Fixed Costs in the U.S. Banking System*

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August 28, 2026

Abstract

Fixed costs account for an increasing share of operating expenses in the U.S. banking system. From 1995 to 2026, estimated fixed costs rose from 37 percent to 62 percent as a share of total noninterest expense. Over the same period, estimated marginal and average operating costs declined, loan spreads and net interest margins fell, and estimated loan markups increased by 21 percentage points. These trends are pervasive across banks but are most pronounced among large banks. We develop a model of bank industry dynamics with endogenous fixed costs to rationalize these long-run trends and examine pro-competitive effects. While competition increases credit supply, it decreases lending efficiency and increases bank risk-taking.

JEL Classification: G21, L11, L13, D24

Keywords: banks, fixed costs, market power, competition, industry dynamics

*We are grateful for comments from Marty Eichenbaum and Johannes Matschke, and seminar participants at the Federal Reserve Bank of Kansas City. The views expressed are those of the authors and do not necessarily reflect the positions of the Federal Reserve Bank of Kansas City or the Federal Reserve System

1 Introduction

Technological change has made production increasingly scalable, with firms incurring greater fixed costs in exchange for lower marginal costs. This shift is evident in the growing importance of inputs such as information technology, data processing, and R&D, which have increased substantially over several decades (De Ridder (2024)). These technologies require recurring fixed cost expenses which are independent of output but can substantially reduce the marginal cost of production, allowing firms to scale more easily.

This paper examines how this shift toward scalable production has affected costs, pricing, and market structure in the U.S. banking system since the 1990s. We develop an estimation methodology that recovers both fixed and marginal bank cost estimates and use it to characterize changes in bank cost structure over time and across banks.

We find that fixed costs are sizable and have increased substantially over time. From 1995 to 2026, estimated fixed costs rose from 37% to 62% as a share of total non-interest expense. The increase is particularly pronounced among large banks (LBOs): their fixed cost share rose from 42.4% to 61.9%, compared with a more modest increase from 25.1% to 32.2% among community banks (CBOs). Traditional production inputs such as branch networks are likely an important component of fixed costs, but branch networks have declined over the same period. Thus, the increase in fixed costs reflects a broader shift in bank technology and costs, of which IT spending provides an instructive but not exhaustive example: hardware and software spending raise fixed costs but improve productivity through back-end capabilities.

While fixed costs have increased, both marginal and average bank costs have declined substantially. Estimated marginal costs fell by 50%–70% in our sample while average lending costs fell by roughly 50%. Over the same period, the price of lending, measured by loan spreads, and the price of intermediation, measured by net interest margins, also declined.[1] Importantly, costs fell even *faster* than prices, resulting in an estimated 21 percentage point increase in the average loan markup, allowing banks to recover some of their fixed cost

[1]The loan spread is measured as the bank loan rate minus an observed money market rate to control for the level of interest rates.

spending through higher markups.

The banking industry has also undergone significant changes in market structure. From 1995 to 2025, the number of bank charters fell by roughly 2,000, a 35% decline in active charters. Market concentration, measured using county-years as an approximation for geographic markets, also increased. While many factors have contributed to the decline in bank charters and limited *de novo* entry, the shift in bank cost structure is undoubtedly an important element, for which we use a model to help isolate the effect.

We develop a model of bank industry dynamics similar to Corbae and Levine (2018) and incorporate endogenous fixed costs to rationalize the documented empirical trends. Heterogeneous banks Cournot compete for lending and make decisions over lending, risk-taking, and their cost structure. Following De Ridder (2024), banks choose between fixed cost and marginal cost combinations, with greater fixed costs generating lower marginal costs.[2] Banks differ in their productivity in converting fixed costs into lower marginal costs, and risk-taking determines the probability of industry exit. Each period, potential entrants decide whether to pay a fixed entry cost which leads to an endogenous market structure in equilibrium.

We calibrate the model to two periods, an *early* period beginning in the 1990s and a *current* period, targeting empirical moments for both LBOs and CBOs. We find that returns to bank franchise value increased by 129% over the sample period, with increases of 175% for LBOs and 110% for CBOs.[3] We decompose this change into three factors: barriers to entry, technological change, and bank productivity in deploying the fixed cost technology. The increase in barriers to entry is the largest contributor, with entry costs more than doubling over the sample period. Changes in bank productivity are the second-largest contributor, but trends differ across bank types: LBO productivity increased substantially, while CBO productivity declined. This divergence accounts for much of the difference in the growth of

[2]For example, consider a bank which each period makes decisions over a variety of IT packages to update its core technology systems. It can choose a *premium* package which significantly boosts efficiency, but it must pay a high fixed cost. Or, the bank can choose a *basic* package which does not greatly improve efficiency but has very low fixed cost.

[3]Returns to franchise value is analogous to returns from holding an index fund of bank stocks.

fixed cost shares across bank types. Last, while improvements in the fixed cost technology (common to all banks) privately benefited each bank, its effect on competition redistributed these gains toward CBOs and away from LBOs.

Finally, we examine the effects of competition in a banking industry characterized by high fixed costs. We model greater competition as a reduction in the entry cost faced by potential entrants. As expected, greater competition increases aggregate lending and entry. However, it also generates two adverse effects when fixed costs are high. First, lending becomes less efficient: competition reduces the individual scale of each bank, thereby making it more difficult to spread out fixed costs across production. Banks respond by lowering fixed costs and increasing marginal costs—an effect that is absent in a model without fixed costs, where marginal and average costs are equal at every scale. Second, competition amplifies risk-taking. Both the high- and no-fixed cost models generate greater risk-taking as competition reduces future expected profits, but risk-taking increases substantially more in the high-fixed cost model due to the greater operational leverage. Thus, while competition expands credit and entry, it also generates less efficient lending and greater risk-taking when fixed costs are present.

Related Literature. Our paper relates to several literatures on firm cost structure, bank pricing, and industry dynamics. We first relate to the broader literature documenting secular trends in markups and market concentration (e.g., De Loecker et al. (2020) and De Ridder (2024)).[4] In banking, a large literature estimates cost efficiency (e.g., Berger and Mester (1997)) and economies of scale (e.g., see Hughes et al. (2019), Berger et al. (1987), Hughes and Mester (2013), and Wheelock and Wilson (2012)), documenting substantial cross-sectional differences in efficiency, particularly by bank size, and compelling evidence of increasing returns to scale. We complement this literature by directly estimating the tradeoff between fixed and marginal costs, and document how this tradeoff has evolved across banks and over time.

Our approach also differs from prior frameworks that measure fixed costs by directly

[4] See also (Ganapati, 2021) and Autor et al. (2020).

assigning particular expense categories to fixed costs, such as Kovner et al. (2014) and Corbae and D'Erasmo (2021). While these approaches provide a straightforward measure of fixed costs, our methodology estimates fixed costs from cost elasticities and is therefore agnostic and more comprehensive in identifying underlying sources of fixed costs. This approach is more related to DeYoung and Roland (2001), who estimate operating leverage for U.S. banks.

Estimating marginal costs also allows us to measure bank markups and study their evolution alongside changes in bank cost structure. The literature on bank markups has primarily examined cross-sectional differences, often associated with underlying product differentiation (e.g., Egan et al. (2017)), or cyclical variation related to monetary policy and the business cycle (Drechsler et al. (2021), Xiao (2020), Wang et al. (2022), and Kashyap and Stein (2000)), or productivity at a given point in time (e.g., Egan et al. (2022)). We instead focus on longer run trends in prices and costs associated with technological change, and the increasing use of fixed cost-intensive production technologies in the banking system. In this respect, we relate to studies of technological change and cost efficiency in banking (e.g., Buchak et al. (2018), Fuster et al. (2019), and Berger (2003)), as well as papers examining the interaction between technological change and competition (e.g., Jiang et al. (2026), Jiang et al. (2025), Vives and Ye (2025), and Hauswald and Marquez (2003)).

Our model framework builds on the firm dynamics framework of Corbae and Levine (2018) in which endogenous entry and exit are governed by entry costs and risk-taking, and the broader literature on firm dynamics beginning with Hopenhayn (1992).[5] We add a bank cost structure decision in which banks choose a bundle, trading off fixed and marginal costs. While some existing models incorporate fixed costs (e.g., Dick (2007) and Corbae and D'Erasmo (2025)) or some form of adjustment cost related to lending and the balance sheet (e.g., De Nicoló et al. (2014)), these are often exogenously imposed and not explicitly linked to the bank's variable cost as in our model framework.

Finally, our analysis relates to the literature on competition and bank risk. Early work emphasized the competition-fragility view, whereby increased competition erodes franchise

[5] See also Corbae and D'Erasmo (2025) and Dia and VanHoose (2018) for related frameworks.

value and encourages banks to take on more risk (e.g., Kwaja and Mian 2008, Allen and Gale 2004, Keeley (1990), and Carvino and Levchenko 2017). Some more recent work, however, has also documented channels through which greater competition may reduce fragility and bank risk, for example through improved loan performance (e.g., Boyd and De Nicolo 2005), while also emphasizing that the relationship between competition and stability need not be monotonic (e.g., Martínez-Miera and Repullo 2010, Whited et al. 2021, and Gödl-Hanisch and Pandolfo 2026). We find a competition-fragility result, consistent with Corbae and Levine 2018 whereby banks increase risk as competition intensifies, and we find that a high fixed cost economy amplifies this channel.

The remainder of the paper is organized as follows. Section 2 reviews our empirical methodology to recover bank fixed cost estimates along with our estimation results. Section 3 presents our model of the bank industry with endogenous fixed costs. Section 4 presents our calibration strategy as well as the main policy experiments related to bank returns over time and the effects of competition in a high fixed cost environment.

2 Empirical Methodology and Results

Data. We use merger-adjusted quarterly FR Y-9C reports, which are reported at the bank holding company level. The data contains detailed balance sheet and income statement information that allows us to construct bank-quarter measures of lending, prices, and costs at varying levels of granularity. We generally use a sample period from 1994 to 2026 to maximize time coverage while also retaining relevant data fields required for our cost estimation. We also use annual data from the FDIC's Summary of Deposits (SOD) to construct market-level measures of bank concentration. Appendix Section B provides details on the data, sample filtering, and variable construction.

Estimating Fixed Costs. Similar to De Ridder (2024), we begin with a simple profit equation, where we assume an affine cost structure such that

$$\begin{aligned} \Pi =& P \cdot Q - MC \cdot Q - F \\ =& P \cdot Q(1 - \frac{1}{\mu}) - F \end{aligned} \tag{1}$$

where F denotes fixed costs and MC denotes the linear marginal cost term. In the second line, we reformulate the variable cost term to be expressed in terms of the markup $\mu = \frac{P}{MC}$ because we are interested in the relationship between fixed costs and bank markups. While profits and revenue are observable in the data, recovering fixed costs F requires an estimate of the markup. We obtain this from the cost elasticity, following Syverson (2024),

$$\begin{aligned} \mu =& \frac{P}{MC} \\ =& \frac{P \cdot Q}{C(Q)} \cdot \frac{1}{\nu}, \end{aligned} \tag{2}$$

where $\nu = \frac{\partial logC}{\partial logQ}$ is the cost elasticity. Thus, the cost elasticity, together with bank revenue, profits, and total costs, allows us to recover both an estimate of markups and fixed costs.

