A Quantitative Model of Bank Merger Dynamics

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Abstract

We develop a simple model of the bank merger process to study the rise in bank concentration following the deregulation of bank branching in the Riegle-Neal Act of 1994. Motivated by the data where currently 4 (dominant) banks have over 40 percent of the U.S. deposit market share while the remaining over 4000 (fringe) banks cover the rest, we apply a dominant-fringe framework with a merger stage to model the rise in concentration following the change in regulation making interstate branching possible. We study the effect of the merger wave on competition, efficiency, and stability of the banking industry. We focus on the heterogeneous response of big and small banks' lending to idiosyncratic deposit shocks (i.e. their marginal propensity to lend) and how this translates to granularity we document in the banking industry. Further, we examine how the effectiveness of monetary policy varies with rising loan market power.

Keywords: Bank Mergers, Industry Dynamics, Imperfect Competition, Allocative Efficiency, Financial Stability, Bank Lending Channel of Monetary Policy.

JEL Classification Numbers: G21, E58.

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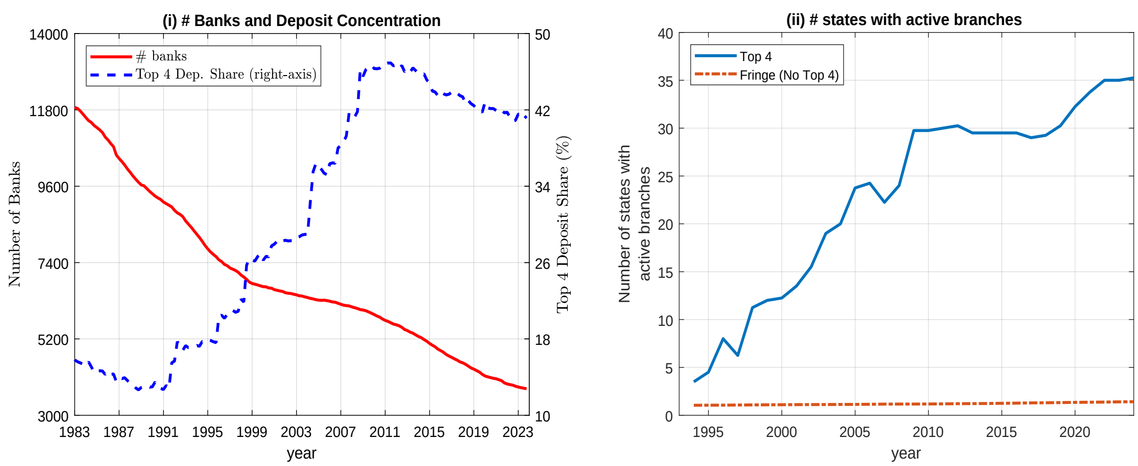
1 Motivation

Geographic expansion of the banking industry followed from the elimination of cross-state branching restrictions that began in the McFadden Act of 1927 which gave states the ultimate authority. While some states permitted cross-state branching prior to 1994, the Riegle-Neal Act removed regulatory obstacles to banks opening branches in other states and provided a uniform set of rules regarding banking in each state. As evident in Figure 1 (Panel (i)), following a relatively stable bank concentration of the top 4 banks of under 15% prior to 1994, concentration rose dramatically to over 40% until stabilizing post-Great Recession. Also significant in (Panel (i)) of Figure 1 is the threefold drop in the number of banks (from over 12,000 in 1983 to under 4000 in 2023). Panel (ii) presents the evolution of the average number states with a dominant bank and a non-dominant bank presence. Dominant banks operation went from 4 states to 35 states on average. The time series average for all other banks equals 1.2 with the end point in 2023 equaling 1.42.

Figure 1: Concentration and Geographic Expansion (1984 - 2023)

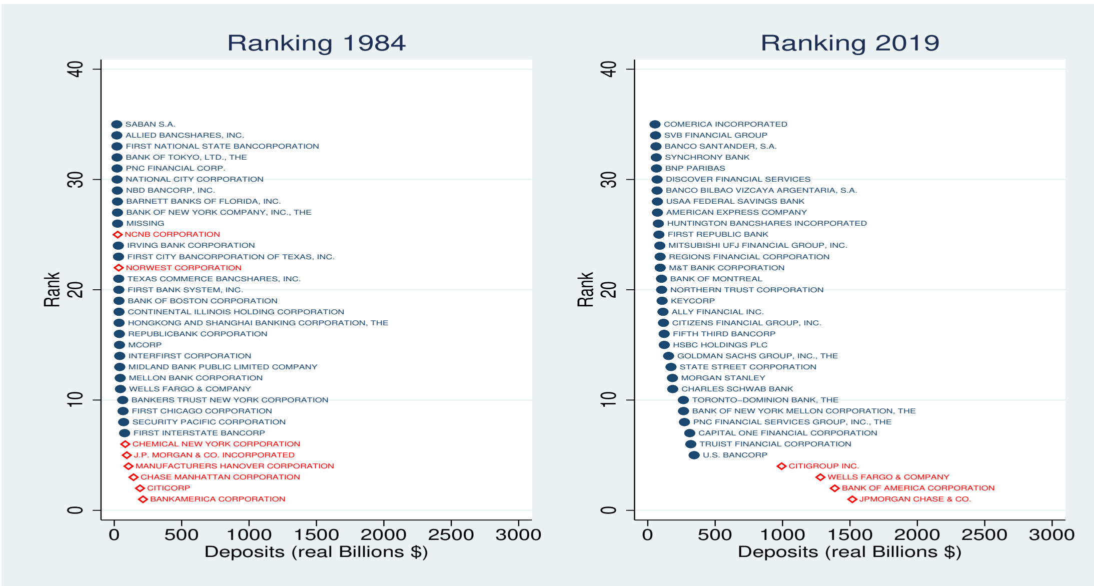


Note: # of banks refers to number of commercial banks in the US (aggregated to the top holding company). Top 4 Dep Share refers to the share of total deposits accounted by the Top 4 banks (when sorted by deposits). Source: Call Reports and Summary of Deposits.

Figure 2 presents the distribution of deposits for the Top 35 banks and makes evident how large the Top 4 have grown even relative to other banks at the top of the deposit distribution. We mark in red in year 1984 bank charters that eventually became part of the top 4 banks in 2019 (Citi, Wells Fargo, Bank of America, and JP Morgan Chase) via mergers and acquisitions. For example, North Carolina National Bank (NCNB) change its name to NationsBank in 1991 and in 1998 acquired BankAmerica Corporation to take on the name Bank of America. Other example, is Norwest Corporation that acquired Wells Fargo in 1998, keeping its charter but adopting the Wells Fargo name. A set of mergers and acquisitions lead to what we know as JP Morgan Chase & Co. In particular, in 1988, Chemical New York Corporation changed its name to Chemical Banking Corporation and in 1991 acquired Manufacturers Hanover Corporation.

In 1996, Chemical acquired Chase Manhattan Corporation which in 2000 acquired JP Morgan & Co. This new company took the JP Morgan Chase & Co. name.

Figure 2: Deposit Distribution 1984 & 2019

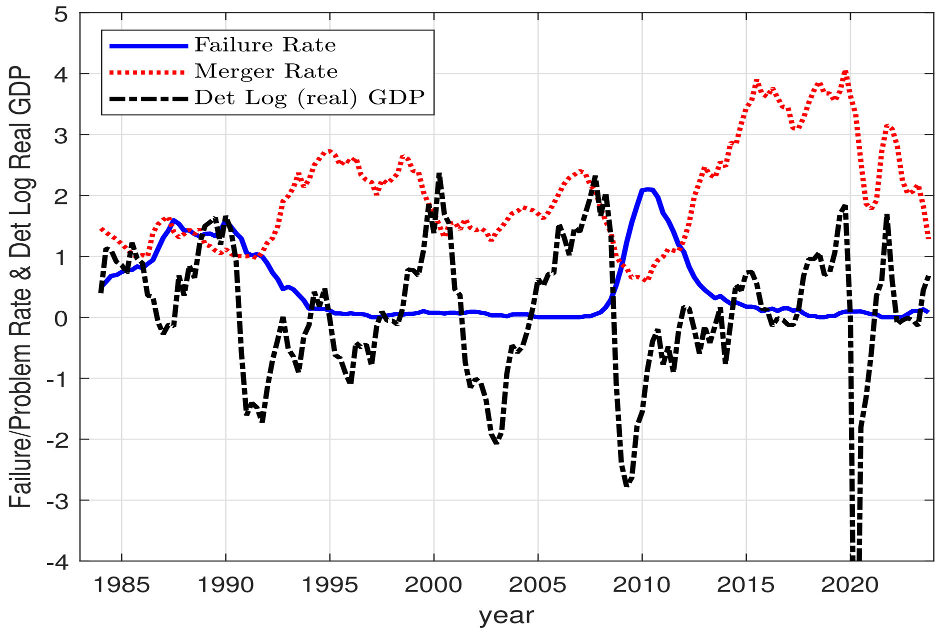


Note: Ranking 1984 and Ranking 2019 show the ranking of banks (and their names) according to total deposits (real billions $ 2015). Red dots correspond to bank charters that eventually become part of the Top 4 banks in 2019. Source: Call Reports and Summary of Deposits.

Figure 3 documents an elevated merger rate following Riegle-Neil as well as post-Great Recession. The figure also provides evidence for countercylical failures and procyclical mergers. Specifically, the correlation between the failure rate and detrended log-real GDP is -0.149 while the correlation between the merger rate and detrended log-real GDP is 0.167. While the 1994 Riegle-Neal Act which facilitated unrestricted nationwide banking expansion can account for the first merger wave of 1994-2000, the Financial Crisis in 2008 resulted in a wave of bank failures that coupled with slower banking system growth and increased competition from other intermediation channels led to the second merger wave in the post crisis period.[1]

[1] The observed higher merger rate post-2010 than the period 1994-2000 is not due to a higher number of mergers (the numerator of the merger rate) but a lower number of banks documented in Panel (i) of Figure 3 (the denominator of the merger rate). This will also be evident in Figure 6 below.

Figure 3: Failure/Merger Rates (1984 - 2023)



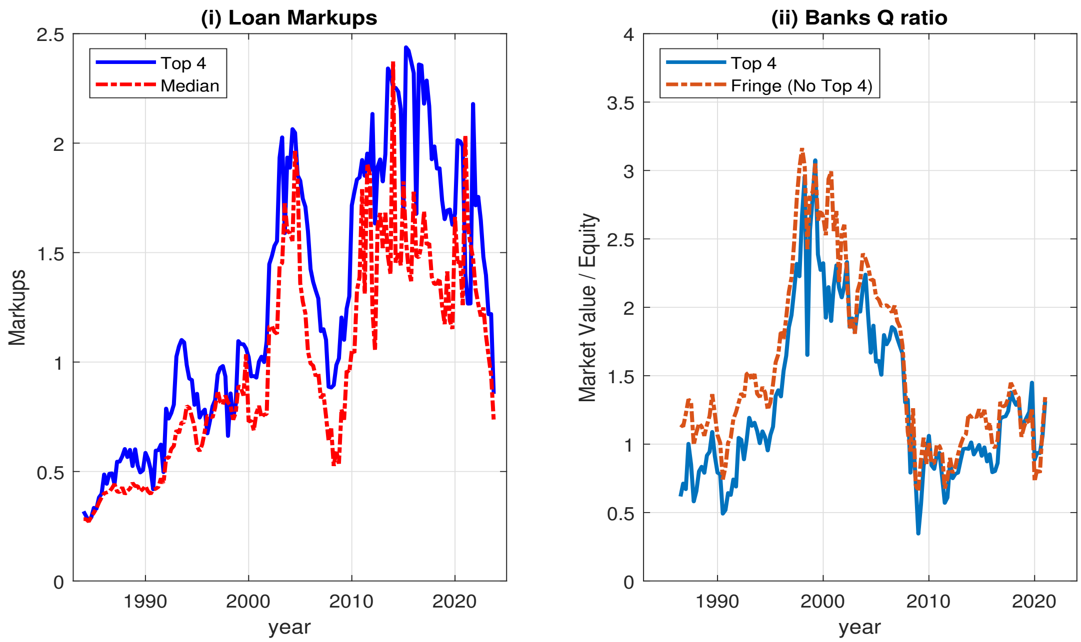
Note: Det. Log (real) GDP refers to detrended log real GDP (quarterly frequency). The trend is extracted using the H-P filter with parameter 1600. Source: Call Reports and FRED.

Figure 4 presents the evolution of loan markups and the market value to equity ratio ($Q-$ratio) in our sample.[2] Regulators use measures based on concentration (e.g. Herfindahl indices) when evaluating whether to allow bank mergers.[3] Regulatory concern about mergers focuses on whether it erodes *competition* leading to market *inefficiency* as measured, for instance, by large markups. Panel (i) in Figure 4 documents the increase in bank markups that may have occurred as a consequence of rising market power. Panel (ii) documents an increase in the $Q-$ratio during the transition between the pre-Riegle-Neal period and the post-Dodd-Frank period where $Q-$ratios are approximately at their "steady state" value of 1. Our transition phase may be interpreted along the lines of Jovanovic and Rousseau (2002) who state "the merger waves of 1900 and the 1920's, 1980's, and 1990's were a response to profitable reallocation opportunities..." As we show below in Section 8.4, the reallocation is consistent with greater allocative efficiency associated with relaxation of regulation.

[2]Our $Q-$ratio definition of market value to book equity, in contrast to the typical definition of market value to replacement cost of capital, is also used for the banking industry by Begenau et al. (2024).

[3]Among the techniques to assess the competitive effects of a proposed merger, the FDIC will consider the degree of concentration within the relevant geographic market(s) in order to approve a proposed merger. See Corbae and D'Erasmo (2025) for Herfindahl measures.

Figure 4: Markups and Q-ratio (1984 - 2023)



Note: Top 4 markups corresponds to the (asset-weighted) average within Top 4 banks when sorted by assets. Banks Q ratio corresponds to the ratio of the bank market value to the book value of equity. Source: Call Reports and Summary of Deposits.

Regulators also face concerns about whether a banking industry characterized by a few large, systemically important banks can lead to *financial instability* when one big bank's troubles spill over to the rest of the economy.[4] While several papers have focused on balance sheet spillovers among financial institutions causing instability[5], granular spillovers along the lines of Gabaix (2011) can also yield instability. Spillovers from an idiosyncratic shock to a big bank to the broader financial system and economy generate challenges to policymakers; are big banks too-big-to-fail? If so, such policies may actually induce excessive risk taking amplifying financial instability that the policy is intended to reduce. On a technical level, an idiosyncratic shock to atomless (measure zero) fringe banks has no aggregate consequences, while an idiosyncratic shock to an atomistic dominant bank can have aggregate consequences as in the granularity literature.[6]

This paper studies the costs and benefits of bank merger activity that spread across states following the Riegle-Neil Act. While the previous paragraphs focused on some costs, there are potential benefits from such deregulation. For instance, geographic diversification as evidenced in Panel (*ii*) in Figure 1 can lead to financial stability in the presence of idiosyncratic regional

[4]Since enactment of the Dodd-Frank Act in 2010, the federal banking agencies have been required by statute to consider risks to financial stability when evaluating proposed bank mergers and acquisitions (12 U.S.C. §1842(c)(7)).

[5]See, for example, Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015).

[6]Note that throughout this paper, we use the terminology "atomless" for a zero measure bank (as in competitive models of firm dynamics where idiosyncratic shocks have no aggregate effects) and "atom" or "atomistic" for a bank of positive measure (as in strategic models of firm dynamics).

shocks to banking portfolios. Specifically, the figure documents that the top 4 banks have diversified to 35 states on average while the remainder are isolated in 1.1 states on average.

To adequately address these costs and benefits given the market structure documented in Figure 1 with 4 dominant banks and 4000 fringe banks in the latest year, we apply and extend industrial organization's dominant-fringe framework of Gowrisankaran and Holmes (2004) with several important exceptions.[7] First, consistent with other papers and our own work (e.g. Corbae and D'Erasmo (2021)) establishing increasing returns in the data, we assume fixed costs which break the constant returns to scale assumption in their paper. This generates fundamental nonlinearities in the pricing of mergers which necessitates a global solution method when solving for a Markov Perfect Equilibrium. Second, we allow for entry and exit which may vary across the cycle as established in Figure 3. This is important with mergers since they can facilitate entry as in other settings; banks may enter to be acquired by a dominant bank. Third, mergers in our model generate a decline in *both* the number of banks and rise in dominant market share documented in Panel (i) of Figure 1 while the Gowrisankaran and Holmes (2004) can *only* account for the rise in market share, not the decline in numbers.

After estimating model parameters and validating that it matches the untargeted transition in market shares pre-Riegle-Neal to post-Dodd-Frank, we use our model as a laboratory to run two policy counterfactuals. First, we ask "What would have happened in the post-financial crisis period if Riegle-Neal was not enacted?" This requires a decomposition between effects associated Dodd-Frank regulation and non-bank technology improvements. A model with merger restrictions (as pre Riegel Neal) but a more efficient nonbank sector (relative to the pre-reform period) induces a significant increase in the share of credit originated by nonbanks. The improvement in nonbank efficiency together with a larger set of competitive banks (due to merger restrictions) leads to a smaller increase in bank loan interest rates and margins relative to the case where merger restrictions are removed in tandem with the increase in nonbank efficiency (post Dodd-Frank equilibrium). This lower margins result in a decline in the value of the banks (as measured by Tobin's Q Value to Asset ratio) and an increase in failure rates.

We use our model to assess whether there was an improvement in allocative efficiency from deregulation. We compare the predictions of the model pre Riegle-Neal (i.e., very restrictive merger/expansion policy) with the predictions after merger restrictions are lifted (we consider the post Dod-Frank world which imposes limited restrictions on mergers as well as a case with no merger restrictions). We find that relaxing merger and expansion restrictions improves allocative efficiency as measured by the correlation of loan market shares and average costs (as in Olley and Pakes (1996a)).

Second, we ask "What are the implications for the bank lending channel of monetary policy pre-Riegle-Neal regulatory action and the post-Dodd-Frank concentrated industry market structure?" We study the effectiveness of the lending channel of monetary policy under the different regulatory environments: pre and post Rieagle Neal merger policies. We find that Pre Riegle

[7] After documenting some similar facts bank size distribution over the 1960-2005 period, Janicki and Prescott (2006) write "We document these facts because they are an important step in developing a theory of bank size distribution. Although we do not provide one, such a theory would be valuable because it could be used to answer important questions such as: How costly were the pre-1980 limits on bank size? How will the bank size distribution continue to evolve? And will there be more concentration? If so, should policy do anything about it?" Our paper can be thought of providing one such theory.

Neal, a (permanent) contractionary monetary policy shock leads to a reduction in bank lending that is mostly explained by a reduction in lending by small liquidity constrained banks (as in Kashyap and Stein (2000)). There is also a decline in lending by nonbanks (as their marginal cost also increases due to the contractionary monetary policy shock). The same monetary policy shock post Dodd-Frank (an economy that displays a more concentrated banking sector but stronger competition from nonbanks) shows a decline in total lending explained only by a reduction in lending by nonbanks. This reduction in lending by nonbanks is signifcant enough to induce an increase in lending by small competitive banks. This increase in lending by small banks reduces the impact on interest rates that increase less than in the pre Riegle-Neal case.

The paper is organized as follows. Section 2 provides data on bank mergers and that informs our model. Section 3 runs simple "marginal propensity to lend" regressions to help understand how idiosyncratic shocks to insured bank funding affects their lending decisions. Section 4 runs simple "granular" regressions to study how those idiosyncratic shocks to large banks have translated to nontrivial aggregate fluctuations. Section 5 describes the model environment and Section 6 defines equilibrium. Section 7 presents the calibration. Section 8 illustrates the model's merger dynamics and presents how untargeted model generated marginal propensities to lend, granularity, and allocative efficency results compare to the data. Section 9 runs two policy counterfactuals to assess the implications of branching restrictions and monetary policy for economic activity. Section 10 concludes.

2 Merger Data

We present new empirical evidence establishing that the majority of mergers are by big (dominant) banks acquiring small (fringe) banks. This motivates the merger stage we introduce below in our model.

