Why Multimarket Banks Exist: A Quantitative Theory With Demand Complementarity

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Abstract

Consumers prefer to obtain multiple financial products from the same bank. We provide causal evidence of this demand complementarity in banking and estimate a dynamic model to study its implications for multimarket banks, quantifying important impacts on bank synergies, pricing strategies, and the interconnection of their services across markets. Using a shift-share design that exploits local variation in Conforming Loan Limits, we identify how exogenous changes in banks' mortgage market shares spill over into deposit demand. We then use this spillover to estimate a dynamic model in which banks compete across multiple markets, and cross-selling emerges endogenously as an optimal response to consumer demand complementarity. Our estimates imply that a mortgage relationship increases a household's probability of choosing the same bank for deposit services by 41.4 percent. This complementarity generates a new mechanism for economies of scope in banks, contributing to 2.5 percent of banks' market value.

Keywords: Multi-market Banks, Demand Complementarity, Deposit-loan Synergy, Conforming Loan Limits, Shift-Share IV, Dynamic Model of Banks

JEL Classification: E44, G21

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1. Introduction

Banks routinely cross-sell financial products—ranging from checking accounts and credit cards to mortgages and investment services—to the same customers. This practice reflects a fundamental feature of consumer demand: customers who hold one product often derive additional convenience and value from related services within the same institution, a pattern we refer to as complementary preferences. Such preferences have been widely documented in markets for retail goods, newspapers, and cable TV, but little is known about how much these preferences matter in financial services, particularly in banking products. Understanding this is crucial, as it shapes the economies of scope within the banking sector and, in turn, influences its competition landscape and market structure.

Studying such demand complementarity is challenging for two main reasons. First, unobserved factors may simultaneously influence consumers' product choices from the same institution across multiple markets, creating spurious correlations. Second, if such demand complementarity exists, banks will respond endogenously to it, inducing coordinated adjustments in their pricing strategies and balance sheet allocations and altering the industry's competitive environment. Properly accounting for these endogenous responses poses a challenge for gauging the aggregate impact of demand complementarity on bank valuations and policies, which are ultimately the objects of interest.

To tackle these challenges, we propose two solutions. First, we employ an identification strategy to estimate how exogenous bank-branch-level changes in mortgage demand affect deposits at the same bank. Our identification strategy exploits banks' heterogeneous responses to changes in the conforming loan limit (CLL). Second, we develop a dynamic model in which banks compete by offering both deposit and mortgage services. In the model, banks' activities across multiple markets are linked through supply-side frictions as well as complementarities in consumer demand. We estimate the model using indirect inference, matching the reduced-form effects identified through the shift-share design. We then use the estimated model to conduct counterfactual analyses, accounting for banks' endogenous responses to customers with complementary demand. Our results indicate that, holding all else equal, an existing relationship with a bank increases a consumer's probability of choosing another service from the same institution by 40 percent. Relative to a counterfactual scenario in which consumers form their product demands independently across markets, banks gain 2.5% additional value from their ability to cross-sell.

We start by describing our strategy to identify a reduced-form relationship. We construct a Bartik-style shift-share instrument that exploits two sources of variation: (i) *local shift* due to CLL changes, measured as the local fraction of mortgage originations that would have been classified as jumbo but would become newly conforming when the CLL increases, and (ii) *bank-level exposure* to CLL changes, measured by the gap between a bank's local conforming market share just below the CLL and its jumbo market share just above the CLL to capture banks' specialization in conforming versus jumbo lending. The interaction of these two components generates branch-level variation in the intensity of mortgage origination shocks that is plausibly exogenous to local deposit market conditions.

Crucially, the instrument uses leave-one-out construction to address potential reflection bias. We exclude the focal bank's own loans when computing the local shift due to CLL changes, and we exclude the focal census division when computing the bank-level exposure. We estimate local projection specifications with granular fixed effects—bank×year and county×year fixed effects—which absorb both time-varying local economic conditions, as well as bank-specific national shocks and policies. This design identifies the effect of mortgage origination shocks on deposit-taking from variation across branches within the same county-year and within the same bank-year cell. Our results show that exogenous increases in mortgage origination lead to significant and persistent deposit growth, with effects of approximately 5 cents per dollar of mortgage origination in a five-mile local radius in four years.

Guided by this relationship, we develop a dynamic structural model in which banks compete oligopolistically in the deposit and mortgage markets and dynamically choose rates, composition of their assets and liabilities, and retained earnings to maximize the present value of cash flows to shareholders. The model captures two linkages between a bank's deposit intake and shifts in its mortgage share. The first channel operates through demand complementarities: when a bank expands its mortgage supply, it raises the marginal value of its deposit services because customers prefer to obtain multiple financial products from the same institution. Holding everything else constant, this mechanism translates into a larger deposit market share and, endogenously, greater market power for the bank in the deposit market.

Our second channel operates through banks' coordinated behaviors on the supply side. Changes in new mortgage originations lead banks to modify other margins—for example, altering their funding structure or retaining a share of increased mortgages on their balance sheets. Retained mortgages require funding liquidity, and they are also subject to capital requirements that depend on profits from activities across all markets. While the demand channel is the novel focus of our paper, our model also endogenizes the supply effects, which are often emphasized in the literature, thereby allowing us to quantify their magnitudes within a unified framework.

We next estimate the model. Our identification strategy consists of several parts. First, we identify parameters governing banks' operational and financial decisions by matching balance-sheet moments such as profit margins and funding composition. Second, we identify consumers' sensitivity to interest rates and other bank characteristics, such as branch density and ATM availability, following the standard demand estimation literature. Finally, and most critically, we identify the parameters governing demand complementarities. To do so, we use the coefficient estimated from our shift-share IV strategy.

Specifically, we simulate a shock to the CLL in the model and compute the corresponding coefficient in the simulated data, that is, the extent to which an increase in a bank's mortgage market share, induced by the shock, leads to higher deposit growth. This simulated effect depends on both the strength of consumers' demand complementarities and banks' optimal responses to the shock given the consumers' complementary demand. This maps consistently into the reduced-form effects observed in the data, allowing us to infer the level of demand complementarity in the model that best replicates the empirical relationship. This identification and estimation strategy therefore follows the indirect inference approach widely used to recover deep structural parameters (Gourieroux, Monfort, and Renault, 1993; Cooper and Haltiwanger, 2006).

Our results suggest that, holding all else equal, customers with an existing mortgage relationship at a bank deposit approximately 40% more funds with that same institution. Likewise, if a customer already holds a deposit account, her likelihood of taking a mortgage from her home bank increases by the same magnitude. This persistence of preferences across markets gives rise to additional bank market power. In our counterfactual analysis, we compare banks' behavior in the baseline scenario, where they optimally cross-sell, to a setting in which consumers have no complementary preferences and make independent choices across deposit and mortgage markets. Relative to this counterfactual, banks in the baseline gain from their ability to cross-sell, leading to a 2.5% increase in the value.

Cross-selling to customers with complementary demand not only generates additional synergies for multi-market banks but also shapes their strategic pricing across markets. Through a series of counterfactuals, we show that greater demand complementarity increases the overall spreads in both deposit and mortgage market because it creates greater market power for banks. Meanwhile, it also tilts banks' distribution of spreads more towards the deposit market and less in the mortgage market because the mortgage market is more price sensitive. Given the differential price sensitives and the demand complementarity across products, banks use the mortgage market as a competitive margin to expand market share and build a broader customer base. They subsequently monetize this expanded customer base by charging higher spreads on deposits. These findings highlight that banks do not operate in each market in isolation. Instead, they strategically price products across markets, internalizing the inherent connections between them. Importantly, our results differ from prior studies of multi-market bank pricing, such as Park and Pennacchi (2008), where cross-market pricing tilts arise from supply-side considerations: banks facing funding constraints subsidize operations in markets that help relax those constraints. In contrast, in our setting, cross-market pricing emerges from consumers' demand-side forces: heterogeneous price sensitivities combined with a preference for obtaining multiple financial services from the same institution.

Customers' demand complementarity also makes banks' operations across markets more interconnected. As a result, shocks in one market transmit more strongly to banks' activities in other markets where customers exhibit such preferences, generating an amplification effect. The prior literature tends to view this interconnectedness through the lens of supply-side channels, such as funding constraints and capital regulation. Our paper shows that interconnectedness can also arise from the demand side. When households value obtaining mortgages and deposits from the same institution, banks strategically cross-sell these products to cater to such preferences, thereby creating cross-market spillovers. Quantitatively, we find that this demand channel accounts for a larger share of overall interconnectedness than supply-side frictions, which have traditionally been the focus of the literature.