Because we are interested in differences in cost structure across banks *and* over time, we partition banks into two groups: large banks (LBOs) with more than \$10 billion in assets and small community banks (CBOs) with less than \$10 billion.[6] We estimate time-varying cost elasticities using a hedonic cost regression similar to Drechsler et al. (2026):

$$\log C_{it}^b = \sum_j \nu_j^b \log Q_{it}^b \, \mathbf{1}\{t \in j\} + X_{it}^{b\prime} \beta^b + \xi_t^b + \alpha_i^b + \varepsilon_{it}^b. \tag{3}$$

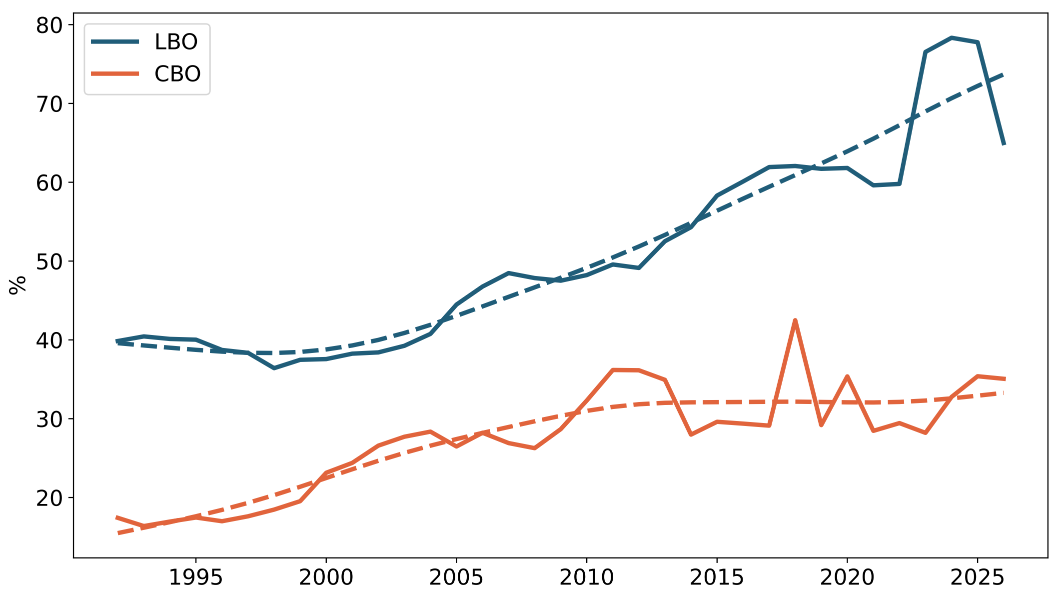
Here, $b \in \{\text{LBO}, \text{CBO}\}$ denotes bank type. The coefficient ν_j^b measures the cost elasticity for all banks of type b in a given time period j. In the main specification, we use annual time periods/interactions as opposed to quarterly interactions, although the data are at the

[6] We categorize banks according to these asset thresholds based upon deflated asset values using an index normalized in the year 2020.

quarterly frequency. The specification also includes bank and time fixed effects and controls for bank profitability, leverage, and asset composition.[7] Total bank cost C_{it}^b is measured as reported non-interest expense which, includes expenditures for labor, physical capital, IT, and all other operating expenses. We measure output Q_{it}^b as total lending, which captures the bank's overall lending activity and because we have limited loan portfolio granularity in the data going back to the 1990s.

Using the estimated cost elasticities and Equation 1, we recover time-varying measures of fixed costs $\hat{F}_t^b$ for each bank type. Figure 1 plots the resulting fixed cost shares $\frac{\hat{F}_t^b}{C_t^b}$. Fixed costs have increased steadily over the past thirty years, particularly among large banks, whose fixed cost share has nearly doubled from roughly 40%. Thus, fixed costs have always been an important component of bank costs but now are the dominant feature of the cost structure of large banks.

FIGURE 1: BANK FIXED COST AS PERCENTAGE OF TOTAL COST



Notes: This figure plots aggregate fixed cost shares for both small, community banks (CBOs) and large banks (LBOs) using cost elasticity estimates from the regression specification in Equation 3. Cost elasticities are used to derive markups and fixed costs using Equations 2 and 1, respectively.

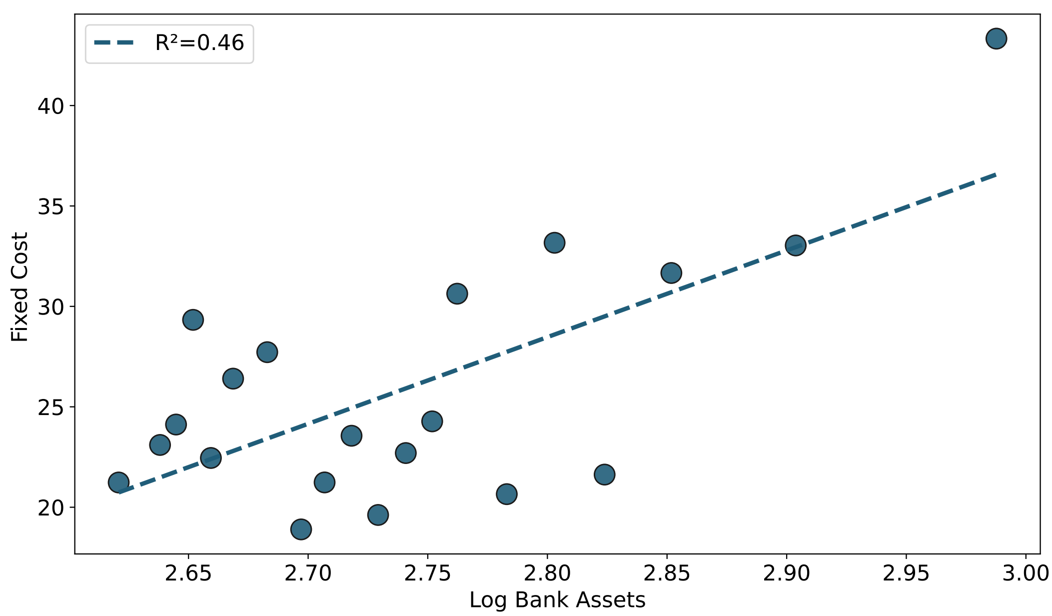
[7]See Appendix Section B for details on the regression specification and variable construction.

We next estimate fixed costs at the individual bank level. To do this, we modify the hedonic cost regression to include bank interactions as opposed to time interactions, such that we may recover bank-level fixed cost estimates:

$$log(Cost_{it}) = \sum_{bank} \nu_{bank} \cdot log(Q_{it}) \cdot I\big[bank = i\big] + \boldsymbol{\beta X}_{it} + \xi_t + \alpha_i + \epsilon_{it}. \tag{4}$$

We use the resulting bank-level cost elasticities $\hat{\nu}_i$ to construct bank-level fixed cost shares. Figure 2 plots the relationship between fixed cost shares and log banks assets in a binned scatter plot. The figure validates the earlier finding that fixed cost shares are strongly, and positively, correlated with bank size, both in the unconditional cross-section as well as across time.

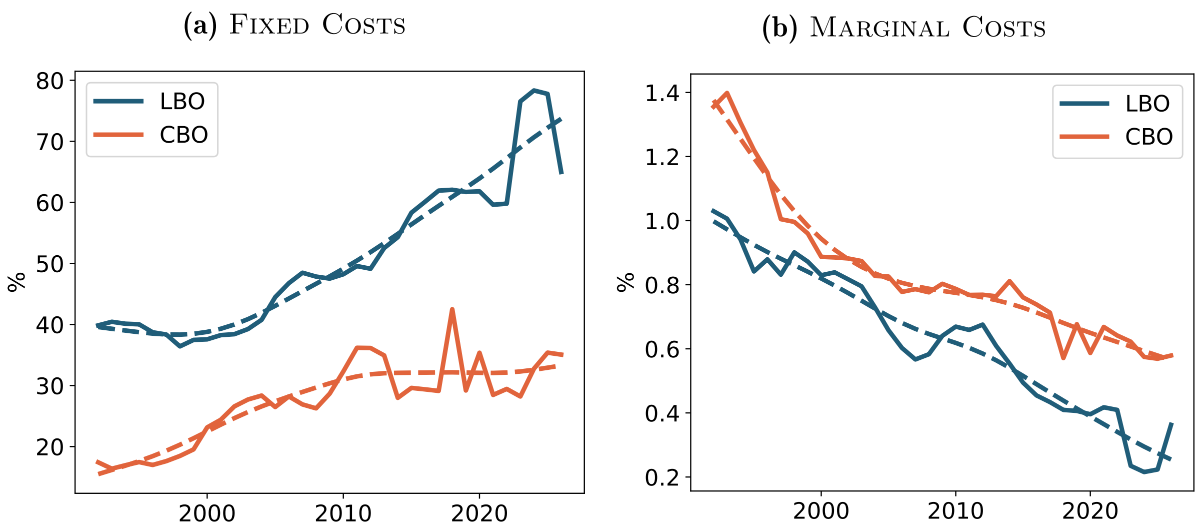
FIGURE 2: Bank Fixed Cost Share and Bank Size



Notes: This figure is a binned scatter plot of bank-level fixed cost shares and log bank assets, using 20 evenly spaced bins according to percentiles of log assets. Bank size is measured as the time-series average of log assets, and fixed cost shares are obtained from the cost-elasticity estimates using the regression specification in Equation 4 where cost elasticities are used to derive markups and fixed costs using Equations 2 and 1, respectively.

Figure 3 plots the evolution of fixed cost shares alongside the implied marginal cost estimates from the same cost specification. The figure illustrates the inverse relationship between fixed and marginal costs: banks with greater fixed costs have lower marginal costs, consistent with a production technology in which fixed investment allows banks to scale marginal lending more efficiently. Because both measures are derived form the same estimation procedure, however, this relationship is partly mechanical. To strengthen the robustness of the finding for marginal cost, we estimate a translog cost function following Hughes and Mester (2013) and Berger et al. (2017). We obtain similar results, with marginal costs declining substantially between 1995 and 2026 (Figure A.1 in Appendix Section A).

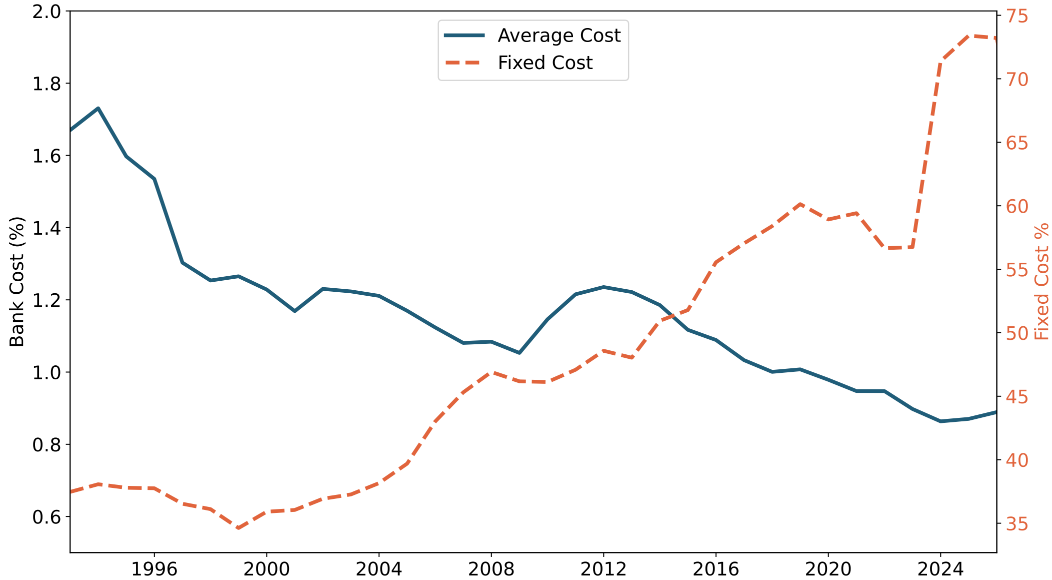
FIGURE 3: Time Trends in Bank Fixed and Marginal Costs



Notes: This figure plots aggregate fixed cost shares (left panel) for large and small banks over time, along with estimated marginal costs, derived from the hedonic cost regression in Equation 3.

