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 10 (dominant) banks have over 55 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. First, we study the effect of the merger wave on competition, efficiency, and stability of the banking industry. Then we use our model to understand the interaction between regulatory and monetary policy. Specifically, how has the bank lending channel of monetary policy been affected by rising concentration; has it amplified or dampened the effectiveness of monetary policy? How might monetary policy itself contribute to mergers and rising concentration?

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

JEL Classification Numbers: G21, E58.

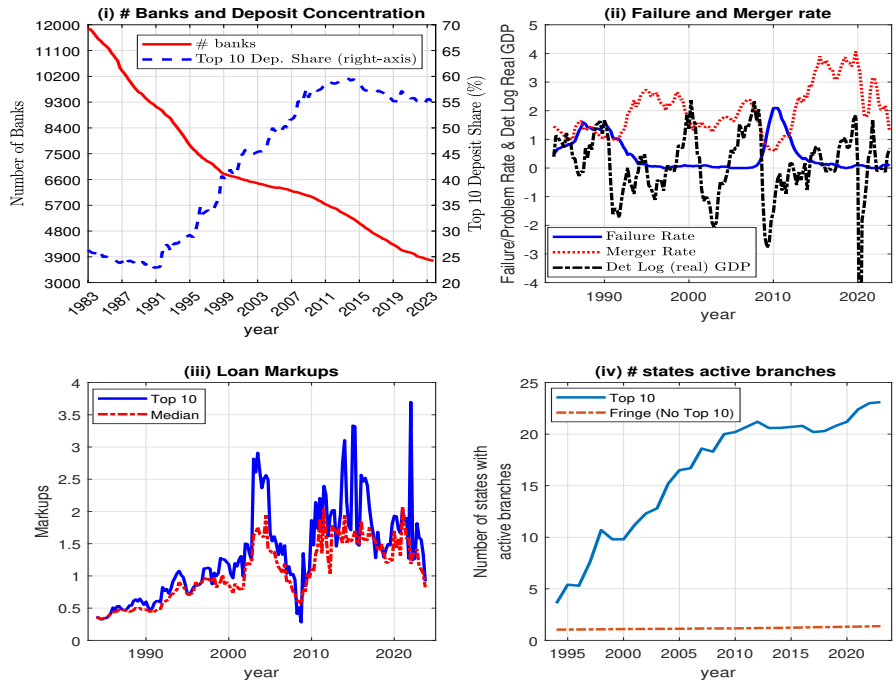
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1 Motivation

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 10 banks of under 25% prior to 1994, concentration rose dramatically to over 60% 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).

Figure 1: Concentration, Failure/Merger Rates, Markups, and Geographic Expansion (1984 - 2023)



Note: # of banks refers to number of commercial banks in the US (aggregated to the top holding company). Top 10 Dep Share refers to the share of total deposits accounted by the Top 10 banks (when sorted by deposits). Det. Log (real) GDP refers to detrended log real GDP (quarterly frequency). The trend is extracted using the H-P filter with parameter 1600. We estimate markups using the estimates of marginal costs as in Corbae and D'Erasmo (2021). Top 10 markups corresponds to the (asset-weighted) average within Top 10 banks when sorted by assets. Number of states refers to the number of states with active branches at the bank holding company level. Source: Call Reports and Summary of Deposits.

Panel (ii) in Figure 1 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]

Regulators use measures based on concentration (e.g. Herfindahl indices) when evaluating whether to allow bank mergers.[2] Regulatory concern about mergers focuses on whether it erodes *competition* leading to market *inefficiency* as measured, for instance, by large markups. Panel (*iii*) in Figure 1 documents the increase in bank markups that may have occurred as a consequence of rising market power.

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.[3] While several papers have focused on balance sheet spillovers among financial institutions causing instability[4], 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 atomistic (measure zero) fringe banks has no aggregate consequences, while an idiosyncratic shock to a non-atomistic dominant bank can have aggregate consequences as in the granularity literature.

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 (*iv*) in Figure 1 can lead to financial stability in the presence of idiosyncratic regional shocks to banking portfolios. Specifically, the figure documents that the top 10 banks have diversified to 23 states on average while the remainder are isolated in 1.2 states on average.

To adequately address these costs and benefits given the market structure documented in Figure 1 with 10 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. 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

[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 1 (the denominator of the merger rate). This will also be evident in Figure 3 below.

[2]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.

[3]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)).

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

for a Markov Perfect Equilibrium. Second, we allow for entry and exit which may vary across the cycle as established in Panel (*ii*) Figure 1. This is important with mergers since they can facilitate entry as in other settings; firms may enter to be acquired by a dominant firm. 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 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 that informs our model. Section 3 runs "granular" regressions to study how shocks to large banks have translated to nontrivial aggregate fluctuations. Section 4 describes the model environment and equilibrium. Section 6 presents the calibration. Section 7 illustrates the model's merger dynamics. Section 8 runs two policy counterfactuals to assess the implications of branching restrictions and monetary

policy for economic activity. Section 9 concludes.

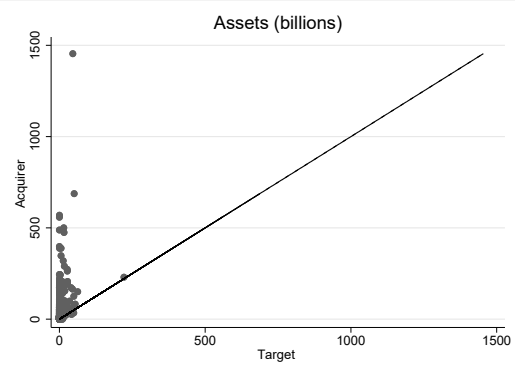
2 Merger Data

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.

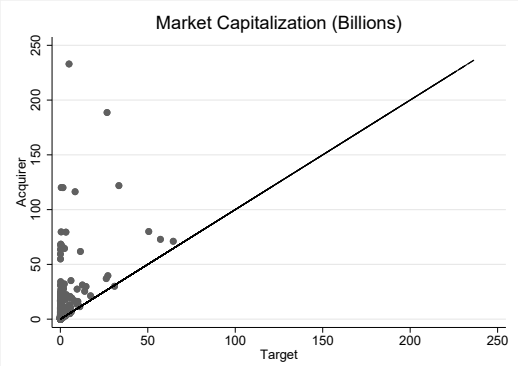
Below, we compare the size (book assets and market capitalization) of targets and acquirers between and 2023.[5] Panel (a) in Figure 2 shows that 96% of bank mergers involve an acquirer that is significantly larger than its target and the median acquirer has over seven times more assets than the target. Panel (b) in Figure 2 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.

Figure 2: Bank Mergers 1990-2023

(a) Size of Acquirers vs Targets (Assets)



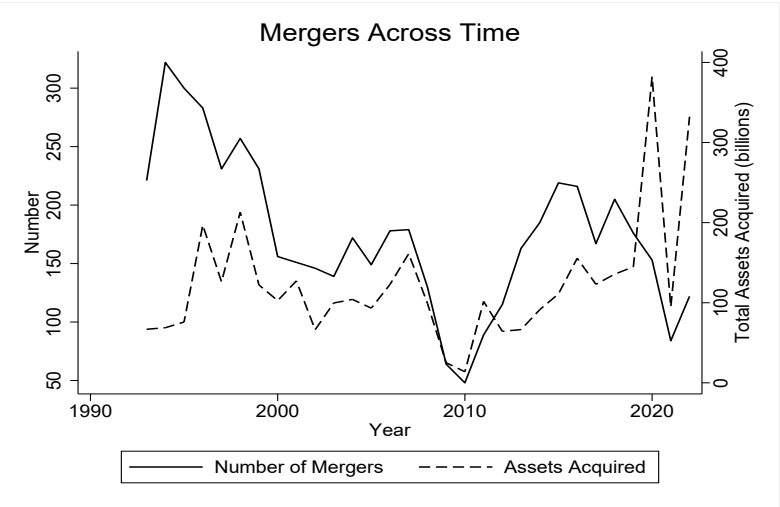
(b) Size of Acquirers vs Targets (Market Cap)



