$
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

$$c_\theta(\ell'_\theta) = c_{\theta,0}\ell'_\theta + c_{\theta,1}(\ell'_\theta)^2. \tag{40}$$

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 $r^D = \bar{r}$ 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

[26] The nominal interest rate is converted to a real interest rate by using CPI inflation (we use the realized inflation rate as a measure of expected inflation).

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: $\zeta_\theta(e, z) = (\zeta_{\theta,0}e + \zeta_{\theta,1}e^2)(\frac{z_4}{z})^{\zeta_z}$. The quadratic form for equity issuance is relatively standard in the corporate finance literature (e.g. Henessy and Whited [41]) and the term $(\frac{z_4}{z})$ captures, in a parsimonious way, changes in the cost of external finance along the business cycle (consistent with the evidence presented in McLean and Zhao [51] and the "financial accelerator" literature pioneered in Bernanke and Gertler [13]). We estimate the parameters of this function by allowing equity issuance costs to depend explicitly on bank type. As our estimates show below there are significant differences between equity issuance costs for big and small banks (much in line with the evidence described in Hughes, Mester, and Moon [42]).

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 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 $w^A_{\theta,z} = 0$ for all θ and z.

Since we do not observe failure or entry by big banks during the calibration period (1984-2007), identification of Υ_b is challenging for identification. We set the value of Υ_b to be the maximum value such that if there were to exist big bank failure, a big bank would replace the failed bank immediately. The entry cost is kept constant for all our counterfactuals.

This leaves us with 20 parameters to estimate via simulated method of moments (SMM):

$$\{\alpha, b, \sigma_\varepsilon, \psi, \overline{\omega}, \gamma, \mu^d_b, \mu^d_f, c_{b,0}, c_{b,1}, c_{f,0}, c_{f,1}, \kappa_b, \kappa_f, \zeta_{b,0}, \zeta_{b,1}, \zeta_{f,0}, \zeta_{f,1}, \zeta_z, \Upsilon_f\}.$$

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 [30], added to help identify parameters associated with the borrower's return $pz'R^*$. The other moment is the elasticity of loan demand (-1.10) as estimated by Bassett, et. al. [8].

The set of targets from commercial bank data includes the loan 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. Since there are two assets in the model, loans (risky assets) and cash and securities (safe assets), once we determine the ratio of risk-weighted assets to total assets (loans to assets in the model) by bank size, the ratio of cash and securities can be obtained as a residual. 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). The risk-weighted capital ratio together with risk-weighted assets to total asset ratio imply the equity to asset ratio and the ratio of deposits to total assets in the model. Effectively, the deposits to asset ratio in the model is equivalent to the ratio of deposits plus other borrowings and other liabilities to assets in the data. Table 3 presents the balance sheet of the banks in the data mapped to variables in the model.

Table 3: Banks' Balance Sheet by Size

Assets	Top 10	Fringe
Cash/Securities	21.75	24.90
Loans (risk-weighted assets)	78.25	75.10
Liabilities		
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 behaves 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

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

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 and c as the ratio of interest expenses from deposits and fed funds over deposits and fed funds plus marginal net non-interest expenses (as reported in column 3 of Table 2). Similarly, the Lerner index is computed as $Lerner = 1 - \frac{c}{p}$. The average markup is 70.75% and the average Lerner is 38.48%,

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

Definition Model Moments

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

The computation of the model is a nontrivial task. We solve the model using an extension of the algorithm proposed by Ifrach and Weintraub [43] adapted to this environment. This entails approximating the distribution of banks by a finite number of moments.[27] In short, the solution entails keeping track of all the states of dominant players (i.e., the big bank), the exogenous aggregate variables and approximating the evolution of the distribution of fringe banks using a set of moments. The state space of the big bank is $\{n_b, \delta_b, z, \mathcal{N}, \mathcal{M}\}$ where $\mathcal{N}$ denotes the average value of $n_f + \delta_f$ (i.e., $\int (n_f + \delta_f) d\mu(n_f, \delta_f)/\mathcal{M}$) and $\mathcal{M} = \int d\mu(n_f, \delta_f)$ is the mass of incumbent fringe banks. The state space of any fringe bank is $\{n_f, \delta_f, n^b, \delta_b, z, \mathcal{N}, \mathcal{M}\}$.

Tables 4.a and 4.b show the calibrated parameters, corresponding to those chosen outside and inside the model, respectively.

[27] Appendix A-1 describes in detail the algorithm we use to compute an approximate Markov perfect industry equilibrium.

Table 4.a: Model Parameters (chosen outside the model)

Parameter		Value	Target
Autocorrel. z	ρ_z	0.256	TFP US (Fernald/SanFran Fed)
Std. Dev. Error (%)	σ_{u^z}	0.87	TFP US (Fernald/SanFran Fed)
Crisis state	z_c	0.976	TFP US (Fernald/SanFran Fed)
Mass Households	N	4.882	Fraction Entrepreneurs
Deposit interest rate (%)	$\bar{r}$	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	$\varphi_{b,z}$	0.04	Basel II Regulation
Capital requirement f bank	$\varphi_{f,z}$	0.04	Basel II Regulation
Liquidity requirement b bank	$\varrho_{b,z}$	$\emptyset$	Basel II Regulation
Liquidity requirement f bank	$\varrho_{f,z}$	$\emptyset$	Basel II Regulation

Table 4.b: Table: Model Parameters (chosen inside the model)

Parameter		Value	Target
Weight agg. shock	α	4.517	Std. dev. net-int. margin (%)
Success prob. param.	b	26.313	Borrower Return (%)
Volatility borrower's dist.	σ_ϵ	0.107	Default freq. (%)
Success prob. param.	ψ	0.922	Net Interest Margin (%)
Max. reservation value	$\overline{\omega}$	0.462	Elasticity loan demand
Discount Factor Manager	γ	0.957	Loans to asset ratio fringe
Avg. deposits f banks	μ_f^d	0.062	Deposits to output ratio
Avg. deposits b bank	μ_b^d	0.092	Deposit mkt share fringe (%)
Cost function b bank	$c_{b,0}$	0.000	Net non-int exp. Top 10 (%)
Cost function b bank	$c_{b,1}$	0.003	Capital ratio (risk-weighted) top 10
Cost function f bank	$c_{f,0}$	0.001	Net non-int exp. Fringe (%)
Cost function f bank	$c_{f,1}$	0.208	Capital ratio (risk-weighted) fringe
Fixed cost b bank	κ_b	0.0010	Fixed cost over loans top 10 (%)
Fixed cost f banks	κ_f	0.0022	Fixed cost over loans fringe (%)
Equity Issuance Cost b bank	$\zeta_{b,0}$	0.025	Equity Issuance to asset ratio Top 10 (%)
Equity Issuance Cost b bank	$\zeta_{b,1}$	0.100	Dividends to asset ratio Top 10 (%)
Equity Issuance Cost f bank	$\zeta_{f,0}$	3.629	Equity Issuance to asset ratio fringe (%)
Equity Issuance Cost f bank	$\zeta_{f,1}$	26.38	Dividends to asset ratio Fringe (%)
Equity Issuance Cost	ζ_z	4.00	Loans to asset ratio Top 10
Entry Cost f banks	Υ_f	0.019	Fringe bank failure rate (%)
Entry Cost b bank	Υ_b	0.028	Big bank failure rate (%)

Table 5 provides the moments generated by the model for the above parameter values relative to the data. This table shows that the model does a relatively good job at matching the targeted moments. At the calibrated parameters, both the big bank and fringe banks display a positive capital buffer (larger for fringe banks). The model also captures correctly the fraction of the deposit market serviced by fringe banks (i.e., the level of concentration in the model is consistent with the data). The model is also in line with the data when it comes to the net interest margin, the default frequency, the borrower return, the balance sheet ratios, and the ratio of equity issuance to assets as well as the ratio of dividends to assets. As a fraction of assets, fringe banks issue more equity than the big bank (like in data), even though, like in Hughes and Mester [42], equity issuance costs are significantly higher for fringe banks than that of the big bank. The model over-predicts bank entry and failure rates and under-predicts the elasticity of loan demand and the marginal cost for big banks.

Table 5: Targeted Data and Model Moments

Moment (%)	Data	Model
Long-Run Averages 1984-2007		
Borrower Return	12.94	13.75
Default freq.	1.84	1.57
Net Interest Margin	4.69	4.49
Elasticity loan demand	-1.10	-0.60
Deposits to output ratio	56.20	56.20
Deposit mkt share fringe	60.99	61.32
Std. dev. net-int. margin	0.34	0.11
Dividends to asset ratio Top 10	0.66	1.66
Dividends to asset ratio fringe	0.62	0.82
Loans to asset ratio Top 10	78.25	63.88
Loans to asset ratio fringe	75.10	78.18
Capital ratio (risk-weighted) top 10	8.48	6.61
Capital ratio (risk-weighted) fringe	11.62	10.55
Net non-int exp. Top 10	0.65	0.04
Net non-int exp. Fringe	1.57	2.58
Fixed cost over loans Top 10	0.84	1.05
Fixed cost over loans fringe	0.75	2.88
Equity Issuance over Assets Top 10	0.02	0.01
Equity Issuance over Assets Fringe	0.11	0.60
Bank failure rate	1.02	2.11

Table 6 provides additional nontargeted moments from the model. Table 6 shows that the model captures relatively well all of the moments in the balance sheets of banks of different sizes. Note that the securities to asset ratio is implied by the loan to asset ratio (since loans and securities are the only two assets in the model). Similarly, the deposit to asset ratio and the equity to asset ratio are implied by the loan to asset ratio and the risk-weighted capital ratio (effectively equal to equity to loans in the model). The model under-predicts the frequency of dividend payments (mostly for fringe banks) and the frequency of equity issuance for big banks (even though costs are substantially low). As we described in Table 5 the model under-predicts the marginal cost for big banks and that results in a level of Markup and Lerner Index higher than in the data in Table 6. However, the loan return and the loan market share in the model are almost perfectly aligned with the values observed in the data.