Our paper contributes to several strands of the literature. First, it relates to studies that estimate consumer demand for financial products (Dick, 2007; Ho and Ishii, 2011; Buchak, Matvos, Piskorski, and Seru, 2018; Koont, 2025; Sarkisyan, 2025). While this literature primarily focuses on how product characteristics influence demand within a given financial market, our paper examines how participation in one market affects demand across others. Thus, our work connects to the industrial organization literature on consumer preferences for bundling and one-stop shopping. Existing studies have documented such preferences in settings such as retail goods (Thomassen, Smith, Seiler, and Schiraldi, 2017), newspapers (Gentzkow, 2007), and cable television (Crawford, 2008), but little is known about how similar complementarities operate in the financial sector and shape competition among banks. Estimating such preferences in banking presents additional challenges, as financial products like mortgages are long-term in nature, which creates persistent demand and complicates the identification of demand complementarities.

Most closely related to our paper, Allen, Clark, and Houde (2019) develop an auction model with search frictions to study price setting in the Canadian mortgage market, where search costs shape consumers' loyalty to their home banks. Using granular Norwegian administrative data, Basten and Juelsrud (2023) show that households are more likely to obtain loans from banks in which they already hold deposit accounts. Our study differs from theirs in several key aspects. We focus on the U.S. market, where the banking industry is more competitive, and exploit variation in conforming loan limits as an identification strategy to isolate how shocks in the mortgage market transmit to consumer demand for bank deposits—the opposite direction of the effect measured by Basten and Juelsrud (2023). Finally, we complement the reduced-form evidence with a structural model that allows us to disentangle supply- and demand-side factors, linking the quantitative effect of the latter, estimated from micro-level data, to a broader macro question: how demand-side complementarities contribute to the economies of scope among banks.

Our paper therefore also connects naturally to the literature on the scope of banks. Prior studies have largely approached this question by emphasizing frictions internal to banks, and therefore view the synergies from combining deposit-taking and lending services primarily as a supply-side phenomenon. In this view, combining deposit and lending services allows banks to mitigate moral hazard problems (Diamond and Rajan, 2000), manage liquidity shocks (Kashyap, Rajan, and Stein, 2002; Gatev, Schuermann, and Strahan, 2009), and reduce the cost of collateral (Piazzesi and Schneider, 2020). Our paper departs from this perspective by shifting the focus to the demand side. In our setting, even in the absence of agency, financial, or regulatory frictions, banks can still derive higher value from jointly providing deposit and loan services because consumers exhibit complementary preferences. Such complementarities imply that a bank's presence in one market increases the marginal value of its products in another, thereby enhancing the bank's effective market power. Banks strategically price their products to cater to such preferences, creating interesting cross-market redistribution and interconnections between the multiple markets in which they operate.

Our identification strategy builds on a rich literature documenting the effects of conforming loan limits (CLLs) on banks' mortgage originations (Adelino, Schoar, and Severino, 2025; Zhang, 2022). Importantly for our purposes, this literature shows that changes in CLLs affect lenders heterogeneously, depending on their size, business model, and access to securitization markets (Loutskina and Strahan, 2009). In addition, banks' exposure to the CLL, captured by the extent of bunching of loans just below the limit, can be used to identify the mortgage demand they face (DeFusco and Paciorek, 2017; Buchak, Matvos, Piskorski, and Seru, 2024). In our setting, we leverage this heterogeneous exposure to trace spillovers across markets: shifts in banks' mortgage origination induce reallocations of funds in the deposit market. We use these cross-market spillovers to identify households' complementary demand.

Finally, we study the implications of consumers' demand complementarities in a dynamic banking model, building on a literature that uses similar frameworks to quantify the effects of regulation (Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2022) or new products (Wang, Whited, Wu, and Xiao, 2022) on banks' optimization and market structure. In our framework, consumers' demand complementarities generate invest–versus–harvest incentives for banks, shaping both their valuation and pricing strategies. Related to our framework, Dempsey and Faria-e Castro (2025) and Egan, Hortaçsu, Kaplan, Sunderam, and Yao (2025) also develop dynamic banking models featuring similar invest-versus-harvest incentives. While these papers focus on how banks trade off such incentives over time within a single market, our framework emphasizes trade-offs across markets. Our results have important implications for the sources of economies of scope in multi-market banking, highlighting how demand linkages across products generate synergies and determine how shocks transmit and propagate within the organization.

2. Data and Summary Statistics

2.1. Data Sources and Sample Construction

We construct a branch-by-year panel that combines branch deposits, nearby mortgage originations, conforming loan limits, and bank balance-sheet information. We construct a panel spanning 2012-2019, the years after the end of the housing price crash but before the start of the COVID-19 pandemic. These years also correspond to the modern conforming loan limit rules.

Branch deposits. Branch deposits are from the FDIC Summary of Deposits (SOD) database, which reports deposit balances as of June 30 for every FDIC-insured bank branch. The SOD data do not include escrow or settlement balances because these are not booked as branch deposits. We measure annual deposit growth by branch as the first difference of log branch deposits. Very large changes in branch deposits may reflect mergers, branch sales, or internal branch transfers rather than funding inflows, so we exclude any branch that ever records annual log deposit growth above 1.1 or below -0.5. These cutoffs are the 99th and 1st percentiles of the annual deposit-growth distribution. Appendix B describes the data construction in more detail.

Mortgage originations. Mortgage originations come from the Home Mortgage Disclosure Act (HMDA) database. We use HMDA mortgage origination records from 2012–2019 to measure both local shift due to the CLL change and banks' exposure in conforming versus jumbo lending near the CLL.

HMDA lenders are mapped to bank RSSD identifiers so that nearby mortgage activity can be linked to branch-level deposit data in SOD, as well as banks' balance-sheet information in Call Reports introduced below. Because HMDA identifies lender and borrower location but not the branch that originated a loan, lending is assigned to branch-centered geographic catchment areas based on distance. A given loan can therefore contribute to the nearby market of more than one branch. Our mortgage variables should be read as local bank-presence measures around a branch rather than as branch-originated production. Our main results use a five-mile radius around a given branch to define the mortgage market. We also show in Figure 3 that the results are similar at three, four, and five miles.

Conforming loan limits. County-year CLLs are from the Federal Housing Finance Administration (FHFA). We use them to measure the share of lending that becomes newly conforming when the CLL rises for a given geographic area. Appendix Figure A.1 maps the county-level schedule in selected years, and Appendix Table A.1 summarizes its annual distribution.

Bank characteristics and local controls. Bank assets and other balance-sheet variables come from Call Reports and are merged at the bank-year level. We measure local house price growth from FHFA data at the ZIP code level, and population from the number of exemptions by ZIP code and year in IRS Statistics of Income data.

2.2. Summary statistics

Table 1 summarizes the main panel. The table uses the same local mortgage market, weighting, and bank-level accounting variables as the main reduced-form analysis. It also reports mean branch deposits and nearby mortgage origination volume for the baseline sample, which we will use to interpret our reduced-form estimates below.