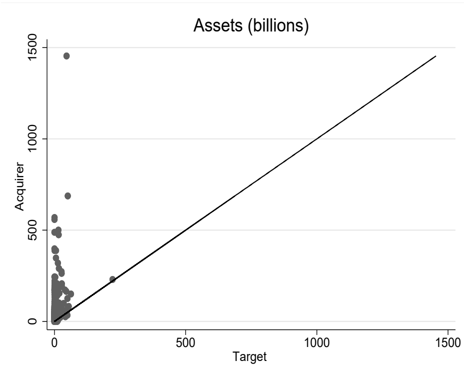
Below, we compare the size (book assets and market capitalization) of targets and acquirers between 1990 and 2023.[8] Figure 5a shows that 96% of bank mergers involve an acquirer that is significantly larger than its target and the median acquirer has over seven times more assets than the target. Figure 5b shows that 99% of bank mergers reported in Capital IQ involve in acquirer that has a larger market capitalization than its target and the median acquirer has a market capitalization that is seven times that of the target. Finally, Figure 5c shows how the relationship between the merger price and the target's market value. We find that (target) size weighted mean of the ratio of merger price to target value is 1.11 and the median is 1.35. This suggests that larger banks have substantial bargaining power in the merger process.[9]

[8]We obtain information on merger activity from the "transformation" table and eliminate transactions between banks that belong to the same top holding company.

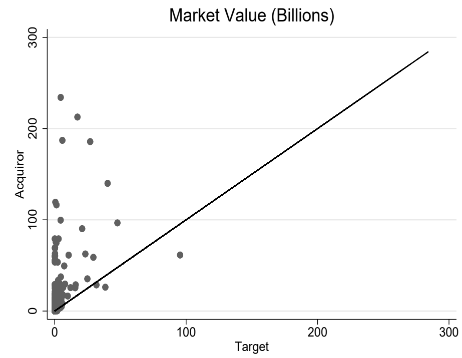
[9]We use an extreme version of this, take-it-or-leave-it offers from dominant acquirer to target banks.

Figure 5: Merger Statistics

(a) Size of Acquirers vs Targets (Assets)



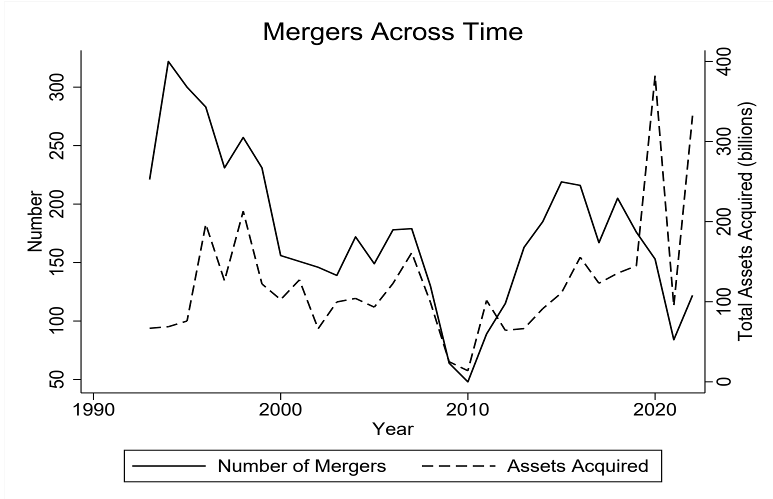
(b) Size of Acquirers vs Targets (Market Capitalization)



(c) Price to Target Market Value

Note (Left Graph): We only include mergers where we can identify both the acquirer and target. We combine mergers that occur in the same quarter where there are multiple RSSDs with the same target holding company acquired by the same acquirer. Source: Statistics on Depository Institutions (SDI) and Federal Financial Institutions Examination Council (FFIEC). Note (Right and Bottom Graph): We restrict to mergers from 1990 to 2023 where both the acquirer and target are banks as defined by SIC code. The target and acquirer value are measured 4 weeks before the merger is announced. Source: Capital IQ

Figure 6: Number of Mergers over time



Note: We only include mergers where we can identify both the acquirer and target. We combine mergers that occur in the same quarter where there are multiple RSSDs with the same target holding company acquired by the same acquirer. Source: Statistics on Depository Institutions (SDI) and Federal Financial Institutions Examination Council (FFIEC).

Figure 6 makes evident that the number of mergers declined since the peak after the introduction of Riegle-Neal to the financial crisis. It rebounded slightly but has generally remained below pre-crisis levels. The total amount of assets acquired each year has remained relatively leveled over time as despite declining mergers, both acquirers and targets have grown over time.

3 The Marginal Propensity to Lend

An input into the calculation of the granular effects of dominant banks on aggregate lending is the marginal propensity to lend. We think of this as an application to banking of the heterogeneous agent, consumption-savings literature studying the marginal propensity to consume (MPC) surveyed in Kaplan and Violante (2022).[10] There are several other papers which have considered related measures.[11]

[10] Kaplan and Violante (2022) focus on the quarterly MPC out of a \$500 windfall. They state that a large body of empirical evidence indicates that the average quarterly MPC on nondurable goods and services out of transitory income changes of \$500– \$1,000 is between 15% and 25%. Importantly, they argue this average masks substantial heterogeneity in MPCs. Specifically, many households have MPCs that are close to zero, but some households have MPCs not far from 1, with a great deal of variation in between. They state that some of this heterogeneity is explained by the distribution of liquid wealth and some by fixed individual characteristics, but most is left unexplained by observable data.

[11] Jamilov and Monacelli (2024) provide an alternative definition of the MPL as the change in loans given a unit change in bank net worth while Gigante (2025) defines it as the change in loans given a unit change in the return on loans. Corell (2025) uses a definition of MPL close to ours.

We start by analyzing the following relationship

$$\Delta L_{it} \;=\; \beta_{k(i)}\Delta D_{it} + \zeta_{it} \tag{1}$$

where $\Delta L_{it} = \log(L_{it}) - \log(L_{it-1})$ denotes the growth rate of loans in bank i in period t (or the log-difference) and $\Delta D_{it} = \log(D_{it}) - \log(D_{it-1})$ the growth rate of deposits and $k(i) \in \{d, f\}$ denotes bank type (i.e. whether bank i is a dominant or fringe type), and ζ_{it} is an iid mean zero shock with variance σ^2_ζ. We define $\beta_{k(i)}$ as the marginal propensity to loan out of deposit funding (MPL) for bank i of type k.

We follow the empirical literature studying the MPC out of income by modeling the deposit shock process with both permanent and transitory components as:

$$\begin{aligned} \log(D_{it}) &= \xi_{k(i)}\mathfrak{X}_{it} + z_{it} + \varepsilon_{it} \quad \text{where} \quad z_{it} = z_{it-1} + \eta_{it} \\ \Rightarrow \Delta D_{it} &= \xi_{k(i)}X_{it} + \underbrace{\eta_{it} + \Delta\varepsilon_{it}}_{=\nu_{it}} \end{aligned} \tag{2}$$

where $\Delta\mathfrak{X}_{it} = X_{it}$ can depend on bank characteristics at time $t-1$ and other aggregate factors such as the stance of monetary policy. The deposit process in (2) implies that log deposits in each period consists of two iid mean-zero innovations η_{it} and ε_{it} with nonzero bank-type dependent variances $\sigma^2_{\eta,k(i)}$ and $\sigma^2_{\varepsilon,k(i)}$, respectively. The shock ε_{it} is transitory and η_{it} is a permanent innovation. One may interpret the permanent innovation η_{it} as driven by mergers as in Corbae, D'Erasmo, and Smith (2025) or geographic expansion as in Corbae and D'Erasmo (2020), both of which are endogenous in those models. We interpret ε_{it} as unanticipated deposit shocks along the lines of the process in Corbae and D'Erasmo (2021) and Corbae and D'Erasmo (2025). We denote the unexplained idiosyncratic variation to deposits in (2) by ν_{it}. Then the deposit process in (2) implies that equation (1) can then be written as:

$$\Delta L_{it} \;=\; \beta_{k(i)}\xi_{k(i)}X_{it} + \beta_{k(i)}\nu_{it} + \zeta_{it}. \tag{3}$$

so that the idiosyncratic innovations ν_{it} help identify the MPL $\beta_{k(i)}$.

Table 1 presents estimates of the marginal propensity to lend from equation (3). To implement the estimation of equation 3, we estimate equation (2) by regressing ΔD_{it} on bank and time fixed effects to then extract the error term $\hat{\nu}_{it}$. We then use these estimated idiosyncratic shocks (or errors) to estimate equation (3) together with bank and time fixed effects as well as several bank controls such as log-assets, equity/assets, loans/assets, return on assets, salaries/assets, expenses on fixed assets/assets, cost of deposits. For the period between 1984 and 2019, we find that the average MPL is 0.510 and that it increases with bank size, with the MPL for the Top 4 banks equal to 0.959.[12] The statistical difference that we find for the MPL across banks of different sizes appears to be driven by the early period in our sample. When

[12] To understand our novel results across the bank size distribution, we look at the link between the MPL and the liquid assets to total asset ratio. We find that banks not in the Top 4 have in general a higher liquid asset ratio than those in the Top 4 (24.30% versus 17.88%). We expect banks with higher liquid asset ratios to be less responsive to unexpected deposit flows. Consistent with this, Table A.12 in Appendix A-2.1 shows that the average MPL declines with the liquid asset to total asset ratio.

focusing on the pre Reagle Neal period (1984-1993) the estimated MPL is larger for the Top 4 banks than for the rest but this difference dissipates in the post GFC period (2011-2019).[13]

Consistent with the findings in Corell (2025), we observe a decline in average MPL between the early period and the most recent years in our sample. Importantly, the pattern we observe in the estimated MPL for dominant banks is consistent with the granular results we discuss in the next section.

Table 1: Marginal Propensity to Lend (Data Estimates)

	Dependent Variable $\Delta \log(L_{it})$			
	Full Period 1984-2019	Pre-reform 1984-1993	Transition 1994-2007	Post-GFC 2011-2019
ν_{it}	0.510***	0.520***	0.499***	0.456***
	(0.00101)	(0.00170)	(0.00165)	(0.00256)
$\nu_{it} \times I_{t4}$	0.449***	0.377***	0.508***	-0.237
	(0.0359)	(0.0698)	(0.0490)	(0.234)
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
N	946299	353150	355389	169536
R-sq	0.362	0.398	0.416	0.287
adj. R-sq	0.348	0.371	0.397	0.260

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (1). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 2. We follow Gabaix (2011) and construct ν_{it} by removing a time and bank fixed effect. $I_{t,k(i)=4}$ is an indicator that takes value 1 if bank i is in the Top 4 of the asset distribution. Bank controls includes log-assets, equity/assets, loans/assets, return on assets, salaries/assets, expenses on fixed assets/assets, cost of deposits. Source: Call Reports

4 Granularity and Aggregate Fluctuations

Given the growth of the largest banks over the past 30 years, we study how idiosyncratic bank shocks to deposit can spill over to the aggregate economy via changes in credit. In the language of Gabaix (2011), and consistent with our model, we treat the largest bank in our model economy as a "granular" bank. In this granular view, an idiosyncratic shock to a dominant banks has the potential to generate nontrivial aggregate fluctuations.

Gabaix (2011) focused on how idiosyncratic shocks to the growth rate of the largest 100 firms can explain 30% of aggregate output fluctuations. We perform a similar empirical analysis by focusing on the largest commercial banks. As in Gabaix (2011), we derived ν_{it}, an idiosyncratic

[13]Our model has direct implications for deposit and loan level concentration. We analyze the relationship between the estimated MPL and the level of deposit concentration in Appendix A-2.1 Table A.13. We find that banks that operate in more concentrated markets respond less to unexpected flows of deposits.

shock to deposits, from equation (2) presented in the previous section. This highlights the role of idiosyncratic deposit shocks in driving the MPL and eventually aggregate fluctuations. The goal is to investigate whether the purely idiosyncratic component ν_{it} of large banks can explain fluctuations in bank lending, aggregate credit, and aggregate output. As in Gabaix (2011), we construct the *granular residual* as follows

$$\Gamma_t \equiv \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \nu_{i,t}, \tag{4}$$

where K represents the K top banks when ranked by assets, ℓ_{it} is total lending by bank i in period t and $L_t = \sum_{i=1}^{N} \ell_{it}$ (N is the total number of banks). We estimate how much of aggregate fluctuations in credit and output can be explained by Γ_t.

To implement this, we construct an equivalent measure of the granular residual in (4) given by $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \hat{\nu}_{it}$.[14] We then regress aggregate bank loan growth, total credit growth, and GDP growth on $\hat{\Gamma}_t$ and some lags and evaluate the value of the R^2. That is, as in Gabaix (2011) we estimate the model

$$\Delta Y_t = \beta_\Gamma \hat{\Gamma}_t + \epsilon_t^\Gamma \tag{5}$$

where Y_t can be the log of real total bank credit, log real total credit, or log real GDP. The R^2 from a regression of equation (5) is given by

$$R^2 = \frac{\beta_\Gamma^2 Var(\hat{\Gamma}_t)}{Var(\Delta L_t)}. \tag{6}$$

Table 2 presents the results when Y_t is total bank credit for the periods 1984-2019 (full sample), 1984-1993 (pre-reform), 1994-2007 (transition), 2011-2019 (post-gfc), and $K = 4$ which is consistent with how we measure a "dominant bank" in the model we present in Section 5.[15] We observed that there is a decline in R^2 between the Pre-reform period and the Post-GFC period. This is consistent with a lower Marginal Propensity to Lend (MPL) out of unexpected deposit shocks (i.e., ν_{it}) for dominant banks in the post-GFC period than in the pre-reform period that we discussed in the previous section (see Table 1). A positive contribution to dominant bank granularity derives from the increase in the market share of dominant banks across periods. However, our estimates imply that the negative effect on bank granularity derived from a lower MPL dominates when looking at bank credit.

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[14] We follow Gabaix (2011) and let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1} \sum_{t=1}^{T} g_{it} + N^{-1} \sum_{i=1}^{N} g_{it}$ (i.e., we control for bank and time fixed effects).

[15] Here we simply run OLS regressions. See Gabaix and Koijen (2024) for an IV approach.

Table 2: Explanatory power of granular residuals of dominant banks on aggregate lending Top 4 by period (R^2)

	Top 4 Banks - Dep. Var. $\Delta\log(L_t)$			
	Full Period 1984-2019	Pre-reform 1984-1993	Transition 1994-2007	Post-GFC 2011-2019
Γ^x_t	0.512***	-0.742	0.562***	-0.380
	(0.141)	(0.515)	(0.152)	(0.351)
Γ^x_{t-1}	0.201	0.232	0.0496	0.0924
	(0.141)	(0.509)	(0.155)	(0.352)
Γ^x_{t-2}	-0.0139	-0.749	-0.0267	-0.442
	(0.142)	(0.517)	(0.157)	(0.353)
(intercept)	0.00834***	0.00165	0.0131***	0.00478**
	(0.00114)	(0.00251)	(0.00143)	(0.00233)
N	144	40	56	36
R^2	0.100	0.104	0.212	0.084

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta\log(L_t)$" refers to growth rate of total real bank loans. Top 4 Banks corresponds to the case when $K = 4$. Period 1984-2019. Source: Call Reports

Tables A.8 and A.10 in the Appendix presents the results for total credit and log real GDP as dependent variables when $K = 4$ across periods in our sample.[16] We find that R^2 are relatively high in the case of bank lending and real GDP, with dominant bank (Top 4) idiosyncratic shocks explaining up to 10% of aggregate bank lending growth and up to 8.5% log real GDP growth. As expected, during the full sample period, idiosyncratic shocks to dominant banks appear to have less explanatory power over fluctuations in total credit and output than over bank credit with R^2s close to 2% and 9% for total credit and GDP, respectively. As we also show in the appendix, these numbers rise as we add more banks to the group of granular banks (e.g. the top 35 SIFI banks or top 100 banks).

4.1 On the connection between granularity and MPL

Here and in the Appendix, we discuss the connection between the marginal propensity to lend by big banks and granularity. There are two clear theoretical takeaways from the granularity results for R^2 in (6) and the MPL regressions in (3) connecting the MPL and granularity. If each of the K dominant banks were literally of measure zero (i.e. $\omega_{it} = 0$), Gabaix's R^2 would be zero. Further, if the MPL of the dominant banks were zero, the idiosyncratic shocks would explain none of the variation in aggregate lending captured by Gabaix's R^2.

[16] Appendix A-2 also presents results for $K = 35$ and $K = 100$ for the full sample period (1984-2019). Table A.6 shows that idiosyncratic shocks to top 35 bank deposits can explain 17% of aggregate bank lending growth. In Table A.9 we document that granular shocks to systemically important banks (i.e. the top 35) explain up to 3.4% of the growth of real GDP.

Table A.14 in the Appendix provides regression estimates of $\beta_\Gamma = 0.517$ in (5) in the data for the case of total bank loans.[17] Thus β_Γ is significantly less than the estimated MPL coefficient $\beta_d = 0.959$ in the data reported in Table 1. In Appendix A-2.2, we explain why Gabaix's β_Γ lies below the MPL estimate β_d. The argument lies in the negative correlation between dominant bank residuals and small bank residuals. Deposits flow from small banks to dominant banks due to mergers or other forms of competition (a "deposit stealing argument") inducing a negative correlation between Γ_t and the residual in equation (5), which then leads to a downward bias estimate of the MPL when using granular type regressions. We also show in Appendix A-2.2 that an approximate estimate of the MPL can be recovered by a granular type regression by replacing the aggregate loan growth rate on the left hand side with the weighted average of bank level loan growth rate (for all banks).[18]

5 Model Environment

Having documented that the largest banks buy smaller banks and that idiosyncratic shocks to the largest banks can have aggregate effects, here we present a version of a dominant-fringe model consistent with other data facts for the banking industry. We think of the dominant-fringe framework as a simple representation of a granular banking industry. Unlike papers that focus solely on the deposit side, we also study how bank mergers affect bank lending. As a result, our model must also account for the fact that growth of the nonbank sector has put further competitive pressure on the banking industry.

We consider an infinite horizon, discrete time model but to save on notation we use the nomenclature that variable x_t is denoted x and x_{t+1} is denoted x'.

5.1 Borrowers

A mass $\mathscr{B}$ of ex-ante identical borrowers demand one period loans in order to fund a large risky project. We think of the risky project as being either a commercial loan that may fail or a household loan like a mortgage that may be foreclosed.[19] The project requires one unit of investment (i.e. a loan from either a bank $k = B$ or non-bank $k = N$) at the beginning of period t. The project returns R units at the end of the period according to:

$$\begin{cases} 1 + R_k & \text{with prob } \theta' \\ 1 - \lambda & \text{with prob } (1 - \theta') \end{cases} \tag{7}$$

in the successful and unsuccessful states, respectively. That is, borrower gross returns are by $1 + R_k$ in the successful state and by $1 - \lambda$ in the unsuccessful state. The probability of the

[17] In this experiment, we do not include lags of $\hat{\Gamma}_t$ to be able to read directly the value of the MPL out of one coefficient.

[18] Appendix A-2.2 shows that the approximate MPL from this regression is 0.951 but not statistically significant from our MPL estimate equal to 0.959 in Table A.14.

[19] Long term mortgages can be thought of as a sequence of one period loans as in Jeske, Krueger, and Mitman (2013).

successful state is an aggregate shock and λ is the fraction lost in default. The aggregate shock θ' follows a persistent process with transition matrix $G(\theta', \theta)$.

The borrower makes a discrete choice over which type of financial institution to borrow from $k \in \{\mathscr{B}, \mathscr{N}\}$. Bank and nonbank interest rates on their loans to the borrower can differ. Taking the vector of interest rates $\mathbf{r} = \{r_{\mathscr{B}}, r_{\mathscr{N}}\}$ on loans as given, borrowers decide whether they want to fund a project given their outside option and then make a discrete choice over whether to borrow from a bank or nonbank. Following Buchak et al. (2018), we assume that the value associated with financing the project with each type of lender is subject to an unobservable idiosyncratic shock $\boldsymbol{\delta} = \{\delta_B, \delta_N\}$ affecting the value of taking a loan from each type of lender additively. We assume that ϵ_k are i.i.d. shocks drawn from a type one extreme value distribution $F_\epsilon(\epsilon; \alpha)$ with scale parameter $1/\alpha$. Using the discrete choice approach from IO, these borrowers create an aggregate demand for loans.

Borrowers have an outside option. At the beginning of period t, they receive a realization of their reservation utility of consumption $\omega \in [\underline{\omega}, \overline{\omega}]$ if they decide not to run the project. These draws from distribution function $\Omega(\omega)$ are i.i.d. over time. The outside option choice $\iota \in \{0, 1\}$ leads to a downward sloping aggregate demand for loans while conditional on choosing to borrow $\iota = 1$ the extreme value shocks determine loan demand across financial institution types.

