Breaking Uniform Pricing*

David Argente[†] Yale University

Marcos Lissauer[‡] Torcuato Di Tella University

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Abstract

Uniform pricing is a defining feature of firms that operate across multiple markets. We study a setting in which it breaks down. We examine home equity lines of credit (HELOCs), where lending capacity depends on local housing conditions. Using branch-level rate data, we show that HELOC pricing is nearly uniform within banks in normal times. During the Great Recession, within-bank pricing dispersion rises sharply in regions more exposed to house price declines, particularly among multiregion banks that are more exposed to these shocks. To interpret these patterns, we develop and estimate a model in which banks operate integrated branch networks with common marginal intermediation costs but face local lending limits tied to collateral conditions. The model implies that the probability a local lending constraint binds is a sufficient statistic for deviations from uniform pricing. It matches both aggregate HELOC lending and the evolution of within-bank dispersion. Counterfactuals show that imposing uniform pricing raises rates, reduces credit, and lowers bank HELOC profits by approximately 29%. Uniform pricing is sustainable when local constraints are slack but becomes distortionary when lending capacity tightens unevenly across regions, raising rates and amplifying credit contractions.

JEL Classification Numbers: G21, R32, E51, E31
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[†]Email: david.argente@yale.edu. Address: Evans Hall, 165 Whitney Ave, New Haven, CT 06511, USA.
[‡]Email: marcos.lissauer@utdt.edu. Address: Av. Figueroa Alcorta 7350, CABA, C1428, ARG.

1 Introduction

Uniform pricing is one of the most striking regularities in markets served by multi-market firms. Firms post essentially the same price across locations that differ sharply in income, demand conditions, and local competitive environments. This pattern has been documented in retail goods, including online and multichannel sellers, where large chains charge nearly identical prices across locations (DellaVigna and Gentzkow 2019; Nakamura 2008; Cavallo 2018; Daruich and Kozlowski 2023); in labor markets, where wages are often set centrally within firms across locations (Hazell et al. 2022); in banking, where deposit rates and many loan terms are uniform across branch networks (Begenau and Stafford 2023; Granja and Paixão 2026; d'Avernas et al. 2023); and in insurance, where premiums are typically invariant to local market conditions (Wenning 2024). Systematic departures from uniform pricing are therefore uncommon.[1]

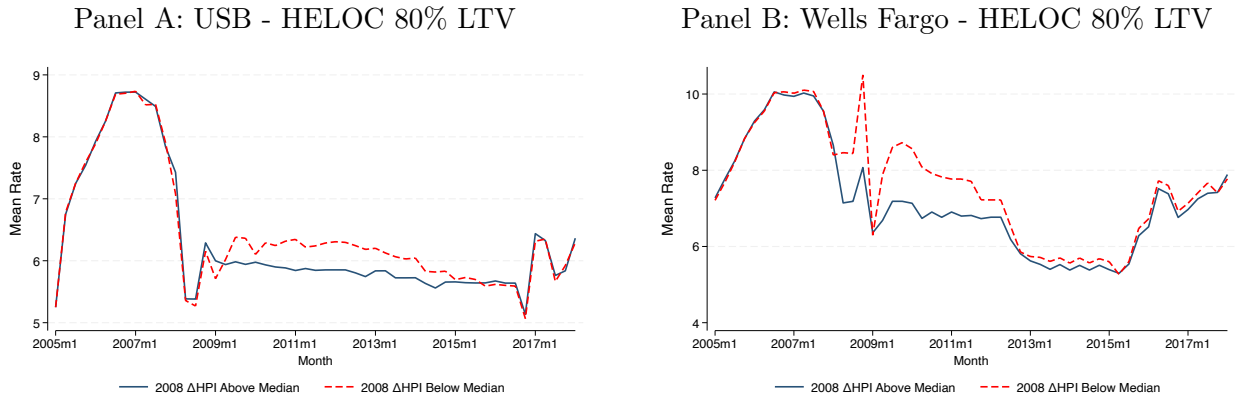
This paper studies a setting in which uniform pricing breaks down. We examine the market for home equity lines of credit (HELOCs), where posted rates are highly uniform within banks in normal times, but depart systematically from uniform pricing when local collateral conditions deteriorate unevenly across space. The central idea is simple. Uniform pricing is sustainable when a bank can serve all of its markets at roughly the same shadow cost of lending. It becomes difficult to sustain when local lending capacity tightens heterogeneously across regions. HELOCs are especially well suited to studying this margin because lending capacity is closely tied to local housing collateral, and because banks set rates before observing realized utilization of the credit line. When local housing conditions weaken and available equity becomes scarce, posted rates begin to reflect not only common bank-wide marginal intermediation costs, but also the expected shadow value of local lending capacity. That mechanism generates persistent within-bank pricing dispersion even when the bank remains an integrated organization with centralized funding and common balance-sheet management.

Figure 1 illustrates this mechanism for two large national banks around the Great Recession, a period marked by a sharp and uneven decline in house prices between 2007 and 2012. Panel (a) shows HELOC rates up to 80 percent loan-to-value for U.S. Bancorp. The blue line plots the average rate charged by branches located in regions where house price declines were above the median in 2008, while the red line plots the average rate in regions that experienced larger house price declines. Prior to 2008, HELOC rates move closely together across regions, consistent with uniform pricing. Following the housing price collapse, rates diverge.

[1] There are, of course, transitory deviations from uniform pricing in all of these settings, such as temporary price changes, promotions, or coarse pricing differences arising from regulation, predefined geographic zones, or taxes. What will become clear below is that we focus instead on persistent deviations from uniform pricing that arise from predictable changes in underlying economic conditions.

Regions more exposed to house price declines exhibit higher interest rates, indicating a break from uniform pricing. Panel (b) presents the same exercise for Wells Fargo, whose branch network was more concentrated in areas that experienced larger housing downturns. The pattern is similar: a clear divergence in rates across regions emerges after 2008, persists for several years, and gradually disappears as house prices recover.

Figure 1: Break in Uniform HELOC Pricing Around the Great Recession



Notes: The figure shows average HELOC rates at 80 percent LTV for two national banks. Branches are grouped by whether local house price changes between 2007 and 2012 were above or below the median across regions. Rates are monthly averages across branches within each group.

Empirically, we show that these patterns hold more broadly in the HELOC market. Outside the housing bust, HELOC pricing closely resembles the uniform-pricing environments documented in other settings. When house prices are high and home equity is abundant, banks offer nearly identical HELOC rates across their branch networks. Within-bank dispersion is small: the within-bank standard deviation of rates is low, and the average absolute rate difference between two branches of the same bank is modest relative to differences across banks. A regression of rates on bank-time fixed effects explains more than 90 percent of the total variation in HELOC rates, implying that within-bank geographic variation accounts for less than 10 percent of overall dispersion.

During the housing bust, however, this pattern changes sharply. As house prices fall and available equity declines, within-bank dispersion rises sharply. The average absolute rate difference within a bank roughly doubles between the boom and the bust, and the within-bank rate standard deviation increases substantially. The breakdown is not uniform across institutions. Community banks, whose branch networks are concentrated in relatively homogeneous areas, continue to price almost uniformly, with within-bank variation accounting for less than 5 percent of the total variation in rates. Regional banks exhibit larger departures, particularly in 2008 when house prices decline most sharply. The largest breaks occur among multiregional national banks operating in heterogeneous housing markets. For these institu-

tions, within-bank variation explains roughly 30 percent of the overall dispersion in HELOC rates during the bust, peaking around 50 percent in 2009:Q2, and then increasing markedly after 2012 as housing markets recover.

To interpret these facts, we develop a banking model of HELOC pricing where banks operate integrated branch networks across many local markets. Households demand credit and supply deposits, and banks fund lending with deposits and wholesale funding. Branches are not independent entities. They share a common balance sheet, and marginal intermediation costs and funding decisions are determined at the bank level rather than locally. At the same time, banks retain local market power in setting loan rates. The key ingredient is that HELOC lending is subject to local capacity constraints that limit how much credit a bank can extend in a given local market. These limits reflect underwriting capacity and collateral-based credit availability that vary across locations with housing conditions. Banks set rates before they observe how much borrowers will draw on their credit lines, so utilization appears as a local demand shock realized after rates are posted. When lending limits are slack everywhere, the optimal rate is effectively the same across markets and uniform pricing is close to optimal. When limits bind, or are expected to bind following credit line utilization or declines in house prices, optimal pricing incorporates the shadow cost of capacity. In constrained markets, higher rates raise margins on capped quantities, generating a local pricing wedge despite common marginal costs across the bank's network. As a result, the model implies that the probability a local lending limit binds is a sufficient statistic for deviations from uniform pricing.

We estimate the model using micro-level HELOC pricing data from RateWatch combined with bank-level balance sheet information from Call Reports and branch-level data from the Summary of Deposits (SOD). Our estimation proceeds in two steps. First, we use micro-level variation in rates and quantities from the Home Mortgage Disclosure Act (HMDA) to estimate key demand parameters, including the elasticities of substitution for loans across banks within regions and across regions, as well as the distribution of bank-level marginal intermediation costs. Second, we embed these estimates into the full model and use it to recover the remaining demand shifters that rationalize observed pricing behavior across banks and regions. The estimated model matches both the aggregate dynamics of HELOC lending and the cross-sectional pricing patterns documented in the data. In particular, it reproduces the low within-bank dispersion observed in normal times, when capacity constraints are rarely binding, and the sharp increase in within-bank pricing dispersion during the housing bust, when constraints are more likely to bind in some regions than others.

We use this framework to compare two pricing regimes. Under uniform pricing, a bank posts a single HELOC rate across its entire branch network. Under flexible pricing, it can

tailor rates to local markets. A key feature of the comparison is that lending capacity is held fixed across regimes: banks face the same local lending limits and the same underlying local conditions that determine how often those limits bind. The only difference is whether rates can adjust locally.

We find that imposing uniform pricing raises HELOC rates, reduces lending, and lowers bank profits. The mechanism is straightforward. In some markets, lending limits bind because housing conditions are weak or available equity is low. In those markets, the quantity of lending is capped, so raising the rate increases the margin on a fixed volume of loans. In other markets, where limits do not bind, borrowing declines when rates rise. Under flexible pricing, the bank can charge higher rates in constrained markets and lower rates in unconstrained ones. Uniform pricing removes that flexibility. When the bank must choose a single rate across all markets, it takes into account that higher rates increase profits in constrained regions but reduce lending in unconstrained regions. The optimal common rate therefore lies above the rates that would prevail in slack markets under flexible pricing. This raises average rates and lowers total lending. In the calibrated counterfactual, moving from flexible to uniform pricing increases HELOC rates and reduces aggregate borrowing, with the largest effects when lending limits are more likely to bind. Overall, the uniform-pricing constraint reduces output in the HELOC market and lowers welfare relative to flexible pricing. Importantly, uniform-pricing lowers bank HELOC profits by approximately 29% on average. The magnitude of this profit loss indicates that uniform pricing is costly when lending constraints bind unevenly across markets, highlighting the value of local pricing flexibility.

Literature Review This paper relates first to the large literature showing that uniform pricing is pervasive across many sectors. In retail, Nakamura (2008) shows that a large share of price variation is coordinated at the chain rather than store level. Cavallo (2018) documents that the growth of online competition increased the degree of uniform pricing across locations. Using daily grocery prices in Argentina, Daruich and Kozlowski (2023) show that, conditional on a product, prices vary little across stores of the same chain, and that prices of multi-region chains react much less to local labor-market conditions than prices of chains operating mostly in one region. DellaVigna and Gentzkow (2019) document that large U.S. retail chains set uniform prices across stores despite substantial variation in local demographics and competition, and discuss explanations rooted in managerial inertia and brand-image concerns. Hitsch et al. (2017) offer a complementary interpretation: within a local market, stores of the same chain appear to face similar demand conditions, and store-level elasticities are often hard to distinguish statistically from the chain-market mean,

making finer pricing difficult in practice. A similar phenomenon arises in labor markets, where Hazell et al. (2022) document that many firms pay near-identical wages across space through national wage setting.[2] Our paper contributes to this literature by identifying a setting in which uniform pricing breaks down endogenously. The key force is not local marginal-cost heterogeneity, but variation in the expected shadow value of local lending capacity. At the same time, our framework helps rationalize why uniform pricing is observed in the first place. When local lending constraints are slack, uniform pricing is sustainable without appealing to managerial frictions or brand-image concerns, because the gains from local price differentiation are negligible and, in the simple benchmark, a common price coincides with the flexible-pricing optimum. When those constraints bind unevenly across markets, however, maintaining uniform pricing becomes costly, which is why banks depart from it in bad times. Although the magnitudes are not directly comparable across settings, the profit losses we estimate are substantially larger than those in the retail and wage-setting papers.

The paper is also closely related to recent work on pricing in banking and on the geography of branch networks. Begenau and Stafford (2023) show that U.S. banks predominantly use uniform deposit-rate policies across branches, especially the largest banks. d'Avernas et al. (2023) show that large banks operate with uniform pricing and sort across locations based on customer demand, with limited gains from flexible pricing once competitors adjust. Granja and Paixão (2026) document that, across deposit and loan products such as HELOCs, auto loans, and unsecured personal loans, within-bank branch-level variation accounts for less than 10 percent of overall rate variation, and that rates converge following mergers. Our results are consistent with these findings on uniform pricing in HELOC markets, particularly in normal times and when all banks, including small community banks, are equally weighted. Oberfield et al. (2024b) provide a complementary perspective by showing that banks expand across regions to pool funds and equalize marginal funding costs across locations, which supports uniform pricing within integrated branch networks. We depart from this literature along two dimensions. First, while existing work shows that large banks are the most likely to sustain uniform pricing, we show that in the HELOC market it is precisely these large, multiregional banks that deviate most from uniform pricing when local housing conditions diverge. Second, our results show that integrated balance sheets and the equalization of marginal funding costs across locations do not guarantee uniform pricing once local lending constraints bind with different probabilities across markets.

Third, the paper contributes to the literature on household credit and housing collateral.

[2]There is also evidence of uniform pricing arising from regulatory restrictions on risk-based pricing. Examples include health insurance (Fang and Ko, 2018), life insurance (Wenning, 2024), government disaster lending (Begley et al., 2024), and the conforming mortgage market, where rates vary little across regions despite predictable differences in local default risk (Hurst et al., 2016).

Mian and Sufi (2011) show that rising house prices fueled home equity-based borrowing and played a central role in the household leverage cycle before the financial crisis. Our paper focuses on a different margin. We show that house-price declines affect credit supply not only by weakening collateral and reducing borrowing capacity directly, but also by changing the pricing incentives of multi-market lenders. When falling house prices raise the probability that local lending constraints bind, banks move away from centralized pricing and adjust spreads locally, generating within-bank differences in credit supply.

The rest of the paper is organized as follows. In Section 2, we describe the data and explain the construction of our branch-level panel. In Section 3, we document the main empirical patterns, including the rise and fall of within-bank geographic pricing dispersion over the housing cycle. Section 4 introduces a simplified model to clarify the economic mechanism linking local lending limits to deviations from uniform pricing. Section 5 develops a quantitative general equilibrium model of multibranch, multiregion banks that accounts for the stylized facts and matches both aggregate lending dynamics and within-bank dispersion. Section 6 describes the model–data mapping and estimation strategy. Section 7 presents the quantitative results and counterfactual exercises comparing flexible and uniform pricing regimes. Section 8 concludes.

2 Data Description

Our primary dataset is RateWatch (S&P Global), a branch-level survey of posted retail bank rates with broad geographic coverage. RateWatch covers roughly 100,000 branches over the 2001–2018 period and reports publicly advertised offer rates for a variety of retail products.[3] For loan products, rates are typically collected at a monthly frequency.

A key feature of RateWatch is its distinction between rate setters and rate followers. The rate-setter file reports, for each surveyed branch, the survey date and the quoted rate for each product. Separately, the follower file links additional branches to a rate setter and records the effective date on which a follower branch begins quoting the same posted rate as its associated setter.[4] In our main branch panel, we treat the implied rates for follower branches as the posted rates of those branches over the relevant effective dates.

We focus on Home Equity Lines of Credit (HELOCs) in *Tier 1* at up to an 80% loan-to-value (LTV) ratio. This product definition is the most consistently available HELOC

[3] S&P Global acquired RateWatch from TheStreet, Inc. in June 2018.

[4] Operationally, RateWatch surveys a subset of branches (setters) and then "feeds out" the setter's quoted rate to affiliated follower branches.

series over time in RateWatch and provides the broadest coverage across institutions and geographies.[5] Our sample includes commercial banks and savings & loan institutions (S&Ls) with at least two branches, as our objective is to measure within-institution variation in posted rates across branches.[6] We exclude non-contiguous states and other residual locations (a very small share of the sample).[7] Finally, we begin the analysis in 2005 because RateWatch coverage increases sharply at that point, i.e., earlier years have substantially lower and less stable coverage.[8]

Working with RateWatch requires care because the institution identifiers in the "institution details" file are typically reported as a snapshot at the end of the sample window in a given dataset version. As a result, a branch may appear to belong to the same bank throughout the sample even if its ownership changed due to mergers or acquisitions. To address this issue, we use RateWatch's ownership-history file, which links each branch identifier to its historical institution identifier (CERT) over time. We use this file to construct a branch-by-time ownership panel and merge it into the rate data by branch identifier, ensuring that posted rates are assigned to the correct bank at each point in time.[9]

We complement RateWatch with two FDIC datasets. First, we use the FDIC Summary of Deposits (SOD), an annual census of branch offices as of June 30. SOD provides branch-level deposit volumes and identifiers that allow us to characterize banks' branch networks (e.g., the number of branches, geographic locations, and deposit shares across locations). Second, we use the FDIC Call Reports (Consolidated Reports of Condition and Income), which contain quarterly balance sheet and income statement information for commercial banks. We merge SOD to RateWatch using institution identifier (CERT) and year, and we merge Call Reports to RateWatch by CERT and quarter.

To summarize heterogeneity across institutions, we classify banks into three size groups following Federal Reserve supervisory conventions: community banks (assets below $10 billion), regional banks ($10–$100 billion), and multiregional banks (assets above $100 billion).

Table 1 reports the evolution of sample coverage for HELOC Tier 1 at 80% LTV from 2005–2018, including the number of institutions, branches, and geographic units covered. Table 2 reports analogous coverage statistics by bank size group, including the average number of branches, states, and counties per bank, as well as the average number of months of

[5] RateWatch reports multiple pricing "tiers" for HELOCs. Tier 1 has substantially greater coverage than higher tiers throughout the sample.

[6] Single-branch institutions are mechanically uninformative for within-bank dispersion.

[7] These observations represent approximately 0.2% of the final branch panel.

[8] We also exclude credit unions because comparable granular institution-level balance sheet and branch network data are not available in a consistent format for the full sample (relative to Call Reports and the Summary of Deposits). Nevertheless, our empirical patterns are robust to including credit unions.

[9] An alternative approach is to reconstruct ownership histories using FFIEC files.

rate observations per branch. These tables are intended to document the stability of the RateWatch HELOC panel and to clarify how coverage differs across bank types. For the year of 2018, coverage drops as our sample reports only the first 3 months. We defer the analysis of pricing patterns to Section 3.

Table 1: RateWatch Sample Coverage on HELOCs 80% LTV

Year	# Institutions	# Banks	# S&Ls	# Branches	# States	# Counties
2005	2058	1887	171	13648	49	2166
2006	1987	1810	177	15262	49	2203
2007	1968	1777	191	20562	49	2263
2008	1966	1769	197	31290	49	2396
2009	1724	1553	171	33966	49	2426
2010	1618	1436	182	39807	49	2531
2011	1550	1367	183	51398	49	2601
2012	1471	1295	176	50601	49	2575
2013	1397	1224	173	52289	49	2573
2014	1327	1169	158	52785	49	2542
2015	1228	1067	161	53294	49	2541
2016	1196	1038	158	53332	49	2538
2017	1135	993	142	50653	49	2559
2018	1061	931	130	46271	49	2555

3 Empirical Analysis

This section documents three facts about posted HELOC pricing. First, HELOC rates are close to uniform within banks in normal times: most cross-sectional variation is explained by bank×month averages, and within-bank geographic dispersion is small. Second, uniform pricing breaks down during the housing bust: within-bank dispersion rises sharply and persistently, with the largest increase among multiregion banks. Third, the geographic pattern of rate increases aligns with local housing shocks: branches in areas with larger house price declines experience larger increases in posted HELOC rates, consistent with tighter local lending limits.

Let r_{ijt} denote the interest rate posted by bank j in region i (county) in month t.[10] We restrict attention to bank-month observations in which bank j operates in at least two distinct counties, so that within-bank geographic dispersion is well-defined.

We begin with the simplest and most widely used measure in the uniform-pricing literature: the average absolute rate difference within a bank across locations. To operationalize

[10]Since the raw RateWatch data may contain multiple branch observations within the same bank–region–month cell, we first collapse the data to the bank×region×month level: $r_{ijt} \equiv \frac{1}{N_{ijt}} \sum_{k \in (i,j,t)} r_{kt}$, where k indexes branches and N_{ijt} is the number of observed branches for bank j in county i at time t.