Table 6: Additional Model and Data Moments

Moment (%)	Data	Model
Long-Run Averages 1984-2007		
Securities to Asset Ratio Top 10	21.75	36.12
Securities to Asset Ratio fringe	24.90	21.82
Dep/Asset ratio Top 10	93.05	95.83
Dep/Asset ratio fringe	90.76	91.21
Equity to Asset Ratio Top 10	6.64	4.17
Equity to Asset Ratio fringe	8.73	8.79
Frequency of Equity Issuance Top 10	9.86	0.10
Frequency of Equity Issuance Fringe	9.59	22.88
Frequency of Div payment Top 10	96.11	78.32
Frequency of Div payment Fringe	85.38	21.79
Loan mkt share fringe	61.87	67.09
Avg Markup	70.75	114.04
Avg Lerner Index	38.48	53.28
Avg Loan Return	4.53	4.51
Bank entry rate	1.35	2.12

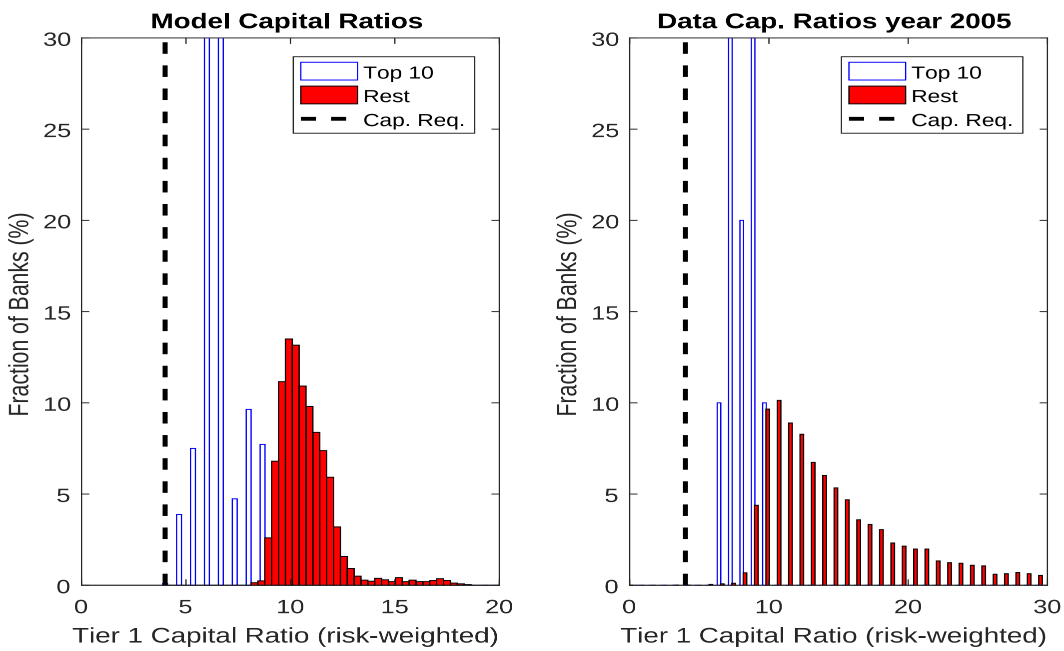
6 Results

For the parameter values in Tables 4.a and 4.b, we find an equilibrium where, for example when aggregate variables are evaluated at their observed mean, exit occurs along the equilibrium path by fringe banks: (i) with the lowest deposit holdings ($\delta_L = 0.0325$, which is 52% lower than the deposits of an average fringe bank) and low net worth levels ($n \leq 0.004$, that is an equity level lower than 6.5% of average loans), and (ii) with up to average deposit holdings ($\delta \leq \delta_M = 0.0621$) but even smaller net worth levels ($n \leq 0.002$, only 3.2% of average loans) if the economy heads into crisis or bad times (i.e. $z = z_M$ and $z' \in \{z_C, z_B\}$). Note that this includes banks with negative net-worth ex-post (i.e., after the realization of z' but before having the option to recapitalize the bank). In other aggregate states, ws the net-worth of its competitors increase (either average net-worth of fringe banks or big bank net-worth), fringe banks with low net-worth exit even with high level of deposits ($\delta \in \{\delta_L, \ldots, \delta_H\}$). Dominant-bank exit is not observed along the equilibrium path. On the equilibrium path, fringe banks that survive the arrival of a bad aggregate shock accumulate securities in order to avoid future exit.

6.1 Capital Ratios

Figure 5 presents the average distribution of risk-weighted bank capital ratios $(A_\theta + \ell_\theta + E_t[\pi_\theta] - \delta_\theta)/\ell_\theta$ by bank size in the model and its data counterpart for year 2005.[28] Figure 5 shows that higher volatility of external funding (i.e. $\sigma^d_{f,u} > \sigma^d_{b,u}$) and higher equity finance costs (i.e. $\zeta_{f,0} > \zeta_{b,0}$ and $\zeta_{f,1} > \zeta_{b,1}$) as in the data, induce fringe banks to hold higher risk-weighted capital ratios (as a buffer) than big banks on average.

Figure 5: Capital Ratios by Bank Size

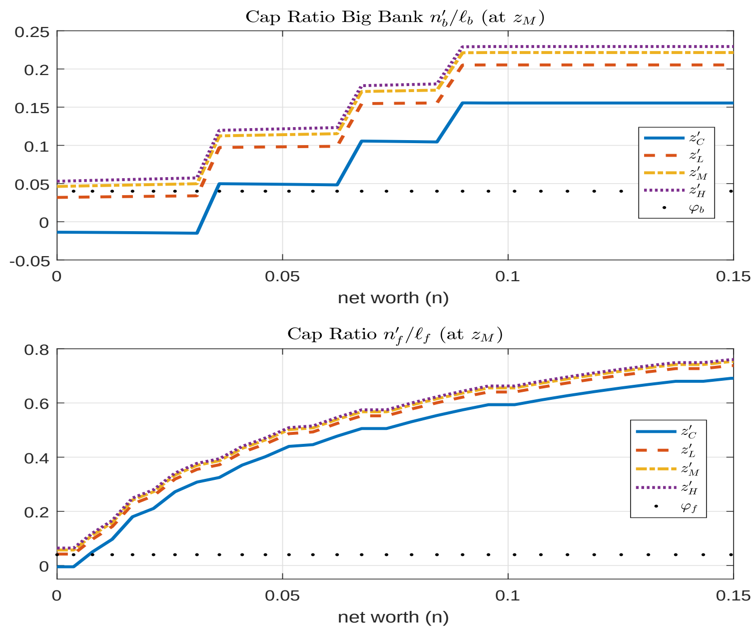


Capital ratios implied by the model's equilibrium decision rules $\frac{n'_\theta}{\ell^\theta}$ are illustrated in Figure 6 (big bank in the top panel and fringe banks in the bottom panel) when $z = z_M$ for different values of z'. The figure also plots the capital requirement $\varphi_{\theta,z} = 0.04$. As shown, capital ratios are decreasing in the aggregate state of the economy (z) and, as described in Figure 5, much larger for fringe banks than for the big bank. Recall that the capital requirement constraint in equation (23) must be satisfied ex-ante but can be violated ex-post as we see in the data in Figures 3 and 4. The small buffer that big banks hold results in a bank in need of recapitalization for low enough net worth when $z = z_C$ or $z = z_B$. This in fact happens on the equilibrium path and as shown in Figure 5 it is the case that big banks operate close to or at the minimum. On the other hand, fringe banks hold a much larger buffer and while operating at the minimum capital required (for continuing banks) is not a zero probability

[28]To be precise, after simulating the model for T periods, we compute the average distribution of fringe banks $\bar{\mu}_f(n,\delta) = \sum_{t=1}^{T} \frac{\mu_{f,t}(n,\delta)}{T}$. We simulate the economy for $10,000$ periods and drop the first $2,000$ periods. Similarly, we compute the frequency of capital ratios that the big bank transits during the simulation.

event, only those with very low net worth end up being undercapitalized when $z = z_C$ and subsequently exit. Since big banks face lower equity issuance costs than fringe banks and are more efficient extending loans and have market power, their charter value is higher than that of fringe banks, making recapitalizing a big bank a more profitable alternative than exiting even when capital ratios are below the minimum. Fringe banks self-select into higher capital ratios since recapitalizing the bank is not a profitable alternative in most cases. In summary, the model is capable of generating big bank recapitalization and small bank failure.

Figure 6: Big Bank and Median Fringe Bank Capital Ratios



6.2 Test I: Business Cycle Properties

We now move on to other economically important moments that the model was not calibrated to match, so that these results can be considered a simple qualitative test (or consistency) of the model with the data. Table 7 provides the correlation between key aggregate variables with output in the data and in the model.[29] We observe that, as in the data, the model generates countercyclical loan interest rates, exit rates, default frequencies, charge-off rates, price-cost margins, and markups. Moreover, the model generates procyclical entry rates as

[29] We use the following dating conventions in calculating correlations. Since some variables depend on z and μ (e.g., loan interest rates $r^L(z,\mu)$) and some other variables depend on z, μ, and z', (e.g. default frequency $1 - p(R(r^L(z,\mu)), z')$), Table 7 displays $corr(GDP(z,\mu,z'), x(z,\mu))$ and $corr(GDP(z,\mu,z'), y(z,\mu,z'))$, where $x(z,\mu)$ is any variable x that depends on (z,μ) and $y(z,\mu,z')$ is any variable y that depends on (z,μ,z').

well as aggregate loans and deposits.[30]

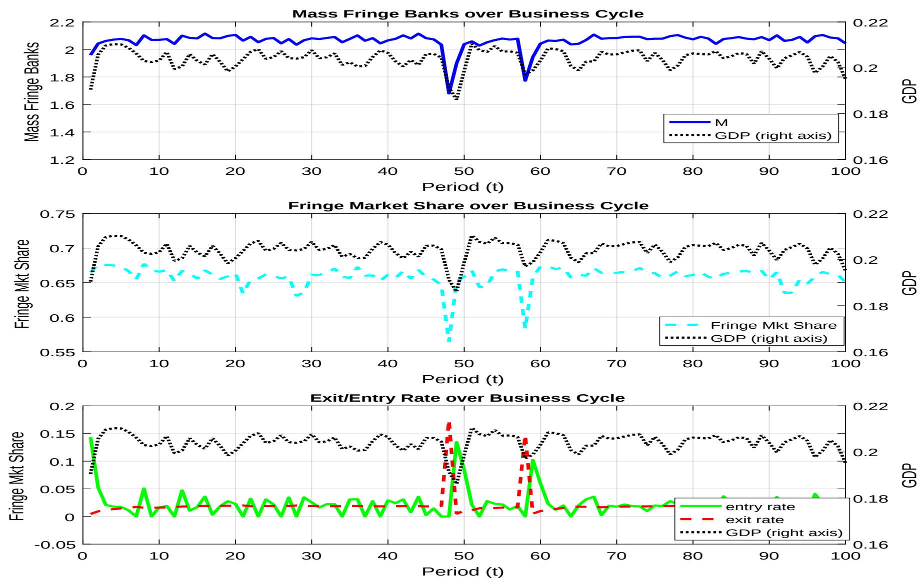
Table 7: Business Cycle Correlations

Business Cycle Correlations	Data	Model
Loan Interest Rate	-0.23	-0.14
Exit Rate	-0.12	-0.36
Entry Rate	0.70	0.37
Loan Supply	0.54	0.86
Deposits	0.29	0.32
Default Frequency	-0.65	-0.54
Charge Off Rate	-0.72	-0.54
Price Cost Margin Rate	-0.36	-0.32
Markup	-0.31	-0.55

Figure 7 presents the evolution of the mass of fringe banks, the loan market share of fringe banks as well as entry and exit rates over the business cycle. When the economy enters into a recession, a larger fraction of fringe banks exit. The reduction in the number of banks is compensated by entry of new banks. However, in some instances entry is gradual and the level of competition is not restored immediately. This is an important amplification mechanism that derives from endogenous changes in competition in our model. Downturns that lead to a more concentrated industry are amplified. This figure also makes clear that the model can generate endogenous cycles in bank level competition. While in the model these cycles tend to be short lived, they are largely consistent with the evidence we presented on banking industry dynamics.

[30]See Appendix A-2 for a set of scatter plots with the simulated data and the corresponding correlations.