There is limited liability on the part of the borrower at the project level so that the project return net of interest payments is bounded below at zero. If r_k is the interest rate on a loan that the borrower faces, the borrower receives $\max\{R_k - r_k, 0\}$ in the successful state and 0 in the failure state. Specifically, in the unsuccessful state she receives $1 - \lambda$, which must be relinquished to the lender.

We assume that ω is private information to the borrower. As in Bernanke and Gertler (1989), success or failure is also private information to the borrower unless the loan is monitored by the lender.[20] With one period loans, since reporting failure (and hence repayment of $1 - \lambda < 1 + r_k$) is a dominant strategy in the absence of monitoring, loans must be monitored. Monitoring is costly as in Diamond (1984).

5.2 Savers

A mass $\mathscr{H}$ of identical, infinitely lived, risk neutral households with discount factor β are endowed with y units of the good each period. We make a "large family" assumption so that any idiosynacratic shocks are pooled. 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, a nonbank, or to an individual borrower. We assume that after observing the deposit interest rate r_D, households who choose to deposit their earnings are randomly matched with a bank at the beginning of any period t (i.e., before the merger stage).

[20]While one interpretation of our borrowers is that they are effectively one period lived (born at the beginning of the period and dead at the end as in the OG model of Bernanke and Gertler (1989)), we could have effectively modeled borrowers as long lived and added enough inter-period anonymity so that financial contracts are one period lived as in Carlstrom and Fuerst (1997) and borrowers are sufficiently impatient to not want to augment net worth. We follow this approach in our previous paper Corbae and D'Erasmo (2021).

After the merger stage, some depositors are reallocated across banks.[21] Given deposit insurance, even if the bank fails, they receive their deposit with interest at the end of the period. Households can hold a portfolio of bank stocks yielding dividends (claims to bank cash flows) and can inject equity to banks. They can also invest in shares of the representative non-bank, which gives a claim to non-bank cash-flows. They pay lump-sum taxes/transfers τ' at the end of any period t which include a lump-sum tax τ'_D used to cover deposit insurance for failing banks as well taxes to cover bank bailouts. Finally, if a household wants to match directly with a borrower (e.g. 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_k 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) and Williamson (1986), there is no benefit to matching directly with borrowers.

5.3 Banks

As in Diamond (1984), banks exist in our environment to pool risk and economize on monitoring costs. We assume there are two classes of banks $i \in \{d, f\}$ for dominant and fringe respectively, with size ranking $f < d$. We assume a dominant-fringe market structure as in Gowrisankaran and Holmes (2004) and that there are sufficient funds to cover all possible loans $\mathscr{H} > \mathscr{B}$.[22] More specifically, each period begins with a measure γ of identical atomless (i.e. measure zero) fringe banks each with D_f deposits as well as an atomistic (representative) dominant bank with D_d deposits. Aggregate deposits in the banking sector at the beginning of each period are $D = D_d + \gamma D_f$. For future reference we define the aggregate state before the merger stage by $s = (\gamma, D_d, \theta)$. While we take D_f as parametrically given, D_d can expand endogenously through the acquisition of fringe banks. Specifically, to expand its deposit base, the dominant bank can make a take-it-or-leave-it (TOLI) offer to a measure $(\gamma - \Gamma)$ of fringe banks. Assuming all fringe banks accept, the measure of fringe banks falls from γ to Γ and the deposits of the dominant bank increases by $(\gamma - \Gamma)D_f$. The dominant bank chooses the size of the merger Γ to maximize its equity value.

We model merger regulatory policy as follows. The regulatory cost of mergers $H_n(\Gamma, s), n \in \{pre-RN, post-RN\}$ has two components. First, under pre-Riegle-Neal restrictions, banks are constrained to operate in one state. As such, the cost of merging is infinite (i.e. $H_{pre-RN}(\Gamma, s) = \infty$). There are several conditions under post-Riegle-Neal restrictions. First, banks cannot merge to greater than 10% deposit market share.[23] As such, the cost of merging such that the dominant

[21] These idiosyncratic matches wash away at the family level as deposits are pooled.

[22] Unlike some of our previous work (e.g. Corbae and D'Erasmo (2021)) there are two types of representative banks (a top 4 representative and a fringe representative) at the beginning of any period. In Corbae and D'Erasmo (2021) we incorporated fringe bank heterogeneity and asset accumulation. In Corbae and D'Erasmo (2025) we allow for more than one type of dominant bank (a "national" geographically diversified and two "regional" banks subject to local shocks) together with an heterogeneous fringe segment.

[23] Section 101 (2) in the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 established nationwide concentration limits and stated that a merger ... "applicant (including all insured depository institutions which are affiliates of the applicant) controls,or upon consummation of the acquisition for which such application is filed would control, more than 10 percent of the total amount of deposits of insured depository institutions in the United States."

bank's deposit market share exceeds 40% (since our dominant bank represents the Top 4) is infinite. Second, to capture costs associated with HHI constraints given in Nocke and Whinston (2022), we compute an implied HHI from the model and the cost associated from the merger is given by the following functional form:

$$H_{post-RN}(\Gamma, s) = \begin{cases} \infty & \text{if } \frac{D'_d}{D_d+\gamma D_f} > 0.40 \\ h(\gamma - \Gamma)^2 & \text{if } HHI > 1800 \text{ or } \{HHI < 1800 \text{ and } \Delta_{HHI} > 100\} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where h is parametrically given measuring the intensity of merger regulation. Note that these costs change with the endogenous market structure of the banking sector as our dominant bank buys up a fraction $\gamma - \Gamma$ of fringe banks.

Following the merger stage, the dominant bank, the fringe banks, and the representative nonbank Cournot compete in the loan market. Each period, incumbent banks are randomly matched with a set of potential household depositors D_i (with $D_d < D_f$) who receive deposit interest rate r_D. Before extending loans, deposits might be reallocated across banks. We assume that banks receive a mean zero idiosyncratic shock to their deposits of size ϵ_i. ϵ_i is iid over time and across banks.[24] Banks choose between allocating their deposits $D_i + \epsilon_i$ to the loan market L_i or securities, where the latter provides an exogenous risk free return of $r_A > r_D$. Dominant banks move first followed by the fringe banks and the nonbank. Market clearing and the nonbank's first-order condition determine equilibrium loan rates (r^L_B, r^L_N). Since $\mathscr{H} > \mathscr{B}$ the cost of deposits, r_D, is pinned down by the outside option of the savers $\overline{r}$ which we calibrate to the average deposit rate.

In Corbae and D'Erasmo (2025), we documented important differences in non-interest income and non-interest expenses across banks of different sizes. Based on this evidence, we assume that banks pay net non-interest expenses (monitoring costs) $C_i(L_i)$ (i.e., the difference between non-interest expenses and non-interest income on loans) per unit of loans extended. We assume $C_i(L_i)$ takes the following form:

$$C_i(L_i) = C_{1i}L_i + C_{2i}L_i^2. \quad (9)$$

Banks also face fixed operating costs κ_i.

Following the loan stage, loan defaults (θ') and chargeoffs (λ') are realized in the payoff stage. We assume that ex-post quality of the borrowers can differ across lenders so $\lambda'_d = \lambda'_N = \overline{\lambda} \in [0, 1]$, and that $\lambda'_f \in [0, 1]$ is iid over time and across fringe banks distributed with a truncated normal $F(\lambda; \overline{\lambda}, \sigma_\lambda)$ where $\overline{\lambda}$ and σ_λ denote the mean and the standard deviation of the distribution, respectively.[25] The profit of bank $i \in \{d, f\}$ is given by:

$$\pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i) = [\theta' r^L_B - (1-\theta')\lambda'_i]L_i + r^A(D_i + \epsilon_i - L_i) - r^D(D_i + \epsilon_i) - C_i(L_i) - \kappa_i. \quad (10)$$

[24]The total level of deposits after ϵ_i shocks are realized is $D_d + \epsilon_d + \gamma \int (D_f + \epsilon_f)$. Since ϵ_f is iid across banks and has mean zero, bank specific shocks to fringe banks have zero aggregate effect on deposits (i.e., $\gamma \int (D_f + \epsilon_f) = \gamma D_f$). This is not the case for a bank specific shock to a dominant bank as total dominant deposits will equal $D_d + \epsilon_d$. Note that as long as the aggregate endowment is large enough (i.e., $y > D_d + \epsilon_d + \gamma D_f$, these fluctuations do not affect household consumption as there is deposit insurance and, in equilibrium, since $r_D = \overline{r}$ households are indifferent between depositing at a bank or using their storage technology.

[25]This is consistent with the evidence presented in Table A.1 in the Appendix. Specifically, the standard deviation of loan loss rate is lower for top 4 banks than fringe banks in both pre- and post-reform periods.

where $S = (\Gamma, D'_d, \theta)$ denotes the aggregate state before the loan stage (i.e., after the merger stage but prior to the realization of θ' and λ').

We assume banks with non-negative profits pay them as dividends (there are no retained earnings). A bank that has negative expected continuation value can exit. Banks with positive continuation value that face negative profits inject costly equity to remain in the market. We denote dividends by:

$$\mathscr{D}_i(L_i, \epsilon_i; S, \theta', \lambda'_i) = \pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i) - \mathbf{1}_{\{\pi_i(\cdot)<0\}}\psi_i(|\pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i)|). \tag{11}$$

where ψ_i captures the costs of equity issuance.

New banks can choose to enter as fringe banks at cost K_f and dominant banks at cost K_d. Entry costs correspond to the initial injection of equity into the bank by its owners. Endogenous exit and entry (γ_e and γ_x) imply that the measure of fringe banks can change through time not only by bank mergers. In sum, the size of the fringe next period is given by $\gamma' = \Gamma + \gamma_e - \gamma_x$ where γ_e and γ_x denote the mass of fringe entrants and exiters, respectively.

5.4 Nonbank Lenders

A representative nonbank that discounts the future at rate $\beta = (1+\overline{r})^{-1}$ specializes in extending loans to borrowers in a perfectly competitive market. To keep the model parsimonious, we assume that the nonbank is financed with equity e_N raised from the household sector and is not subject to limited liability. When lending to borrowers nonbanks face a marginal monitoring cost c_N. Like banks, the representative nonbank can diversify entrepreneurs' idiosyncratic risk but it is subject to aggregate fluctuations in default frequencies.

Let $\pi_N(S, \theta', \lambda'_N)$ denote the profits of the non-bank after the realization of loan defaults and charge-offs associated with its current lending L_N given by

$$\pi_N(L_N, S, \theta', \lambda'_N) = \left[\theta' r_N(S, r^L_B) - (1-\theta')\lambda'_N\right] L_N - c_{\mathcal{N}} L_N \tag{12}$$

subject to flow constraint $E_N = L_N$. Since the nonbank operates in a perfectly competitive market it takes the interest rate $r_{\mathcal{N}}$ as given. The nonbank cash-flows to households is $\mathscr{D}_N = \pi_N(S, \theta', \lambda'_N)$.

The objective function of the non-bank is to maximize the expected present discounted value of future cash-flows to households with discount factor β. We assume that there is free entry into the non-bank sector, and to simplify the analysis we set the entry cost to zero.

5.5 Government Budget Constraint

The government collects lump-sum taxes to cover the cost of deposit insurance and unpaid securities. Treating banks in a given state $(\{D_i, \epsilon_i, \lambda'_i\})$ symmetrically, post-liquidation cost to the deposit insurance fund is given by

$$\begin{aligned}\Delta_i(D_i, \epsilon_i, \lambda'_i) &= (1+r_D)(D_i+\epsilon_i) - \zeta_i(1+r^A)\max\{(D_i+\epsilon_i-L_i), 0\} \\ &- \zeta_\theta[\theta'(1+r^L_B) + (1-\theta')(1-\lambda'_i)]L_i - C_i(L_i) - \kappa_i,\end{aligned} \tag{13}$$

where $\zeta_i \leq 1$ is the post-liquidation value of the bank's asset portfolio. The government also collects taxes (or pays transfers) to cover the cost (or receive the proceeds) from the security market. Then, aggregate taxes are given by

$$\tau' \cdot \mathscr{H} = \int x_i' \max\{0, \Delta_i(D_i, \epsilon_i, \lambda_i')\} di + (A' - A) + Ar^A, \tag{14}$$

where $A = \int \max\{0, D_i + \epsilon_i - L_i\} di$.

5.6 Timing

The timing in any period is as follows:

M1. Merger Stage: The dominant bank makes a take-it-or-leave-it merger bid to a measure $(\gamma - \Gamma)$ of fringe banks subject to regulatory costs of doing so in order to grow its deposit base.

M2. Loan Stage: Banks receive temporary shock to deposits. Banks allocate their deposits to the loan market or securities. Dominant banks move first in the loan market followed by the fringe banks and nonbanks.

M3. Payoff Stage: At the end of the period, loan defaults and charge-offs are realized. Exit and entry decisions are made and dividends paid.

6 Equilibrium

We present saver's and borrowers' problems first to then move into the description of the merger stage and loan stage.

6.1 Saver Problem

The problem of a representative household is

$$V_H(\{\Phi_{s_\theta}\}_{\forall\{\theta\}}, \Phi_{\mathcal{N}}) = \max_{\{A^h, D, \{\Phi'_{s_\theta}\}_{\forall\theta}, \Phi'_{\mathcal{N}}\}} E\left[C' + \beta V_H(\{\Phi'_{s_\theta}\}_{\forall\{\theta\}}, \Phi'_{\mathcal{N}})\right] \tag{15}$$

subject to

$$\begin{aligned} & C' + A^h + D^h + \int [P_i + \mathbf{1}_{\{e_i=1\}} \cdot K_i] \Phi_i di + \Phi'_{\mathcal{N}} P_{\mathcal{N}} \\ & = y + (1 + \bar{r}) A^h + (1 + r_D) D^h + \int (\mathscr{D}_i + P_i) \Phi_i di + (\mathscr{D}_{\mathcal{N}} + P_{\mathcal{N}}) \Phi_{\mathcal{N}} - \tau', \end{aligned} \tag{16}$$

and $C' \geq 0$ where P_i and Φ_i' are the post-dividend stock price and stock holding of bank i, respectively, and $P_{\mathcal{N}}$ and $\Phi'_{\mathcal{N}}$ are the price of a claim to non-bank dividends cum equity and stock holdings of the non-bank, respectively, given zero initial holdings. Given exit and entry decision rules, in cases in which a bank has exited, $P_i = 0$ on the right-hand side of the budget constraint (16), and, in cases in which a bank has entered, $P_i > 0$ on its left-hand side.

6.2 Borrower Problem

Every period, given r_B^L, r_N^L, and shock ω, borrowers choose whether to invest ($\iota = 1$) or not ($\iota = 0$). They solve

$$\max_{\{\iota\}} (1-\iota)\cdot\omega + \iota \cdot E_{\boldsymbol{\delta}}[\Pi_E(\theta, r_B^L, r_N^L, \boldsymbol{\delta})]. \tag{17}$$

Conditional on choosing $\iota = 1$, entrepreneurs observe $\boldsymbol{\delta} = \{\delta_B, \delta_N\}$ and then choose which type of lender $k \in \{B, N\}$ to borrow from to solve:

$$\Pi_E(\theta, r_B^L, r_N^L, \delta) = \max_{k\in\{B,N\}} \alpha E_{\theta'|\theta}[\pi_E(r_k^L, \theta)] + \delta_k \tag{18}$$

where

$$\pi_E(r_k^L, \theta') = \begin{cases} \max\{0, R - r_k^L\} & \text{with prob } \theta' \\ \max\{0, -(\lambda' + r_k^L)\} & \text{with prob } 1-\theta' \end{cases}.$$

The solution to (18) implies that the share of borrowers choosing a loan from a lender of type k is

$$\Psi_k(\theta, r_B^L, r_N^L) = \frac{\exp\left(\alpha E_{\theta'|\theta}\left[\pi_E(r_k^L, \theta')\right]\right)}{\sum_{\hat{k}\in\{B,N\}} \exp\left(\alpha E_{\theta'|\theta}\left[\pi_E(r_{\hat{k}}^L, \theta')\right]\right)}. \tag{19}$$

The ex-ante value for the borrower is given by:

$$U_B(\theta, r_B^L, r_N^L) = \frac{1}{\alpha} E_\omega[\iota] E_{\boldsymbol{\delta}}[\Pi_E(\theta, r_B^L, r_N^L, \boldsymbol{\delta})], \tag{20}$$

where the expected value of taking out a loan has a convenient closed form:

$$E_{\boldsymbol{\delta}}[\Pi_E(\theta, r_B^L, r_N^L, \boldsymbol{\delta})] = \ln\left(\sum_{k\in\{B,N\}} \exp\left(E_{\theta'|\theta}\left[\pi_E(r_k^L, \theta')\right]\right)\right).$$

The borrowers problem creates a demand system. In particular, the total demand for credit is given by

$$L(\theta, r_B^L, r_N^L) = \int_{\underline{\omega}}^{\overline{\omega}} \mathbf{1}_{\{\omega \le E_{\boldsymbol{\delta}}[\Pi_E(\theta, r_B^L, r_N^L, \boldsymbol{\delta})]\}} d\Omega(\omega). \tag{21}$$

The loan demand for commercial banks is given by

$$L_B(\theta, r_B^L, r_N^L) = \Psi_B(\theta, r_B^L, r_N^L) L(\theta, r_B^L, r_N^L). \tag{22}$$

6.3 Merger Equilibrium

Aggregate deposits in the banking sector are $D = D_d + \gamma D_f$. Starting in aggregate state $s = (\gamma, D_d, \theta)$, the dominant bank makes a TOLI offer to a measure $\gamma - \Gamma \ge 0$ of fringe banks to gain deposits.[26] Assuming all fringe banks accept, the measure of the fringe banks after the merger adjusts to Γ and the deposits of the dominant bank is given by

$$D'_d = D_d + (\gamma - \Gamma)D_f. \tag{23}$$

Similarly, the equity of the dominant bank is given by

$$K'_d = K_d + (\gamma - \Gamma)K_f. \tag{24}$$

If the price of a unit of deposits in the merger stage is denoted $p(\Gamma, s)$, then the total cost of the merger deal to the dominant bank is given by $p(\Gamma, s)(\gamma - \Gamma)D_f$. Since mergers (weakly) increase the dominant bank's deposit market share, we can match the data fact of rising dominant bank market share and falling number of banks evident in figure 1. The latter result - the falling number of banks - arises as the endogenous measure of fringe banks evolves in our model which is absent in Gowrisankaran and Holmes (2004).

The dominant bank chooses a deposit market share to maximize its profitability recognizing that the fringe banks must be willing to accept their offer of size $p(\Gamma, s)(\gamma - \Gamma)D_f$. Specifically, we write the dominant bank's dynamic programming problem at the beginning of the merger stage as:

$$v_d(s) = \max_{\Gamma \in [0,\gamma]} -p(\Gamma, s)(\gamma - \Gamma)D_f - H_n(\Gamma, s) + \int w_d(S, \epsilon_d)dF_d(\epsilon_d) \tag{25}$$

subject to

$$p(\Gamma, s)D_f \geq \int w_f(S, \epsilon_f)dF_d(\epsilon_f) \tag{26}$$

where $H_n(\Gamma, s)$ are any additional regulatory costs in regime $n \in \{pre - RN, post - RN\}$ and $w_i(S)$ is the expected present discounted value of a type $i \in \{d, f\}$ bank in loan stage state $S = (\Gamma, D'_d, \theta)$. Constraint (26) incentivizes the fringe to accept the take-it-or-leave-it offer of the dominant bank.

Taking a first order condition with respect to Γ and assuming the constraint binds, we get:

$$\frac{\partial \int w_d(S, \epsilon_d)dF_d(\epsilon_d)}{\partial \Gamma} = \frac{\partial \int w_f(\Gamma, \epsilon_f)dF_d(\epsilon_f)}{\partial \Gamma}(\gamma - \Gamma) + \frac{\partial H_n(\Gamma)}{\partial \Gamma} - \int w_f(\Gamma, D'_d(\Gamma), \theta, \epsilon_f)dF_d(\epsilon_f) \tag{27}$$

where we denote $\frac{\partial f(\Gamma, D'_d(\Gamma), \theta)}{\partial \Gamma} + \frac{\partial f(\Gamma, D'_d(\Gamma), \theta)}{\partial D'_d} D_f$ as $\frac{\partial f(\Gamma)}{\partial \Gamma}$. The left hand side is the marginal benefit for the dominant bank. It depends on how the acquisitions limits competition and improves the dominant bank profitability. The right hand side is the marginal cost of the merger, which incorporates both the marginal cost due to greater merger regulation (H_n) and due to rising fringe value functions (w_f).