Table 2: Sample Coverage Over Time by Bank Type

Year	# Banks	Avg # Branches	Avg # States	Avg # Counties	Avg Months/Branch
Panel A: Community Banks					
2005	1,987	3.08	1.08	2.17	7.51
2006	1,916	3.29	1.07	2.27	8.19
2007	1,898	3.80	1.08	2.38	7.60
2008	1,904	5.57	1.10	2.83	7.33
2009	1,669	6.55	1.11	3.12	7.32
2010	1,566	8.52	1.12	3.60	7.20
2011	1,500	12.44	1.20	4.48	7.08
2012	1,420	12.68	1.20	4.55	7.91
2013	1,348	13.51	1.22	4.78	7.72
2014	1,275	13.67	1.24	4.78	8.14
2015	1,172	14.65	1.27	5.11	7.74
2016	1,139	15.36	1.29	5.34	7.27
2017	1,074	16.12	1.32	5.78	7.63
2018	989	14.13	1.28	5.01	2.39
Panel B: Regional Banks					
2005	60	53.65	3.07	27.48	7.88
2006	60	67.57	3.13	33.57	9.83
2007	57	91.09	2.91	27.93	8.80
2008	47	127.55	3.34	35.74	8.18
2009	40	185.12	3.42	45.30	8.54
2010	38	176.82	3.58	43.32	9.09
2011	36	253.17	4.28	53.00	9.13
2012	38	229.32	3.79	48.58	8.97
2013	36	244.83	4.14	53.86	9.09
2014	38	245.55	4.18	56.26	9.36
2015	43	224.21	3.86	50.95	9.33
2016	41	226.39	4.00	51.17	9.29
2017	44	172.18	3.80	45.39	9.33
2018	56	151.30	3.73	43.38	2.56
Panel C: Multiregional Banks					
2005	11	427.18	11.45	175.09	8.67
2006	11	484.64	11.55	186.18	10.63
2007	13	670.46	12.23	216.77	8.39
2008	15	998.67	11.80	234.40	8.73
2009	15	1122.87	11.93	236.40	7.72
2010	14	1525.93	13.29	277.21	8.77
2011	14	1721.07	13.71	283.07	9.11
2012	13	1892.31	14.77	288.92	9.64
2013	13	1991.23	14.85	287.23	10.39
2014	14	1906.64	13.86	261.36	10.28
2015	13	2080.00	15.15	283.15	9.82
2016	16	1725.00	12.50	237.75	9.25
2017	17	1540.00	12.24	230.47	10.02
2018	16	1491.19	12.38	233.56	2.65

this measure in our branch-level data, we form random pairs of branches within the same bank and compute the absolute difference in their quarterly average posted rates. Table 3 reports summary statistics for these within-bank quarterly absolute rate differences for the HELOC 80% LTV product during the boom (2005–2006) and bust (2007–2010), both unweighted and HELOC-weighted (pairs receive higher weight when they come from bank-quarters with greater HELOC activity). Outside the housing bust, posted HELOC rates are close to uniform within banks: within-bank absolute differences are modest. During the housing bust, this pattern changes sharply. As house prices fall and available equity declines, within-bank absolute differences rise markedly, roughly doubling from the boom to the bust in the unweighted statistics, and increasing even more when weighting by HELOC activity.

Table 3: Within-bank Quarterly Absolute Rate Differences: Boom vs Bust

	Boom (2005–2006)			Bust (2007–2010)		
Measure	Mean	Median	SD	Mean	Median	SD
Unweighted	0.192	0.156	0.172	0.443	0.394	0.469
HELOC-Weighted	0.202	0.172	0.164	0.563	0.499	0.504

Notes: This table reports summary statistics for within-bank rate dispersion, measured as the absolute difference in quarterly average posted rates between two branches of the same bank. For each subperiod (Boom: 2005–2006; Bust: 2007–2010), we construct 10,000 random within-bank branch pairs. For a given pair, we compute quarterly average rates for each branch and form $|\Delta r_{ijq}|$, the absolute rate difference in quarter q. We retain only pairs with at least eight overlapping quarters within the subperiod and then collapse to a pair-level statistic equal to the mean of $|\Delta r_{ijq}|$ across the overlapping quarters. The Unweighted row treats each pair equally when computing the mean, median, and standard deviation across pairs. The HELOC-Weighted row weights observations using bank-level HELOC lending from Call Reports: in each bank-quarter, the weight equals HELOC_{bq}/N_{bq}, where N_{bq} is the number of branch-quarter observations for bank b in quarter q; pair-level dispersion is computed as the weighted mean of $|\Delta r_{ijq}|$ across quarters using these bank-quarter weights, and the cross-pair summary statistics weight each pair by the sum of its bank-quarter weights.

We next study within-bank dispersion using a metric that isolates geographic price differences within a bank at a point in time and abstracts from common aggregate movements in interest rates. Since posted rates exhibit strong time-series variation driven by macro-financial conditions, we first residualize rates with respect to quarter fixed effects:

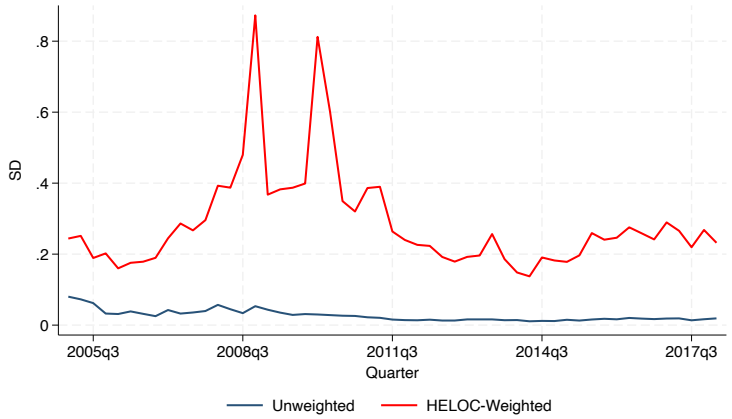
$$r_{ijq} \;=\; \gamma_q + \widetilde{r}_{ijq},$$

where γ_q is a full set of quarter fixed effects and $\widetilde{r}_{ijq}$ denotes detrended rates. We then estimate a bank×quarter fixed-effect specification on detrended rates:

$$\widetilde{r}_{ijq} \;=\; \alpha_{jq} + \varepsilon_{ijq},$$

where α_{jq} absorbs bank j's average detrended pricing level in quarter q and ε_{ijq} captures deviations in county-level pricing from that bank-quarter mean. For each bank-quarter pair (j, q),

Figure 2: Within-Bank Geographic Dispersion in Posted HELOC Rates



Notes: The figure plots the quarterly average of σ_{jq} defined in equation (3), where σ_{jq} is the within-bank cross-county standard deviation of deviations from the bank-quarter mean in detrended rates. Detrending removes quarter fixed effects. "Unweighted" gives equal weight to each bank-quarter observation; "HELOC-weighted" weights bank-quarters by bank j's HELOC activity.

we summarize within-bank geographic dispersion by the cross-county standard deviation of residuals:

$$\sigma_{jq} \equiv SD(\varepsilon_{ijq} \,|\, j, q)\,.$$

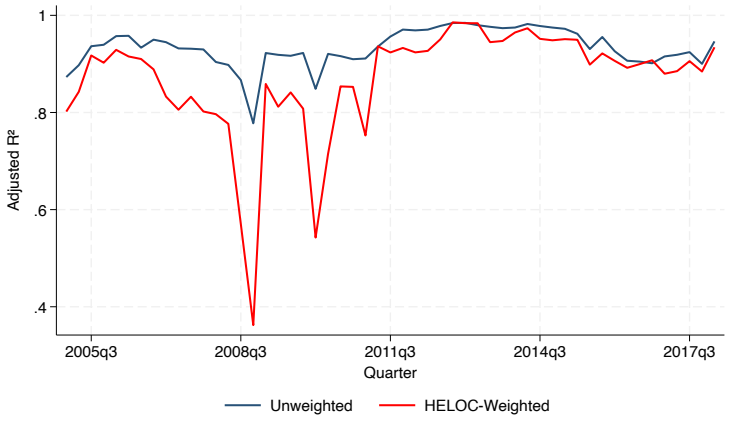
Figure 2 plots the time series of average within-bank dispersion, $\mathbb{E}[\sigma_{jq}]$, computed either unweighted or HELOC-weighted. Two patterns stand out. First, outside the housing bust, within-bank dispersion is small: the unweighted series remains near zero, consistent with near-uniform pricing on average. Second, uniform pricing breaks sharply during the bust: within-bank dispersion rises abruptly and remains elevated for several years. The increase is far larger in the HELOC-weighted series, indicating that the breakdown is concentrated among the banks that account for the bulk of HELOC lending—precisely the multiregional institutions most exposed to heterogeneous local housing shocks.

An alternative way to gauge uniform pricing is to ask how much of the cross-sectional variation in rates is captured by bank fixed effects at a given point in time. Under uniform pricing, a bank's posted rate should be nearly identical across counties within the period, so bank effects should explain almost all within-period dispersion. We therefore estimate the following specification separately within each quarter q:

$$r_{ijq} = \alpha_{jq} + u_{ijq}, \tag{1}$$

where r_{ijq} is the quarterly average posted HELOC rate of bank j in county i during quarter q, and α_{jq} denotes bank fixed effects estimated separately in each quarter. The adjusted

Figure 3: Bank-Time Explanatory Power in HELOC Rates



Notes: The figure plots the adjusted R^2 from quarter-by-quarter cross-sectional regressions using HELOC Tier 1 rates at 80% LTV collapsed to the bank×county×quarter level. In each quarter q, we estimate equation (1) by absorbing bank fixed effects α_{jq}. "Unweighted" gives equal weight to each bank×county observation. "HELOC-weighted" uses bank-quarter Call Report data to weight observations by HELOC_total$_{jq}$, split evenly across the bank's county observations within the quarter.

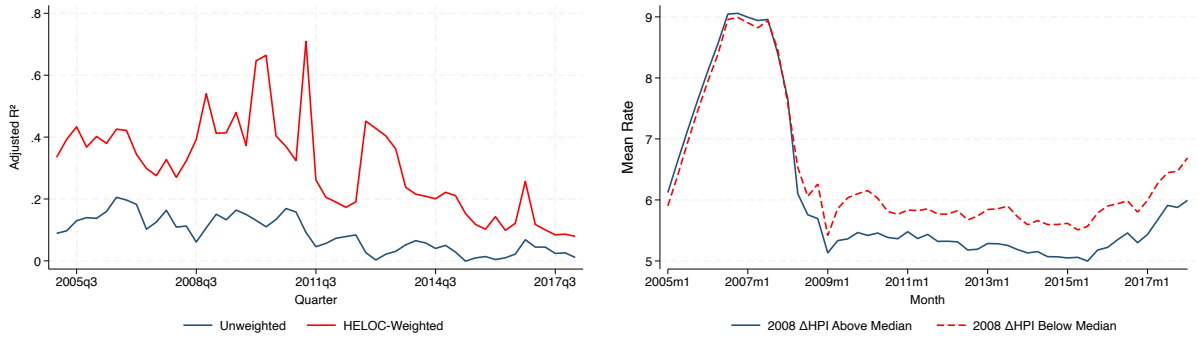
R^2 from equation (1) measures the share of within-quarter cross-county rate variation explained by bank-level averages. Consistent with near-uniform pricing outside the housing bust, Figure 3 shows that bank effects explain the vast majority of HELOC rate dispersion in normal times. During the bust, however, the explanatory power of bank averages declines sharply (particularly in the HELOC-weighted series) implying that within-bank geographic rate variation becomes quantitatively important precisely when home equity collapses. Appendix Figure C1 shows that this breakdown is largely driven by multiregional banks: while bank fixed effects continue to explain nearly all dispersion for community and regional banks, the R^2 shows a modest fall for regional banks and markedly for multiregional lenders during the bust. This is consistent with multiregional banks being more exposed to regional heterogeneity (Table 2) and therefore having stronger incentives to deviate from uniform pricing when local collateral conditions diverge.

To assess whether the widening within-bank dispersion reflects common location-level shocks, we also estimate a complementary specification for each quarter q:

$$r_{ijq} \;=\; \delta_{iq} + v_{ijt}, \tag{2}$$

where δ_{iq} denotes the county fixed effects estimated separately in each quarter. The adjusted R^2 from equation (2) measures the share of cross-sectional rate variation accounted for by county-level pricing components that are common across banks in a given period. Panel (a) of Figure 4 shows that the explanatory power of county fixed effects rises substantially

Figure 4: Local Housing Shocks and Location-Level Components in Posted HELOC Rates



Notes: Panel (a) plots the adjusted R^2 from equation (2) (county×month fixed effects), estimated separately by quarter and aggregated to a quarterly time series. "Unweighted" gives equal weight to each bank-month observation; "HELOC-weighted" weights observations by bank j's HELOC activity. Panel (b) plots average posted HELOC rates for branches in counties split by the change in local house prices (ΔHPI): the "high ΔHPI" group includes counties with above-median house price changes, and the "low ΔHPI" group includes counties with below-median changes.

during the housing bust, with a particularly pronounced increase in the HELOC-weighted series. This pattern indicates that local conditions account for an unusually large share of posted-rate movements precisely when within-bank geographic dispersion increases. Panel (b) provides a direct illustration of the underlying geography: counties experiencing larger house price declines (lower ΔHPI) exhibit much larger increases in posted HELOC rates during the bust, while rates are similar across the two county groups before the housing bust. Taken together, Panels (a) and (b) point to a geographically structured tightening in effective lending capacity during the housing bust.

The patterns in Figure 4 suggest that the widening dispersion is closely aligned with local housing shocks. Table 4 formalizes this connection by relating posted HELOC rates to local house price growth using three complementary specifications, reported both unweighted and HELOC-weighted. Across all specifications, the estimated relationship is negative and precisely estimated: counties with weaker house price growth (larger declines) are associated with higher posted HELOC rates.

Columns (1) and (4) exploit within bank×county variation over time, controlling for quarter effects and bank–county fixed differences. The negative coefficient implies that, within the same bank and county, posted rates rise when local house prices fall, even after netting out aggregate movements in HELOC pricing. Columns (2) and (5) instead compare counties within a bank in the same quarter, absorbing bank×quarter effects and county fixed effects. The negative coefficient in these columns implies that, in the same quarter, banks post higher rates in the counties where housing conditions deteriorate more. Finally, Columns (3) and (6) use the change in posted rates as the dependent variable, Δr_{bcq}, and include bank×quarter and county fixed effects. These specifications ask whether, within

the same bank and quarter, counties experiencing weaker house price growth also see larger increases in posted HELOC rates.

Importantly, across specifications, the relationship between local house price growth and posted HELOC rates is economically larger and statistically sharper in the HELOC-weighted columns. This pattern is consistent with the idea that the largest, multiregion lenders, which account for the bulk of HELOC activity and face the most heterogeneous geographic exposures, drive the systematic departure from uniform pricing during the bust. Moreover, the within-bank comparisons in Columns (2) and (5) and the change specification in Columns (3) and (6) indicate that dispersion is not merely driven by bank-wide or aggregate shocks: in periods of house price declines, posted HELOC pricing becomes increasingly tied to county-level conditions, consistent with uneven tightening of local lending limits across markets.

Table 4: House Prices and Posted HELOC Rates

	Unweighted			HELOC-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
β	-0.002***	-0.004***	-0.001***	-0.008***	-0.008***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Observations	390,615	391,037	391,037	390,615	391,037	391,037
Adjusted R^2	0.867	0.974	0.778	0.844	0.947	0.601
Bank×Location FEs	Yes	No	No	Yes	No	No
Quarter FEs	Yes	No	No	Yes	No	No
Bank×Quarter FEs	No	Yes	Yes	No	Yes	Yes
Location FEs	No	Yes	Yes	No	Yes	Yes

Notes: Each column reports a regression of posted HELOC (and growth) rates on county-level year-on-year house price growth, $\Delta HP_{c,t}$. Unweighted columns weight each bank–county–quarter observation equally. HELOC-weighted columns use analytic weights proportional to bank-quarter HELOC balances (split evenly across the bank's observed counties in that quarter). All specifications include the fixed effects indicated in the table. Standard errors (in parentheses) are clustered at the county (location) level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 A Simple Model

We begin with a stripped-down version of the model to clarify the economic mechanism behind our empirical results. A bank operates an integrated branch network across many local markets. In each market, the bank posts a HELOC rate and faces downward-sloping loan demand. Marginal intermediation costs are common across the bank's network. The bank also faces an aggregate funding constraint that links lending decisions across branches by limiting the total amount of credit the bank can extend. In addition, each market is subject to a market-specific lending limit $\bar{L}_{ij}$ that restricts how much credit can be extended

there, capturing collateral-based and underwriting capacity that varies with local housing conditions.

$$\max_{\{r_{ij}\}} \int_{\Omega_i} \left[r_{ij}^L L_{ij} - w_j L_{ij} \right] di$$

subject to

$$\begin{aligned} L_{ij} &= L_i \theta_{ij} \left(\frac{r_{ij}}{r_i} \right)^{-\eta} \\ \int_{\Omega_i} L_{ij} di &= E_j \\ L_{ij} &\leq \bar{L}_{ij}. \end{aligned}$$

The solution in this simple version of the model is:

$$\begin{aligned} r_{ij} &= \frac{\eta}{\eta - 1} \left(w_j + \lambda_j \right) && \text{Unconstrained} \\ \bar{r}_{ij} &= \frac{\eta}{\eta - 1} \left(w_j + \mu_{ij} + \lambda_j \right) && \text{Constrained} \end{aligned}$$

Under flexible pricing, the bank can set a different HELOC rate in each market. In markets where the local lending limit is not binding, the bank chooses the familiar constant-elasticity markup over marginal cost, adjusted for the shadow value of bank funding, λ_j. In markets where the lending limit binds, quantities are fixed at $\bar{L}_{ij}$ and households are effectively rationed at the posted rate. In that case, the bank has an additional incentive to raise the local rate to reduce excess demand and increase the margin on the fixed quantity. This generates a local wedge, μ_{ij}, between constrained and unconstrained markets: rates are higher precisely where lending capacity is scarce. Inverting the demand function implies that the rate consistent with the lending limit is

$$\bar{r}_{ij} = r_i \left(\frac{L_i \theta_{ij}}{\bar{L}_{ij}} \right)^{\frac{1}{\eta}}.$$

Now suppose uniform pricing is imposed within a bank, so that $r_{ij} = r_j$ for all $i \in \Omega_i$. Uniform pricing removes the bank's ability to tailor rates to local conditions. When all markets are unconstrained, the optimal uniform rate coincides with the unconstrained rate.

When some local lending limits bind, the common rate must satisfy the implied lower bound

$$r_j \;\geq\; \bar{r}_{ij} \;\equiv\; r_i \left(\frac{L_i \theta_{ij}}{\bar{L}_{ij}} \right)^{1/\eta}, \qquad \forall i \in \Omega_i.$$

As a result, the optimal uniform rate is higher than the set of flexible local rates that would prevail under decentralized pricing.

Substituting the demand function into the aggregate funding constraint,

$$E_j = \int_{\Omega_i} L_i \, \theta_{ij} \left(\frac{r_j}{r_i} \right)^{-\eta} di = r_j^{-\eta} \int_{\Omega_i} L_i \, \theta_{ij} \, r_i^{\eta} \, di,$$

yields the uniform-pricing equilibrium rate

$$r_j^{\mathrm{UP}} = \left(\frac{\int_{\Omega_i} L_i \, \theta_{ij} \, r_i^{\eta} \, di}{E_j} \right)^{1/\eta}.$$

When uniform pricing binds relative to flexible pricing, the higher common rate reduces borrowing in markets where lending would otherwise expand. Aggregate HELOC lending therefore falls under uniform pricing. In equilibrium, fewer markets reach their lending limits, since the higher rate depresses demand before the local constraint becomes binding.

In what follows, we generalize this intuition by developing a quantitative general equilibrium model of banking with deposits, an interbank market, multibranch multiregion banks, and uncertainty about loan demand. The model embeds the same balance-sheet interactions described above and allows local lending limits to vary with housing conditions, reflecting differences in collateral values across regions. Rates are set before demand is realized, and lending is constrained locally. This richer framework enables us to evaluate counterfactual pricing regimes and quantify their implications for rates, credit allocation, and aggregate lending.

5 Quantitative Model

In this section, we develop a static equilibrium model with heterogeneous banks operating across a continuum of distinct markets (regions), indexed by i. A given bank does not necessarily operate in all markets, which we take as given. In each market i, a mass $\mathcal{J}_i$ of banks is active. We interpret this as a continuum of branches, each represented by a bank and indexed by $j \in [0, \mathcal{J}_i]$, integrated with respect to the Lebesgue measure; hence, each individual branch has measure zero (i.e., is atomistic). For simplicity, we normalize the

market space to $[0,1]$ with the Lebesgue measure, so each individual market also has measure zero and the total mass of locations is one.