As a descriptive, estimation-free measure of bank cost trends, Figure 4 plots average bank costs over time. Average loan costs have declined steadily over the sample period. While average cost does not distinguish between fixed and variable costs, its decline is consistent with broader improvements in lending efficiency and reductions in the marginal cost of production.

FIGURE 4: Bank Average Costs Over Time



Notes: This figure plots average total cost, measured as bank non-interest expense relative to total lending. Variable definitions are reported in Appendix Section B.1.

Bank Prices and Markups. Having documented changes in bank cost structure and the decline in overall costs, we next examine changes in bank prices. We use two measures of bank prices. The first is the loan spread,

$$s_{it}^{\ell} = r_{it}^{\ell} - r_t, \tag{5}$$

where r_{it}^{ℓ} is the bank's imputed loan rate and r_t is a benchmark interest rate, accounting for the level of interest rates at any given time. In our application, we use the federal funds rate as the benchmark rate. While our focus is on lending, we also account for variation in banks' funding costs using net interest margin,

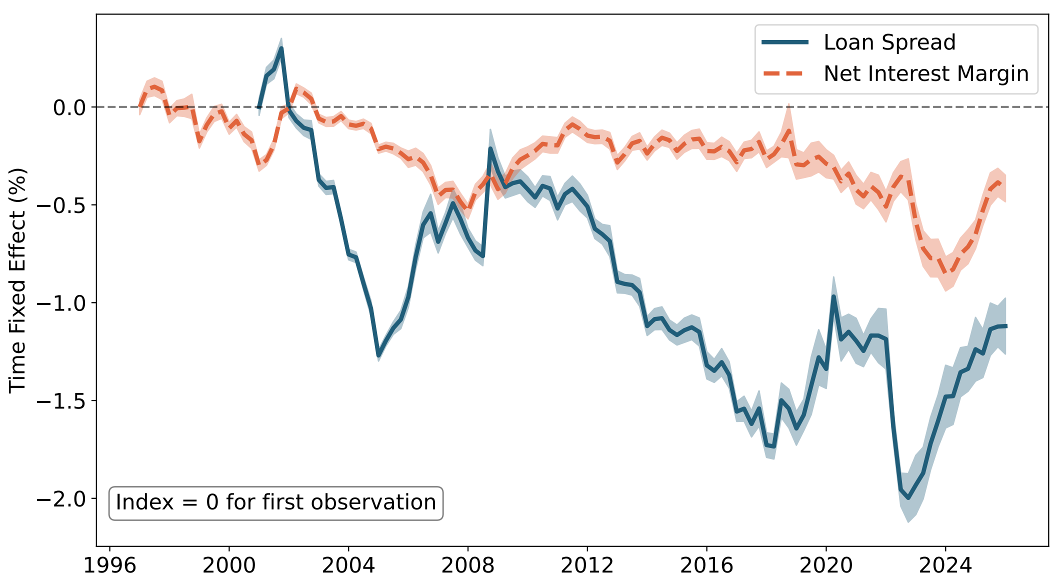
$$\text{NIM}_{it} = \frac{\text{interest income}_{it} - \text{interest expense}_{it}}{\text{assets}_{it}} \approx r_{it}^{\ell} - r_{it}^{d}. \tag{6}$$

Thus, while the loan spread measures the price of lending relative to the market interest rate, net interest margin measures the net price of bank intermediation between borrowers and savers. For each price measure, we estimate its time trend using a two-step procedure. We first regress bank-quarter prices on bank fixed efffects and macroeconomic controls,

$$p_{it} = \alpha_i + \boldsymbol{X}_t \boldsymbol{\beta} + \epsilon_{it}, \tag{7}$$

where the controls include measures of real economic growth and monetary policy. We then regress the residuals on time fixed effects to recover price trends that are orthogonal to these macroeconomic factors. Figure 5 plots the resulting time effects. While both series exhibit some cyclicality, particularly the loan spread, both show substantial declines over the sample period. The loan spread falls by roughly 100 basis points, while net interest margin falls by roughly 50 basis points. Thus, banks have substantially reduced their prices over the same period in which fixed costs increased while average (and marginal) costs declined.

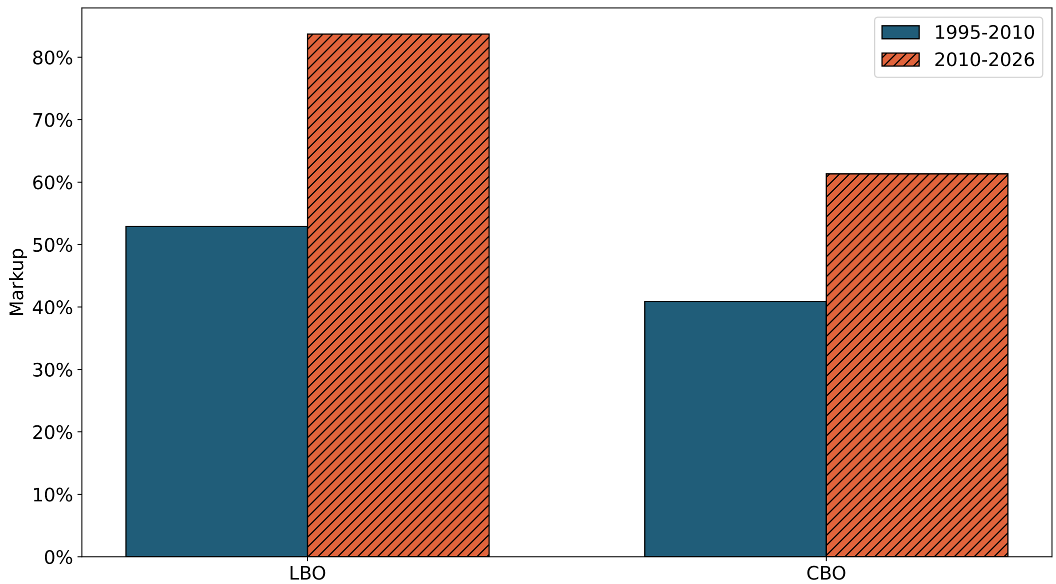
FIGURE 5: Bank Price Trends over Time



Notes: This figure plots the estimated time effects $\hat{\xi}t$ from the second-stage regression of residuals from pit $= \alpha_i + \boldsymbol{X}t\boldsymbol{\beta} + \epsilon it$, where $\boldsymbol{X}_{it}$ contains time-varying macroeconomic controls. Time effects are normalized to zero in the first observation period and expressed in annualized net percentage terms.

Given our estimates of marginal costs and loan prices, we next examine the evolution of loan markups. Figure 6 shows that loan markups increased substantially over the sample period. The average LBO loan markup increased from 52.9% to 83.7%, while the average CBO loan markup increased from 40.9% to 61.3%. Thus, while bank costs and prices declined over the sample period, costs declined faster, resulting in higher markups. The increase is most pronounced among LBOs, consistent with their larger increase in fixed cost spending.

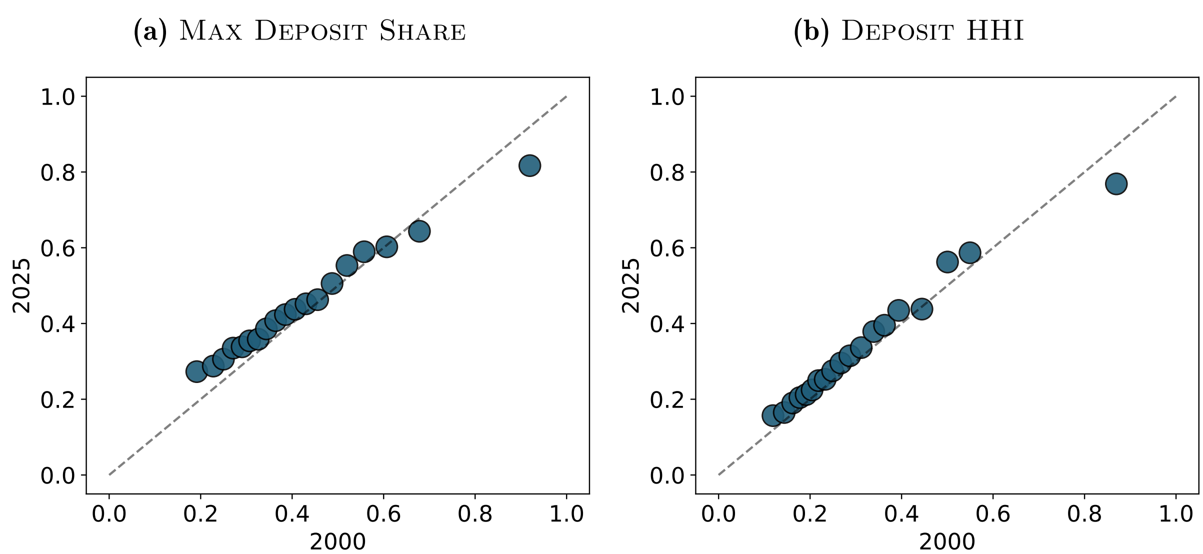
FIGURE 6: Bank Loan Markups



Notes: This figure plots average loan markups for large banks (LBOs) and small banks (CBOs), based on marginal cost estimates from the hedonic cost regression in Equation 3 and the markup expression in Equation 2. Averages are computed over 1995–2010 and 2010–2026.

Market Structure and Pricing. The U.S. banking system has also undergone substantial consolidation over the past three decades. The number of bank charters fell from 5,343 in 1995 to 3,486 in 2025, a 35% decline (Appendix Figure A.2). This decline reflects several factors, including regulatory changes such as the removal of interstate banking restrictions, barriers to entry, and potentially the increase of fixed costs. Using county-year observations as a measure of geographic markets, Figure 7 shows changes in market concentration between 2000 and 2025 using the largest bank's deposit share (left panel) and the Herfindhal-Hirschman Index (right panel). Both measures indicate a general increase in concentration, with the largest increases occurring in markets that were initially less concentrated.