Let $\Gamma^*(s)$ solve (25)-(26) noting that if the dominant bank chooses not to acquire any fringe banks, then $\Gamma^*(s) = \gamma$. Since, in the loan stage, the dominant bank will use its market power

[26] In equilibrium, as there are two types of representative banks (a top 4 representative and a fringe representative), the state space includes the measure of fringe banks γ and the deposits of dominant bank D_d. Our previous work Corbae and D'Erasmo (2021) and Corbae and D'Erasmo (2025) with additional fringe bank heterogeneity or different types of dominant banks require an expanded state space.

to withhold loans, fringe banks recognize that the more mergers occur, the more valuable it is to remain in the market. As a result, the dominant bank faces a trade-off between acquiring a few fringe banks at a low price or many fringe banks at a high price.

6.4 Loan Market Equilibrium

Following the merger stage, the dominant bank, fringe banks, and a representative nonbank compete in the loan market. The dynamic programming problem of the dominant bank can then be written as:

$$w_d(S, \epsilon_d) = \max_{L_d \leq D'_d + \epsilon_d} \mathbb{E}_{\theta'|\theta}\Big[\max_{x'_d \in \{0,1\}} (1 - x'_d)\beta\big(\mathscr{D}_d(L_d, \epsilon_d; S, \theta', \lambda'_d) + v_d(s')\big)\Big], \tag{28}$$

subject to

$$\mathscr{L}_B \equiv L_d + \Gamma L^*_f(L_d, \epsilon_d, S) = L_B(\theta, r^L_B, r^L_N(\theta)), \tag{29}$$
$$\gamma' = F(L_d, \epsilon_d, S, \theta'). \tag{30}$$

where $s' = (\gamma', D'_d, \theta')$ and the function $F(L_d, \epsilon_d, S, \theta')$ captures the transition of the measure of fringe banks. Equation (29) illustrates both loan market clearing and that the dominant bank takes into account both how their loan decision affects affects the aggregate fringe loan supply, L_f, and the bank interest rate, r^L_B. We also make use of the solution of the nonbank problem and the equilibrium nonbank interest rate r^L_N which as we show below is only a function of θ. Equation (30) ensures that the dominant bank internalizes its impact on market structure in the future. Banks with negative profits can choose to exit $x'_d = 1$ or inject equity to remain in the market $x'_d = 0$.

Given the stackelberg game in the loan market, taking the interest rates r^L_B and r^L_N as given, the problem of fringe bank i where $j(i) = f$ solves[27]

$$w_f(S, \epsilon_f, L_d) = \max_{\ell_f \leq D_f + \epsilon_f} \mathbb{E}_{\theta', \lambda'_f|\theta}\Big[\max_{\chi'_f \in \{0,1\}} (1 - \chi'_f)\beta\big(\mathscr{D}_f(\ell_f, \epsilon_f; L_d, S, \theta', \lambda'_f) + v_f(s')\big)\Big] \tag{31}$$

Letting $\ell^*_f(L_d, S, \epsilon_f)$ be the solution to (31), we define the aggregate supply of loans by fringe banks as $L^*_f(L_d, S, \epsilon_f)$ here as $\int \ell^*(L_d, S, \epsilon_f) dF_d(\epsilon_f)$.

Turning to non-bank competition, the first order condition of the non-bank with respect to L_N is given by

$$\overline{r} = E_{\theta'|\theta}\left[\theta' r^L_N - (1 - \theta')\lambda'\right] - c_N. \tag{32}$$

The solution to equation (32) provides the equilibrium nonbank loan interest rate $r^L_N(\theta)$. Equation (32) makes evident that assuming a linear marginal cost for nonbanks simplifies the solution of the problem considerably as the equilibrium r^L_N is a function of parameters and independent of the bank interest rate r^L_B. That is, nonbanks display a perfectly elastic supply at $r^L_N(\theta)$.

[27] To save on notation, we neglect adding L_f and x_f as state variables in (31).

6.4.1 Bank Entry and Industry Law of Motion

New fringe entrants choose whether to enter. The entry decision satisfies

$$v_i^e(L_d, S, \theta'; \gamma^e(x_d', e_d')) = \max_{e_i' \in \{0,1\}} (1 - e_i') \{-K_i + v_i(s')\}. \tag{33}$$

In equilibrium, $v_i^e(L_d, S, \theta'; \gamma^e(x_d', e_d')) \times \gamma^e(x_d', e_d') = 0$, that is either $v_i^e(L_d, S, \theta'; \gamma^e(x_d', e_d')) = 0$, $\gamma^e(x_d', e_d') = 0$, or both.

The evolution of the mass of fringe banks then is given by

$$\gamma' = F(L_d, S, \theta') = \Gamma - \gamma^x(L_d, S, \theta') + \gamma^e(L_d, S, \theta'). \tag{34}$$

6.5 Definition of Equilibrium

Definition 1. *Taking r^A and r^D as given, a* ***Markov Perfect Merger Equilibrium*** *is a set of value functions $\{v_i, w_i\}$ and policy functions $\{\Gamma, L_i, \ell_f, x_i', \chi_f', e_i'\}$ for $i \in \{d, f\}$, ℓ_N, prices $\{p, r_B^L, r_N^L\}$, and transition functions for $\{\gamma', D_d'\}$ such that:*

1. *The pre-merger value function v_d solves (25). The merger quantity Γ maximizes (25).*
2. *The merger pricing function p satisfies (26).*
3. *The post-merger value functions w_d and w_f solve (28) and (31). The loan supply policy functions (L_d, ℓ_f) and exit decision rules (x_d',χ_f') maximize (28) and (31).*
4. *Consistency requires $\ell_f = L_f$ and $\chi_f' = x_f'$.*
5. *r_B^L clears the loan market (29).*
6. *r_N^L satisfies the shadow bank first order condition (32)*
7. *The mass of entrants γ^e solves the entry problem (33)*
8. *Transition functions are consistent with mergers, entry, and exit (34)*

6.6 On Multiplicity

As in Gowrisankaran and Holmes (2004), we have the possibility of multiple steady states. In Gowrisankaran and Holmes (2004), they find three steady states, one with no dominant firm, one with no fringe firms, and one with both a mass fringe firms and a dominant firm. Given that we have entry, as long as entry costs are sufficiently small, we always have a mass of fringe banks in any steady state. Given the large fixed costs for dominant banks, we find steady states with no dominant bank. We do not focus on these because banking is defined by a few large, dominant banks. Finally, we find a steady state with both a dominant bank and a mass of fringe banks as illustrated in table 4.

7 Calibration

Our calibration strategy is as follows. While all endogenous variables defined in our equilibrium are derived from an economy with aggregate uncertainty about borrower failure rates $1-\theta$, we calibrate parameters for our Pre-Riegle-Neal long run equilibrium using a realization of aggregate shocks which do not include the small probability crisis event since our annual data span only 10 years prior to Riegle-Neal. The Pre-Riegle-Neal long run equilibrium assumes that $H(\Gamma, s) = \infty$ for all s which is how we enforce the state branching restrictions. In the transition between Pre-Riegle-Neal and Post-Dodd-Frank we simply relax the assumption $H(\Gamma, s) = \infty$ in equation (8) maintaining all other parameter values. We calibrate h to match the dominant bank market share at the end of the period that ends with the Dodd-Frank Act. For the post-Dodd-Frank period, we maintain all of the previous parameters except for "regulatory" costs associated with the Dodd-Frank Act. Specifically, we choose the fixed costs to fringe and dominant banks, κ_f and κ_d respectively, to match rising fixed costs to loans. Further, we choose the marginal cost to extending loans by non-banks c_N to match the declining bank share of loans also in the post-Dodd-Frank data. All parametric changes are unexpected from the point of view of banks (i.e. implemented as MIT shocks). The solution of the model does not require any aggregate or equilibrium function approximation (i.e., we work with the full state space) as there is a representation dominant bank and a representative fringe bank. Section A-6 provides the general computational approach to solving the model.[28]

We calibrate the model parameters via Simulated Method of Moments to match key statistics of the U.S. banking industry described in Corbae and D'Erasmo (2025). Our main source for bank level variables (and aggregates derived from them) is the Consolidated Report of Condition and Income for Commercial Banks (regularly called "call reports").[29] We aggregate commercial bank level information to the Bank Holding Company level. As discussed above, moments from the Call Report data are computed beginning in 1984 (due to an overhaul of the data in that year). We also use data from the Summary of Deposits (SOD), and FRED, federal reserve economic data for aggregate economic series (GDP, CPI, etc).

A model period is set to be one year. Before moving into the details of the calibration, we provide functional forms for the stochastic process of the borrower idiosyncratic shock, the distribution of borrower's outside option, the aggregate shock, the regional shock, the distribution of net expenses for fringe banks and banks' external financing cost function.

There are two types of banks $i \in \{d, f\}$ in our model. Consistent with the data size differences we described in the data section, we identify Dominant banks $i = d$ with those in the Top 4 (when banks are sorted by assets) and the rest (i.e., the competitive fringe $i = f$) with those outside the Top 4.

The full set of parameters of the model are divided into two groups. The first group of parameters can be estimated directly from the data (i.e. they can be pinned down without

[28] Our previous work (e.g. Corbae and D'Erasmo (2021)) incorporated additional fringe bank heterogeneity and asset accumulation, so the solution required an approximation similar to the one proposed by Krusell and Smith (1998). In Corbae and D'Erasmo (2020) we consider a model with a large number of banks with different degree of loan market power and the solution required the approximation proposed by Ifrach and Weintraub (2017).

[29] Source: FDIC, Call and Thrift Financial Reports, Balance Sheet and Income Statement, link here.

solving the model). After those are set, a second group is estimated using simulated method of moments. In what follows, we describe both groups of parameters as well as our calibration strategy and targeted moments.

The parameters in the first group include the return on the storage technology for households $\overline{r}$, the interest rate on deposits r^D, the household discount factor β, the return on securities r^A, the process for θ (the aggregate default frequency), and the charge-off rate processes. We calibrate these parameters using the full sample between 1984-2019 as they will remain unchanged throughout all of our experiments. We set the deposit rate $r^D = \overline{r}$ and calibrate the deposit interest rate r^D to match the ratio of interest expenses on deposits and federal funds borrowed over total deposits plus federal funds borrowed. We let the discount factor be $\beta = 1/(1+\overline{r})$.[30] Similarly, we calibrate r^A to match the ratio of interest income on securities over total securities.

We parameterize the stochastic process for the aggregate likelihood of default with two states $\theta \in \{\theta_G, \theta_B\}$, where $\theta_G > \theta_B$. We denote the transition between θ_B and θ_G as p^θ_{BG} and the transition between θ_G and θ_B as p^θ_{GB}. We calibrate θ_B to match the default probability during the GFC (2008-2010) and θ_G to match the average in all other years between 1984 and 2019. The transition probabilities are calibrated so the average crisis does not last longer than two years (implying that p^θ_{BG} equals 0.5) and set $p^\theta_{GB} = 0.02$ to reflect that we have observed only 1 crisis during this period.

We calibrate $\overline{\lambda}$ to match the average charge-off rate (across banks and time) and set σ_λ to match the difference between the observed standard deviation of the charge-off rates of the fringe banks and that of dominant banks.[31] $\lambda'_d = \lambda'_N \equiv \overline{\lambda} \in [0,1]$, $\lambda'_f \in [0,1]$ is iid over time and across fringe banks distributed with a truncated normal $\mathcal{N}(\lambda; \overline{\lambda}, \sigma_\lambda)$ where $\overline{\lambda}$ and σ_λ denote the mean and the standard deviation of the distribution, respectively.

The second set of parameters (i.e., those calibrated to match moments computed after solving the model) are pinned down using the Pre Riegle–Neal period (1984-1993). This implies that after removing merger restrictions or implementing further regulatory changes observed after the Dodd-Frank Act we can use these moments to validate the model in the Post Riegle–Neal era. This set of parameters include the deposit shocks by bank type, borrower's parameters (which control the demand for loans), the size of deposits at fringe banks D_f, banks' cost structure, the external finance parameters, as well as the parameters that control merger policy, and finally, the marginal cost of nonbanks.

We let ϵ_i take on a negative and positive value $\epsilon_i \in \{\epsilon_i^-, \epsilon_i^+\}$ and denote the probability of $\epsilon_i = \epsilon_i^-$ by ρ_i^ϵ. We calibrate $\{\epsilon_i^-, \epsilon_i^+\}$ and ρ_i^ϵ to match the standard deviation of log-deposits for top 4 and fringe banks (after controlling for year and bank fixed effects). We set $\Omega(\omega)$ as the Uniform distribution with support $[\underline{\omega}, \overline{\omega}]$. We calibrate loan demand parameters α, R, N, and $\bar{\omega}$ to match the elasticity of loan demand, net interest margin, the deposit-to-output ratio, and average dividend issuance. We normalize $\underline{\omega}$ to be the value of never borrowing (i.e. the value of the borrower at the highest possible interest rates from both lender types $E_\delta[\Pi_E(\theta, r^L_B = R, r^L_N = R, \delta)]$).

[30] In this case, the use of the full sample between 1984 and 2019 is convenient as the estimated (real) interest rate on deposits for the period 2011-2019 is negative which would result in a discount factor above 1.

[31] See table A.1 in the Appendix. Specifically, the standard deviation of loan loss rate is lower for top 4 banks than fringe banks in both pre- and post-reform periods which is consistent with a diversification argument.

We assume $C(L_i)$ is a quadratic function of L_i with linear term C_i^1 and quadratic term C_i^2 and calibrate it to match the bank net marginal expenses and the elasticity of net marginal expenses.[32] Fixed costs are chosen to match the fixed cost over loans ratio. We let the external seasoned equity financing cost take the following form $\psi_i(x) = \psi_i^1 x$ for $i \in \{d, f\}$ and calibrate it to the average equity issuance to asset ratio by banks of type $i \in \{d, f\}$. The marginal cost for nonbanks is chosen to match the bank loan to total loans ratio. The regulatory merger cost h is chosen so Post Dodd-Frank the model matches the market share of Top 4.

To find the long-run equilibrium in the Pre Riegle–Neal period, we assume that banks expect that merger restrictions will remain in place for ever. In this initial long-run equilibrium, we set D_f, and D_d to match the relative size of fringe banks and the market share of Top 4 banks. The value of γ is set so that on average equals 3000 which matches the ratio of fringe banks to Top 4 banks in the data. We select the entry cost K_f so that the entry rate is on average the same as the bank failure rate (which implies that the number of fringe banks fluctuates but it does not grow to infinity or shrink to zero in the long-run). In all experiments that follow, γ and D_d are determined endogenously and the entry cost remains constant at the set value. In each experiment, we simulate 10 periods (15 if transition) 1000 times and report the average values over those 1000 iterations.

Table 3 presents the parameters of the model and the targets that were used. Entries above the line correspond to parameters chosen outside the model while entries below the line correspond to parameters chosen within the model by simulated method of moments using data from the Pre Riegle-Neal period. In all, we have 17 parameters and 23 targeted moments as part of the simulated method of moments estimation (i.e. an overidentified model).

[32] See Corbae and D'Erasmo (2025) for a detailed description of how net marginal expenses are estimated. Table A.2 in Appendix A-1.3 present the estimates of marginal net expenses and the elasticity.

Table 3: Parameters and Targets

Parameter		Value	Target
Deposit Interest Rate (%)	$\overline{r} = r^D$	0.0014	Avg Int Exp. Deposits (1984-2019)
Bank Discount Factor	β	0.998	$(1 + r^D)^{-1}$
Return on Securities	r_A^+	0.0180	Return on Net Securities (1984-2019)
Default Frequency (Good Times)	θ_G	0.968	Mean Default Freq. (Non-Crisis)
Default Frequency (Bad Times)	θ_B	0.920	Mean Default Freq. (Financial Crisis)
Loan Loss Rate	$\overline{\lambda}$	0.31	Average Charge-off rate (1984-2019)
Standard Dev Loan Loss rate f	σ_λ	0.145	Std dev charge off rates f (1984-2019)
Standard Dev Loan Loss rate d	σ_λ	0.13	Std dev charge off rates d (1984-2019)
Size of deposit shocks d	$\{\epsilon_d^-, \epsilon_d^+\}$	$\{-0.0515, .0074\}$	Std. of shocks to deposits d
Size of deposit shocks f	$\{\epsilon_f^-, \epsilon_f^+\}$	{-0.445, 0.0332} $\times D_f$	Std. of shocks to deposits f
Probability of negative shock d	ρ_d^ϵ	0.125	$Pr(\epsilon_d < -std)$
Probability of negative shock f	ρ_f^ϵ	0.08	$Pr(\epsilon_f < -std)$
Number of Borrowers	N	5.60	Deposit to Output
Return on investing	R	0.180	Net Interest Margin
Price coefficient	α	47.0	Elasticity of Loan Demand
Lower bound demand shock	$\underline{\omega}$	0.00	Normalization
Upper bound demand shock	$\bar{\omega}$	0.40	Dividend Issuance d and f
Mean size of Dominant Bank d	D_d	0.15	Deposit Market Share Top 4
Mean size of Fringe Bank f	D_f	0.00039	Relative Size Fringe to Top 4
Linear Cost Loans d	C_d^1	0.007	Net Marginal Expenses Top 4
Quadratic Cost Loans d	C_d^2	0.00005	Elasticity Net Marginal Expenses Top 4
Fixed cost d	κ_d	0.00345	Fixed cost over loans Top 4
Mean Dist Cost Loans f	C_f^1	0.007	Net Marginal Expenses Fringe
Quadratic Cost Loans f	C_f^2	$\frac{0.0065}{D_f}$	Elasticity Net Marginal Expenses Fringe
Fixed cost f	κ_f	$0.0183 \times D_f$	Fixed cost over loans Fringe
External finance param. d	ψ_d^1	0.20	Avg. equity issuance to loan ratio Top 4
External finance param. f	ψ_f^1	3.10	Avg. equity issuance to loan ratio Fringe
Entry Cost d	K_d	0.125	Q Top 4 Banks
Entry Cost f	K_f	$0.09 \times D_f$	Q Fringe Banks
Marginal Cost Nonbank	c_N	0.027	Bank Loan to Total Loans

Note: If not noted on the Table, Target moments refer to the Pre Riegle-Neal period (years 1984-1993).

Table 4 columns (i) and (iii) present a comparison between the data and the model for targeted moments (i.e., moments above the line in the Pre Riegle Neal period). The model is in line with the charge off rates, the deposit processes, the deposit market share of Top 4 banks, the share of lending by banks (relative to total lending), and the relative size of dominant to fringe banks. At the estimated parameters, marginal net expenses in the model for both dominant and fringe banks under predict the values in the data. Dominant banks in the model pay much higher dividends than in the data (relative to assets) and the model under predicts the failure rate of fringe banks.