Figure 7: Competition over the Business Cycle



6.3 Test II: Monetary Policy and Bank Lending

Kashyap and Stein ([46]) argued that if the bank lending channel of monetary policy is correct, one should expect the loan portfolios of large and small banks to respond differently to a contraction in monetary policy. We ask the question, is the impact of monetary policy on lending behavior stronger for smaller banks who are more likely to have difficulty substituting into non-deposit sources of external finance? They find strong empirical evidence in favor of this bank lending channel. The result is driven largely by the smaller banks (those in the bottom 95% of the size distribution). We perform a similar experiment with our model to determine if it is qualitatively consistent with Kashyap and Stein's empirical findings.

To understand their results, consider two small banks, both of which face limitations in raising uninsured external finance. The banks are alike except that one has a much more liquid balance sheet position than the other. Now imagine that these banks are hit by a contractionary monetary shock, which causes them both to lose insured deposits. In the extreme case where they cannot substitute at all toward other forms of finance, the asset side of their balance sheets must shrink. But the more liquid bank can relatively easily protect its loan portfolio, simply by drawing down on its large buffer stock of securities. In contrast, the less liquid bank is likely to have to cut loans significantly if it does not want to see its securities holdings sink to a dangerously low level.

We implement this policy experiment by analyzing how a permanent rise in the cost of external debt finance (in particular, a one standard deviation increase $\overline{r}$ from 0.65% to 2.1%) affects the balance sheet and lending behavior of banks of different sizes. We simulate the model and construct a pseudo-panel of banks under each value of $\overline{r}$.

We then follow Kashyap and Stein ([46]) and estimate the following panel regression by bank size:

$$\Delta \ell_{it} = a_0 + a_1 \Delta \overline{r} + a_2 X_{it} + u_{it}, \tag{41}$$

where $\Delta \ell_{it}$ denotes the growth rate of loans, $\Delta \overline{r}$ is the measure of monetary impulse and X_{it} are other bank or aggregate controls. To estimate this regression, we simulate the model and construct a pseudo-panel of banks under each value of $\overline{r}$. Table 8 presents the estimated coefficients for banks of different sizes:

Table 8: Kashyap and Stein ('95) Regressions (Model Pseudo-Panel)

	Dependent Variable $\Delta \ell_{it}$
Specification	Coeff. on Monetary Impulse ($\Delta \overline{r}$)
Small 98%	-0.3512
s.e.	0.003***
Small 92%	-0.3726
s.e.	0.003***
Small 68%	-0.4023
s.e.	0.004***

Note: All specifications include one lag of the dependent variable, and growth rate of GDP. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

These regression results (i.e., a negative and more sizable coefficient on the monetary impulse for small banks than big banks) are broadly consistent with their findings. A contraction in monetary policy does indeed lead to a decline in lending in all size categories of small banks. Small banks find it harder to raise financing with instruments other than deposits. Importantly, results show that the effect is larger the smaller the bank.

To understand the mechanism at play, Table 9 presents the aggregate and industry effects of the unexpected policy change. We present the effects of the policy change in the short-run (after five periods) and in the long-run.[31] Increasing the cost of bank finance decreases the

[31] In particular, we compute the initial conditions of the benchmark model as the average $\bar{\mu}(n, \delta)$ that arises during the simulation of the model conditional on $z = z_M = 1$. That is, $\bar{\mu}(n, \delta | z = z_M) = \sum_{t=1}^{T} I_{\{z=z_M\}} \frac{\mu_{\theta,t}(n,\delta)}{T_{z=z_M}}$ where $T_{z=z_M}$ is the number of periods such that $z = z_M$. Using $\bar{\mu}(n, \delta | z = z_M)$ (that implies a value for $\mathcal{M}$ and $\mathcal{N}$) and $z = z_M$ as a starting point, the policy change is announced and put into effect immediately. We simulate the economy forward using the decision rules of the model with

value of both types of banks in the short run as well as small banks in the long run. This leads to high exit rates for small banks and a subsequent drop in the number (measure) of small banks in the long run. Their loan and deposit market share decline considerably in the short and long run. The tightening of monetary policy and the subsequent increase in deposit finance costs of 145 basis points leads to a short run increase in loan rates of 71 basis points and a long run rise of 119 basis points. Despite the rise in loan rates, net interest margins fall by 74 basis points in the short run and 28 basis points in the long run. Further, there is a large fall in markups. In summary, the model exhibits incomplete pass-through of contractionary monetary policy which is consistent with models of imperfect competition such as Dreschler, Savov, and Schnabl [31] who find (page 1854) that deposit spread betas (with respect to changes in the fed funds rate) are less than one.

Table 9: Aggregate and Industry Effects of Contractionary Monetary Policy

Moment (%)	Benchmark ($\bar{r} = 0.0065$)	Monetary Policy ($\bar{r} = 0.021$)	
		Short Run	Long Run
Capital Ratio Top 10	6.10	6.05	5.41
Capital Ratio Fringe	10.54	35.52	30.48
Exit Rate	2.10	21.36	3.32
Entry Rate	1.57	7.72	3.36
Loan mkt sh. Fringe	67.77	56.57	45.46
Deposit mkt sh. Fringe	61.21	49.05	38.04
Loan Interest Rate	5.20	5.91	6.39
Net Interest Margin	4.44	3.70	4.16
Avg. Markup	106.63	39.99	53.86
Additional Moments		Δ (%)	
Measure Banks Fringe		-34.03	-59.63
Loan Supply		-8.11	-13.70
Int. Output		-8.04	-13.80

6.4 Test III: Competition-Stability Tradeoff

Many authors have tried to empirically estimate the relation between bank concentration/competition and banking system fragility using a reduced form approach. In this section, we follow this approach using simulated data from our model to show that the model is qualitatively consistent with the empirical findings. As in Beck et. al. [11], we estimate a logit model of the probability of a crisis as a function of the degree of banking industry

higher capital requirements. The moments reported as the "short-run" effects correspond to the moments that arise five periods after the policy change and the "long-run" effects correspond to the average for a 10,000 period simulation. See the appendix for further details.

concentration and other relevant aggregate variables. Moreover, as in Berger et. al. [12], we estimate a linear model of the aggregate default frequency as a function of banking industry concentration and other relevant controls. The banking crisis indicator takes value equal to one in periods whenever: (i) the loan default frequency is higher than 5%; (ii) deposit insurance outlays as a fraction of GDP are higher than 2%; (iii) large dominant banks are liquidated; or (iv) the exit rate is higher than two standard deviations from its mean. The concentration index corresponds to the loan market share of the big bank. We use as extra regressors the growth rate of GDP and lagged growth rate of loan supply.[32] Table 10 displays the estimated coefficients and their standard errors.

Table 10: Competition and Stability

Model Dependent Variable	Logit Crisis_{t+1}	Linear Default Freq._{t+1}
Concentration_t	-10.429	0.057
	$(0.248)^{***}$	$(0.001)^{***}$
GDP growth in t	-5.495	0.0074
	$(3.258)^{*}$	(0.010)
Loan Supply Growth_t	-4.579	0.0182
	$(2.780)^{*}$	$(0.009)^{**}$
R^2	0.72	0.58

Note: Standard Errors in parenthesis. R^2 refers to Pseudo R^2 in the logit model.
*** Statistically significant at 1%, ** at 5% and * at 10%.

Consistent with the empirical evidence in Beck, et. al. [11], we find that banking system concentration is highly significant and negatively related to the probability of a banking crisis. The results suggest that concentrated banking systems are less vulnerable to banking crises. Higher monopoly power induces periods of higher profits that prevent bank exit (see also Corbae and Levine [25]). This is in line with the findings of Allen and Gale [5]. Consistent with the evidence in Berger et. al. [12] we find that the relationship between concentration and loan portfolio risk is positive. This is in line with the view of Boyd and De Nicolo [18], who showed that higher concentration is associated with riskier loan portfolios.

7 Counterfactuals

7.1 Higher Capital Requirements with Imperfect Competition

Here we ask the question, how much does an increase from 4% to 8.5% in capital requirements affect bank exit and outcomes? Table 11 (columns (*ii*) and (*iii*)) presents the results

[32] Beck et. al. [11] also include other controls like “economic freedom” which are outside of our model.

Table 11: Capital Requirements Counterfactuals

Moment (%)	(*i*) Baseline ($\varphi_\theta = 0.04$)	(*ii*) Higher Cap Req. ($\varphi_\theta = 0.085$)	(*iii*)	(*iv*) Size Dep. Cap Req. ($\varphi_b = 0.105, \varphi_f = 0.085$)	(*v*)	(*vi*) Count. Cap Req. ($\varphi_{b,z} \in [0.085, 0.11]$)	(*vii*)	(*viii*) Zero Cap Req. ($\varphi_\theta = 0$)	(*ix*)
		Short Run	Long Run	Short Run	Long Run	Short Run	Long Run	Short Run	Long Run
Capital Ratio Top 10	6.10	11.80	11.77	16.18	15.07	13.92	12.57	2.90	1.95
Capital Ratio Fringe	10.54	19.17	19.18	18.92	19.04	17.72	16.97	9.06	10.16
Exit Rate	2.10	9.83	4.34	8.95	4.20	8.61	3.37	3.59	2.63
Entry Rate	1.57	8.34	4.23	8.71	4.34	4.28	3.46	0.10	2.73
Prob. of Crisis	3.11	-	2.85	-	2.69	-	1.94	-	2.89
Loan mkt sh. Fringe	67.77	61.39	64.34	64.84	68.28	58.02	58.65	64.58	59.76
Dep. mkt sh. Fringe	61.21	60.84	60.17	60.80	61.22	58.69	56.95	58.71	54.62
Loan Interest Rate	5.20	5.95	5.48	6.22	5.51	6.20	5.75	5.49	5.80
Borrower Return	13.70	13.72	13.70	13.72	13.69	13.72	13.68	13.73	13.68
Default Frequency	1.87	1.89	1.94	1.98	1.94	1.97	2.01	1.75	2.02
Net Interest Margin	4.44	5.18	4.71	5.44	4.75	5.42	4.97	4.73	5.02
Avg. Markup	106.63	157.21	141.89	173.62	131.61	193.46	166.98	138.75	161.73
Loan to Assets Top 10	62.70	65.54	64.55	56.39	56.52	68.00	71.40	67.91	74.70
Loan to Assets Fringe	79.50	65.86	72.69	67.05	73.55	66.76	74.20	82.73	85.60
Sec to Asset Ratio Top 10	37.30	34.46	35.45	43.61	43.48	32.00	28.60	32.09	25.31
Sec to Asset Ratio Fringe	20.50	34.14	27.31	32.95	26.45	33.24	25.80	17.27	14.40
E.I. to Assets Top 10	0.00	0.20	0.08	0.89	0.19	0.86	0.01	0.00	0.01
E.I. to Assets Fringe	0.54	0.47	0.19	0.49	0.18	0.60	0.29	0.31	0.40
Div. over Assets Top 10	2.00	1.54	1.82	1.67	1.72	1.99	2.15	2.58	2.17
Div. over Assets Fringe	0.86	2.09	1.46	1.96	1.46	1.36	1.09	0.75	1.12
Additional Moments		Δ (%)		Δ (%)		Δ (%)		Δ (%)	
Measure Banks Fringe		-3.97	-4.34	-3.80	0.14	-12.67	-17.08	-10.73	-23.98
Loan Supply		-8.60	-3.28	-11.66	-3.65	-11.39	-6.34	-3.33	-6.88
Int. Output		-8.52	-3.28	-11.47	-3.66	-11.38	-6.38	-3.19	-6.90
Taxes/Output		88.20	-25.52	74.65	-18.63	37.49	-62.39	84.95	39.07
Borrower Project (R^*)		0.13	0.02	0.18	0.03	0.18	0.07	0.05	0.07
Avg loans Fringe ℓ^f		-7.58	-2.21	-6.19	-1.27	-7.34	-1.08	4.26	8.27
Avg Loans Top 10 ℓ^b		8.74	6.95	-4.85	-5.40	15.06	20.22	6.08	16.26
Net Cash flow Fringe (π^f)		13.85	6.86	19.83	8.51	17.73	13.14	11.96	20.67
Net Cash flow Top 10 (π^b)		28.16	13.32	21.90	5.03	39.71	31.30	12.58	25.57

of this counterfactual. We present the effects of the policy change in the short-run (after five model periods) and in the long-run.[33]