FIGURE 7: Market Concentration

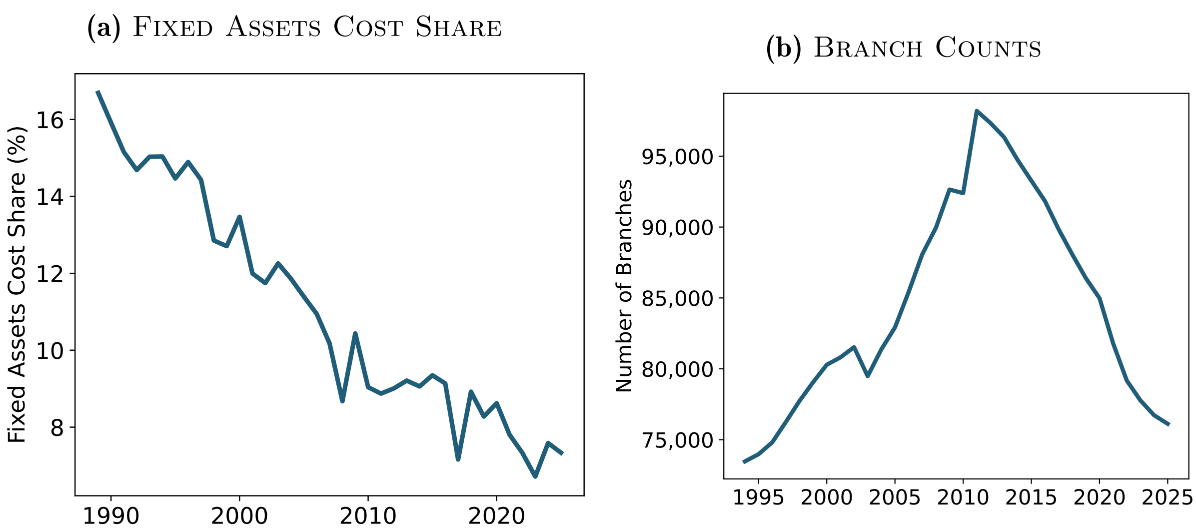


Notes: For both panels, this figure presents a binned scatter plot based upon market-level concentration in 2000 which are then re-measured in 2025 and plotted in ascending order for the 2020 values. In this application, markets are defined by year-county pairs and the measure max deposit share provides the largest bank's share of total deposits in each county-year, whereas deposit HHI represents the Herfindahl-Hirschman index within each county-year observation.

A Motivating Example: IT/Software. So far, we have documented that fixed costs have become a dominant component of banks' total cost, effectively increasing their operational leverage. Because our methodology recovers fixed costs from total cost elasticities, it is agnostic about the underlying production inputs generating these costs. This contrasts with approaches that normally categorize specific inputs as fixed or variable cost in bank Call Report data. Given the size of our estimates, it is clear that increasing fixed costs is a ubiquitous trend across all relevant input categories for banks, including traditional inputs such as labor and physical capital. While it is not necessary to assign relevant inputs as the *source* of fixed costs, we nonetheless focus on IT/Software spending as a useful example of production inputs that increase fixed costs but lower marginal costs.

Recent work documents substantial changes in bank spending on software, communications, hardware, and related IT services (e.g., He et al. (2026) and Kovner et al. (2014)). Traditionally, branch networks and office space were viewed as important components of bank fixed costs. As shown in the left panel of 8, spending on fixed assets, including branches, has declined from roughly 17% of total cost in the early 1990s to 7% in 2026. The right panel shows a similar decline in the number of operating bank branches, particularly since 2010. Thus, while branch networks and offices remain an important component of bank costs and likely fixed costs, their declining importance cannot explain the rise in estimated fixed costs.

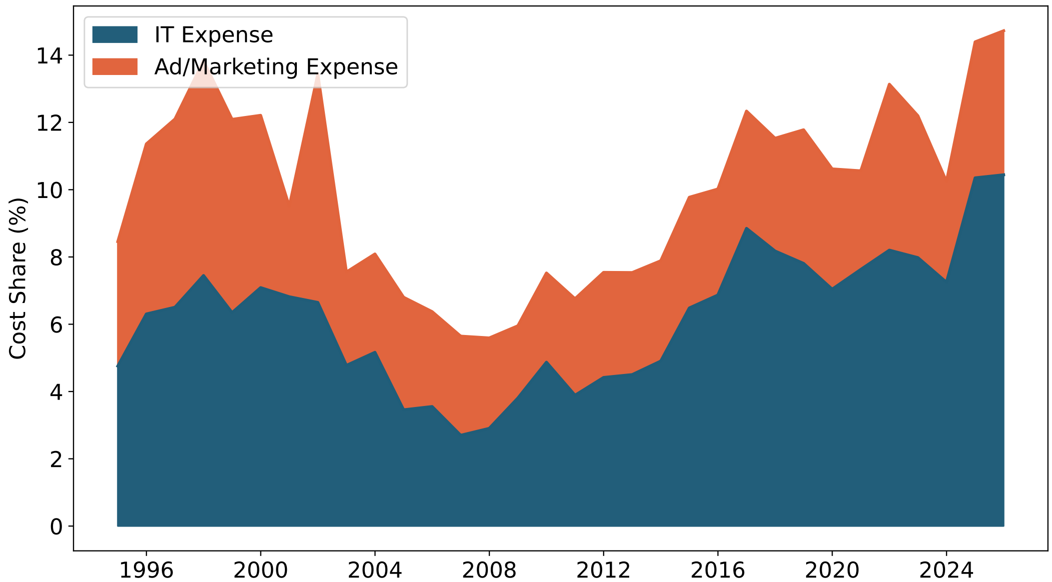
FIGURE 8: Spending on Branches and Buildings



Notes: Fixed assets cost share are based upon reported fixed assets in bank Y9C reports, and includes spending on physical premises such as branches and offices, as well as other physical capital. Aggregate branch counts for the US banking system are collected from the FDIC's annual summary of deposits (SOD) database. See Section B.1 for details on relevant data and explicit derivations of cost terms.

Figure 9 shows that the decline in fixed asset spending has coincided with *increased* spending on IT, data processing, and advertising/marketing. IT spending declined during the early 2000s, but it has steadily increased and now makes up about 10% of aggregate bank spending, while the average bank in 2026 has an IT cost share of 16%. IT and data processing have therefore become important inputs into lending and bank intermediation.

FIGURE 9: IT/Software and Advertising/Marketing Spending



Notes: This figure plots aggregate bank spending on IT/Software as well as Advertising/Marketing. Refer to Appendix Section B for details on variable construction.

A prominent example of this type of expenditure is the development and maintenance of core banking systems which often requires large fixed costs (see Alcazar et al. (2024)). The following quote from an OCC Request for Information highlights the cost and operational tradeoffs faced by banks:

> *Many community banks continue to operate on legacy core systems that were implemented decades ago...Core conversions are widely understood within the industry as among the most complex a bank can undertake, requiring years of planning, extensive staff retraining, and significant financial investment...For many community banks, these options are financially or operationally impractical.*
>
> — *OCC-2025 0537-0016*

Many banks are faced with a continual, periodic decision of how much to update their core systems, often building on layers of previous modifications. These investments can improve back-end capabilities and reduce marginal costs–for example, by automating and increasing the speed of loan processing. These updates are performed with the explicit goal of reducing marginal cost at the cost of paying a higher fixed costs.[8] Further:

> *Converting to a new core takes time, resources, and significant staff retraining to learn the operations and functionality of a new core platform. Often, banks will make the decision to update a legacy system instead of converting to new architecture.*
>
> — *OCC-2025 0537-0020*

The quote above also demonstrates the banks make a clear decision, which is not necessarily binary. Instead, banks choose from a menu of decisions which come with different combinations of fixed and marginal costs. Thus, this specific example helps make a more general point about the nature of bank fixed costs: banks have access to scalable technology and make specific decisions about their cost structure, knowing the implications it has for operational efficiency, *and* that there exists significant heterogeneity across banks in terms of their ability to implement such changes.

3 Model

In this section, we develop a model of bank industry dynamics with endogenous fixed costs. We use the model to rationalize the empirically-documented changes in bank cost structure, market structure, and pricing, and use calibrated versions of the model to examine if bank fixed costs matter when competition increases, with a particular focus on bank efficiency and risk-taking. In the model, time is discrete, and we use recursive notation throughout, with x and x' denoting objects decided (or realized) in the current period and next period, respectively.

[8] Many banks, particularly small banks, rely on third-party service providers known as *core providers*, which can limit their ability to customize and update their systems. We abstract from these differences in the empirical analysis and capture them through differences in bank productivity in the model Section 3 of the paper.

Competition. We assume there exists J types of banks that differ in their cost technology, with N_j banks of type $j \in J$ and the total number of banks $N = \sum_j N_j$. Each period, banks Cournot compete in the loan market such that the loan rate $R^L(Z)$ is determined by aggregate lending $Z = \sum_i \sum_j L_{ij}$ for a bank i of type j.

Technology. Bank lending has both variable and fixed costs. Similar to De Ridder (2024), banks choose the composition of these costs through a cost-scale decision $S_i \in (0, 1]$, which jointly determines marginal cost as $S_i \overline{mc}$ and fixed cost as

$$F_j(S_{ij}) = \phi_j \left(S_{ij}^{-\theta} - 1 \right), \tag{8}$$

where $\phi_j > 0$ is a bank type-specific productivity parameter and $\theta > 0$ is a technology parameter, common across all banks. The technology implies that lower marginal costs require a higher fixed costs. At $S_{ij} = 1$, for example, banks pay no fixed cost and face the maximum marginal cost $\overline{mc}$. The only source of heterogeneity across bank types is their productivity ϕ_j, which determines how effectively banks convert fixed costs into lower marginal costs.

Endogenous Exit. Similar to Corbae and Levine (2018), banks choose loan risk $\omega_{ij} \in [0, 1]$, which generates an additive risk premium $\mu \cdot \omega_{ij}$ on loan returns where $\mu > 0$ but increases the probability of exit,

$$1 - p(\omega_{ij}) = \omega_{ij}^2. \tag{9}$$

Thus, greater risk increases current period profits but reduces the probability of survival into the following period. We assume that bank receives a payoff of zero in the event of exit.

Bank Profit and Objective. Now, we have all the model elements to state the bank's profit function and objective. Bank profits are

$$\pi_{ij} = L_{ij} \left[R^L(Z) + \mu \cdot \omega_{ij} - R^D - S_{ij}\overline{mc} \right] - F_j(S_{ij}), \tag{10}$$

where we assume loans are fully financed by deposits and the deposit rate R^D is fixed. Each period, banks choose lending L_{ij}, cost scale S_{ij}, and risk ω_{ij}, which jointly determine variable profits and fixed costs $F_j(S_{ij})$.

Bank optimization can be stated in terms of the Bellman equation, where banks condition upon current period market structure N and their technology type j. The bank's problem can be written recursively as

$$V_j(N) = \max_{L_{ij}, S_{ij}, \omega_{ij}} \quad \pi_i(L_{ij}, S_{ij}, \omega_{ij}) + p(\omega_{ij})\beta V_j(N'). \tag{11}$$

Entry and Exit. The bank's risk decision ω_{ij} generates an endogenous flow of bank exits each period. We also assume there exists a mass of new entrant banks each period, who may potentially enter the market. In order for a new bank to enter, it must pay the fixed entry cost κ. Bank entrants are uncertain over their technology type. Specifically, banks know that the distribution of new entrants technology corresponds to the exogenous, discrete probability distribution $\{q_j\}_{j=1}^{J}$. We assume entrants have linear preferences such that they enter as long as expected franchise value exceeds the entry cost,

$$E_q\big[V_j(N)\big] \geqslant \kappa, \tag{12}$$

which defines the free-entry condition.