The representative household allocates its endowment between deposits supplied to banks and a non-deposit (risk-free) outside asset earning rate r, and chooses desired borrowing from banks. Loan supply is subject to a bank–market-specific lending limit in region i: for each bank j, the amount of credit that can be extended in market i is capped by $\bar{L}_{ij}$. Banks combine deposits and their equity endowment to fund loans and can borrow from or lend to the interbank market at the exogenous rate r. Within each market, banks compete monopolistically à la Dixit and Stiglitz (1977) by setting interest rates on loans and deposits.[11]

5.1 Households

The economy is populated by a representative household endowed with Y units of the consumption good. The household can allocate these resources to bank deposits and can also borrow from banks. We denote by D_{ij} and L_{ij} the household's deposits with and borrowing from bank j in region i, respectively. These financial services are aggregated across regions and banks using a nested CES structure:

$$L = \left(\int_0^1 \phi_i^{\frac{1}{\varepsilon_L}} \, L_i^{\frac{\varepsilon_L - 1}{\varepsilon_L}} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}} \quad \text{and} \quad L_i = \left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{\frac{\eta_L - 1}{\eta_L}} \, dj \right)^{\frac{\eta_L}{\eta_L - 1}}, \tag{3}$$

$$D = \left(\int_0^1 \chi_i^{\frac{1}{\varepsilon_D}} \, D_i^{\frac{\varepsilon_D - 1}{\varepsilon_D}} \, di \right)^{\frac{\varepsilon_D}{\varepsilon_D - 1}} \quad \text{and} \quad D_i = \left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \xi_{ij}^{\frac{1}{\eta_D}} \, D_{ij}^{\frac{\eta_D - 1}{\eta_D}} \, dj \right)^{\frac{\eta_D}{\eta_D - 1}}. \tag{4}$$

The parameters $\eta_L > 1$ and $\varepsilon_L > 1$ govern the elasticities of substitution for loans across banks within a region and across regions, respectively. For deposits, $\eta_D > 1$ and $\varepsilon_D > 1$ govern substitutability across banks and across regions in the same way. We assume $\eta_L > \varepsilon_L$ and $\eta_D > \varepsilon_D$, so that each financial service is more substitutable within than across regions. The parameters ϕ_i and χ_i capture region-specific demand conditions, shifting the household's desired borrowing and deposit holdings toward region i. The parameters θ_{ij} and ξ_{ij} are bank–region-specific weights that govern the household's allocation of borrowing and deposits across banks within region i.

The household derives utility from consumption and from financial services associated with deposits and loans. It chooses deposits D_{ij} and borrowing L_{ij} from bank j in region i,

[11] We adopt this framework because mortgage markets are highly competitive in the U.S.

as well as end-of-period consumption C, to maximize

$$\begin{aligned} \max_{\{C,\, L_{ij},\, D_{ij}\}} \quad & C + \underbrace{U(D,L)}_{\text{financial services}} \\ \text{s.t.} \quad & C = (1+r)Y + \Pi - \int_0^1 \int_0^{\mathcal{J}_i} (r - r_{ij}^D)\, D_{ij}\, dj\, di - \int_0^1 \int_0^{\mathcal{J}_i} (r_{ij}^L - r)\, L_{ij}\, dj\, di \end{aligned} \tag{5}$$

where r_{ij}^D and r_{ij}^L denote the deposit and loan rates offered by bank j in region i, respectively, Π denotes aggregate bank profits rebated lump-sum to the household, and r is the return on the non-deposit asset. This outside option implies that the relevant opportunity cost of holding deposits is $p_{ij}^D \equiv (r - r_{ij}^D)$, while the relevant cost of borrowing is $p_{ij}^L \equiv (r_{ij}^L - r)$. The function $U(D,L)$ is increasing in both arguments and is chosen to generate an upward-sloping deposit supply schedule and a downward-sloping loan demand schedule.[12]

The solution to problem (5) yields demand function for loans:

$$L_{ij} = \mathcal{J}_i^{-\eta_L} \theta_{ij} L_i \left(\frac{p_{ij}^L}{p_i^L} \right)^{-\eta_L}, \quad \text{where} \quad L_i = \phi_i L \left(\frac{p_i^L}{p^L} \right)^{-\varepsilon_L} \tag{6}$$

and prices indices are

$$p_i^L = \left(\frac{1}{\mathcal{J}_i^{\eta_L}} \int_0^{\mathcal{J}_i} \theta_{ij} \left(p_{ij}^L \right)^{1-\eta_L} dj \right)^{\frac{1}{1-\eta_L}} \quad \text{and} \quad p^L = \left(\int_0^1 \phi_i \left(p_i^L \right)^{1-\varepsilon_L} di \right)^{\frac{1}{1-\varepsilon_L}}. \tag{7}$$

Similarly, for deposits:

$$D_{ij} = \mathcal{J}_i^{-\eta_D} \xi_{ij} D_i \left(\frac{p_{ij}^D}{p_i^D} \right)^{-\eta_D}, \quad \text{where} \quad D_i = \chi_i D \left(\frac{p_i^D}{p^D} \right)^{-\varepsilon_D} \tag{8}$$

with price indices

$$p_i^D = \left(\frac{1}{\mathcal{J}_i^{\eta_D}} \int_0^{\mathcal{J}_i} \xi_{ij} \left(p_{ij}^D \right)^{1-\eta_D} dj \right)^{\frac{1}{1-\eta_D}} \quad \text{and} \quad p^D = \left(\int_0^1 \chi_i \left(p_i^D \right)^{1-\varepsilon_D} di \right)^{\frac{1}{1-\varepsilon_D}}. \tag{9}$$

Notice that a higher mass $\mathcal{J}_i$ lowers demand for j in region i. In equilibrium, lending by bank j in market i may be capped by a bank–market-specific lending limit $\overline{L}_{ij}$, introduced

[12] In the context of HELOCs, L in the utility function can be understood as home-improvement services and could be re-labelled as a consumption good produced one-for-one with loan draw-downs, as one of the main reasons that households in U.S take up HELOCs is for home improvements.

in the bank problem below.

5.2 Banks

The banking sector consists of a continuum of heterogeneous banks. Bank j operates in a subset of regions, captured by the indicator $\mathcal{I}_j(i) \in \{0,1\}$.[13] Within each region, active banks compete monopolistically in loan and deposit rates. Each bank can also borrow from or lend to the interbank market at the exogenous rate r, and chooses rates to maximize expected end-of-period profits subject to its balance sheet and household demand.

A key source of heterogeneity across banks is that the marginal cost of intermediating loans and deposits varies at the bank level and is given by

$$W_j(D,L) \;=\; w_j^L \cdot L \;+\; w_j^D \cdot D\,.$$

That is, branches within a bank share the same intermediation technology.[14] We view (w_j^L, w_j^D) as capturing bank-wide intermediation technology and funding management that are largely centralized, while local branch costs (e.g., staffing and rents) are captured separately through region-specific fixed costs κ_{ij}.

In each market i, bank j faces a lending (capacity/underwriting) limit $\overline{L}_{ij}$ that caps the amount of credit it can extend in that market at the posted terms. In the context of HELOCs, $\overline{L}_{ij}$ reflects both borrower-side collateral and risk characteristics (e.g., home value, existing mortgage balance, credit score) and bank-side supply conditions and policies in market i (e.g., risk limits, underwriting stringency, and balance-sheet capacity). We emphasize that this is a *bank feasibility constraint*: households choose desired borrowing, but realized lending cannot exceed $\overline{L}_{ij}$.[15]

We allow for two pricing regimes. Under *flexible (decentralized) pricing*, the bank can post branch-level spreads $\{p_{ij}^L, p_{ij}^D\}_i$ (equivalently rates $\{r_{ij}^L, r_{ij}^D\}_i$). Under *uniform pricing*, the bank posts common spreads across its operating markets, $p_{ij}^L = p_j^L$ and $p_{ij}^D = p_j^D$ for all i such that $\mathcal{I}_j(i) = 1$.[16] Below we write the problem in the general case; the uniform-pricing case is obtained by imposing these cross-market equality restrictions on the choice variables.

[13] We take banks' geographic locations as given.

[14] This assumption is in line with Morelli et al. (2025), Oberfield et al. (2024a) and Granja and Paixão (2026). As in Ulate (2021), the cost of issuing loans is positive (screening, origination, etc.), while the cost of issuing deposits may be negative, reflecting benefits from a larger deposit base.

[15] This constraint could alternatively be imposed on the household's problem. The Appendix shows that doing so yields the same optimal pricing rule for banks.

[16] Equivalently, $r_{ij}^L = r_j^L$ and $r_{ij}^D = r_j^D$ across the bank's branch network.

Given these assumptions, the (realized) profit of bank j is

$$\Pi_j = \int_0^1 \pi_{ij}\, \mathcal{I}_j(i)\, di = \int_0^1 \left[(1 + r_{ij}^L)\, L_{ij} - (1 + r_{ij}^D)\, D_{ij} - W_j(D_{ij}, L_{ij}) - \kappa_{ij}\right] \mathcal{I}_j(i)\, di + (1+r)\, R_j,$$

where R_j denotes the bank's net position in the interbank market.

The only uncertainty banks face concerns the loan-demand shifter θ_{ij}. Banks set loan and deposit rates before observing θ_{ij}, which is realized later. The timing is as follows:

1. **Rate setting.** Banks post loan and deposit rates (equivalently spreads) across their branch network, taking aggregates and demand shifters as given. Regional preferences (ϕ_i, χ_i) and deposit weights ξ_{ij} are known at this stage. By contrast, the loan-demand shifter θ_{ij} is uncertain and distributed on $[\underline{\theta}, \overline{\theta}]$.

2. **Shock realization.** The shocks θ_{ij} are realized.

3. **Quantity determination and balance sheet adjustment.** Given posted rates and realized θ_{ij}, households choose desired deposits and desired borrowing implied by (8) and (6). Realized lending is then

$$L_{ij} \;=\; \min\left\{L_{ij}^d(p_{ij}^L; \theta_{ij}),\, \overline{L}_{ij}\right\}, \tag{10}$$

   while deposits satisfy $D_{ij} = D_{ij}^d(p_{ij}^D)$. Banks then choose their interbank position R_j to satisfy the balance sheet constraint

$$\int_0^1 L_{ij}\, \mathcal{I}_j(i)\, di + R_j \;=\; \int_0^1 D_{ij}\, \mathcal{I}_j(i)\, di + E_j, \tag{11}$$

   where E_j is the equity endowment of the bank. Since loan rates are posted before θ_{ij} is realized, banks cannot adjust loan pricing ex post. Any mismatch between realized lending and deposit funding is absorbed through R_j at rate r.

4. **Settlement.** Deposits and interbank positions are repaid with interest and loans are repaid with interest.

5. **Consumption.** The household consumes.

Substituting the balance sheet constraint into profits, the bank's expected profit maxi-

mization problem can be written as

$$\begin{aligned}\max_{\{r_{ij}^L, r_{ij}^D\}} \quad & \mathbb{E}_\theta\left\{\int_0^1 \Big[(r_{ij}^L - r)\, L_{ij} \;+\; (r - r_{ij}^D)\, D_{ij} \;-\; W_j(D_{ij}, L_{ij}) \;-\; \kappa_{ij}\Big]\mathcal{I}_j(i)\, di \;+\; (1+r)E_j\right\} \\ \text{s.t.} \quad & L_{ij} \le \overline{L}_{ij} \quad \text{for all } i \text{ with } \mathcal{I}_j(i) = 1, \\ & L_{ij}, D_{ij} \text{ satisfy (10) and deposit demand (8).}\end{aligned} \tag{12}$$

Notice that choosing interest rates is equivalent to choosing the associated spreads $p_{ij}^D \equiv r - r_{ij}^D$ and $p_{ij}^L \equiv r_{ij}^L - r$. We therefore formulate the bank's problem in terms of (p_{ij}^D, p_{ij}^L) moving forward. In the uniform-pricing regime, these choices satisfy $p_{ij}^L = p_j^L$ and $p_{ij}^D = p_j^D$ across all operating markets.

To highlight our mechanism, i.e., that bank–region lending limits can make uniform pricing suboptimal, we begin with a full-information benchmark. Specifically, we assume the loan-demand shifter θ_{ij} is observed by banks at the rate-setting stage. We then derive optimal pricing under flexible (branch-level) pricing and under uniform (bank-wide) pricing, and use this comparison to build intuition for the role of binding constraints. We subsequently relax full information and return to the baseline model with uncertainty.

5.3 Full Information

5.3.1 Flexible Pricing

We start by characterizing the optimal pricing rule.

Proposition 1. Under full information and flexible pricing, optimal pricing scheme of bank j is given by

$$(p_{ij}^L)^* = \max\left\{\frac{\eta_L}{\eta_L - 1} w_j^L, p_i^L \left(\frac{\mathcal{J}_i^{-\eta_L} \theta_{ij} L_i}{\overline{L}_{ij}}\right)^{1/\eta_L}\right\}. \tag{13}$$

Proposition 1 delivers a simple pricing logic. When the lending limit is slack in region i, bank j chooses the loan spread to satisfy the standard interior first-order condition. Under CES demand, this implies the familiar constant-elasticity markup over marginal cost,

$$p^{int} \;=\; \frac{\eta_L}{\eta_L - 1} w_j^L,$$

so marginal profitability is equalized across unconstrained regions by a common pricing rule.

When instead the lending limit binds, the bank cannot implement this marginal-profit equalization. If $L_{ij} = \overline{L}_{ij}$, quantities are pinned down by the cap and profits become locally increasing in the spread; the optimum is therefore attained at the boundary value p_i^{cap} that makes demand just equal the cap, i.e. $L_{ij}^d(p_i^{cap}; \theta_{ij}) = \overline{L}_{ij}$. Consequently, optimal spreads depend on local demand conditions and local lending capacity in constrained regions.

Figure 5 illustrates this logic for a bank operating in two markets. In market B the cap is slack at the interior optimum, so the bank sets p^{int}. In market A the cap binds at p^{int}, generating a kink in the profit function and shifting the optimum to the corner $p_A^{cap} > p^{int}$.

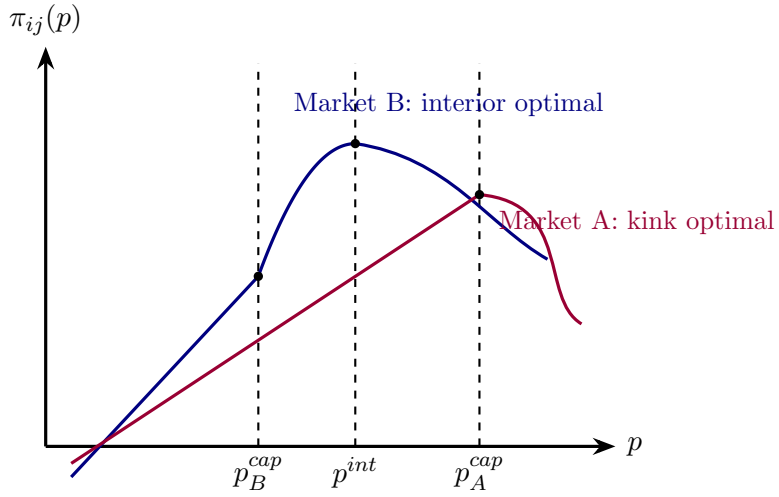


Figure 5: Optimal Pricing Under Full Information and Flexible Pricing

5.4 Uniform Pricing

PROPOSITION 2. Under full information and uniform pricing, the optimal uniform loan spread p for bank j solves

$$\frac{(p_j^L)^* - w_j^L}{(p_j^L)^*} = \frac{1}{\eta_L}\left(1 + \frac{\overline{L}_B((p_j^L)^*)}{Q_S((p_j^L)^*)}\right), \tag{14}$$

where

$$\overline{L}_B(p) \equiv \int_{B(p)} \overline{L}_{ij}\, di, \qquad Q_S(p) \equiv \int_{S(p)} L_{ij}^d(p)\, di,$$

and the sets of binding and slack markets are

$$B(p) = \{\, i \in [0,1] : \mathcal{I}_j(i) = 1 \text{ and } p \le p_{ij}^{cap} \,\},$$
$$S(p) = \{\, i \in [0,1] : \mathcal{I}_j(i) = 1 \text{ and } p > p_{ij}^{cap} \,\},$$

where p_{ij}^{cap} is the threshold spread that satisfies $L_{ij}^d(p_{ij}^{cap}) = \overline{L}_{ij}$.

equation (14) generalizes the standard CES markup rule to the presence of capped regions under a common price. When some regions bind, $\overline{L}_B(p) > 0$, the optimal uniform price is higher: capped (binding) quantities are inframarginal with respect to a small increase in p (as long as the region remains binding), so raising the uniform price increases the margin on those units without reducing their quantity. Slack regions, by contrast, have elastic demand proportional to $p^{-\eta_L}$ and therefore discipline the markup. The no-cap benchmark, in which $\overline{L}_B(p) = 0$, is discussed next.

Because the identity of binding markets changes with p, the objective is piecewise smooth and (potentially) non-differentiable at values of p for which some market satisfies $p = p_{ij}^{cap}$. Under our maintained regularity conditions, these threshold points are negligible, so equation (14) characterizes the optimal uniform spread (i.e., the FOC holds almost everywhere in p).[17]

Lemma 1. (No-cap duality) Suppose lending limits are never binding at the interior CES markup, i.e.,

$$\overline{L}_{ij} \;\ge\; L_{ij}^d\big(p^{int}\big) \quad \text{for all } i \text{ with } \mathcal{I}_j(i) = 1, \qquad p^{int} \equiv \frac{\eta_L}{\eta_L - 1} w_j^L.$$

Then the flexible-pricing optimum is uniform across markets and coincides with the uniform-pricing optimum:

$$(p_{ij}^L)^* = (p_j^L)^* \;=\; p^{int}.$$

Equivalently, when $\overline{L}_{ij} \to \infty$ (so $\overline{L}_B(p) = 0$ for all p), maximizing profits under flexible pricing is equivalent to maximizing profits under uniform pricing.

[17] Fix a bank j and a posted uniform spread p. Under the maintained assumption that the cross-market distribution of thresholds p_{ij}^{cap} is atomless (e.g., because θ_{ij} is continuously distributed and p_{ij}^{cap} varies continuously and strictly monotonically with θ_{ij}), the switching set $\{\, i : p = p_{ij}^{cap} \,\}$ has Lebesgue measure zero for any p.

5.5 Imperfect Information

We now analyze the case with uncertainty, where the loan-demand shifter θ_{ij} is stochastic with support $[\underline{\theta}, \overline{\theta}]$ and probability density function $f(\theta)$ (with cdf F). Banks set rates before θ_{ij} is realized. As in the full-information case, lending in region i is capped by $\overline{L}_{ij}$, so realized lending equals desired demand when the cap is slack and equals $\overline{L}_{ij}$ when it binds.

For a given posted loan spread p_{ij}^L, define the cutoff type $\tilde{\theta}_{ij}(p_{ij}^L)$ such that desired loan demand equals the cap:

$$\tilde{\theta}_{ij}(p_{ij}^L) = \frac{\overline{L}_{ij}}{\mathcal{J}_i^{-\eta_L} L_i} \left(\frac{p_{ij}^L}{p_i^L} \right)^{\eta_L}. \tag{15}$$

For realizations $\theta_{ij} > \tilde{\theta}_{ij}(p_{ij}^L)$ the credit constraint binds and $L_{ij} = \overline{L}_{ij}$, while for $\theta_{ij} \leq \tilde{\theta}_{ij}(p_{ij}^L)$ it is slack and $L_{ij} = L_{ij}^d(p_{ij}^L; \theta_{ij})$. We proceed as before: we first characterize optimal pricing under flexible (branch-level) pricing and then turn to uniform (bank-wide) pricing.

5.5.1 Flexible Pricing

Since the bank's objective equation (12) is additive across regions under flexible pricing, bank j chooses (p_{ij}^L, p_{ij}^D) to maximize expected profits in each operated region i:

$$\max_{\{p_{ij}^L, p_{ij}^D\}} \mathbb{E}_\theta[\pi_{ij}] = \max_{\{p_{ij}^L, p_{ij}^D\}} \left[\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p_{ij}^L)} \pi_{ij}^s(\theta) f(\theta)\, d\theta + \int_{\tilde{\theta}_{ij}(p_{ij}^L)}^{\overline{\theta}} \pi_{ij}^c f(\theta)\, d\theta \right],$$

where $\pi_{ij}^s(\theta)$ denotes profits when the constraint is slack and $\pi_{ij}^c = (p_{ij}^L - w_j^L)\overline{L}_{ij}$ denotes profits when the constraint binds. Expanding,

$$\begin{aligned} \mathbb{E}_\theta[\pi_{ij}] = &\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p_{ij}^L)} (p_{ij}^L - w_j^L)\, \mathcal{J}_i^{-\eta_L} L_i \left(\frac{p_{ij}^L}{p_i^L} \right)^{-\eta_L} \theta\, f(\theta)\, d\theta \\ &+ \int_{\tilde{\theta}_{ij}(p_{ij}^L)}^{\overline{\theta}} (p_{ij}^L - w_j^L)\overline{L}_{ij}\, f(\theta)\, d\theta \\ &+ \left[D_{ij}(p_{ij}^D - w_j^D) - \kappa_{ij} \right]. \end{aligned} \tag{16}$$

The first-order condition with respect to p_{ij}^D is unchanged relative to the deterministic case, since deposit demand does not depend on θ. The next proposition characterizes optimal loan pricing under uncertainty.

PROPOSITION 3. Under uncertainty, the loan pricing rule of bank j is given by

$$p_{ij}^L = \underbrace{\frac{\eta_L}{\eta_L - 1} w_j^L}_{\text{standard mark-up}} + \underbrace{\frac{\mathcal{J}_i^{\eta_L} (p_{ij}^L)^{1+\eta_L} \overline{L}_{ij} \left[1 - F\left(\tilde{\theta}_{ij}(p_{ij}^L)\right)\right]}{(\eta_L - 1) L_i (p_i^L)^{\eta_L} \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p_{ij}^L)} \theta f(\theta)\, d\theta}}_{\text{regional risk premium } >0}.$$

Proposition 3 shows that, unlike the deterministic case, the optimal spread p_{ij}^L is pinned down by an implicit (fixed-point) condition. The spread appears on both sides through $(p_{ij}^L)^{1+\eta_L}$ and through the cutoff type $\tilde{\theta}_{ij}(p_{ij}^L)$ that governs whether the credit constraint binds. Economically, the bank chooses p_{ij}^L ex–ante by trading off (i) the marginal benefit of a higher spread on inframarginal units in states in which the cap binds against (ii) the marginal loss from reducing demand in states in which the cap is slack. A higher spread also raises the cutoff $\tilde{\theta}_{ij}(p_{ij}^L)$, shrinking the set of binding states.[18]

Despite being implicit, the expression yields a transparent decomposition. The first term,

$$\frac{\eta_L}{\eta_L - 1} w_j^L,$$

is the standard constant-elasticity markup over marginal cost, which would obtain if the credit constraint never bound. The second term is a strictly positive wedge that captures the effect of uncertainty and the endogenous probability that the cap becomes binding. Intuitively, when the constraint binds (i.e. for $\theta_{ij} > \tilde{\theta}_{ij}(p_{ij}^L)$), realized lending is locally insensitive to the spread, so raising p_{ij}^L increases the margin on those capped units without reducing their quantity. As a result, optimal pricing incorporates an additional premium relative to the standard markup. This premium is increasing in the probability of a binding state, $1 - F\left(\tilde{\theta}_{ij}(p_{ij}^L)\right)$, and decreasing in expected demand in slack states, summarized by $\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p_{ij}^L)} \theta f(\theta)\, d\theta$.

