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# Rising Bank Concentration

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The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

# Rising Bank Concentration\*

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## Abstract

Concentration of insured deposit funding among the top four commercial banks in the U.S. has risen from 15% in 1984 to 44% in 2018, a roughly three-fold increase. Regulation has often been attributed as a factor in that increase. The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 removed many of the restrictions on opening bank branches across state lines. We interpret the Riegle-Neal act as lowering the cost of expanding a bank's funding base. In this paper, we build an industry equilibrium model in which banks endogenously climb a funding base ladder. Rising concentration occurs along a transition path between two steady states after branching costs decline.

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# 1 Introduction

Concentration of insured deposit funding in the U.S. has risen from 15% in 1984 to 44% in 2018 (when measured as the fraction of deposits held at the top 4 banks relative to deposits held at all U.S. bank holding companies), a roughly three-fold increase. Regulation has often been attributed as a factor in that increase. The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 removed many of the restrictions on opening bank branches across state lines imposed under the McFadden Act of 1927 and other laws that attempted to address long-standing concerns about the concentration of financial activity. We interpret the Riegle-Neal act as lowering the cost of expanding a bank’s funding base. More generally, the methods in our paper can be applied to any government regulation that loosens or restricts the size of banks.<sup>1</sup>

In this paper, we build an industry equilibrium model in which banks endogenously climb a funding base ladder along the lines of Ericson and Pakes (1995).<sup>2</sup> Specifically, a bank can raise the mean size of its deposits at a cost. Idiosyncratic shocks to its deposits and to the success of its loan portfolio lead to an endogenous size distribution of banks. The specific method of (deposit) capacity accumulation we apply is due to Besanko and Doraszelski (2004).<sup>3</sup>

Our paper is related to the delegated monitoring model of Diamond (1984). Diamond provides a framework where large banks arise to economize on the fixed costs of monitoring individual borrowers more efficiently than a large number of small depositors. Economies of scale in monitoring (decreasing average costs) induce size. The problem of monitoring the monitor is also solved by size; large diversified banks can offer non-contingent (and hence incentive compatible) deposit contracts. There are numerous empirical papers documenting the existence of scale economies in banking such as Berger and Hannan (1998) or Berger and Mester (1997).<sup>4</sup> A large pool of depositors is also consistent with geographic diversification as described in Liang and Rhoades (1988).

Quantitative models of imperfect competition in the deposit market have been offered by Aguirregabiria, Clark, and Wang (2016), Egan, Hortaçsu, and Matvos (2017), Drechsler, Savov, and Schnabl (2017) and Corbae and Levine (2019). In this paper we focus on imperfect competition in the loan market as in Corbae and D’Erasmus (2019).<sup>5</sup> To solve the model, we use the computational methods in Weintraub, Benkard, and Van Roy (2008). In particular,

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<sup>1</sup>For instance, the proposal in Dodd-Frank to limit concentration is applicable. See <https://corpgov.law.harvard.edu/2014/06/11/proposed-dodd-frank-concentration-limit-on-financial-institution-ma-transactions/>

<sup>2</sup>In our earlier paper Corbae and D’Erasmus (2013) we exogenously change the cost structure so that banks can branch across two regions and examine the impact on competition in the loan market.

<sup>3</sup>For an application of these methods to study the regulatory burden of the Dodd-Frank Act on small banks see Liu (2019).

<sup>4</sup>For a more recent paper, see Wheelock and Wilson (2018).

<sup>5</sup>There is a strand of literature that focuses on dynamic general equilibrium models with a representative bank under perfect competition in loan and deposit markets (e.g., Van den Heuvel (2008), Aliaga-Díaz and Olivero (2012), and Begenau (2018)). There are several papers with a competitive banking sector which induce a size distribution of banks (e.g. Mankart, Michaelides, and Pagratis (2015) and Rios Rull, Takamura, and Terajima).

the approximation methods allow for there to be strategically important (dominant) banks. We think of rising concentration as occurring along a transition path between two steady states following a decline in branching costs.

The paper is organized as follows. Section 2 describes some aspects of the data that motivate our paper. Section 3 describes our environment while Section 4 describes the Markov Perfect Equilibrium of our model. Section 5 describes the parameterization of the model. Section 6 describes equilibrium properties of the model. Finally, Section 7 describes our main experiment; we lower the cost of expanding a regional bank’s funding base due, for example, to a regulatory change like Riegle-Neal and quantify the change in bank concentration. Section 8 provides directions for future research.

## 2 Data

As in Corbae and D’Erasmus (2019), we use data from the Consolidated Report of Condition and Income (known as Call Reports) that insured banks in the U.S. submit to the Federal Reserve each quarter.<sup>6</sup>

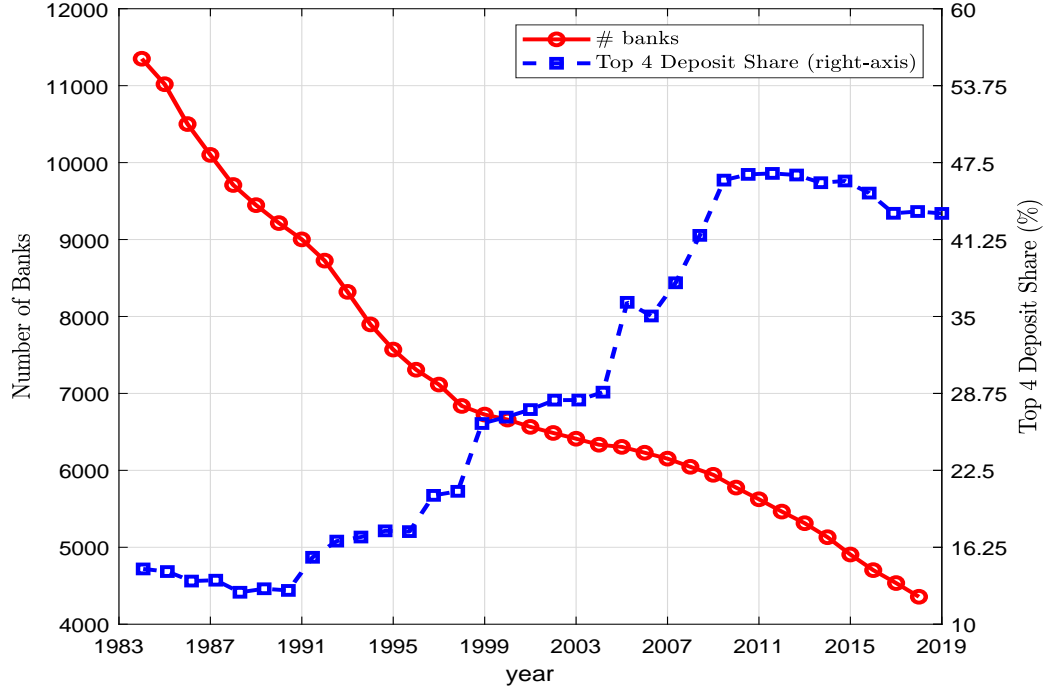
As Figure 1 makes clear, the number of commercial banks in the U.S. has fallen from over 11,000 in 1984 to under 5000 in 2018 while the deposit market share of the top 4 banks has grown from 15% in 1984 to 44% in 2018, a roughly three-fold increase. Another clear fact from Figure 1 is that there was relative stability in those shares in the decades 1984-1993 and 2009-2018.

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.

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<sup>6</sup>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.

Figure 1: Number of Banks and Bank Concentration (Top 4 Deposit Share)

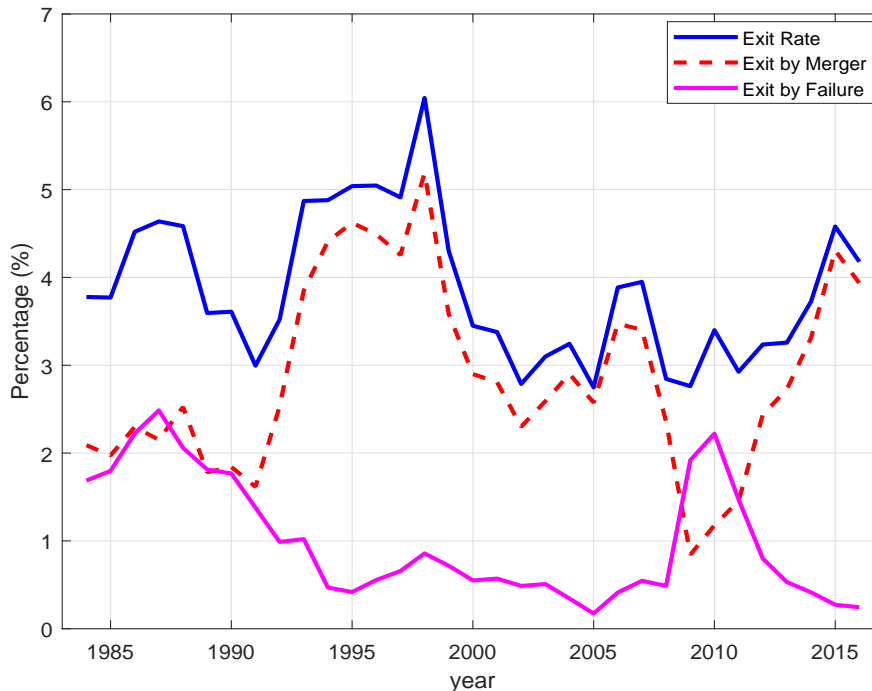


Note: Number of Banks refers to the number of bank holding companies. Top 4 Deposit share refers to the share of total deposits in the hands of the top 4 banks in the asset distribution. Source: Call Reports.

As Figure 2 makes clear, exit by merger rose tremendously around the time of the Riegle-Neal Act. That fact motivates the model in our paper. Rather than an explicit model of the merger process, we take a more reduced form approach where a bank can pay a cost to acquire a larger market share. The figure also makes clear that there was substantial exit by failure during the financial crisis. That fact motivates us to include an exit choice in the bank decision problem. The second round of consolidation apparent in the figure was due in large part to the acquisition of unprofitable banks following the crisis by large banks.<sup>7</sup>

<sup>7</sup>For the post-crisis consolidation see Federal Deposit Insurance Corporation (2017) and Kowalik et al. (2015). Unlike Corbae and D’Erasmus (2019), here we do not include aggregate shocks since we think of the regulatory reform as a long run change.

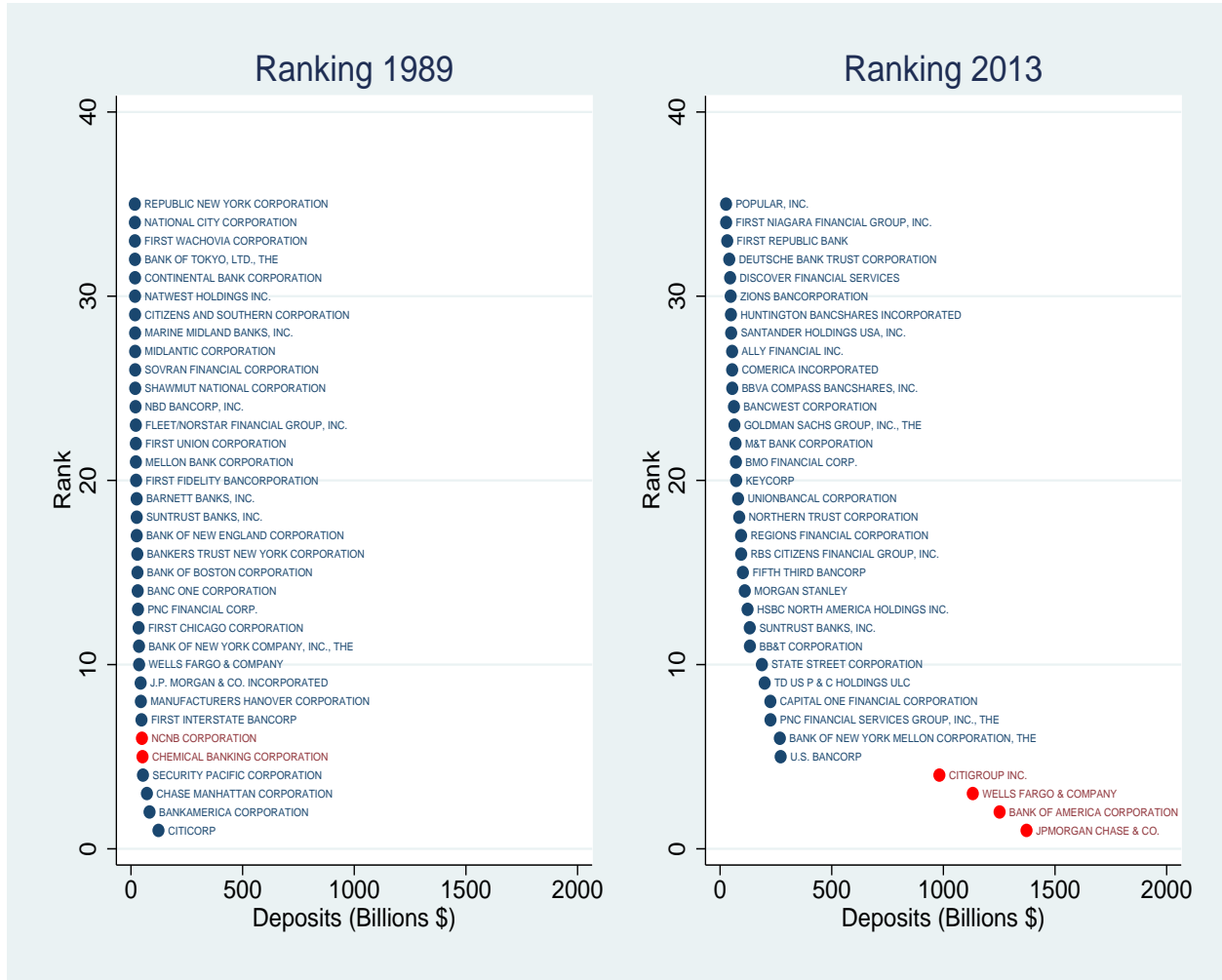
Figure 2: Decomposition of Exit Rate (1984 - 2018)



Note: Exit Rate corresponds to the ratio of the number of discontinued bank charters to the total number of banks. Exit by Merger refers to the ratio of those banks that exit and were targets of a merger to total banks. Exit by Failure refers to the ratio of banks that failed (as classified by the Federal Deposit Insurance Corporation) to the total number of banks. Source: Call Reports and Federal Deposit Insurance Corporation.