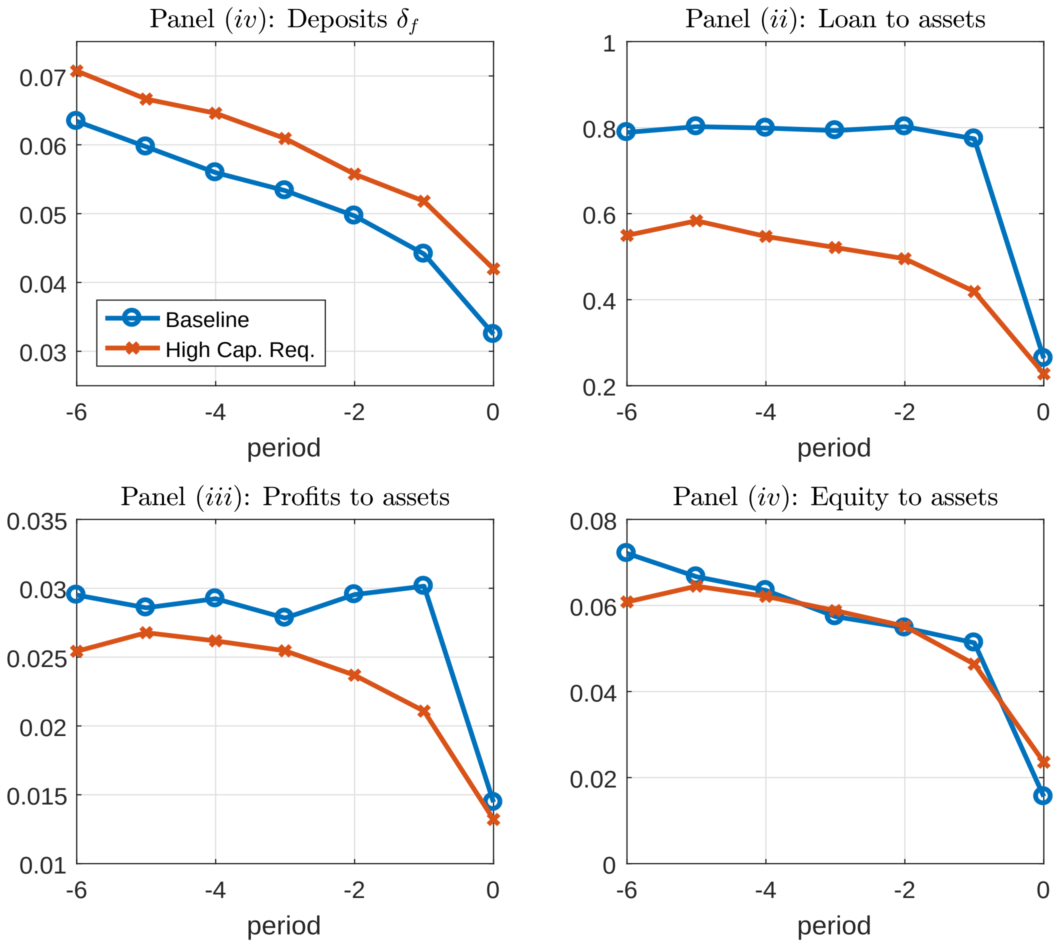
As Table 11 (see columns (*ii*) and (*iii*)) shows, we find that a rise in capital requirements from 4% to 8.5% actually leads to an increase in long run exit rates of small banks from the model's long run benchmark of 2.10% to 4.38% and a more concentrated industry (a decline in the loan market share of fringe banks from 67.8% to 64.3%). After the increase in the minimum capital requirement, banks still sustain a significant capital buffer. In the short run, big banks decide to strategically gain loan market share financed by issuing more equity, cutting dividends, shifting out of securities, and retaining more earnings. This results in a short run loss of market share of fringe banks of 23% and a long run loss of 5%. Most of these changes in market share are explained by a drop in the number (measure) of fringe banks in the economy but the intensive margin is also important (average lending by fringe banks decline by 7.6% in the short run and 2.2% in the long run). The net effect of higher big bank lending and lower small bank lending is a decrease in aggregate lending of 8.6% in the short run and 3.3% in the long run. This leads to an increase in interest rates on loans of 75 basis points in the short run but only a modest 28 basis points in the long run. Higher interest rates lead to lower intermediated output (8.5% in the short run and 3.3% in the long run), but lower costs of funding failed banks relative to output in the long run (-25.5%). While there is an increase in exit rates due to lower profitability, the decline in taxes to output derives from the fact that losses on failed banks decline. Exiting banks are better capitalized and have a smaller share of their assets invested in loans whose recovery is less than one.

The results on entry and exit follow from a selection effect. In the short run, after the increase in capital requirements, banks with low net-worth and deposits prefer to exit and liquidate the bank rather re-capitalize it. Small banks that are not well capitalized and face a high cost of injecting equity into the bank shift their portfolio composition towards securities which reduces their profitability. To analyze this in depth, we present an event study of bank failure in the baseline economy and in the one with higher capital requirements. We simulate a panel of banks in each case and collect all bank failures. We sort each bank such that period 0 corresponds to its exit and take the average across banks in each period. Figure 8 shows the evolution of average deposits for banks that exit (Panel (*i*)), their loan to asset ratio (Panel (*ii*)), profits to assets (Panel (*iii*)), and equity to assets (Panel (*iv*)).

Figure 8 shows that exit is triggered by a significant decline in deposits (Panel (*i*)) but importantly that banks that fail with higher capital requirements have a larger share of securities to assets (or a smaller share of loans to assets, see Panel (*ii*)) and that leads to lower profits to assets (panel (*iii*)). A relatively smaller decline in profits leads to failure in the high capital requirements equilibrium. A selection effect is also evident in Panel (*i*) that shows that the average value of delta is higher when capital requirements are higher. This reinforces the shift in the portfolio composition. Finally, Panel (*iv*) shows that capital ratios are higher in the equilibrium with higher capital requirements (as one would expect) and that the decline in capital ratios are similar in the two economies.

[33]For a detailed explanation of how the experiment is implemented and the definition of short-run and long-run see footnote 31.

Figure 8: Exit Event Analysis



Since the expected deposits (δ) for entrants is above the lowest value and profits for incumbents increase (as shown in Table 11), higher capital requirements also leads to some entry. In the long-run, the increase in the entry rate coincides with the increase in the failure rate. It is also relevant to note that, while the failure rate by small banks is higher under the new capital requirement regime, the probability of a crisis (as defined in Section 6.4) declines in the long-run from 3.1% to 2.9%. Thus, higher capital requirements achieve their objective of increasing financial stability.

7.2 Size Dependent Capital Requirements

Another proposal in Basel III calls for large, systemically important financial institutions (SIFI) to face a higher capital requirement than small banks. Table 11 (see columns (*iv*) and (v)) presents the model predictions for a counterfactual where the capital requirement is 2% higher on big banks than small banks.

Relative to the benchmark where big banks faced an 8.5% capital requirement, the higher rate of 10.5% in Table 11 (see columns (iv) and (v)) leads big banks to decrease their lending in the short and the long run. Fringe banks also cut their lending; however, since the number of fringe banks does not decline (the mass increases slightly in the long run) the loan market share of fringe banks rises. The extensive margin is dominated by the intensive margin and the combination of lower lending by big and small banks leads to a lower loan supply and higher interest rates than in the baseline experiment.

7.3 Countercyclical Capital Requirements

Basel III calls for banks to maintain a "countercyclical" capital buffer of up to 2% of risk-based Tier 1 capital. More specifically, a buffer of capital will be required only during periods of credit expansion. Since in our model aggregate credit and aggregate productivity are highly correlated, we implement this change in capital regulation by setting the minimum capital requirement to 8.5% in periods where $z = z_c$ and 11% in periods where z_g. The implementation in the U.S. calls for this countercyclical capital buffer to be applied only to large banks, for this reason we set capital requirements for fringe banks at 8.5% ($\varphi_{\theta,z} = 0.085$) and let the capital requirements for big banks move with the cycle between 8.5% and 11.0% ($\varphi_{b,z_C} = 0.085, \varphi_{b,z_B} = 0.095, \varphi_{b,z_M} = 0.103, \varphi_{b,z_G} = 0.110$). Table 11 (see columns (vi) and (vii)) presents the model predictions.

Unsurprisingly, relative to the results in Subsection 7.1, we find even higher levels of capital buffers held in this counterfactual. We find lower long run exit rates in Table 11 columns (vi) and (vii) than in columns (ii) and (iii), though still higher than the benchmark. Unlike the previous case (higher capital requirements for large banks), we find that big banks actually increase their lending resulting in a larger market share vis-a-vis fringe banks. The reduction in the market share of fringe banks is also the result of a decline in lending by fringe banks and the mass of incumbent banks. The overall effect is lower aggregate loan supply which leads to higher long run interest rates by 55 basis points. Again, higher interest rates lead to lower intermediated output, but significantly lower costs of funding failed banks relative to output in the long run (-62%).

7.4 Risk Taking without Capital Requirements

Should there be capital requirements at all? Is the charter value of a bank sufficiently valuable to induce a bank to self-insure and not take on too much risk? In this section, we analyze the model predictions when capital requirements are completely absent.

As expected, both big and small banks lower their capital buffers in Table 11 columns ($viii$) and (ix) when the capital requirement is lifted. However, in keeping with the charter value hypothesis they do not set them to zero for fear of exit. While exit rates do rise, they do not rise dramatically (again in keeping with the charter value hypothesis). Interestingly, the probability of a banking crisis declines slightly from the baseline case.

7.5 Liquidity Requirements

Table 12 (columns (*ii*) and (*iii*)) presents the model predictions in response to a rise in liquidity requirements (ϱ_θ) from zero in the benchmark to 8% in the counterfactual. In contrast to our previous results, higher liquidity requirements lead to lower exit rates. The market share of fringe banks declines in both the short and long run. This decline is the result not only of an increase in lending by the big bank but also a strong selection effect (only the well funded small banks remain in the economy) resulting in a drop in the measure of fringe banks in both the short and long run. Importantly, the implementation of liquidity requirements without changing the level of capital requirements results in a much smaller decline in the probability of a crisis from 3.11% to 3.01%.