Table 1: Summary statistics for the benchmark branch-bank-year panel

Variable	Mean	SD	P25	Median	P75	Wgt. mean	N
Panel A. Main regression variables							
Branch deposits, baseline level ($m)	79.5	203.4	29.6	49.6	82.8	100.4	154,323
Annual deposit growth ($100 \times \Delta$ log)	3.9	11.8	-1.6	3.1	8.0	4.6	154,323
5-mile mortgage vol., baseline ($m)	13.7	32.8	1.0	3.5	11.9	42.7	154,323
Annual 5-mile mortgage vol. growth ($100 \times \Delta$ log)	-1.8	60.4	-30.3	1.5	25.5	-13.4	154,323
5-mile mortgage loan count	59.9	104.3	7.0	22.5	65.7	154.3	154,323
Lagged local mortgage loan count	28.1	40.0	5.1	14.4	34.9	85.1	154,323
Raw shift: local newly conforming share (pp)	0.39	0.94	0.00	0.00	0.33	0.40	154,323
Simple wide-gap bank exposure ($\times$100)	-0.39	1.48	-0.27	-0.05	0.00	-0.63	154,323
Raw Bartik = exposure $\times$ shift ($\times 10^4$)	-0.21	1.00	-0.01	-0.00	0.00	-0.33	154,323
Local HPI growth, lagged ($100 \times \Delta$ log)	4.1	4.5	1.4	3.8	6.6	4.5	154,311
Local population growth, lagged ($100 \times \Delta$ log)	-0.04	2.49	-1.06	0.00	1.00	0.10	152,398
Indicator: positive raw shift	0.466	0.499	0.000	0.000	1.000	0.482	154,323
Indicator: positive raw Bartik	0.084	0.277	0.000	0.000	0.000	0.069	154,323
Panel B. Bank characteristics							
Log assets	17.49	2.96	14.88	18.14	19.90	18.46	153,276
Deposits / assets (%)	76.8	8.1	71.8	77.5	82.2	74.4	153,276
Mortgage loans / assets (%)	5.0	3.5	2.9	4.3	6.1	4.7	153,276
Tier 1 capital / assets (%)	10.0	1.9	9.0	9.6	10.6	9.8	18,368
Mortgage servicing assets / assets (bp)	6.27	32.85	0.00	0.00	0.67	7.28	154,323
Securitization income / assets (bp)	0.07	1.28	0.00	0.00	0.00	0.07	154,323
Loan sale gains / assets (bp)	6.47	23.48	1.20	3.68	6.56	7.14	154,323
Large time deposits / deposits (%)	3.2	2.5	1.4	2.5	4.3	3.1	153,276

Notes. The observation is at bank-branch-year level from 2012 to 2019. "Wgt. mean" uses the same lagged local mortgage-loan-count weights as the main regressions. Baseline levels are lagged values in the corresponding branch-by-year panel. Panel B reports current-year bank characteristics merged onto the branch-by-year sample, so the means are branch-sample-weighted bank characteristics. The table uses variable-specific non-missing observations. Notably, the small N for Tier 1 capital is due to missing Call Report items.

3. Empirical Strategy and Reduced-Form Results

3.1. Institutional Background

For decades, the conforming loan limit (CLL) has been defined as the threshold between the conventional mortgage segment that can be readily sold to Fannie Mae and Freddie Mac and the jumbo segment that must be funded in other ways (Federal Housing Finance Agency, 2024). Loans at or below the CLL are conforming and, conditional on underwriting requirements, are eligible for GSE purchase or guarantee. Loans above the limit are jumbo and must instead be funded on balance sheet or through non-GSE securitization channels. A change in the CLL therefore directly changes funding conditions for the loans around the threshold, which is why this threshold has been central in the empirical mortgage literature (Loutskina and Strahan, 2009; DeFusco and Paciorek, 2017).

When a loan moves from jumbo to conforming, it becomes eligible for GSE purchase or guarantee and is therefore cheaper and easier to fund. Some lenders are set up to fund loans through their own balance sheets and therefore find it more feasible to make jumbo loans, but not all lenders are. Lenders that operate at scale in conforming lending can pass some of the funding advantage through either lower rates or improved borrowing convenience to borrowers when the limit rises, while lenders oriented toward balance-sheet jumbo lending do not benefit to the same degree (Buchak et al., 2024). A rise in the CLL should therefore reallocate mortgage market share toward conforming-oriented lenders within the same local market.

Before 2008, the market was organized largely around a national baseline limit rather than a county-specific schedule. The Economic Stimulus Act of 2008 introduced temporary higher limits in selected high-cost counties, and later that year HERA established the permanent modern system: county limits equal 115 percent of local median house value, subject to a cap of 150 percent of the national baseline. In practice, the transition was not immediate. Temporary crisis-era limits remained in place through September 30, 2011, so

2008–2011 combines the permanent HERA formula with temporary exceptions. Starting in October 2011, new originations moved fully onto the permanent HERA regime.

We study the modern period following the house price crash of 2005–2011, when house prices were rising nationally. We report results for both an all-counties sample and a national-only sample. We use the all-counties sample as the benchmark because it uses the broadest set of counties under the modern CLL regime. The national-only sample is restricted to counties that remain on the national baseline rather than on locally determined high-cost limits, so it is a useful comparison when one worries that local limits reflect local conditions. In the national-only counties, the CLL remains at $417,000 through 2016 and then rises to $424,100 in 2017, $453,100 in 2018, and $484,350 in 2019 (Federal Housing Finance Agency, 2015, 2016, 2017, 2018).

3.2. Empirical strategy

Our design exploits changes in the conforming loan limit that reallocate lending within local mortgage markets, and then traces out how those reallocations spill over to branch deposits. The key idea is straightforward. When the CLL rises, markets with more lending just above the old threshold gain more borrowers in the conforming segment of the market. Banks differ in how much they specialize in lending just below versus just above that boundary. Interacting those two objects generates a branch-by-year Bartik term that predicts how much each lender will gain or lose from the change. Then we see how those benefits and losses spill over to deposits.

A simple correlation of loan growth and deposit growth would not identify the spillover we are interested in. Bank-wide changes in pricing, underwriting, advertising, or balance-sheet policy can move both outcomes across all branches of a lender. Local housing demand, income, or credit conditions can do the same within a place. Our fixed effects absorb those common shocks: bank×year effects capture bank-level changes, and county×year effects capture shocks common to branches operating in the same county and year. The remaining variation comes from the fact that lenders differ in their fixed exposure to newly conforming lending, and branch markets differ in how much newly conforming opportunity appears when the CLL rises.

Bank exposure. We construct bank exposure to the CLL using HMDA loan size histograms. For each bank-county-year cell, we compute the gap between the bank's share of loans in the range $[0.95, 1.00)\times$ the local CLL and its share of loans in the range $(1.00, 1.05]\times$ the local CLL. Loans exactly at the CLL are excluded from the above-threshold bin because they are already conforming and because bunching exactly at the boundary appears to behave differently from lending just above it.[1] A higher value of this gap indicates greater specialization in conforming lending just below the threshold, while a low value indicates greater specialization in jumbo lending just above the threshold.

To mitigate reflection bias, we construct a leave-one-out exposure measure. For each bank i and census division d, we define a simple static exposure measure, $\text{Exposure}_{id}^{-d}$, by averaging the above gaps for bank i across all county-years, weighted by total loan counts, while holding out county-years in census division d. The superscript $(-d)$ here indicates this leave-one-out construction. Thus, when estimating the effect of a bank's exposure to CLL changes on its deposit branches and nearby mortgage markets in a given census division, the exposure measure is constructed using only the bank's lending behavior in other census divisions.

To illustrate the lender heterogeneity underlying this simple exposure measure, Figure 1 presents the HMDA loan size histograms for two banks with very different loan-size distributions. Barrington Bank & Trust, a small regional lender, places substantial mass at and below the conforming threshold and has little lending above it. Bank of America's distribution is much smoother through the threshold and has more lending on the jumbo

[1] In the course of this project, we also discovered that some lenders appear to specialize in origination exactly-conforming loans. Thus, loans precisely at the CLL do not necessarily come from either conforming-specialists or jumbo-specialists, and they respond to CLL changes in ways that differ from both groups of interest.

side. This figure highlights the central cross-sectional variation in the raw HMDA loan-size distribution that the exposure measure is designed to capture. When the CLL increases, more loans become newly conforming, so Barrington Bank & Trust that specializes more in conforming lending will likely gain more.