In Figure 3, we show real (1984 dollar) deposit holdings of the largest 35 bank holding companies at the midpoints of the 1984-1993 and 2009-2018 periods. The rising share of the top 4 banks following Riegle-Neal is clearly evident. The rise of the top 4 in 2018 (JP Morgan Chase, Bank of America, Wells Fargo, Citibank) came about in part by a string of mergers. In particular, from 1989 to 1992, North Carolina National Bank acquired over 200 (small) banks and in 1992 changed its name to Nationsbank. In 1996, Chemical bought Chase but kept the Chase name. In 1997, Norwest bought Wells Fargo (and took their name) and Nationsbank bought Bank of America (and took their name). In 2000, Chase bought JP Morgan (and added their name). These facts motivate our dynamic modeling of acquiring capacity size as in Besanko and Doraszelski (2004).

Figure 3: Deposit Distribution Pre- and Post-Reform



Note: Banks are ranked according to deposits. Deposits are in reported in real terms. Red bubbles identify banks that end up in the Top 4 of the distribution post-reform (2013). Source: Call Reports.

As in Diamond (1984), the motives to get bigger are increasing returns and diversification. We follow the empirical literature in banking (and our previous work Corbae and D’Erasmus (2019)) by estimating bank level costs.<sup>8</sup> We focus on banks in the top 2% of the asset distribution. Consistent with Figure 3, in the pre-reform period (1984-1993), we split the sample into two groups, Top 35 (denoted  $\theta^2$ ) and the rest (i.e., the Top 36 - 2%, denoted  $\theta^1$ ). Banks in the  $\theta^2$  group are the large regional banks and most of them were still confined to operate only in one state since in most states regulation prevented them from expanding across state borders. In the post-reform period (2009-2018), we split the Top 35 group into two groups and consider the Top 4 (denoted  $\theta^3$ ) separately from the Top 5-35 (denoted  $\theta^2$ ),

<sup>8</sup>Appendix A-3 presents the details of the estimation.

so we estimate the cost structure for three groups. Table 1 presents evidence that average costs are decreasing in size pre- and post-reform. This is indirect evidence for increasing returns.

Table 1: Cost Structure by Bank Size (Pre and Post - Reform)

<i>Pre-Reform Estimates (1984 - 1993)</i>				
Size Group		Avg. Cost	Mg Net Exp $c_\theta(\ell_\theta)/\ell_\theta$	Fixed Cost $f_\theta/\ell_\theta$
Data	Model			
Top 35	$\theta^2$	2.16	1.34	0.82
Top 36 - 2%	$\theta^1$	2.81	2.00	0.81
<i>Post-Reform Estimates (2009 - 2018)</i>				
Size Group		Avg. Cost	Mg Net Exp $c_\theta(\ell_\theta)/\ell_\theta$	Fixed Cost $f_\theta/\ell_\theta$
Data	Model			
Top 4	$\theta^3$	1.24	0.61	0.63
Top 5 - 35	$\theta^2$	1.56	0.98	0.58
Top 36 - 2%	$\theta^1$	1.96	1.44	0.52

Note: We study banks in the top 2% of the asset distribution. We group all banks in the Top 35 for the pre-reform period (these are primarily large regional banks by construction since regulation prevented them to expand across state borders). For the post-reform period, we split this group and consider Top 4 separately from the Top 5-35. Estimates corresponds to (asset-weighted) averages across banks in a given group. Source: Call Reports.

One of the drivers of bank differences in our model is the capacity to capture depositors. Using our panel of commercial banks in the U.S., we estimate how that process of deposits evolves for bank holding companies of different sizes. We keep the same grouping convention that we described above. 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  $j$  of type  $\theta \in \{\theta^1, \theta^2, \theta^3\}$  in period  $t$ :

$$\log(d_{\theta,t}^j) = (1 - \rho_\theta^d)\bar{d}_\theta + \rho_\theta^d \log(d_{\theta,t-1}^j) + u_{\theta,t}^j, \quad (1)$$

where  $d_{\theta,t}^j$  is the sum of deposits and other borrowings in period  $t$  for bank  $j$ , and  $u_{\theta,t}^j$  is iid and distributed  $N(0, \sigma_{\theta,u}^2)$ . Assuming the process is stationary, the variance of the deposit process is given by  $\sigma_\theta = \frac{\sigma_{\theta,u}}{(1 - \rho_\theta^d)^2)^{1/2}}$ . Since this is a dynamic model we use the method proposed by Arellano and Bond (1991). Consistent with the evidence presented in Figure 1, we estimate this process for the pre-reform period (1984-1993) and for the latest period in our sample (2009-2018).

Table 2 presents the results. Consistent with the diversification story in Diamond (1984), we find that the variance of deposit inflows decrease as banks grow in size.



Table 2: Deposit Process Parameters

Size Group		<i>Pre-Reform Estimates (1984 - 1993)</i>				
Data	Model	$e^{d_\theta}$	$\bar{d}_\theta$	$\rho_\theta$	$\sigma_{u,\theta}$	$\sigma_\theta$
Top 35	$\theta^2$	1.00	1.00	0.806	0.123	0.208
Top 36 - 2%	$\theta^1$	0.12	0.88	0.830	0.140	0.250
Size Group		<i>Post-Reform Estimates (2009 - 2018)</i>				
Data	Model	$e^{d_\theta}$	$\bar{d}_\theta$	$\rho_\theta$	$\sigma_{u,\theta}$	$\sigma_\theta$
Top 4	$\theta^3$	19.26	1.19	0.827	0.037	0.066
Top 5 - 35	$\theta^2$	1.73	1.03	0.762	0.086	0.132
Top 36 - 2%	$\theta^1$	0.1956	0.91	0.738	0.106	0.157

Note: We study banks in the top 2% of the asset distribution. We group all banks in the Top 35 ( $\theta^2$ ) for the pre-reform period (these are large regional banks by construction since regulation prevented them to expand across state borders). For the post-reform period, we split this group and consider Top 4 ( $\theta^3$ ) separately from the Top 5-35 ( $\theta^2$ ). Average deposits are normalized to 1 for the Top 35 group in the pre-reform period.  $\bar{d}_\theta$  is reported relative to this group.

### 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  $H > 1$  of identical, households (the potential depositors). Time is discrete and there is an infinite horizon.

#### 3.1 Households

Infinitely lived, risk neutral households with discount factor  $\beta$  are endowed with  $1/H$  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  $1 + \bar{r}$  between any two periods with  $\bar{r} \geq 0$  and  $\beta(1 + \bar{r}) = 1$ . 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  $\tau_t$  which include a lump-sum tax  $\tau_t^D$  used to cover deposit insurance for failing banks. Finally, if a household was to match directly with an entrepreneur (i.e. directly fund an entrepreneur's project), it must compete with bank loans. Hence, the household could not expect to receive more than the bank lending rate  $r^L$  in successful states and must pay a monitoring cost. Since households can purchase claims to bank cash flows, and banks can more efficiently minimize costly

monitoring along the lines of Diamond (1984), there is no benefit to matching directly with entrepreneurs. Finally, households make initial equity injections to fund entry by banks.

### 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:

$$\begin{cases} 1 + R_t & \text{with prob } p(R_t) \\ 1 - \lambda_t & \text{with prob } [1 - p(R_t)] \end{cases} \quad (2)$$

in the successful and unsuccessful states, respectively. That is, borrower gross returns are given by  $1 + R_t$  in the successful state and by  $1 - \lambda_t$  in the unsuccessful state where  $\lambda_t$  is the chargeoff rate. We assume that  $\log(\lambda_t) \sim N(\mu_\lambda, \sigma_\lambda)$  and it is i.i.d. across borrowers and time. The success of a borrower's project, which occurs with probability  $p(R_t)$ , is independent across borrowers and time *conditional* on the borrower's choice of technology  $R_t \geq 0$ .

The entrepreneur can save  $a_{E,t+1} \in \mathbb{R}_+$  with return  $\bar{r}$  (i.e. the same storage technology as households) and can choose how much of the project to finance with retained earnings  $I_{t+1} \in [0, 1]$ . We assume a parameterization such that the entrepreneur is sufficiently impatient that she would not choose to undertake any of these alternatives. That is, the discount factor  $\beta_E$  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.

As for the likelihood of success or failure, a borrower who chooses to run a project with a higher return  $R_t$  has more risk of failure. Specifically,  $p(R_t)$  is assumed to be decreasing in  $R_t$ . Thus, the technology exhibits a risk-return trade-off. Further, since  $R_t$  is a choice variable, project returns and failure rates are endogenously determined. 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  $\max\{R_t - r_t^L, 0\}$  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 3 summarizes the risk-return tradeoff that the borrower faces if the cross-sectional distribution of banks is  $\mu_t$  (that is described in detail below).

Table 3: Borrower’s Problem

Borrower Chooses $R_t$	Receive	Pay	Probability
Success	$1 + R_t$	$1 + r^L(\mu_t)$	$p(R_t)$
Failure	$1 - \lambda$	$1 - \lambda$	$1 - p(R_t)$

Borrowers have an outside option (reservation utility)  $\omega_t \in [\underline{\omega}, \bar{\omega}]$  drawn at the beginning of the period from a cumulative 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  $\omega_t$  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 (1989), 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 (1984).

### 3.3 Banks

We build a model along the lines of Ericson and Pakes (1995) where banks Cournot compete in a single-good market (loans) and there is endogenous entry and exit. As in Diamond (1984), banks exist in our environment to pool risk and economize on monitoring costs. We assume there are 3 types of banks:  $\theta \in \Theta = \{\theta^1, \theta^2, \theta^3\}$ . We will say that bank of type  $\theta^{i+1}$  is bigger than bank  $\theta^i$ . In our application, we call banks of type  $\theta^3$  national, banks of type  $\theta^2$  regional, and banks of type  $\theta^1$  local. There can be multiple banks of each type operating and banks of all types have some degree of market power.

Each incumbent bank is assigned a unique positive integer-valued index  $j$ . As in Corbae and D’Erasmus (2019), bank type  $\theta$  determines the mean and variance of a bank’s deposits  $d_\theta$ . In particular, banks in the model face the deposit process we estimated in equation (1). To make our definition of type consistent with the data presented in Table 2, the mean of the deposit process satisfies  $\bar{d}_{\theta^{i+1}} > \bar{d}_{\theta^i}$  so that higher types have a bigger funding base. Furthermore, also consistent with the data presented in Table 2, the variance of deposits satisfy  $\sigma_{\theta^{i+1}} \leq \sigma_{\theta^i}$  so that bigger banks have lower variance consistent with diversification. We discretize the deposit process so  $d_\theta \in D_\theta = \{d_\theta^1, \dots, d_\theta^{N^d}\}$  and denote its transition matrix by  $G_\theta(d_{\theta,t+1}, d_{\theta,t})$ . Unlike Corbae and D’Erasmus (2019), here deposits are the only source of funding besides seasoned equity.