7.6 Policy Interaction

Basel III introduced liquidity requirements *and* higher capital requirements together. Table 12 (columns (*iv*) and (*v*)) presents the model predictions when liquidity requirements are implemented jointly with higher capital requirements. Introducing higher capital requirements together with liquidity requirements reduces the increase in small bank exit and entry rates relative to the case with only higher capital requirements by more than 100 basis points. Fringe banks hold a larger ratio of securities to assets. The decline in exit rates and the shift toward safe assets results in a considerably larger decline in the cost of deposit insurance (as a ratio to output). Higher concentration leads to higher interest rates and markups in the long run. It is also worth noting that the probability of crisis reduces to one third of its original value after implementing both policies together. The results in (columns (*ii*) and (*iii*)) together with the results in Table 11 show that liquidity requirements and capital requirements have large complementary effects on the probability of a crisis. The largest decline in this probability is observed when both policies are combined and the sum of the effects only accounts for a small fraction of the overall effect.

Table 12: Liquidity Requirements Counterfactuals

Moment (%)	(*i*) Baseline ($\varphi_\theta = 0.04$)	(*ii*) Liq Req. ($\varphi_\theta = 0.04, \varrho_\theta = 0.08$)	(*iii*)	(*iv*) High CR & Liq Req. ($\varphi_\theta = 0.085, \varrho_\theta = 0.08$)	(*v*)
		Short Run	Long Run	Short Run	Long Run
Capital Ratio Top 10	6.10	7.35	6.62	10.63	10.53
Capital Ratio Fringe	10.54	11.62	13.34	18.24	19.79
Exit Rate	2.10	1.98	1.96	6.19	3.20
Entry Rate	1.57	0.77	2.05	3.88	3.30
Prob. of Crisis	3.11	-	3.01	-	1.00
Loan mkt sh. Fringe	67.77	64.45	62.83	60.90	63.00
Dep. mkt sh. Fringe	61.21	60.62	59.39	60.43	59.11
Loan Interest Rate	5.20	5.54	5.46	6.08	5.61
Borrower Return	13.70	13.73	13.69	13.72	13.69
Default Frequency	1.87	1.76	1.93	1.92	1.97
Net Interest Margin	4.44	4.78	4.69	5.30	4.84
Avg. Markup	106.63	144.82	144.84	180.28	149.77
Loan to Assets Top 10	62.70	65.87	69.57	65.89	66.34
Loan to Assets Fringe	79.50	74.35	75.40	65.10	72.55
Sec to Asset Ratio Top 10	37.30	34.13	30.43	34.11	33.66
Sec to Asset Ratio Fringe	20.50	25.66	24.60	34.90	27.45
E.I. to Assets Top 10	0.00	0.01	0.02	0.03	0.05
E.I. to Assets Fringe	0.54	0.59	0.57	0.73	0.31
Div. over Assets Top 10	2.00	1.74	1.88	1.53	1.92
Div. over Assets Fringe	0.86	0.56	0.82	0.96	1.06
Additional Moments		Δ (%)		Δ (%)	
Measure Banks Fringe		-2.37	-6.79	-5.55	-9.04
Loan Supply		-3.87	-3.01	-9.99	-4.73
Int. Output		-3.76	-3.00	-9.95	-4.76
Taxes/Output		-32.89	-31.49	-27.91	-68.87
Borrower Project (R^*)		0.06	0.02	0.15	0.04
Avg loans Fringe ℓ^f		-6.35	-3.55	-10.77	-1.44
Avg Loans Top 10 ℓ^b		6.06	11.81	8.56	9.19
Net Cash flow Fringe (π^f)		4.25	3.45	12.67	10.65
Net Cash flow Top 10 (π^b)		14.97	15.38	30.39	18.10

7.7 Policy with Perfect Competition

In this subsection, we ask, how much does an increase in capital requirements affect bank outcomes under an assumption that all banks are perfectly competitive? This experiment is meant to assess the interaction between market structure and changes in government policy. It provides a comparison between our work and models with perfect competition and an indeterminate bank-size distribution (such as Van Den Heuvel [63] and Aliaga-Diaz and Olivero [3]). Since our model nests a perfectly competitive environment (our fringe banks), we simply increase the entry cost for the big bank to a value that prevents entry. All other parameters remain identical to those used for the benchmark model. The spirit of this exercise is to endogenously generate an environment where all banks are perfectly competitive (i.e., all banks take prices as given). Table 13 compares the responses to capital requirement changes in both the benchmark imperfect competition environment to the same policy change in the perfectly competitive model.

Without competition from big banks (moving from column 2 to column 4), there is a significant inflow of fringe banks (a 32% increase) but not large enough to compensate for the absence of the big bank. This results in a lower loan supply (11% lower) leading to higher loan interest rates (a 95 basis points higher difference). Since fringe banks have higher net marginal costs of extending loans than big banks, once the industry moves into one where only fringe banks operate, a higher interest rate is needed to induce a charter value that is consistent with the entry cost. However, this increase in interest rates is not associated with higher markups. On the contrary, as one would expect markups decline substantially when we move from the model with imperfect competition to the one with perfect competition (a more than 60% decline). In a perfectly competitive environment, positive markups are only necessary to cover entry costs and fixed operating costs. Further, the increase in interest rates results in more risk taking by borrowers (0.17%) and a higher default frequency (a 0.33% difference).

Table 13 also shows an important increase in capital ratios (a 4.7% difference) between the competitive environment and the benchmark. Banks' portfolio compositions are driven by the valuable smoothing role that securities provide in cases of bank distress (negative profits) and the cost arising from differences in the expected spread of loans over securities. In the competitive environment, higher interest rates induce banks to shift toward loans.

Table 13: Benchmark Model vs Perfectly Competitive Model

Moment (%)	Benchmark Model $\varphi = 0.04$	Benchmark Model $\varphi = 0.085$	Competitive Model $\varphi = 0.04$	Competitive Model $\varphi = 0.085$
	Long Run		Long Run	
Capital Ratio Top 10	6.57	11.77	-	-
Capital Ratio Fringe	10.86	19.18	15.58	20.57
Exit Rate	2.47	4.34	2.58	2.60
Entry Rate	2.64	4.23	2.68	2.69
Probability of Crisis	3.11	2.85	2.36	3.77
Loan mkt sh. Fringe	66.94	64.34	100.00	100.00
Deposit mkt sh. Fringe	61.07	60.17	100.00	100.00
Loan Interest Rate	5.24	5.48	6.19	6.34
Borrower Return	13.69	13.70	13.67	13.67
Default Frequency	1.87	1.938	2.20	2.23
Net Interest Margin	4.49	4.71	5.39	5.54
Avg. Markup	125.25	141.89	45.16	43.57
Loan to Asset Ratio Top 10	63.98	64.55	-	-
Loan to Asset Ratio Fringe	78.31	72.69	76.00	75.88
Sec to Asset Ratio Top 10	36.02	35.45	-	-
Sec to Asset Ratio Fringe	21.69	27.31	20.48	20.45
Equity Issuance over Assets Top 10	0.04	0.08	-	-
Equity Issuance over Assets Fringe	0.63	0.19	1.30	0.84
Dividends over Assets Top 10	1.61	1.82	-	-
Dividends over Assets Fringe	0.89	1.46	1.26	1.20
Additional Moments		Δ (%) from bench.	Δ (%) from bench.	Δ (%) from perf comp.
Measure Banks Fringe		-3.68	32.38	-5.97
Loan Supply		-2.70	-10.81	-2.00
Int. Output		-2.73	-10.87	-2.09
Taxes/Output		-46.27	87.82	-58.15
Borrower Project (R)		0.04	0.17	0.02
Avg loans Fringe ℓ^f		-12.87	-11.59	4.59
Avg Loans Top 10 ℓ^b		4.94	-	-
Net Cash flow Fringe (π^f)		5.75	16.67	10.71
Net Cash flow Top 10 (π^b)		9.92	-	-

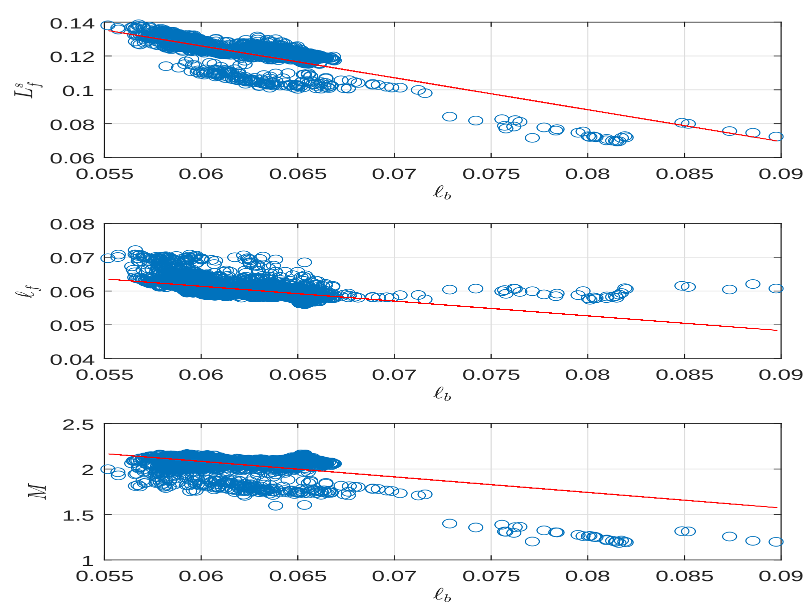
Table 14 compares volatility in the imperfect competition environment and the perfectly competitive environment. Consistent with higher capital ratios under perfect competition, this table makes clear that the volatility of virtually all aggregates is higher in the perfectly competitive environment. The incentives to self-insure are increased and generate higher capital ratios in the perfectly competitive economy than in the benchmark.

Table 14: Volatility in Benchmark versus Perfect Competition

Std Dev. (%)	Benchmark	Comp. Model	Δ (%)
Loan Interest Rate	0.1824	0.8978	392.21
Borrower Return	0.3653	0.4034	10.43
Default Frequency	1.8844	2.1593	14.59
Int. Output	0.5420	2.2962	323.65
Loan Supply	0.0043	0.0200	365.12
Capital Ratio Fringe	1.5362	1.6687	8.63
Measure Banks	0.0950	0.0674	-29.05
Markup	0.2710	0.4321	59.47
Loan Supply Fringe	0.0064	0.0200	212.50

The main driving force of the increase in the volatility of aggregates when moving to the perfectly competitive environment is the absence of large banks which take into account that fringe banks respond to their lending decision and adjust lending preemptively. Figure 9 presents a scatter plot of ℓ_b against L_f^s (the loan supply of the fringe sector) and its components ℓ_f (the average loan supply by fringe banks and $\mathcal{M}$ (the mass of incumbents).

Figure 9: Correlation between ℓ_b and L_f^s with imperfect competition



It is clear that big bank lending ℓ_b and fringe bank aggregate lending L^{sf} (as well as its intensive margin and extensive margin components) move in opposite directions. Since the variance of the aggregate loan supply can be written as $\text{Var}(L^s) = \text{Var}(\ell_b) + \text{Var}(L_f^s) + 2\text{Cov}(\ell_b, L_f^s)$, the negative covariance between ℓ_b and L_f drives down the variance of the loan supply and with it all other variables in the imperfectly competitive environment.