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 Graph): We restrict to mergers from 1990 to 2023 where both the acquirer and target are banks as defined by SIC code. Source: Capital IQ

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

Figure 3: 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 3 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 Granularity and Financial Stability

Given the growth of the largest banks over the past 30 years, we study how idiosyncratic bank shocks to deposit flows or profitability 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. More specifically, let x_{it} the log of the variable of interest for bank i in period t (real deposits). The growth rate of real deposits is $g_{it} = D_{it} - D_{it-1}$. As in Gabaix (2011), we assume that g_{it} evolves as

$$g_{it} = \beta' X_{it} + \nu_{it}, \tag{1}$$

where X_{it} is a vector of factors that may depend on bank characteristics at time $t-1$ and of factors at time (e.g., a time fixed effect or other aggregate variables). The goal is to investigate

whether the purely idiosyncratic component ν_{it} of large banks can explain fluctuations in aggregate credit and aggregate output. As in Gabaix (2011), we construct the *granular residual* as follows

$$\Gamma_t \equiv \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \nu_{i,t}, \tag{2}$$

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 estimate (1) and obtain $\hat{\nu}_{it} = g_{it} - \hat{\beta}' X_{it}$ to then construct

$$\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} \hat{\nu}_{it}. \tag{3}$$

We then regress aggregate loan 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

$$\Delta Y_t = \beta_\Gamma \hat{\Gamma}_t + \epsilon_t^\Gamma \tag{4}$$

where Y_t can be the log of real total bank credit, log real total credit, or log real GDP. If only aggregate shocks were important (i.e., shocks to dominant banks would not influence aggregate fluctuations) the R^2 would be low. Table 1 presents the results when aggregate fluctuations are measured using total bank lending growth. We find that R^2 are relatively high with dominant bank idiosyncratic shocks explaining between 15% and 28% of aggregate lending growth. Changes in the predicted power of idiosyncratic shocks appear to increase at a smaller pace when we move from Top 35 to Top 100 than when we go from Top 10 to Top 35 banks.

Table 1: Explanatory power of granular residuals of dominant banks on aggregate lending (R^2)

	Dep. Var. $\Delta \log(L_t)$					
	Top 10 Banks		Top 35 Banks		Top 100 Banks	
(intercept)	0.00774***	0.00772***	0.00788***	0.00794***	0.00775***	0.00779***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Γ_t	0.220***	0.219***	0.328***	0.326***	0.381***	0.376***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Γ_{t-1}	-0.0221	-0.0225	-0.0363	-0.0365	-0.0335	-0.0314
	(0.567)	(0.562)	(0.420)	(0.419)	(0.466)	(0.495)
Γ_{t-2}		0.0118		0.0391		0.0464
		(0.761)		(0.388)		(0.315)
N	191	190	191	190	191	190
R^2	0.149	0.149	0.224	0.227	0.273	0.277
Adjusted R^2	0.140	0.136	0.215	0.214	0.265	0.265

Note: Table presents the R^2 from a regression of the corresponding dependent variable on Γ_t, Γ_{t-1}, and Γ_{t-2} is real deposits. "$\Delta \log(L_t)$" refers to growth rate of total real bank loans. Top 10 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 10$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_t = N^{-1} \sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} (g_{it} - \overline{g}_t)$. Source: Call Reports

Table 2 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.[6] We find that the R^2 declines compared to those presented in Table 1 but are still sizeble. In particular, we find that granular bank idiosyncratic shocks explaining up to 15.2% of the fluctuations in aggregate credit.[7] As before, we find that, while still increasing, the effect appears to flatten out when going beyond the Top 35 banks.

[6] 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.)

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

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

	Dep. Var. $\Delta \log(totcredit_t)$					
	Top 10 banks		Top 35 banks		Top 100 banks	
(intercept)	-0.00589***	-0.00577***	-0.00579***	-0.00564***	-0.00583***	-0.00568***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Γ_t	0.101***	0.101***	0.167***	0.166***	0.212***	0.208***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Γ_{t-1}	0.0468	0.0471	0.0523	0.0528	0.0677*	0.0709*
	(0.145)	(0.144)	(0.172)	(0.169)	(0.086)	(0.073)
Γ_{t-2}		0.0222		0.0373		0.0545
		(0.490)		(0.333)		(0.169)
N	191	190	191	190	191	190
R^2	0.061	0.063	0.100	0.105	0.143	0.152
Adjusted R^2	0.051	0.048	0.091	0.091	0.134	0.138

Note: Table presents the R^2 from a regression of the corresponding dependent variable on Γ_t, Γ_{t-1}, and Γ_{t-2} is real deposits. "$\Delta \log(totcredit_t)$" refers to growth rate of real total credit to private non-financial sector. Top 10 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 10$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_t = N^{-1} \sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} (g_{it} - \overline{g}_t)$. Source: FRED and Call Reports

Table 3 presents the results when aggregate fluctuations are measured using the growth of real gdp. We find that R^2 are smaller but still significant with dominant bank idiosyncratic shocks explaining up to 4% of fluctuations in real gdp.[8]

[8]Table 3 in the Appendix shows that result also hold when using the growth rate of detrended GDP as the dependent variable.

Table 3: Explanatory power of granular residuals of dominant banks on aggregate output (R^2)

	Dep. Var. $\Delta \log(gdp_t)$					
	Top 10 banks		Top 35 banks		Top 100 banks	
(intercept)	0.00645***	0.00678***	0.00644***	0.00673***	0.00652***	0.00677***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Γ_t	-0.0201	-0.0224	-0.0278	-0.0323	-0.0345	-0.0423
	(0.522)	(0.472)	(0.469)	(0.397)	(0.395)	(0.292)
Γ_{t-1}	-0.0298	-0.0293	-0.0407	-0.0398	-0.0267	-0.0211
	(0.344)	(0.347)	(0.289)	(0.295)	(0.510)	(0.598)
Γ_{t-2}		0.0738**		0.0876**		0.102**
		(0.019)		(0.023)		(0.012)
N	191	190	191	190	191	190
R^2	0.007	0.036	0.009	0.036	0.006	0.039
Adjusted R^2	0.000	0.020	0.000	0.021	0.000	0.024

Note: Table presents the R^2 from a regression of the corresponding dependent variable on Γ_t, Γ_{t-1}, and Γ_{t-2} is real deposits. "$\Delta \log(gdp_t)$" refers to growth rate of real gdp. Top 10 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 10$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_t = N^{-1} \sum_{i=1}^{N} g_{it}$, so $\hat{\Gamma}_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} (g_{it} - \overline{g}_t)$. 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 1 we document that idiosyncratic shocks to top 10 and top 35 bank deposits can explain 15% and 23% of aggregate bank lending growth (measured via R^2), respectively. In addition, in table 2, we document that granular shocks to systemically important banks (i.e. the top 35) explain up to 10% of the fluctuations in real total credit to the private non-financial sector. Finally, in table 3 we document that granular shocks to systemically important banks (i.e. the top 35) explain up to 4% of the growth of real GDP.

3.1 The Marginal Propensity to Lend and Bank Granularity

As a way to understand the origins of the granular effects of dominant banks, we study how idiosyncratic (transitory and permanent) bank innovations to deposit flows affect lending and how that translates into bank granularity. We start by analyzing the following relationship

$$\Delta L_{it} \quad = \quad \beta_{k(i)} \Delta D_{it} + \zeta_{it} \tag{5}$$

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.[9] 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]

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

$$\begin{aligned} \log(D_{it}) &= \xi_{k(i)} X_{it} + z_{it} + \varepsilon_{it} \quad \text{where} \quad z_{it} = z_{it-1} + \eta_{it} \\ \Rightarrow \Delta D_{it} &= \xi_{k(i)} \Delta X_{it} + \underbrace{\eta_{it} + \Delta \varepsilon_{it}}_{=\nu_{it}} \end{aligned} \tag{6}$$

where 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 (6) 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 (6) by ν_{it}. Then the deposit process in (6) implies that equation (5) can then be written as:

$$\Delta L_{it} = \beta_{k(i)} \xi_{k(i)} \Delta X_{it} + \beta_{k(i)} \nu_{it} + \zeta_{it}. \tag{7}$$

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

Table 4 presents estimates of the marginal propensity to lend from equation (7). For the period between 1984 and 2019, we find that the average MPL is 0.519 and that it increases with bank size, with the MPL for the Top 10 banks equal to 0.888.[11] The ranking of MPL across the bank size distribution remains the same when looking at the pre Reagle Neal period (1984-1993) and the post GFC period (2011-2019).[12] Consistent with the findings in Corell (2025),

[9] 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.