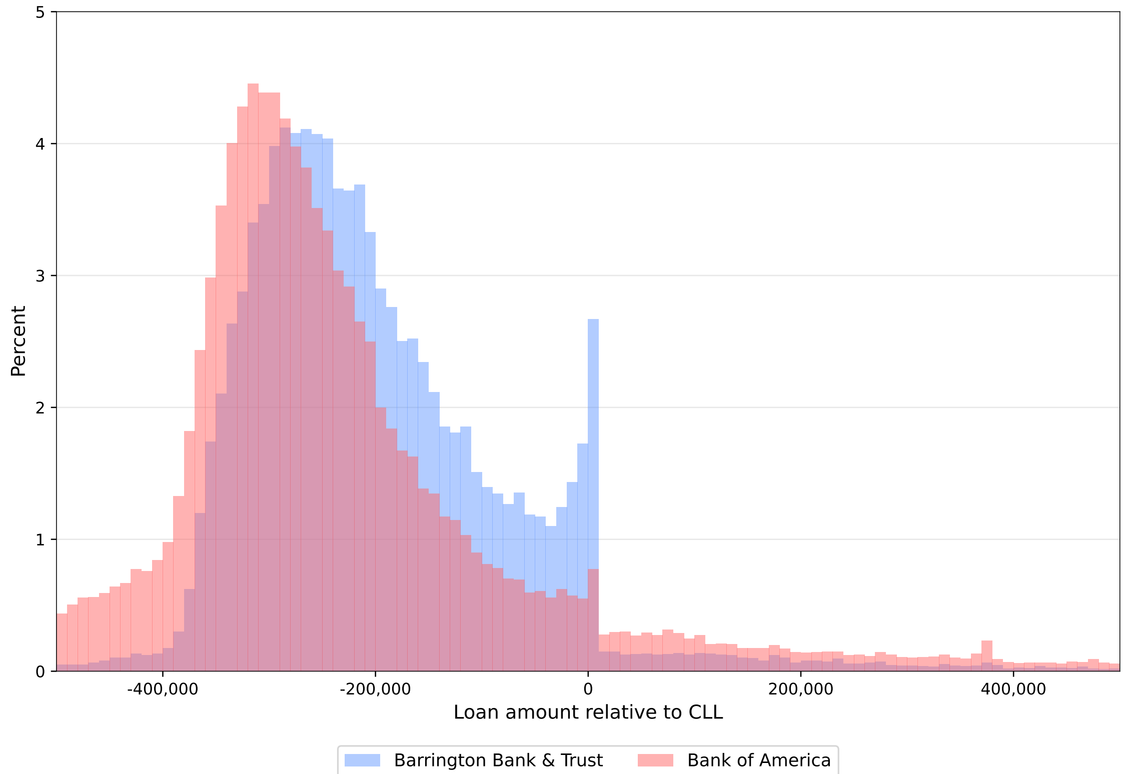

Figure 1: Lender heterogeneity around the conforming loan limit

Notes. The figure plots raw HMDA loan-size histograms for Barrington Bank & Trust and Bank of America, with loan amounts measured relative to the county-year conforming loan limit. Zero on the horizontal axis marks the conforming threshold. The comparison is descriptive and is shown to illustrate that lenders differ sharply in how their mortgage originations are distributed around the CLL.

We also report an alternative regression-based exposure measure as a robustness check. This alternative uses the same HMDA loan-size histograms but summarizes them by regressing first differences in each bank's market share within loan-size bins on an indicator for bins that become newly conforming when the CLL rises. We allow the coefficient on the newly-conforming indicator to vary by bank, and use this bank-specific coefficient as an alternative measure of bank exposure to CLL changes. A higher coefficient means that the bank tends to gain market share in loan-size bins that switch from jumbo to conforming when the limit rises. As with the simple benchmark measure, we use a census-division holdout version, so that a branch's own division is excluded when constructing the exposure measure.

Local shift. For each branch b of bank i in year t, we compute the share of nearby lending that becomes newly conforming when the CLL rises:

$$\text{Shift}_{ibt}^{(-i)} = \frac{\text{Nearby loan count between the old and new CLLs}}{\text{Total nearby loan count}}. \tag{1}$$

The benchmark shift uses a five-mile radius around the branch b and excludes the focal bank i's own lending, indicated by the superscript $(-i)$. The numerator counts loans strictly above the old CLL and at or below the new CLL, so loans exactly at the old CLL are treated as already conforming and do not enter the shift. This shift varies between branches within the same county-year because different branches face different mortgage market competition within their five-mile radius, even when they are exposed to the same common CLL change.

Instrument. The bank-branch-year instrument is the interaction of these two components,

$$Z_{ibt} = \text{Exposure}_{id}^{(-d)} \times \text{Shift}_{ibt}^{(-i)}. \tag{2}$$

All benchmark regressions include bank×year and county×year fixed effects. The bank×year effects absorb lender-wide changes in funding, pricing, underwriting, or balance-sheet policy. The county×year effects absorb county-wide shocks, including local housing demand, income movements, and local drivers of house prices. Therefore, the identifying variation comes from branches that belong to lenders with different exposure to newly conforming lending or experience different nearby mortgage-market shifts, within the same county-year. Because the bank exposure and local shift are both constructed in leave-one-out form, the estimates are not mechanically driven by the focal bank's own nearby lending.

To identify the deposit market spillover, our assumption is that within the same county-year and bank-year, conditional on the lag controls, branches of lenders with different exposure would not have experienced different deposit paths except through CLL-induced mortgage reallocation. The main remaining threats are finer local trends inside counties and the possibility that local newly conforming opportunity proxies for other local forces. In Section 3.3, we present additional validation exercises showing that these are unlikely to drive the results.

Timing and identification. We use the full 2012–2019 panel to construct the instrument as well as lag controls, but restrict the regression sample to the 2017–2019 shock years. This ensures that the identifying time variation comes from the years in which the national CLL changes. Our benchmark analysis uses the all-counties sample, and the 2017–2019 restriction allows us to replicate the analysis in the cleaner national-only sample as validation. In the national-only sample, CLL changes are national rather than local, and therefore less likely to be correlated with unobserved local forces. In addition, because the national CLL is flat through 2016, the pre-2017 years provide natural placebo periods in the national-only sample where we should expect no change in mortgage-market outcomes. Consistent with this, Figure A.6 in the appendix shows no detectable effects in the pre-2017 period.

Local projections. We estimate dynamic responses with local projections (Jorda, 2005; Ramey, 2016). This framework is particularly useful here because the national CLL change is persistent and this framework makes the timing of the mortgage and deposit responses transparent. It is also a natural way to trace a sequence in which mortgage-flow gains arrive first and deposit responses build with a lag. For each horizon h years, we estimate a first-stage projection of mortgage-flow growth at the bank branch level on the current

Bartik term,

$$g^L_{ib,t+h} = \theta_h Z_{ibt} + \Gamma_h X_{ibt} + \alpha_{it} + \delta_{ct} + u_{ib,t+h}, \tag{3}$$

and a corresponding reduced-form projection for deposit growth,

$$g^D_{ib,t+h} = \rho_h Z_{ibt} + \Pi_h X_{ibt} + \alpha_{it} + \delta_{ct} + v_{ib,t+h}. \tag{4}$$

Here $g^L_{ib,t+h}$ is growth in the bank's mortgage origination volume within five miles of branch b, $g^D_{ib,t+h}$ is branch b's deposit growth, α_{it} denotes bank×year fixed effects, and δ_{ct} denotes county×year fixed effects. The benchmark control set includes two lags of the Bartik term, two lags of deposit growth, and two lags of mortgage growth. All regressions are weighted by lagged nearby loan count and clustered at the branch level. In the figures, the point at $h = 0$ is a normalization to zero rather than an estimated contemporaneous coefficient. The point at $h = -1$ is a pre-trend coefficient built from lagged growth, and the positive horizons trace the subsequent mortgage-flow and deposit responses from the same starting-year branch observation.

3.3. Reduced-form Results

Main dynamic responses. Figure 2 reports the benchmark local projections result. We present the coefficients as dollar effect of one-standard-deviation increase in the Bartik instrument at the average baseline deposit and mortgage volume. Its first stage is strong and precisely estimated. At $h = +1$, the coefficient on the current Bartik term is \$1.0 million with a t-statistic of 4.66. It stays positive through $h = +4$, where the coefficient is \$0.9 million ($t = 2.57$). The point at horizon zero is fixed mechanically at zero and is plotted without a confidence interval.

The deposit response is positive at $h = +1$ and continues to build: the coefficient is \$0.2 million at $h = +1$, \$0.5 million at $h = +2$, \$0.6 million at $h = +3$, and \$0.8 million at $h = +4$ ($t = 3.19$). Because the specification includes bank×year and county×year fixed effects, these coefficients should be interpreted as relative deposit gains for more-exposed lenders within the same county-year rather than as county-wide deposit booms. Appendix Figure A.3 show similar estimates when we use the alternative regression-based bank exposure measure and the national-only sample.

The timing of the mortgage growth and the deposit growth is consistent with the demand complementarity mechanism. The mortgage gains arrive first in response to the CLL changes. Then, because mortgage customers prefer getting both services from the same bank, they are gradually converted into broader deposit relationships.