Along the lines of Besanko and Doraszelski (2004), a given bank of type  $\theta$  can invest  $\iota_{\theta,t} \in \mathbb{R}_+$  to become a larger type bank (i.e., a small local bank can invest to become a regional bank and a medium sized regional bank can invest to become a large national bank). We think about this investment technology as a reduced form way of capturing

mergers and acquisitions. In particular, we let  $\Delta\bar{d}_{\theta^{i+1}} = (\bar{d}_{\theta^{i+1}} - \bar{d}_{\theta^i}) > 0$ . The probability that a bank of type  $\theta_t = \theta^i$  transitions to type  $\theta_{t+1}$  is given by

$$T(\theta_{t+1}|\theta_t = \theta^i, \iota_{\theta,t}) = \begin{cases} \frac{(1-\delta)\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}}{1+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^{i+1} \\ \frac{1-\delta+\delta\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}}{1+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^i \\ \frac{\delta}{1+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^{i-1} \end{cases}, \quad (3)$$

where the parameters  $\alpha > 0$  and  $\xi > 0$  measure the effectiveness of investment (at  $\iota_{\theta,t} = 0$  to be precise).<sup>9</sup> Investment in deposit capacity depends on the level of investment and the size of the expected increase (captured by  $\Delta\bar{d}_{\theta^{i+1}}$ ). Clearly banks cannot move further down from the lowest size so that

$$T(\theta_{t+1}|\theta_t = \theta^1, \iota_{\theta,t}) = \begin{cases} \frac{\alpha(\Delta\bar{d}_{\theta^2})^{-\xi\iota_{\theta,t}}}{1+\alpha(\Delta\bar{d}_{\theta^2})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^2 \\ \frac{1}{1+\alpha(\Delta\bar{d}_{\theta^2})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^1 \end{cases} \quad (4)$$

and depending on the state of regulation, the highest size banks (either  $\theta^2$  with size (e.g. branching) restrictions or  $\theta^3$  without size restrictions) cannot move higher so that

$$T(\theta_{t+1}|\theta_t = \theta^i, \iota_{\theta,t}) = \begin{cases} \frac{1-\delta+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}}{1+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^i \\ \frac{\delta}{1+\alpha(\Delta\bar{d}_{\theta^{i+1}})^{-\xi\iota_{\theta,t}}} & \text{if } \theta_{t+1} = \theta^{i-1} \end{cases}. \quad (5)$$

After the realization of  $\theta_t$ , a given incumbent bank is randomly matched with a set of potential household depositors  $d_{\theta,t}$  who receive deposit interest rate  $r_{\theta,t}^D$  and then decide how many loans to extend. When extending loans  $\ell_{\theta,t}$ , banks maximize profits and face a capacity constraint  $\ell_{\theta,t} \leq d_{\theta,t}$ . If a bank chooses an amount of loans lower than its capacity constraint (i.e.,  $\ell_{\theta,t} < d_{\theta,t}$ ), the leftover deposits (i.e.  $a_{\theta,t} = d_{\theta,t} - \ell_{\theta,t}$ ) can be invested in the same risk-free technology that the households have access to with return equal to  $\bar{r}$ . Note that since the outside option for a household matched with a bank is to store at rate  $\bar{r}$ , we know  $r_{\theta,t}^D \geq \bar{r}$ . Finally, there is a realization of charge-off rates  $\lambda_t$  which are i.i.d. across time and bank. Static profits (denoted  $\pi_\ell(\theta_t, d_t, \lambda_t; \mu_t)$ ) for an incumbent bank of type  $\theta_t$ , with deposits  $d_{\theta,t}$ , charge-off rate  $\lambda_t$  in industry state  $\mu_t$  (to be described below) are realized from its lending  $\ell_{\theta,t}$  given by

$$\pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t) = \{p_t r^L(\mu_t) - (1-p_t)\lambda_t\} \ell_{\theta,t} + \bar{r}a_{\theta,t} - r_{\theta,t}^D d_{\theta,t} - c_\theta(\ell_{\theta,t}) - f_\theta \quad (6)$$

where  $p_t$  denotes the fraction of loans that repay (an endogenous object that is consistent with the borrower's problem),  $c_\theta(\ell_{\theta,t})$  the marginal cost of extending  $\ell_{\theta,t}$  loans, and  $f_\theta$  the fixed operating cost. Note that  $r^L(\mu_t)$  depends on the distribution via the loan choice of bank  $j$  and all its competitors.

Given profits  $\pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t)$ , banks can choose to exit. To keep the computation of the model tractable, we also incorporate a type specific exogenous probability of exit

<sup>9</sup>This specification nests Besanko and Doraszelski (2004) when  $\xi = 0$ .

$\rho_\theta^x$ . If a bank decides to continue, it then decides how much to invest in order to improve their capacity to collect deposits. Banks can finance investment with internal funds ( $\pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t)$ ) or by issuing equity  $e_{\theta,t}$  whenever  $\iota_{\theta,t} > \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t)$ . That is  $e_{\theta,t} = \max\{\iota_{\theta,t} - \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t), 0\}$ . Issuing equity is costly with cost function given by  $\varsigma_\theta(e_{\theta,t})$ . For tractability, unlike Corbae and D’Erasmus (2019), here we assume that banks cannot retain earnings. Dividends net of equity injections are given by

$$\mathcal{D}_{\theta,t} = \begin{cases} \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t) - \iota_{\theta,t} & \text{if } \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t) - \iota_{\theta,t} \geq 0 \\ \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t) - \iota_{\theta,t} - \varsigma_\theta(\iota_{\theta,t} - \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t)) & \text{if } \pi_\ell(\theta_t, d_{\theta,t}, \lambda_t; \mu_t) - \iota_{\theta,t} < 0 \end{cases}$$

The objective function of the bank is to maximize the expected present discounted value of future dividends net of equity injections with discount factor  $\beta$ . It is important to note that while deposits conditional on bank size ( $d_{\theta,t}$ ) are exogenous, external finance is endogenous since bank size ( $\theta_t$ ) via investment ( $\iota_{\theta,t}$ ) and seasoned equity ( $e_{\theta,t}$ ) are endogenous.

We assume there is limited liability and that incumbent banks have the option to exit after extending loans. The value of exiting is given by

$$\max\{0, \zeta_\theta[1 + p_t r^L(\mu_t) - (1 - p_t)\lambda_t]\ell_{\theta,t} - c_\theta(\ell_{\theta,t}) - f_\theta - (1 + r_{\theta,t}^D)d_{\theta,t} + \zeta_\theta(1 + \bar{r})(d_{\theta,t} - \ell_{\theta,t})\}, \quad (7)$$

where  $\zeta_\theta$  captures the recovery rate of a bank’s assets at the exit stage,

We consider an entry process similar to Farias, Saure, and Weintraub (2012). At time period  $t$ , there are a finite but large number of potential entrants. Each potential entrant is assigned a unique positive integer-valued index  $j$ . Each period, potential entrants observe a positive integer-valued cost  $\kappa_t$  funded by an initial equity injection by households. Potential entrants make entry decisions simultaneously. Entrants do not earn profits in the period they decide to enter. They appear in the following period in state  $(\theta_{t+1} = \theta^1, d_{\theta^1, t+1})$  (i.e., we assume that all entrants start as a small bank) where  $d_{\theta^1, t+1}$  is drawn from  $\overline{G}_{\theta^1}(d_{\theta^1})$  the invariant distribution associated with  $G_{\theta^1}(d_{\theta^1, t+1}, d_{\theta^1, t})$ .

For each bank  $j$ , the timing of events is as follows:

1. At the beginning of period  $t$ ,  $\theta_t^j$  and  $d_{\theta_t^j, t}^j$  are realized.
2. Loans  $\ell_{\theta_t^j, t}^j$  are chosen.
3. The portfolio of performing and non-performing loans is drawn from  $p_t$  and chargeoff rates  $\lambda_t^j$  are realized inducing a realization of  $\pi_\ell^j$ .
4. Exit and entry choices are made.
5. Investment  $\iota_{\theta_t^j, t}^j$  is chosen.
6. Dividends net of equity injections  $\mathcal{D}_{\theta_t^j, t}^j$  are paid.

In summary, the simple balance sheet of a bank in our environment is given by: book assets equal loans ( $\ell$ ), storage ( $a$ ), and fixed capital ( $\kappa$ ) while book liabilities equal deposits ( $d$ ) and the initial equity injection.<sup>10</sup>

<sup>10</sup>In the call report data, we consider fixed capital ( $\kappa$ ) as “premises and fixed assets” as well as “intangible assets”.

### 3.4 Information

There is asymmetric information on the part of entrepreneurs (borrowers) and banks/households (lenders). Only entrepreneurs know the riskiness of the project they choose ( $R_t$ ) and their outside option ( $\omega_t$ ). Project success or failure is unobservable unless the project is monitored. The history of past borrowing and repayment by the entrepreneur is also unobservable. Other information is publicly observable.

## 4 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

$$\max_{\{C_t, a_{h,t+1}, d_{h,t+1}, \{S_{t+1}^j\}_{j=1}^{\infty}\}} E_0 \left[ \sum_{t=0}^{\infty} \beta^t C_t \right] \quad (8)$$

subject to

$$\begin{aligned} & C_t + a_{h,t+1} + d_{h,t+1} + \sum_j [P_t^j + \mathbf{1}_{\{\hat{e}_t^j=1\}} \kappa_t] S_{t+1}^j \\ &= \frac{1}{H} + \sum_j [\mathcal{D}_{\theta,t}^j + P_t^j] S_t^j + (1 + \bar{r}) a_{h,t} + (1 + r_t^D) d_{h,t} - \tau_t. \end{aligned} \quad (9)$$

where  $P_t^j$  and  $S_{t+1}^j$  are the post-dividend stock price and stock holdings of bank  $j$  respectively,  $\mathbf{1}_{\{\cdot\}}$  is an indicator function that takes the value one if the argument  $\{\cdot\}$  is true and zero otherwise, and  $\hat{e}_t^j = 1$  denotes the entry decision of bank  $j$  in period  $t$ . Given exit and entry decision rules, in cases in which a bank has exited,  $P_t^j = 0$  on the right-hand side of the budget constraint, and, in cases in which a firm has entered,  $P_t^j > 0$  on the left hand side of the budget constraint.

The first order condition for  $S_{t+1}^j$  for an incumbent bank  $j$  is:

$$P_t^j = \beta [\mathcal{D}_{\theta,t+1}^j + P_{t+1}^j]. \quad (10)$$

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

If banks offer the same interest rates on deposits as households can receive from their storage opportunity (i.e.  $r_{t+1}^D = \bar{r}$ ), then a household would be indifferent between matching

with a bank and using the autarkic storage technology. In that case, any household who is matched with a bank would be willing to deposit at the insured bank. Furthermore, the first order condition for saving in the form of deposits or storage technology implies  $\beta(1 + \bar{r}) = 1$ , which we assume parametrically.

## 4.2 Entrepreneur's Problem

Every period, given  $\{r_t^L, \omega_t\}$ , 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, and how much to save  $a_{E,t+1} \in \mathbb{R}_+$  to maximize the expected discounted utility of consumption. That is,

$$\max_{\{C_{E,t}, a_{E,t+1}, I_{t+1}, \iota_{E,t}, R_t\}_{t=0}^{\infty}} E_0 \left[ \sum_{t=0}^{\infty} \beta^t C_{E,t} \right] \quad (11)$$

subject to

$$C_{E,t} + a_{E,t+1} + I_{t+1} = (1 - \iota_{E,t})(\omega_t + I_t) + \iota_{E,t}\pi_E(I_t, R_t; r_t^L) + (1 + \bar{r})a_{E,t} \quad (12)$$

where

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

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

$$m_t = 1 - \beta_E(1 + \bar{r}). \quad (13)$$

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

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

$$\frac{\partial \pi_E(I_t, R_t; r_t^L)}{\partial r_t^L} = -p(R_t) < 0. \quad (14)$$

Thus, participating borrowers are worse off the higher is the interest rate 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

$$L^d(r_t^L) = \int_0^{\bar{\omega}} \mathbf{1}_{\{\omega_t \leq \pi_E(I_t, R_t; r_t^L)\}} d\Omega(\omega_t), \quad (15)$$

In that case, (14) implies  $\frac{\partial L^d(r_t^L)}{\partial r_t^L} < 0$ . That is, the loan demand curve is downward sloping.

### 4.3 Incumbent Bank Problem

Bank  $j$ 's individual state is  $(\theta_t^j, d_{\theta,t}^j)$ , which lies in a finite set, while the industry state is denoted  $\mu_t$ , which is a counting measure. We will write an individual bank's problem recursively, denoting a variable  $y_t$  by  $y$  and  $y_{t+1}$  by  $y'$ .

As in Ericson and Pakes (1995)), we will be looking for a symmetric equilibrium in the sense that all banks in the same individual state (i.e.  $(\theta^j, d_\theta^j) = (\theta^k, d_\theta^k)$ ) are treated identically. The cross-sectional distribution  $\mu_t$  specifies the number of banks in each state  $(\theta, d_\theta) \in \{\Theta \times D_\theta\}$ . We let  $n$  denote the number of incumbent banks at time period  $t$ , that is,  $n = \sum_{\theta, d_\theta} \mu(\theta, d_\theta)$ . Further, the law of motion for the industry state is denoted  $\mu' = \mathcal{H}(\mu, N^e)$  where  $N^e$  denotes the number of entrants and the transition function  $\mathcal{H}$  is defined explicitly below.

After being matched with  $d_\theta$  potential depositors and making them a take-it-or-leave-it deposit rate offer  $r_\theta^D$ , an incumbent bank of type  $\theta$  chooses loans  $\ell$  in order to maximize profits. Given the take-it-or-leave-it deposit rate offer and that the outside storage option for a household is  $\bar{r}$ , we know in equilibrium  $r_\theta^D = \bar{r}$ . After profits are realized, banks can choose to exit setting  $x_\theta = 1$  or choose to remain  $x_\theta = 0$ . When choosing its loan supply the bank solves<sup>11</sup>

$$\ell(\theta, d_\theta; \mu) = \arg \max_{\ell \leq d_\theta} E_\lambda [\pi_\ell(\theta, d_\theta, \lambda; \mu)]. \quad (16)$$

Given that all banks have some degree of market power, a bank takes into account that its loan supply affects the loan interest rate and that other banks will best respond to its loan supply. The first order condition (of problem (16)) with respect to  $\ell$  is

$$E_\lambda \left[ \underbrace{\left( pr^L - (1-p)\lambda - c'_\theta \right)}_{(+)\text{ or }(-)} + \ell \left( \underbrace{p}_{(+)} + \underbrace{\frac{\partial p}{\partial R} \frac{\partial R}{\partial r^L} (r^L + \lambda)}_{(-)} \right) \underbrace{\frac{dr^L}{d\ell}}_{(-)} \right] - \psi_\theta = 0, \quad (17)$$

where  $\psi_\theta \geq 0$  represents the multiplier on the  $\ell \leq d_\theta$  constraint. 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. A change in interest rates also endogenously affects the fraction of delinquent loans faced by banks (i.e. the term  $\frac{\partial p}{\partial R} \frac{\partial R}{\partial r^L} < 0$ ). Given limited liability entrepreneurs take on more risk when their financing costs rise.