[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] 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 10 have in general a higher liquid asset ratio than those in the Top 10 (29.61% versus 19.36%). We expect banks with higher liquid asset ratios to be less responsive to unexpected deposit flows. Consistent with this, Table A.6 in Appendix A-1.3 shows that the average MPL declines with the liquid asset to total asset ratio.

[12] 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-1.3 Table A.7. We find that banks that operate in more concentrated markets respond less to unexpected flows of deposits.

we observe a decline in average MPL between the early period and the most recent years in our sample.

Table 4: Marginal Propensity to Lend (Data Estimates)

	Dependent Variable $\Delta \log(L_{it})$					
ν_{it}	0.510***	0.509***	0.520***	0.519***	0.456***	0.455***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\nu_{it} \times I_{t10}$		0.379***		0.345***		0.305***
		(0.000)		(0.000)		(0.000)
Bank FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Period	1984-2019		1984-1993		2011-2019	
N	946,299	946,299	353,150	353,150	169,536	169,536
R-sq	0.362	0.362	0.398	0.398	0.287	0.287
adj. R-sq	0.348	0.348	0.371	0.371	0.260	0.260

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (5). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 6. We follow Gabaix (2011) and construct ν_{it} by removing a time fixed effect. $I_{t,k(i)=10}$ is an indicator that takes value 1 if bank i is in the Top 10 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. For Period 1984-2019 we incorporate a dummy for the Financial Crisis interacted with the regressors. This dummy takes value 1 between 2007.Q4 and 2009.Q2 (NBER recession dates). Source: Call Reports

We are interested in studying the foundation of the granular results we presented above. That is, we would like to show that there is a connection between the MPL and our version of Gabaix's granularity results. Note that when it comes to bank credit, we estimate

$$\Delta L_t = \beta_\Gamma \Gamma_t + \epsilon_t^\Gamma. \tag{8}$$

and the R^2 from the equation (8) is given by

$$R^2 = \frac{\beta_\Gamma^2 Var(\Gamma_t^d)}{Var(\Delta L_t)}. \tag{9}$$

To see the connection between the Gabaix's results and the MPL regressions, after multiplying both sides of equation (7) 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 (8) can be written

$$\Delta L_t \approx \sum_{i=1}^N \omega_{it} \Delta L_{it} = \beta_d \underbrace{\sum_{i=1}^K \omega_{it} \nu_{it}}_{\Gamma_t} + \underbrace{\beta_f \sum_{i=K+1}^N \omega_{it} \nu_{it} + \sum_{i=1}^N \omega_{it}(\beta_k \xi_k X_{it} + \zeta_{it})}_{=\epsilon_t^\Gamma} \tag{10}$$

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, (10) 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 5 provides estimates of (8) in the first column and (10) in the second column. The estimated coefficient β_d of the MPL regression (7) in Table 4 equals 0.509+0.379=0.888 for the period 1984-2019. The estimated coefficient from the last column of Table 5 equals 0.935 with a standard error equal to 0.141, statistically not different than 0.888.[13] 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 (7).

Table 5: Granular Banks and the Marginal Propensity to Lend (Data Estimates)

	Dependent Variable	
	ΔL_{it}	$\sum_{i=1}^{N} \omega_{it} \Delta L_{it}$
Γ_t	0.457***	0.935***
	(0.125)	(0.141)
constant	0.00805***	0.0141***
	(0.000)	(0.00123)
Period	1984-2019	1984-2019
N	144	144
R^2	0.120	0.312
Adjusted R^2	0.108	0.302

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. We incorporate a dummy for the Financial Crisis interacted with the regressors. This dummy takes value 1 between 2007.Q4 and 2009.Q2 (NBER recession dates). Source: Call Reports.

The estimated coefficient from the Gabaix (2011) equation (8) equals $\beta_\Gamma = 0.475$, a downward biased estimate of the MPL of 0.888 in (7). To understand this downward bias we compute the group level innovation of the change in total deposits for the Top 10 banks and for banks not in the Top 10.[14] 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

[13] 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 (10), $\beta_d = 0.935$ is an upward biased estimate of $\beta_d = 0.888$ in (7). 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.

[14] More specifically, we let $D_{d,t} = \sum_{i=1}^{K} D_{it}$ (Top 10 total deposits) and $D_{f,t} = \sum_{i=K+1}^{N} D_{it}$ (No Top 10 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.

negatively correlated (the correlation is -0.939). 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.

4 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'.

4.1 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.[15] 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:

$$\begin{cases} 1 + R_k & \text{with prob } \theta' \\ 1 - \lambda & \text{with prob } (1 - \theta') \end{cases} \tag{11}$$

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 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

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

$F_\epsilon(\epsilon;\alpha)$ 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 $\omega \in [0, \overline{\omega}]$ if they decide not to run the project. These draws from distribution function $\Omega(\omega)$ are i.i.d. over time and across regions. 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.[16] 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).

4.2 Savers

A mass $\mathscr{H}$ of infinitely lived, risk neutral households with discount factor β are endowed with one unit of the good each period. We assume households are sufficiently patient such that they choose to exercise their savings opportunities. In particular, households have access to an exogenous risk-free storage technology yielding $1 + \overline{r}$ between any two periods with $\overline{r} \geq 0$ and $\beta(1 + \overline{r}) = 1$. They can also choose to supply their endowment to a bank, 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. 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

[16] 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).

along the lines of Diamond (1984) and Williamson (1986), there is no benefit to matching directly with borrowers.

4.3 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 $\mathscr{H} > \mathscr{B}$.

More specifically, each period begins with a measure γ of identical atomistic (i.e. measure zero) fringe banks each with D_f deposits as well as a non-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. First, in the pre-Riegle-Neal restrictions, banks were restricted to operating in one state. As such, we assume the cost of merging such that their deposit market share exceeds 25% (the pre-Riegle-Neal deposit market share of the top 10 banks) is infinite. Second, to capture costs associated with HHI constraints as shown 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:

$$H(\Gamma, s) = \begin{cases} \infty & \text{if pre-Riegle-Neal and } \frac{D'_d}{D_d + \gamma D_f} > 0.25 \\ 2h(\gamma - \Gamma)^2 & \text{if } HHI > 1800 \\ h(\gamma - \Gamma)^2 & \text{if } HHI < 1800 \text{ and } \Delta_{HHI} > 100 \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

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. 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_B^L, r_N^L). 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:

$$C_i(L_i) = C_{1i}L_i + C_{2i}L_i^2. \tag{13}$$

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.[17] The profit of bank $i \in \{d, f\}$ is given by:

$$\pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i) = [\theta' r_B^L - (1-\theta')\lambda'_i]L_i + r^A(D_i + \epsilon_i - L_i) - r^D(D_i + \epsilon_i) - C_i(L_i) - \kappa_i. \tag{14}$$

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:

$$\mathcal{D}_i(L_i, \epsilon_i; S, \theta', \lambda'_i) = \pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i) - \mathbf{1}_{\{\pi_i(\cdot)<0\}}\psi_i(|\pi_i(L_i, \epsilon_i; S, \theta', \lambda'_i)|). \tag{15}$$

where ψ_i captures the costs of equity issuance.

New banks can choose to enter as fringe banks at cost K_f. 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.

4.4 Nonbank Lenders

A representative nonbank that discounts the future at rate β 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.

[17] 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 10 banks than fringe banks in both pre- and post-reform periods.

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

$$\pi_N(L_N, S, \theta', \lambda'_N) = \left[\theta' r_N(S, r_B^L) - (1-\theta')\lambda'_N\right] L_N - c_N L_N \tag{16}$$

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

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.

4.5 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.