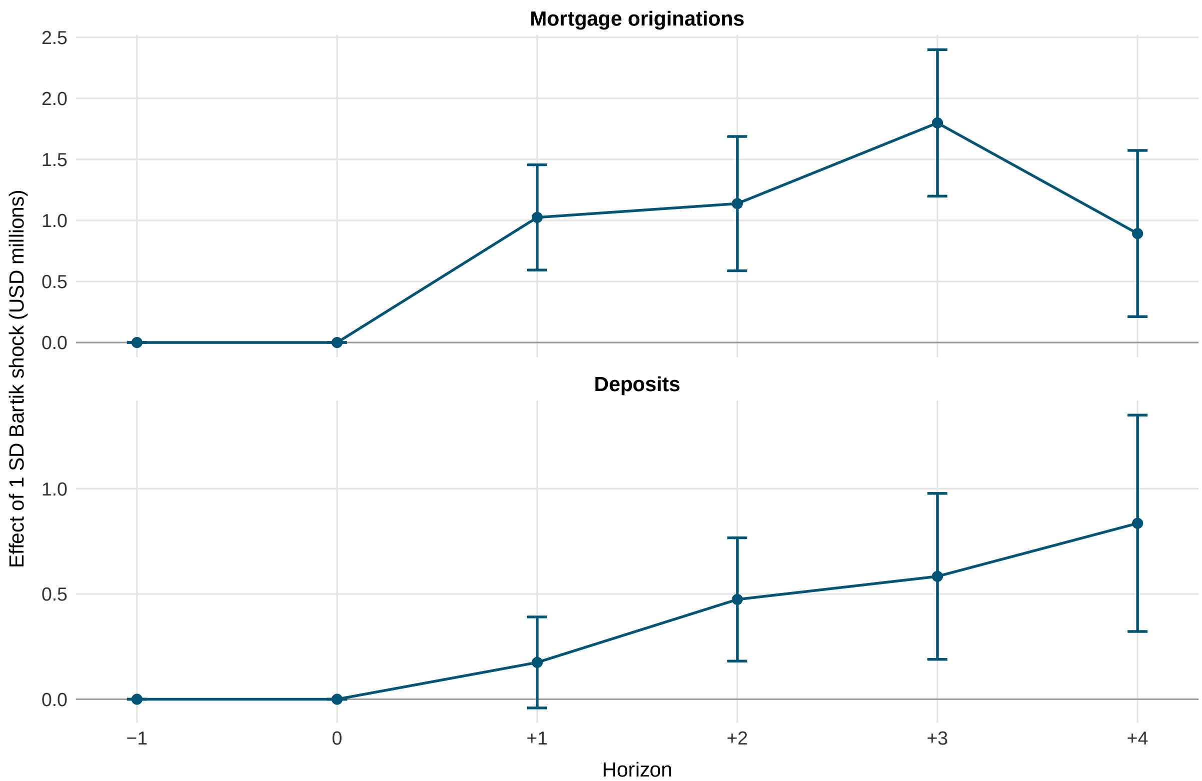

Figure 2: Local projections: mortgage and deposit response to CLL changes
Notes. The figure plots the dollar response of mortgage origination volume and deposit volume to a one-standard-deviation increase in the Bartik instrument under the benchmark specification. The specification uses the simple bank exposure measure, the all-counties sample for 2017–2019, and a five-mile radius to define the local mortgage market. The estimates include bank-by-year and county-by-year fixed effects, VAR controls, and lagged nearby loan-count weights, with standard errors clustered at the branch level. The point at horizon zero is normalized to zero and is plotted without a confidence interval. Error bars report 95 percent confidence intervals.

Since we express both mortgage and deposit responses in dollar terms, we compute the deposit–mortgage sensitivity by dividing the annualized deposit response by the sum of the induced mortgage-flow responses at horizons $h = +1$ to $h = +4$. Figure 3 reports this sensitivity for the full sample, using the simple exposure measure with a 5-mile radius as our baseline.

The results imply that each additional dollar of mortgage origination generates approximately 4.7 cents in deposit growth. This measure reflects a within-market, lender-level elasticity, capturing deposit gains at a given lender relative to other lenders operating in the same county-year that experience different changes in mortgage origination. It does not reflect changes in aggregate deposits in the local economy. Our results are robust to using regression-based exposure measures and to varying the radius.

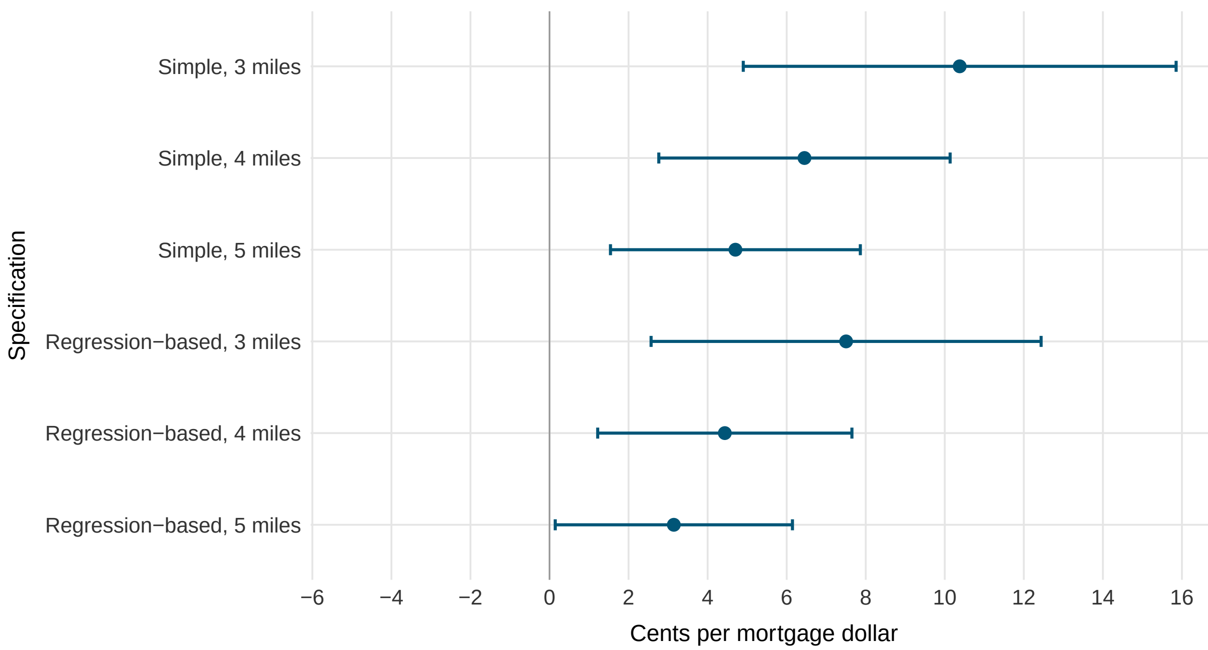

Figure 3: Pass-through from mortgage originations to deposits

Notes. The figure plots the pass-through from mortgage demand shocks to deposit demand, measured as the change in deposits associated with a one-dollar increase in mortgage originations. Each row reports the implied pass-through for a different specification, varying both the exposure measure, simple versus regression-based, and the radius used to define the local mortgage market. The horizontal axis reports pass-through in cents per mortgage dollar.

Validation of the instrument. A natural concern is that the instrument may proxy for broader local conditions rather than for the conforming-loan-limit margin itself. This concern is especially important because the local shift is mechanically related to the local loan-size distribution, and hence to the local housing environment. To this end, we conduct two sets of robustness checks to show that this is unlikely to drive our results.

First, we show that the effect of the Bartik instrument is concentrated near the loan-sized distribution directly affected by the CLL change. Figure 4 reports this check for the all-counties benchmark. We replace the mortgage-growth outcome with the change in the bank's local lending share in coarse bins of loan amount relative to the local conforming limit. If the instrument were primarily capturing broad local demand, the response would be diffuse across the loan-size distribution. Instead, the response peaks just above the conforming threshold, precisely where loans become newly conforming when the national baseline rises. The bins well below the threshold are much smaller and often near zero. This localized effect shows that the identifying variation is concentrated in the part of the loan-size distribution that the policy actually moves, so it is less likely to be driven by changes in broader local conditions. Appendix Figure A.4 shows that the same pattern persists with alternative bank exposure measures and in the national-only sample.

Second, we show that the Bartik instrument have no effect in the placebo years when there is no change in the CLL. The national CLL remains flat through 2016 and rises only in 2017–2019, so we use the national-only sample as a natural pre-trend check. We find no evidence of significant pre-trends, and the results are robust to alternative lag specifications in the VAR controls (Appendix Figure A.5). Appendix Figure A.6 provides a more restrictive pre-trend check by freezing the Bartik instrument at its 2017 value. Exposure to the national CLL change has a similar positive effect after 2017, albeit with lower statistical power, while there is no detectable effect before 2017. Together, these two robustness checks provides the main evidence that the benchmark patterns are not simply reflecting pre-existing differences.