Equilibrium. We consider a stationary, type-symmetric equilibrium in which all banks of a given type make the same decisions. The equilibrium consists of bank decisions and a market structure

$$\left\{ \left(L_j^*, S_j^*, \omega_j^*\right)_{j=1}^{J}, N^* \right\}, \tag{13}$$

satisfying the 3J bank first order conditions

$$[L_{ij}]: \quad R^L - R^d + \mu\omega_{ij} - S_{ij}\overline{mc} + L_{ij}\frac{\partial R^L}{\partial L_{ij}} = 0, \tag{14}$$

$$[S_{ij}]: \quad -\overline{mc}L_{ij} + \phi_j\theta S_{ij}^{-(1+\theta)} = 0, \tag{15}$$

$$[\omega_{ij}]: \quad L_{ij}\mu + \beta\frac{\partial p}{\partial\omega_{ij}}V_j(N') = 0, \tag{16}$$

and the law of motion for the number of competing banks of type j,

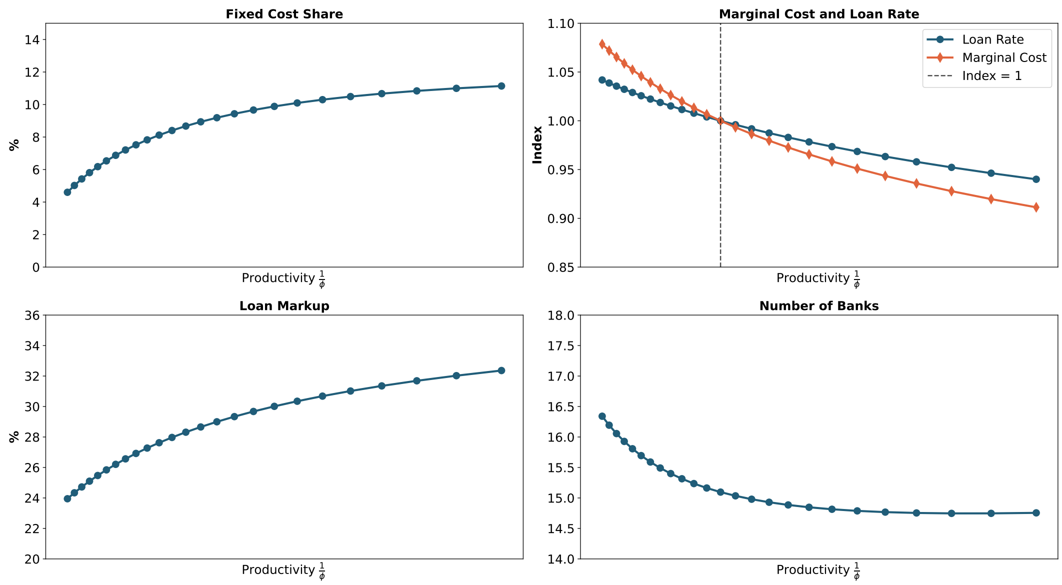
$$N'_j = p(\omega_j)N_j + Mq_j, \tag{17}$$

where M is the total mass of entrants, such that next period banks consists of the share $p(\omega_j)$ of surviving incumbents and the mass of new entrants of type j. In equilibrium, there exists a constant mass of each bank type such that $N_j^* = \frac{M^*q_j}{1-p(\omega_j^*)}$.

Technological Change Figure 10 illustrates the model's mechanisms using a single-bank-type economy and an informal parameterization of the model. This static exercise demonstrates equilibrium effects when the productivity parameter ϕ is varied. Greater productivity (i.e. a larger value of $\frac{1}{\phi}$) lowers the fixed cost required to achieve a given marginal cost and therefore induces banks to shift toward a more fixed cost-intensive technology (top left panel).[9] The resulting increase in fixed costs reduces marginal costs (top right panel), allowing the equilibrium loan rate to fall. Because the loan rate falls less than marginal cost, loan markups increase (bottom left panel). Higher markups allow banks to recover the additional fixed cost they spent. Finally, greater productivity increases the equilibrium scale of each bank, reducing the number of competing banks and increasing industry concentration (bottom right panel).

[9]Note that a lower S need not increase the fixed cost share. For example, if banks lower S to increase fixed costs but lending grows even faster, banks may experience a reduction in fixed costs.

FIGURE 10: Changes in Bank Fixed Cost Productivity



Notes: This figure plots equilibrium values for a single-bank model economy. Each point corresponds to a new equilibrium given the change in the fixed cost productivity parameter.

The same qualitative changes in cost, pricing, and market structure can also arise from changes in the common technology parameter θ, which governs the curvature of the cost function. For example, a lower θ makes the tradeoff between fixed and marginal costs more linear and induces banks to increase fixed costs, generating the same effects as a drop in ϕ.[10] Distinguishing between changes in bank productivity and common technological change will therefore be an important focus of the quantitative analysis in Section 4.

4 Model Results

In this section, we review our calibration strategy, which identifies model parameters for both the early and current periods of our sample. We use the calibrated model to identify which secular changes in the banking system contributed most to the change in bank franchise value over the last thirty years. We then examine whether pro-competitive forces have the same

[10]See Figure A.3 in the Appendix Section A.

equilibrium effects on the banking industry in a model with and without high fixed costs.

4.1 Changes in the Banking System over Time

Model Calibration. We assume there are two types of banks corresponding to the large-bank and community-bank definitions used in the empirical section of the paper, such that $j \in \{\text{LBO}, \text{CBO}\}$. To examine how changes in technology, productivity, and entry barriers have affected the banking system over the last thirty years, we calibrate the model separately for two periods: 1995-2010 and 2010-2026. Each model period corresponds to one quarter, although we annualize relevant model moments.

We first externally calibrate a set of parameters $\{\beta, q_j, R^D\}$ using values from the bank data and literature, and hold these parameter values fixed across the two time periods. Table 1 provides the values for the external calibration. The chosen discount rate is consistent with similar values in the literature. The share of new entrants for large banks (i.e. $j = LBO$) is based upon the observed relative frequency of large banks in our total sample, which is 29%. While the share of new entrants is not the same as the equilibrium share of bank types, we find it to be a reasonable approximation. Further, we keep this parameter fixed across sample periods because, while markets have become relatively more concentrated, the relative frequency of bank types has not changed considerably. Last, we choose a deposit rate which delievers a 1% annual spread relative to the interest rate implied by the discount factor. Specifically, we choose a spread between $\frac{1}{\beta} - R^d$ that is 25 basis points in the model, or 1% when annualized, which is consistent with the average level of deposit spreads observed over our sample period.

TABLE 1: EXTERNALLY CALIBRATED MODEL PARAMETERS

Parameter	Label	Value	Target
β	Discount Factor	0.992	Literature
q_{LBO}	Share of LBOs	0.29	Call Report/Y9C
R^d	Deposit Rate	1.0025	1% deposit spread

Notes: Parameters correspond to a model period with quarterly frequency.

We are then left with a set of internal parameters $\Phi = \left\{\{\phi_j\}_j, \overline{mc}, \mu, \theta, \kappa, a, b\right\}$ which include bank productivity, the maximum marginal cost, the risk-return premium, the curvature of the fixed-cost technology function, the entry cost, and parameters governing loan demand. We determine these parameters by targeting empirical moments in the data across both time periods. We specify a simple linear inverse demand function $R^L(Z) = a - bZ$ where parameters (a, b) govern the level and slope of borrower demand. Unlike the externally calibrated parameters, we allow the internal parameters to vary across the two sample periods.

For each period, we target the same set of moments relating to bank profitability, pricing, markups, cost structure, risk, and market concentration. Although model moments are jointly determined by the full set of parameters, individual moments provide natural guidance for identifying particular parameters.

For the cost of entry κ, we target the average deposit-based Herfindahl-Hirschman Index (HHI) across county-year markets using branch and deposit data from the FDIC's summary of deposits (SOD) database. Higher entry costs κ generate less entry and therefore greater market concentration. For the risk-return parameter μ, we target the average annual *exit rate* of banks, measured using changes in the number of active bank charters over time, therefore capturing both exit through failure as well as exit through acquisition.

For the common technology parameter θ, which determines curvature in the fixed cost function, we target the average fixed cost share of large banks (LBOs). Changes in θ affect the cost elasticity of the bank, giving it incentive to increase or decrease its use of fixed costs (through S_{ij})) to lower marginal cost. We use the productivity parameters $\{\phi_j\}$ to target the CBO fixed cost share and the loan markup of LBOs. This allows the calibration to distinguish between changes in the common technology available to all banks and changes in the productivity with which individual bank types utilize that technology. Finally, we use the two parameters governing loan demand, $\{a, b\}$, to target average return on equity for large and small banks which is a comprehensive measure of bank profitability.

Calibration Results. Results for both the early (1995 to 2010) and current (2010 to 2026) period model calibration are shown in Table 2. The model moments achieve a close fit to their empirical targets across both time periods. Importantly, the calibrated models capture the change in cost structure as both CBOs and LBOs increased their fixed cost shares from 25.1% to 29.2% and from 42.4% to 61.9%, respectively, as well as the respective increase in loan markups.

The calibrated common technology parameter θ falls from 0.04 to 0.02, consistent with a flattening of the fixed-cost technology and a greater ability to substitute fixed costs for marginal costs. In addition, the productivity parameters also move in opposite directions across bank types. For large banks, ϕ_{LBO} falls from 0.84 to 0.68 which implies an *increase* in bank productivity; conversely, small banks experienced a *decline* in productivity given that ϕ_{CBO} increased from 1.17 to 2.38. Finally, the entry cost κ increased significantly over the sample periods, more than doubling from 2.36 to 5.54, suggesting that barriers to entry have substantially increased over the last thirty years.