5 Equilibrium

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

5.1 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:

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

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:

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

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

$$L(\theta, r_B^L, r_N^L) = \int_0^{\overline{\omega}} \mathbf{1}_{\{\omega \leq E_{\boldsymbol{\delta}}[\Pi_E(\theta, r_B^L, r_N^L, \boldsymbol{\delta})]\}} d\Omega(\omega). \tag{21}$$

The loan demand for commercial banks is given by

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

5.2 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 $\gamma - \Gamma \geq 0$ of fringe banks to gain deposits. 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

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

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:

$$v_d(s) = \max_{\Gamma \in [0,\gamma]} -p(\Gamma, s)(\gamma - \Gamma) D_f - H(\Gamma, s) + w_d(\Gamma, D_d', \theta) \tag{24}$$

subject to

$$p(\Gamma, s) D_f \geq w_f(S) \tag{25}$$

where $H(\Gamma, s)$ are any additional regulatory costs 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 (25) 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:

$$\frac{\partial w_d(\Gamma)}{\partial \Gamma} = \frac{\partial w_f(\Gamma)}{\partial \Gamma}(\gamma - \Gamma) + \frac{\partial H(\Gamma)}{\partial \Gamma} - w_f(\Gamma, D'_d(\Gamma), \theta) \tag{26}$$

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 firm. 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) and due to rising fringe value functions (w_f).

Let $\Gamma^*(s)$ solve (24)-(25) 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 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.

5.3 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:

$$w_d(\epsilon_d, S, r_N^L) = \max_{L_d \leq D'_d + \epsilon_d} \mathbb{E}_{\theta'|\theta}\Big[\max_{x'_d \in \{0,1\}} (1 - x'_d)\big(\mathcal{D}_d(L_d, \epsilon_d; S, \theta', \lambda'_d) + \beta v_d(s')\big)\Big], \tag{27}$$

subject to

$$L_d + \Gamma L_f^*(L_d, \epsilon_d, S, r_N^L) = L_B(r_B^L, r_N^L), \tag{28}$$

$$\gamma' = F(L_d, \epsilon_d, S, \theta'). \tag{29}$$

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 (28) illustrates both loan market clearing and that the dominant bank takes into account both how their loan decision affects the fringe loan decision, L_f, and the bank interest rate, r_B^L. Equation (29) 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_B^L and r_N^L as given, the problem of the fringe bank solves[18]

$$w_f(L_d, \epsilon_f, S, r_N^L) = \max_{\ell_f \leq D_f + \epsilon_f} \mathbb{E}_{\theta', \lambda'_f|\theta}\Big[\max_{\chi'_f \in \{0,1\}} (1 - \chi'_f)\big(\mathcal{D}_f(\ell_f, \epsilon_f; L_d, S, \theta', \lambda'_f) + \beta v_f(s')\big)\Big] \tag{30}$$

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

$$\overline{r} = E_{\theta'|\theta}\left[\theta' r_N^L - (1 - \theta')\lambda'\right] - c_N. \tag{31}$$

[18] To save on notation, we neglect adding L_f and x_f as state variables in (30).

5.3.1 Bank Entry and Industry Law of Motion

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

$$v_i^e(L_d, S, r_N^L, \theta'; \gamma^e(x'_d, e'_d)) = \max_{e'_i \in \{0,1\}} (1 - e'_i) \{-K_i + v_i(s')\}, \tag{32}$$

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

$$\gamma' = F(L_d, S, \theta') = \Gamma - \gamma^x(L_d, S, \theta') + \gamma^e(L_d, S, \theta'). \tag{33}$$

5.4 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 (24). The merger quantity Γ maximizes (24).*
2. *The merger pricing function p satisfies (25).*
3. *The post-merger value functions w_d and w_f solve (27) and (30). The loan supply policy functions (L_d, ℓ_f) and exit decision rules (x'_d,χ'_f) maximize (27) and (30).*
4. *Consistency requires $\ell_f = L_f$ and $\chi'_f = x'_f$.*
5. *r_B^L clears the loan market (28).*
6. *r_N^L satisfies the shadow bank first order condition (31)*
7. *The mass of entrants γ^e solves the entry problem (32)*
8. *Transition functions are consistent with mergers, entry, and exit (33)*

5.5 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 8.

6 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 (12) maintaining all other parameter values. We calibrate h to match the post-Dodd-Frank dominant bank market share. Thus, our transition path should be seen as a validation exercise. 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).

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").[19] 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 10 (when banks are sorted by assets) and the rest (i.e., the competitive fringe $i = f$) with those outside the Top 10.

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 calibrate θ to match the average default probability. We calibrate the size and probability of deposit shocks $\{\epsilon_d, \epsilon_f\}$ to match the expectation and standard deviation of the shocks to top 10 and fringe bank deposits.

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.[20] $\lambda'_d = \lambda'_N \equiv \overline{\lambda} \in [0,1]$, $\lambda'_f \in [0,1]$ is iid over time and

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

[20] See table A.1 in the Appendix. Specifically, the standard deviation of loan loss rate is lower for top 10 banks than fringe banks in both pre- and post-reform periods which is consistent with a diversification argument.

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.

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 marginal expenses and the elasticity of net marginal expenses.

We let the discount factor be $\beta = 1/(1 + r^D)$ and calibrate the deposit interest rate r^D to match the ratio of interest expenses on deposits over total deposits. Similarly, we calibrate r^A to match the ratio of interest income on securities over total securities. 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 $i \in \{d, f\}$.

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 $E_\epsilon[\Pi_E(\theta, r_B^L = R, r_N^L = R, \epsilon)]$).

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 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 targeted moments. Table 6 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. In all, we have 17 parameters and 23 targeted moments as part of the simulated method of moments estimation (i.e. an overidentified model).

Table 6 presents all the parameters of the model. Table 7 presents the parameters that change after Dodd-Frank's implementation. We increase fixed costs for both dominant and fringe banks to capture the rising fixed cost to loan ratio. We decrease the marginal cost of the nonbank to capture the declining share of bank loans to total loans. Since there were minimal changes to FDIC bank merger policy during this period, h is unchanged. Table 8 present a set of data moments (targeted and not targeted) together with their model generated counterparts.

Table 6: Parameters and Targets

Parameter		Value	Target
Deposit Interest Rate (%)	$\overline{r} = r^D$	0.0014	Avg Interest Expense Deposits
Bank Discount Factor	β	0.998	$(1 + r^D)^{-1}$
Return on Securities	r_A^+	0.0180	Return on Net Securities
Default Frequency (Good Times)	θ_G	0.969	Mean Default Frequency (Non-Crisis)
Default Frequency (Bad Times)	θ_B	0.85	Mean Default Frequency (Financial Cr
Loan Loss Rate	$\overline{\lambda}$	0.31	Average Charge-off rate
Standard Dev Loan Loss rate f	σ_λ	0.145	Std dev charge off rates f
Standard Dev Loan Loss rate d	σ_λ	0.13	Std dev charge off rates d
Size of deposit shocks d	ϵ_d	$\{-0.118, .0131\}$	Std. of shocks to deposits d
Size of deposit shocks f	ϵ_f	{-0.43, 0.0477} $\times D_f$	Std. of shocks to deposits f
Probability of negative shock d		0.10	$Pr(\epsilon_d < -std)$
Probability of negative shock f		0.10	$Pr(\epsilon_f < -std)$
Number of Borrowers	N	8.25	Deposit to Output
Return on investing	R	0.18	Net Interest Margin
Price coefficient	α	45.0	Elasticity of Loan Demand
Lower bound demand shock	$\underline{\omega}$	0.693	Normalization
Upper bound demand shock	$\bar{\omega}$	1.093	Dividend Issuance d and f
Mean size of Fringe Bank f	D_f	0.001	Relative Size Fringe to Top 10
Linear Cost Loans d	C_d^1	0.008	Net Marginal Expenses Top 10
Quadratic Cost Loans d	C_d^2	0.006	Elasticity Net Marginal Expenses Top
Fixed cost d	κ_d	0.0025	Fixed cost over loans Top 10
Mean Dist Cost Loans f	C_f^1	0.006	Net Marginal Expenses Fringe
Quadratic Cost Loans f	C_f^2	$\frac{0.0095}{D_f}$	Elasticity Net Marginal Expenses Fring
Fixed cost f	κ_f	$0.010 \times D_f$	Fixed cost over loans Fringe
External finance param. d	ψ_d^1	0.50	Avg. equity issuance to loan ratio Frin
External finance param. f	ψ_f^1	1.00	Avg. equity issuance to loan ratio Frin
Entry Cost f	K_f	$0.50 \times D_f$	Entry Rate
Regulatory Merger Cost	h	$0.0025 \times D_f$	Post-Dodd-Frank Bank Market Share T
Marginal Cost Nonbank	c_N	0.030	Bank Loan to Total Loans

Note: The entry cost is set as part of the equilibrium selection.