Table 4: Moments Data vs Model (Targets)

		Data		Model	
		Pre	Post	Pre	Post
Moment		Riegle-Neal	Dodd-Frank	Riegle-Neal	Dodd-Frank
		(i)	*(ii)*	*(iii)*	*(iv)*
Average Charge-off	$E'_\theta[(1-\theta')\lambda']$	0.96%	0.94%	1.04%	1.04%
Std. of Deposit Shocks Top 4	$Std(log(D_d+\epsilon_d))$	0.148	0.044	0.155	0.045
Std. of Deposit Shocks Fringe	$Std(log(D_f+\epsilon_f))$	0.182	0.156	0.167	0.167
Freq. Neg. Deposit Shocks Top 4	$P(\epsilon_d < -\sigma_d)$	0.125	0.278	0.125	0.125
Freq. Neg. Deposit Shocks Fringe	$P(\epsilon_f < -\sigma_f)$	0.081	0.085	0.08	0.08
Elasticity of Loan Demand	$-\alpha r_B^L(1-s_B)$	-1.1	-1.1	-1.29	-1.45
Deposit Market Share Top 4	$\frac{D_d}{D_d+\gamma D_f}$	14.40%	44.76%	13.90%	43.38%
Bank Loans to Total Loans	$\frac{L_d+\gamma L_f}{L_n+L_d+\gamma L_f}$	44.54%	33.28%	42.05%	36.35%
Deposit to Output Ratio	$\frac{D_d+\gamma D_f}{\sum Output}$	39.01%	57.19%	46.29%	44.89%
Net Interest Margin	$E_\theta[\theta' r_B^L - r_D]$	4.94%	4.35%	4.43%	4.54%
Net Expenses Top 4	$c'(L_D)$	1.16%	0.92%	0.70%	0.70%
Net Expenses Fringe	$c'(L_F)$	1.89%	1.45%	1.70%	1.76%
Elasticity Net Expenses Top 4	$\frac{d\log(C_d(L_d))}{d\log(L_d)}$	0.97%	1.05%	1.00%	1.00%
Elasticity Net Expenses Fringe	$\frac{d\log(C_f(L_f))}{d\log(L_f)}$	0.80%	0.87%	1.42%	1.43%
Fixed cost/loans Top 4	$\frac{\kappa_d}{L_d}$	0.90%	0.60%	2.54%	2.09%
Fixed cost/loans Fringe	$\frac{\kappa_f}{L_f}$	0.85%	0.56%	2.39%	2.26%
Equity Issuance to Assets Top 4	$\frac{\mathbf{1}_{\{\pi_d<0\}}(-\pi_d)}{D_d}$	0.07%	0.01%	0.19%	0.00%
Equity Issuance to Assets Fringe	$\frac{\mathbf{1}_{\{\pi_f<0\}}(-\pi_f)}{D_f}$	0.13%	0.04%	0.36%	0.31%
Bank Failure Rate Top 4	$\frac{\gamma_x}{\gamma}$	0.00%	0.00%	0.00%	0.00%
Bank Failure Rate Fringe	x_d	0.76%	0.29%	1.23%	1.53%
Relative Size Dominant/Fringe	$\frac{D_d}{D_f}$	415.80	998.31	384.62	1175.81
Dividends/Assets Top 4	$\frac{\mathcal{D}_d}{D_d}$	0.36%	0.74%	0.36%	1.11%
Dividends/Assets Fringe	$\frac{\mathcal{D}_f}{D_f}$	0.39%	0.66%	0.32%	0.40%
Tobin's Q Top 4	V_d/K_d	0.87	1.55	1.00	9.53
Tobin's Q Fringe	V_f/K_f	1.19	1.25	0.61	0.63
Loan Market Share Top 4	$\frac{L_d}{L_d+\gamma L_f}$	17.04%	41.46%	17.25%	35.10%
Bank Merger Rate	$\frac{(\gamma-\Gamma)}{\gamma}$	1.27%	2.89%	0.00%	0.04%
Loan Markup Top 4	$\frac{\theta r^L}{r_D+c'(L_d)}-1$	56.17	221.46	442.80	455.67
Loan Markup Fringe	$\frac{\theta r^L}{r_D+c'(L_f)}-1$	47.82	152.57	148.59	145.99
Interest Rate	r^L	6.69%	3.18%	4.73%	4.85%
Loans/Deposits ratio Top 4	$\frac{L_d}{D_d}$	78.01%	63.23%	99.28%	57.54%
Loans/Deposits ratio Fringe	$\frac{L_f}{D_f}$	67.60%	73.26%	77.62%	82.34%

Note: Targets for the method of moments procedure include in the Pre-Riegle Neal period all moments above the line, and in the Post Dodd-Frank period only the deposit market share of Top 4, fixed cost over loans Top 4 and Fringe, and nonbank market share. All other moments are not a target.

In the Pre Reagle Neal period, among the set of moments that we do not target (those below the line), we note that the model is in line with the level of concentration in the loan market (loan share of Top 4 banks) but generates loan markups that are significantly larger than in the data both for dominant banks and fringe banks. As the model generates loan interest rates that are in line with the data, this difference derives from the previously described difference between net marginal net expenses in the model and the data. The asset side of the balance sheet is in line with the data for fringe banks but dominant banks in the model invest most deposits into loans as opposed to the 78 percent estimated in the data. By construction, a long-run equilibrium in the model in the Pre Reagle Neal period is 0% while we observe a few mergers in the data.

After calibrating the model to Pre Riegle Neal moments, we introduce two set of structural parameter changes. Each of these changes arrive as a surprise to agents in the model. The first one corresponds to the Riegle-Neal Act and it is modeled as a change in merger policy that allows bank to merge (see equation (8)). This policy change leads to a transition period that goes until the implementation of the Dodd-Frank Act (17 years - 1994 to 2010). The second set of parameter changes are introduced in the model period consistent with the beginning of the post Dodd-Frank era. We use deposit market share of Top 4 banks in the final period of the transition period (model period 17) to calibrate the value of h in equation (8). The value of h remains constant throughout the experiments. In the post Dodd-Frank period, we adjust banks' fixed operating costs (associated with an increase in regulatory costs) as well as the marginal operating costs for nonbanks (associated with changes in technology). Fixed costs of dominant and fringe banks are set to match the observed fixed costs over loans Post Dodd-Frank. We set the marginal cost of the nonbank to capture the declining share of bank loans to total loans. Table 5 presents the parameters that change after Pre Riegle Neal.

Table 5: Parameter Changes Post Riegle Neal

Parameter		Pre-Riegle-Neal	Transition	Post-Dodd-Frank
Regulatory Merger Cost	h	-	$0.002 \times D_f$	$0.002 \times D_f$
Fixed cost d	κ_d	0.00345	0.00345	0.00635
Fixed cost f	κ_f	$0.0183 \times D_f$	$0.0183 \times D_f$	$0.0186 \times D_f$
Marginal Cost nonbank	c_N	0.027	0.027	0.023

Implementing these two set of parameter (policy) changes requires us to solve the model along a transition path as both the elimination of merger restrictions and the joint change in the cost structure of banks and nonbanks lead to respective transition periods. After removing merger restrictions, we iterate on the value of the banks as well as transition functions $\gamma' = F(L_d, \epsilon_d, S, \theta')$ and D'_d until convergence (i.e., the functions are consistent with the solution to banks' problem both at the merger and loan stages). We note that this transition is not long enough to reach a new long-run equilibrium of the model (i.e., γ and D_d are still adjusting to the removal of merger restrictions when banks are surprised with the post Dodd-Frank parameter changes). For that reason, after the removal of merger restrictions the transition to a new long-run equilibrium is interrupted with a new set of parameter changes. After adjusting the parameters consistent with the Post Dodd-Frank period, the transition is solved until we reach a new long-run equilibrium. In many cases, when comparing the model to the data we show only the first 10 periods of this transition to represent the years between 2011 and 2019.

Table 4 present a set of data moments (column (*ii*)) together with their model generated counterparts (column (*iv*)) for the Post Dodd-Frank period (years 2010-2019). Recall that the only targets in these columns are the fixed cost over assets for dominant and fringe banks, the bank loan to total credit, and the deposit market share of the Top 4. All other moments are not targets of the calibration exercise. The model moments presented in column (*iv*) are computed using the initial 9 periods after adjusting κ_i and c_N. The model does a good job in capturing the estimated changes in the financial sector such as the failure rate and the loan markup for fringe banks, as well as the balance sheet structure across bank sizes. The model under predicts the deposit and loan market share of Top 4 banks, the deposit to output ratio, the net marginal expenses across banks, and the merger rate. The model still over predicts the dividend to asset ratio for dominant banks, the equity issuance of fringe banks, and the loan markup for Top 4 banks. The model fails to capture the decline in loan interest rates with the caveat that we keep both the cost of deposits as well as the return on assets constant across periods.

Comparing model results from the pre-Riegle-Neal long-run equilibrium to the post-Dodd-Frank long-run equilibrium suggests that the combination of mergers, changing bank fixed costs, and changing nonbank marginal costs, have lead to greater dominant bank market shares in both deposit and loan markets, higher interest margins, greater dominant bank value, lower fringe bank value, and had minimal effect on borrower value. In order to decompose these various changes driven by bank regulation, below we run policy counterfactuals. These counterfactuals allow us to answer the following questions i) what would happen if Riegle-Neal was never implemented? ii) How much of the nonbank sectors growth can be attributed to post-Riegle-Neal mergers as opposed to technological improvement?

8 Model Properties

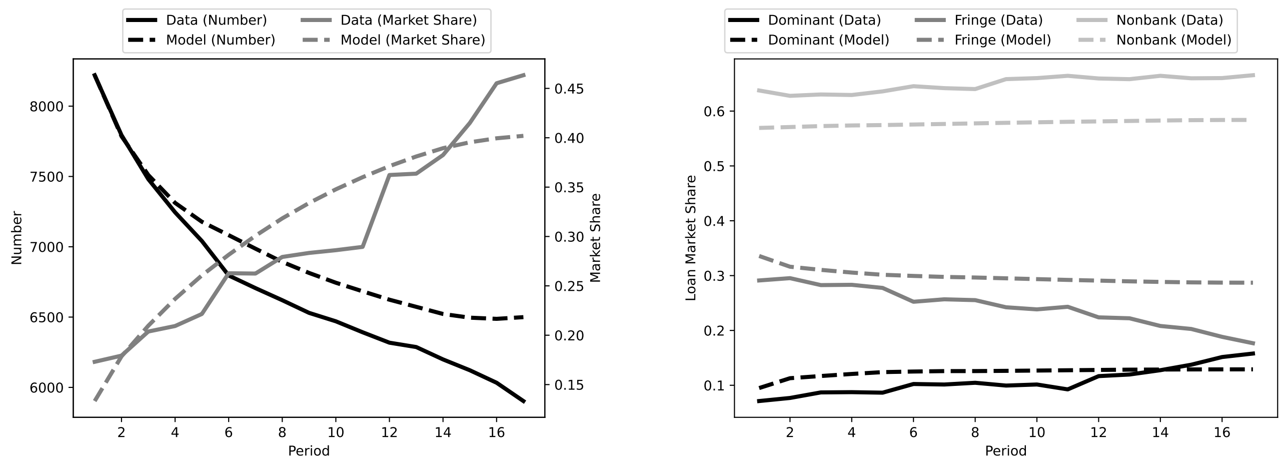
8.1 Transition Path

To illustrate that our model captures the appropriate merger dynamics in the transition period, we present the evolution of the endogenous state variables during the 15 year transition period between Riegle-Neil and the post-crisis Dodd-Frank regulations.

Figure 7: Model vs Data Transition

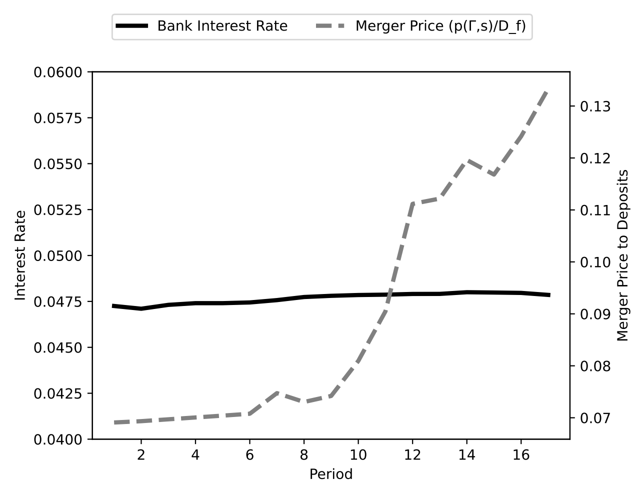
(a) Deposit Market

(b) Loan Market Shares



Note (Left Graph): This plot presents the number of fringe banks and the market share of the largest 4 banks and the analogous model moments from 1994 (the introduction of Riegle-Neal) to 2007 (the end of our transition period). The ratio of the number of fringe banks to number of dominant banks in data in 1994.q1 (the beginning of the transition period) equals 2055. For presentation purposes, in this figure, we re-normalize the mass of fringe banks in the model to match this value. The difference between model and data derives from the fact that the number of fringe declines slightly in the data during the pre-reform period but it is constant in our stationary pre-reform equilibrium and calibrated to 2500.

Figure 8: Market Prices



Note (Left Graph): This plot the model interest rate and merger prices

In Figure 7a, we illustrate the growth of the dominant bank and the decline in the number of fringe banks, matching the transition dynamics in panel (i) of Figure 1. The dominant bank grows from 15% deposit market share to just under 40% over 14 years, driven by an average 2.6% merger rate (as opposed to 1.84% in the data). Because of these mergers, the number of fringe banks declines substantially. The growth of the dominant bank in our model is driven entirely by mergers.

Finally, in Figure 7b, we illustrate how mergers affect lending and the growth of the nonbank sector. As the dominant bank grows, it uses its market power to decrease the supply of loans and increase the prevailing interest rate. As a result, potential borrowers switch to nonbanks. Hence, the growth of the nonbank sector is partially explained by banking mergers.

In Figure 8, we illustrate the effect of bank mergers on prices and values. Due to mergers, the prevailing bank interest rate, r_L^B increases from 4.70% to 4.80%. Due to rising prices and declining competition, the value of fringe banks increases.

8.2 Marginal Propensity to Lend

We can also use our model to study how bank lending responds to changes in deposits. Heuristically, the first order condition of the bank's value function with respect to loans L_i is given by [33]

$$\begin{aligned}\mu_i(\epsilon_i, S) &= E_{\theta', \lambda_i' \leq \lambda_i^{x'=1}|\theta} \left\{ \underbrace{[\theta' r_B^L - (1-\theta')\lambda_i'}_{a} + \underbrace{\left[\theta' \frac{\partial r_B^L}{\partial \mathscr{L}_B} \frac{\partial \mathscr{L}_B}{\partial L_i} L_i\right]}_{b} + \underbrace{\left[\beta \frac{\partial v_i(s')}{\partial s'} \frac{\partial s'}{\partial L_i}\right]}_{c} \right\} \\ &- E_{\theta', \lambda_i' \leq \lambda_i^{x'=1}|\theta} \left\{ \underbrace{\left[\frac{\partial Pr(\pi_i < 0, x_i' = 0))}{\partial L_i} \frac{\partial \psi_i(|\pi_i|)}{\partial |\pi_i|}\right]}_{d} + \underbrace{r^A}_{e} + \underbrace{\frac{\partial C_i(L_i)}{\partial L_i}}_{f} \right\}\end{aligned} \tag{35}$$

where μ_i is the multiplier on the constraint that $L_i \leq D_i + \epsilon_i$, $\lambda_i^{x'=1}$ is bank i's exit threshold where a high fraction of chargeoffs $\lambda_i' > \lambda_i^{x'=1}$ in its loan portfolio induce bank i to exit (i.e. optimally choose $x_i' = 1$), $\mathscr{L}_B$ is the aggregate supply of loans by banks, and simply to save on notation we have neglected conditioning μ_f on L_d. Equation (35) trades off the expected benefit of investing in risky loans (a) net of monitoring costs (f) and equity injections in unprofitable states of the world (d) versus the opportunity cost of investing in riskless securities (e). The dominant bank internalizes how its lending spills over to lowering interest rates (b) and the future state of the economy (c), which is absent for measure zero fringe banks.

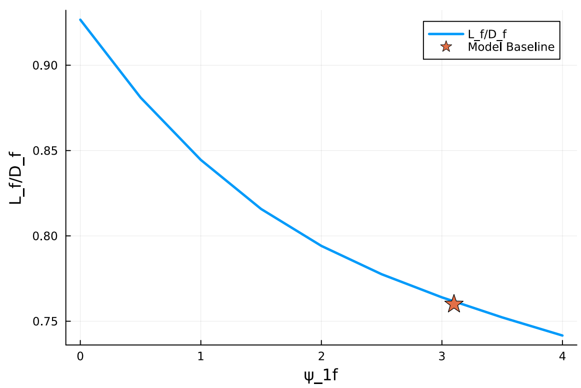
Notice, if $\mu_i > 0$, then the bank is constrained and would lend any additional deposits. However, if $\mu_i = 0$, then the bank is unconstrained, and would not lend more if they received additional deposits. Hence, banks MPL is either 0 or 1 across different states. In certain states (e.g. $\epsilon_i < 0$), banks behave similar to "hand-to-mouth" consumers. Notice that differences in seasoned equity issuance costs across dominant and fringe banks also influences loan supply in (35) as well as differences in monitoring costs. Since lending is risky and can lead banks to

[33] By "heuristically" we mean (35) presents an "approximate" first order condition assuming all functions are differentiable, the problem is concave, and that the exit threshold $\lambda_i^{x'=1}$ does not vary. In Section A-6 we provide the general computational approach to solving for optimal loan supply by bank type.

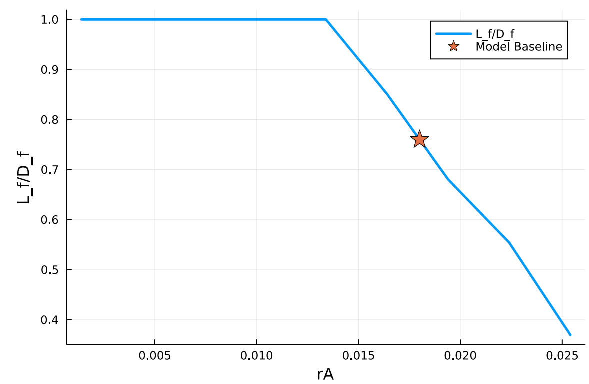
negative profits, lower external finance costs for dominant banks means lower expected cost to lending (ceteris paribus) and hence higher loan supply.

To illustrate how equity issuance costs and the return on securities affect fringe bank lending, as well as optimal bank exit decisions, we present plots illustrate the fringe bank's policy functions and profitability. These plots are created in the Pre-Riegle-Neal environment and take the actions of all other banks and nonbanks fixed.

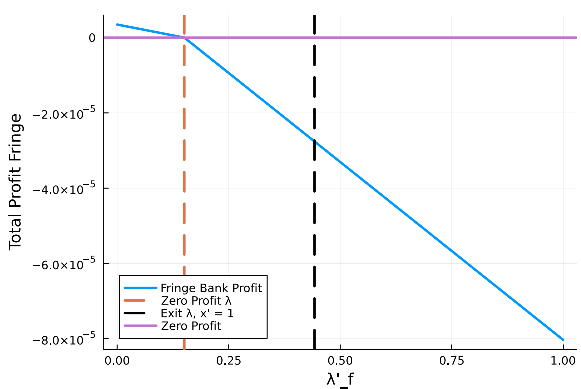
Figure 9: Policy and Profit Functions



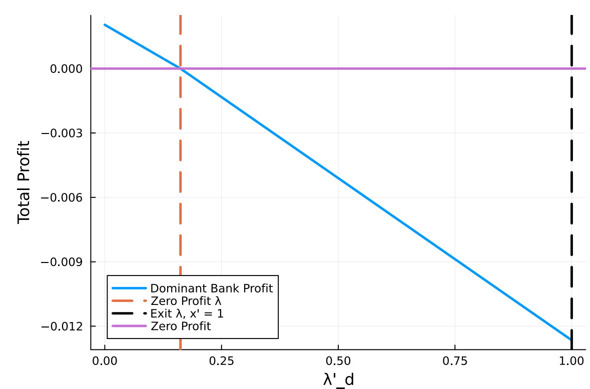
(a) This presents fringe lending with respect to their equity issuance cost, ψ_f



(b) This presents fringe lending with respect to the policy rate, r_A



(c) This presents fringe bank profit as a function of their idiosyncratic draw of λ'_f in the case of $\epsilon_d > 0, \epsilon_f < 0, \theta' = \theta_B$.



(d) This presents dominant bank profit as a function of their idiosyncratic draw of λ'_f in the case of $\epsilon_d < 0, \theta' = \theta_B$.

Note: This figure shows fringe bnak policy functions. Panel A illustrates that as equity issuance costs rise, the fringe bank lends less due to the risky nature of lending. Panel B shows that as the return on securities rise, the fringe bank lends less due to the improved outside option. Panel C presents fringe bank profit and exit thresholds. Panel D presents dominant bank profit and exit thresholds.

To estimate the MPL, we simulate a panel of banks in the pre Riegle-Neal and the post Dodd-Frank environments. We then run the regression in equation (3). The results are presented below in 6. We repeat that process 10,000 times and report the median coefficients across those 10,000 iterations. Our model implied MPL are very close to the data in the pre-Riegle-Neal period. The model implies MPLs of 44% and 95% for fringe and dominant banks respectively, compared to 52% and 89% in the data. In the post-Dodd-Frank period, our model implied MPLs are slightly lower for fringe banks (42% as opposed to 44%), but much lower for the dominant bank (10% as opposed to 95%).

This decline in dominant bank MPL is also consistent with the decline observed in data. More specifically, Table 1 shows that, in the data, the dominant bank MPL declines from 95% to 46% (the interaction coefficient on the dominant bank dummy is negative but not significant). We can use (35) to understand the decline in dominant bank MPL. Specifically, as dominant bank loan market concentration rises Post-Dodd Frank, the impact of lending on loan rates in (b) of (35) becomes more important, raising the cost of making loans (substituting into less risky securities) which slackens the funding constraint in more states of the world.