The uncertainty case therefore replaces the full-information *cap level* $\overline{L}_{ij}$ as the main driver of pricing differences with a measure of *binding risk*. In particular, conditional on demand curvature η_L, the pricing wedge is governed by the likelihood that the cap binds and by the expected volume of lending in slack states. These objects can be interpreted as a sufficient statistic for deviations from uniform pricing in the uncertain environment: markets with a higher probability of binding (or lower expected slack-state demand) optimally receive a higher ex–ante spread, even when the bank's marginal intermediation cost

[18] This endogenous feedback is what makes the pricing rule a fixed point.

w_j^L is common across its branch network. In Appendix A.6 we show, in particular, that $\partial p_{ij}^L / \partial \left(1 - F\left(\tilde{\theta}_{ij}(p_{ij}^L)\right)\right) > 0$.

This has direct implications for uniform pricing across regions. In the deterministic environment, if the credit constraint is slack in all regions at the interior markup, the bank's optimal spread is the same everywhere and uniform pricing is without loss. Under uncertainty, however, the optimal spreads are generically region-specific because the binding risk differs across markets through $(\overline{L}_{ij}, \mathcal{J}_i, L_i, p_i^L)$, which jointly pin down $\tilde{\theta}_{ij}(p)$ and hence the probability of binding. A single common spread cannot, in general, equalize marginal profits across regions. Uniform pricing can arise only in knife-edge cases in which the sufficient statistics governing the wedge are identical across the bank's operated markets, for example, (i) when the constraint is never binding even at the highest demand realization, so the wedge vanishes everywhere, i.e.,

$$\overline{L}_{ij} \geq \overline{\theta}\, \mathcal{J}_i^{-\eta_L} L_i \left(\frac{p_{ij}^L}{p_i^L}\right)^{-\eta_L} \qquad \forall i \text{ with } \mathcal{I}_j(i) = 1,$$

or (ii) when markets are sufficiently similar (in $\mathcal{J}_i$, L_i, p_i^L, and $\overline{L}_{ij}$) that the binding-risk wedge coincides across regions.

A useful interpretation is that in practice loan caps are not frictionless choice variables: raising $\overline{L}_{ij}$ may require additional screening, monitoring, or risk-management capacity, or reflect organizational and regulatory constraints that are costly to adjust locally. These frictions make it difficult for banks to eliminate binding states uniformly across markets, thereby generating systematic deviations from uniform pricing. In this sense, the model predicts that larger, multiregional banks, which face more heterogeneous local conditions and greater organizational complexity, should exhibit greater dispersion in spreads than smaller, geographically concentrated banks, for which uniform pricing is easier to sustain.

A compact Lerner form for flexible pricing. For a given region i and bank j, define the cutoff $\tilde{\theta}_{ij}(p)$ as in equation (15), and define the expected slack-state and binding-state quantities at price p by

$$Q_{ij}^S(p) \equiv \mathbb{E}_\theta\left[L_{ij}^d(p;\theta)\, \mathbf{1}\{\theta \leq \tilde{\theta}_{ij}(p)\}\right] = \mathcal{J}_i^{-\eta_L} L_i \left(\frac{p}{p_i^L}\right)^{-\eta_L} \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\, d\theta,$$
$$Q_{ij}^B(p) \equiv \mathbb{E}_\theta\left[\overline{L}_{ij}\, \mathbf{1}\{\theta > \tilde{\theta}_{ij}(p)\}\right] = \overline{L}_{ij}\left(1 - F(\tilde{\theta}_{ij}(p))\right).$$

Then Proposition 3 can be equivalently written as the Lerner-style condition

$$\frac{p_{ij}^L - w_j^L}{p_{ij}^L} = \frac{1}{\eta_L}\left(1 + \frac{Q_{ij}^B(p_{ij}^L)}{Q_{ij}^S(p_{ij}^L)}\right).$$

This expression would be helpful to compare with the uniform pricing case, described below.

5.5.2 Uniform Pricing

We now characterize optimal uniform (bank-wide) loan pricing under uncertainty. Bank j chooses the single spread p to maximize expected total lending profits across its operated network:

$$\max_{p \geq 0} \Pi_j^L(p), \qquad \Pi_j^L(p) = \int_0^1 \mathbb{E}_\theta\Big[(p - w_j^L)\tilde{L}_{ij}(p, \theta_{ij})\Big]\mathcal{I}_j(i)\, di, \tag{17}$$

where

$$\tilde{L}_{ij}(p, \theta_{ij}) = \min\{\overline{L}_{ij},\, A_i\, \theta_{ij}\, p^{-\eta_L}\}, \qquad A_i \equiv \mathcal{J}_i^{-\eta_L} L_i(p_i^L)^{\eta_L}.$$

Define the cutoff type $\tilde{\theta}_{ij}(p)$ at which desired demand equals the cap:

$$A_i\, \tilde{\theta}_{ij}(p)\, p^{-\eta_L} = \overline{L}_{ij} \qquad \Longleftrightarrow \qquad \tilde{\theta}_{ij}(p) = \frac{\overline{L}_{ij}}{A_i}\, p^{\eta_L}. \tag{18}$$

Proposition 4. Under uncertainty and uniform pricing, the optimal uniform loan spread p for bank j satisfies

$$\frac{p - w_j^L}{p} = \frac{1}{\eta_L} \frac{\displaystyle\int_0^1 Q_{ij}(p)\, \mathcal{I}_j(i)\, di}{\displaystyle\int_0^1 A_i p^{-\eta_L}\left(\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\, d\theta\right)\mathcal{I}_j(i)\, di}, \tag{19}$$

where the expected realized quantity in region i is

$$Q_{ij}(p) \equiv \mathbb{E}_\theta\Big[\tilde{L}_{ij}(p, \theta)\Big] = A_i p^{-\eta_L}\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\, d\theta + \overline{L}_{ij}\Big(1 - F(\tilde{\theta}_{ij}(p))\Big), \tag{20}$$

and $\tilde{\theta}_{ij}(p)$ is given in equation (18).

Proposition 4 generalizes the standard Lerner condition to a bank-wide price set under state-dependent binding constraints. Each region contributes an expected quantity $Q_{ij}(p)$ composed of two parts: (i) slack states, where demand is elastic and proportional to $p^{-\eta_L}$, and (ii) binding states, where quantity is capped at $\overline{L}_{ij}$ and therefore locally insensitive to p.

The optimal uniform spread balances three forces, aggregated across operated regions:

1. **Margin effect:** a higher p increases the per-unit margin $(p - w_j^L)$ everywhere.
2. **Elastic-demand effect (slack states):** a higher p reduces desired demand in slack states because $L_{ij}^d(p;\theta) = A_i \theta p^{-\eta_L}$.
3. **Binding-probability effect:** a higher p raises the cutoff $\tilde{\theta}_{ij}(p)$, which lowers the probability of binding, $1 - F(\tilde{\theta}_{ij}(p))$, and hence reduces the frequency with which the bank earns the spread on capped quantities.

Relative to flexible pricing, uniform pricing forces the bank to internalize these forces *jointly* across regions: a change in p simultaneously affects the distribution of binding vs. slack states in every operated market through $\tilde{\theta}_{ij}(p)$, and therefore the bank trades off profits in high-binding-risk regions against profits in more elastic, slack regions.

Importantly, the model does not deliver an a priori ranking between uniform and flexible pricing in either the optimal spread or total lending under uncertainty.

6 Model–Data Mapping

This section describes how we map the data into the objects that enter the model, and how we discipline the key parameters that govern (i) substitution across banks in the HELOC market and (ii) bank-level marginal intermediation costs. While the model is static, we index the economy by quarter t to emphasize which primitives vary over time and to align the model with the panel structure of the data.

Since the model is expressed in spreads over a short benchmark rate, we convert posted HELOC rates into spreads using the effective federal funds rate (FFER) at a monthly frequency and then aggregate to quarterly frequency:

$$p_{ijt}^L \equiv \frac{\text{HELOC rate}_{ijt} - \text{FFER}_t}{100},$$

so that p_{ijt}^L is expressed in decimal units.

The model targets bank-level HELOC volumes from Call Reports. We construct:

$$L_{jt}^{\text{used}} \equiv \text{HELOC used (drawn balance)}$$
$$L_{jt}^{\text{tot}} \equiv \text{HELOC used + HELOC unused commitments},$$

measured at the bank–quarter level. We measure the number of banks active in each county using FDIC Summary of Deposits (SOD), restricting to banks with at least two branches.

6.1 Estimating Elasticities of Substitution

We now describe our procedure for estimating η_L, the elasticity of substitution for HELOC credit across banks within a county. We follow an instrumental variable strategy similar to Morelli et al. (2025), constructing a Bartik-type instrument that generates cross-bank variation in HELOC spreads through exogenous variation in wages paid to mortgage-related occupations. The identifying assumption is that changes in the average wage rate of mortgage related occupations affects bank cost of providing loans through w_j^L but do not affect borrowers' preference θ_{ij}. For each bank j, the instrument is a weighted average of relative mortgage-related wage levels across all MSAs in which bank j operated during a base period t_0:

$$Z_{jt}^{\text{IV}} \equiv \sum_{k \in \mathcal{M}_{j,t_0}} \omega_{kj,t_0} \left(\ln W_{kt}^{\text{HELOC}} - \ln W_{kt}^{\text{All}} \right),$$

where W_{kt}^{HELOC} denotes the employment-weighted average wage in MSA k at time t for three HELOC-related occupations: loan officers, appraisers and assessors of real estate, and credit analysts, and W_{kt}^{All} is the average wage across all occupations in the same MSA.[19] We subtract the all-occupation component to remove general wage variation that may be correlated with local HELOC demand.[20]

The weights ω_{kj,t_0} measure the importance of MSA k in bank j's mortgage lending during the base period:

$$\omega_{kj,t_0} = \frac{\text{MtgOrig}_{kj,t_0}}{\sum_{m \in \mathcal{M}_{j,t_0}} \text{MtgOrig}_{mj,t_0}},$$

where $\text{MtgOrig}_{kj,t_0}$ is the dollar volume of closed-end mortgage originations by bank j in MSA k during the base period, as reported in the Home Mortgage Disclosure Act (HMDA) Loan Application Register.[21]

[19] Wage and employment data are from the Bureau of Labor Statistics Occupational Employment and Wage Statistics (OEWS) program, which provides disaggregation at the MSA level.

[20] If wages for all occupations rise together due to improving local economic conditions, the resulting higher household income could independently affect HELOC demand, so using relative wages isolates variation specific to the mortgage origination sector.

[21] We use the average of mortgage originations over 2014–2016 as the base period. A multi-year average smooths year-to-year noise in origination volumes, and setting t_0 sufficiently before the estimation period ensures that the weights are predetermined. While publicly available HMDA microdata extend back to 2007, using base-period weights from the 2007–2011 housing bust would be problematic: banks' geographic lending patterns during that period reflect crisis-driven reallocation rather than stable branch-network presence. Moreover, we choose mortgage origination weights because they directly measure the intensity of bank j's housing lending operations in each MSA. HMDA provides comprehensive coverage of closed-end mortgage originations for FDIC-insured institutions throughout our sample, unlike HELOC data, which was reported on a voluntary basis prior to 2018. For the pre-2018 HMDA dataset, we use the Woodstock Institute's Crosswalk File to match the respondent ID to the legal entity identifier.

Notice that the instrument is at the bank level, exploiting regional heterogeneity across banks. The identification strategy is that economic conditions prevailing in the bank's other operated markets shape the bank's optimal pricing (through costs) but do not independently affect how much a borrower in county i wants to borrow from that bank. A household in county i choosing between two banks responds to posted rates, branch convenience, local reputation, etc, not to whether the bank's other branches are located in economically strong or weak MSAs.

The first stage regresses bank–county HELOC spreads on the instrument:

$$\ln p^{L}_{ij,2018} \;=\; \gamma_i \;+\; \alpha_s \;+\; \beta\, Z^{\mathrm{IV}}_{j,2018} \;+\; \epsilon_{ij}, \tag{21}$$

where γ_i is a county fixed effect and α_s denotes bank-type fixed effects. The second stage leverages the demand structure in equation (6) and regresses HELOC origination volumes on the instrumented spreads:

$$\ln L_{ij,2018} \;=\; \gamma^{L}_i \;+\; \alpha^{L}_s \;+\; \beta^{L}\, \widehat{\ln p^{L}_{ij,2018}} \;+\; \epsilon^{L}_{ij}, \tag{22}$$

with $\eta_L = -\beta^L$. We cluster standard errors at the county level. County fixed effects absorb all local demand and supply conditions common across banks in a given county, and bank-type fixed effects absorb differences across community, regional, and multiregional banks. We estimate equations (21)–(22) using the year 2018, which is the earliest year in which HELOC originations are reported on a mandatory basis in HMDA.[22] For HELOC quantities $L_{ij,2018}$, we use the HMDA Snapshot National Loan-Level Dataset, filtering to originated open-end lines of credit and aggregating the dollar volume of originations to the bank×county level.[23] Table 5 reports the estimation results across four specifications that vary in whether the Bartik instrument is winsorized at the 1st and 99th percentiles and whether bank-type fixed effects are included.

Across all specifications, the coefficient on the instrumented spread is negative and statistically significant, consistent with downward-sloping demand for HELOC credit. Our preferred specification is column (3), which includes county and bank-type fixed effects with the winsorized Bartik instrument. This specification yields $\hat{\eta}_L \approx 1.86$, with an F-statistic of 133. The addition of bank-type fixed effects substantially strengthens the first stage (the

[22] Prior to 2018, HELOC reporting under HMDA was voluntary (see Regulation C, §1003.3(c)(12)), so pre-2018 HMDA data do not provide reliable bank–county HELOC quantities. From 2018 onward, institutions originating at least 500 open-end lines of credit in each of the two preceding calendar years are required to report.

[23] We restrict to consumer-purpose, non-reverse-mortgage, owner-occupied HELOCs. The dollar volume of originations measures the total committed credit line at origination.

Table 5: Within-County Elasticity of Substitution: IV Estimates

	$\ln L_{ij}$			
	(1)	(2)	(3)	(4)
$\hat{\beta}^L$	-2.275**	-2.612**	-1.864***	-1.597**
	(0.986)	(1.186)	(0.674)	(0.700)
County FE	Yes	Yes	Yes	Yes
Winsorized	Yes	No	Yes	No
Bank-type FE	No	No	Yes	Yes
Observations	6,030	6,030	6,030	6,030
First-stage F-stat	25.52	14.68	133.23	125.64

Notes: This table reports IV estimates of the within-county elasticity of substitution $\eta_L = -\hat{\beta}^L$ from equation (22). The dependent variable is the log of HELOC origination volume by bank×county in 2018. The endogenous variable is the log posted HELOC spread, instrumented with a Bartik-type IV based on the bank's predetermined geographic exposure to MSA-level relative HELOC-occupation wages. Bank-type fixed effects are indicator variables for community banks (assets below $10 billion), regional banks ($10–$100 billion), and multiregional banks (assets above $100 billion). "Winsorized" indicates that the Bartik instrument is winsorized at the 1st and 99th percentiles. Standard errors clustered at the county level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F-statistic rises from 26 to 133) while moderating the point estimate, confirming that absorbing coarse bank-level heterogeneity sharpens the instrument's identifying variation. The estimates are stable across specifications: $\hat{\eta}_L$ ranges from approximately 1.6 to 2.6, with the tighter confidence intervals in columns (3) and (4) reflecting the stronger first stage. The preferred estimate implies that, within a county and conditional on bank type, a 1% increase in a bank's posted HELOC spread reduces its HELOC origination volume by approximately 1.9%.

For the across-county elasticity of substitution ε_L, which governs the reallocation of HELOC lending across counties in response to relative price changes, we set $\varepsilon_L = 1.05$. This value is close to the Cobb-Douglas of 1, which we view as natural in the HELOC market. Unlike retail goods or tradable products, where consumers can shop across locations in response to price differences, HELOC borrowing is inherently tied to the location of the borrower's property. A homeowner in county i i seeking a home equity line of credit can only pledge the house located in county i as collateral–she cannot substitute to a HELOC in county j, where rates may be lower. Therefore, the relevant margin of substitution for households is across banks within their county (governed by η_L), not across counties. The across-county elasticity therefore captures how the geographic distribution of lending responds to local price variation, rather than an active household reallocation decision. With ε_L close to one, a county's share of (national) HELOC lending is largely pinned down by its demand shifter ϕ_i.

6.2 Estimating Marginal Costs

Recall that the model implies the pricing representation

$$p_{ijt}^{L} = \mu(\eta_L)\, w_{jt}^{L} + RP_{ijt}, \qquad \mu(\eta_L) \equiv \frac{\eta_L}{\eta_L - 1}, \tag{23}$$

where p_{ijt}^{L} denotes the spread posted by bank j in location i at time t, w_{jt}^{L} is the bank–time marginal cost component that is common across the bank's branch network, and RP_{ijt} is the equilibrium regional wedge (risk-premium component) that varies across locations.

We interpret equation (23) as a reduced-form decomposition of observed spreads into a bank–time component and a location–time component. In particular, we estimate the two-way fixed effect specification

$$p_{ijt}^{L} = \alpha_{jt} + \delta_{it} + \varepsilon_{ijt},$$

where α_{jt} is a bank×time fixed effect and δ_{it} is a location×time fixed effect. This specification is consistent with equation (23) under the maintained approximation that the equilibrium wedge admits the decomposition

$$RP_{ijt} = \delta_{it} + \tilde{\varepsilon}_{ijt},$$

i.e. that the dominant location–time forces affecting HELOC spreads are common across banks operating in a given county–quarter, while residual bank–location deviations are absorbed by ε_{ijt}.

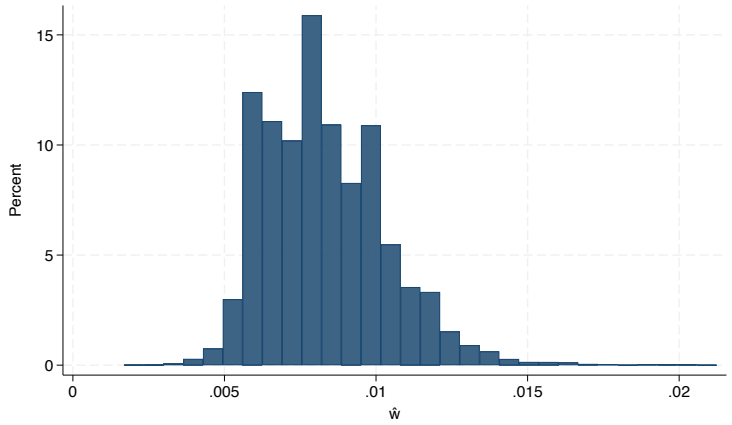
Given an estimate of η_L, the bank–time fixed effect provides a model-consistent proxy for the bank–time term in equation (23). We therefore define an implied marginal cost index as

$$\widehat{w}_{jt}^{L} \equiv \frac{\widehat{\alpha}_{jt}}{\mu(\eta_L)}.$$

Intuitively, $\widehat{w}_{jt}^{L}$ captures the component of spreads that is common across a bank's locations at time t, after netting out county×quarter forces that shift all lenders' spreads in the same local market. The location–time fixed effect $\widehat{\delta}_{it}$ summarizes the corresponding local component, which we interpret as a reduced-form proxy for RP_{ijt}.

Because fixed effects are identified only up to an additive constant, mapping $\widehat{\alpha}_{jt}$ into a level of w_{jt}^{L} requires a normalization. Our baseline normalization anchors the level of the cost index to the unconditional mean spread in the sample. Let $\bar{p}$ denote the unconditional mean

Figure 6: Distribution of HELOC Marginal Costs



Notes: The figure plots the distribution of the bank–quarter marginal cost index for HELOCs, $\widehat{w}_{jt}^{L}$, constructed from the bank×quarter fixed effect in the two-way fixed-effects decomposition of posted spreads (bank×quarter and county×quarter fixed effects) and scaled by the model markup $\mu(\eta_L) = \eta_L/(\eta_L - 1)$ as in equation (24).

of p_{ijt}^{L}. We define the mean-anchored bank–time cost index as

$$\widehat{w}_{jt}^{L,\text{norm}} \equiv \frac{\bar{p} + \widehat{\alpha}_{jt}}{\mu(\eta_L)}. \tag{24}$$

This normalization preserves the cross-bank and time-series variation in $\widehat{\alpha}_{jt}$ while selecting a convenient level that is comparable across products and specifications. Operationally, equation (24) amounts to shifting all bank×time fixed effects by a common constant so that the resulting cost index is expressed in the same units as spreads and centered at a meaningful benchmark. Figure 6 shows the distribution of marginal costs from our procedure.