Table 7: Parameter Changes Post-Dodd-Frank

Parameter		Pre-Riegle-Neal	Post-Dodd-Frank
Fixed cost d	κ_d	0.0025	0.0045
Fixed cost f	κ_f	$0.010 \times D_f$	$0.015 \times D_f$
Marginal Cost nonbank	c_N	0.030	0.025

To illustrate the calibration, we present the moments in the data relative to our model output in both the pre (1984-1993) and post (2010-2019) periods.

Table 8: Moments Data vs Model (Targets)

Name	Calc	Data Pre	Data Post	Model Pre	Model Post
Average Charge-off rate	$E'_\theta[(1-\theta')\lambda']$	0.96%	0.94%	0.96 %	0.96 %
Std. of Deposit Shocks Top 10	$Std(log(D_d+\epsilon_d))$	0.168	0.070	0.144	0.069
Std. of Deposit Shocks Fringe	$Std(log(D_f+\epsilon_f))$	0.182	0.156	0.182	0.182
Freq. Neg. Deposit Shocks Top 10	$Pr(\epsilon_d < -std)$	0.176	0.139	0.10	0.10
Freq. Neg. Deposit Shocks Fringe	$Pr(\epsilon_f < -std)$	0.081	0.085	0.10	0.10
Elasticity of Loan Demand	$-\alpha r_B^L(1-s_B)$	-1.1	-1.1	-1.23	-1.42
Deposit Share Top 10 to Fringe	$\frac{D_d}{D_d+\gamma D_f}$	24.77%	57.79%	24.36%	51.77%
Loan Share Top 10 to Fringe	$\frac{L_d}{L_d+\gamma L_f}$	28.55%	52.86%	23.33%	36.48%
Bank Loans to Total Loans Ratio	$\frac{L_d+\gamma L_f}{L_n+L_d+\gamma L_f}$	44.54%	33.28%	41.29%	34.70%
Deposit to Output Ratio	$\frac{D_d+\gamma D_f}{\sum_{borrower} Output}$	39.01%	57.19%	44.10%	43.58%
Net Interest Margin	$E_\theta[\theta' r_B^L - r_D]$	4.94%	4.35%	4.94%	5.14%
Net Marginal Expenses Top 10	$\frac{c(L_D)}{L_D}$	1.15%	1.35%	0.95%	1.00%
Net Marginal Expenses Fringe	$\frac{c(L_F)}{L_F}$	2.00%	1.69%	0.78%	0.84%
Elasticity Net Mg Expenses Top 10	$\frac{dC_D(L_d)}{dL_d}$	0.95%	1.03%	1.11%	1.21%
Elasticity Net Mg Expenses Fringe	$\frac{dC_f(L_f)}{dL_f}$	0.78%	0.84%	2.18%	2.35%
Fixed cost over loans Top 10	$\frac{\kappa_D}{L_D}$	0.89%	0.78%	1.02%	1.33%
Fixed cost over loans Fringe	$\frac{\kappa_F}{L_F}$	0.99%	5.83%	1.40%	1.96%
Equity issuance to assets Top 10	$\frac{\mathbf{1}_{\{\pi_d<0\}}(-\pi_d)}{D_d}$	0.01%	0.04%	1.25%	0.79%
Equity issuance to assets Fringe	$\frac{\mathbf{1}_{\{\pi_f<0\}}(-\pi_f)}{D_f}$	0.07%	0.13%	2.27%	5.04%
Bank Failure Rate Top 10	x_d	0.00%	0.00%	0.00%	0.00%
Bank Failure Rate Fringe	$\frac{\gamma_x}{\Gamma}$	0.76%	0.44%	0.00%	0.00%
Bank Merger Rate	$\frac{(\gamma-\Gamma)}{\gamma}$	1.27%	2.69%	0.00%	2.67%
Relative Size Dominant to Fringe	$\frac{D_d}{D_f}$	324.79	688.47	324.05	688.50
Dividends/Assets Top 10	$\mathscr{D}_d/D_d$	0.36%	0.74%	1.76%	1.63%
Dividend/Assets Fringe	$\mathscr{D}_f/D_f$	0.39%	0.66%	1.48%	1.13%
Loan Markup Top 10	$\frac{\theta r^L}{r_D+c'(L_d)}-1$	56.29%	205.37%	241.87%	213.26%
Loan Markup Fringe	$\frac{\theta r^L}{r_D+c'(L_f)}-1$	46.64%	149.73%	184.45%	160.67%
Interest Rate	r_B^L	6.69%	3.18%	5.24%	5.45%
Ratio of Loans to Deposits Top 10	$\frac{L_d}{D_d}$	83.3%	64.1%	95.11%	58.06%
Ratio of Loans to Deposits Fringe	$\frac{L_f}{D_d}$	73.3%	79.7%	82.54%	91.93%

Note: Data Pre corresponds to the period 1984 - 1994 and Data Post to the period 2011 to 2019. Moments below the line are not-targeted moments.

7 Validation

7.1 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 4: Model vs Data Transition

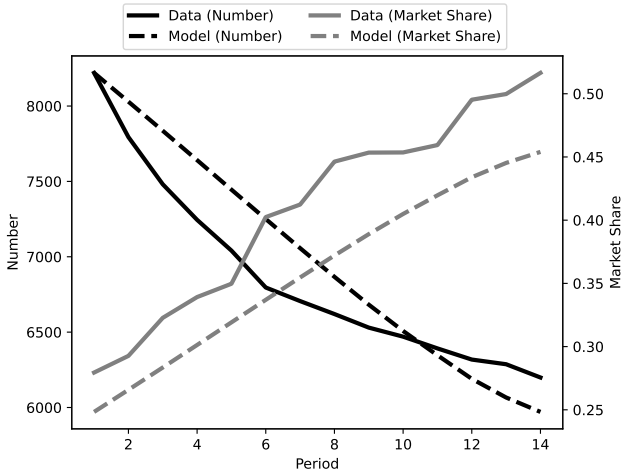
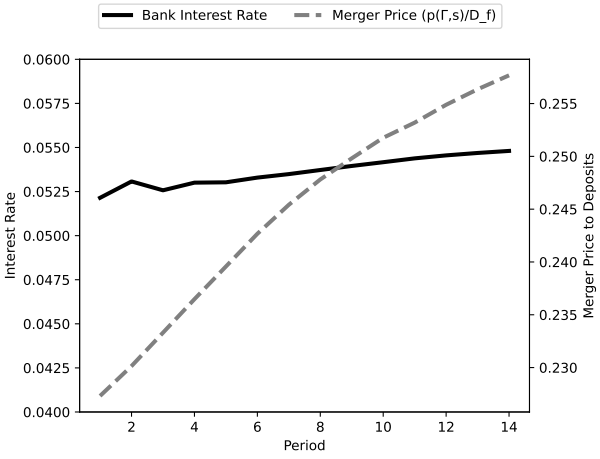
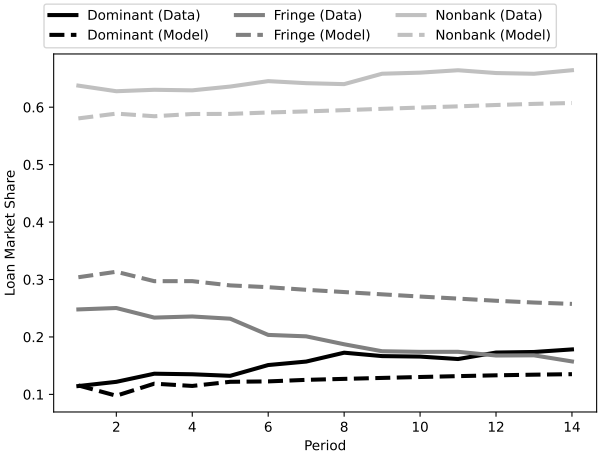


Figure 5: Effects of Transition

(a) Market Prices



(b) Loan Market Shares



In Figure 4, 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 25% deposit market share to 55% over 14 years, driven by an average 2% merger

rate (as opposed to 1.84% in the data). The number of fringe banks declines substantially.[21] The growth of the dominant bank in our model is driven entirely by mergers.