TABLE 2: Internal Model Calibration

Panel A: 1995-2010

Parameter	Label	Value	Target	Data	Model
ϕ_{LBO}	LBO prod.	0.84	LBO Markup	52.9	52.0
$\bar{mc}$	Cost	0.60	CBO Markup	40.9	38.8
μ	Risk	4.42	Exit Rate	1.42	1.62
a	Demand	3.74	LBO ROE	9.7	5.7
b	Demand	8.71	CBO ROE	9.6	4.4
θ	Scale	0.04	LBO Fixed Cost	42.4	44.7
ϕ_{CBO}	CBO prod.	1.17	CBO Fixed Cost	25.1	25.1
κ	Entry	2.36	HHI Concentration	0.29	0.29

Panel B: 2010-2026

Parameter	Label	Value	Target	Data	Model
ϕ_{LBO}	LBO prod.	0.68	LBO Markup	83.7	93.3
$\bar{mc}$	Cost	0.79	CBO Markup	61.3	59.3
μ	Risk	7.60	Exit Rate	1.42	1.63
a	Demand	4.89	LBO ROE	9.7	6.2
b	Demand	10.2	CBO ROE	9.6	4.4
θ	Scale	0.02	LBO Fixed Cost	61.9	63.7
ϕ_{CBO}	CBO prod.	2.38	CBO Fixed Cost	32.2	29.2
κ	Entry	5.54	HHI Concentration	0.29	0.33

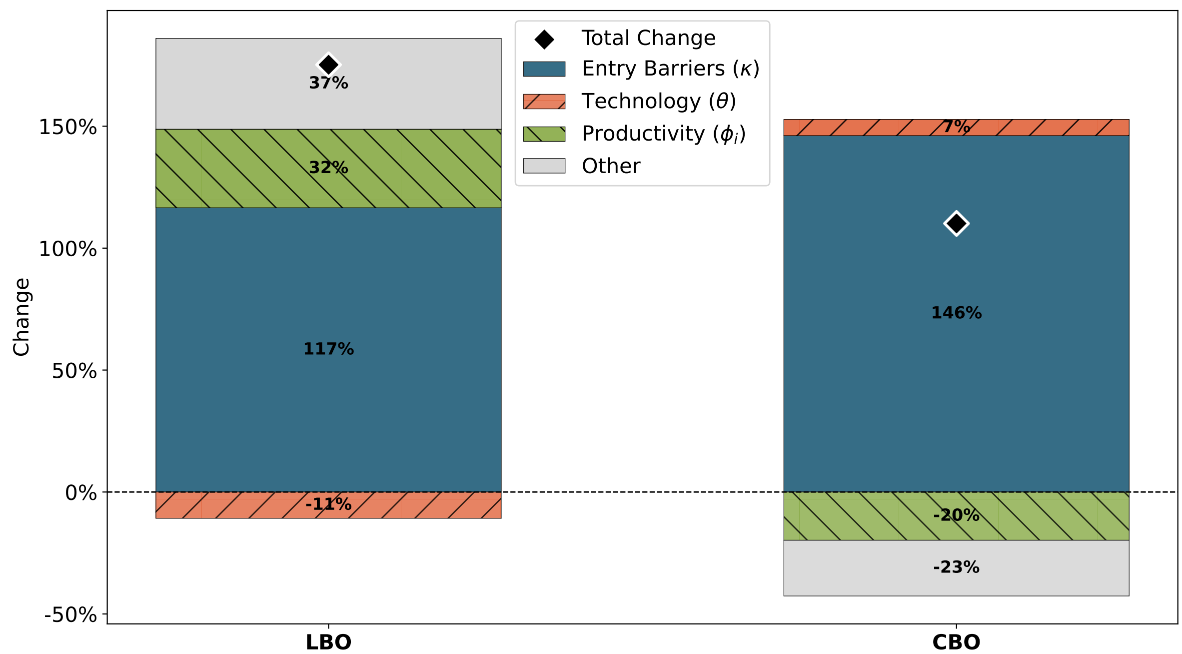
Notes: This figure shows the calibrated parameters for two time periods. Panel A presents the 1995-2010 calibration, while Panel B shows the 2010-2026 calibration. The model targets various moments including markups, ROE, fixed costs, exit rates, and market concentration.

Bank Franchise Value. We next use the calibrated versions of the bank model to examine how bank franchise value has changed over time. We define each bank's franchise value as the value of its Bellman equation V_{jt} according to Equation 11. This object is the discounted, expected stream of profits to the bank and can interpreted as the market value of a broad index fund of bank stocks.

The model-implied returns to bank franchise value over the sample period is 175% for LBOs and 110% for CBOs. As a benchmark, the inflation-adjusted returns to the NASDAQ Bank Index were approximately 250% over the same time period, suggesting our results are consistent with realized equity returns, although there are reasons why these measures would be different.[11]

We next decompose the change in bank franchise value into the contributions of changes in the common technology parameter (θ_t), bank productivity (ϕ_{jt}), and entry costs (κ_t) to understand what secular changes are driving bank performance over the past thirty years. Figure 11 presents the decomposition for both bank types.

FIGURE 11: DECOMPOSING BANK RETURNS OVER TIME



Notes: This figure shows the decomposition of changes in bank franchise value based upon the early and current period versions of the calibration according to changes in Table 2. We also include a residual category Other which accounts for unexplained co-variation to balance the joint change in bank franchise value.

Not surprisingly, the largest contribution to the increase in franchise value comes from the substantial increase in entry costs κ. This effect is particularly pronounced for community banks. The result is consistent with the broader decline in *de novo* bank entry and suggests that increased barriers to entry have allowed incumbent banks to capture greater franchise value, similar to Buchak et al. (2018).

[11]For example, many banks such as CBOs, are not publicly listed and so the equity-based measures does not capture their performance over the sample period.

Changes in productivity are the second largest contributor to bank returns, particularly for LBOs which experienced a 32% increase in franchise value. These results are not uniform across bank types; small CBOs experience a decline in productivity, which is consistent with their more muted change in cost structure and markups over time.

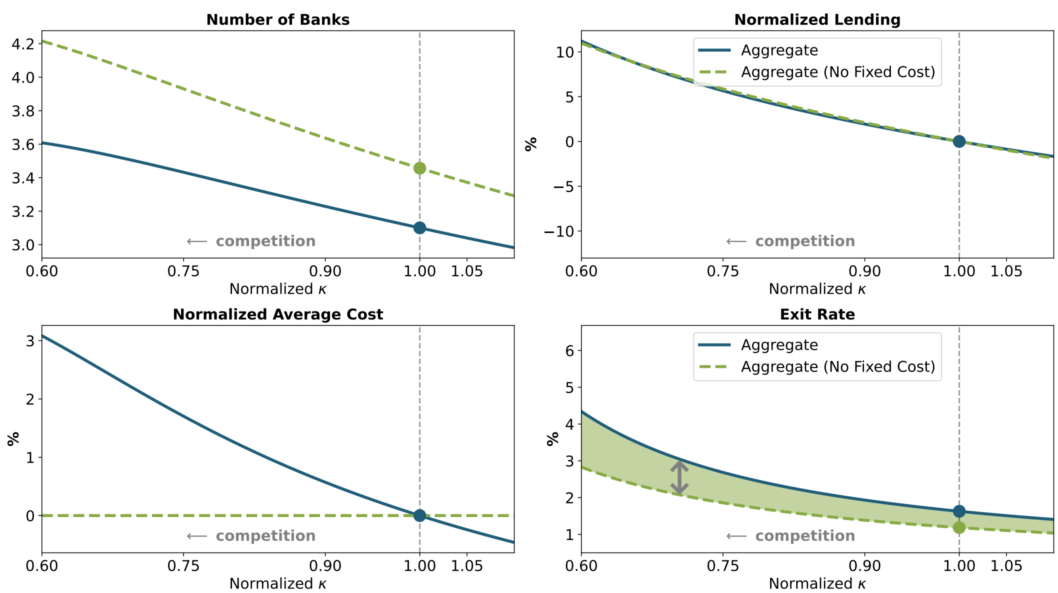
Finally, the common technological change induces an asymmetric effects on bank returns. The decline in θ from 0.04 to 0.02 flattens the fixed cost technology function, making it easier for banks to substitute fixed costs for lower marginal costs. Holding other changes fixed, this technological improvement raises bank franchise value; for example, it generates a 7% increase in franchise value for CBOs. However, because the technology is common to all banks, it also changes the competitive environment. In this case, because LBOs started from a position of greater market power, the change in θ intensified market competition by making cost-reduction more accessible for all banks, leading to a negative net effect for LBOs who lost market power. Thus, while the change in technology was individually beneficial for banks, the endogenous change in market structure and competition had unequal distributional effects on incumbent banks.

4.2 Pro-Competitive Effects with Fixed Costs

In this section, we examine whether the effects of increased competition differ in a banking system characterized by high fixed costs. We model an increase in competition as a reduction in the the entry cost parameter $\kappa \rightarrow 0$, which allows more banks to enter and compete for loans. This change in entry cost κ can be thought as a regulatory change which lowers barriers of entry for new, fintech lenders, for example. We solve for equilibrium outcomes under this counterfatual both in our baseline model with endogenous fixed costs and an alternative version of our baseline with no fixed costs, where banks pay the maximum marginal cost $\overline{mc}$ each period.

Figure 12 plots equilibrium outcomes for both versions of the model. For the baseline model, as competition intensifies (i.e. $\kappa \rightarrow 0$), more banks enter the market (top left panel) and total lending expands (top right panel) in both versions of the model. These are standard pro-competitive effects of increased entry under Cournot competition. Importantly, though, while aggregate lending increases, the individual loan size of each bank decreases with competition, which has important implications for bank costs. Because fixed costs are spread out across each unit of lending, banks have less incentive to incur fixed costs when their size is smaller. As a result, average lending costs increase as competition intensifies in the baseline model making banks *less efficient*. This effect on cost efficiency is absent in the model without fixed costs where marginal cost equals average cost for all levels of competition.

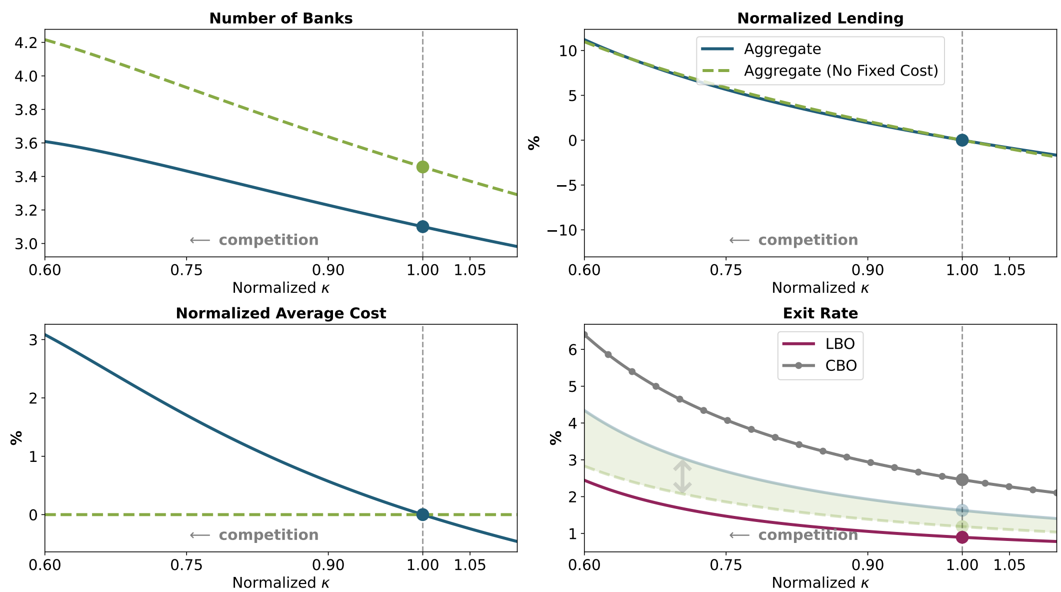
FIGURE 12: Pro-Competitive Effects in the Baseline Model



Notes: This figure plots equilibrium outcomes for the baseline calibrated model as well as a counterfactual version without fixed costs. In both versions of the model, cost of entry κ is normalized to 1 in the baseline model. Further, figures related to lending (top right panel) and average cost (bottom left panel) are normalized to zero in the baseline model and reported as percentage change and percentage point difference, respectively. Unless otherwise specified, all relevant variables are reported in aggregated or loan-weighted average terms.

Competition also generates greater risk-taking. In both models, banks respond to increased competition by choosing higher risk, consistent with the competition-fragility mechanism that is documented by Corbae and Levine (2018), Keeley (1990), and Allen and Gale (2004). However, the response is substantially stronger in the high fixed cost environment of the baseline model. Completely eliminating entry barriers increases the bank exit rate from approximately 1.6 percent to 4.3 percent. Figure 13 demonstrates that the sensitivity is largely driven by CBOs in the baseline model.