6.3 Algorithm to Solve the Model

We describe the computational procedure tu estimate the equilibrium of the model for each quarter t. Denote $\mathcal{B}_{it}$ and $\mathcal{J}_{it}$ the set and total amount of banks active in region i, respectively.[24] From the loan demand:

$$\theta_{ijt} = \mathcal{J}_{it}^{\eta_L} \frac{L_{ijt}}{L_{it}} \left(\frac{p_{ijt}^{L}}{p_{it}^{L}} \right)^{\eta_L} \quad \Longrightarrow \quad \sum_{j \in \mathcal{B}_{it}} \theta_{ijt} = \frac{\mathcal{J}_{it}^{\eta_L} \sum_{j \in \mathcal{B}_{it}} (p_{ijt}^{L})^{\eta_L} L_{ijt}}{L_{it} (p_{it}^{L})^{\eta_L}}.$$

[24] In this case, to make the estimation internally consistent, we take $\mathcal{J}_{it}$ from RateWatch.

Normalizing $\sum_{j\in\mathcal{B}_{it}} \theta_{ijt} = \mathcal{J}_{it}$:

$$\mathcal{J}_{it} L_{it} (p^L_{it})^{\eta_L} = \mathcal{J}_{it}^{\eta_L} \sum_{j\in\mathcal{B}_{it}} (p^L_{ijt})^{\eta_L} L_{ijt} \implies \theta_{ijt} = \frac{\mathcal{J}_{it} (p^L_{ijt})^{\eta_L} L_{ijt}}{\sum_{m\in\mathcal{B}_{it}} (p^L_{imt})^{\eta_L} L_{imt}}$$

1. **Inputs.** Data/parameters $\{D_{ijt}, L^{\text{tot}}_{jt}, p^L_{ijt}, w^L_{jt}, \eta_L, \mathcal{J}_{it}, \mathcal{B}_{it}\}$, a lending scale $\{L_{jt}\}$, and tolerances $(\varepsilon, \varepsilon_L)$.

2. **Step 0: Initialization.** Set iteration counter $k = 0$. Initialize the loan allocation using observed deposit shares:

$$s^{(0)}_{ijt} \equiv \frac{D_{ijt}}{\sum_i D_{ijt}}, \qquad L^{(0)}_{ijt} \equiv s^{(0)}_{ijt}\, L^{\text{tot}}_{jt}.$$

3. **Iterate for $k = 0, 1, 2, \ldots$:**

   (a) **Step 1: Given $L^{(k)}_{ijt}$, update $\theta^{(k)}_{ijt}$.** For each market (i,t) with bank set $\mathcal{B}_{it}$ and each $j \in \mathcal{B}_{it}$, set

$$\theta^{(k)}_{ijt} = \frac{\mathcal{J}_{it}\,(p^L_{ijt})^{\eta_L}\, L^{(k)}_{ijt}}{\sum_{m\in\mathcal{B}_{it}} (p^L_{imt})^{\eta_L}\, L^{(k)}_{imt}}.$$

   (b) **Step 2: Update regional price and quantity indices.** For each market (i,t), compute

$$p^{L,(k)}_{it} = \left(\mathcal{J}_{it}^{-\eta_L} \sum_{j\in\mathcal{B}_{it}} \theta^{(k)}_{ijt} (p^L_{ijt})^{1-\eta_L} \right)^{\frac{1}{1-\eta_L}}, \qquad L^{(k)}_{it} = \left(\frac{1}{\mathcal{J}_{it}} \sum_{j\in\mathcal{B}_{it}} (\theta^{(k)}_{ijt})^{\frac{1}{\eta_L}} (L^{(k)}_{ijt})^{\frac{\eta_L - 1}{\eta_L}} \right)^{\frac{\eta_L}{\eta_L - 1}}.$$

   (c) **Step 3: Compute $\tilde{\theta}^{(k)}_{ijt}$ and implied caps $\overline{L}^{(k)}_{ijt}$.** Assume $\theta \mid (i,t) \sim U[0, \overline{\theta}]$. Under the normalization

$$\sum_{j\in\mathcal{B}_{it}} \theta_{ijt} = \mathcal{J}_{it} \implies \mathbb{E}[\theta] = 1 \implies \overline{\theta} = 2.$$

   From optimal pricing FOC:

$$\tilde{\theta}^{(k)}_{ijt} = \frac{2\overline{\theta}}{(\eta_L + 1) - \eta_L \frac{w^L_{jt}}{p^L_{ijt}}} = \frac{4}{(\eta_L + 1) - \eta_L \frac{w^L_{jt}}{p^L_{ijt}}},$$

   which is well-defined and positive when $p^L_{ijt} > \frac{\eta_L}{\eta_L + 1} w^L_{jt}$. Then compute the implied

cap

$$\overline{L}_{ijt}^{(k)} = \mathcal{J}_{it}^{-\eta_L}\, \tilde{\theta}_{ijt}^{(k)}\, L_{it}^{(k)} \left(\frac{p_{it}^{L,(k)}}{p_{ijt}^{L}} \right)^{\eta_L}.$$

(d) **Step 4: Update unconstrained demand $\widehat{L}_{ijt}^{(k)}$.** For each (i, j, t), compute

$$\widehat{L}_{ijt}^{(k)} = \mathcal{J}_{it}^{-\eta_L}\, \theta_{ijt}^{(k)}\, L_{it}^{(k)} \left(\frac{p_{ijt}^{L}}{p_{it}^{L,(k)}} \right)^{-\eta_L}.$$

(e) **Step 5: Update realized lending.** Apply the cap:

$$L_{ijt}^{(k+1)} = \min \left\{ \widehat{L}_{ijt}^{(k)},\ \overline{L}_{ijt}^{(k)} \right\}.$$

(f) **Step 6: Convergence check.** Stop if

$$\max_{i,j,t} \left| \frac{L_{ijt}^{(k+1)} - L_{ijt}^{(k)}}{\max\{\varepsilon_L,\ |L_{ijt}^{(k)}|\}} \right| < \varepsilon.$$

Otherwise set $k \leftarrow k + 1$ and return to Step 1.

4. **Regional Shifters.** Normalize

$$\sum_i \phi_{it} = 1,$$

so that in the special case with no dispersion in regional spreads ($p_{it}^L = \bar{p}_t^L$ for all i), the aggregate spread satisfies $p_t^L = \bar{p}_t^L$. Given $\{L_{it},\, p_{it}^L\}_i$. Compute

$$\phi_{it} = \frac{(p_{it}^L)^{\varepsilon_L}\, L_{it}}{\sum_m (p_{mt}^L)^{\varepsilon_L}\, L_{mt}}.$$

5. Compute L from the aggregator definition and recover r^L from the FOC.

A similar approach is followed to solve for shifters in the deposit market.

7 Results

This section evaluates the quantitative implications of the model. We start by studying how well it accounts for two key features of the HELOC market: (i) the time-series evolution of within-bank cross-regional price dispersion, and (ii) the aggregate dynamics of HELOC borrowing. A central prediction of the theory is that deviations from uniform pricing are

tightly linked to the extent to which local lending limits bind. In the certainty version of the model, the sufficient statistic was the indicator of whether a given market hits its capacity constraint. Under uncertainty, the same mechanism implies that pricing dispersion depends on the *probability* that the constraint binds. We therefore focus on the within-bank mean binding probability as a sufficient statistic for within-bank dispersion in spreads, and then examine whether the model reproduces the aggregate boom–bust pattern in HELOC lending.

Figure 7: Model Predictions

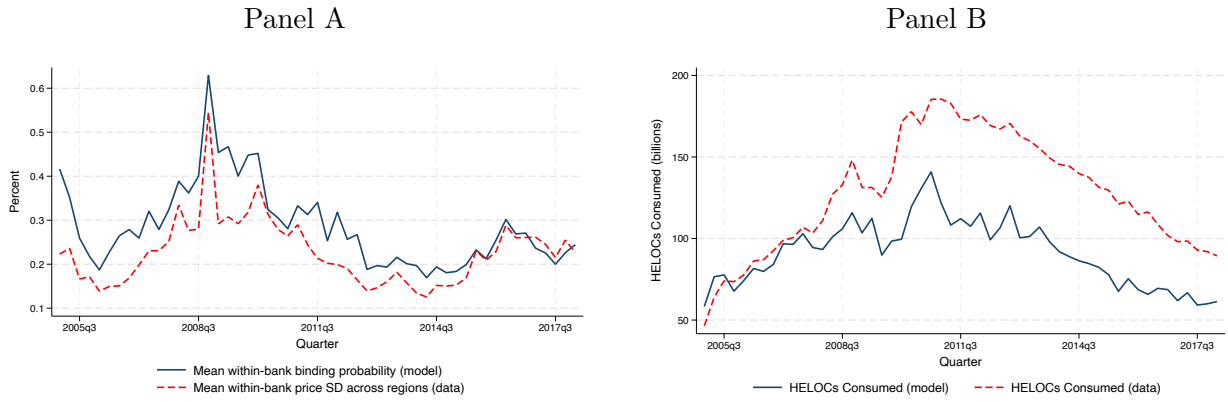


Figure 7 summarizes the model's predictions. Panel A compares the model-implied mean within-bank binding probability to the mean within-bank standard deviation of spreads across regions in the data. Panel B compares total HELOC borrowing in the model to the data.

Panel A: binding probability as the sufficient statistic for dispersion. Panel A shows that the within-bank probability of binding tracks closely the within-bank cross-regional dispersion in spreads. This comovement is a direct implication of the model's pricing structure. In the certainty case, the sufficient statistic determining whether local pricing departs from the uniform (unconstrained) markup is the indicator

$$\mathbf{1}\{L_{ij} \geq \overline{L}_{ij}\},$$

that is, whether market i served by bank j is constrained (actual lending reaches the local cap). When the constraint does not bind, pricing follows the standard constant-elasticity markup, and there is little force generating within-bank cross-regional dispersion. When the constraint binds, the shadow value of capacity generates an additional local wedge, producing higher spreads in constrained markets and thus dispersion within the bank.

Under uncertainty about local demand and/or capacity utilization, the same logic implies that the indicator is naturally replaced by its expectation. That is, the relevant sufficient

statistic becomes the *probability* that the constraint binds,

$$\mathbb{P}\big(L_{ij} \geq \overline{L}_{ij}\big)\,,$$

because prices must internalize the expected shadow cost of capacity rather than its realized value. As a result, when binding risk rises (for example, during the crisis), the model predicts larger and more heterogeneous wedges across regions within a bank, increasing the within-bank standard deviation of spreads. Conversely, when binding risk falls, those wedges compress and dispersion declines. The tight tracking in Panel A therefore provides direct support for the mechanism that (expected) capacity scarcity, captured by binding probabilities, is the driver of departures from uniform pricing.

Panel B: aggregate lending dynamics. Panel B plots total HELOC borrowing in the model against the data. The model reproduces the shape of aggregate dynamics very closely: the run-up prior to the crisis, the contraction around the bust, and the gradual decline thereafter. Quantitatively, the model predicts a lower level of total lending than observed in the data. This gap is expected given differences in measurement and sample coverage: the data reflect HELOC borrowing across the full distribution of borrower characteristics (e.g., a wide range of credit profiles, loan-to-value ratios, and contract terms), whereas the model is calibrated to a more narrowly defined segment, this is, HELOC originations up to an 80% LTV cutoff and concentrated in the best borrower profile. In this sense, Panel B shows that the model captures the main aggregate time-series variation despite abstracting from higher-risk and higher-LTV segments that contribute to aggregate volume in the data.

7.1 Geography of binding Probabilities

Figure 8 also suggests a natural supply-side channel linking house prices to binding risk. When house prices fall, collateral values and expected recovery rates deteriorate, which can induce lenders to scale back credit availability, tighten underwriting, or reduce credit limits. In the model, these forces are summarized by a decline in local lending capacity $\overline{L}_{it}$. Holding demand fixed, a lower $\overline{L}_{it}$ mechanically raises the probability of binding,

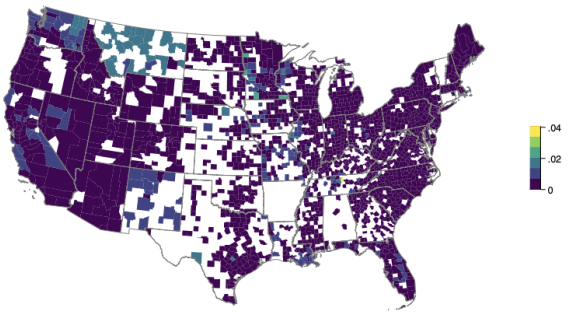
$$p_{it}^{bind} = \Pr(L_{it} \geq \overline{L}_{it}),$$

and therefore increases the expected shadow value of capacity that governs pricing wedges under uncertainty. Consistent with this interpretation, Panels (c)–(d) show that several regions that transition from strong house price growth in 2005 to sharp declines by 2008 also

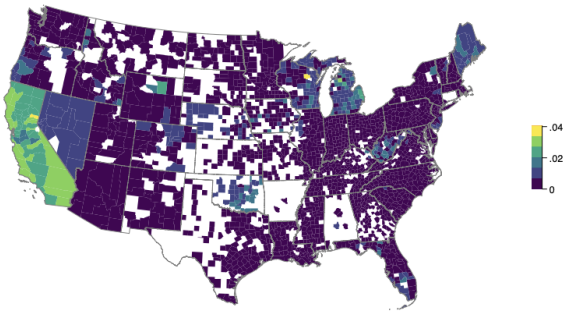
exhibit rising binding probabilities in Panels (a)–(b). This pattern should be interpreted as suggestive: house prices affect both demand and supply determinants of HELOC markets. Nevertheless, the co-movement is consistent with a tightening of $\overline{L}_{it}$ in declining-price markets that amplifies binding pressure during the bust and relaxes pressure during the boom.

Figure 8: Binding Probabilities and House Price Growth Across Regions

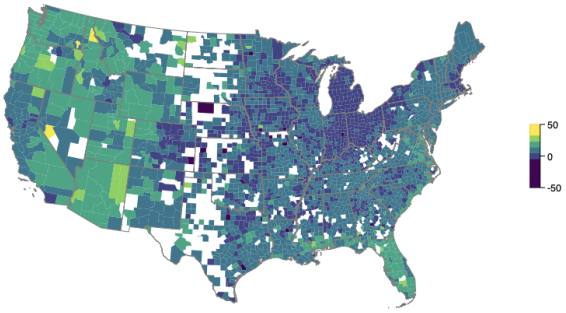
(a) Binding probability, 2005



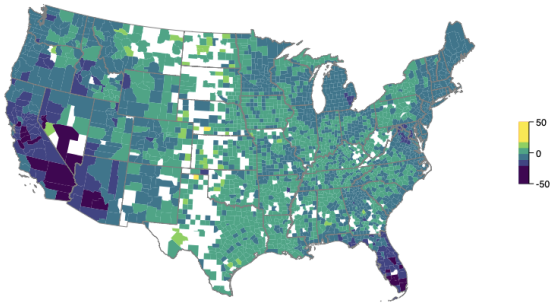
(b) Binding probability, 2008



(c) Annual house price % change, 2005



(d) Annual house price % change, 2008



Notes: The top row maps the model-implied binding risk $p_{it}^{bind} = \Pr(L_{it} \geq \overline{L}_{it})$. The bottom row maps annual house price growth using the FHFA house price index.

7.2 Counterfactual: From Flexible to Uniform Pricing

In this section we perform our main counterfactual experiment: we study the implications of restricting banks to set a single (uniform) HELOC spread across all regions they serve, rather than allowing flexible (region-specific) pricing. The goal is to quantify how prices, quantities, and bank profitability adjust when banks lose the ability to target local conditions. We also evaluate the welfare implications of moving between pricing regimes.

We proceed as follows. We fix lending capacities $\overline{L}_{ijt}$, and solve for the equilibrium under

a *uniform pricing constraint* in which each bank j chooses a single spread that applies to all regions i at time t.[25] We compare this equilibrium to the flexible-pricing benchmark, where spreads can vary across regions within the same bank. Figure 9 reports the time-series of percentage differences in spreads and lending (uniform relative to flexible), and Table 6 summarizes unconditional averages.

Figure 9: Flexible to Uniform Pricing: Price and Quantity Effects

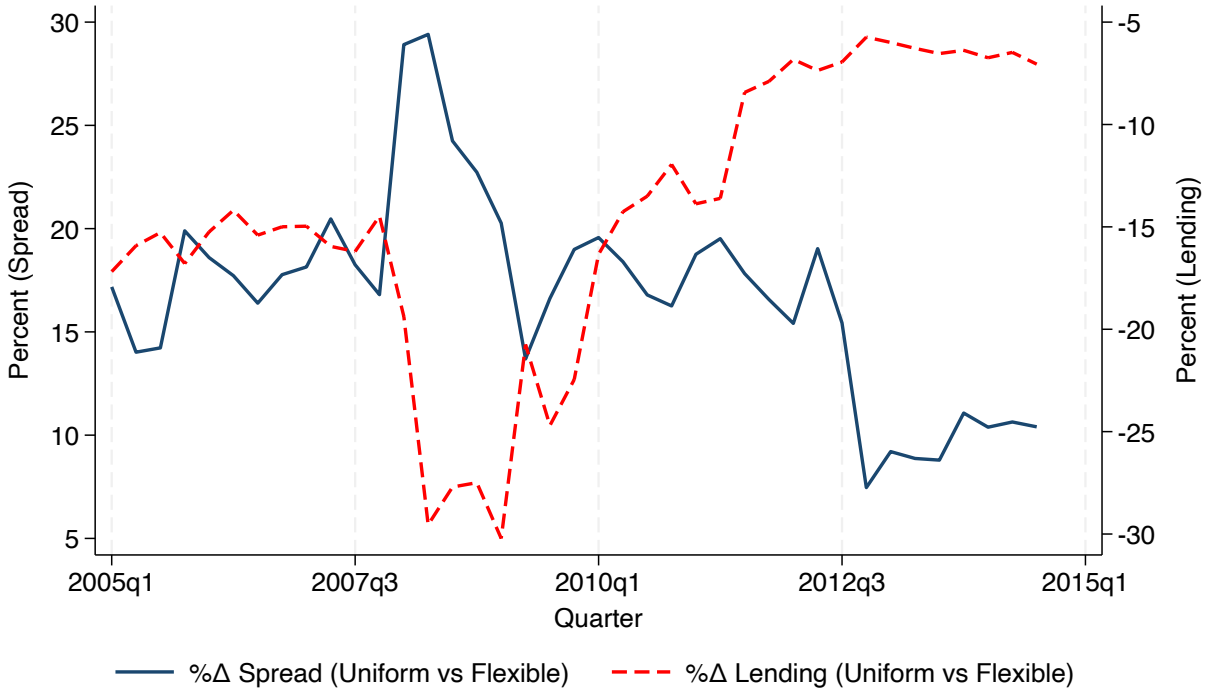


Table 6: Quarterly Time-Series Averages: Flexible vs. Uniform Pricing

	Flexible	Uniform
Avg. Spread	4.6%	5.2%
Avg. Lending	91.3B	79.0B
Avg. Ex-post Binding share	15.8%	0.03%

Figure 9 shows that imposing uniform pricing increases spreads and reduces lending. On average, the spread rises from 4.6% under flexible pricing to 5.2% under uniform pricing, while average lending falls from 91.3B to 79.0B (Table 6). The time-series confirms that the spread wedge is typically positive and that lending contracts throughout the sample, with

[25] Appendix Section A.7 describes the algorithm in detail.

particularly large lending losses in periods when regional conditions are most heterogeneous as the financial crisis.

The mechanism is straightforward. Under flexible pricing, banks can keep spreads relatively low in slack regions while charging higher spreads in tight regions where the expected shadow cost of capacity is high. Uniform pricing forces the bank to choose a single spread that trades off profits across heterogeneous markets. Because the single price must be viable even in the bank's tightest (highest-demand / lowest-capacity) regions, it tends to be set above what would prevail in slack regions. The resulting higher spread applies everywhere, reducing borrowing in regions that would otherwise be served at lower prices. Since tight regions cannot expand much beyond capacity, the uniform regime primarily reduces lending through lost volume in slack, more elastic markets.

A striking implication of Table 6 is that the average ex-post binding share falls from 15.8% under flexible pricing to essentially zero (0.03%) under uniform pricing. This pattern is a natural consequence of having only one pricing instrument. When banks can price flexibly, they can raise spreads in constrained regions while maintaining lower spreads elsewhere, so it is relatively common that realized demand reaches local caps in the highest-pressure markets. Under uniform pricing, however, the bank cannot raise spreads *only* where capacity is scarce. Instead, the optimal uniform spread is chosen high enough to prevent frequent binding in the most constrained/highest-demand locations, which mechanically suppresses demand across all regions. In equilibrium, the economy moves from rationing via local capacity constraints (binding ex post in some regions) to rationing primarily via a higher common spread, leaving most markets with slack capacity most of the time.

Equivalently, uniform pricing induces the bank to "buy insurance" against binding in its worst markets by setting a single spread that keeps realized demand below $\overline{L}_{ijt}$ almost everywhere, hence the near-zero ex-post binding rate. This feature underscores that uniform pricing changes not only the level of prices and quantities, but also the *mode* of rationing: from localized quantity constraints under flexible pricing to system-wide price-based rationing under uniform pricing.