Table 6: Model-based MPL regressions

Coefficient	Pre Riegle-Neal	Transition	Post Dodd-Frank
(intercept)	8.98e-8	4.25e-6	-2.28e-6
	(2.04e-6)	(1.09e-6)	(8.99e-7)
β	0.439	0.487	0.423
	(0.032)	(0.039)	(0.007)
$\beta \times 1_D$	0.512	-0.305	-0.318
	(0.494)	(0.403)	(0.137)
N	21964	18167	13149
R^2	0.556	0.065	0.047

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 15% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$. Standard errors are in parenthesis.

8.3 Granular Regressions

We also use our model to study how an idiosyncratic shock to the dominant bank can generate nontrivial aggregate fluctuations. We construct the *granular residual* as $\Gamma_t^{\hat{D}_d} = [L_{d,t-1}/(L_{d,t-1} + \Gamma L_{f,t-1})]\epsilon_{dt}$. We then estimate how much aggregate fluctuations in credit can be explained by $\Gamma_t^{\hat{D}_d}$. To do so, we start by regressing bank lending growth on $\Gamma_t^{\hat{D}_d}$ and its lags. We then run similar regressions for total credit. We run these regressions under different regulatory regimes to understand how regulation affects the explanatory power of granular residuals. We use the same sequence of shocks for all regressions. Tables 7 and 8 present the results.

Table 7: Model-based granular regressions (Bank Lending)

Coefficient	Pre Riegle-Neal	Transition	Post Dodd-Frank
(intercept)	-0.0011	-0.0079	-0.0272
$\Gamma_t^{\hat{D}_d}$	2.186	0.0694	1.839
# obs	90,000	90,000	90,000
R^2	0.476	0.143	0.102

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 15% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$. # obs refers to number of observations, 9 model period sequences repeated 10,000 times.

Table 8: Model-based granular regressions (Total Lending)

Coefficient	Pre Riegle-Neal	Transition	Post Dodd-Frank
(intercept)	-0.0	-0.0020	-0.0077
$\Gamma_t^{\hat{D}_d}$	0.2305	-0.0154	0.4897
# obs	90,000	90,000	90,000
R^2	0.255	0.054	0.093

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 15% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$. # obs refers to number of observations, 9 model period sequences repeated 10,000 times.

As in the data, we find that how granular dominant banks are (i.e., what portion of aggregate fluctuations can be explain by dominant bank shocks as measured by the R^2) declines between the Pre Reagle Neal and the Post Dodd Frank period. There are two important forces at play. As dominant banks increase their market share in the loan market, everything else equal, a shock to a dominant bank can explain a larger fraction of fluctuations in bank lending. It is easy to see this in the case of a monopoly where bank credit and dominant bank loans coincide. However, the results in Table 6 show that there is a decline in the MPL for dominant banks between the two periods. That is, the fraction of funds that dominant banks are willing to lend out of unexpected deposit shocks declines between the Pre Reagle Neal period and the Post Dodd Frank period. Then, it is possible that dominant banks become less granular. The results in Tables 7 and 8 are consistent with the effect of a reduction in dominant banks MPL dominating the increase in loan market share. The results in the data also aligns with this view.

It is not surprising that we find higher R^2s in the model based approach than in the data. Not only there are other relevant banks in the middle of the distribution that could affect the level of granularity of the Top 4 banks in the data but also other factors that are present in the data and not in the model such as for example fluctuations in the stance of monetary policy.

8.4 Allocative Efficiency

One potential benefit of mergers is that mergers can reallocate resources from high cost banks to low cost banks. In order to assess these benefits, we measure allocative efficiency in both the data and model. We use the following decomposition of weighted average bank-level net marginal cost, along the lines of the measure of allocative efficiency proposed by Olley and Pakes (1996b),

$$\hat{c} \equiv \sum_{i \in \{D,F\}} C_i'(L_i)\omega(L_i) = \bar{c} + Cov(C_i'(L_i), \omega(L_i)), \tag{36}$$

where $\omega(L_i)$ is the loan market share of bank i. The loan weighted net marginal cost $\hat{c}$ can be decomposed into two terms: the un-weighted average of net marginal cost $\bar{c}$ and a covariance term between loan shares and net marginal cost. A more negative value for the covariance term captures an improvement in allocative efficiency as a larger share of loans are provided by banks with lower costs. Recall that our evidence points to increasing returns to scale (as shown in Table 9 below), so a shift towards dominant banks might induce a decline in the average marginal cost in the industry.

Table 9: Cost Structure (Data Pre and Post)

	Pre-reform 1984 - 1993			Post-reform 2011 - 2019		
	All Banks	Top 4	Fringe	All Banks	Top 4	Fringe
Net Mg Expenses %	1.78	1.16	1.89	1.19	0.92	1.45
Fixed Cost / Loans %	0.86	0.90	0.85	0.58	0.60	0.56
Avg Total Mg Cost %	2.64	2.05	2.74	1.77	1.53	2.01

Note: Net Mg Expenses refers to Marginal Net Expenses and are estimated using a trans-log cost function on Total Non-Interest Expenses and Total Non-Interest Income (see Corbae and D'Erasmo (2025) for a detailed explanation of the construction of these estimates). Source: Call Reports

Table 10 presents the comparison between the results in the data and the model.In both data and model, we find evidence for improved allocative efficiency following Riegle-Neal as measured by an increase in (the absolute value of) the covariance of c and ω. The measure becomes more negative in the post-Dodd-Frank setting as mergers reallocate lending from relatively high cost fringe banks to the lower cost dominant bank. Following a merger, both $C_d'(L_d)$ and $C_f'(L_f)$ increase because both have increasing marginal costs and both types of banks weakly increase lending. This causes an increase in $\bar{c}$. However, because $C_d'(L_d) < C_f'(L_f)$, after a merger share of lending by high marginal cost fringe firms decreases and the share of lending by the low marginal cost dominant bank increases. This leads a slight decline in average loan weighted cost. As a result, we find an improvement in allocative efficiency. In the model, improved allocative efficiency comes at the cost of a substantial reduction in overall bank lending due to growing dominant bank market power.

Table 10: Allocative Efficiency Data vs Model

	Data		Model	
Moment	Pre Riegle-Neal	Post Dodd-Frank	Pre Riegle-Neal	Post Dodd-Frank
Avg (loan-weighted) mg net exp. $\hat{c}$	0.0178	0.0119	0.0152	0.0139
Avg mg net exp $\bar{c}$	0.0244	0.0198	0.0170	0.0176
$Cov(C_i'(L_i), \omega_i)$	-0.0065	-0.0079	-0.0017	-0.0037
Total Bank Loans $(L_d + \Gamma L_f)$			0.864	0.758

Note: Marginal Net Expenses in the data are estimated using a trans-log cost function on Total Non-Interest Expenses and Total Non-Interest Income (see Corbae and D'Erasmo (2025) for a detailed explanation of the construction of these estimates). Model net marginal expenses correspond to $C_i'(L_i)$.

9 Policy Counterfactuals

9.1 What if Riegle-Neal never happened?

We can use our model as a laboratory to run counterfactuals. One interesting counterfactual is, what would have happened to competition, market efficiency, and stability if Riegle-Neal was never implemented? In our first two experiments, we present the moments from the transition period following the implementation of the Reagle Neal Act (denoted "Post RN, short-run" for short run moments Post Riegle-Neal) and moments from the most recent period if we would have observed only changes to merger regulation (denoted Post RN long-run). The only change we introduce to the parameterization of the baseline model in these experiments is a change in the function H that goes from $H(\Gamma, s) = \infty$ to the bottom portion in equation (8). These experiments allow us to discuss the short-run and long-run effects of Riagle Neal. Table 11 presents the results.

Comparing the "Pre" to the "Post RN" short-run and "Post RN" long-run columns, we can directly measure the effects of the post-Riegle-Neal merger wave (short run and long-run). The model is consistent with a merger wave as the merger rate increases to 2% in the short-run and declines to 0.02% in the long-run. The dominant bank's market share grows from 13.9% to 35.6% (42.3%) in the deposit market and from 17.3% to 32.5% (35.4%) in the loan market in the short-run (long-run). The increase in concentration leads to an increase in loan interest rates of 8bp (16bp). This increase in loan interest rates reduces bank participation in total lending as the share of bank lending declines to 41.2% (40.3%). Thus mergers themselves can explain some (albeit small) of the lost credit market share of banks to non-banks. The increase in bank concentration, while costly for borrowers as interest rates and markups increase, improves financial stability as the fringe failure rate declines from 1.23% to 1.09% (1.15%). The increase in markups is also reflected in an increase in Tobin's Q for both fringe and dominant banks.

Table 11: Model With Mergers vs Model With Merger Restriction (Short- and Long-Run)

Moment	Pre	Post RN short-run	Post RN long-run
Initial Γ	2500.00	2500.00	1645.34
Initial D_d	0.15	0.15	0.46
Deposit Share Top 4	13.90%	35.62%	42.34%
Loan Share Top 4	17.25%	32.54%	35.42%
Bank Lending Share	42.05%	41.18%	40.33%
Interest Rate	4.73%	4.81%	4.89%
Loans/Deposits Top 4	99.28%	69.24%	63.58%
Loans/Deposits Fringe	77.62%	81.01%	85.65%
Fringe Failure Rate	1.23%	1.09%	1.15%
Merger Rate	0.00%	2.21%	0.02%
Loan Markup Top 4	4.43	4.51	4.60
Loan Markup Fringe	1.49	1.47	1.43
Tobin's Q Top 4	1.00	15.32	14.97
Tobin's Q Fringe	0.61	0.91	0.98
Tobin's Q Bank Sector	0.70	13.21	13.06

Note: Model "Pre" constrains the dominant bank from merging. Model "Post RN short-run" removes the pre–Riegle-Neal merger restriction and computes the values along the transition path. "Post RN long-run" presents the values in the long-run.

We also perform a set of counterfactual experiments to decompose the overall change from Pre Riegle-Neal to Post Dodd-Frank which includes not only changes to merger policy but also to bank fixed costs and nonbank marginal costs. More specifically, in our third experiment (denoted "Post Reg ($\downarrow H, \uparrow \kappa_i$)") we relax merger restrictions and increase banks' operating costs to reflect rising fixed costs in the data associated with the Dodd-Frank Act. In our fourth experiment (denoted "Post Tech ($\downarrow H, \downarrow c_N$)") we study the relaxation of merger restrictions together with a decline in marginal costs for nonbanks which can be thought of as technological innovation as a partial explanation for rising nonbank market share in the data. Results from these experiments are presented in Table A.18 in Appendix A-5.1 presents the results. The final column in Table A.18 ("post DF ($\downarrow H, \uparrow \kappa_i, \downarrow c_N$)") presents the Post Dodd-Frank equilibrium which corresponds to the relaxation of merger restrictions together with changes in banks' and nonbanks' costs (the moments align with those presented in Table 4).

By comparing "Post (Reg)" to "Post RN, long-run" we find that increased fixed costs for banks associated with Dodd-Frank regulations have little effect on the interest rates, markups, or other measures of competition. While the level of fixed costs increase, the ratio of fixed costs over loans decline for both dominant and fringe banks (see Tables 4 and 5). This change in average profitability results in a small decline in failure rate for fringe. Column "Post (Tech)" shows that technological improvements associated with nonbank competition led to a substantial reduction in the bank lending share, from 40% to 36%. The competitive preasure from the nonbank sector leads to lower interest rates on bank loans (from 4.89% to 4.82%), and lower lending by both the dominant and fringe bank which shift their balance sheet towards securities. This shift in the balance sheet composition is not enough to compensate for the decline in loan profitability and the failure rate increases to 1.24%. Finally, comparing the "Post RN, long-run" to the "Post DF" column allows us to evaluate the total effect of both Dodd-Frank regulations and technological improvements. We find that the interest rate declines from 4.89% to 4.85% and the failure rate of fringe bank rises to 1.53%. The value of the banking sector declines, but remains well above pre-Riegle-Neal levels.

In sum, our results illustrate the costs and benefits of Riegle-Neal. Following the Riegle-Neal induced merger wave, bank profitability rose and financial stability improved. This came at the cost of higher interest margins and higher markups for borrowers. However, both the costs and benefits were mitigated by improved competition from the nonbank sector.

9.2 Monetary Policy and Bank Mergers

In order to understand the effectiveness of monetary policy under different regulatory regimes, as well as how monetary policy can affect the market structure of the banking industry, we conduct monetary policy counterfactuals in both the pre-Riegle-Neal and post-Dodd-Frank settings to study how endogenous changes in market structure can affect the effectiveness of monetary policy. We let monetary policy affect r^D, the deposit rate and r^A, the return on securities. In our first experiment, we increase r_A and r^D by 25 basis points for two periods.[34] The results are presented in Table 12.

Table 12: Monetary Policy Counterfactual:

Moment	Pre-Riegle-Neal	Post-Dodd-Frank
Total Loans by Dominant Bank	0.00%	-0.40%
Total Loans by Fringe Banks	-0.40%	-0.19%
Total Bank Loans	-0.29%	-0.26%
Total Loans by Nonbanks	-0.38%	-0.34%
Total Loans	-0.34%	-0.31%
Share of Deposits Lent Top 4	0.00%	-0.38%
Share of Deposits Lent Fringe	-0.53%	-0.35%
Interest Rate	+5.0bp	+4.7bp
Net Interest Margin	-0.2bp	-0.3bp
Number of Fringe Banks	-0.10%	+0.15%
Merger Rate	0.00%	+0.36%
Failure Rate (Fringe)	-6.86%	-3.77%

Note: This table reports percent deviations from the baseline "Pre-Riegle-Neal" and "Post-Dodd-Frank" steady state, except interest rates and net interest margins which are reported in basis points. Here we increase both r^D and r_A by 25 basis points for two periods.

We find that monetary policy is slightly more effective in the pre-Riegle-Neal environment, as interest rates increase more and total lending declines more. This is due to a substantial

[34] The length of the increase in the monetary policy rate is consistent with the length of the past 5 monetary policy tightening cycles in the US that lasted between 1 to 3 years (Ferroni, Fisher, and Melosi (2023)).

reduction in fringe lending as well as a more substantial decline in nonbank lending. However, due to the higher dominant bank MPL in the pre-Riegle-Neal period, dominant lending is more responsive to monetary policy in the post-Dodd-Frank period. We also note that bank failure is more sensitive to monetary policy pre-Riegle-Neal.

In our second experiment, we permanently increase r_A by 15 basis points and r^D by 10 basis points. This aligns with the incomplete pass-through of Drechsler, Savov, and Schnabl (2017). The results are presented in Table A.19 in Appendix A-5.2. We observe that a permanent monetary policy contraction has a more significant effect on the share of deposits lent after the consolidation of the banking industry (in our model driven by the relaxation of merger restrictions and the technological advance of nonbanks).

10 Conclusion

In this paper, we study the effect of Riegle-Neal on banking mergers. We provide a model laboratory consistent with the ensuing large merger wave and, in the framework of Gabaix (2011), can contribute to spillovers by which idiosyncratic shocks to dominant (atomistic) banks can have substantial aggregate effects. Given that most bank mergers are done by acquirers that are substantially larger than their targets, we believe a dominant-fringe model suitably extended to capture essential elements of the banking sector is appropriate to study the effects of Riegle-Neal.

The calibrated model allows us to perform counterfactuals to assess the effects of Riegle-Neal and increased nonbank competition on financial stability, bank profitability, and borrower surplus. We also show that changes in market structure can influence the effectiveness of monetary policy. Our quantitative laboratory can provide regulators with a tool to set optimal merger policy which trades off possible market inefficiency, misallocation of capital, and financial instability that might arise as a result of merger activity. Since mergers are endogenous outcomes of the economic environment, it avoids the Lucas critique associated with reduced form empirical approaches.

One important counterfactual left as future work is to assess optimal dynamic regulatory merger policy along the lines of Nocke and Whinston (2010)? That is, what should $H(\Gamma, s)$ be to maximize market efficiency and minimize financial instability? Given our dynamic model, we can consider whether regulators should consider how mergers today affect the market structure not just tomorrow, but well into the future. The results in Pakes, Whinston, and Zheng (2024) show that consumer (household and firm) welfare fell significantly, economically and statistically, in single-merger counties compared to no-merger counties. Our model has the potential to quantify the optimal level of mergers by incorporating allocative efficiency and financial stability in addition to measures of consumer/borrower welfare. The model will also afford us with a tool to access the regulatory costs across different $H(\Gamma, s)$.

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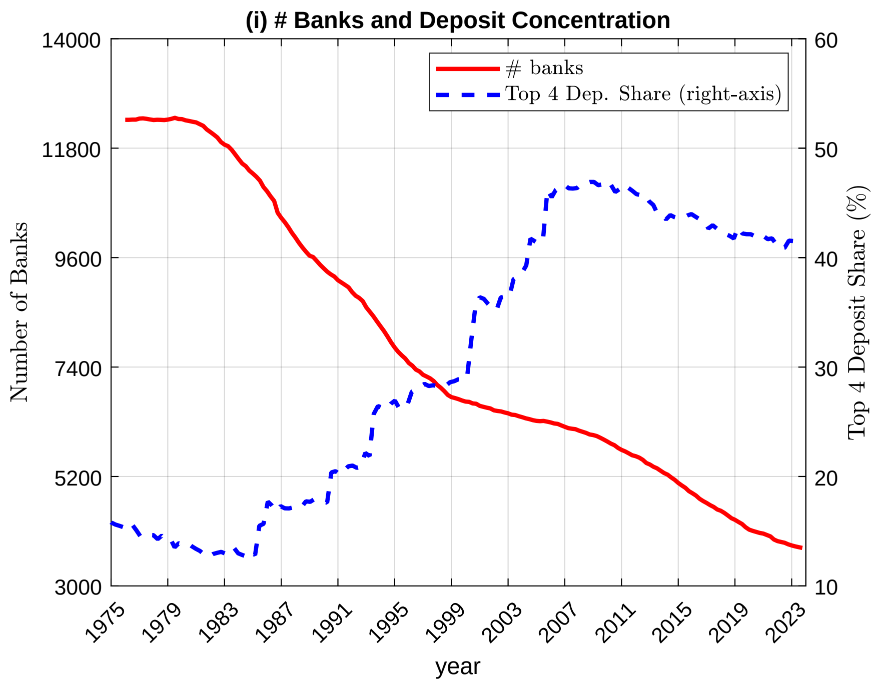
A-1 Appendix

A-1.1 Concentration 1976-2024

Figure A.1 shows that the decline in the number of banks starts around 1981, not a lot earlier than shown in Figure 1 in the main text. We present the figure in the main text from 1984-2024 for consistency with other panels for which data is not available before 1984.

Figure A.1: Concentration (1976 - 2023)



Note: # of banks refers to number of commercial banks in the US (aggregated to the top holding company). Top 4 Dep Share refers to the share of total deposits accounted by the Top 4 banks (when sorted by deposits). Source: Call Reports and Summary of Deposits.

A-1.2 Pricing of Loans and Deposits by Bank Size

Table A.1 describes the structure of asset returns and funding costs across the bank size distribution.[35]

[35] Following the notation of the model we present, the charge off rate corresponds to $(1-\theta')\lambda'$ where $(1-\theta')$ is the default probability and λ' the recovery in default as it is estimated as the charge-off on loans net of recoveries over total loans. Our estimate of the default probability $(1-\theta)$ is found by taking the ratio of loans past due 90 days plus non-accrual loans over total loans. The cost of deposits (denoted as r_D in the model) is estimated as the ratio of interest expenses on deposits over total deposits. The loan interest rate is computed by taking the ratio of interest income from loans over loans and dividing by one minus the default frequency. The loan markup is computed as in Corbae and D'Erasmo (2021).