Moving now into the effects of higher capital requirements with perfect competition, columns 4 and 5 of Table 13 show that, even though the capital requirement constraint is not binding, on average banks endogenously increase their capital buffer (a nearly 5% difference). Intuitively, since profitability of banks is lower when capital requirements are higher, there is less entry and the measure of fringe banks falls (6% lower). A lower mass of banks implies a higher loan interest rate (a 15 basis points difference) and a default frequency that is slightly larger than that of the model with lower capital requirements. The higher loan interest rate also results in fewer projects being operated and a lower intermediated output (2% lower). The increase in capital ratios does not result in a significant change in the exit rate. This is in contrast with what we see when we analyze the model with imperfect competition.

7.8 Allocative Efficiency in the Banking Industry

An important aspect of the policy reforms that we studied is that they may change the level of allocative efficiency in the economy by shifting lending between heterogeneous banks. In order to explain this change and to provide a measure that captures how efficiently lending is allocated in the economy, we use the following decomposition of weighted average bank-level marginal cost (proposed originally by Olley and Pakes [55] to measure productivity):

$$\widehat{c} \equiv \sum_{\theta} \int \sum_{\delta_\theta} c_\theta(\ell'_\theta)\omega(\ell'_\theta) d\mu_\theta = \overline{c} + cov(c(\ell'_\theta), \omega(\ell'_\theta)),$$

where $\widehat{c}$ is the loan-weighted average of bank-level cost, $c_\theta(\ell'_\theta)$ is the net cost of extending ℓ'_θ (as defined in equation (40)), $\omega(\ell'_\theta)$ is the loan share, and $\overline{c}$ is the un-weighted mean cost (i.e., $\sum_\theta \int \sum_{\delta_\theta} c_\theta(\ell'_\theta) d\mu_\theta$).[34] That is, loan weighted cost can be decomposed into two terms: the un-weighted average of bank-level cost and a covariance term between loan shares and cost. A smaller value for the covariance term captures an improvement in allocative efficiency (since the distribution of loans shifts towards banks with lower costs).

Table 15 shows the values for this decomposition. We observe that while average (un-weighted) costs decline between 3.3% (with High Capital Requirements and Liquidity Requirements) and 7.0% (with Countercyclical Capital Requirements) relative to the baseline economy, changes in loan-weighted costs range between approximately 0% (with Size Dependent Capital Ratios) and -13.1% (with Countercyclical Capital Ratios). A large fraction (40% on average) of the decline in loan-weighted costs can be explained by an increase in allocative efficiency (as measured by a smaller or more negative covariance term that results in most cases).[35] That is, for most policy experiments, we observe that the decline in loan-weighted average costs results from a better allocation of loans across banks of different sizes

[34] It should be evident that ℓ'_θ and μ_θ are functions of n_θ and δ_θ.

[35] For example, the decline in Avg. (loan-weighted) cost $\hat{c}$ of moving to higher capital requirements is

and costs. This increase in allocative efficiency derives from a selection effect that is evident in higher exit rates (lower survival of less efficient banks) and a lower mass of fringe banks in all counterfactuals in which the covariance term declines (see also Tables 11 and 12). This shift toward more efficient banks (including the rise in market share of lower cost big banks) induces the efficiency gains.

Table 15 shows that Size Dependent Capital Requirements reduce allocative efficiency significantly to the point where all the gains in average costs are lost. Intuitively, big banks (who operate with lower average marginal costs) are the ones facing higher capital requirements and that results in a decline in their market share in the long-run.

In sum, after almost all policy changes, the distribution of loans shifts towards banks with lower costs and that drives the improvement in allocative efficiency. This relationship between banking regulation and allocative efficiency is consistent with the findings of Berger and Hannon [14] that present evidence in favor of efficiency gains from an increase in bank concentration.

Table 15: Allocative Efficiency of Capital and Liquidity Requirements

Moment (%)	Baseline $\varphi_{\theta,z} = 0.04$	Higher Cap. Req. $\varphi_{\theta,z} = 0.085$	Size Dep. Cap. Req. $\varphi_{b,z} = 0.105$ $\varphi_{f,z} = 0.085$	Countercyclical Cap. Req. $\varphi_{f,z} = 0.085$ $\varphi_{b,z} \in [0.085, 0.11]$	High Cap. Req. & Liq. Req. $\varphi_{\theta,z} = 0.085$ $\varrho_\theta = 0.08$
Avg. (loan-weighted) cost $\hat{c}$	1.755	1.640	1.754	1.525	1.662
Avg. cost $\bar{c}$	1.766	1.695	1.736	1.642	1.708
$Cov(c, \omega)$	-0.011	-0.055	0.018	-0.117	-0.047
Fringe Loan Market Share	66.94	64.34	68.28	58.65	64.91

7.9 Welfare Implications of Capital and Liquidity Requirements

To assess the welfare consequences of changes in banking regulation that we presented in the previous subsections, we ask the question, "What would households and entrepreneurs be willing to pay (or be paid) to increase capital and liquidity requirements?"

To answer this question, we calculate ex-ante consumption equivalents for each type of agent: households and entrepreneurs. Specifically, let $\{C_t^{pre}\}_{t=0}^{\infty}$ be the equilibrium sequence of aggregate household consumption in the baseline economy (i.e., pre- capital and liquidity requirements reforms). In addition, let $\{C_t^{post}\}_{t=0}^{\infty}$ be the equilibrium sequence of aggregate household consumption post-reforms (i.e., after, for example, minimum capital requirements increase to 8.5%). The *welfare gain* for the representative household as a result of the reforms is defined as the constant percentage increase in consumption in the pre-reform case

equal to 1.64-1.75=-0.11. The change in the term that measures allocative efficiency (i.e, $cov(c, \omega)$) equals -0.06-(-0.01)=-0.05. Then, 45.5% (-0.05/-0.11) of the change in loan-weighted cost $\hat{c}$ can be explained by an increase in allocative efficiency. The rest is explained by changes in average costs.

that gives the household the same expected utility as when the corresponding reform is implemented. Thus, the welfare gain (or loss if negative) for the household is the value of α_H that solves the following equation:

$$E_0\left[\sum_{t=0}^{\infty}\beta^t C_t^{post}\right] = E_0\left[\sum_{t=0}^{\infty}\beta^t(1+\alpha_H)C_t^{pre}\right]. \tag{42}$$

Equation (42) makes clear that, since household preferences are linear, computing ex-ante consumption equivalents amounts to computing the difference between long-run aggregate household consumption. Similarly, let $\{C_{E,t}^{pre}\}_{t=0}^{\infty}$ denote the equilibrium sequence of aggregate entrepreneurs' consumption pre-reforms and $\{C_{E,t}^{post}\}_{t=0}^{\infty}$ the equilibrium consumption sequence post-reforms. The welfare gain (or loss if negative) for entrepreneurs is the value of α_E that solves the following equation:

$$E_0\left[\sum_{t=0}^{\infty}\beta_E^t C_{E,t}^{post}\right] = E_0\left[\sum_{t=0}^{\infty}\beta_E^t(1+\alpha_E)C_{E,t}^{pre}\right]. \tag{43}$$

Since there is a mass N of households and a unit mass of entrepreneurs, the ex-ante aggregate consumption equivalent for a utilitarian planner that assigns equal weight to all agents in the economy is given by

$$\overline{\alpha} = \frac{N}{1+N}\alpha_H + \frac{1}{1+N}\alpha_E.$$

A note of caution about our welfare measure before presenting our results. Since we work with linear preferences, our welfare measure does not capture the effects of changes in aggregate volatility.[36] Hence, our measure of welfare gains should be taken as a lower bound in cases in which consumption volatility declines and as an upper bound in cases in which volatility increases. Moreover, in this paper, we focus on an equilibrium that takes as given (i.e., as determined uniquely by government policy) the return on safe securities r^A. This price would be subject to change in a full general equilibrium model (i.e., a model that captures how changes in demand for securities affects is price).

Table 16 presents the average welfare gain (or loss if negative) for each reform as well as the change in the standard deviation of consumption for each type of agent ($\Delta\sigma_{C_H}$ and $\Delta\sigma_{C_E}$ for consumers and entrepreneurs, respectively) and for the aggregate (i.e, the weighted average). The table shows that adjusting capital and liquidity regulation generates significant welfare losses in the short-run (between -1.216% and -0.724%) and more modest welfare gains in the long-run (between 0.140% and 0.205%). While short run losses are uniform across the agents in the economy (i.e., consumers and entrepreneurs), long-run gains are driven by the observed higher household consumption. Except for the size dependent capital requirements, the average standard deviation of consumption increases (between 20.51% and 34.59%), implying that our results can be thought as an upper bound.

[36]Linear preferences are also consistent with a constant banks' discount factor.

Table 16: Welfare Consequences of Capital and Liquidity Requirements

	Higher Cap. Req. $\varphi_{\theta,z} = 0.085$		Size Dep. Cap. Req. $\varphi_{b,z} = 0.105$ $\varphi_{f,z} = 0.085$		Countercyclical Cap. Req. $\varphi_{f,z} = \varphi_{b,z_C} = 0.085$ $\varphi_{b,z_G} = 0.11$		High Cap. Req. & Liq. Req. $\varphi_{\theta,z} = 0.085$ $\gamma_\theta = 0.08$	
	short-run	long-run	short-run	long-run	short-run	long-run	short-run	long-run
α_H	-1.063	0.220	-0.988	0.275	-1.343	0.315	-0.779	0.187
$\Delta\sigma_{C_H}$	19.38		-1.80		15.48		29.31	
α_E	-0.591	-0.167	-0.799	-0.345	-0.592	-0.333	-0.453	-0.087
$\Delta\sigma_{C_E}$	63.88		7.52		45.09		60.33	
$\overline{\alpha}$	-0.983	0.154	-0.956	0.170	-1.216	0.205	-0.724	0.140
$\overline{\Delta\sigma_C}$	26.95		-0.22		20.51		34.59	

Note: α_H and α_E are defined in equations (42) and (43). Positive values correspond to a welfare gain from the reform and a negative value corresponds to a welfare loss.

Starting with the welfare effects after increasing capital requirements to 8.5%, Table 16 shows that agents lose close to 1.0% in consumption terms in the short-run but the loss is reversed for households in the long-run resulting in an aggregate welfare gain. Short run losses can be explained by the significant increase in the cost of funding deposit insurance (due to the higher exit rate), the cost of recapitalizing the banks that continue operating under the new regime, and the reduction in intermediated output. In the long-run, the positive change in household consumption is explained by an increase in dividend payments from incumbent banks (mostly fringe banks, consistent with the increase in dividend to asset ratio shown in Table 11) and from a reduction in taxes to pay for deposit insurance (-50%) that results from better capitalized failing banks (i.e., failing banks suffer smaller losses). Since holdings of securities increase, taxes to service these securities also increase (+25%) as well as the aggregate cost of initial equity injections to cover entry costs (+62%). However, these losses are not enough to reverse the factors pushing consumption higher. As in the short-run, the negative value for the entrepreneurs' welfare can be explained almost one to one by the reduction in the fraction of projects being operated and lower output (shown in Table 11).