It is important to note that changes in the loan interest rate (i.e.  $\frac{dr^L}{d\ell}$ ) in (17) are derived from the market clearing condition  $L^d(r^L) = L^s(\mu)$  where  $L^d(r^L)$  is given above in (15) and  $L^s(\mu_t)$  denotes the total supply of loans given by

$$L^s(\mu) = \sum_{\theta, d_\theta} \ell_t(\theta, d_\theta; \mu) \mu(\theta, d_\theta). \quad (18)$$

<sup>11</sup>Note that when  $r_\theta^D = \bar{r}$  and  $c_\theta(\ell_\theta)$  is sufficiently small, then  $\ell_\theta = d_\theta$  will tend to hold in equilibrium and equation (6) reduces to

$$\pi_\ell(\theta, d_\theta, \lambda; \mu) = \{pr^L(\mu) - (1-p)\lambda - \bar{r}\} \ell_\theta - c_\theta(\ell_\theta) - f_\theta.$$



For a given bank distribution  $\mu(\theta, d_\theta)$ , changes in the loan supply of a given bank have a direct effect on the aggregate loan supply but also an indirect effect via changes in the response of its competitors.

After loans have been extended, the value of an incumbent bank in period  $t$  (i.e., at the exit stage 4 in timing) is

$$V(\theta, d_\theta, \lambda; \mu) = \max_{x \in \{0,1\}} \{V^{x=0}(\theta, d_\theta, \lambda; \mu), V^{x=1}(\theta, d_\theta, \lambda; \mu)\} \quad (19)$$

where  $V^{x=1}(\theta, d_\theta, \lambda; \mu)$  is defined in equation (7) and  $V^{x=0}(\theta, d_\theta, \lambda; \mu)$  is given by

$$V^{x=0}(\theta, d_\theta, \lambda; \mu) = \max_{\iota} \left\{ \pi_\ell(\theta, d_\theta, \lambda; \mu) - \iota - 1_{\{\pi_\ell(\theta, d_\theta, \lambda; \mu) - \iota < 0\}} \cdot \varsigma_\theta (\iota - \pi_\ell(\theta, d_\theta, \lambda; \mu)) \right. \\ \left. + \beta \rho_\theta^x E_{\theta', d'_{\theta'}, \lambda' | d_\theta, \iota} [V(\theta', d'_{\theta'}, \lambda'; \mu')] \right\} \quad (20)$$

subject to the transition functions  $T(\theta' | \theta, \iota)$  and  $\mu' = \mathcal{H}(\mu, N_e)$ .

#### 4.4 Bank Entry

The value of an entrant net of entry costs in the industry state  $\mu$  is

$$V^e(\mu) = -\kappa + \beta E_{d', \lambda'} [V(\theta^1, d'_{\theta^1}, \lambda'; \mu')] \quad (21)$$

Recall that entrants do not operate in the period they enter and, consistent with the data, they all start small (i.e., with  $\theta = \theta^1$ ). Potential entrants will decide to enter if  $V^e(\mu) \geq 0$ . The number of entrants  $N^e$  is determined endogenously in equilibrium. Free entry implies that

$$V^e(\mu) \times N^e = 0. \quad (22)$$

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  $\mu' = \mathcal{H}(\mu, N_e)$  where each component is given by:

$$\mu'(\theta', d'_{\theta'}) = \sum_{\theta, d_\theta} \int_{\lambda} (1 - x(\theta, d_\theta, \lambda))(1 - \rho_\theta^x) T(\theta' | \theta, \iota(\theta, d_\theta, \lambda)) G_\theta(d'_{\theta'}, d_\theta) \mu(\theta, d_\theta) df(\lambda) + N^e \sum_{d_{\theta^1}} G^e(d_{\theta^1}) \quad (23)$$

where  $f(\lambda)$  represents the cumulative distribution of  $\lambda$  and  $G^e(d_{\theta^1})$  the distribution from which deposits for entrants are drawn. Equation (23) makes clear how the law of motion for the distribution of banks is affected by entry ( $N^e$ ) and exit ( $x$ ) decisions as well as the accumulating size decision ( $\iota$ ).

## 4.6 Funding Deposit Insurance and Servicing Securities

The government collects lump-sum taxes (or pays transfers if negative) denoted  $\tau$  that cover the cost of deposit insurance  $\tau^D$  in the event of bank failure. Let post-liquidation net transfers be given by

$$\Delta(\theta, d_\theta, \lambda; \mu) = (1 + r^D)d_\theta - \zeta_\theta[1 + pr^L(\mu) - (1 - p)\lambda]\ell_\theta - \zeta_\theta(1 + \bar{r})(d_\theta - \ell_\theta)$$

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

$$\tau^D(\mu) \cdot H = \sum_{\theta, d_\theta} \left[ \int_{\lambda} (x(\theta, d_\theta, \lambda; \mu) + (1 - x(\theta, d_\theta, \lambda))\rho_\theta^x) \max\{0, \Delta(\theta, d_\theta, \lambda; \mu)\} \mu(\theta, d_\theta) df(\lambda) \right]. \quad (24)$$

## 4.7 Definition of Equilibrium

Given  $\bar{r}$ , a pure strategy Markov Perfect Equilibrium (MPE) 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,  $\{\ell(\theta, d), \iota(\theta, d, \lambda), x(\theta, d, \lambda), e(\mu)\}$  describing loan, investment, exit and entry behavior, a bank value function  $V(\theta, d, \lambda)$ , a cross-sectional distribution of banks  $\mu$ , a function describing the number of entrants  $N^e$ , a loan interest rate  $r^L(\mu)$ , a deposit interest rate  $r^D$ , stock prices  $P_\theta$ , and a tax function  $\tau^D$  such that:

1. Given  $r^L$  and  $\bar{r}$ ,  $\{a'_E, I', \iota_E, R\}$  are consistent with entrepreneur optimization (11)-(12) inducing an aggregate loan demand function  $L^d(r^L)$  in (15).
2. Given  $r^D = \bar{r}$  and  $P_\theta$ ,  $\{a'_h, d'_h, S'_\theta\}$  are consistent with household optimization (8)-(9) inducing a deposit matching process.
3. Given the loan demand function and deposit matching process,  $\{\ell(\theta, d), \iota(\theta, d, \lambda), x(\theta, d, \lambda)\}$  and  $V(\theta, d, \lambda)$  are consistent with bank optimization (19)-(20) inducing an aggregate loan supply function defined in (18).
4. The entry rule is consistent with entrant bank optimization (21) and the free-entry condition is satisfied (22).
5. The law of motion for the industry state induces a sequence of cross-sectional distributions that are consistent with entry, exit, and investment decision rules in (23).
6. The interest rate  $r^L(\mu)$  is such that the loan market clears. That is,

$$L^d(r^L) = L^s(\mu) = \sum_{\theta, d} \ell(\theta, d; \mu) \mu(\theta, d).$$

7. Stock prices satisfy (10).
8. Taxes/transfers  $\tau^D(\mu)$  cover the cost of deposit insurance in (24).

## 5 Parameterization

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”).<sup>12</sup> We aggregate commercial bank level information to the Bank Holding Company level. To solve the model, we use the computational methods in Weintraub, Benkard, and Van Roy (2008).<sup>13</sup> In particular, the approximation methods allow for there to be strategically important (dominant) banks. We think of rising concentration as occurring along a transition path between two stationary ergodic (long run average) bank distributions following a decline in branching costs.

Given the relative stability of deposit market shares prior to the passing of the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 evidenced in Figure 1, we calibrate the model to an initial period from 1984 - 1993 where restrictions on opening bank branches across state lines were in place. In this initial period, only transitions between two types of banks  $\{\theta^1, \theta^2\}$  are feasible since investing to transition into  $\theta^3$  is assumed to be infinitely costly (due to branching regulation prior to its repeal in Riegle-Neal). We identify these banks with local banks and large regional banks in the Top 2% of the asset distribution. Specifically, in the pre-reform period, the top 2% corresponds to 190 banks on average. Of these banks in the top 2%, we classify those in the Top 35 as  $\theta^2$ -type banks and those in the Top 36-190 (i.e., the other 155 banks) as  $\theta^1$ -type banks. Parameters governing the investment transition probability and the cost of extending loans are assumed to be type and period specific. In the post-reform period, the top 2% banks in the asset distribution correspond to 103 banks on average. Of these banks, we classify those in the Top 4 as  $\theta^3$ -type banks, those in the Top 5-35 as  $\theta^2$ -type banks, and the rest (68 banks) as  $\theta^1$ -type banks. Notably the number of banks in the top 2% fell by 45.79% consistent with the drop in the total number of banks presented in Figure 1.

We parameterize the stochastic process for the borrower’s project as follows. For each borrower, let  $s = a - bR + \varepsilon_e$ , where  $\varepsilon_e$  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  $\varepsilon_e$  success is more likely. Then

$$\begin{aligned}
 p(R) &= 1 - \Pr(s \leq 0 | R) \\
 &= 1 - \Pr(\varepsilon_e \leq -a + bR) \\
 &= \Phi(a - bR),
 \end{aligned} \tag{25}$$

where  $\Phi(x)$  is a normal cumulative distribution function with zero mean and variance  $\sigma_\varepsilon^2$ . The stochastic process for the borrower outside option,  $\Omega(\omega)$ , is simply taken to be the uniform distribution  $[0, \bar{\omega}]$ . To reduce the number of parameters to calibrate and since we do not have enough information on the liquidation value of the assets of large banks (since we do not observe liquidations in the largest category) we set  $\zeta_\theta = \zeta$  and calibrate  $\zeta$  using

<sup>12</sup>Source: FDIC, Call and Thrift Financial Reports, Balance Sheet and Income Statement (<http://www2.fdic.gov/hsob/SelectRpt.asp?EntryTyp=10>). See Appendix A-2 for a description of the data.

<sup>13</sup>Appendix A-1 describes the solution algorithm we use to approximate a Markov Perfect Equilibrium.

data from the FDIC. We parameterize the equity issuance cost function  $\varsigma_\theta(e_\theta) = (\varsigma_\theta^0 + \varsigma_\theta^1 e_\theta)$  where  $e_\theta = \max\{0, -(\pi_\theta - \iota_\theta)\}$  and the cost of extending loans  $c_\theta(\ell_\theta) = c_\theta^0 \ell_\theta + c_\theta^1 \ell_\theta^2$ .

As part of the calibration exercise, we estimate transition probabilities between banks of different sizes. In particular, we estimate transition matrices by counting the number of banks in each bin-year and dividing by the total number of banks of each type in a given year. We then take the time series average of the corresponding bin for each period. For example, to compute the fraction of banks that remain in state  $\theta^1$ , we first count how many  $\theta^1$  banks in period  $t$  are still of type  $\theta^1$  in period  $t + 1$ . Let this number be  $N_t^{1,1}$ . Then, the value in  $\hat{T}_t(\theta'|\theta)$  equals  $\frac{N_t^{1,1}}{N_t^1}$  where  $N_t^1$  corresponds to all banks of type  $\theta^1$  in period  $t$ . The reported value in Table 6 corresponds to the time-average of  $\hat{T}_t(\theta'|\theta)$ . The failure state incorporates the transition to a bank outside the top 2%.

Table 4 presents the parameters of the model and the targets that were used. We use several moments from our panel of banks in the U.S., estimates in Table 6, and the estimates of the deposit process presented in Table 2.

Table 4: Parameters

Parameter		Value	Target
Deposit Interest Rate (%)	$r^D$	0.010	Avg Interest Expense Deposits
Mean Charge Off Rate	$\lambda$	0.424	Avg Charge Off Rate
Std. Dev Charge Off Rate	$\sigma_\lambda$	0.199	Std Dev Charge Off Rate
Exit Value Recovery	$\zeta$	0.804	Recovery Value Bank Failures (FDIC)
Bank Discount Factor	$\beta$	0.988	$1/(1 + \bar{r})$
Measure Households	$H$	270.0	Number of Banks Top 2%
Borrower Success Prob. Function	$a$	4.291	Avg. Borrower Return
Borrower Success Prob. Function	$b$	26.31	Avg. Default Frequency
Borrower Success Prob. Function	$\sigma_e$	0.107	Avg. Loan Interest Rate
Outside Option	$\bar{\omega}$	0.462	Elasticity of Loan Demand
Cost Function Loans $\theta^1$	$c_{\theta^1}^0$	0.012	Avg Net Mg Expense $\theta^1$
Cost Function Loans $\theta^1$	$c_{\theta^1}^1$	0.050	Elasticity Mg Expense $\theta^1$
Fixed Cost $\theta^1$	$f_{\theta^1}$	0.001	Fixed Cost / Loans $\theta^1$
Cost Function Loans $\theta^2$	$c_{\theta^2}^0$	0.009	Avg Net Mg Expense $\theta^2$
Cost Function Loans $\theta^2$	$c_{\theta^2}^1$	0.005	Elasticity Mg Expense $\theta^2$
Fixed Cost $\theta^2$	$f_{\theta^2}$	0.006	Fixed Cost / Loans $\theta^2$
Transition Probability Function	$\alpha$	50.00	Loan Market Share $\theta^1$
Transition Probability Function	$\delta$	0.450	Fraction of Banks $\theta^1$
Transition Probability Function	$\xi$	0.850	Transition $\theta^1$ to $\theta^2$
Equity Issuance Costs $\theta^1$	$\varsigma_{\theta^1}^0$	0.001	Avg Equity Issuance $\theta^1$
Equity Issuance Costs $\theta^1$	$\varsigma_{\theta^1}^1$	0.350	Fract $\theta^1$ Banks Issue Equity
Equity Issuance Costs $\theta^2$	$\varsigma_{\theta^2}^0$	0.020	Avg Equity Issuance $\theta^2$
Equity Issuance Costs $\theta^2$	$\varsigma_{\theta^2}^1$	0.350	Fract $\theta^2$ Banks Issue Equity
Exogenous Exit $\theta^1$	$\rho_{\theta^1}^x$	0.025	Transition $\theta^1$ to exit
Exogenous Exit $\theta^2$	$\rho_{\theta^2}^x$	0.000	Transition $\theta^2$ to exit
Entry Cost	$\kappa$	0.092	Exit Rate

Note: The entry cost is set as part of the equilibrium selection. In particular, in the baseline case, the entry cost is the one that satisfies the zero entry condition for the value of entrants  $N^e$  that provides the best fit of the model. This entry cost is kept constant when running the main experiment presented in Section 7.