FIGURE 13: Pro-Competitive Effects in the Baseline Model without Fixed Costs



Notes: This figure plots equilibrium outcomes for the baseline calibrated model as well as a counterfactual version without fixed costs. In both versions of the model, cost of entry κ is normalized to 1 in the baseline model. Further, figures related to lending (top right panel) and average cost (bottom left panel) are normalized to zero in the baseline model and reported as percentage change and percentage point difference, respectively. Unless otherwise specified, all relevant variables are reported in aggregated or loan-weighted average terms.

To understand the risk-taking response, we examine banks' first-order condition with respect to risk. When a banks increases risk ω_{ij}, it balances the marginal increase in loan returns for each unit of lending ($L_{ij}\mu$) with the discounted, marginal risk of exit ($\beta \frac{\partial p}{\partial \omega_{ij}} V_j(N')$) which is is dependent upon the bank's franchise value. The risk decision, therefore, depends on both the bank's loan scale and its franchise value.

Taking the total derivative of the risk first order condition in Equation 16 with respect to competition κ, we can express optimal risk in elasticity terms:

$$\underbrace{\epsilon^j_\omega, \kappa}_{\text{risk elasticity}} = \underbrace{\epsilon^j_{L,\kappa}}_{\text{loan elasticity}} - \underbrace{\epsilon^j_{V,\kappa}.}_{\text{franchise value elasticity}} \tag{18}$$

The two components work in opposite directions. Greater competition reduces the lending of individual banks, which lowers the marginal benefit of taking risk. At the same time, competition reduces franchise value, making future profits less valuable to the bank and increasing its incentive to take risk today. In the calibrated model, the decline in franchise value dominates the decline in lending, generating an overall increase in risk-taking. The mechanism is particularly strong for community banks. In summary, the counterfactual highlights two distinct consequences of competition in a high-fixed cost banking system: competition reduces the efficiency with which banks produce loans and strengthens incentives to shift toward greater risk.

5 Conclusion

Bank fixed costs constitute a substantial and growing component of banks' total cost structure. From 1995 to 2026, fixed-cost shares increased while estimated marginal and average costs declined, accompanied by declines in measures of bank prices and an increase in loan markups. These changes are particularly pronounced among large banks.

We rationalize these trends using a model of bank industry dynamics with endogenous fixed costs, heterogeneous bank productivity, and endogenous exit. The model highlights two distinct sources of change. First, banks have become better able to substitute fixed costs for lower marginal costs, although the gains from this technological change have differed across bank types. Second, barriers to entry have increased substantially, generating a large increase in incumbent bank franchise value.

The model also shows that the effects of competition depend importantly on the underlying cost structure. Greater competition increases entry and aggregate lending, as in a standard

Cournot environment. But when banks face endogenous fixed costs, competition also reduces individual bank scale, induces banks to economize on fixed-cost investment, and thereby raises marginal and average lending costs. Competition also increases risk-taking, with this response especially acute for small banks. These results suggest that understanding the cost structure of banks is important not only for interpreting long-run changes in bank pricing and market structure, but also for evaluating the broader effects of policies that increase competition.

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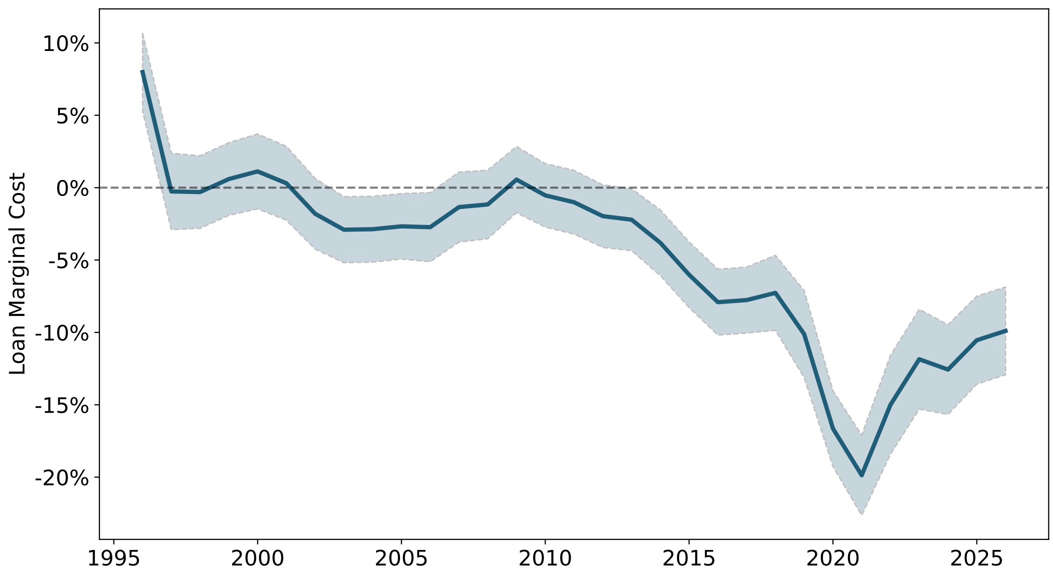
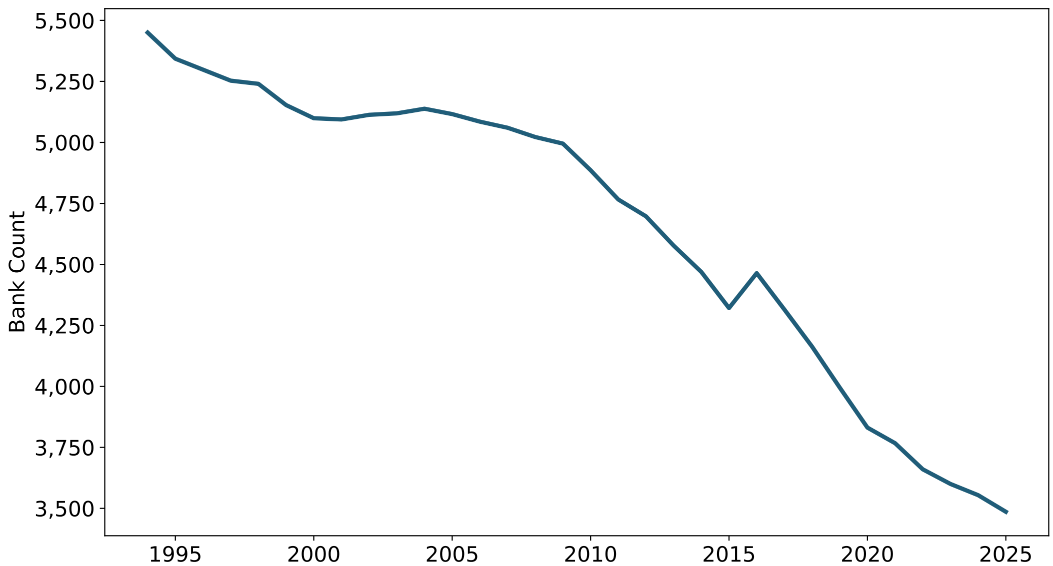
A Tables and Figures

FIGURE A.1: Alternative Marginal Cost



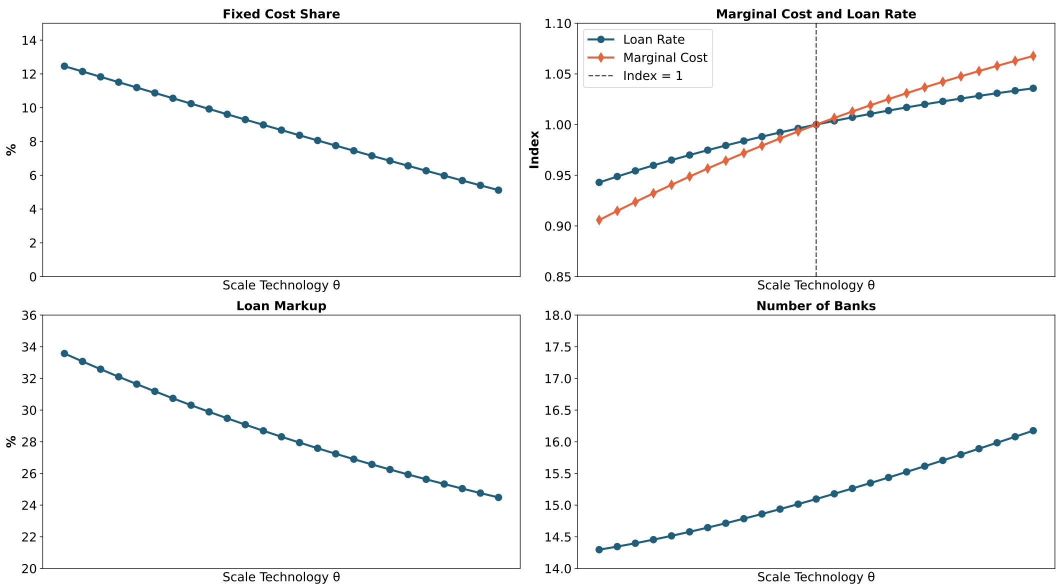
Notes: This figure illustrates estimated trends in bank marginal cost using a two-part procedure and translog bank cost functions. In the first stage, we estimate the translog bank cost function $Cost_{it} = F(\mathbf{q}_{it}, \mathbf{w}_{it}, \mathbf{x}_{it}, \epsilon_{it}; \boldsymbol{\beta})$ *like where outputs* $\mathbf{q}_{it}$ *include total lending and total demand deposits, input prices* $\mathbf{w}_{it}$ *related to interest expense, labor expense, and fixed asset expense, and a set of bank and time fixed effects along with interactions between all input prices and outputs* $\mathbf{x}_{it}$*. From this estimation, we recover loan marginal cost* $\hat{mc}^{\ell}_{it}$*. In the second stage, we regress* $\hat{mc}^{\ell}_{it}$ *on a set of macro controls, collect residuals* e_{it}*, then Regress* e_{it} *on time fixed effects. This figure plots the average time trends in lending marginal cost residuals from the second stage.*

FIGURE A.2: Bank Charters Over Time



Notes: This figure plots the total number of active bank charters over time based upon data from the FDIC's summary of deposits (SOD).

FIGURE A.3: Changes in Bank Fixed Cost Curvature



Notes: This figure plots equilibrium values for a single-bank model economy and a manually chosen model parameterization. Each point corresponds to a new equilibrium given the change in the fixed cost productivity parameter.

B Data Definitions

Balance-sheet items are quarter-end stocks. Income-statement items on the FR Y-9C are calendar-year-to-date flows. For a flow variable x, quarterly amounts can be recovered as

$$x_{it}^{q} = \begin{cases} x_{it}^{\text{YTD}}, & t \text{ is the first quarter of a calendar year,} \\ x_{it}^{\text{YTD}} - x_{i,t-1}^{\text{YTD}}, & t \text{ is the second, third, or fourth quarter of the same year.} \end{cases} \tag{19}$$

Annual observations use the fourth-quarter year-to-date amount when a complete fourth-quarter report is available. Quarterly ratios use quarterly flows and the average of beginning-of-quarter and end-of-quarter stocks when both observations are available.