The welfare results for the remaining cases are driven by the same factors. Short-term losses derive, to a large extent, from an increase in taxes to finance deposit insurance, the cost of recapitalizing incumbent banks, the increase in initial equity injections, and the reduction in intermediated output that reduces entrepreneur's consumption. The case of the higher capital and liquidity requirement joint policy is slightly different in that taxes to finance deposit insurance decline in the short-run. However, the other factors generating a decline in household consumption are larger than this positive effect and short-term losses are still present. The long-term gains for consumers can be explained by the decline in the cost of deposit insurance, and a higher flow of dividends from incumbent fringe banks. While most cases display a significant increase in consumption volatility, the case with size dependent capital requirements results in a modest decline. This is driven by a decline in volatility of dividend payments from big banks which are forced to shift their portfolio towards securities which pay a constant return.

8 Directions for Future Research

The main data source for our paper, like that of Kashyap and Stein, is the Consolidated Report of Condition and Income submitted to the Federal Reserve. That public Call Report data simply provides aggregate information on commercial bank balance sheets such as commercial loans, etc. As discussed in an important empirical paper by Jimenez, et. al. [45], credit demand and balance- sheet channels have testable predictions at the firm or bank level, but one aspect of the bank risk-taking channel involves compositional changes in credit supply at the bank-firm level. Since our call report data does not allow us to identify this aspect of the bank risk-taking channel, we have not included borrower heterogeneity in our model. Bank risk-taking in our framework is associated with loan extension across particular states of the world associated with aggregate shocks and bank level heterogeneity. It would, however, be possible to extend our framework to include borrower heterogeneity. Specifically, here borrowers are ex-ante identical but ex-post heterogeneous. Private information about borrower outside options with one-period lived borrowers results in pooling loan contracts and one aggregate state dependent loan rate (as in Bernanke and Gertler [13]). In our previous work [23], our spatial framework included regional specific shocks to borrower production technologies which were observable and contractible generating heterogeneity in interest rates across different location specific borrowers. To address the type of heterogeneity found in the Jimenez, et. al. data, we could include heterogeneity in the success/failure across borrower projects. In particular, the success of a borrower's project, which occurs with probability $p_h(R_t, z_{t+1})$, could be independent across borrowers of type $h \in \{H, L\}$ but depends on the borrower's choice of technology $R_t \geq 0$ at the beginning of the period and an aggregate technology shock at the end of the period denoted z_{t+1}. Riskier borrowers would then be modeled, ceteris paribus, through the assumption that $p_H(R_t, z_{t+1}) < p_L(R_t, z_{t+1}) <$ where H stands for "High" risk and L stands for "Low" risk. Banks would continue to pool the idiosyncratic uncertainty within a risk class, but depending on informational assumptions associated with screening would offer a targeted menu of contracts to borrowers resulting in a distribution of loan rates much the same way as in Chatterjee, et. al. [19].

Another direction for future research is to incorporate mergers into the model. One reduced form way is to enrich the size-dependent autoregressive funding shock process in equation (36) to include a jump process to model random mergers that discretely increase the size of a given bank. Since failures and Mergers & Acquisitions come in waves, but the sum of exit by failure plus M&A is less variable owing to the countercyclicality of failures and procyclicality of M&A (see McCord and Prescott [52] Table 4 for the recent experience), we have not modeled mergers in our already complex model. One important factor in M&A activity is deregulation. In our previous work Corbae and D'Erasmo [23], our spatial framework included regional and national banks with market power. One experiment (in

Subsection 7.2) that we ran was to raise the entry cost for national banks in order to consider an economy with branching restrictions creating a system of regional banks prior to the mid 1990s that was largely the result of the McFadden Act in 1927. Then we interpreted results from a decrease in entry costs for national banks as a regulatory change eliminating branching restrictions such as the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 which induced consolidation via mergers. There we found that branching restrictions actually raised concentration in the regional markets, lowering loan supply and raising interest rates. In the presence of region specific shocks, consolidation to a national bank generated a more diversified loan portfolio and competition between regional and national banks generated lower interest rates post deregulation.

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Appendix

A-1 Computational Algorithm

We solve the model using a variant of Krusell and Smith [48] and Ifrach and Weintraub [43]. The main difficulty arises in approximating the distribution of fringe banks and computing the reaction function from the fringe sector to clear the loan market:

$$\ell_b(n,\delta,z,\mu) + \underbrace{\int_{\mathbf{N}\times\mathbf{D}} \ell_f(n,\delta,z,n_b,\delta_b,\mu,\ell_b)d\mu(n,\delta)}_{=L_f^s(z,n_b,\delta_b,\mu,\ell_b)} = L^d(r^L,z).$$

As part of the solution algorithm, we iterate on these functions until finding a fixed point. Note that since the big bank is a dominant player (i.e., it has market power), its individual state variables $\{n_b,\delta_b\}$ are part of the state space of fringe banks. This allows fringe banks incorporate in full the equilibrium big bank's loan decision when making their own loan decisions.

Another difficulty in solving this problem arises due to the fact that μ is an infinitely large object. For this reason, we approximate the cross-sectional distribution of fringe banks using a finite set of moments:

- The cross-sectional avg of net-worth plus deposits (denoted by $\mathcal{N}$) since that determines feasible loan and asset choices at the beginning of the period

$$\mathcal{N} = \int_{\mathbf{N}\times\mathbf{D}} (n+\delta)d\mu(n,\delta),$$

- The mass of incumbent fringe banks (denoted $\mathcal{M}$) where

$$\mathcal{M} = \int_{\mathbf{N}\times\mathbf{D}} d\mu(n,\delta).$$

  This moment is relevant since the model features endogenous entry and exit and the mass of incumbent bank fluctuates with the business cycle.

The evolution of these moments is approximated using log-linear functions that have $\{n_b,\delta_b,z,\mathcal{N},\mathcal{M},z'\}$ as states. In order to predict the evolution of the mass of banks $\mathcal{M}'$ we use the solution to the problem of the entrant (that provides M_e') and use a log-linear function to predict the mass of survivors after exit (denoted by $\mathcal{M}_x'$). The mass of entrants M_e', survivors $\mathcal{M}_x'$ and future incumbents $\mathcal{M}'$ are linked since the distribution evolves according to:

$$\mu_\theta'(n_\theta',\delta_\theta') = \int \sum_{\delta_\theta}(1-x_\theta'(n_\theta,\delta_\theta;z,\mu,\cdot,z'))\mathbf{1}_{\{n_\theta'=n_\theta'(n_\theta,\delta_\theta,z,\mu,\cdot,z'))\}}G_\theta(\delta_\theta',\delta_\theta)d\mu_\theta(n_\theta,\delta_\theta)$$
$$+M_{e,\theta}'\mathbf{1}_{\{n_\theta'=n_{e,\theta}'(z,\mu,z',M_{e,\theta}')\}}G_{e,\theta}(\delta_\theta)$$

and $\mathcal{M}_x' = \int\sum_{\delta_\theta}(1-x_\theta'(n_\theta,\delta_\theta;z,\mu,\cdot,z'))d\mu_\theta(n_\theta,\delta_\theta)$.

In summary, in equilibrium, the state space of the big bank is $\{n_b, \delta_b, z, \mathcal{N}, \mathcal{M}\}$ and the state for each fringe banks is $\{n_f, \delta_f, z, \mathcal{N}, \mathcal{M}, n_b, \delta_b\}$. This implies that for each combination of state variables $\{n_b, \delta_b, z, \mathcal{N}, \mathcal{M}\}$, in order to find an equilibrium, and in addition to solving the problem of the big bank and the fringe banks, we iterate on the aggregate functions as well as $\ell_b(\cdot)$ and $L^s_f(\cdot)$ until we find a fixed point (i.e. the equilibrium in the Stackelberg game):

$$\ell^*_b(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}) + L^s_f(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, \ell^*_b(\cdot)) = L^d(r^L, z).$$

More specifically, to find an equilibrium we perform the following steps:

1. Guess **aggregate functions**. Make an initial guess of $L^s_f(n_b, \delta_b, z, \mathcal{N}, \mathcal{M})$, M'_e and the law of motion for $\mathcal{N}'$ and $\mathcal{M}'_x$ where $\mathcal{M}'_x$ is the mass of survivors after exit decisions (note that $\mathcal{M}' = \max\{\mathcal{M}'_x, \mathcal{M} + \mathcal{M}'_e\}$) .

$$\begin{aligned} L^s_f &= H^{\mathcal{L}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}). \\ \mathcal{N}^{'} &= H^{\mathcal{N}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z'). \\ \mathcal{M}^{'}_x &= H^{\mathcal{M}_x}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z'). \end{aligned}$$

2. Solve the **dominant bank** problem to obtain the big bank value function and decision rules.

3. Solve the problem of **fringe banks** to obtain the fringe bank value function and decision rules.

4. Solve the **entry problem** of the fringe bank and big bank to obtain the number of entrants as a function of the state space.

5. **Simulate** to obtain a sequence $\{n_{b,t}, \delta_{b,t}, \mathcal{N}_t, \mathcal{M}_t, \mathcal{M}_{x,t}, \mathcal{M}_{e,t}\}_{t=1}^T$.

6. If convergence achieved (i.e., if the evolution of aggregate variables during the simulation is consistent with those implied by the aggregate functions used to solve the banks' problem) stop. If not, update the aggregate functions and return to (2).

A-1.1 Equilibrium Aggregate Functions

We use linear equations to estimate the evolution of aggregate variables. Table A.1 presents the estimated coefficients for the function $H^{\mathcal{N}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z')$. Each column presents the coefficients for each corresponding z'.

Table A.1: $\mathcal{N}' = H^{\mathcal{N}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z')$

	Dep. Var. $\mathcal{N}'$			
	z_C	z_B	z_M	z_G
constant	-0.0756	0.0298	0.0188	0.1450
s.e.	0.0107	0.0023	0.0025	0.0053
n_b	-0.0380	-0.0421	-0.0395	-0.0341
s.e.	0.0989	0.0224	0.0256	0.0537
δ_b	-0.0108	-0.0010	-0.0016	-0.0185
s.e.	0.0099	0.0019	0.0018	0.0036
$\mathcal{N}$	0.4669	0.5411	0.6132	0.4992
s.e.	0.0625	0.0091	0.0116	0.0234
$\mathcal{M}$	-0.0075	-0.0088	-0.0061	-0.0070
s.e.	0.0007	0.0005	0.0004	0.0009
z'	0.1354	0.0246	0.0238	-0.0884
s.e.	0.0087	0.0017	0.0018	0.0039
N obs	48,960	336,960	464,400	349,680
R^2	0.9744	0.9361	0.9735	0.9844

Table A.2 presents the estimated coefficients for the function $H^{\mathcal{M}_x}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z')$.

Table A.2: $\mathcal{M}_x' = H^{\mathcal{M}_x}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M}, z')$

	Dep. Var. $\mathcal{M}'$			
	z_C	z_B	z_M	z_G
constant	-0.5750	-4.6193	-3.3230	-10.6300
s.e.	0.1040	0.2008	0.1941	0.4206
n_b	-0.0987	-0.6438	1.2858	3.6660
s.e.	0.9580	1.9712	1.9255	4.2901
δ_b	0.0291	-0.1098	-0.0275	0.5876
s.e.	0.0957	0.1661	0.1364	0.2881
$\mathcal{N}$	-0.1334	3.4883	0.9796	5.7656
s.e.	0.6055	0.7993	0.8732	1.8719
$\mathcal{M}$	0.9895	0.9748	0.8103	0.8647
s.e.	0.0065	0.0415	0.0366	0.0746
z'	0.5911	4.3768	3.5949	10.3110
s.e.	0.0848	0.1501	0.1373	0.3096
N obs	48,960	336,960	464,400	349,680
R^2	0.9974	0.9015	0.8961	0.9263

Table A.3 presents the estimated coefficients for the function $H^{\mathcal{L}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M})$.