In Figure 5a, we illustrate the effect of bank mergers on prices and values. Due to mergers, the prevailing bank interest rate, r_L^B increases from 5.25% to 5.45%. Due to rising prices and declining competition, the value of fringe banks also rises.

Finally, in Figure 5b, we illustrate the growth of the nonbank sector as a result of banking mergers. Since the dominant bank uses its market power to decrease the supply of loans and increase the prevailing interest rate, potential borrowers switch to nonbanks. As a result, the growth of the nonbank sector is partially explained by banking mergers.

7.2 Marginal Propensity to Lend

We can also use our model to study how bank lending responds to changes in deposits. Taking a first order condition of the firms value function with respect to loans, we get:

$$E_{\theta'|\theta}[\theta' r_B^L - (1-\theta')\lambda_i'] + E_{\theta'|\theta}[\theta' \frac{\partial r_B^L}{\partial L}\frac{\partial L}{\partial L_i}L_i] + \beta \frac{\partial v_i(s')}{\partial s'}\frac{\partial s'}{\partial L_i} - r^A - \frac{\partial C_i(L_i)}{\partial L_i} - \mu_i = 0 \tag{34}$$

where μ_i is the multiplier on the constraint that $L_i \leq D_i$. For fringe banks $\frac{\partial L}{\partial L_i} = \frac{\partial s'}{\partial L_i} = 0$, as they do not internalize how their lending affects interest rates or the evolution of the state variables. Hence,

$$E_{\theta'|\theta}[\theta' r_B^L - (1-\theta')\lambda_i'] - r^A - \frac{\partial C_f(L_f)}{\partial L_f} - \mu_f = 0 \tag{35}$$

Notice, if $\mu_f > 0$, then the fringe bank is constrained and would lend any additional deposits. However, if $\mu_f = 0$, then the fringe bank is unconstrained, and would not lend more if they received additional deposits. So, fringe banks marginal propensity to lending is either 0 or 1. Fringe banks, in our model, behave similar to "hand-to-mouth" consumers. For the dominant bank, the marginal propensity to lend also depends on how lending affects interest rates and the evolution of future states.

To estimate the MPL, we simulate a panel of firms in the pre Riegle-Neal and the post Dodd-Frank environments. We then run the regression in equation (7). The results are presented below in 9. Our model implied MPL are very close to the data in the pre-Riegle-Neal period. The model implies MPLs of 56% and 92% for fringe and dominant banks respectively, compared to 52% and 86% in the data. In the post-Dodd-Frank period, our model implied MPLs are much higher for fringe banks (84% as opposed to 45%), but much lower for the dominant bank (0% as opposed to 75%).

[21] Given that the dominant bank is matching data from the 10 largest banks, the initial size of the fringe (1000 banks) is close to the size of the fringe in the data (8000 banks)

Table 9: Model-based MPL regressions

Coefficient	Pre Riegle-Neal	Post Dodd-Frank
(intercept)	-0.0	0.0
β	0.563	0.842
$\beta \times 1_D$	0.360	-0.859
N	9054	5781
R^2	0.457	0.325

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 25% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$.

7.3 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 $\Gamma_t^{\hat{D}_d} = \frac{L_{d,t-1}}{L_{d,t-1}+\Gamma L_{f,t-1}} \epsilon_{dt}$. We then estimate how much aggregate fluctuations in credit can be explained by $\Gamma_t^{\hat{D}_d}$. To do so, we regress total lending growth on $\Gamma_t^{\hat{D}_d}$ and its lags. 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. Table 10 and Table 11 presents the regression results for total lending and bank lending.

Table 10: Model-based granular regressions (Total Lending)

Coefficient	Pre Riegle-Neal	Post Dodd-Frank
(intercept)	0.0029	0.0002
$\Gamma_t^{\hat{D}_d}$	1.165	0.0437
N	7	7
R^2	0.649	0.216

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 25% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$.

Table 11: Model-based granular regressions (Bank Lending)

Coefficient	Pre Riegle-Neal	Post Dodd-Frank
(intercept)	0.0003	-0.0039
$\Gamma_t^{\hat{D}_d}$	0.1519	0.1136
N	7	7
R^2	0.426	0.173

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 25% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$.

We find substantially higher R^2 from the model based approach than from the data. We find the explanatory power is higher in the Pre Riegle-Neal period than in the Post Dodd-Frank period. This is driven by the fact that the dominant bank has a substantially higher MPL in the Pre Riegle-Neal period.

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 Policy Counterfactuals

8.1 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? To run this counterfactual, we obtain a new long-run equilibrium of the model as parameterized for the post-reform period but we restrict mergers as in the pre-reform period by setting $H(\Gamma, s) = \infty$. Since there are other differences between the pre-reform and the post-reform parameterization other than merger restrictions (i.e. (i) increased fixed costs for both dominant and fringe banks to reflect rising fixed costs in the data associated with Dodd -Frank bank regulation and (ii) declining nonbank marginal costs which can be thought of as technological innovation as a partial explanation for rising nonbank market share in the data), we need to decompose the numerous sources of change. The new long-run equilibrium associated with those changes are listed in "Post - No Mergers" in Table 12.

The solution to this version of the model with merger restrictions but a more efficient nonbank sector (relative to the pre-reform period) induces a significant increase in the share of credit originated by nonbank (as measured by one minus the ratio of bank loans to total loans). The more efficient nonbank sector together with the prevalence of a large set of competitive banks leads to a smaller increase in loan interest rates and interest margins and a smaller markup for both bank types (all relative to the changes observed between the pre-reform and the post-reform). Lower margins result in a decline in the value of the banks (as measured by Tobin's Q Value to Asset ratio). Since our focus is on how deposit growth funds bank lending, unlike papers solely focusing on effects on the deposit market, nonbank competition in the loan market is particularly relevant here.

In addition to our main counterfactual experiment, we also evaluate how much of the changes between the pre-reform and the post-reform can be explained by the increase in efficiency in the nonbank sector. We implement this decomposition by obtaining the long-run equilibrium of the model as parametrized in the post-reform period but by keeping the marginal cost of the

nonbank sector as in the pre-reform period. The results for that equilibrium are listed in "Post - c_N Same" in Table 12. We observe in this case that bank loans to total credit declines by less than the decline observed in the post-reform period. We can interpret this result as showing that the increase in concentration coupled with a decline in the efficiency of the banking sector (as banks' costs increase in the post-reform period) explain about 54% of the percentage point decline in bank lending.[22] The Post-c_N Same shows a larger increase in loan bank concentration which leads to higher interest rates, markups, and bank value as measured by Tobin's Q. This also illustrates that the rise of nonbank lending can be partially attributed to bank mergers.