Table 5 (first two columns) and Table 6 present a set of data moments together with their model counterparts for the pre-reform period (i.e., the period used in the calibration).<sup>14</sup>

<sup>14</sup>We discuss the post-reform moments in Table 5 when we present the results from our experiment in Section 7.

Table 5: Data &amp; Model Moments Pre and Post-reform

Moment (%)	Pre-Reform		Post-Reform	
	Data	Model	Data	Model
Charge - Off Rate	1.08	0.81	1.15	0.63
Avg. Borrower Return	12.94	15.18	12.94	15.20
Avg. Default Frequency	3.16	1.84	2.94	1.41
Loan Interest Rate	6.42	6.64	3.13	4.29
Elasticity of Loan Demand	-1.10	-0.75	-1.10	-0.39
Avg Net Mg Expense $\theta^1$	2.00	2.03	1.44	1.62
Avg Net Mg Expense $\theta^2$	1.34	1.31	0.98	0.89
Fixed Cost / Loans $\theta^1$	0.81	0.82	0.52	0.44
Fixed Cost / Loans $\theta^2$	0.82	0.85	0.58	0.67
Loan Market Share $\theta^1$	34.00	45.23	9.82	11.43
Fraction of Banks $\theta^1$	81.85	80.06	65.71	61.96
Avg Equity Issuance $\theta^1$	0.06	0.76	0.08	4.30
Avg Equity Issuance $\theta^2$	0.05	0.00	0.08	0.00
Exit (Failure) Rate	1.00	2.08	0.65	3.31
Frac Banks Ei/Assets > 0 $\theta^1$	10.33	30.02	7.05	94.90
Frac Banks Ei/Assets > 0 $\theta^2$	12.88	0.00	6.40	0.00
Total Number of Banks	190.00	190.00	103.00	52.00
Avg Net Mg Expense $\theta^3$	-	-	0.61	0.69
Fixed Cost / Loans $\theta^3$	-	-	0.63	0.75
Avg Cost $\theta^1$	2.81	2.85	1.96	2.06
Avg Cost $\theta^2$	2.16	2.15	1.56	1.56
Avg Cost $\theta^3$	-	-	1.24	1.44
Fraction of Banks $\theta^2$	18.15	19.94	30.37	34.11
Fraction of Banks $\theta^3$	0.00	0.00	3.92	3.92
Deposit Market Share $\theta^1$	35.67	45.22	9.27	10.67
Deposit Market Share $\theta^2$	64.33	54.77	36.59	38.24
Deposit Market Share $\theta^3$	0.00	0.00	54.14	51.09
Loan Market Share $\theta^2$	66.00	54.77	37.76	40.95
Loan Market Share $\theta^3$	0.00	0.00	52.42	47.62
Avg. Net Interest Margin	4.77	5.27	4.43	3.74
Number of Banks $\theta^1$	155.00	152.00	68.00	32.00
Number of Banks $\theta^2$	35.00	38.00	31.00	18.00
Number of Banks $\theta^3$	0.00	0.00	4.00	2.00
Avg Div/Assets $\theta^1$	0.45	0.33	0.48	0.00
Avg Div/Assets $\theta^2$	0.38	2.28	0.51	0.04
Avg Div/Assets $\theta^3$	-	-	0.73	1.61
Frac Banks Ei/Assets > 0 $\theta^3$	-	-	1.95	0.00

Note: Moments above the line in the “pre-reform” period correspond to calibration targets. All other moments in the pre-reform period are not targeted. Section 7 describes the main experiment and post-reform moments.

At the calibrated parameters, the transition probabilities for different values of investment are those presented in Figure 4. Table 6 presents a comparison between the transition probabilities in the data and those in the model when evaluated at the optimal investment.

Figure 4: Transition Probabilities

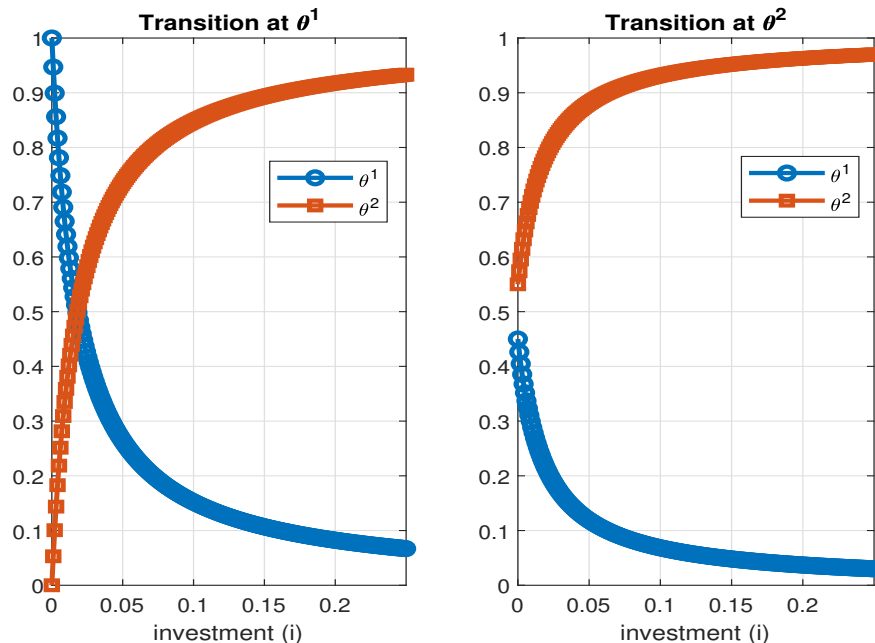


Table 6: Bank-Type Transition Matrix  $\hat{T}(\theta'|\theta)$

	<i>Data</i>			<i>Model</i>		
	<i>Pre - Reform Period</i> <i>(1984 - 1993)</i>			<i>Pre - Reform Period</i> <i>(1984 - 1993)</i>		
	$\theta^1_{t+1}$	$\theta^2_{t+1}$	Failure	$\theta^1_{t+1}$	$\theta^2_{t+1}$	Failure
Entrant	1.00*	0.00	0.00	1.00	0.00	0.00
$\theta^1_t$	0.96*	0.01	0.03*	0.85	0.12	0.03
$\theta^2_t$	0.05	0.95	0.00*	0.44	0.55	0.00

Note: \* denotes targeted moment. We study banks in the top 2% of the asset distribution. In the pre-reform period, we group all banks in the Top 35 ( $\theta^2$ ). These are large regional banks by construction since regulation prevented them to expand across state borders.

The model does a reasonable job in explaining some of the moments. The model underpredicts the default frequency and to some extent the persistence of bank type. The model overpredicts slightly the deposit and loan market share of small banks ( $\theta^1$ ). It misses on

some of the equity issuance moments. The model does a good job in capturing the fraction of small banks ( $\theta^1$ ), the net interest margin, and the cost structure by bank size (i.e., the model captures scale economies observed in the data since average costs are decreasing in size).

## 6 Model Properties

In this section, we provide a description of the workings of the model for the calibration discussed above. Banks of different types and at all deposit levels find it optimal to set  $\ell(\theta, d_\theta) = d_\theta$ . This is because the estimated costs, which are in line with the increasing returns observed in the data, are not large enough to induce banks to use less than the full amount of available deposits. Figure 5 presents expected profits evaluated at the optimal decision rules. It is clear that profits are increasing in bank type and deposits. The fact that expected profits are increasing in deposits provides the incentive for banks to invest to acquire a higher type state (i.e. a higher deposit base).

Figure 5: Expected Profits  $E_\lambda[\pi_\ell(\theta, d, \lambda)]$

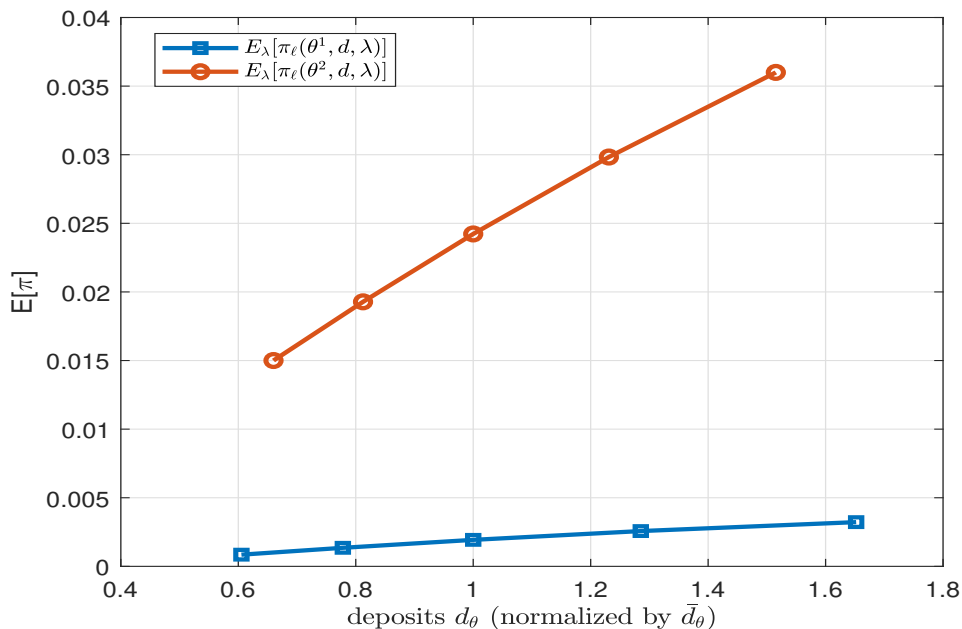


Figure 6 displays the realized profit function and Figure 7 displays the bank value function. As one would expect, properties of expected profits in Figure 5 induce the ordering that realized profits and value functions are increasing in bank-type (conditional on  $\lambda$ ). Importantly, realized profits are decreasing in charge-off rates  $\lambda$ . This fact accounts for exit in the model (i.e. high charge-off banks are more likely to exit) as evident in Figure 8.



Figure 6: Realized Profits  $\pi(\theta, d, \lambda)$

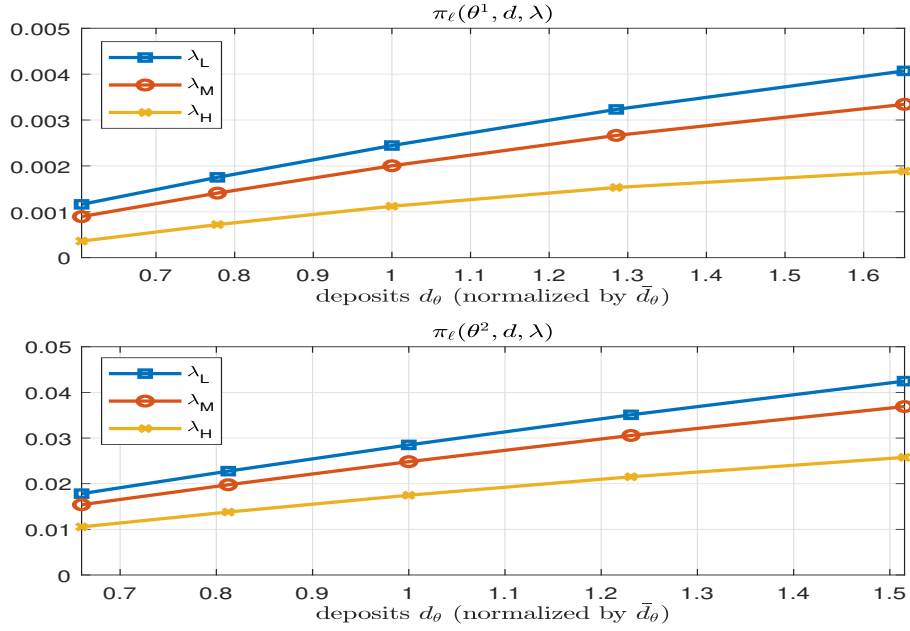


Figure 7: Bank Value Function  $V(\theta, d, \lambda)$

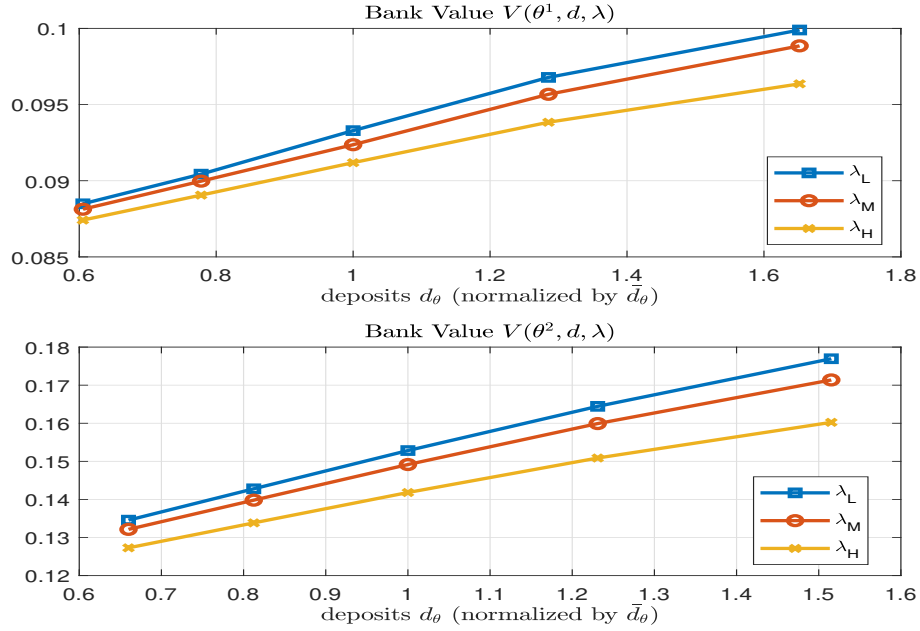


Figure 8 shows the exit decision rule. Small local banks ( $\theta^1$ -type banks) exit for low

deposit levels when  $\lambda$  is above its mean. However, when the charge-off rate is low, small banks with high deposits (above its mean) choose to continue operating. Banks of  $\theta^2$ -type choose not to exit for all levels of  $\lambda$ . It is important to note that this decision is driven not only by realized profits but also by the expected charter value of the bank  $V(\theta, d, \lambda; \mu)$  displayed in Figure 7.