This appendix records the accounting definitions and aggregation rules used in the empirical analysis and in the calibration. The underlying panel is quarterly. Monetary variables are converted to January 2020 dollars using the all-items Consumer Price Index for

All Urban Consumers, FRED series `CPIAUCSL`. If X_{it} is a nominal amount, the code applies

$$X_{it}^{2020} = X_{it}\frac{\mathrm{CPI}_{\text{Jan. 2020}}}{\mathrm{CPI}_t}. \tag{20}$$

This adjustment leaves ratios of contemporaneous dollar values unchanged. The bank identifier is the Federal Reserve RSSD identifier, denoted i, and t denotes the report date.

Table B.1 reviews how bank statistics and measures are constructed. For most bank data, we rely on quarterly, merger-adjusted balance sheet and income data from bank holding company Y9C reports. Some data series are discontinued or experience a change in definition throughout the sample period. When this occurs, series are appropriately adjusted to maintain a consistent variable/measure. In addition, variables are winsorized at the 1st and 99th percentile to control for outliers, and all banks with less than 8 years of observations are dropped from the sample.

TABLE B.1: Bank Variable Construction and Definitions

Name	Definition	Call Report Item
Loan quantity	$Q_{it} = \sum_{\ell=1}^{11} L_{\ell,it}$	BHCKF158, BHCK1797, BHDM1798, BHDM1460, BHDM1480, BHDM1766, BHDM1420, BHCK1590, BHCKJ454, BHCK2081, BHCKB538,BHCKB539,BHCKK137,BHCKK207
Operating cost	$C_{it} = \mathrm{NIExp}_{it}$	BHCK4093
Revenue	$R_{it} = \mathrm{NetInterestIncome}_{it}$	BHCK4074
Operating profit	$\Pi_{it}^{\mathrm{op}} = R_{it} + \mathrm{NIInc}_{it} - C_{it}$	BHCK4074+BHCK4079−BHCK4093
Capital ratio	E_{it}/A_{it}	BHCKG105/BHCK2170
Loan share	Q_{it}/A_{it}	Loan items/BHCK2170
Return on assets	$\mathrm{NetIncome}_{it}/A_{it}$	BHCK4340/BHCK2170
Return on equity	$\mathrm{NetIncome}_{it}/E_{it}$	BHCK4340/bc02050
Net interest margin	R_{it}/A_{it}	BHCK4074/BHCK2170

B.1 Bank Profit, Quantity and Cost Definitions

Bank types and sample screens. The type classification is fixed using consolidated assets on December 31, 2018. A holding company observed on that date is classified as a community banking organization, or CBO, when assets are at most \$10 billion and as a large banking organization, or LBO, when assets exceed \$10 billion. The classification is carried backward and forward for the same RSSD identifier.

We retain organizations with at least 20 quarterly observations and require assets to exceed \$10 million. Before estimation, the capital ratio, return on assets, loan share, log loans, and log cost are clipped at their pooled 0.5th and 99.5th percentiles. The cost-elasticity regression is first estimated on this sample. It is then re-estimated after removing observations whose residual is more than ten residual standard deviations from zero.

Loan quantity. Bank output, Q_{it}, is total loans. The code constructs it as the sum of eleven portfolio components:

$$\begin{aligned} Q_{it} = {} & L_{it}^{\text{dev}} + L_{it}^{\text{revres}} + L_{it}^{\text{closedres}} + L_{it}^{\text{multi}} + L_{it}^{\text{nonfarm}} + L_{it}^{\text{ci}} \\ & + L_{it}^{\text{farmland}} + L_{it}^{\text{ag}} + L_{it}^{\text{nbf}} + L_{it}^{\text{gov}} + L_{it}^{\text{consumer}}. \end{aligned} \tag{21}$$

The components are construction and land-development loans, revolving residential loans, closed-end residential loans, multifamily loans, nonfarm nonresidential loans, commercial and industrial loans, loans secured by farmland, agricultural-production loans, loans to nonbank financial institutions, government loans, and consumer loans. A missing component is set to zero before summation. The loan share used as a control is

$$\text{LoanShare}_{it} = \frac{Q_{it}}{A_{it}}, \tag{22}$$

where A_{it} is consolidated assets.

Operating cost, revenue, and profit. The cost measure is total noninterest expense,

$$C_{it} = \text{NIExp}_{it}. \tag{23}$$

The baseline revenue variable used in the cost-based markup calculation is net interest income and the operating-profit variable used in the analysis file is

$$\Pi_{it}^{\text{op}} = \text{NetInterestIncome}_{it} + \text{NoninterestIncome}_{it} - \text{NIExp}_{it}. \tag{24}$$

Balance-sheet and profitability controls. The variable called book leverage in the analysis code is the equity-to-assets ratio,

$$\text{CapitalRatio}_{it} = 100\frac{E_{it}}{A_{it}}, \tag{25}$$

where E_{it} is book equity. The quarterly return measures are

$$\text{ROA}_{it}^{q} = \frac{\text{NetIncome}_{it}}{A_{it}}, \qquad \text{ROE}_{it}^{q} = \frac{\text{NetIncome}_{it}}{E_{it}}. \tag{26}$$

The cost-elasticity regression uses the unannualized quarterly return on assets. Reported annualized ROA and ROE moments multiply the corresponding quarterly ratios by four and express them in percent. Net interest margin is constructed as

$$\text{NIM}_{it} = 4 \times 100\frac{\text{NetInterestIncome}_{it}}{A_{it}}. \tag{27}$$

When relevant, quarterly flows and ratios are annualized by multiplying the object by four.

B.2 Empirical and Model Moments

B.2.1 Moment-matching method

The model is calibrated separately for each period. Parameters assigned from external evidence, β, q_j, and R^D, are held fixed during this step. For calibration period t, collect the eight internally selected parameters in

$$\Gamma_t = \left(\phi_{\text{LBO},t}, \overline{mc}_t, \mu_t, a_t, b_t, \theta_t, \phi_{\text{CBO},t}, \kappa_t\right)'. \tag{28}$$

For each candidate $\Gamma \in \mathcal{G}$, we solve the quarterly model and collect the annualized model counterparts in the vector $\mathbf{m}_t(\Gamma)$. The empirical target vector $\widehat{\mathbf{m}}_t$ contains, in order, the LBO and CBO loan markups, the reporter-count contraction rate, LBO and CBO returns on equity, the LBO and CBO fixed-cost shares, and the deposit HHI. The calibrated parameter vector solves

$$\widehat{\Gamma}_t \in \arg\min_{\Gamma \in \mathcal{G}} Q_t(\Gamma), \qquad Q_p(\Gamma) = \sum_{r=1}^{8} \frac{\left[m_{r,t}(\Gamma) - \widehat{m}_{r,t}\right]^2}{\widehat{m}_{r,t}}. \tag{29}$$

B.2.2 Deposit concentration

Local concentration is constructed from the FDIC Summary of Deposits, measured annually on June 30 from 1994 through 2025. A local market is a county, formed by concatenating the state and county codes. Offices are assigned to holding-company owners using RSSDHCR. For holding company h, county m, and year y, deposits are summed across offices and the deposit share is

$$s_{hmy} = \frac{D_{hmy}}{\sum_{h'} D_{h'my}}. \tag{30}$$

The county-year concentration measures are

$$\mathrm{HHI}_{my} = \sum_h s_{hmy}^2, \qquad \mathrm{MaxShare}_{my} = \max_h s_{hmy}. \tag{31}$$

The calibration HHI is the median deposit HHI across the market-year observations in the constructed file. The 2000-to-2025 concentration figures compare county-level maximum shares and HHIs. Branch shares and branch-based HHIs are constructed analogously from the number of offices in each county.

B.2.3 Translog Cost Estimation

As a robustness exercise, we estimate a translog cost function of the bank. The two outputs are loans and demand deposits,

$$y_{1,it} = \log(1 + Q_{it}), \qquad y_{2,it} = \log(1 + D_{it}), \tag{32}$$

where D_{it} denotes demand deposits. The three input-price ratios are premises and fixed-asset expense divided by fixed assets, interest expense divided by liabilities, and employee expense divided by the number of employees. We denote these by $w_{1,it}$, $w_{2,it}$, and $w_{3,it}$. The estimated equation is

$$\log(1 + C_{it}) = \alpha_i + \delta_t + \beta_1 y_{1,it} + \beta_2 y_{2,it} + \beta_{11} y_{1,it}^2 + \beta_{22} y_{2,it}^2 + \beta_{12} y_{1,it} y_{2,it} \\ + \sum_{m=1}^{3} \gamma_m w_{m,it} + \sum_{m \leqslant n} \gamma_{mn} w_{m,it} w_{n,it} + \sum_{a=1}^{2} \sum_{m=1}^{3} \eta_{am} y_{a,it} w_{m,it} + e_{it}. \qquad (33)$$

The regression includes bank and and time fixed effects and uses heteroskedasticity-robust covariance estimates. The loan marginal cost implied by equation (33) is

$$\widehat{\mathrm{MC}}_{it}^{\ell} = \frac{C_{it}}{Q_{it}} \left(\widehat{\beta}_1 + 2\widehat{\beta}_{11} y_{1,it} + \widehat{\beta}_{12} y_{2,it} + \sum_{m=1}^{3} \widehat{\eta}_{1m} w_{m,it} \right). \qquad (34)$$

The corresponding expression for the marginal cost of demand deposits replaces the leading ratio by C_{it}/D_{it} and uses the derivative with respect to $y_{2,it}$. Both marginal-cost estimates are clipped at their 1st and 99th percentiles.

B.2.4 Residualized price and cost trends

For the long-run price and marginal-cost figures, the first stage residualizes each bank-level outcome using bank fixed effects, the federal funds rate and its square, the capital ratio, ROA, the loan share, the ten-year ACM term premium, real GDP growth, CPI inflation, and the VIX. The second stage regresses the first-stage residual on time fixed effects and clusters standard errors by bank . The plotted time effects are normalized to zero in their first observation. The loan-spread and NIM figures use the same two-stage logic.

B.3 Identifying IT Spending

The fixed cost measure covers a broad range of recurring operating inputs. This subsection documents reported information-technology-related expense, which provides one accounting example of a scalable input. The IT series is descriptive and is constructed separately from the recovery of total fixed cost.

B.3.1 Incomplete structured reporting

Some noninterest-expense memorandum items are subject to reporting-frequency and materiality conditions. An unreported item therefore does not establish that the holding company incurred no expense in the corresponding category. He et al. (2026) illustrates this limitation in their appendix. For example, in the JPMorgan Chase report reproduced in their paper, BHCKC017, "Data processing expenses," and BHCKF559, "Telecommunication expenses," are absent. The form subjects these memorandum items to size, frequency, and materiality conditions. Also, reporting requirements changed during the sample, creating variation in observed coverage across holding companies and dates. Fortunately, the Y-9C also permits components of other noninterest expense to be reported through manual, write-in items.

B.3.2 Recovery of write-in expenses

We obtain the public holding-company files from the Federal Reserve Bank of Chicago's Holding Company Data archive for 1986 through 1999 and the FFIEC Financial Data Download portal from 2000 onward. The estimation sample begins in 1994. For each reporting date, we retain the consolidated FR Y-9C observations, the RSSD identifier, every available `TEXT` field, and the numerical amount paired with each text field. Using string matches for words related to IT, such as 'IT', 'information', 'data', etc., we identify bank-quarter entries which we categorize as IT spending. We then add these terms to the existing entries for data processing expenses (BHCK C017) and telecommunication expenses (BHCK F559) as a total measure of bank IT spending.