Table A.1: Loan Interest Rates, Deposit Costs, and Markup by bank size (1984-2019)

	All Banks		Top 4		Fringe (No Top 4)	
Moment	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Charge-off Rate %	0.86	0.91	1.10†	0.94	0.63	0.81
Default freq. %	2.15	1.98	2.63†	2.07	1.72	1.79
Cost Deposits %	0.11	1.63	-0.24	1.62	0.39	1.58
Loan Interest Rate %	4.90	2.05	4.52	2.04	5.22	2.01
Return Securities %	1.58	9.96	1.72	11.90	1.44	7.45
Loan markup %	98.23	79.52	138.52†	105.51	85.87	64.85

Note: Loan interest income as well interest expenses on deposits are deflated using the CPI. All estimates correspond to annualized values (computed using quarterly data). Top 4 Banks refers to the Top 4 banks when sorted by assets. Fringe Banks refers to all banks outside the top 4. † denotes statistically significant difference (at 1% level) between the average for Top 4 banks and the average of fringe banks. To test for statistical significance we regress the corresponding variable of a dummy that takes value equal to 1 if the value corresponds to a bank in the Top 4 and 0 otherwise. Data correspond to commercial banks in the U.S. between 1984 and 2019. Source: Consolidated Reports of Condition and Income

A-1.3 Other Moments

Table A.2: Moments Data

	Pre-reform 1984 - 1993			Post-reform 2011 - 2019		
	All Banks	Top 4	Fringe	All Banks	Top 4	Fringe
Cost Deposits %	1.57	1.94	1.46	-1.31	-1.37	-1.22
Return on Securities %	0.79	0.33	0.99	0.87	0.67	1.44
Default freq. %	3.10	4.64	2.49	2.48	3.03	1.65
Charge-off Rate %	0.96	1.22	0.86	0.94	1.18	0.55
Loan Loss Rate %	31.42	28.66	32.63	31.04	34.36	25.75
Std Dev Loan Loss Rate %	18.59	15.41	19.72	21.04	21.21	19.71
Net Mg Expenses %	1.78	1.16	1.89	1.19	0.92	1.45
Elasticity Net Mg Expenses	0.83	0.97	0.80	0.95	1.05	0.87
Fixed Cost / Loans %	0.86	0.90	0.85	0.58	0.60	0.56
Avg. Equity Issuance / Assets %	0.11	0.07	0.13	0.03	0.01	0.04
Avg. Dividends / Assets %	0.38	0.36	0.39	0.71	0.74	0.66
Interest Rate % r_B^L	6.69	6.98	6.58	3.18	3.27	3.03
Interest spread % $(r_B^L - r_D)$	5.25	5.24	5.25	4.50	4.67	4.22
Interest margin % $(\theta r_B^L - r_D)$	4.94	4.77	5.00	4.35	4.50	4.11
Loan markups % $\frac{\theta r_B^L}{r_D + c_i'(L_i)}$	49.08	56.17	47.82	178.48	221.46	152.57

Note: Data Pre corresponds to the period 1984 - 1993 and Data Post to the period 2011 to 2019. All moments reported correspond to asset weighted averages. Source: Call Reports

Table A.3: Moments Data (cont.)

	Pre-reform 1984 - 1993	Post-reform 2010 - 2019
Number of Fringe Banks (National)	9,962	5,030
Deposit HHI (national)	93.90	538.74
Number Top 4 Banks (state)	0.627	2.310
Number Fringe Banks (state)	168.510	116.965
Deposit HHI (state)	1019.39	1584.59
Number Top 4 Banks (county)	0.203	0.646
Number Fringe Banks (county)	5.660	6.899
Deposit HHI (county)	2191.70	2606.58
Deposit Market Share Top 4	14.395	44.76
Loan Market Share Top 4	17.0436	41.46
Relative Size Top 4 / Fringe (Deposits)	415.80	998.31
Relative Size Top 4 / Fringe (Loans)	505.23	863.38
Bank Entry (denovo) rate	5.00	1.25
Bank Failure Rate	0.76	0.29
Bank Failure Rate Top 4	0.00	0.00
Bank Failure Rate Fringe	0.76	0.29
Bank Merger Rate	1.27	2.89
Deposit to Output Ratio	39.01	57.19
Bank Loans to Output Ratio[#]	32.46	43.721
Bank Loans to Output Ratio[†]	43.15	60.22
Bank Loans to Output Ratio[‡]	51.77	50.525
Bank Loans to Total Loans Ratio[*]	44.54	33.28

Note: Data Pre corresponds to the period 1984 - 1993 and Data Post to the period 2010 to 2019. [#] Loans and Leases in Bank Credit (All Commercial Banks) [†] Bank Credit, All Commercial Banks [‡] Credit to Private Non Financial Sector by Banks [*] Credit to Private Non-Financial Sector by Banks / Total Credit to Private Non-Financial Sector

Table A.4: Moments Data

		Pre-reform 1984-1993			Post-reform 2011-2019		
Ratio to Assets (%)		All Banks	Top 4	Fringe	All Banks	Top 4	Fringe
Securities	$A_i/(A_i + L_i + K_i)$	32.84	24.87	34.38	34.93	38.72	31.61
Loans	$L_i/(A_i + L_i + K_i)$	60.61	69.10	58.98	53.79	50.07	57.05
Fixed and Other Assets	$K_i/(A_i + L_i + K_i)$	6.57	5.70	6.74	11.20	10.64	11.69
Deposits	$D_i/(A_i + L_i + K_i)$	93.42	94.30	93.26	88.73	89.33	88.21
Equity	$E_i/(A_i + L_i + K_i)$	6.57	5.70	6.74	11.20	10.64	11.69
Loans to Deposits	L_i/D_i	64.79	73.29	63.16	60.76	56.11	64.83

Note: Data Pre corresponds to the period 1984 - 1993 and Data Post to the period 2011 to 2019. All moments reported correspond to asset weighted averages. Source: Call Reports

A-1.4 Deposit Process

Table A.5: Deposit Process

	ρ_i^d	$\sigma_{i,u}$	$\sigma_{i,d}$	$Pr(\epsilon < -std)$
i	Full Sample 1984 - 2019			
Top 4 Banks	0.618	0.118	0.150	0.100
Fringe Banks	0.805	0.167	0.281	0.097
All Banks	0.806	0.167	0.281	0.097
i	Pre 1984 - 1993			
Top 4 Banks	0.512	0.127	0.148	0.125
Fringe Banks	0.538	0.153	0.182	0.081
All Banks	0.538	0.153	0.182	0.081
i	Post 2011 - 2019			
Top 4 Banks	0.638	0.034	0.044	0.278
Fringe Banks	0.669	0.116	0.156	0.085
All Banks	0.669	0.116	0.156	0.085

A-2 Bank Granularity

Table A.6 presents the results when aggregate fluctuations are measured using total bank lending growth for the period 1984-2019. We let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1}\sum_{t=1}^{T} g_{it} + N^{-1}\sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}}(g_{it} - \overline{g}_t)$. We find that R^2 are relatively high with dominant bank idiosyncratic shocks explaining between 10% and 23% of aggregate bank lending growth. Changes in the predicted power of idiosyncratic shocks appear to increase at when we move from Top 4 to Top 35 and from Top 35 to Top 100.

Table A.6: Explanatory power of granular residuals of dominant banks on aggregate lending (R^2)

	Dep. Var. $\Delta\log(L_t)$					
	Top 4 banks		Top 35 banks		Top 100 banks	
Γ_t^x	0.513***	0.512***	0.413***	0.418***	0.429***	0.432***
	(0.140)	(0.141)	(0.0890)	(0.0892)	(0.0811)	(0.0810)
Γ_{t-1}^x	0.201	0.201	-0.0618	-0.0674	-0.0576	-0.0628
	(0.141)	(0.141)	(0.0890)	(0.0893)	(0.0811)	(0.0811)
Γ_{t-2}^x		-0.0139		0.0811		0.103
		(0.142)		(0.0892)		(0.0810)
(intercept)	0.0084***	0.0083***	0.0084***	0.0086***	0.0085***	0.0089***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	144	144	144	144	144	144
R^2	0.100	0.100	0.133	0.138	0.166	0.176
Adjusted R^2	0.087	0.080	0.121	0.120	0.155	0.158

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta\log(L_t)$" refers to growth rate of total real bank loans. Top 4 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 4$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1}\sum_{t=1}^{T} g_{it} + N^{-1}\sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}}(g_{it} - \overline{g}_i - \overline{g}_t)$. Period 1984-2019. Source: Call Reports

Table A.7 presents the results when x_{it} corresponds to real deposits and aggregate fluctuations are measured using the growth of real total credit to the private non-financial sector.[36] We find that the R^2 declines compared to those presented in Table A.6. In particular, we find that granular bank idiosyncratic shocks explain up to 2.4% of the fluctuations in aggregate credit.[37]

[36] We use data from the Federal Reserve Bank of St. Louis "Total Credit to Private Non-Financial Sector, Adjusted for Breaks, for United States (QUSPAMUSDA)" (see here.)

[37] Results are similar when using the total credit to the non-financial sector normalized by GDP.

Table A.7: Explanatory power of granular residuals of dominant banks on aggregate credit (R^2)

	Dep. Var. $\Delta \log(totcredit_t)$					
	Top 4 banks		Top 35 banks		Top 100 banks	
Γ^x_t	0.0732	0.0787	0.0732	0.0727	0.0981	0.0983
	(0.104)	(0.105)	(0.0677)	(0.0680)	(0.0626)	(0.0628)
Γ^x_{t-1}	0.165	0.163	-0.00482	-0.00415	-0.0131	-0.0135
	(0.104)	(0.104)	(0.0677)	(0.0681)	(0.0626)	(0.0629)
Γ^x_{t-2}		0.0695		-0.00968		0.00851
		(0.105)		(0.0680)		(0.0628)
(intercept)	0.00889***	0.00899***	0.00877***	0.00874***	0.00884***	0.00886***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	144	144	144	144	144	144
R^2	0.021	0.024	0.008	0.008	0.017	0.017

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta \log(totcredit_t)$" refers to growth rate of real total credit to private non-financial sector. Top 4 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 4$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1}\sum_{t=1}^{T} g_{it} + N^{-1}\sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}}(g_{it} - \overline{g}_i - \overline{g}_t)$. Period 1984-2019. Source: Call Reports

Table A.8 extends the results in Table A.7 to incorporate not only the full sample (1984-2019) but also the decomposition across periods: pre-reform (1984-1993), transition (1994-2017), post-GFC (2011-2019) for the case of the Top 4 banks (i.e., $K = 4$). Granular residuals explain up to 14% of aggregate credit pre-reform which is consistent with higher participation of banks in total credit during that time than in the most recent periods.

Table A.8: Explanatory power of granular residuals on aggregate credit - Top 4 (All Periods)

	Top 4 Banks - Dep. Var. $\Delta\log(totcredit)$			
	Full Period 1984-2019	Pre-reform 1984-1993	Transition 1994-2007	Post-GFC 2011-2019
Γ_t^x	0.0787	-0.823**	0.0572	-0.317
	(0.105)	(0.403)	(0.0845)	(0.217)
Γ_{t-1}^x	0.163	-0.258	-0.0102	-0.190
	(0.104)	(0.398)	(0.0864)	(0.217)
Γ_{t-2}^x	0.0695	-0.764*	0.0214	-0.123
	(0.105)	(0.405)	(0.0873)	(0.218)
(intercept)	0.00899***	0.00822***	0.0133***	0.00242
	(0.000844)	(0.00197)	(0.000796)	(0.00143)
N	144	40	56	36
R^2	0.024	0.144	0.011	0.094

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta\log(totcredit_t)$" refers to growth rate of real total credit to private non-financial sector. Top 4 Banks correspond to the cases when $K = 4$. Source: Call Reports

Table A.9 presents the results when aggregate fluctuations are measured using the growth of real gdp. We find that R^2 are of similar magnitude and still significant with dominant bank idiosyncratic shocks explaining up to 8.5% of fluctuations in log real gdp.[38]

[38] Table A.9 in the Appendix shows that result also hold when using the growth rate of detrended GDP as the dependent variable.

Table A.9: Explanatory power of granular residuals of dominant banks on aggregate output (R^2)

	Dep. Var. $\Delta \log(gdp_t)$					
	Top 4 banks		Top 35 banks		Top 100 banks	
Γ_t^x	0.171***	0.181***	0.0455	0.0491	0.0528	0.0546
	(0.0602)	(0.0596)	(0.0397)	(0.0396)	(0.0369)	(0.0367)
Γ_{t-1}^x	0.00734	0.00510	-0.0277	-0.0322	-0.0153	-0.0183
	(0.0602)	(0.0595)	(0.0398)	(0.0396)	(0.0369)	(0.0367)
Γ_{t-2}^x		0.130**		0.0638		0.0593
		(0.0597)		(0.0396)		(0.0367)
(intercept)	0.00703***	0.00721***	0.00684***	0.00702***	0.00690***	0.00708***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	144	144	144	144	144	144
R^2	0.054	0.085	0.012	0.030	0.015	0.033

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta \log(gdp_t)$" refers to growth rate of real gdp. Top 4 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 4$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1}\sum_{t=1}^{T} g_{it} + N^{-1}\sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}}(g_{it} - \overline{g}_i - \overline{g}_t)$. Period 1984-2019. Source: Call Reports

Table A.10 extends the results in Table A.9 to incorporate not only the full sample (1984-2019) but also the decomposition across periods: pre-reform (1984-1993), transition (1994-2017), post-GFC (2011-2019) for the case of the Top 4 banks (i.e., $K = 4$). Granular residuals explain up to 11% of aggregate output (transition period).

Table A.10: Explanatory power of granular residuals on aggregate output - Top 4 (All Periods)

	Top 4 Banks - Dep. Var. $\Delta\log(gdp_t)$			
	Full Period 1984-2019	Pre-reform 1984-1993	Transition 1994-2007	Post-GFC 2011-2019
Γ_t^x	0.181***	0.142	0.137**	0.0822
	(0.0596)	(0.205)	(0.0661)	(0.141)
Γ_{t-1}^x	0.00510	0.118	0.0337	-0.139
	(0.0595)	(0.203)	(0.0676)	(0.141)
Γ_{t-2}^x	0.130**	0.132	0.0719	0.0639
	(0.0597)	(0.206)	(0.0683)	(0.141)
(intercept)	0.00721***	0.00837***	0.00794***	0.00589***
	(0.000481)	(0.00100)	(0.000623)	(0.000933)
N	144	40	56	36
R^2	0.085	0.023	0.107	0.045

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. "$\Delta\log(totcredit_t)$" refers to growth rate of real total credit to private non-financial sector. Top 4 Banks correspond to the cases when $K = 4$. Source: Call Reports

In sum, we find evidence for a granular view (in the language of Gabaix (2011)) of how idiosyncratic shocks to bank deposit flows of the largest U.S. banks spill over to the aggregate economy via changes in credit. Specifically, in table A.6 we document that idiosyncratic shocks to top 4 and top 35 bank deposits can explain 10% and 18% of aggregate bank lending growth (measured via R^2), respectively. Finally, in table A.9 we document that granular shocks to systemically important banks (i.e. the top 35) explain up to 3.4% of the growth of real GDP.

Table A.11 presents the results when x_{it} corresponds to real deposits and aggregate fluctuations are measured using the growth of detrended real gdp. We find that R^2 are smaller but still significant with granular bank idiosyncratic shocks explaining upt to 5% of cyclical fluctuations in detrended real gdp.

Table A.11: Explanatory power of granular residuals of dominant banks on aggregate output (R^2)

	Dep. Var. $\Delta \log(det\ gdp_t)$					
	Top 4 banks		Top 35 banks		Top 100 banks	
Γ_t^x	0.145***	0.153***	0.0384	0.0413	0.0431	0.0444
	(0.0530)	(0.0527)	(0.0349)	(0.0348)	(0.0324)	(0.0323)
Γ_{t-1}^x	-0.0187	-0.0205	-0.0378	-0.0413	-0.0274	-0.0297
	(0.0531)	(0.0526)	(0.0349)	(0.0348)	(0.0324)	(0.0324)
Γ_{t-2}^x		0.101*		0.0516		0.0453
		(0.0528)		(0.0348)		(0.0323)
(intercept)	0.0003	0.0005	0.0002	0.0003	0.0002	0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	144	144	144	144	144	144
R^2	0.051	0.075	0.016	0.031	0.017	0.030
Adjusted R^2	0.037	0.055	0.002	0.010	0.003	0.009

Note: Table presents the R^2 from a regression of the corresponding dependent variable on Γ_t^x, Γ_{t-1}^x, and Γ_{t-2}^x when x is real deposits. "$\Delta \log(det\ gdp_t)$" refers to growth rate of detrended real gdp.Top 4 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 4$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_i + \overline{g}_t = T^{-1} \sum_{t=1}^{T} g_{it} + N^{-1} \sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} (g_{it} - \overline{g}_i - \overline{g}_t)$. Period 1984-2019. Source: Call Reports

A-2.1 The Marginal Propensity to Lend: Additional Tests

We explore further the determinants of the Marginal Propensity to Lend (MPL). We evaluate the link between bank liquidity and the MPL. We estimate a version of equation (3) by adding an interaction term between the liquid assets to total assets ratio and the unexpected shock to deposits: $\nu_{it} \times (Liq/Assets)_{it-1}$.[39] We note that the average ratio of liquid assets to total assets between 1984-2019 for the Top 4 banks and fringe banks is 17.88% and 24.30%, respectively. The results for the MPL estimation are presented in Table A.12. Consistent with Corell (2025) we find that a higher ratio of liquid assets reduces the MPL. That is, lending by banks responds less to unexpected changes in deposit inflows for banks with a larger buffer of liquid assets. We find that this effect does not vary by bank size. Evaluated at average liquid assets, the MPL for small banks is 0.516 (0.564-0.198*0.243). The MPL for the Top 4 banks is 0.529 (0.564-0.198*0.178), not statistically significantly different thatn 0.516.

[39]Liquid assets correspond to cash plus safe securities where safe securities include US Treasury securities, Agency securities and State issued securities.

Table A.12: MPL (Data Estimates): The role of liquid assets

	Dependent Variable $\Delta\log(L_{it})$							
ν_{it}	0.564***	0.564***	0.534***	0.533***	0.524***	0.523***	0.647***	0.647***
	(0.00191)	(0.00191)	(0.00318)	(0.00318)	(0.00328)	(0.00328)	(0.00460)	(0.00460)
$\nu_{it}\times$(Liq / Assets)$_{it-1}$	-0.199***	-0.198***	-0.0504***	-0.0499***	-0.0861***	-0.0839***	-0.710***	-0.710***
	(0.00594)	(0.00594)	(0.00970)	(0.00970)	(0.01000)	(0.01000)	(0.0143)	(0.0143)
$\nu_{it}\times I_{t4}$		0.550***		0.496		0.468		-0.523
		(0.145)		(0.373)		(0.313)		(0.754)
$\nu_{it-1}\times I_{t4}\times$(Liq / Assets)$_{it-1}$		-0.694		-0.628		0.173		1.107
		(0.811)		(1.869)		(1.707)		(3.095)
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Period	1984-2019		1984-1993		1994-2007		2011-2019	
N	946,299	946,299	380,034	353,150	369,336	355,389	176,178	169,536
R-sq	0.363	0.363	0.425	0.398	0.453	0.416	0.297	0.298
adj. R-sq	0.349	0.349	0.401	0.371	0.435	0.397	0.272	0.271

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (1). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 2. We follow Gabaix (2011) and construct ν_{it} by removing bank and time fixed effects. (Liq/Assets)$_{it-1}$ refers to the ratio of liquid assets to total assets. $I_{t,k(i)=4}$ is an indicator that takes value 1 if bank i is in the Top 4 of the asset distribution. Bank controls includes log-assets, equity/assets, loans/assets, return on assets, salaries/assets, expenses on fixed assets/assets, cost of deposits. Source: Call Reports

Our model has direct implications for deposit and asset level concentration. We analyze the relationship between a measure of concentration at the bank level and the MPL. In particular, we collect yearly data from the Summary of Deposits between 1994 and 2019. This data provides information on deposits by bank at the branch level that we use to compute county level Herfindahl-Hirschman Index (HHI) for deposits. We take the deposit-weighted average for each bank to obtain an average measure of the level of concentration each bank faces (HHI_{it}).[40] We link this data back to our Call Report data to evaluate how the MPL changes with this bank level measure of concentration. Table A.13 presents the results. In line with the estimates presented in Corell (2025), we find that a higher level of concentration impacts negatively on the MPL.[41] Banks that on average operate in more concentrated markets respond less to unexpected flows of deposits. This is also consistent with the time series changes we observe as more the MPL declines between pre Reagle-Neal and post GFC.

[40] In particular, let HHI_{ct} denote the HHI in county c at time t. HHI_{it} is computed as the deposit weighted sum of HHI_{ct} across counties where bank i operates: $HHI_{it} = \sum_c I_{\{D_{ict}>0\}} \frac{D_{ict}}{D_{it}} HHI_{ct}$ where D_{ict} denotes deposits of bank i in county c.

[41] The average HHI for a bank in the Top 4 and for a bank not in the Top 4 is 2587.6 and 2330.5, respectively. The difference is not statistically significant.