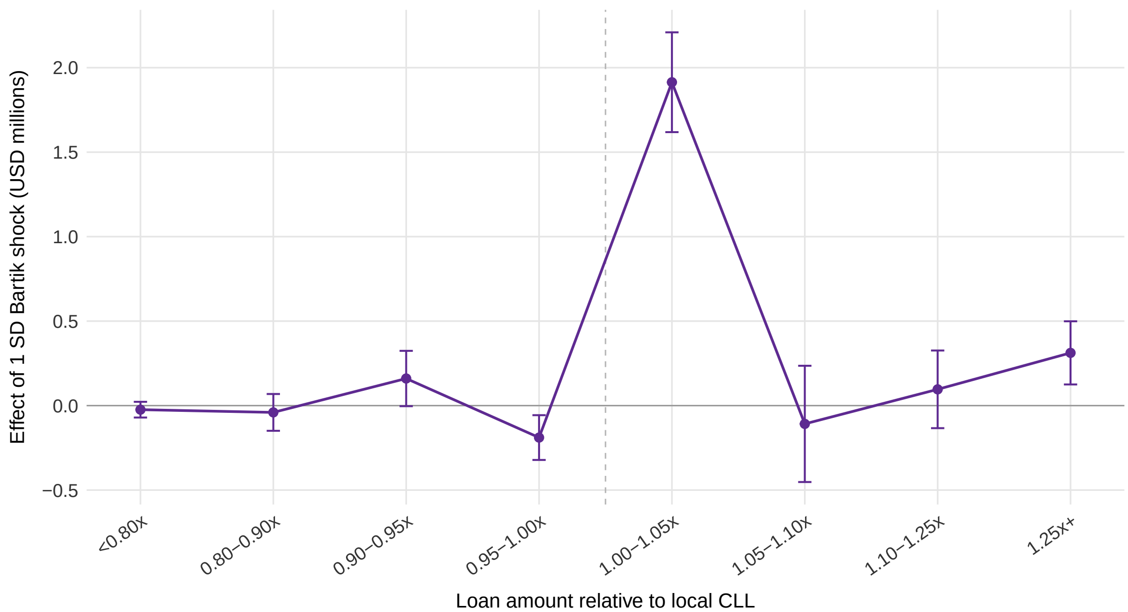

Figure 4: Mortgage response is concentrated around the conforming threshold
Notes. The figure plots the dollar response of mortgage origination volume to a one-standard-deviation increase in the Bartik instrument across loan-amount bins defined relative to the local CLL. The specification follows the simple all-counties benchmark: it uses the simple bank exposure measure, the all-counties sample for 2017–2019, and a five-mile radius to define the local mortgage market. The estimates include bank-by-year and county-by-year fixed effects, VAR controls, and lagged nearby loan-count weights, with standard errors clustered at the branch level. The vertical dashed line marks the conforming threshold. Error bars report 95 percent confidence intervals.

4. Model

These empirical findings motivate a structural framework that allows us to quantify the mechanism linking mortgage activity to deposit outcomes and to evaluate its implications for banks' pricing and value. To this end, we embed the estimated spillover into a dynamic model in which banks compete in deposit and mortgage markets under demand complementarities.

We start with an overview of the model. In each period t, first, a mass of W depositors arrive and choose where to deposit their money. Then, a mass of M mortgage seekers arrive and choose where to originate mortgages.

In the deposit market, each depositor i chooses to deposit in one of the J banks in the locality, which constitutes the first J options in their choice set $\mathcal{J} \equiv \{1, 2, ..., J\}$, to invest in money market mutual funds(MMF), which we label as option $J+1$, or to hold the money as cash, which we label as option 0.

In the mortgage market, each mortgage seeker i chooses to originate a mortgage from one of the J banks in the locality $\mathcal{J}$, or to borrow from a shadow bank, which we label as option $J+1$. If a mortgage borrower chooses not to borrow, we label this choice as option 0.

4.1. Depositors

Depositor i's utility from choosing option $j \in \{0, 1, 2, ...J, J+1\}$ in period t is given by

$$u^d_{i,j,t} = \alpha^d r^d_{j,t} + \beta^d x^d_{j,t} + \xi^d_{j,t} + \gamma \mathbb{I}^m_{i,j,t-1} + \epsilon^d_{i,j,t}, \tag{5}$$

where $r^d_{j \in J,t}$ is the deposit rate offered by bank j, and $r^d_{J+1,t}$ represents the return from investing in money market mutual funds, which equals the short-term federal funds rate. α^d captures depositors' rate sensitivity. β^d is a vector of sensitivities to the non-rate product characteristics, $x^d_{j,t}$. $\xi_{j,t}$ is an unobservable product-level demand shock, and $\epsilon^d_{i,j,t}$ is a relationship-specific shock to the choice of option j by depositor i.

$\mathbb{I}^m_{i,j,t-1}$ is a dummy that indicates whether the depositor is also a client of the bank in the mortgage market in the previous period $t-1$. The demand complementarity between deposit and mortgage market is captured by γ: a higher value of γ suggests that households place a high premium on depositing with their mortgage banks, indicating greater complementarity in their preferences.

Finally, $\epsilon^d_{i,j,t}$ captures horizontal differentiation across banks and induces imperfect product substitution. Banks, therefore, have pricing power, which means they can offer different deposit rates, $r^d_{j,t}$. We define $q^d_{j,t} \equiv \beta^d x^d_{j,t} + \xi^d_{j,t}$ as the perceived quality of product j on the deposit market. We normalize the quality of depositors' outside option (holding cash) to zero, and cash also offers zero nominal return, which implies $u^d_{i,0,t} = \epsilon^d_{i,j,t}$.

The optimal choice for depositor i in period t is presented by an indicator function:

$$\mathbb{I}^d_{i,j,t} = \begin{cases} 1, & \text{if } u^d_{i,j,t} \geq u^d_{i,k,t} \text{ for } k \in \{0,1,2,...J+1\}, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

We aggregate the optimal choices across all depositors to compute the deposit market share of each bank j and adopt the standard assumption that $\epsilon^d_{i,j,t}$ follows an i.i.d. Type I extreme value distribution with a cumulative distribution function $F(\epsilon) = \exp\left(-\exp(-\epsilon)\right)$. Then, we can derive the overall deposit share for bank j, $s^d_{j,t}$, as follows:

$$\begin{aligned} s^d_{j,t} &= \left(\sum_{k \in \mathcal{J}} s^d_{j,t|k} \cdot s^m_{k,t-1}\right) + s^d_{j,t|J+1} \cdot s^m_{J+1,t-1} + s^d_{j,t|0} \cdot s^m_{0,t-1} \\ &= \frac{\exp\left(\alpha^d r^d_{j,t} + q^d_{j,t} + \gamma\right)}{1 + \exp\left(\alpha^d r^d_{j,t} + q^d_{j,t} + \gamma\right) + \sum_{h \in \mathcal{J} \backslash j \cup \{J+1\}} \exp\left(\alpha^d r^d_{h,t} + q^d_{h,t}\right)} \cdot s^m_{j,t-1} \\ &+ \sum_{k \in \mathcal{J} \backslash j} \frac{\exp\left(\alpha^d r^d_{j,t} + q^d_{j,t}\right)}{1 + \exp\left(\alpha^d r^d_{k,t} + q^d_{k,t} + \gamma\right) + \sum_{h \in \mathcal{J} \backslash k \cup \{J+1\}} \exp\left(\alpha^d r^d_{h,t} + q^d_{,t}\right)} \cdot s^m_{k,t-1} \end{aligned}$$

$$+\frac{\exp\left(\alpha^d r^d_{j,t}+q^d_{j,t}\right)}{1+\sum_{k\in\mathcal{J}}\exp\left(\alpha^d r^d_{k,t}+q^d_{k,t}\right)}\cdot\left(1-\sum_{k\in\mathcal{J}}s^m_{k,t-1}\right). \tag{7}$$

The second line in the equation (7) captures the market share among households who are also the mortgage borrowers of banks j; the third line captures the market share among households who are mortgage borrowers of other banks who are also competing in the deposit market in this locality; the last line corresponds to the market share among households who are not mortgage customers of any banks—some of them borrow directly from the non-bank, and a fraction of households do not participate in the mortgage market. One feature of our demand system is that demand depends not only on the characteristics of products in the focal market, but also on characteristics across markets where customers exhibit complementary demand.