Figure 8: Exit Decision Rule  $x(\theta, d, \lambda)$

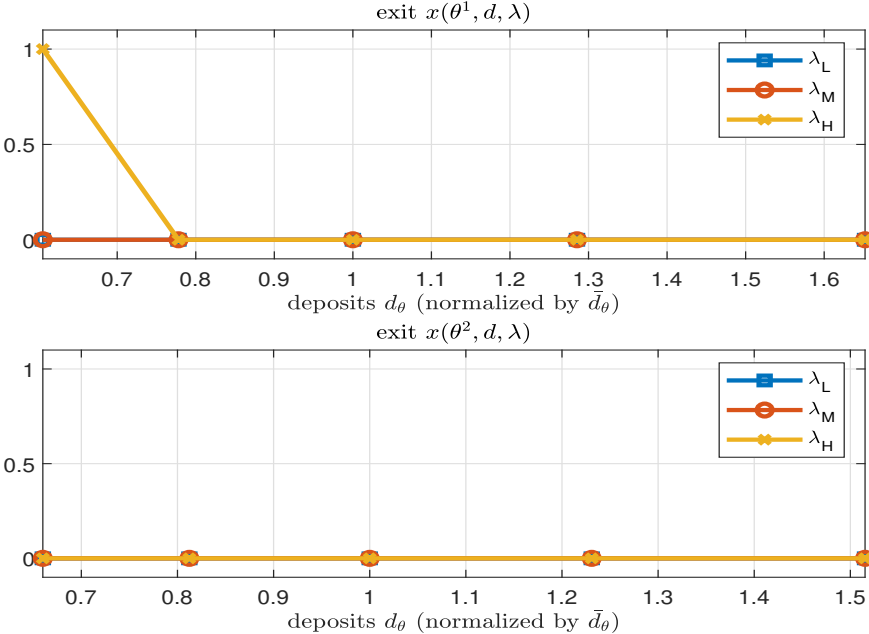


Figure 9 introduces the investment decision rule. Investment is, in general, slightly decreasing in deposits for  $\theta^1$  banks, with banks at the low end of the deposit distribution choosing to invest in order to grow. On the other hand, investment is increasing for  $\theta^2$ -type banks which invest in order to maintain their larger deposit base. The difference derives from the link between the marginal benefit of investment (as captured by how the expected value of the bank  $E_{\theta', d'_\theta, \lambda' | d, \theta, \iota} [V(\theta', d'_\theta, \lambda'; \mu')]$  changes with investment  $\iota$ ) and the value of deposits  $d_\theta$ . The marginal benefit of investment is decreasing in  $d_\theta$  for  $\theta^1$  banks while the opposite is true for  $\theta^2$  banks. The intuition is simple. The smallest  $\theta^1$  banks benefit the most from an increase in the likelihood of moving up in  $\theta$  and the largest  $\theta^2$  banks benefit the most from increasing the probability of staying at the highest  $\theta = \theta^2$ .

Figure 9: Investment Decision Rule  $\iota(\theta, d, \lambda)$

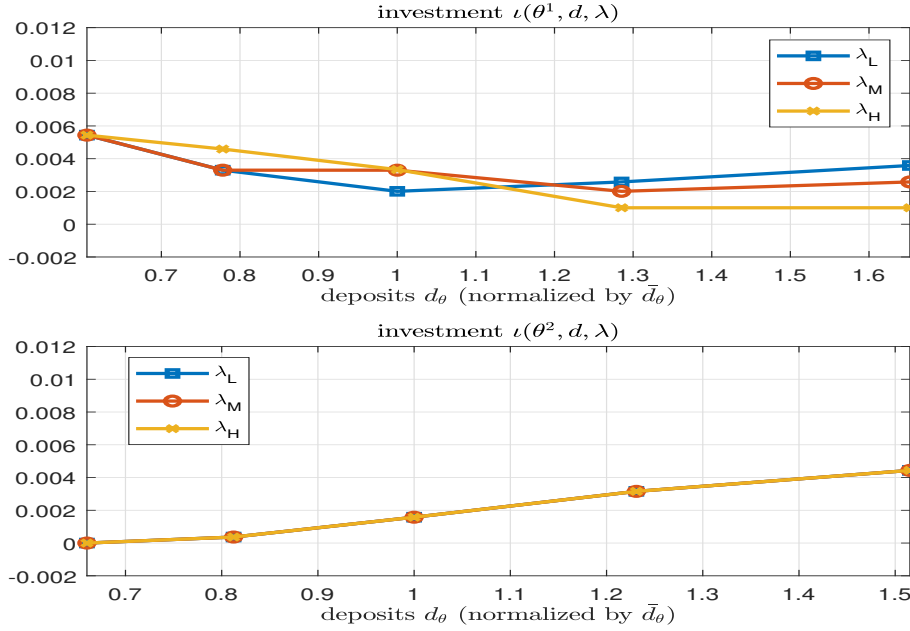


Figure 10 presents the resulting dividends net of equity injections (before equity costs) for the bank ( $\pi(\theta, d, \lambda) - \iota(\theta, d, \lambda)$ ) that corresponds to dividend payments when positive and equity issuance when negative. This figure makes clear that, given profit levels, small  $\theta^1$  banks are willing to issue equity to attain their optimal level of investment while large  $\theta^1$  banks and  $\theta^2$  banks make enough profits to cover both investment and dividends. Table 5 (pre-reform period) also shows that this is consistent with the data.

Figure 10: Dividends net of equity injections  $(\pi(\theta, d, \lambda) - \iota(\theta, d, \lambda))$

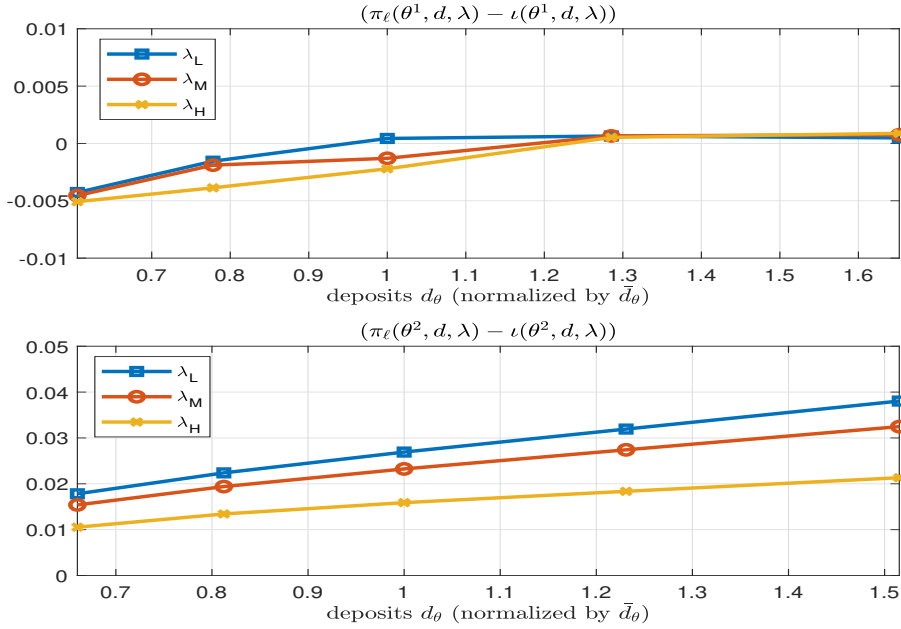
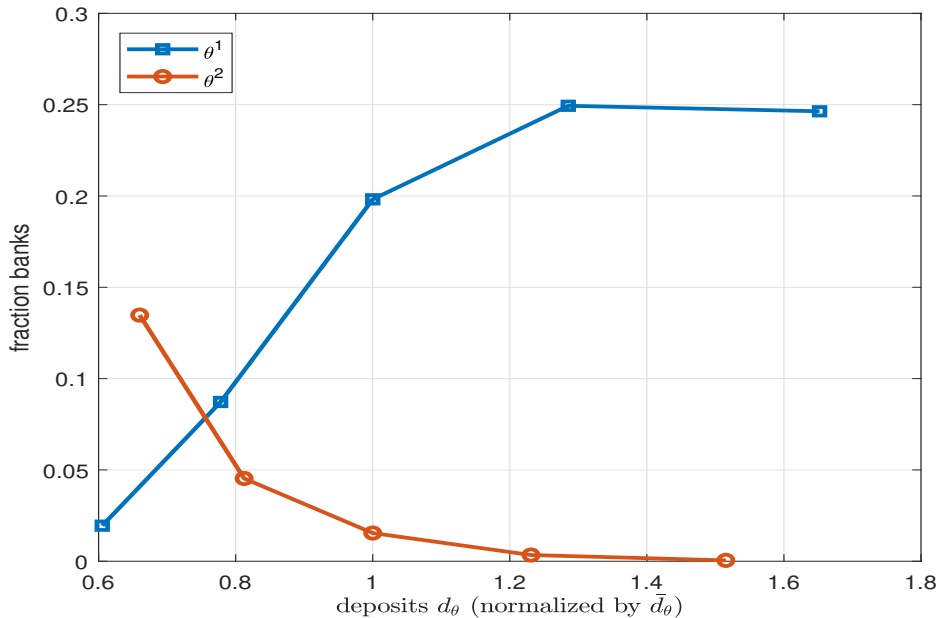


Figure 11 presents the equilibrium ergodic distribution of banks for the pre-reform period. As clear from the law of motion in equation (23), the exit decision rule in Figure 8 and the investment decision rule in Figure 9 induce the long run distribution. The model generates a fraction of banks of  $\theta^1$ -type that is close to the data (80.1% in the model vs 81.9% in the data). Since all Figures 5 through 9 are normalized by mean deposits of each type of bank, we present the distributions in Figure 11 normalized as well. If the figure was presented on non-normalized deposits, the left tail of the distribution would entail the fraction of  $\theta^1$  banks which is increasing in deposit size and the right tail of the distribution would entail the fraction of  $\theta^2$  banks which is decreasing in deposit size. In this way, the distribution would appear bell shaped.

Figure 11: Pre-Reform Distribution of Banks



## 7 Rising Concentration Experiment

We calibrated the model to an initial (1984-1993) stationary ergodic equilibrium where restrictions on opening bank branches across state lines were in place. Specifically, we calibrated to an initial equilibrium where only transitions between two types of banks  $\{\theta^1, \theta^2\}$  are feasible since investing to transition into  $\theta^3$  is assumed to be infinitely costly (due to branching regulations prior to its repeal in Riegle-Neal).

Our experiment involves a second stationary ergodic equilibrium in which banks of three types  $\{\theta^1, \theta^2, \theta^3\}$  operate corresponding to the relatively stable period 2009-2018. In this stationary ergodic equilibrium, we still have local and regional banks but we also incorporate the possibility of transitioning into becoming a  $\theta^3$ -type bank which corresponds to large national banks (Top 4). The experiment amounts to reducing the cost of investment so transitioning into  $\theta^3$  is feasible (but we keep the values of  $\alpha$ ,  $\delta$ , and  $\xi$  unchanged) and we also incorporate the observed changes in the cost structure of banks and the evolution of deposits from the period 2009-2018.<sup>15</sup>

<sup>15</sup>More specifically, we solve for a new stationary ergodic equilibrium of the model where the transition function allows for movements between the three bank types. In addition, we adjust the cost parameters  $\{\phi_\theta^0$  and  $f_\theta\}$  to match the average net marginal expenses and fixed costs by bank type after the reform. We set  $\rho_\theta^x$  according to values in Table 7. The parameters of the deposit process are set according to Table 2 (post-reform period) and  $\bar{r} = 0.005$  a small number as observed in the post-reform data. Equity issuance costs parameters of  $\theta^3$  banks are set equal to those of  $\theta^2$  banks. All other parameters remain the same. Table A.1 presents the set of parameters that change between the pre- and post-reform period.