Table 12: Model With Mergers vs Model With Merger Restriction

Name	Pre	Post	Post - c_N Same	Post - No Mergers
Deposit Market Share Top 10 to Fringe	24.36%	51.77%	53.92%	24.39%
Loan Market Share Top 10 to Fringe	23.33%	36.48%	38.76%	23.23%
Bank Loans to Total Loans Ratio	41.29%	34.70%	37.70%	37.60%
Interest Rate	5.24%	5.45%	5.63%	5.12%
Net Interest Margin	4.94%	5.14%	5.31%	4.83%
Bank Failure Rate Top 10	0.00%	0.00%	0.00%	0.00%
Bank Failure Rate Fringe	0.00%	0.00%	0.00%	0.00%
Loan Markup Top 10	241.87%	213.26%	230.99%	165.20%
Loan Markup Fringe	184.45%	160.67%	167.50%	144.65%
Tobin's Q (Dominant)	6.20%	23.65%	26.01%	12.93%
Tobin's Q (Fringe)	9.30%	18.39%	22.12%	10.40%
Total Bank Sector Value	0.1136	0.2837	0.3260	0.1464

Note: Model "Post" has no restriction on the size of the dominant bank. Model "Post - cN Same" does not alter the marginal cost of nonbanks. Model "Post - No Mergers" maintains the pre-Riegle-Neal restriction that the dominant bank cannot merge to greater than 25% deposit market share. Tobin's Q is computed as $\frac{V_i}{D_i}$ for banks of type i.

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 the growing nonbank sector.

8.1.1 On Allocative Efficiency

In order to understand optimal merger policy, we measure allocative efficiency under a variety of merger policies. Given large fixed costs, as illustrated in Table 8, mergers can improve allocative efficiency due to increasing returns to scale. However, due to market power and potential reductions in loan quantity, mergers could also exacerbate these fixed costs. We use the following decomposition of weighted average bank-level cost, as proposed by Olley and Pakes (1996b).

[22]The difference between pre-reform and Post-c_N same equals 3.6pp which represents 54.5% of the decline observed between pre and post-reform (6.6pp).

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

where $\omega(L_i)$ is the loan market share of bank i. The loan weighted average cost can be decomposed into two terms: the un-weighted average of bank-level cost and a covariance term between loan shares and cost. A smaller value for the covariance term captures an improvement in allocative efficiency as a larger share of loans are provided by banks with lower costs.

Table 13: Allocative Efficency

Moment	Pre Riegle-Neal	Post Dodd-Frank	No Merger Regulation
Avg. (loan-weighted) cost $\hat{c}$	0.0247	0.0282	0.0245
Avg. cost $\bar{c}$	0.0261	0.0315	0.0310
$Cov(c, \omega)$	-0.0013	-0.0033	-0.0065
Total Bank Loans $L_d + \Gamma L_f$	0.955	0.8269	0.6805

Note: Model "Pre Riegle-Neal" requires that the dominant bank cannot merge to greater than 25% market share. "Post Dodd-Frank" removes that restriction, but retains the other regulatory merger costs of $H(\Gamma, s)$. "No Merger Regulation" sets $h = 0$, removing all regulatory merger costs.

We find evidence for improved allocative efficiency follow Riegle-Neal as measured by the covariance of c and ω. The measure becomes more negative following Riegle-Neal as mergers decrease total fixed costs for the banking sector. We find that under a no-regulation equilibrium (i.e. $h = 0$) allocative efficiency further improves due to greater mergers. However, this allocative efficiency comes at the cost of a substantial reduction in bank lending.

8.2 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 three counterfactuals in both the pre-Riegle-Neal and post-Dodd-Frank settings. We let monetary policy affect r^D, the deposit rate and r^A, the return on securities. We consider a monetary policy contraction permanently multiplying r_A and r^D by 1.05. We also decompose the effects of monetary policy by the effect on the return on securities and cost of deposits. The results are presented below in tables 14 and 15 for the "Pre-Riegle-Neal" and "Post-Dodd-Frank" parametrizations.

Table 14: Monetary Policy Counterfactuals: Pre-Riegle-Neal

Moment	Contractionary MP	Increased r^D	Increased r_A
Total Loans by Dominant Bank	-8.59%	3.40%	-3.70%
Total Loans by Fringe Banks	-0.27%	-0.49%	-1.13%
Total Loans by Nonbanks	1.13%	-0.19%	0.94%
Total Loans	-0.22%	0.09%	-0.07%
Interest Rate	1.97%	-0.10%	1.62%
Net Interest Margin	1.88%	-0.24%	1.67%

Note: This table presents the percent change from the baseline "Pre-Riegle-Neal" Model using the "Pre-Riegle-Neal" calibration. "Contractionary MP" multiplies both r^D and r_A parameters by 1.05. "Increased r^D" multiplies r^D by 1.05. "Increased r_A" multiplies r_A by 1.05.

Table 15: Monetary Policy Counterfactuals: Post-Dodd-Frank

Moment	Contractionary MP	Increased r^D	Increased r_A
Deposit Share Top 10 to Fringe	0.03%	0.02%	0.03%
Bank Merger Rate	0.13%	0.26%	0.50%
Total Loans by Dominant Bank	-4.61%	1.20%	-2.18%
Total Loans by Fringe Banks	-0.94%	0.36%	-1.25%
Total Loans by Nonbanks	0.53%	-0.16%	0.56%
Total Loans	-0.32%	-0.03%	-0.07%
Interest Rate	1.49%	0.10%	1.31%
Net Interest Margin	1.39%	-0.24%	1.35%

Note: This table presents the percent change from the baseline "Post Dodd-Frank" Model using the "Post Dodd-Frank" calibration. "Contractionary MP" multiplies both r^D and r_A parameters by 1.05. "Increased r^D" multiplies r^D by 1.05. "Increased r_A" multiplies r_A by 1.05.

Comparing these two tables, we can measure the effectiveness of monetary policy under the two different market structures. We find total lending declines by more under Dodd-Frank than before Riegle-Neal, suggesting that market structure can influence the effectiveness of monetary policy.

9 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 (nonatomistic) 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 find that Riegle-Neal improved bank profitability and financial stability, at the cost of higher interest rates (lower efficiency) for borrowers. Our counterfactuals also show that rising non-bank competition has mitigated these effects. 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.

We also use the model to assess how the bank lending channel of monetary policy has been affected by changes in rising concentration (due to changes in merger policies)? We find that Pre-Riegle 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 banks (as in Kashyap and Stein (2000)). Post Dodd-Frank a contractionary monetary policy shock also leads to a decline in total lending explained by a decline in lending by nonbanks (which see their marginal cost increase with the policy rate). The reduction in lending by nonbanks leads to an increase in small bank lending and a smaller increase in the bank loan interest rate post monetary policy shock than in the pre Riegel-Neal period. Hence, the bank lending channel of monetary policy is weaker in a more concentrated banking industry.

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.

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A-1 Supplementary Appendix

A-1.1 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.[23]

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

	All Banks		Top 10		Fringe (no Top 10)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Charge-off Rate %	0.85	0.55	1.08 †	0.71	0.61	0.38
Default freq. %	2.14	1.27	2.80 †	1.82	1.66	0.92
Cost Deposits %	0.03	1.49	0.08	1.62	0.05	1.45
Loan Interest Rate %	4.85	1.80	4.93	1.86	4.80	1.80
Markup	1.08	0.54	1.27 †	0.71	0.96	0.43

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 10 Banks refers to the Top 10 banks when sorted by assets. Fringe Banks refers to all banks outside the top 10. † denotes statistically significant difference (at 1% level) between the average for Top 10 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 10 and 0 otherwise. Data correspond to commercial banks in the U.S. between 1984 and 2019. Source: Consolidated Reports of Condition and Income

[23] 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).