4.2. Borrowers

Mortgage seeker i's utility from choosing options $j \in \{0, 1, 2, ..., J+1\}$ in period t is given by

$$u^m_{i,j,t}=\beta^m_j x^m_{j,t}-\alpha^m r^m_{j,t}+\xi^m_{j,t}+\gamma\mathbb{I}^d_{i,j,t}+\epsilon^m_{i,j,t}, \tag{8}$$

where $r^m_{j\in\mathcal{J},t}$ is the mortgage rate charged by bank j. We denote the rate charged by the non-bank as $r^m_{J+1,t}$, and α^m captures households' mortgage rate sensitivity. β^m_j represents the sensitivities of borrowers' utility to certain non-rate characteristics, including the CLL, which reflects consumers' preference for the convenience of conforming mortgages (Buchak et al., 2024). Specifically, we allow the demand sensitivity to CLL to vary across banks (so the sensitivity is indexed by j) to account for the idea that different banks have distinct business models and areas of expertise. Consequently, their demand is influenced by the CLL to varying degrees.[2] ξ^m_j is an unobservable product-level demand shock. $\mathbb{I}^d_{i,j,t}$

[2] We model demand as depending on the CLL, which can also capture, in reduced form, that banks generate cost savings from making conforming loans and partially pass through to their customers. The coefficient $\beta^m_{CLL,j}$ therefore captures the differential degrees of cost pass-throughs.

is a dummy variable, indicating whether the mortgage seeker is also a client of the bank in the deposit market. Finally, $\epsilon^m_{i,j,t}$ is a relationship-specific shock to the choice of option j by the borrower i in period t. We define $q^m_{j,t} \equiv \beta^m_j x^m_{j,t} + \xi^m_{j,t}$ as the perceived quality associated with option j on the mortgage market. We normalize the perceived quality of the shadow bank to 0, and we use q^m_N to denote the perceived quality of the outside option, which is not borrowing, on the mortgage market.

The optimal choice for depositor i is given by an indicator function:

$$\mathbb{I}^m_{i,j,t} = \begin{cases} 1, & \text{if } u_{i,j,t} \geq u_{i,k,t}, \text{ for } k \in \{0, 1, 2, ...J+1\} \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Similarly, we aggregate the optimal choices across all mortgage seekers to compute bank j's market share of new mortgage origination $s^{org}_{j,t}$:

$$\begin{aligned} s^{org}_{j,t} &= \sum_{k\in\mathcal{J}} s^{org}_{j,t|k} \cdot s^d_{k,t} + s^{org}_{j,t|J+1} \cdot s^d_{J+1,t} + s^{org}_{j,t|0} \cdot s^d_{0,t} \\ &= \frac{\exp\left(q^m_{j,t} - \alpha^m r^m_{j,t} + \gamma\right)}{\exp(q^m_N) + \exp(-\alpha^m r^m_{J+1,t}) + \exp\left(q^m_{j,t} - \alpha^m r^m_{j,t} + \gamma\right) + \sum_{h\in\mathcal{J}\setminus j} \exp\left(q^m_{h,t} - \alpha^d r^m_{h,t}\right)} \cdot s^d_{j,t}, \\ &+ \sum_{k\in\mathcal{J}\setminus j} \frac{\exp\left(q^m_{j,t} - \alpha^m r^m_{j,t}\right)}{\exp(q^m_N) + \exp(-\alpha^m r^m_{J+1,t}) + \exp\left(q^m_{k,t} - \alpha^m r^m_{k,t} + \gamma\right) + \sum_{h\in\mathcal{J}\setminus k} \exp\left(q^m_{h,t} - \alpha^d r^m_{h,t}\right)} \cdot s^d_{k,t} \\ &+ \frac{\exp\left(q^m_{j,t} - \alpha^m r^m_{j,t}\right)}{\exp(q^m_N) + \exp(-\alpha^m r^m_{J+1,t}) + \sum_{h\in\mathcal{J}} \exp\left(q^m_{h,t} - \alpha^d r^m_{h,t}\right)} \cdot \left(1 - \sum_{k\in\mathcal{J}} s^d_{k,t}\right). \end{aligned} \tag{10}$$

We use $s^m_{j,t}$ to denote the overall market share of bank j in the mortgage market, which consists of borrowers with newly originated mortgages, $s^{org}_{j,t}$, and borrowers who have previously obtained mortgages from the bank. These borrowers form the customer base that can potentially exhibit complementary preferences toward the bank's deposit products. A bank's total mortgage market share evolves according to:

$$s^m_{j,t} = (1-\mu)s^m_{j,t-1} + \mu s^{org}_{j,t}, \tag{11}$$

where $s^m_{j,t-1}$ represents bank j's share of mortgage borrowers in the previous period, and μ denotes the per-period mortgage repayment rate, which in a stationary environment also equals the fraction of newly originated mortgages in each period. The term $(1 - \mu)s^m_{j,t-1}$ therefore captures the bank's mortgage market share carried over from previous origination activities, while $\mu s^{org}_{j,t}$ corresponds to the bank's newly originated mortgages in period t.

Equation (11) highlights the dynamic nature of the household-bank relationship on the mortgage market and the potential long-term impact of households exhibiting complementary preferences. This dynamic aspect is especially significant in the mortgage market, where most households choose their mortgage lender only once every 7–10 years but continue to make repayments and engage in other transactions on a monthly or even daily basis.

4.3. Bank's optimization problem

In each period, each bank simultaneously sets rates for its deposits and mortgages, $\{r^m_{j,t}\}$. These rate-setting decisions implicitly determine the bank's market share of deposits accepted from depositors and mortgages newly extended to borrowers. For example, given banks' optimal deposit rates, depositors solve the utility maximization problem in equation (6). The solution provides the share of deposits supplied to each bank, given by equation (7). Given banks' optimal mortgage rates, borrowers solve the utility maximization problem in equation (9). The solution provides the share of mortgages originated by each bank in the current period, given by equation (10).

The bank subsequently allocates its funds available, including its equity capital $K_{j,t}$, deposit intake $Ws^d_{j,t}$, and any wholesale borrowings $N_{j,t}$, to risk-free government securities $G_{j,t}$, the fraction of mortgage held on its balance sheet $b_{j,t}$, and other risky asset investment opportunities $A_{j,t}$.

Banks that borrow wholesale funding incur a quadratic financing cost on top of the Fed funds rate:

$$\Phi^N_{j,t} = f N_{j,t} + \phi N^2_{j,t} \tag{12}$$

On the asset side, investing in risk-free government securities generates a return that equals the risk-free rate f. $b_{j,t}$ denotes the fraction of mortgage the bank keeps on its balance sheet, so the rest $1 - b_{j,t}$ will be securitized, incurring a securitization cost:

$$\Phi^b_{j,t} = \eta(1 - b_{j,t}) \cdot M s^m_{j,t}, \tag{13}$$

where M represents the size of the mortgage market, and $s^m_{j,t}$ is the bank's mortgage market share, shaped by the banks' past mortgage origination decisions. Note that even when banks securitize mortgages, they can continue servicing them. As a result, the customer remains a mortgage client and is likely to maintain a preference for using the bank's other services. Therefore, we model the base of customers who may exhibit complementary preferences as $s^m_{j,t}$, rather than just the fraction of customers whose mortgages the bank retains on its balance sheet. η captures the bank's cost to securitize, consisting of the current interest rate and the agency fees.

Finally, the bank also holds a portfolio of other risky assets, denoted by $A_{j,t}$, on its balance sheet, which generates a stochastic revenue $\omega_{j,t} \cdot A^\theta_{j,t}$, as modeled in Egan, Lewellen, and Sunderam (2022). $\omega_{j,t}$ is the bank's productivity from holding risky assets:

$$\log \omega_{j,t} - \mu_\omega = \rho \left(\log \omega_{j,t} - \mu_\omega\right) + (1-\rho)\mu_\omega + \epsilon_\omega, \text{ where } \epsilon_\omega \sim N(0, \sigma^2_\omega), \tag{14}$$

and θ captures the returns to scale in banks' risky asset investment.