Since the parameters governing the transition function are independent of bank type and the cost parameters are estimated “outside” the model, the resulting level of concentration in the second stationary ergodic equilibrium is an endogenous object that we did not target.<sup>16</sup> Below, we present a decomposition to show how much of the change in concentration can be explained by changes in the distribution versus pure changes in the deposit process. We find that approximately half of the change in concentration corresponds to endogenous changes in the distribution. We then ask “how much of the untargeted observed increase in deposits of the top 4 banks can the model generate?”

Table 5 (see Section 5) and 7 present a set of relevant moments from the data and the model post-reform. Recall that the moments targeted in the calibration correspond only to those above the line for the pre-reform period. In addition, for the post-reform period, we also used as targets average net expenses and fixed costs. No moments in Table 7 are targeted except for the transition into failure. Furthermore, the transition probabilities (as a function of investment) post-reform are presented in Figure 12. The model moments presented in Table 7 result from combining the function in Figure 12, the optimal investment decision (Figure 15) and the ergodic distribution (Figure 13).

Table 7: Bank-Type Transition Matrix  $\hat{T}(\theta'|\theta)$

	<i>Data</i>				<i>Model</i>			
	<i>Post - Reform Period</i> <i>(1994<sup>†</sup> - 2018)</i>				<i>Post - Reform Period</i> <i>(1994 - 2018)</i>			
	$\theta_{t+1}^1$	$\theta_{t+1}^2$	$\theta_{t+1}^3$	Failure	$\theta_{t+1}^1$	$\theta_{t+1}^2$	$\theta_{t+1}^3$	Failure
Entrant	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
$\theta_t^1$	0.93	0.02	0.00	0.05	0.72	0.23	0.00	0.05
$\theta_t^2$	0.02	0.97	0.01	0.00	0.41	0.54	0.05	0.00
$\theta_t^3$	0.00	0.02	0.98	0.00	0.00	0.43	0.57	0.00

Note: We study banks in the top 2% of the asset distribution. For the post-reform period, we consider Top 4 ( $\theta^3$ ) separately from the Top 5-35 ( $\theta^2$ ). <sup>†</sup> Note that the initial year of the post-reform period used to estimate this matrix differs from that presented Table 5. The small number of bank types we consider prevents us from using the 2008-2018 period and obtain a meaningful transition matrix.

<sup>16</sup>Strictly speaking, since the average level of deposits post-reform is set to that observed in the data and, as Table 2 shows, the average deposit for banks in the Top 35 increases between the pre-reform and the post-reform, a fraction of the increase in concentration can be attributed to exogenous changes in the deposit process. However, the distribution of banks is endogenous which in the end is what determines the overall level of concentration.

Figure 12: Transition Probabilities Post- Reform

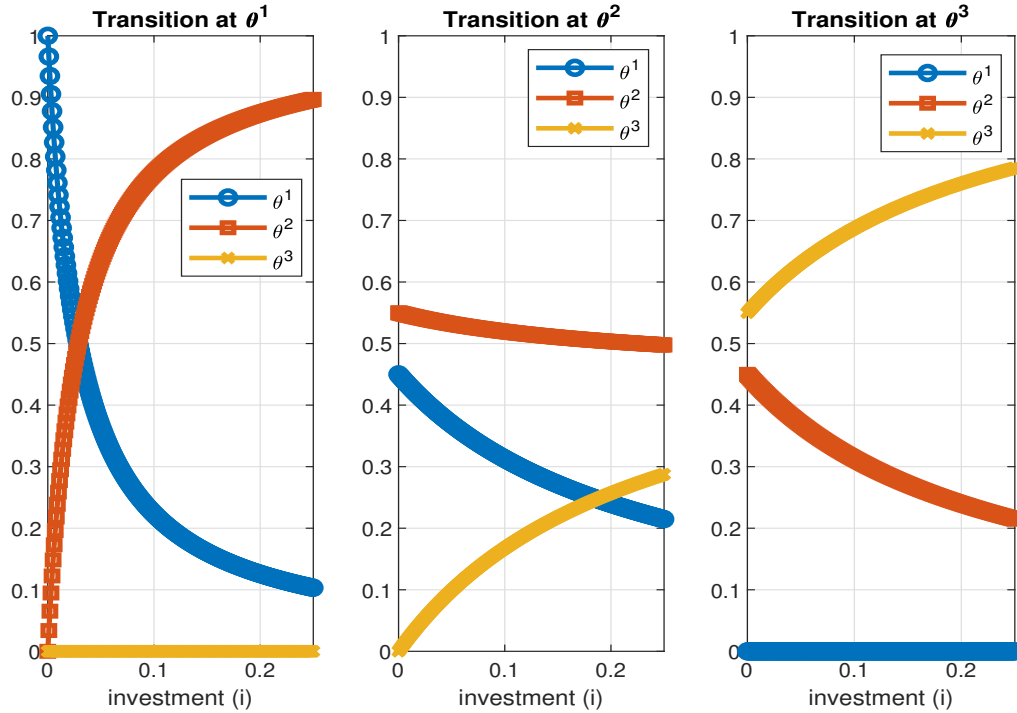
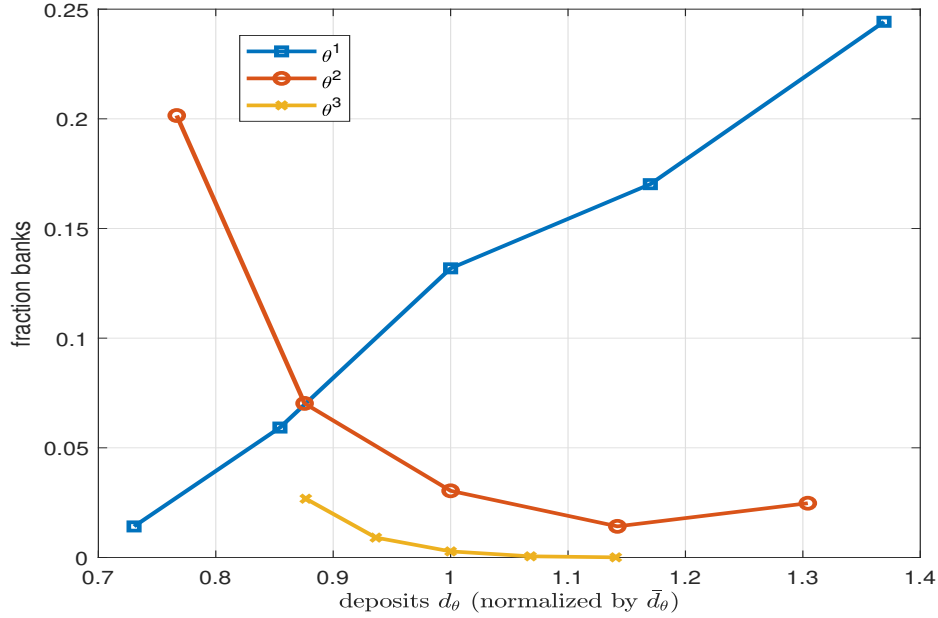


Table 5 shows that the model does a fairly good job predicting the actual increase in concentration in the deposit and loan market in the stationary ergodic equilibrium associated with the elimination of branching restrictions. After the reform, the deposit market share of the Top 4 banks is 54.1% in the data versus 51.09% in the model. A similar result is observed for the loan market (52.42% versus 47.62%, in the data and the model, respectively). Note that while parameters of the deposit process are set so that the average size of a bank of type  $\theta^3$  is that of a bank in the Top 4, the endogenous distribution of banks that results from solving the model determines the untargeted market shares in the deposit and loan market. As in the data, while there are many more small banks than large banks, the deposit and loan market shares in the model are increasing in bank size. In addition, the number of banks drops over time in our equilibrium (which indirectly mimics paying for an acquisition which lowers competition). The drop is larger in the model (72.6%) than in the data (45.8%).

Figure 13 presents the post-reform stationary ergodic (long-run average) equilibrium distribution of banks. The model generates a fraction of banks that is decreasing in size as we observe in the data. More specifically, the fraction of banks by bank type are 65.71%, 30.37%, and 3.92% in the data versus 61.96%, 34.11%, and 3.32% in the model, for banks of type  $\theta^1$ ,  $\theta^2$ , and  $\theta^3$ , respectively.

Figure 13: Distribution Banks Post-reform



What accounts for the change? We decompose the changes in the deposit market share for the top 35 banks ( $\theta^2$ -type pre-reform and  $\theta^2$  plus  $\theta^3$ -type banks post-reform) into what can be explained by endogenous changes in the distribution and what is driven by changes in the deposit and cost processes taken from the data. Without changes in the deposit processes (i.e., the level of concentration that would arise by combining the pre-reform deposit levels with the post-reform bank distribution), the market share of the Top 35 banks would have increased from 64.3% to 75.8% as opposed to 89.3%. That is, endogenous changes explain about 46.0% of the change in deposit market share of large banks. The post-reform deposit market share of  $\theta^2$  and  $\theta^3$  banks is 38.2% and 51.1%. Without changes in the deposit process these figures would have been 68.7% and 7.12%. That is, while changes in the distribution help to generate the shift towards large banks (since many small banks disappear in the post-reform period), the growth in the deposit base helps to explain the skewness observed post-reform.

There are some interesting differences in decision rules in the post-reform stationary ergodic equilibrium. Figure 14 shows the loan decision rule. Importantly, since type  $\theta^3$  banks have such a large deposit base (i.e. from Table 2 the mean of the deposit process for type  $\theta^3$  is more than double the size of that for type  $\theta^2$  banks), the monitoring costs  $c_{\theta^3}(\ell_{\theta^3})$  of extending  $\ell_{\theta^3} = d_{\theta^3}$  loans is excessively high, so that type  $\theta^3$  set  $\ell_{\theta^3} < d_{\theta^3}$  (or equivalently  $a_{\theta^3} > 0$  at all levels of realized deposits).



Figure 14: Loan Decision Rule  $\ell(\theta, d)$

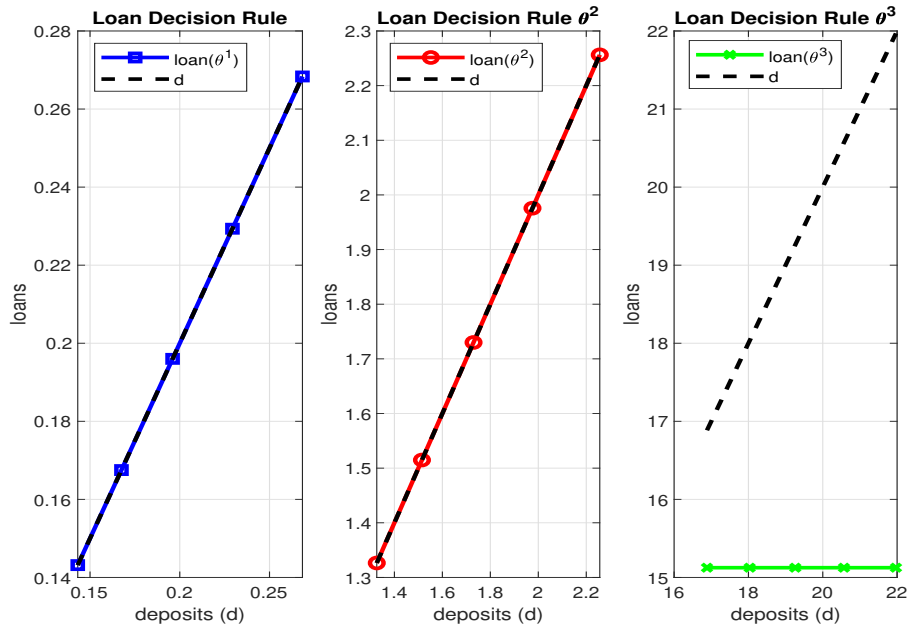


Figure 15 presents the investment decision rules. Investment is constant in  $d$  for banks of type  $\theta^1$  and  $\theta^3$  and rises for banks of type  $\theta^2$ . Further, the  $\theta^2$  banks invest the most in order to grow while  $\theta^3$  banks invest more than  $\theta^1$  in order to maintain their size.