Interpretation and Summary. Overall, the counterfactual highlights a sharp trade-off. Flexible pricing improves spatial allocation by concentrating rationing where capacity is scarce while preserving volume where it is not. Uniform pricing compresses within-bank price differences, but does so by raising the average spread and reducing total lending, and by shifting rationing away from binding local caps toward a higher common price. Importantly, banks forgo substantial profits under uniform pricing: average HELOC profit losses from imposing uniform pricing are approximately 28.6%. The magnitude of this profit loss

reinforces the central mechanism of the paper. When local lending constraints bind unevenly across regions, the ability to tailor spreads to local conditions is highly valuable—banks earn significantly higher margins on capped quantities in constrained markets while maintaining volume in slack ones. If the profit losses from uniform pricing were small, the observed departures from uniform pricing during the housing bust would be difficult to rationalize through local credit rationing alone and would instead point to alternative mechanisms. The large profit stake in flexible pricing is consistent with banks actively adjusting local spreads in response to heterogeneous binding risk, precisely as the model predicts. The next subsection uses these equilibrium changes to quantify the welfare consequences of moving between pricing regimes.

7.3 Welfare

This section describes how we compute the welfare effect of imposing a uniform-pricing constraint relative to the flexible-pricing equilibrium. The key implication of our quasi-linear specification of the utility function is that welfare differences are money-metric: they are measured directly in consumption units. As a result, standard monetary welfare measures such as equivalent variation (EV) and compensating variation (CV) coincide with the change in indirect utility.

Let $R \in \{\text{flex}, \text{unif}\}$ denote the equilibrium regime (flexible pricing vs uniform pricing). Define the household's indirect utility (welfare) in regime R as

$$V^R \equiv C^R + \frac{(L^R)^{1-\nu}}{1-\nu} + \frac{(D^R)^{1-\gamma}}{1-\gamma}. \tag{25}$$

Using the budget constraint, we can rewrite equation (25) as

$$V^R = Y(1+r) + \Pi^R - \int p_{ij}^{D,R} D_{ij}^R \, dj \, di - \int p_{ij}^{L,R} L_{ij}^R \, dj \, di + \frac{(L^R)^{1-\nu}}{1-\nu} + \frac{(D^R)^{1-\gamma}}{1-\gamma}.$$

Welfare differences between regimes are defined by

$$\Delta W \equiv V^{\text{unif}} - V^{\text{flex}}. \tag{26}$$

In our counterfactual exercise, deposit allocations do not change. Therefore, the deposit utility term cancels in ΔW:

$$\frac{(D^{\text{unif}})^{1-\gamma}}{1-\gamma} - \frac{(D^{\text{flex}})^{1-\gamma}}{1-\gamma} = 0.$$

Hence, equation (26) reduces to

$$\Delta W = \left(\Pi^{\text{unif}} - \Pi^{\text{flex}}\right) - \left(\int p_{ij}^{L,\text{unif}} L_{ij}^{\text{unif}}\, dj\, di - \int p_{ij}^{L,\text{flex}} L_{ij}^{\text{flex}}\, dj\, di\right) + \left(\frac{(L^{\text{unif}})^{1-\nu}}{1-\nu} - \frac{(L^{\text{flex}})^{1-\nu}}{1-\nu}\right). \tag{27}$$

The household owns the banks, so profits Π are rebated lump-sum. This implies that interest margin payments $\int p_{ij}^{L} L_{ij}\, dj\, di$ are transfers from the household to banks that return to the household as part of Π. Holding deposits and equity fixed, the only regime-dependent terms in profits are those involving loans:

$$\Pi^{\text{unif}} - \Pi^{\text{flex}} = \left(\int p_{ij}^{L,\text{unif}} L_{ij}^{\text{unif}}\, dj\, di - \int p_{ij}^{L,\text{flex}} L_{ij}^{\text{flex}}\, dj\, di\right) - \left(\int_0^1 W_j(D_j, L_j^{\text{unif}})\, dj - \int_0^1 W_j(D_j, L_j^{\text{flex}})\, dj\right), \tag{28}$$

where constant terms (deposit margins, fixed costs, endowments) drop out because they do not change in the counterfactual.

Substituting equation (28) into equation (27) yields an exact cancellation of the loan payment terms:

$$\begin{aligned}
\Delta W = {} & \underbrace{\left(\int p_{ij}^{L,\text{unif}} L_{ij}^{\text{unif}}\, dj\, di - \int p_{ij}^{L,\text{flex}} L_{ij}^{\text{flex}}\, dj\, di\right)}_{\text{from } \Delta\Pi} - \underbrace{\left(\int p_{ij}^{L,\text{unif}} L_{ij}^{\text{unif}}\, dj\, di - \int p_{ij}^{L,\text{flex}} L_{ij}^{\text{flex}}\, dj\, di\right)}_{\text{loan payments}} \\
& - \left(\int_0^1 W_j(D_j, L_j^{\text{unif}})\, dj - \int_0^1 W_j(D_j, L_j^{\text{flex}})\, dj\right) + \left(\frac{(L^{\text{unif}})^{1-\nu}}{1-\nu} - \frac{(L^{\text{flex}})^{1-\nu}}{1-\nu}\right) \\
= {} & \left(\frac{(L^{\text{unif}})^{1-\nu}}{1-\nu} - \frac{(L^{\text{flex}})^{1-\nu}}{1-\nu}\right) - \left(\int_0^1 W_j(D_j, L_j^{\text{unif}})\, dj - \int_0^1 W_j(D_j, L_j^{\text{flex}})\, dj\right).
\end{aligned} \tag{29}$$

Equation equation (29) shows that, under our assumptions, welfare changes depend only on (i) the change in household utility from aggregate borrowing and (ii) the change in real intermediation costs. Changes in loan spreads per se are transfers that wash out because profits are rebated.

With $W_j(D, L) = w_j^L L + w_j^D D$ and canceling deposits,

$$W_j(D_j, L_j^{\text{unif}}) - W_j(D_j, L_j^{\text{flex}}) = w_j^L \left(L_j^{\text{unif}} - L_j^{\text{flex}}\right).$$

Hence the welfare change becomes

$$\Delta W = \frac{(L^{\text{unif}})^{1-\nu} - (L^{\text{flex}})^{1-\nu}}{1-\nu} - \int_0^1 w_j^L \left(L_j^{\text{unif}} - L_j^{\text{flex}}\right) dj. \tag{30}$$

or in the data:

$$\Delta W_t = \frac{(L_t^{\text{unif}})^{1-\nu} - (L_t^{\text{flex}})^{1-\nu}}{1-\nu} - \Delta \text{Cost}_t.$$

Figure 10: Welfare Gain of Flexible Relative to Uniform Pricing

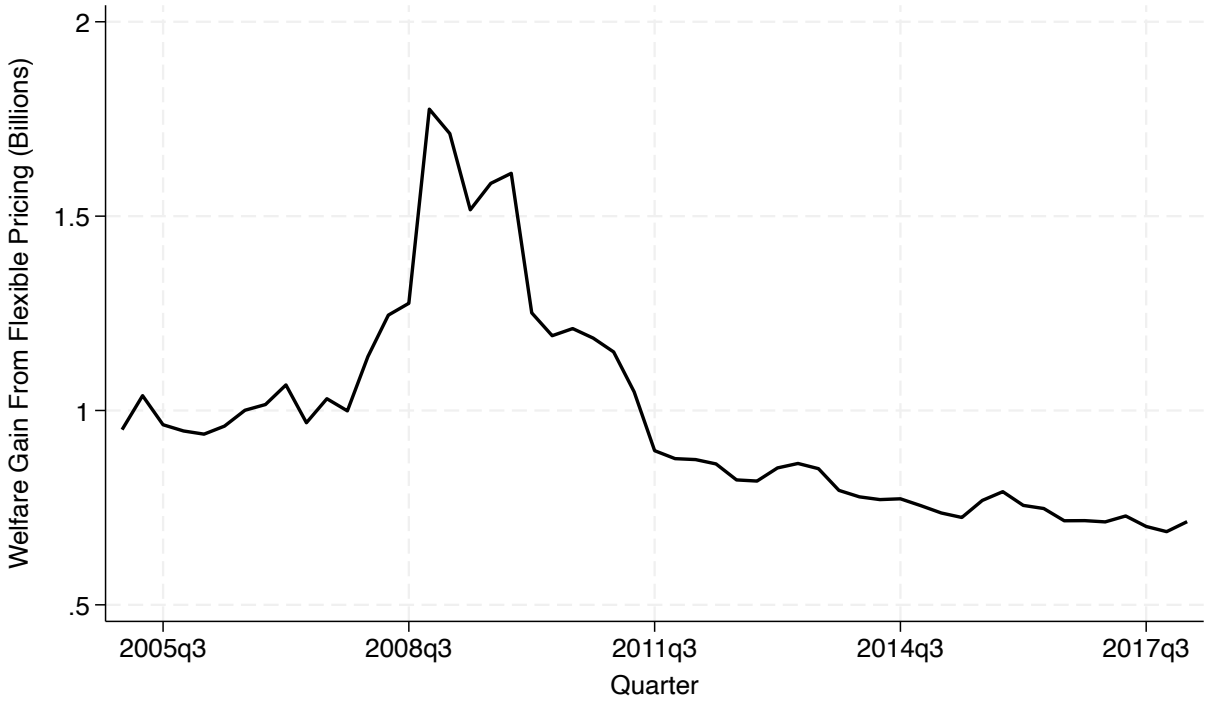


Figure 10 shows that flexible pricing increases welfare relative to uniform pricing because it allows banks to better align loan rates with local lending conditions. When lending constraints are heterogeneous across regions, a uniform rate is too high and reduces borrowing. The welfare gains from flexible pricing are substantially larger during the housing bust, when dispersion in local conditions—and hence the probability that lending limits bind—rises sharply. In normal times, when constraints are rarely binding, the two pricing regimes yield similar allocations and welfare differences are modest.

8 Conclusion

Uniform pricing is a striking and pervasive feature of multi-market firms, including banks that operate large branch networks. In the HELOC market, however, we show that this regularity breaks down in a systematic and persistent way during periods of uneven collateral shocks. Using branch-level posted HELOC rates, we document that within-bank pricing dispersion

is small in normal times, but rises sharply during the Great Recession, especially in regions with larger house price declines and among multiregional banks with more heterogeneous exposure to local housing conditions.

We interpret these patterns through a model of integrated multi-branch banks that share common marginal intermediation costs and balance-sheet management, yet face local lending limits tied to collateral conditions. A key ingredient is that banks set rates before observing realized utilization shocks, so posted rates embed the shadow value of local capacity when constraints are likely to bind. The model implies that the probability a local lending constraint binds is a sufficient statistic for deviations from uniform pricing: when lending capacity tightens unevenly across markets, optimal pricing becomes locally distorted away from a single bank-wide rate.

We estimate the model by combining micro HELOC pricing data with bank balance-sheet and branch network information, and show that it reproduces both aggregate HELOC lending dynamics and the time-series evolution of within-bank dispersion. In counterfactual exercises that hold local lending limits fixed, we compare flexible (local) pricing to a uniform-pricing constraint. We find that imposing uniform pricing raises equilibrium rates, reduces credit, and lowers bank profitability substantially—average HELOC profit losses from uniform pricing are approximately 28.6%. The mechanism is that a common rate internalizes the profitability of higher margins in constrained markets at the expense of depressed demand in unconstrained markets, pushing the uniform rate above the flexible-pricing rates that would prevail in slack regions. The magnitude of the profit loss confirms that the stakes of local pricing flexibility are large, consistent with the observed willingness of banks to deviate from uniform pricing when local constraints bind unevenly.

More broadly, our results highlight that uniform pricing is sustainable when local constraints are slack but becomes distortionary when lending capacity tightens heterogeneously, amplifying credit contractions in exposed regions. This perspective helps rationalize why the largest departures from uniform pricing emerge for multiregional banks precisely during the housing bust, and it provides a quantitative framework to evaluate the aggregate and distributional consequences of centralized pricing rules in retail credit markets.

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Online Appendix for Breaking Uniform Pricing

March 2026

David Argente
Yale University

Marcos Lissauer
Torcuato Di Tella University

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Appendix for Online Publication

A Model Derivations

A.1 CES Aggregator Within Location

The CES aggregator within a location is defined as

$$L_i \;=\; \left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{\frac{\eta_L - 1}{\eta_L}} \, dj \right)^{\frac{\eta_L}{\eta_L - 1}}.$$

The factor $1/\mathcal{J}_i$ turns the inner integral into an average, making the CES composite invariant to measure-preserving refinements of the branch index. For example, if $\theta_{ij} \equiv 1$ and $L_{ij} \equiv x$ for all j, then without normalization

$$L_i^{\text{no-norm}} = \left(\int_0^{\mathcal{J}_i} x^{\frac{\eta_L - 1}{\eta_L}} \, dx \right)^{\frac{\eta_L}{\eta_L - 1}} = \left(\mathcal{J}_i \, x^{\frac{\eta_L - 1}{\eta_L}} \right)^{\frac{\eta_L}{\eta_L - 1}} = \mathcal{J}_i^{\frac{\eta_L}{\eta_L - 1}} \, x,$$

so the index scales mechanically with $\mathcal{J}_i$. With the normalization,

$$L_i = \left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} x^{\frac{\eta_L - 1}{\eta_L}} \, dx \right)^{\frac{\eta_L}{\eta_L - 1}} = x,$$

independent of $\mathcal{J}_i$. By contrast, if one branch of level x is split into two sub-branches each at $x/2$ (keeping $\int_0^{\mathcal{J}_i} L_{ij} \, dj$ fixed), the CES composite does change even with the normalization:

$$L_i = \left(\tfrac{1}{2} \left[(x/2)^{\frac{\eta_L - 1}{\eta_L}} + (x/2)^{\frac{\eta_L - 1}{\eta_L}} \right] \right)^{\frac{\eta_L}{\eta_L - 1}} = \left((x/2)^{\frac{\eta_L - 1}{\eta_L}} \right)^{\frac{\eta_L}{\eta_L - 1}} = \tfrac{x}{2},$$

as the CES index is an intensive (per-unit-mass) object that reflects substitution across branches, not total volume. Total loans scale with the mass of branches via $\int_0^{\mathcal{J}_i} L_{ij} \, dj$, while the index L_i remain invariant to changes in the measure of labels.

A.2 Price Index Across Locations

Let $p_i^L \equiv r_i^L - r$ be the regional spread index. The household minimizes:

$$\min_{\{L_i\}_{i\in[0,1]}} \int_0^1 p_i^L \, L_i \, di,$$

subject to the aggregator constraint:

$$L = \left(\int_0^1 \phi_i^{\frac{1}{\varepsilon_L}} L_i^{\frac{\varepsilon_L - 1}{\varepsilon_L}} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}}.$$

Let μ be the Lagrange multiplier. The Lagrangian is:

$$\mathcal{L} = \int_0^1 p_i^L L_i \, di - \mu \left[\left(\int_0^1 \phi_i^{\frac{1}{\varepsilon_L}} L_i^{\frac{\varepsilon_L - 1}{\varepsilon_L}} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}} - L \right].$$

The FOC is given by

$$\frac{\partial \mathcal{L}}{\partial L_i} = p_i^L - \mu \cdot \left(\int_0^1 \phi_j^{\frac{1}{\varepsilon_L}} L_j^{\frac{\varepsilon_L - 1}{\varepsilon_L}} \, dj \right)^{\frac{1}{\varepsilon_L - 1}} \phi_i^{\frac{1}{\varepsilon_L}} L_i^{-1/\varepsilon_L} = 0 \implies L_i = \phi_i L \left(\frac{\mu}{p_i^L} \right)^{\varepsilon_L}.$$

Plug back into aggregator:

$$L = \left(\int_0^1 \phi_i^{\frac{1}{\varepsilon_L}} \left[\phi_i L \left(\frac{p_i^L}{\mu} \right)^{-\varepsilon_L} \right]^{\frac{\varepsilon_L - 1}{\varepsilon_L}} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}}.$$

Factor out L:

$$L = L \cdot \left(\int_0^1 \phi_i \left(\frac{p_i^L}{\mu} \right)^{-(\varepsilon_L - 1)} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}}.$$

Cancel L:

$$1 = \left(\int_0^1 \phi_i \left(\frac{p_i^L}{\mu} \right)^{-(\varepsilon_L - 1)} \, di \right)^{\frac{\varepsilon_L}{\varepsilon_L - 1}}.$$

Raise both sides:

$$1 = \int_0^1 \phi_i \left(\frac{p_i^L}{\mu} \right)^{-(\varepsilon_L - 1)} \, di \Rightarrow \mu^{\varepsilon_L - 1} = \int_0^1 \phi_i (p_i^L)^{1 - \varepsilon_L} \, di.$$

$$\Rightarrow \mu \equiv p^L = \left(\int_0^1 \phi_i (p_i^L)^{1-\varepsilon_L} \, di \right)^{\frac{1}{1-\varepsilon_L}}.$$

We can obtain p^D following the same steps. Notice also that

$$\int_0^1 p_i^L L_i di = \int_0^1 p_i^L \phi_i L \left(\frac{p^L}{p_i^L} \right)^{\varepsilon_L} di = L (p^L)^{\varepsilon_L} \int_0^1 \phi_i (p_i^L)^{1-\varepsilon_L} di.$$

Using $(p^L)^{1-\varepsilon_L} = \int_0^1 \phi_i (p_i^L)^{1-\varepsilon_L} di$,

$$\int_0^1 p_i^L L_i di = L \cdot p^L.$$

A.3 Price Index Within Locations

Define the loan price as $p_{ij}^L = r_{ij}^L - r$. The household minimizes:

$$\min_{\{L_{ij}\}_{j \in [0, \mathcal{J}_i]}} \int_0^{\mathcal{J}_i} p_{ij}^L \, L_{ij} \, dj \quad \text{s.t.} \quad L_i \;=\; \left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{\frac{\eta_L - 1}{\eta_L}} \, dj \right)^{\frac{\eta_L}{\eta_L - 1}}.$$

Let λ be the multiplier on the CES constraint. The Lagrangian is

$$\mathcal{L} \;=\; \int_0^{\mathcal{J}_i} p_{ij}^L \, L_{ij} \, dj \;-\; \lambda \left[\left(\frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{\frac{\eta_L - 1}{\eta_L}} \, dj \right)^{\frac{\eta_L}{\eta_L - 1}} - L_i \right].$$

Let

$$S_i \;\equiv\; \frac{1}{\mathcal{J}_i} \int_0^{\mathcal{J}_i} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{\frac{\eta_L - 1}{\eta_L}} \, dj \quad \Rightarrow \quad L_i \;=\; S_i^{\frac{\eta_L}{\eta_L - 1}}.$$

Differentiating,

$$0 \;=\; \frac{\partial \mathcal{L}}{\partial L_{ij}} \;=\; p_{ij}^L \;-\; \lambda \, S_i^{\frac{1}{\eta_L - 1}} \, \frac{1}{\mathcal{J}_i} \, \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{-\frac{1}{\eta_L}}.$$

Absorb the constant $\mathcal{J}_i^{-1}$ into $\tilde{\lambda} \equiv \frac{\lambda}{\mathcal{J}_i}$ to get

$$p_{ij}^L \;=\; \tilde{\lambda} \, S_i^{\frac{1}{\eta_L - 1}} \theta_{ij}^{\frac{1}{\eta_L}} \, L_{ij}^{-\frac{1}{\eta_L}}.$$

The Hicksian demand is

$$L_{ij} \;=\; \theta_{ij} \, L_i \left(\frac{\tilde{\lambda}}{p_{ij}^L} \right)^{\eta_L}.$$

Plugging L_{ij} back into the aggregator,

$$1 \;=\; \frac{1}{\mathcal{J}_i}\int_0^{\mathcal{J}_i} \theta_{ij}\left(\frac{p_{ij}^L}{\tilde{\lambda}}\right)^{-(\eta_L-1)} dj \;\Longrightarrow\; \tilde{\lambda}^{\,1-\eta_L} \;=\; \frac{1}{\mathcal{J}_i}\int_0^{\mathcal{J}_i} \theta_{ij}\left(p_{ij}^L\right)^{1-\eta_L} dj.$$

Since $\tilde{\lambda} = \lambda/\mathcal{J}_i$, we have $\lambda = \mathcal{J}_i\tilde{\lambda}$ and thus

$$\lambda^{1-\eta_L} = \mathcal{J}_i^{\,1-\eta_L}\tilde{\lambda}^{\,1-\eta_L} = \frac{1}{\mathcal{J}_i^{\eta_L}}\int_0^{\mathcal{J}_i} \theta_{ij}\left(p_{ij}^L\right)^{1-\eta_L} dj.$$

Identifying $\lambda \equiv p_i^L$ (expenditure for one unit of L_i), the within-location CES price index is

$$p_i^L \;=\; \left(\frac{1}{\mathcal{J}_i^{\eta_L}}\int_0^{\mathcal{J}_i} \theta_{ij}\left(p_{ij}^L\right)^{1-\eta_L} dj\right)^{\frac{1}{1-\eta_L}}.$$

Using the demand and the definition above,

$$\int_0^{\mathcal{J}_i}\left(p_{ij}^L\right) L_{ij}\, dj = L_i\,\tilde{\lambda}^{\eta_L}\,\frac{1}{\mathcal{J}_i}\int_0^{\mathcal{J}_i}\theta_{ij}\left(p_{ij}^L\right)^{1-\eta_L} dj = L_i\,\tilde{\lambda}^{\eta_L}\,\tilde{\lambda}^{\,1-\eta_L} = L_i\,\tilde{\lambda} = L_i\,\frac{p_i^L}{\mathcal{J}_i}.$$