Table A.13: HHI: Marginal Propensity to Lend (Data Estimates)

	Dependent Variable $\Delta\log(L_{it})$					
ν_{it}	0.545***	0.544***	0.547***	0.546***	0.531***	0.531***
	(0.00262)	(0.00262)	(0.00355)	(0.00355)	(0.00488)	(0.00488)
$\nu_{it} \times HHI_{it-1}$	-0.223***	-0.223***	-0.178***	-0.177***	-0.348***	-0.348***
	(0.00972)	(0.00972)	(0.0130)	(0.0130)	(0.0181)	(0.0181)
$\nu_{it} \times I_{t4}$		0.606**		0.345		-0.669
		(0.243)		(0.346)		(0.812)
$\nu_{it-1} \times I_{t4} \times HHI_{it-1}$		-0.543		0.737		1.576
		(1.077)		(1.625)		(2.634)
Bank FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Period	1994-2019		1994-2007		2011-2019	
N	574349	574349	344953	344953	161953	161953
R-sq	0.378	0.378	0.413	0.413	0.331	0.331
adj. R-sq	0.364	0.364	0.394	0.394	0.304	0.304

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (1). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 2. We follow Gabaix (2011) and construct ν_{it} by removing a time fixed effect. $I_{t,k(i)=4}$ is an indicator that takes value 1 if bank i is in the Top 4 of the asset distribution. Bank controls includes log-assets, equity/assets, loans/assets, return on assets, salaries/assets, expenses on fixed assets/assets, cost of deposits. Source: Call Reports

A-2.2 On the connection between granularity and MPL

This appendix discussses the connection between the MPL and our version of Gabaix's granularity results. Note that when it comes to bank credit, we estimate

$$\Delta L_t = \beta_\Gamma \Gamma_t + \epsilon_t^\Gamma. \tag{A.2.1}$$

where the *granular residual* is

$$\Gamma_t \equiv \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \nu_{i,t}$$

and the R^2 from the equation (A.2.1) is given by

$$R^2 = \frac{\beta_\Gamma^2 Var(\Gamma_t^d)}{Var(\Delta L_t)}. \tag{A.2.2}$$

where the *granular residual* is

$$\Gamma_t \equiv \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \nu_{i,t}$$

and the R^2 from the equation (A.2.1) is given by

$$R^2 = \frac{\beta_\Gamma^2 Var(\Gamma_t^d)}{Var(\Delta L_t)}. \quad \text{(A.2.3)}$$

To see the connection between the Gabaix's results and the MPL regressions, after multiplying both sides of equation (3) by ω_{it} and summing over i while assuming the weighted average growth rate of loans $\sum_{i=1}^N \omega_{it}\Delta L_{it} \equiv \sum_{i=1}^N \omega_{it}(\log(L_{it}) - \log(L_{it-1}))$ is a good approximation of the growth rate of aggregate loans $\Delta L_t \equiv \log(\sum_{i=1}^N L_{it}) - \log(\sum_{i=1}^N L_{it-1})$, equation (A.2.1) can be written

$$\Delta L_t \approx \sum_{i=1}^N \omega_{it}\Delta L_{it} = \beta_d \underbrace{\sum_{i=1}^K \omega_{it}\nu_{it}}_{\Gamma_t} + \underbrace{\beta_f \sum_{i=K+1}^N \omega_{it}\nu_{it} + \sum_{i=1}^N \omega_{it}(\beta_k \xi_k X_{it} + \zeta_{it})}_{=\epsilon_t^\Gamma} \quad \text{(A.2.4)}$$

which shows a relationship between the estimated MPL β_d and the estimated coefficient on the granular residual β_Γ. Clearly, if the MPL for dominant banks out of idiosyncratic deposit innovations was zero, Gabaix's R^2 would be zero. Further, (A.2.4) also makes clear that as the market share of granular banks $\sum_{i=1}^K \omega_{it} \leq 1$ increase, the fit of the model also increases. Clearly, if each of the K dominant banks were of measure zero, $\omega_{it} = 0$ so that again, Gabaix's R^2 would be zero.

Table A.14 provides estimates of (A.2.1) in the first column and (A.2.4) in the second column. The estimated coefficient β_d of the MPL regression (3) in Table 1 equals 0.510+0.449=0.959 for the period 1984-2019. The estimated coefficient from the last column of Table A.14 equals 0.951 with a standard error equal to 0.161, statistically not different than 0.959.[42] These estimates confirm that there is a close connection between β_d from a Gabaix type regression where the dependent variable is the weighted-average bank level loan growth and that of MPL regressions in (3).

[42] We note that given weights ω_{it} for $k(i) = d$ in Γ_t^d covary positively with those weights in ϵ_t^Γ in (A.2.4), $\beta_d = 0.951$ is an upward biased estimate of $\beta_d = 0.888$ in (3). This occurs because the model incorrectly attributes the effect of the omitted variable to the included independent variable, causing the estimated coefficient to be larger than its true value.

Table A.14: Granular Banks and the Marginal Propensity to Lend (Data Estimates)

	Dependent Variable	
	ΔL_t	$\sum_{i=1}^{N} \omega_{it} \Delta L_{it}$
Γ_t^d	0.517***	0.968***
	(0.141)	(0.170)
constant	0.0081***	0.0141***
	(0.001)	(0.001)
Period	1984-2019	1984-2019
N	144	144
R^2	0.087	0.185
Adjusted R^2	0.080	0.180

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Source: Call Reports.

The estimated coefficient from the Gabaix (2011) equation (A.2.1) equals $\beta_\Gamma = 0.517$, a downward biased estimate of the MPL of 0.959 in (3). To understand this downward bias we compute the group level innovation of the change in total deposits for the Top 4 banks and for banks not in the Top 4.[43] With these group-level innovations at hand, we compute the weighted residual as in Gabaix (2011) as follows: $\Gamma_t^d = (L_{dt-1}/L_{t-1})\nu_{dt}$ and $\Gamma_t^f = (L_{ft-1}/L_{t-1})\nu_{ft}$. We then compute the correlation for years 1984-2019 (outside the financial crisis) to find that they are highly negatively correlated (the correlation is -0.925). The economics behind this difference rests on a "deposit stealing argument". Dominant banks steal deposits from fringe banks whether through mergers or other types of competition. That would suggest that the weighted sum of dominant ν_{it} shocks for $k(i) = d$ in Γ_t^d is negatively correlated with the weighted sum of fringe ν_{it} shocks for $k(i) = f$ in ϵ_t^Γ having controlled for time, etc.

A-3 Model Balance Sheet

Here, we present the model-based balance sheet moments for the dominant bank and the fringe bank.

Pre D + E = 0.45 + 0.125 = 0.275 Loans = 0.15 Securities = 0.0

Post D + E 0.45 + 0.125 = 0.575 Loans = 0.2589 Securities = 0.1911

Pre Fringe D = 0.00039 E = 0.0000351 D + E = 0.0004251

Loans = 0.000302718 Securities = 0.000087282

Post Fringe Loans = 0.000321126 Securities = 0.000068874

[43] More specifically, we let $D_{d,t} = \sum_{i=1}^{K} D_{it}$ (Top 4 total deposits) and $D_{f,t} = \sum_{i=K+1}^{N} D_{it}$ (No Top 4 total deposits). We estimate $\Delta D_{k,t} = \log(D_{k,t}) - \log(D_{k,t-1}) = \xi_k \Delta X_{kt} + \nu_{kt}$ for $k \in \{d, f\}$ to obtain ν_d and ν_f. These group level innovations allow us to capture changes in the group level deposits which are missing in the panel regressions as banks that are acquired disappear from the sample after a merger.

Table A.15: Moments Model

		Pre-reform 1984-1993		Post-reform 2011-2019	
Ratio to Assets (%)		Top 4	Fringe	Top 4	Fringe
Securities	$A_i/(A_i + L_i + K_i)$	0.39	20.53	33.23	16.20
Loans	$L_i/(A_i + L_i + K_i)$	54.15	71.21	45.02	75.54
Deposits	$D_i/(A_i + L_i + K_i)$	54.54	91.00	78.26	91.00
Equity	$E_i/(A_i + L_i + K_i)$	45.45	9.00	21.74	9.00
Loans to Deposits	L_i/D_i	99.28	77.62	57.54	82.34

Note: Data Pre corresponds to the period 1984 - 1993 and Data Post to the period 2011 to 2019. All moments reported correspond to asset weighted averages. Source: Call Reports

A-4 Allocative Efficiency

Here, we present alternative measures of allocative efficiency using the model. Table A.16, presents results measuring cost as the cost of loan monitoring to lending, $(\frac{C_i(L_i)}{L_i})$. Table A.17 also includes fixed costs $(\frac{C_i(L_i)+\kappa_i}{L})$. Regardless of how we measure cost, we find an improvement in allocative efficiency.

Table A.16: Model Allocative Efficiency $\frac{c(L)}{L}$

Moment	Pre Riegle-Neal	Post Dodd-Frank
Avg. (loan-weighted) cost $\hat{c}$	0.0149	0.0132
Avg. cost $\bar{c}$	0.0166	0.0163
$Cov(c, \omega)$	-0.0017	-0.0032

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 15% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$.

Table A.17: Model Allocative Efficiency $\frac{c(L)+\kappa}{L}$

Moment	Pre Riegle-Neal	Post Dodd-Frank
Avg. (loan-weighted) cost $\hat{c}$	0.0357	0.0357
Avg. cost $\bar{c}$	0.0368	0.0377
$Cov(c, \omega)$	-0.0012	-0.0020

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 15% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$.

A-5 Counterfactuals

A-5.1 Decomposition Post-Dodd Frank

In this section, we present results from a set of counterfactual experiments to decompose the overall change from Pre Riegle-Neal to Post Dodd-Frank which includes not only changes to merger policy but also to bank fixed costs and nonbank marginal costs. More specifically, in our third experiment (denoted "Post Reg ($\downarrow H, \uparrow \kappa_i$)") we relax merger restrictions and increase banks' operating costs to reflect rising fixed costs in the data associated with the Dodd-Frank Act. In our fourth experiment (denoted "Post Tech ($\downarrow H, \downarrow c_N$)") we study the relaxation of merger restrictions together with a decline in marginal costs for nonbanks which can be thought of as technological innovation as a partial explanation for rising nonbank market share in the data. The final column in Table A.18 ("post DF ($\downarrow H, \uparrow \kappa_i, \downarrow c_N$)") presents the Post Dodd-Frank equilibrium which corresponds to the relaxation of merger restrictions together with changes in banks' and nonbanks' costs (the moments align with those presented in Table 4). Results from these experiments are presented in Table A.18.

Table A.18: Model With Mergers vs Model With Merger Restriction (Short Run)

Moment	Pre	Post RN $\downarrow H$ short-run	Post RN $\downarrow H$ long-run	Post (Reg) ($\downarrow H, \uparrow \kappa_i$)	Post (Tech) ($\downarrow H, \downarrow c_N$)	Post DF ($\downarrow H, \uparrow \kappa_i, \downarrow c_N$)
Initial Γ	2500.00	2500.00	1645.34	1645.34	1645.34	1645.34
Initial D_d	0.15	0.15	0.46	0.46	0.46	0.46
Deposit Share Top 4	13.90%	35.62%	42.34%	42.41%	42.77%	43.38%
Loan Share Top 4	17.25%	32.54%	35.42%	35.62%	34.76%	35.10%
Bank Lending Share	42.05%	41.18%	40.33%	40.36%	36.55%	36.35%
Interest Rate	4.73%	4.81%	4.89%	4.88%	4.82%	4.85%
Loans/Deposits Top 4	99.28%	69.24%	63.58%	64.18%	57.67%	57.54%
Loans/Deposits Fringe	77.62%	81.01%	85.65%	85.88%	81.60%	82.34%
Fringe Failure Rate	1.23%	1.09%	1.15%	1.10%	1.24%	1.53%
Merger Rate	0.00%	2.21%	0.02%	0.02%	0.01%	0.04%
Loan Markup Top 4	4.43	4.51	4.60	4.59	4.53	4.56
Loan Markup Fringe	1.49	1.47	1.43	1.42	1.46	1.46
Tobin's Q Top 4	0.75	45.01	45.17	36.44	41.71	40.35
Tobin's Q Fringe	0.61	0.91	0.98	0.88	0.70	0.63
Tobin's Q Bank Sector	0.70	32.18	33.63	27.20	31.14	30.25
Value Bank Sector	0.13	5.67	5.69	4.59	5.24	5.07

Note: Model "Pre" constrains the dominant bank from merging. Model "Post RN, short-run" removes the pre–Riegle-Neal merger restriction and computes the values along the transition path. "Post RN, long-run " computes moments after the transition. "Post Reg" adds fixed regulatory costs to banks. "Post Tech" improves nonbank technology by lowering c_N. "Post DF" combines both regulatory fixed costs and technological improvements.

A-5.2 Monetary Policy

Table A.19: Monetary Policy Counterfactual:

Moment	Pre-Riegle-Neal	Post-Dodd-Frank
Total Loans by Dominant Bank	+0.07%	-8.48%
Total Loans by Fringe Banks	-1.55%	+4.11%
Total Bank Loans	-1.26%	-0.32%
Total Loans by Nonbanks	-0.31%	-0.85%
Total Loans	-0.69%	-0.66%
Share of Deposits Lent Top 4	-0.01%	-10.25%
Share of Deposits Lent Fringe	-1.48%	-4.50%
Interest Rate	+11.9bp	+8.9bp
Net Interest Margin	+1.7bp	-1.3bp
Number of Fringe Banks	+0.00%	+6.02%
Merger Rate	-1.26%	+10.97%
Failure Rate (Fringe)	-70.08%	-23.31%

Note: This table reports percent deviations from the baseline "Pre-Riegle-Neal" and "Post-Dodd-Frank" steady state, except interest rates and net interest margins which are reported in basis points. In this experiment, we permanently increase r_A by 15 basis points and r^D by 10 basis points.

A-6 Computational Algorithm

Our computational algorithm proceeds as follows. For each state (γ, D_d, θ), we make an initial guess of bank value functions (v_i, w_i), bank exit thresholds $(\lambda_i^{exit}(\theta'))$, mass of entrance and exits (γ_e, γ_x) and lending L_i for banks of type $i \in \{d, f\}$. Taking the initial guess as given:

In the innermost loop, we solve for optimal lending L_i^* as a function of the previous iteration's value functions and exit thresholds. In the second loop, we solve for exit thresholds $\lambda_i^{*exit}(\theta')$ as a function of newly computed optimal lending, L_i^*, and the previous iteration's value functions. In the outermost loop, we solve for value functions (v_i, w_i) and entry decisions (γ_e) as a function of newly computed optimal lending,L_i^*, newly computed exit thresholds, $\lambda_i^{*exit}(\theta')$, and implied exit masses (γ_x). We will describe the procedure starting from the innermost loop and proceeding outward.

Having solved for the new policy and value functions, we compute the error as the difference between the initial guess and the new policy and value functions. If the error is the less than tolerance, we have found the policy and value functions. If not, we do another iteration.

A-6.1 Loan Supply Decision

To solve for banks' optimal L_i, given exit decisions and value functions, we first write the banks' problem as follows:

$$w_i(\epsilon_i, S, r_N^L) = \max_{L_i \le D_i + \epsilon_i} \mathbb{E}_{\theta'|\theta}\Bigg[\max_{\lambda_i^{\text{exit}}(\theta')} \Bigg\{ \int_0^{\lambda_i^{\text{neg}}(\theta')} \Big(\pi_i(L_i, \epsilon_i; S, \theta', \lambda_i') + \beta v_i(s')\Big)\, d\lambda_i' \tag{A.6.5}$$

$$+ \int_{\lambda_i^{\text{neg}}(\theta')}^{\lambda_i^{\text{exit}}(\theta')} \Big((1+\psi_i)\, \pi_i(L_i, \epsilon_i; S, \theta', \lambda_i') + \beta v_i(s')\Big)\, d\lambda_i' \Bigg\}\Bigg]. \tag{A.6.6}$$

where $\lambda_i^{neg}(\theta')$ is the threshold when profit switches from positive to negative and requires costly equity issuance. $\lambda_i^{exit}(\theta')$ is the bank's exit threshold, where they choose to exit for any $\lambda_i \ge \lambda_i^{exit}(\theta')$.

With these regions, we can derive the first order condition given $\lambda_i^{exit}(\theta')$ and $v_i(s')$, as follows:

$$0 = \Pr(\lambda_i' < \lambda_i^{\text{neg}}) \Bigg[\mathbb{E}_{\theta'|\theta,\, \lambda_i' < \lambda_i^{\text{neg}}}\left[\theta' r_B^L - (1-\theta')\lambda_i'\right] \tag{A.6.7}$$

$$+ \mathbb{E}_{\theta'|\theta}\left[\theta' \frac{\partial r_B^L}{\partial L}\frac{\partial L}{\partial L_i} L_i\right] - r^A - \frac{\partial C_i(L_i)}{\partial L_i}\Bigg] \tag{A.6.8}$$

$$+ \Pr\big(\lambda_i' \in \{\lambda_i^{\text{neg}}, \lambda_i^{\text{exit}}\}\big)\,(1+\psi_i) \Bigg[\mathbb{E}_{\theta'|\theta,\, \lambda_i' \in \{\lambda_i^{\text{neg}}, \lambda_i^{\text{exit}}\}}\left[\theta' r_B^L - (1-\theta')\lambda_i'\right] \tag{A.6.9}$$

$$+ \mathbb{E}_{\theta'|\theta}\left[\theta' \frac{\partial r_B^L}{\partial L}\frac{\partial L}{\partial L_i} L_i\right] - r^A - \frac{\partial C_i(L_i)}{\partial L_i}\Bigg] \tag{A.6.10}$$

$$+ \Pr\big(\lambda_i' < \lambda_i^{\text{exit}}\big)\, \mathbb{E}_{\theta'|\theta}\left[\beta \frac{\partial v_i(s')}{\partial s'}\frac{\partial s'}{\partial L_i}\right] - \mu_i. \tag{A.6.11}$$

The first term captures the marginal benefit and cost of lending when the bank draws a low enough λ_i that they are profitable and is weighted by the probability that occurs. The second term captures the marginal benefit and cost of lending when the bank draws a λ_i such that they make negative profit, but choose to remain. This term is weighted by $(1+\psi_i)$ as the bank has to issue costly equity. The final term captures the effect of lending on the future states and is weighted by the probability that the bank does not exit. The final term captures the constraint that the bank cannot lend more than it has in deposits.

A-6.2 Bank Exit Decision

For a given realization of shocks $\epsilon_i, \theta', \lambda_i$, and lending L_i, we compute the bank's optimal exit from it's value function:

$$w_i(\epsilon_i, \theta', L_i) = \max_{\lambda_i^{exit}(\theta') \in (\lambda_i^{neg}(\theta'), 1)} \int_{\lambda_i^{\text{neg}}(\theta')}^{\lambda_i^{\text{exit}}(\theta')} \Big((1+\psi_i)\, \pi_i(L_i, \epsilon_i; S, \theta', \lambda_i') + \beta v_i(s')\Big)\, d\lambda_i'. \tag{A.6.12}$$

The optimal choice $\lambda_i^{*exit}(\theta')$ sets:

$$(1+\psi_i)\pi_i(L_i, \epsilon_i; S, \theta', \lambda_i^{*exit}(\theta')) = -\beta v_i(s') \tag{A.6.13}$$

A higher value function, higher interest rate, and lower equity issuance costs lead to less exit, all else equal.

A-6.3 Bank Value Function

Taking bank exit thresholds ($\lambda_i^{exit}(\theta')$), mass of entrance and exits ($\gamma_e, \gamma_x(\theta')$) and lending L_i for banks of type $i \in \{d, f\}$, we can just iterate until convergence for the value functions using the following equation:

$$w_i(\epsilon_i, S, r_N^L) = \max_{L_i \le D_i + \epsilon_i} \mathbb{E}_{\theta'|\theta}\Bigg[\max_{\lambda_i^{\text{exit}}(\theta')}\Bigg\{\int_0^{\lambda_i^{\text{neg}}(\theta')}\Big(\pi_i(L_i, \epsilon_i; S, \theta', \lambda_i') + \beta v_i(s')\Big)\, d\lambda_i' \tag{A.6.14}$$

$$+ \int_{\lambda_i^{\text{neg}}(\theta')}^{\lambda_i^{\text{exit}}(\theta')}\Big((1+\psi_i)\,\pi_i(L_i, \epsilon_i; S, \theta', \lambda_i') + \beta v_i(s')\Big)\, d\lambda_i'\Bigg\}\Bigg]. \tag{A.6.15}$$