Figure 15: Investment Decision Rule  $\iota(\theta, d, \lambda)$

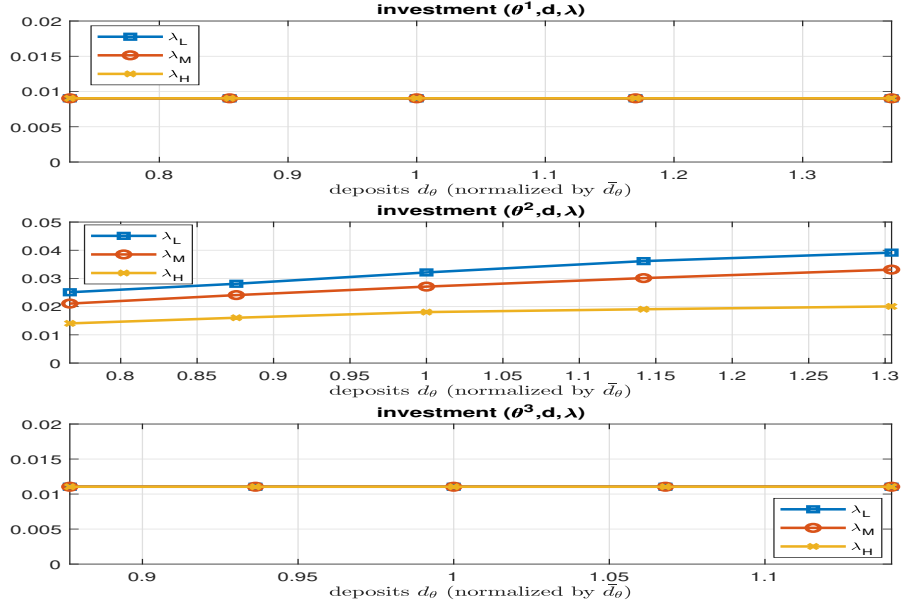
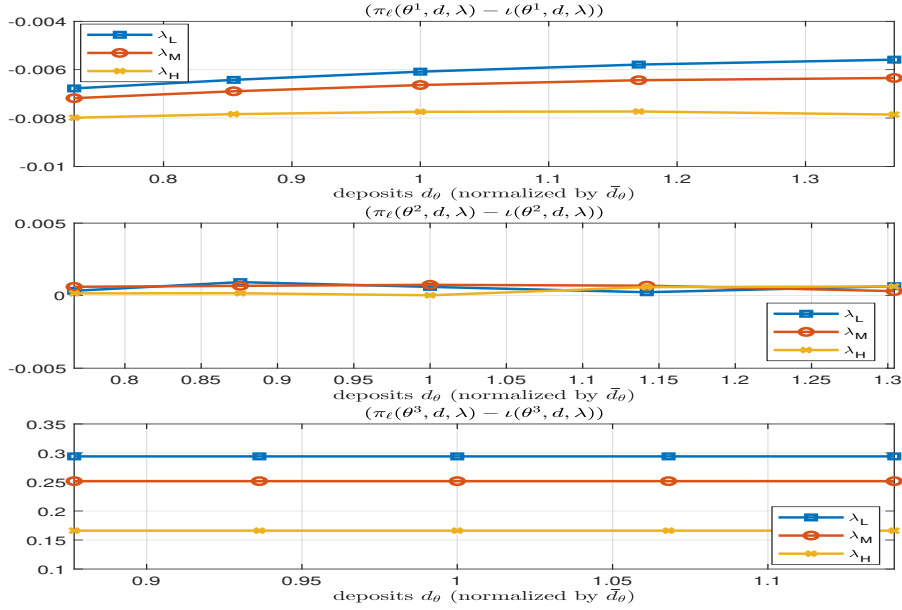


Figure 16 presents the resulting net cash flow for the bank ( $\pi(\theta, d, \lambda) - \iota(\theta, d, \lambda)$ ) that corresponds to dividend payments when positive and equity issuance when negative. Consistent with the data, as Table 5 also shows, dividend payments post reform are increasing in  $\theta$ .

Figure 16: Net Cash Flow  $(\pi(\theta, d, \lambda) - \iota(\theta, d, \lambda))$



Another interesting outcome of the experiment is that the model captures how changes in monetary policy (here we think of them as changes in  $\bar{r}$ ) affects the interest rate on loans. In this experiment, we have set  $\bar{r}$  at 1.25% pre-reform and at 0.5% post-reform. Even though there is a large increase in concentration, the model is consistent with the decline in loan interest rates observed in the data. The loan interest rate goes from 6.4% to 3.13% in the data and the model generates a decline from 6.6% to 4.3%.

## 8 Directions for Future Research

We modeled the incentive to grow (acquire a broader deposit base in the presence of increasing returns) following a decrease in regulation in a simple dynamic model of imperfect competition. Without targeting the rise in concentration, the model does incredibly well at matching the observed concentration moments over the last decade. Our model can serve as a framework to conduct policy counterfactuals to understand rising concentration in the banking industry.

To keep the analysis tractable, we made several simplifying assumptions which we hope to address in future research. First, we assume there is no retained earnings by banks. Second, we neglected the transition between the two steady states. Third, while a size ladder may be a tractable reduced form way of modeling mergers, to match data we plan to explicitly modeling the merger process in future work.

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# Appendix

## A-1 Solution Algorithm

The analysis of Markov-Perfect Equilibrium with imperfect competition is generally limited to industries with just a few firms, less realistic than the number of banks we consider in this paper. The main restriction is that since firms have market power their decision rules are a function of the decision rules of all their competitors. Even if one were to restrict to symmetric strategies in which decision rules become a function of the industry state, the number of industry states to be considered becomes very large quickly. For this reason, we solve the model following the approach in Weintraub, Benkard, and Van Roy (2008). The algorithm approximates a Markov-perfect equilibrium by assuming that firms, at each time, make decisions based on their own state and the *long-run* average industry state that prevails in equilibrium. This reduces the computational cost considerably since firms' decision rules are not explicitly a function of the sequence of industry states but rather a function of the ergodic distribution. The results in Weintraub, Benkard, and Van Roy (2008) establish conditions under which this approximation works well asymptotically.

In short, the algorithm searches over an entry rate until the free entry condition is satisfied (provided all other equilibrium conditions are met). More specifically, to find an equilibrium we perform the following steps:

1. Set tolerances  $\epsilon^\ell$ ,  $\epsilon^l$ ,  $\epsilon^x$ , and  $\epsilon^e$  to small values. Start with an entry rate  $N^{e,g}$  where iteration  $g = 0$  is an initial guess.
2. Start with an investment decision rule  $\iota^h(\theta, d, \lambda)$  and an exit decision rule  $x^h(\theta, d, \lambda)$  where iteration  $h = 0$  is an initial guess.
3. Using  $N^{e,g}$ ,  $\iota^h(\theta, d, \lambda)$ , and  $x^h(\theta, d, \lambda)$  compute the long-run industry state  $\mu^h(\theta, d; N^{e,g})$ .
4. Obtain an equilibrium in the loan market:
  - a. Guess a loan decision rule  $\ell^k(\theta, d)$  where iteration  $k = 0$  is an initial guess.
  - b. For each  $\{\theta, d\}$ , given that the industry state  $\mu^h(\theta, d; N^{e,g})$  and  $\ell^k(\theta, d)$  determines the residual loan supply function, obtain the best response  $\ell^{k+1}(\theta, d)$  by maximizing profits.
  - c. Compute  $\Delta^\ell = \|\ell^{k+1}(\theta, d) - \ell^k(\theta, d)\|$ .
  - d. If  $\Delta^\ell < \epsilon^\ell$ , an equilibrium in the loan market has been found, continue to the next step. If not, return to step 4b with the updated loan decision rule  $\ell^{k+1}(\theta, d)$ .
5. Solve the bank problem to obtain investment and exit rules:
  - a. For each  $\{\theta, d, \lambda\}$ , solve the bank problem to obtain  $\iota^{h+1}(\theta, d, \lambda)$  and  $x^{h+1}(\theta, d, \lambda)$ .
  - b. Using  $\iota^{h+1}(\theta, d, \lambda)$  and  $x^{h+1}(\theta, d, \lambda)$ , compute a new long-run industry state  $\mu^{j+1}(\theta, d; N^{e,g})$ .

- c. Compute  $\Delta^l = \|\iota^{h+1}(\theta, d, \lambda) - \iota^h(\theta, d, \lambda)\|$  and  $\Delta^x = \|x^{h+1}(\theta, d, \lambda) - x^h(\theta, d, \lambda)\|$ .
  - d. If  $\Delta^l < \epsilon^l$  and  $\Delta^x < \epsilon^x$  continue to the next step. If not, return to step 4b with the updated industry state  $\mu^{j+1}(\theta, d; N^{e,g})$ .
6. Obtain the value of an entrant  $V^e(\mu^{j+1})$ . If  $\|V^e(\mu^{j+1})\| < \epsilon^e$  an equilibrium has been found. If not, return to step 3 with the updated entry rate  $N^{e,g+1}$ . The update of  $N^{e,g}$  is done taking into account the value of  $V^e(\mu^{j+1})$ . If  $V^e(\mu^{j+1}) > 0$ , set  $N^{e,g+1} > N^{e,g}$ . If  $V^e(\mu^{j+1}) < 0$ , set  $N^{e,g+1} < N^{e,g}$ .

While the algorithm just described has been proven to converge, we also experimented with a slightly modified version where we evaluate the value of the entrant for many possible values of the number of entrants (i.e., we compute points 1 through 5 for many  $N^e$ ) and define an equilibrium as one where the condition in point 6 is satisfied. This modified version of the algorithm is more costly computationally but robust.

## A-2 Data Description

As in Corbae and D’Erasmus (2019), we compile a large panel of banks from 1984 to 2018 using data for the last quarter of each year.<sup>17</sup> The source for the data is the Consolidated Report of Condition and Income (known as Call Reports) that banks submit to the Federal Reserve each quarter.<sup>18</sup> 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 (2000) and Den Haan, Sumner, and Yamashiro (2007) 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. In addition to information from the Call Reports, we identify bank failures using public data from the Federal Deposit Insurance Corporation (FDIC).<sup>19</sup> We also identify mergers and acquisitions using the Transformation Table in <https://www.ffiec.gov/npw/FinancialReport/DataDownload>. We identify “events” where the acquired and acquiring firms are commonly owned in some form before the acquisition (i.e., the listed merger is only a corporate reorganization) and discard these events from the merger sample.

To deflate balance sheet and income statement variables we use the CPI index. When we report weighted aggregate time series we use the asset market share as the weight. To

<sup>17</sup>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.

<sup>18</sup>Balance Sheet and Income Statements items can be found at <https://cdr.ffiec.gov/public/>.

<sup>19</sup>Data is available at <https://www.fdic.gov/bank/individual/failed/banklist.html>.

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.

### A-3 Cost Estimation

We estimate the marginal cost of producing a loan  $c_\theta(\ell_{\theta,t})$  and the fixed cost  $\kappa_\theta$  following the empirical literature on banking (see, for example, Berger, Klapper, and Turk-Ariss (2009)).<sup>20</sup> 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 for bank  $j$  are derived from the following trans-log cost function:

$$\begin{aligned} \log(NIE_t^j) &= g_1 \log(w_t^j) + h_1 \log(\ell_t^j) + g_2 \log(q_t^j) + g_3 \log(w_t^j)^2 & (A.3.1) \\ &+ h_2 [\log(\ell_t^j)]^2 + g_4 \log(q_t^j)^2 + h_3 \log(\ell_t^j) \log(q_t^j) + h_4 \log(\ell_t^j) \log(W_t^j) \\ &+ g_5 \log(q_t^j) \log(W_t^j) + g_6^1 t + g_6^2 t^2 + g_{8,t} + g_9^j + \epsilon_t^j, \end{aligned}$$

where  $NIE_{\theta,t}^j$  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),  $g_9^j$  is a bank fixed effect,  $W_t^j$  corresponds to input prices (labor expenses),  $\ell_t^j$  corresponds to real loans (one of the two bank  $j$ 's outputs),  $q_t^j$  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.<sup>21</sup> Non-interest marginal expenses are then computed as:

$$\text{Mg Non-Int Exp.} \equiv \frac{\partial NIE_t^j}{\partial \ell_t^j} = \frac{NIE_t^j}{\ell_t^j} \left[ h_1 + 2h_2 \log(\ell_t^j) + h_3 \log(q_{jt}) + h_4 \log(w_t^j) \right]. \quad (A.3.2)$$

Marginal non-interest income (Mg Non-Int Inc.) is estimated using an equation similar to equation (A.3.1) (without input prices) where the left hand side corresponds to total non-interest income. Net marginal expenses (Mg Net Exp.) are computed as the difference between marginal non-interest expenses and marginal non-interest income. The fixed cost  $\kappa_\theta$  is estimated as the total cost on expenses of premises and fixed assets. Table 1 presents the estimated average net expense, the fixed cost, as well as the average cost by bank size.

### A-4 Pre and Post Reform Parameters

When running the post-reform experiment, we solve for a new stationary ergodic equilibrium of the model where the transition function allows for movements between the three bank

<sup>20</sup>The marginal cost estimated is also used to compute our measure of Markups and the Lerner Index.

<sup>21</sup>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.



types. We adjust the cost parameters  $\{\phi_\theta^0$  and  $f_\theta\}$  to match the average net marginal expenses and fixed costs by bank type after the reform. We set  $\rho_\theta^x$  according to values in Table 7. The deposit interest rate  $\bar{r} = 0.005$  is set to the smallest number that allowed us to solve the model (the value of the real return on the deposits for the post-reform period equals -1.34%). Equity issuance cost parameters of  $\theta^3$  banks are set equal to those of  $\theta^2$  banks. All other parameters remain the same. The parameters of the deposit process are set according to Table 2 (post-reform period). Table A.1 presents the set of parameters that change or are added in the post-reform period (except those already displayed in Table 2).

Table A.1: Pre and Post Reform Parameters

Parameter		Pre-Reform	Post Reform
Deposit Interest Rate (%)	$\bar{r} = r^D$	0.013	0.005
Bank Discount Factor	$\beta = (1 + \bar{r})^{-1}$	0.988	0.995
Cost Function Loans $\theta^1$	$c_{\theta^1}^0$	0.012	0.0045
Fixed Cost $\theta^1$	$f_{\theta^1}$	0.001	0.001
Cost Function Loans $\theta^2$	$c_{\theta^2}^0$	0.009	0.001
Fixed Cost $\theta^2$	$f_{\theta^2}$	0.006	0.010
Exogenous Exit $\theta^1$	$\rho_{\theta^1}^x$	0.025	0.051
Cost Function Loans $\theta^3$	$c_{\theta^3}^0$	-	0.0061
Cost Function Loans $\theta^3$	$c_{\theta^3}^1$	-	0.0001
Fixed Cost $\theta^3$	$f_{\theta^3}$	-	0.114
Equity Issuance Costs $\theta^3$	$\varsigma_{\theta^3}^0$	-	0.020
Equity Issuance Costs $\theta^3$	$\varsigma_{\theta^3}^1$	-	0.350
Exogenous Exit $\theta^3$	$\rho_{\theta^3}^x$	-	0.000