A.4 Households Optimization

We First start deriving the budget constraint. Let B denote the amount invested in the non-deposit asset. At the allocation stage ("beginning of the period"),

$$\int_0^1\int_0^{\mathcal{J}_i} D_{ij}djdi + B = Y + \int_0^1\int_0^{\mathcal{J}_i} L_{ij}djdi$$

and at the settlement stage ("end of the period"), deposits are returned with interest; loan principal is repaid with interest

$$C = \Pi + (1+r)B + \int_0^1\int_0^{\mathcal{J}_i}(1+r_{ij}^D)D_{ij}djdi - \int_0^1\int_0^{\mathcal{J}_i}(1+r_{ij}^L)L_{ij}djdi.$$

Combining both, the constraint is

$$C = Y(1+r) + \Pi + \int_0^1\int_0^{\mathcal{J}_i}(r_{ij}^D - r)D_{ij}djdi - \int_0^1\int_0^{\mathcal{J}_i}(r_{ij}^L - r)L_{ij}djdi.$$

Now we turn into the optimization problem of households, which solves

$$\begin{aligned}\max_{\{C,L_{ij},D_{ij}\}} \quad & C+\frac{L^{1-\nu}}{1-\nu}+\frac{D^{1-\gamma}}{1-\gamma}\\ \text{s.t.} \quad & C=Y(1+r)+\Pi-\int_0^1\int_0^{\mathcal{J}_i}\underbrace{(r-r_{ij}^D)}_{\equiv p_{ij}^D}D_{ij}djdi-\int_0^1\int_0^{\mathcal{J}_i}\underbrace{(r_{ij}^L-r)}_{\equiv p_{ij}^L}L_{ij}djdi.\end{aligned}$$

The Lagrangian Lagrangian is

$$\mathcal{L}=C+\frac{D^{1-\gamma}}{1-\gamma}+\frac{L^{1-\nu}}{1-\nu}+\lambda\left(Y+\Pi-\int_0^1\int_0^{\mathcal{J}_i}p_{ij}^DD_{ij}djdi-\int_0^1\int_0^{\mathcal{J}_i}p_{ij}^LL_{ij}djdi-C\right)$$

Using the prices indices identities, the FOCs are:

$$\begin{aligned}
(C) \quad &: \quad 1-\lambda=0 \implies \lambda=1\\
(D) \quad &: \quad D^{-\gamma}-p^D=0 \implies D=(p^D)^{-1/\gamma}\\
(L) \quad &: \quad L^{-\nu}-p^L=0 \implies L=(p^L)^{-1/\nu}\\
(D_i) \quad &: \quad D^{-\gamma}\frac{\partial D}{\partial D_i}-p_i^D=0 \implies D^{-\gamma}\left(\frac{D}{D_i}\right)^{1/\varepsilon_D}\chi_i^{1/\varepsilon_D}-p_i^D=0 \implies D_i=\chi_iD\left(\frac{p_i^D}{p^D}\right)^{-\varepsilon_D}\\
(L_i) \quad &: \quad L^{-\nu}\frac{\partial L}{\partial L_i}-p_i^L=0 \implies L^{-\nu}\left(\frac{L}{L_i}\right)^{1/\varepsilon_L}\phi_i^{1/\varepsilon_L}-p_i^L=0 \implies L_i=\phi_iL\left(\frac{p_i^L}{p^L}\right)^{-\varepsilon_L}\\
(D_{ij}) \quad &: \quad D^{-\gamma}\frac{\partial D}{\partial D_i}\frac{\partial D_i}{\partial D_{ij}}-p_{ij}^D=0 \implies D^{-\gamma}\left(\frac{D}{D_i}\right)^{1/\varepsilon_D}\chi_i^{1/\varepsilon_D}\xi_{ij}^{1/\eta_D}\left(\frac{D_i}{D_{ij}}\right)^{1/\eta_D}\frac{1}{\mathcal{J}_i}-p_{ij}^D=0\\
&\implies \quad D_{ij}=\mathcal{J}_i^{-\eta_D}\xi_{ij}D_i\left(\frac{p_{ij}^D}{p_i^D}\right)^{-\eta_D}\\
(L_{ij}) \quad &: \quad L^{-\nu}\frac{\partial L}{\partial L_i}\frac{\partial L_i}{\partial L_{ij}}-p_{ij}^L=0 \implies L^{-\nu}\left(\frac{L}{L_i}\right)^{1/\varepsilon_L}\phi_i^{1/\varepsilon_L}\theta_{ij}^{1/\eta_L}\left(\frac{L_i}{L_{ij}}\right)^{1/\eta_L}\frac{1}{\mathcal{J}_i}-p_{ij}^L=0\\
&\implies \quad L_{ij}=\mathcal{J}_i^{-\eta_L}\theta_{ij}L_i\left(\frac{p_{ij}^L}{p_i^L}\right)^{-\eta_L}
\end{aligned}$$

A.5 Existence and Uniqueness Under Uncertainty

PROPOSITION 5. (Well-definedness and existence.) Consider the fixed-point equation

$$p_{ij}^L=\frac{\eta_L}{\eta_L-1}w_j^L+\frac{\mathcal{J}_i^{\eta_L}(p_{ij}^L)^{1+\eta_L}\overline{L}_{ij}\left[1-F(\tilde{\theta}(p_{ij}^L))\right]}{(\eta_L-1)L_i(p_i^L)^{\eta_L}\int_{\underline{\theta}}^{\tilde{\theta}(p_{ij}^L)}\theta f(\theta)\,d\theta}, \tag{A.1}$$

where θ has support $[\underline{\theta}, \overline{\theta}]$, pdf f and cdf F, and the cutoff type is

$$\tilde{\theta}(p) = \frac{\overline{L}_{ij}\, \mathcal{J}_i^{\eta_L}}{L_i} \left(\frac{p}{p_i^L}\right)^{\eta_L}. \tag{A.2}$$

A necessary condition for equation (A.1) to be well-defined at a candidate solution is

$$\int_{\underline{\theta}}^{\tilde{\theta}(p_{ij}^L)} \theta f(\theta)\, d\theta > 0, \tag{A.3}$$

equivalently $\tilde{\theta}(p_{ij}^L) > \underline{\theta}$. Moreover, suppose f is continuous on $[\underline{\theta}, \overline{\theta}]$ and $f(\theta) > 0$, and that there exists $p_0 \geq \frac{\eta_L}{\eta_L - 1} w_j^L$ such that $\tilde{\theta}(p_0) \in (\underline{\theta}, \overline{\theta})$. Then there exists at least one $p^* \geq \frac{\eta_L}{\eta_L - 1} w_j^L$ that solves equation (A.1).

Proof. (of Proposition 5) We go by steps.

Step 1: Well-definedness. Define $m \equiv \frac{\eta_L}{\eta_L - 1} w_j^L$. The right-hand side of equation (A.1) involves the ratio

$$\frac{1 - F(\tilde{\theta}(p))}{\int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta)\, d\theta}.$$

Since the numerator is finite and bounded in $[0, 1]$, the expression is well-defined only if the denominator is strictly positive. Because $\theta f(\theta) \geq 0$, the condition

$$\int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta)\, d\theta > 0$$

is equivalent to $\tilde{\theta}(p) > \underline{\theta}$. Hence equation (A.3) is necessary for equation (A.1) to be well-defined at a solution.

Step 2: Existence. Let $H(p)$ denote the right-hand side of equation (A.1), and define

$$G(p) \equiv H(p) - p.$$

A fixed point p^* corresponds to a zero of G. Under the stated assumptions, $\tilde{\theta}(p)$ is continuous and strictly increasing in p by equation (A.2). Since f is continuous and positive, both

$$q(p) \equiv 1 - F(\tilde{\theta}(p)) \qquad \text{and} \qquad M(p) \equiv \int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta)\, d\theta$$

are continuous in p whenever $\tilde{\theta}(p) \in (\underline{\theta}, \overline{\theta})$, with $M(p) > 0$. Hence $H(p)$ and $G(p)$ are continuous on any interval where $\tilde{\theta}(p) \in (\underline{\theta}, \overline{\theta})$.

Consider p such that $\tilde{\theta}(p) \downarrow \underline{\theta}$. Then $M(p) \downarrow 0$ while $q(p) \to 1 - F(\underline{\theta}) > 0$. Therefore the second term in equation (A.1) diverges to $+\infty$, implying $H(p) \to +\infty$ and thus $G(p) \to +\infty$.

Next, for p sufficiently large, $\tilde{\theta}(p) \geq \overline{\theta}$ and hence $q(p) = 1 - F(\tilde{\theta}(p)) = 0$. In this region, equation (A.1) reduces to $H(p) = m$, so $G(p) = m - p \to -\infty$ as $p \to \infty$.

Since G is continuous on a region where it takes both positive and negative values, the intermediate value theorem implies there exists at least one p^* such that $G(p^*) = 0$, i.e. p^* solves equation (A.1). ■

PROPOSITION 6. (Uniqueness.) Let p_{ij}^L solve the fixed-point equation equation (A.1), and define the mapping

$$H(p) \equiv m + R(p), \qquad m \equiv \frac{\eta_L}{\eta_L - 1} w_j^L,$$

where $R(p)$ is given in equation (A.5). Suppose H is continuously differentiable on a feasible interval $\mathcal{P} = [\underline{p}, \overline{p}] \subset (0, \infty)$ such that $\tilde{\theta}(p) \in (\underline{\theta}, \overline{\theta})$ for all $p \in \mathcal{P}$. If

$$\sup_{p \in \mathcal{P}} H'(p) = \sup_{p \in \mathcal{P}} R'(p) < 1, \tag{A.4}$$

then there exists a unique solution $p^* \in \mathcal{P}$ to $p = H(p)$.

Proof. (of Proposition 6) The fixed-point equation equation (A.1) can be written as $p = H(p)$, where H is continuous on $\mathcal{P}$. Under the slope restriction equation (A.4), the mapping H is a contraction on $\mathcal{P}$:

$$|H(p) - H(\hat{p})| \leq \left(\sup_{u \in \mathcal{P}} H'(u) \right) |p - \hat{p}| \quad \text{for all } p, \hat{p} \in \mathcal{P}.$$

By the Banach fixed-point theorem, H admits a unique fixed point in $\mathcal{P}$. Hence there is a unique $p^* \in \mathcal{P}$ satisfying $p^* = H(p^*)$, equivalently equation (A.1). ■

A.6 Comparative Statics Under Uncertainty

Proposition 2 characterizes the optimal loan spread p_{ij}^L as the fixed point of

$$p_{ij}^L = m + R(p_{ij}^L), \qquad m \equiv \frac{\eta_L}{\eta_L - 1} w_j^L,$$

where

$$R(p) \equiv \frac{\mathcal{J}_i^{\eta_L} \, p^{1+\eta_L} \, \overline{L}_{ij}}{(\eta_L - 1) L_i (p_i^L)^{\eta_L}} \cdot \frac{1 - F(\tilde{\theta}(p))}{\int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta) \, d\theta}.$$

Define

$$q(p) \equiv 1 - F(\tilde{\theta}(p)), \qquad M(p) \equiv \int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta)\, d\theta,$$

so that $R(p)$ can be written more compactly as

$$R(p) = \underbrace{\frac{\mathcal{J}_i^{\eta_L}\, p^{1+\eta_L}\, \overline{L}_{ij}}{(\eta_L - 1) L_i (p_i^L)^{\eta_L}}}_{\equiv A(p)} \cdot \frac{q(p)}{M(p)}. \tag{A.5}$$

Implicit function theorem. Let

$$G(p; x) \equiv p - m - R(p; x),$$

where x denotes a generic parameter (e.g. $x \in \{\overline{L}_{ij}, \mathcal{J}_i\}$). The equilibrium spread satisfies $G(p_{ij}^L; x) = 0$. By the implicit function theorem,

$$\frac{\partial p_{ij}^L}{\partial x} = \frac{\partial R(p_{ij}^L; x)/\partial x}{1 - \partial R(p_{ij}^L; x)/\partial p}. \tag{A.6}$$

Under the regularity (stability) condition

$$1 - \frac{\partial R(p_{ij}^L; x)}{\partial p} > 0, \tag{A.7}$$

the sign of $\partial p_{ij}^L / \partial x$ is governed by the sign of $\partial R / \partial x$.[26]

Cutoff type and its derivatives. Write equation (15) as

$$\tilde{\theta}(p) = \frac{\overline{L}_{ij}\, \mathcal{J}_i^{\eta_L}}{L_i} \left(\frac{p}{p_i^L} \right)^{\eta_L}.$$

Hence, the partial derivatives of $\tilde{\theta}(p)$ are

$$\frac{\partial \tilde{\theta}}{\partial p} = \frac{\eta_L}{p} \tilde{\theta}, \qquad \frac{\partial \tilde{\theta}}{\partial \mathcal{J}_i} = \frac{\eta_L}{\mathcal{J}_i} \tilde{\theta}, \qquad \frac{\partial \tilde{\theta}}{\partial \overline{L}_{ij}} = \frac{1}{\overline{L}_{ij}} \tilde{\theta}. \tag{A.8}$$

[26] The regularity condition ensures that the fixed point is locally unique and stable (i.e. the schedule $p = m + R(p)$ crosses the 45-degree line with slope less than one). Economically, this condition rules out explosive feedback from loan pricing into the regional wedge.

Moreover, since $q(p) = 1 - F(\tilde{\theta}(p))$ and $M(p) = \int_{\underline{\theta}}^{\tilde{\theta}(p)} \theta f(\theta)\, d\theta$,

$$\frac{dq}{d\tilde{\theta}} = -f(\tilde{\theta}), \qquad \frac{dM}{d\tilde{\theta}} = \tilde{\theta} f(\tilde{\theta}). \tag{A.9}$$

Effect of binding probability. Consider an increase in $q(p) = 1 - F(\tilde{\theta}(p))$ holding other arguments fixed. From (A.5),

$$\frac{\partial R(p)}{\partial q} = A(p) \cdot \frac{1}{M(p)} > 0,$$

and therefore, using (A.6)–(A.7),

$$\frac{\partial p_{ij}^L}{\partial \left(1 - F(\tilde{\theta}(p_{ij}^L))\right)} > 0.$$

Thus, greater probability mass in binding states increases equilibrium loan spreads.

Effect of $\mathcal{J}_i$. To highlight the competing channels, it is convenient to work with elasticities. Taking logs of (A.5),

$$\ln R(p) = \ln A(p) + \ln q(p) - \ln M(p),$$

where

$$\ln A(p) = \eta_L \ln \mathcal{J}_i + (1 + \eta_L) \ln p + \ln \overline{L}_{ij} - \ln\big((\eta_L - 1) L_i (p_i^L)^{\eta_L}\big).$$

Holding p fixed, the elasticity of R with respect to $\mathcal{J}_i$ is

$$\frac{\partial \ln R(p)}{\partial \ln \mathcal{J}_i} = \eta_L + \frac{\partial \ln\big(q(p)/M(p)\big)}{\partial \ln \mathcal{J}_i}.$$

Using (A.9) and the chain rule,

$$\frac{\partial \ln(q/M)}{\partial \ln \mathcal{J}_i} = \frac{\partial \ln(q/M)}{\partial \tilde{\theta}} \cdot \frac{\partial \tilde{\theta}}{\partial \ln \mathcal{J}_i}, \qquad \frac{\partial \tilde{\theta}}{\partial \ln \mathcal{J}_i} = \eta_L \tilde{\theta},$$

and

$$\frac{\partial \ln(q/M)}{\partial \tilde{\theta}} = \frac{1}{q}\frac{dq}{d\tilde{\theta}} - \frac{1}{M}\frac{dM}{d\tilde{\theta}} = -\frac{f(\tilde{\theta})}{q} - \frac{\tilde{\theta} f(\tilde{\theta})}{M}.$$

Substituting yields

$$\frac{\partial \ln R(p)}{\partial \ln \mathcal{J}_i} = \eta_L \left[1 - \frac{\tilde{\theta} f(\tilde{\theta})}{q} - \frac{\tilde{\theta}^2 f(\tilde{\theta})}{M}\right].$$

The first term in brackets reflects the direct scaling effect of $\mathcal{J}_i$ in $R(p)$, while the last two terms reflect the indirect effect through the cutoff $\tilde{\theta}(p)$, which changes the probability of binding states and the expected demand shifter in slack states. Consequently, the sign of $\partial R/\partial \mathcal{J}_i$ (and thus $\partial p_{ij}^L/\partial \mathcal{J}_i$) is not determined a priori. Formally, under (A.7),

$$\operatorname{sign}\left(\frac{\partial p_{ij}^L}{\partial \mathcal{J}_i}\right) = \operatorname{sign}\left(\frac{\partial R(p_{ij}^L)}{\partial \mathcal{J}_i}\right).$$

Effect of $\overline{L}_{ij}$. Analogously, holding p fixed,

$$\frac{\partial \ln R(p)}{\partial \ln \overline{L}_{ij}} = 1 + \frac{\partial \ln\big(q(p)/M(p)\big)}{\partial \ln \overline{L}_{ij}}.$$

Since $\partial\tilde{\theta}/\partial \ln \overline{L}_{ij} = \tilde{\theta}$ from (A.8), the chain rule implies

$$\frac{\partial \ln(q/M)}{\partial \ln \overline{L}_{ij}} = \frac{\partial \ln(q/M)}{\partial \tilde{\theta}} \cdot \frac{\partial \tilde{\theta}}{\partial \ln \overline{L}_{ij}} = \tilde{\theta}\left(-\frac{f(\tilde{\theta})}{q} - \frac{\tilde{\theta} f(\tilde{\theta})}{M}\right).$$

Thus,

$$\frac{\partial \ln R(p)}{\partial \ln \overline{L}_{ij}} = 1 - \frac{\tilde{\theta} f(\tilde{\theta})}{q} - \frac{\tilde{\theta}^2 f(\tilde{\theta})}{M}.$$

As for $\mathcal{J}_i$, the sign is ambiguous because $\overline{L}_{ij}$ affects $R(p)$ both directly (through scaling of profits in binding states) and indirectly via $\tilde{\theta}(p)$, which shifts the likelihood of binding states. Under (A.7),

$$\operatorname{sign}\left(\frac{\partial p_{ij}^L}{\partial \overline{L}_{ij}}\right) = \operatorname{sign}\left(\frac{\partial R(p_{ij}^L)}{\partial \overline{L}_{ij}}\right).$$

A.7 Uniform Pricing Solution Algorithm

1. **Inputs.** Data/parameters $\{\overline{L}_{ijt},\, L_{ijt},\, \mathcal{B}_{it},\, \mathcal{I}_j(i),\, \eta_L,\, \bar{\theta},\, w_{jt}^L\}$ and a convergence tolerance ε_p^{conv}.

2. **Initialization (Step 0).** Fix $\overline{L}_{ijt}$ from the baseline steady state. Initialize

$$p_{jt}^{(0)} = \frac{\eta_L}{\eta_L - 1}\, w_{jt}^L, \qquad L_{ijt}^{(0)} = L_{ijt},$$

3. **Iterate for $k = 0, 1, 2, \ldots$:**

(a) **Step 1: Update $\theta_{ijt}^{(k)}$.** For each market (i,t) and each bank $j \in \mathcal{B}_{it}$, update

$$\theta_{ijt}^{(k)} = \frac{\mathcal{J}_{it}\left(p_{jt}^{(k)}\right)^{\eta_L} L_{ijt}^{(k)}}{\sum_{m\in\mathcal{B}_{it}}\left(p_{mt}^{(k)}\right)^{\eta_L} L_{imt}^{(k)}}.$$

(b) **Step 2: Update market price and quantity indices.** Given $\{p_{jt}^{(k)}, L_{ijt}^{(k)}, \theta_{ijt}^{(k)}\}$, compute for each market (i,t)

$$p_{it}^{(k)} \equiv \left(\mathcal{J}_{it}^{-\eta_L}\sum_{j\in\mathcal{B}_{it}}\theta_{ijt}^{(k)}\,(p_{jt}^{(k)})^{1-\eta_L}\right)^{\frac{1}{1-\eta_L}},$$

$$L_{it}^{(k)} \equiv \left(\frac{1}{\mathcal{J}_{it}}\sum_{j\in\mathcal{B}_{it}}\left(\theta_{ijt}^{(k)}\right)^{\frac{1}{\eta_L}}\,(L_{ijt}^{(k)})^{\frac{\eta_L-1}{\eta_L}}\right)^{\frac{\eta_L}{\eta_L-1}}.$$

(c) **Step 3: Update uniform price $p_{jt}^{(k+1)}$ by solving the bank-level FOC.**

Step 3(a): Define the within-market cutoff as a function of a candidate price p. For each operated market (i,t) of bank j (i.e. $\mathcal{I}_j(i)=1$), define

$$\tilde{\theta}_{ijt}(p) \;\equiv\; \frac{\overline{L}_{ijt}}{\mathcal{J}_{it}^{-\eta_L}\,L_{it}^{(k)}}\left(\frac{p}{p_{it}^{(k)}}\right)^{\eta_L}.$$

Step 3(b): For $\theta \sim U[0,\bar{\theta}]$, compute binding probability and truncated moment. Define

$$q_{ijt}(p) \equiv \Pr(\theta > \tilde{\theta}_{ijt}(p)) = 1 - \frac{\tilde{\theta}_{ijt}(p)}{\bar{\theta}}, \quad M_{ijt}(p) \equiv \int_0^{\tilde{\theta}_{ijt}(p)} \theta f(\theta)\,d\theta = \frac{\left(\tilde{\theta}_{ijt}(p)\right)^2}{2\bar{\theta}}.$$

Step 3(c): Construct the two bank-level aggregates $S_{jt}(p)$ and $B_{jt}(p)$. For a candidate price p, define

$$S_{jt}(p) \equiv \sum_{i:\,\mathcal{I}_j(i)=1}\left[\mathcal{J}_{it}^{-\eta_L}\,\theta_{ijt}^{(k)}\,L_{it}^{(k)}\left(\frac{p}{p_{it}^{(k)}}\right)^{-\eta_L}\right] M_{ijt}(p),$$

$$B_{jt}(p) \equiv \sum_{i:\,\mathcal{I}_j(i)=1}\overline{L}_{ijt}\,q_{ijt}(p).$$

Step 3(d): Solve the one-dimensional FOC for $p_{jt}^{(k+1)}$. Update $p_{jt}^{(k+1)}$ as any solu-

tion $p > 0$ to

$$G_{jt}(p) \equiv S_{jt}(p)\left(1 - \eta_L \frac{p - w_{jt}^L}{p}\right) + B_{jt}(p) = 0. \tag{A.10}$$

Equivalently, solve the fixed-point mapping

$$p = \frac{w_{jt}^L}{1 - \frac{1}{\eta_L}\left(1 + \frac{B_{jt}(p)}{S_{jt}(p)}\right)}. \tag{A.11}$$

We solve equation (A.10) via a robust one-dimensional root finder (e.g. bisection or Brent), or iterate equation (A.11) with damping.