A-1.2 Other Moments

Table A.2: Moments Data

	Pre-reform 1984 - 1993			Post-reform 2010 - 2019		
	All Banks	Top 10	Fringe	All Banks	Top 10	Fringe
Cost Deposits % r_D	1.57	1.94	1.46	-1.31	-1.37	-1.22
Return on Securities % r_A	4.17	4.48	4.03	2.96	2.26	4.06
Default freq. % θ	3.10	4.64	2.49	2.48	3.03	1.65
Default freq. Autocorrel.	0.700	0.711	0.700	0.797	0.974	0.797
Std Dev Error Default freq. (σ_{u^θ})	0.008	0.006	0.008	0.004	0.002	0.004
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 %	15.41	14.12	15.94	12.54	11.47	14.09
Net Mg Expenses %	1.78	1.15	2.00	1.48	1.35	1.69
Elasticity Net Mg Expenses	0.83	0.95	0.78	0.95	1.03	0.84
Fixed Cost / Loans %	0.96	0.89	0.99	2.81	0.78	5.83
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 % $\frac{\theta r_B^L}{r_D + c'(L^*)}$	49.08	56.29	46.64	175.58	205.37	149.73

Note: Data Pre corresponds to the period 1984 - 1993 and Data Post to the period 2010 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)	10,392	5,183
Deposit HHI (national)	93.90	541.99
Number Top 10 Banks (state)	1.471	4.109
Number Fringe Banks (state)	167.667	116.876
Deposit HHI (state)	1019.39	1555.86
Number Top 10 Banks (county)	0.444	1.069
Number Fringe Banks (county)	5.428	6.495
Deposit HHI (county)	2191.70	2575.50
Deposit Market Share Top 10	24.77	57.79
Loan Market Share Top 10	28.55	52.86
Relative Size Top 10 / Fringe (Deposits)	324.79	688.47
Relative Size Top 10 / Fringe (Loans)	394.64	556.01
Bank Entry (denovo) rate	5.00	1.25
Bank Failure Rate	0.76	0.44
Bank Failure Rate Top 10	0.00	0.00
Bank Failure Rate Fringe	0.76	0.44
Bank Merger Rate	1.27	2.69
Deposit to Output Ratio	39.01	57.19
Bank Loans to Output Ratio$^{\#}$	32.46	43.72
Bank Loans to Output Ratio†	43.15	60.22
Bank Loans to Output Ratio‡	51.77	50.53
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 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 4% of cyclical fluctuations in real gdp.

Table A.4: Explanatory power of granular residuals of dominant banks on aggregate output (R^2)

	Dep. Var. $\Delta \log(gdp_t)$					
	Top 10 banks		Top 35 banks		Top 100 banks	
(intercept)	-0.000133	0.000207	-0.000169	0.000127	-0.000109	0.000136
	(0.866)	(0.795)	(0.829)	(0.872)	(0.888)	(0.861)
Γ^x_t	-0.0182	-0.0204	-0.0280	-0.0324	-0.0395	-0.0468
	(0.550)	(0.497)	(0.449)	(0.377)	(0.312)	(0.226)
Γ^x_{t-1}	-0.0282	-0.0276	-0.0414	-0.0405	-0.0323	-0.0270
	(0.354)	(0.359)	(0.263)	(0.270)	(0.407)	(0.484)
Γ^x_{t-2}		0.0754**		0.0869**		0.0966**
		(0.013)		(0.019)		(0.013)
N	191	190	191	190	191	190
R^2	0.006	0.039	0.010	0.039	0.009	0.041
Adjusted R^2	0.000	0.024	0.000	0.023	0.000	0.025

Note: Table presents the R^2 from a regression of the corresponding dependent variable on Γ^x_t, Γ^x_{t-1}, and Γ^x_{t-2} when x is real deposits. "$\Delta \log(gdp_t)$" refers to growth rate of detrended real gdp. Top 10 Banks, Top 35 Banks, and Top 100 Banks correspond to the cases when $K = 10$, $K = 35$, and $K = 100$, respectively. We let $X_{it} = \overline{g}_t = N^{-1} \sum_{i=1}^{N} g^x_{it}$, so $\hat{\Gamma}^x_t = \sum_{i=1}^{K} \frac{\ell_{it-1}}{L_{t-1}} (g^x_{it} - \overline{g}_t)$. Source: Call Reports

Table A.5: Deposit Process

	ρ^d_i	$\sigma_{i,u}$	$\sigma_{i,d}$	$Pr(\epsilon < -std)$
i	Full Sample 1984 - 2019			
Top 10 Banks	0.777	0.119	0.189	
Fringe Banks	0.805	0.167	0.281	
All Banks	0.806	0.167	0.281	
i	Pre 1984 - 1993			
Top 10 Banks	0.715	0.118	0.168	0.176
Fringe Banks	0.538	0.153	0.182	0.081
All Banks	0.538	0.153	0.182	
i	Post 2011 - 2019			
Top 10 Banks	0.557	0.058	0.070	0.139
Fringe Banks	0.669	0.116	0.156	0.085
All Banks	0.669	0.117	0.158	

A-1.3 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 (7) by adding an interaction term between the liquid assets to total assets ratio and the unexpected shock to deposits: $\nu_{it} \times (Liq/Assets)_{it-1}$.[24] We note that the average ratio of liquid assets to total assets between 1984-2019 for the Top 10 banks and fringe banks is 19.36% and 29.61%, respectively. The results for the MPL estimation are presented in Table A.6. 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 when using the full sample (1984-2019) but it declines with bank size for the 2011-2019 period. In particular, the MPL for small banks during this period (evaluated at average $(Liq/Assets)_{it-1}$) is 0.436 (0.641-0.689*0.2961). The MPL for the Top 10 banks is 0.579 (0.64-0.689*0.1936+0.35-1.436*0.1936).

Table A.6: MPL (Data Estimates): The role of liquid assets

	Dependent Variable $\Delta \log(L_{it})$							
ν_{it}	0.549***	0.547***	0.532***	0.531***	0.502***	0.499***	0.641***	0.640***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ν_{it}×(Liq/Assets)$_{it-1}$	-0.142***	-0.140***	-0.0420***	-0.0411***	-0.00731	-0.00301	-0.692***	-0.689***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.458)	(0.760)	(0.000)	(0.000)
$\nu_{it} \times I_{t10}$		0.298***		0.121		0.0668		0.350***
		(0.000)		(0.474)		(0.449)		(0.000)
$\nu_{it-1} \times I_{t10}$×(Liq/Assets)$_{it-1}$		0.371		1.082		1.813***		-1.436***
		(0.128)		(0.176)		(0.000)		(0.003)
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Period	1984-2019		1984-1993		1994-2007		2011-2019	
N	946,299	946,299	353,150	353,150	355,389	355,389	169,536	169,536
R-sq	0.362	0.362	0.398	0.398	0.416	0.416	0.297	0.297
adj. R-sq	0.348	0.349	0.371	0.371	0.396	0.397	0.271	0.271

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (5). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 6. We follow Gabaix (2011) and construct ν_{it} by removing a time fixed effect. (Liq/Assets)$_{it-1}$ refers to the ratio of liquid assets to total assets. $I_{t,k(i)=10}$ is an indicator that takes value 1 if bank i is in the Top 10 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

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

level Herfindahl-Hirschman Index (HHI) for deposits. We take the deposit-weighted average for each bank to obtain an average measure of concentration for each bank HHI_{it}. 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.7 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.[25] 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.

Table A.7: HHI: Marginal Propensity to Lend (Data Estimates)

	Dependent Variable $\Delta \log(L_{it})$					
ν_{it}	0.543***	0.542***	0.546***	0.544***	0.531***	0.531***
	(0.00261)	(0.00261)	(0.00354)	(0.00354)	(0.00490)	(0.00490)
$\nu_{it} \times HHI_{it}$	-0.215***	-0.215***	-0.172***	-0.171***	-0.350***	-0.353***
	(0.00969)	(0.00969)	(0.0129)	(0.0129)	(0.0182)	(0.0182)
$\nu_{it} \times I_{t10}$		0.526***		0.331*		0.378
		(0.119)		(0.171)		(0.361)
$\nu_{it-1} \times I_{t10} \times HHI_{it}$		-0.475		0.328		-0.115
		(0.479)		(0.734)		(1.137)
Bank FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Period	1994-2019		1994-2007		2011-2019	
N	0	0	0	0	0	0
R-sq	0.378	0.378	0.413	0.414	0.331	0.331
adj. R-sq	0.364	0.365	0.394	0.394	0.304	0.305

Note: Standard Errors in parenthesis. *** significant at 1%, ** significant at 5%, * significant at 10% level. Table presents the estimates from equation (5). L_{it} refers to loans and leases. ν_{it} corresponds to the error term as defined in equation 6. We follow Gabaix (2011) and construct ν_{it} by removing a time fixed effect. $I_{t,k(i)=10}$ is an indicator that takes value 1 if bank i is in the Top 10 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

[25] The average HHI for Top 10 banks and banks not in the Top 10 is 2534.6 and 2461.22, respectively. The difference is not statistically significant.