Table A.3: $L_f^s = H^{\mathcal{L}}(n_b, \delta_b, z, \mathcal{N}, \mathcal{M})$

	Dep. Var. L_f^s			
	z_C	z_B	z_M	z_G
constant	-0.0862	-0.1030	-0.1229	-0.1621
s.e.	0.0079	0.0057	0.0079	0.0046
n_b	0.5130	-0.1797	-0.5057	-0.0737
s.e.	0.1279	0.0819	0.1154	0.0719
δ_b	-0.1099	-0.0249	0.1570	0.3170
s.e.	0.0128	0.0069	0.0082	0.0048
$\mathcal{N}$	0.9958	1.5879	1.6575	1.8077
s.e.	0.0809	0.0332	0.0523	0.0313
$\mathcal{M}$	0.0688	0.0518	0.0510	0.0562
s.e.	0.0009	0.0017	0.0022	0.0013
N obs	48,960	336,960	464,400	349,680
R^2	0.9877	0.9760	0.8735	0.9748

A-1.2 Computing Policy Counterfactuals

We present the results of the policy changes in the short-run and in the long-run. To perform these experiments we proceed as follows. First, we compute the initial conditions of the benchmark model as the average $\bar{\mu}(n, \delta)$ that arises during the simulation of the model conditional on $z = 1$. That is, $\bar{\mu}(n, \delta | z = 1) = \sum_{t=1}^{T} I_{\{z=1\}} \frac{\mu_{\theta,t}(n,\delta)}{T_{z=1}}$ where $T_{z=1}$ is the number of periods such that $z = 1$. Using $\bar{\mu}(n, \delta | z = 1)$ (that implies a value for $\mathcal{M}$ and $\mathcal{N}$) and $z = 1$ as a starting point, the policy change is announced and put into effect immediately. We assume that once the policy change takes effect banks implement the decision rules of the model with higher capital requirements. Using these decision rules we simulate the economy forward. The moments reported as the "short-run" effects correspond to the moments that arise in the first period after the policy change has been implemented and the "long-run" effects correspond to the average of the economy for a 10,000 period simulation.

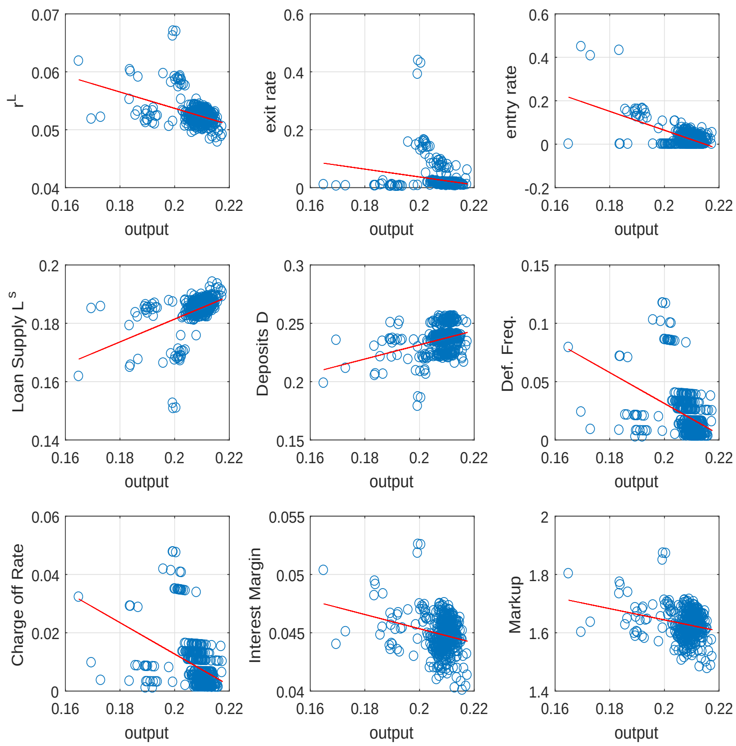
A-2 Test I: Business Cycle Properties

We present business cycle correlations as qualitative test of the model. Table 7 provides the correlation between key aggregate variables with output. This appendix presents the graphical representation of those correlations and the estimated coefficient of a linear regression between the corresponding variable and output.[37] Figure A.1 plots a set of scatter plots of

[37] We use the following dating conventions in calculating correlations. Since some variables depend on z and μ (e.g., loan interest rates $r^L(z, \mu)$) and some other variables depend on z, μ, and z', (e.g. default frequency

each variable included in Table 7 and output.

Figure A.1: Business Cycle Correlations



We observe that, as in the data, the model generates countercyclical loan interest rates, exit rates, default frequencies, charge-off rates, price-cost margins, and markups. Moreover, the model generates procyclical entry rates as well as aggregate loans and deposits.

A-3 Data Appendix

We compile a large panel of banks from 1984 to 2016 using data for the last quarter of each year.[38] The source for the data is the Consolidated Report of Condition and Income

$1-p(R(r^L(z,\mu)),z'))$, Table 7 displays $corr(output(z,\mu,z'),x(z,\mu))$ and $corr(output(z,\mu,z'),y(z,\mu,z'))$, where $x(z,\mu)$ is any variable x that depends on (z,μ) and $y(z,\mu,z')$ is any variable y that depends on (z,μ,z').

[38]There was a major overhaul to the Call Report format in 1984. Since 1984 banks are, in general, required to provide more detailed data concerning assets and liabilities. Due to changes in definitions and the creation of new variables after 1984 some of the variables are only available after this date.

(known as Call Reports) that banks submit to the Federal Reserve each quarter.[39] Report of Condition and Income data are available for all banks regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency. All financial data are on an individual bank basis.

We consolidate individual commercial banks to the bank holding company level and retain those bank holding companies and commercial banks (if there is not top holder) for which the share of assets allocated to commercial banking (including depository trust companies, credit card companies with commercial bank charters, private banks, development banks, limited charter banks, and foreign banks) is higher than 25 percent. We follow Kashyap and Stein [47] and den Haan, Summer and Yamashiro [26] in constructing consistent time series for our variables of interest. Finally, we only include banks located within the fifty states and the District of Columbia. (0 <RSSD9210< 57). In addition to information from the Call Reports, we identify bank failures using public data from the Federal Deposit Insurance Corporation (FDIC).[40] We also identify mergers and acquisitions using the Transformation table in the Call Reports.

To deflate balance sheet and income statement variables we use the CPI index. To compute business cycle correlations, variables are detrended using the HP filter with parameter 6.25. When we report weighted aggregate time series we use the asset market share as weight. To control for the effect of a small number of outliers, when constructing the loan returns, cost of funds, charge offs rates and related series we eliminate observations in the top and bottom 1% of the distribution of each variable. We also control for the effects of bank entry, exit and mergers by not considering the initial period, the final period or the merger period (if relevant) of any given bank.

Tables A.4 and A.5 present the balance sheet variables, the income statement variables and derived variables used respectively.

[39]Balance Sheet and Income Statements items can be found at https://cdr.ffiec.gov/public/.

[40]Data is available at https://www.fdic.gov/bank/individual/failed/banklist.html

Table A.4: Variable Mapping to Call Report Data

Variable Name	Code	Number	year start	year end
Balance Sheet				
Total Assets	RCFD	2170	1984	2016
Loans	RCFD	1400	1984	2016
Deposits	RCFD	2200	1984	2016
Federal Funds Purchased	RCFD	2800	1984	2001
	RCFD	B993 + B995	2002	2016
Loans Non-Accrual	RCFD	1403	1984	2016
Loans Past Due 90 Days	RCFD	1407	1984	2016
Tier 1 Capital	RCFD	8274	1996	2013
	RCFA	8274	2014	2016
Risk-Weighted Assets	RCFD	A223	1996	2013
	RCFA	A223	2014	2016
Other borrowings	RCFD	2835	1984	2000
	RCFD	3190	2001	2016
U.S. Treasury Securities	RCFD	0400	1984	1993
	RCFD	0211 + 1287	1994	2016
U.S. Agency Obligations	RCFD	0600	1984	1993
	RCFD	1289+1294+1293+1298+1698+1702+	1994	2008
		1703+1707+1714+1717+1718+1732		
		1289+1294+1293+1298+G300+G303+G304+	2009	2010
		G307+G312+G315+G316+G319+G324+G327		
		1289+1294+1293+1298+G300+G303+G304+	2011	2016
		G307+G312+G+15+G316+G319+K142+K145		
Income Statement				
Interest Income Loans	RIAD	4010 + 4065	1984	2016
Interest Expense Deposits	RIAD	4170	1984	2016
Interest Expense Fed Funds	RIAD	4180	1984	2016
Charge Off Loans	RIAD	4635	1984	2016
Recovery Loans	RIAD	4605	1984	2016
Total expenses	RIAD	4130	1984	2016
Expenses on premises and fixed assets	RIAD	4217	1984	2016
Labor expenses	RIAD	4135	1984	2016
Total Non-interest Income	RIAD	4079	1984	2016
Interest Income Safe Securities	RIAD	4027	1984	2000
		B488	2001	2016
Equity Issuance	RIAD	4346 + B510	1984	2000
	RIAD	B509 + B510	2001	2016
Dividends	RIAD	4470 + 4460	1984	2016

Note: Source Call and Thrift Financial Reports.

Table A.5: Derived Variables

Variable Name	
Interest Return on Loans	Int. Income Loans / Loans
Interest Cost Deposits	Int. Expense Deposits / Deposits
Loan Interest Margin	Int. Return on Loans - Int. Cost Deposits
Cost Fed Funds	Int. Expense Fed Funds / Fed Funds Purchased
Charge Off Rate Loans	(Charge Off Loans - Recovery Loans) / Loans
Delinquency Rate Loans	(Loans Non-Accrual + Loans Past Due 90 Days) / Loans
Tier 1 Capital Ratio (risk-weighted)	Tier 1 Capital / Risk-Weighted Assets
Safe Securities	U.S. Treasury Securities + U.S. Agency Obligations
Cost of Funds	(Int. Exp. Dep. + Int. Exp. Fed Funds) /(Dep. + Fed Funds)
Interest Return on Safe Assets	Int. Inc. Safe Securities / Safe Securities
Return Safe Securities	Int. Return on Safe Assets - Mg Non-Int. Exp. on Safe Securities
Return on Loans	Interest Return on Loans - Charge Off Rate Loans
Mg. Net Exp	Mg Non-Int. Expense - Mg Non Int. Inc.
Markup	Int. Return on Loans / (Cost of Funds + Mg. Net Exp)-1
Lerner Index	1-(Cost of Funds + Mg. Net Exp)/Int. Return on Loans

Note: “Int.” denotes Interest, “Exp.” Expenses, “Dep.” Deposits, “Mg” Marginal, “Inc.” Income. Source Call and Thrift Financial Reports.