(d) **Step 4: Update loan demand and impose caps.** Given $\{p_{jt}^{(k+1)}, p_{it}^{(k)}, L_{it}^{(k)}, \theta_{ijt}^{(k)}\}$, compute unconstrained demand

$$\widehat{L}_{ijt}^{(k+1)} = \mathcal{J}_{it}^{-\eta_L}\, \theta_{ijt}^{(k)}\, L_{it}^{(k)} \left(\frac{p_{jt}^{(k+1)}}{p_{it}^{(k)}}\right)^{-\eta_L},$$

and apply the cap:

$$L_{ijt}^{(k+1)} = \min\left\{\widehat{L}_{ijt}^{(k+1)},\, \overline{L}_{ijt}\right\}.$$

(e) **Step 5: Convergence check.** Stop if

$$\max_{j,t}\left|\frac{p_{jt}^{(k+1)} - p_{jt}^{(k)}}{\max\{\varepsilon_p,\ |p_{jt}^{(k)}|\}}\right| < \varepsilon_p^{conv}.$$

Otherwise set $k \leftarrow k + 1$ and repeat.

4. Solve for the remaining objects as in the flexible pricing algorithm.

B Proofs

Proof. (of Proposition 1) The bank's flow payoff is

$$\pi_{ij} = p_{ij}^L L_{ij} + p_{ij}^D D_{ij} - W_j(D_{ij}, L_{ij}) - \kappa_{ij}.$$

Deposits. Using (8), D_{ij} is CES in p_{ij}^D so that

$$\frac{\partial D_{ij}}{\partial p_{ij}^D} = -\eta_D \frac{D_{ij}}{p_{ij}^D}.$$

The FOC for p_{ij}^D implies the usual markup condition

$$p_{ij}^D = \frac{\eta_D}{\eta_D - 1} w_j^D, \qquad w_j^D \equiv \frac{\partial W_j(D_{ij}, L_{ij})}{\partial D_{ij}}.$$

Loans. Household realized demand is kinked:

$$L_{ij}(p_{ij}^L) = \min\left\{\overline{L}_{ij}, \widetilde{L}_{ij}(p_{ij}^L)\right\}, \qquad \widetilde{L}_{ij}(p_{ij}^L) = \mathcal{J}_i^{-\eta_L} \theta_{ij} L_i \left(\frac{p_{ij}^L}{p_i^L}\right)^{-\eta_L}.$$

If the cap does not bind ($\widetilde{L}_{ij}(p_{ij}^L) < \overline{L}_{ij}$), the FOC delivers the standard markup

$$p_{ij}^{L,\text{int}} = \frac{\eta_L}{\eta_L - 1} w_j^L, \qquad w_j^L \equiv \frac{\partial W_j(D_{ij}, L_{ij})}{\partial L_{ij}}.$$

If instead the cap binds, then $L_{ij} = \overline{L}_{ij}$ and profits are increasing in p_{ij}^L as long as the cap binds. Hence the optimal spread is the largest p_{ij}^L such that demand still equals the cap, i.e. $\widetilde{L}_{ij}(p_{ij}^L) = \overline{L}_{ij}$, which yields

$$p_{ij}^{L,\text{cap}} = p_i^L \left(\frac{\mathcal{J}_i^{-\eta_L} \theta_{ij} L_i}{\overline{L}_{ij}}\right)^{1/\eta_L}.$$

Combining the two cases gives

$$(p_{ij}^L)^* = \max\left\{\frac{\eta_L}{\eta_L - 1} w_j^L,\ p_i^L \left(\frac{\mathcal{J}_i^{-\eta_L} \theta_{ij} L_i}{\overline{L}_{ij}}\right)^{1/\eta_L}\right\}.$$

■

Proof. (of Proposition 2) Under uniform pricing, bank j posts a common loan spread p across all operated regions, i.e., $p_{ij}^L = p$ for all i such that $\mathcal{I}_j(i) = 1$. Realized lending in region i is therefore

$$L_{ij}(p) = \min\{\overline{L}_{ij},\ L_{ij}^d(p)\},$$

where $L_{ij}^d(p)$ denotes desired loan demand at spread p.

For a given p, define the subsets of operated regions in which the lending limit binds or is slack:

$$B(p) = \{\, i \in [0,1] : \mathcal{I}_j(i) = 1 \text{ and } p \le p_{ij}^{cap} \,\}, \qquad S(p) = \{\, i \in [0,1] : \mathcal{I}_j(i) = 1 \text{ and } p > p_{ij}^{cap} \,\},$$

where p_{ij}^{cap} is the threshold spread that satisfies $L_{ij}^d(p_{ij}^{cap}) = \overline{L}_{ij}$. Define aggregate capped

quantity and aggregate slack demand:

$$\overline{L}_B(p) \equiv \int_{B(p)} \overline{L}_{ij}\, di, \qquad Q_S(p) \equiv \int_{S(p)} L_{ij}^d(p)\, di.$$

Then total loan profits can be written as

$$\Pi_j^L(p) = (p - w_j^L)\big[\overline{L}_B(p) + Q_S(p)\big]. \tag{B.1}$$

Because the sets $B(p)$ and $S(p)$ change only when p crosses a threshold p_{ij}^{cap}, the objective is differentiable at any p for which the switching set $\{\, i : \mathcal{I}_j(i) = 1 \text{ and } p = p_{ij}^{cap} \,\}$ has Lebesgue measure zero. Fix such a p and treat $B(p)$ and $S(p)$ as locally constant. For $i \in S(p)$, desired demand has constant elasticity η_L, so $\partial L_{ij}^d(p)/\partial p = -\eta_L L_{ij}^d(p)/p$. Hence,

$$Q_S'(p) = \int_{S(p)} \frac{\partial L_{ij}^d(p)}{\partial p}\, di = -\eta_L \frac{1}{p} \int_{S(p)} L_{ij}^d(p)\, di = -\eta_L \frac{Q_S(p)}{p}. \tag{B.2}$$

Differentiating equation (B.1) and using equation (B.2) yields

$$(\Pi_j^L)'(p) = \overline{L}_B(p) + Q_S(p) + (p - w_j^L)Q_S'(p) = \overline{L}_B(p) + Q_S(p) - \eta_L \frac{p - w_j^L}{p}\, Q_S(p).$$

Therefore, any interior optimum p (away from switching points) satisfies

$$0 = (\Pi_j^L)'(p) \quad \Longleftrightarrow \quad \frac{p - w_j^L}{p} = \frac{1}{\eta_L}\left(1 + \frac{\overline{L}_B(p)}{Q_S(p)}\right),$$

which is equation (14). ■

Proof. (of Proposition 3) Applying Leibniz' rule, the FOC w.r.t to loan pricing is:

$$\begin{aligned}\frac{d\mathbb{E}_\theta[\pi_{ij}]}{dp_{ij}^L} = {} & \underbrace{\pi_{ij}^s(\tilde{\theta}) f(\tilde{\theta}) \tilde{\theta}'(p_{ij}^L)}_{\text{upper bound of 1st int.}} - \underbrace{\pi_{ij}^s(\underline{\theta}) f(\underline{\theta}) \underline{\theta}'(p_{ij}^L)}_{\text{lower bound of 1st int.}} + \int_{\underline{\theta}}^{\tilde{\theta}(p_{ij}^L)} \frac{\partial \pi_{ij}^s}{\partial p_{ij}^L} f(\theta) d\theta \\ & + \underbrace{\pi_{ij}^c(\bar{\theta}) f(\bar{\theta}) \bar{\theta}'(p_{ij}^L)}_{\text{upper bound of 2nd int.}} - \underbrace{\pi_{ij}^c(\tilde{\theta}) f(\tilde{\theta}) \tilde{\theta}'(p_{ij}^L)}_{\text{lower bound of 2nd int.}} + \int_{\tilde{\theta}(p_{ij}^L)}^{\bar{\theta}} \frac{\partial \pi_{ij}^c}{\partial p_{ij}^L} f(\theta) d\theta.\end{aligned}$$

Since $\pi_{ij}^s(\tilde{\theta}) = \pi_{ij}^c(\tilde{\theta}) \equiv (p_{ij}^L - w_j^L)\overline{L}_{ij}$, the terms with "$\tilde{\theta}$" cancel each other. The term with $\underline{\theta}$ and $\overline{\theta}$ also drops about because the derivative is zero. Therefore, the FOC reduces to

$$\frac{d\mathbb{E}_\theta[\pi_{ij}]}{dp_{ij}^L} = \int_{\underline{\theta}}^{\tilde{\theta}} \frac{\partial \pi_{ij}^s}{\partial p_{ij}^L} f(\theta) d\theta + \int_{\tilde{\theta}}^{\bar{\theta}} \frac{\partial \pi_{ij}^c}{\partial p_{ij}^L} f(\theta) d\theta = 0,$$

which is equivalent to

$$\mathcal{J}_i^{-\eta_L} L_i \left(\frac{p_{ij}^L}{p_i^L}\right)^{-\eta_L} [1 - \eta_L(p_{ij}^L - w_j^L)(p_{ij}^L)^{-1}] \int_{\underline{\theta}}^{\tilde{\theta}(p_{ij}^L)} \theta f(\theta) d\theta + \overline{L}_{ij} \left[1 - F\left(\tilde{\theta}(p_{ij}^L)\right)\right] = 0. \quad \text{(B.3)}$$

Solving for p_{ij}^L yields the desired expression. ■

Proof. (of Proposition 4) Under uniform pricing, bank j posts a common spread p across all operated regions, i.e. $p_{ij}^L = p$ for all i such that $\mathcal{I}_j(i) = 1$. Realized lending in region i is

$$\tilde{L}_{ij}(p, \theta) = \min\{\overline{L}_{ij},\, A_i \theta p^{-\eta_L}\}.$$

Expected total lending profits are therefore

$$\Pi_j^L(p) = \int_0^1 \mathbb{E}_\theta\Big[(p - w_j^L)\tilde{L}_{ij}(p, \theta)\Big]\mathcal{I}_j(i)\, di = (p - w_j^L) \int_0^1 Q_{ij}(p)\, \mathcal{I}_j(i)\, di, \quad \text{(B.4)}$$

where $Q_{ij}(p) \equiv \mathbb{E}_\theta[\tilde{L}_{ij}(p, \theta)]$. Using the cutoff equation (18),

$$\begin{aligned} Q_{ij}(p) &= \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} A_i \theta p^{-\eta_L} f(\theta)\, d\theta + \int_{\tilde{\theta}_{ij}(p)}^{\overline{\theta}} \overline{L}_{ij} f(\theta)\, d\theta \\ &= A_i p^{-\eta_L} \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\, d\theta + \overline{L}_{ij}\Big(1 - F(\tilde{\theta}_{ij}(p))\Big). \end{aligned} \quad \text{(B.5)}$$

We next compute $Q'_{ij}(p)$. Write equation (B.5) as

$$Q_{ij}(p) = A_i p^{-\eta_L} M(\tilde{\theta}_{ij}(p)) + \overline{L}_{ij}\big(1 - F(\tilde{\theta}_{ij}(p))\big), \qquad M(x) \equiv \int_{\underline{\theta}}^{x} \theta f(\theta)\, d\theta,$$

so that $M'(x) = xf(x)$. Differentiating and applying the product and Leibniz rules,

$$\begin{aligned} Q'_{ij}(p) &= A_i(-\eta_L)p^{-\eta_L - 1} M(\tilde{\theta}_{ij}) + A_i p^{-\eta_L} M'(\tilde{\theta}_{ij})\, \tilde{\theta}'_{ij}(p) - \overline{L}_{ij} f(\tilde{\theta}_{ij})\, \tilde{\theta}'_{ij}(p) \\ &= -\eta_L A_i p^{-\eta_L - 1} M(\tilde{\theta}_{ij}) + A_i p^{-\eta_L} \tilde{\theta}_{ij} f(\tilde{\theta}_{ij})\, \tilde{\theta}'_{ij}(p) - \overline{L}_{ij} f(\tilde{\theta}_{ij})\, \tilde{\theta}'_{ij}(p). \end{aligned} \quad \text{(B.6)}$$

Using the cutoff identity $\overline{L}_{ij} = A_i \tilde{\theta}_{ij}(p) p^{-\eta_L}$, the last two terms in equation (B.6) cancel, yielding

$$Q'_{ij}(p) = -\eta_L\, A_i\, p^{-\eta_L - 1} \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\, d\theta. \quad \text{(B.7)}$$

Differentiating equation (B.4) and substituting equation (B.7) gives

$$(\Pi_j^L)'(p) = \int_0^1 \Big[Q_{ij}(p) + (p - w_j^L)Q'_{ij}(p)\Big]\mathcal{I}_j(i)\,di$$
$$= \int_0^1 \left[Q_{ij}(p) - \eta_L \frac{p - w_j^L}{p} A_i p^{-\eta_L} \int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\,d\theta\right]\mathcal{I}_j(i)\,di.$$

An interior optimum p satisfies $(\Pi_j^L)'(p) = 0$, which can be rearranged to yield

$$\frac{p - w_j^L}{p} = \frac{1}{\eta_L} \frac{\displaystyle\int_0^1 Q_{ij}(p)\,\mathcal{I}_j(i)\,di}{\displaystyle\int_0^1 A_i p^{-\eta_L}\left(\int_{\underline{\theta}}^{\tilde{\theta}_{ij}(p)} \theta f(\theta)\,d\theta\right)\mathcal{I}_j(i)\,di},$$

which is equation (19). Substituting equation (B.5) delivers the expression for $Q_{ij}(p)$ in equation (20). ■

Proof. (of Lemma 1) Fix a bank j and suppose that lending limits are never binding at the interior CES markup,

$$\overline{L}_{ij} \;\geq\; L_{ij}^d\big(p^{int}\big) \quad \text{for all } i \text{ with } \mathcal{I}_j(i) = 1, \qquad p^{int} \equiv \frac{\eta_L}{\eta_L - 1} w_j^L.$$

Then, in every operated market i, the cap constraint is slack at p^{int} and realized lending equals desired lending whenever $p_{ij} \leq p_{ij}^{cap}$ is not satisfied. In particular, any optimum that sets $p_{ij} = p^{int}$ will be interior with respect to the cap.

Step 1 (Flexible pricing reduces to independent interior problems). Under flexible pricing, bank j chooses $\{p_{ij}\}_{i:\mathcal{I}_j(i)=1}$ to maximize

$$\Pi_j^L(\{p_{ij}\}) = \int_0^1 (p_{ij} - w_j^L)\, L_{ij}^d(p_{ij})\,\mathcal{I}_j(i)\,di,$$

because the cap never binds at the relevant optimum under the maintained condition. Since the integrand is separable across i, the optimal p_{ij} solves, for each operated market i,

$$\max_{p \geq 0} (p - w_j^L)\, L_{ij}^d(p).$$

For CES demand with within-market elasticity η_L, we have $L_{ij}^d(p) = K_{ij}\, p^{-\eta_L}$ for some

constant $K_{ij} > 0$ (depending on (i, j) but not on p). Thus the first-order condition is

$$0 = \frac{d}{dp}\big[(p - w_j^L)K_{ij}p^{-\eta_L}\big] = K_{ij}p^{-\eta_L}\Big[1 - \eta_L\frac{p - w_j^L}{p}\Big],$$

which implies the unique interior optimizer

$$p_{ij}^* = \frac{\eta_L}{\eta_L - 1}w_j^L \equiv p^{int}.$$

This is independent of (i, j) other than through w_j^L, so the flexible-pricing optimum is uniform across markets:

$$(p_{ij}^L)^* = p^{int} \qquad \forall i : \mathcal{I}_j(i) = 1.$$

Step 2 (Uniform pricing yields the same optimum). Under uniform pricing the bank chooses a single p to maximize

$$\Pi_j^L(p) = \int_0^1 (p - w_j^L)\, L_{ij}^d(p)\, \mathcal{I}_j(i)\, di = (p - w_j^L) \int_{\{i:\mathcal{I}_j(i)=1\}} K_{ij}\, p^{-\eta_L}\, di = (p - w_j^L)\, \widetilde{K}_j\, p^{-\eta_L},$$

where $\widetilde{K}_j \equiv \int_{\{i:\mathcal{I}_j(i)=1\}} K_{ij}\, di > 0$ is constant in p. The first-order condition is identical:

$$0 = \frac{d}{dp}\big[(p - w_j^L)\widetilde{K}_j p^{-\eta_L}\big] = \widetilde{K}_j p^{-\eta_L}\Big[1 - \eta_L\frac{p - w_j^L}{p}\Big],$$

so the unique optimizer is again $p^* = p^{int}$. Therefore $(p_j^L)^* = p^{int}$ and it coincides with the flexible-pricing optimum.

Step 3 (Equivalence as $\overline{L}_{ij} \to \infty$). If $\overline{L}_{ij} \to \infty$ for all operated markets, then the cap never binds for any p, hence $\overline{L}_B(p) = 0$ for all p and both the flexible- and uniform-pricing problems coincide with the standard CES monopoly-pricing problem. The unique optimum is p^{int} in either regime. ■

C Figures

Figure C1: Bank-Time Explanatory Power in HELOC Rates by Bank Type

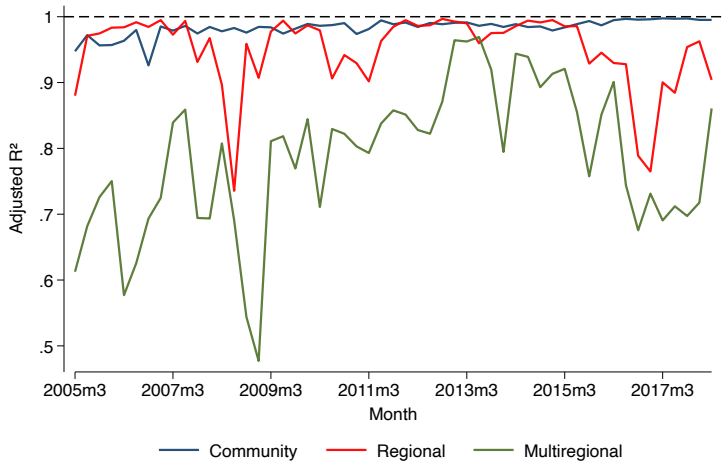


Figure C2: Quarterly Absolute Rate Differences: Within-bank vs Between-bank

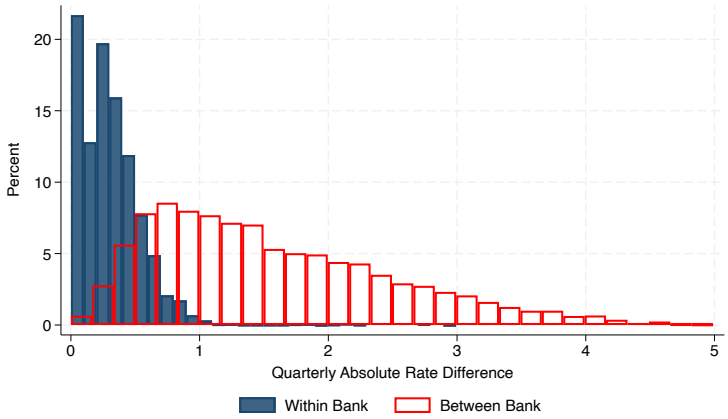


Figure C3: Monthly Rate Correlation: Within-bank vs Between-bank

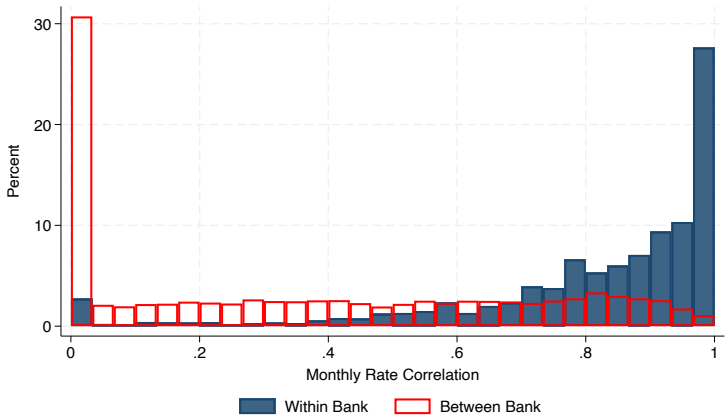


Figure C4: Monthly Share of Identical Rates: Within-bank vs Between-bank