Banks' balance sheet condition states that:

$$A_{j,t} + G_{j,t} + b_{j,t} M s^m_{j,t} = W s^d_{j,t} + N_{j,t} + K_{j,t} \tag{15}$$

We use Π_t is the bank's profit from issuing deposits, originating and securitizing mortgages, and investing in risk-free and risky assets:

$$\Pi_t = \omega_{j,t} \cdot A^{\theta}_{j,t} + [\iota(r^m_{j,t} - c^m)] \cdot Ms^{org}_{j,t} + fG_{j,t} - \Phi^b_{j,t} - \Phi^N_{j,t} - Ws^d_{j,t} \cdot (r^d_{j,t} + c^d) - \chi, \quad (16)$$

where $\iota(\cdot)$ represents the discounted present value of all future interest payments from each dollar of mortgage originated in t:[3]

$$\iota(r^m_{j,t} - c^m) = \mu \sum_{n=0}^{\infty} \frac{(1-\mu)^n \left(r^m_{j,t} - c^m\right)}{(1+f)^n}, \quad (17)$$

where f stands for the risk-free interest rate. c^m and c^d in equation (16) capture the marginal cost to originate mortgages and issue deposits, respectively, and χ is the bank's fixed cost of operation.

Banks will choose their deposit and mortgage pricing, wholesale borrowing, risky and risk-free investments, and profit retention in each period to maximize the present value of cash dividend stream, $\{C_t\}$ to shareholders:

$$V^j(\omega_{j,t}, s^m_{j,t}, K_{j,t}|\Gamma_t) = \max_{\substack{r^d_{j,t}, r^m_{j,t}, b_{j,t}, A_{j,t}, N_{j,t} \\ G_{j,t}, C_{j,t}, K_{j,t+1}}} C_{j,t} + \frac{1}{1+f}\left\{\mathbb{E}V^j(\omega_{j,t+1}, s^m_{j,t+1}, K_{j,t+1}\middle|\Gamma_{t+1})\right\}, \quad (18)$$

s.t. equations (7), (10), (11), (14), (15), (16)

$$K_{j,t} \geq \kappa \times \left(A_{j,t} + b_{j,t} Ms^m_{j,t}\right) \quad (19)$$

$$K_{j,t+1} = K_{j,t} + \Pi_{j,t}(1-\tau) - C_{j,t}, \quad (20)$$

where τ is the tax rate and $K_{j,t}$ stands for the bank's equity capital. Equation (19) captures the capital regulation faced by the bank: capital must exceed a fraction κ of mortgage holdings and risky assets on the balance sheet. In the model, a negative shock to bank capital, for example, a period of very low returns on risky investments, tightens this constraint. As a result, the bank reduces both the mortgages it retains on its balance sheet

[3]This is equivalent to modeling the bank as earning interest payments from each dollar of outstanding mortgage because the mortgage rates are fixed since origination and not affected by future banks' pricing strategy.

and its holdings of risky assets. Because risky investments exhibit decreasing returns to scale, the bank chooses its level so that the marginal return equals η, the marginal cost of securitizing mortgages. The bank also adjusts its mortgage holdings. If the bank holds a positive amount of mortgages on its balance sheet, the total size of on-balance-sheet assets, including both mortgages and risky investments, must satisfy that the marginal cost of funding an additional dollar of on-balance-sheet assets, including both the direct funding cost and the shadow cost of the capital constraint, also equals η.

Equation (20) captures the evolution of the bank capital, which says the bank capital next period should equal the previous period's capital, plus new after-tax profit generated in the current period, minus the dividend distributed to shareholders.

4.4. The shadow bank's optimization problem.

There is one non-bank competing oligopolistically with banks in originating mortgages for households. The nonbank chooses its pricing to maximize the discounted present value of its profit stream::

$$V^{J+1}(\Gamma_t) = \max_{r^m_{J+1,t}} \beta \left\{ \iota(r^m_{J+1,t} - c^s - f) \cdot M s^{org}_{J+1,t} + \mathbb{E} V^{J+1}(\Gamma_{t+1}) \right\}, \text{ s.t. equations (10)}, \quad (21)$$

where $s^{org}_{J+1,t}$ stands for the new mortgages originated by the non-bank and $r^m_{J+1,t}$ is the rate charged by the non-bank. The main differences between banks and the non-bank are three-fold: 1) unlike banks, the non-bank does not take any deposits. It only deals with borrowers on the mortgage market, and thus, there is no room for them to benefit from households' complementary preferences. 2) Non-banks operate under a different technology than banks in originating and securitizing mortgages. At the same time, they do not have access to an internal capital market, so their marginal costs may differ from those of banks. We use c^s to jointly capture their marginal cost of mortgage origination and securitization. 3) The non-banks are not facing leverage constraints. However, similar to banks, the non-bank also needs to take into account the other competitors' (the banks') pricing strategies in the mortgage market when they optimize their own pricing decisions.

4.5. Equilibrium

Definition 1 *Let Γ_t denote the cross-sectional distribution of bank states in period t, and P^{Γ} denote the probability law governing the evolution of Γ_t. such that $\Gamma_{t+1} = P^{\Gamma}(\Gamma_t)$. A Markov Perfect Industry Equilibrium occurs when:*

1. *All banks solve the problem given by equation (18), taking as given the other banks' pricing strategies in the deposit market and the mortgage market, and the non-bank pricing strategy in the mortgage market.*
2. *The non-bank solves the problem given by equation (21), taking as given all banks' pricing strategies in the mortgage market.*
3. *Depositors and mortgage borrowers maximize their utilities in equations (5) and (8), given the list of rates put forth by banks and the non-bank.*
4. *In each period, the deposit and mortgage markets clear.*
5. *The probability law governing the evolution of the industry, P^{Γ}, is consistent with the market participants' optimal choices.*

One of the state variables for the banks' problem (Γ_t) is an object whose dimension depends on the number of banks in the economy. We use a low-dimensional approximation of Γ_t, as in Wang et al. (2022). The strategy follows from an algorithm in the spirit of Krusell and Smith (1998) proposed by Weintraub, Benkard, and Van Roy (2008) and Weintraub, Benkard, and Van Roy (2010).

5. Estimation

Our estimation recovers two sets of parameters. The first governs consumer demand and includes interest rate sensitivities in the deposit and mortgage markets ($\{\alpha^d, \alpha^m\}$), product quality terms ($\{q^d_{j\in J}, q^m_{j\in J}\}$), and the degree of demand complementarity across markets (γ).

To capture this complementarity, we construct moments based on the shift-share IV design introduced in Section 2. In the model, instead of including the CLL, which varies at the county level, we include the Bartik instrument directly to capture the heterogeneous exposure to CLL changes in a way that is consistent with our reduced-form evidence. More specifically, we introduce a one-percentage-point increase in the CLL, roughly in line with the average change observed in our sample. We then calibrate banks' heterogeneous exposure to this change, denoted by $\beta^m_{CLL,j}$, such that the distribution of $\beta^m_{CLL,j} \times 1\%$ in the model matches the variation implied by the data—that is, the average first-stage coefficient, $\frac{\sum h=1^4 \hat{\theta}_h}{4}$, multiplied by the empirical distribution of the Bartik instrument (reported in Figure A.2). This procedure ensures that CLL changes generate comparable variation in the mortgage market in both the model and the data, providing a consistent mapping between the two.

Second, we estimate the supply-side parameters, including marginal costs of issuing deposits and originating mortgages, $\{c^d, c^m\}$, the cost of wholesale funding, ϕ, the cost of securitization, η, the mean, persistence, and standard deviation of shocks to banks' productivity in their risky asset investments, $\{\mu_\omega, \rho_\omega, \sigma_\omega\}$, returns to scale in holding risky assets, θ, and banks' fixed operating cost, χ.

We calibrate several institutional parameters outside the model. We normalize banks' deposit size to 100 and set the mortgage market size M to match the average mortgage-to-deposit ratio in the U.S. during our sample period, which is 0.758. We calibrate the federal funds rate f to its sample average of 0.025. The corporate tax rate τ is set to its statutory level of 35%, and the capital requirement κ is set to 6% in line with the Basel Accord. We also calibrate the repayment maturity parameter μ to match the average effective life of U.S. residential mortgages, approximately six years. The cost of securitization is set to the federal funds rate plus the average annualized G-fee on outstanding mortgage balances, about 50 basis points. Finally, we calibrate the mean quality of not borrowing to match the quality differential between the outside option and bank loans estimated in Wang et al. (2022).

We use the following set of moments to identify the parameters governing consumers' demand: (i) covariance of unobserved demand shock $\xi^d_{j,t}$ and instruments $Z_{j,t}$ in the deposit market; (ii) covariance of unobserved demand shock $\xi^m_{j,t}$ and instruments $Z_{j,t}$ in the mortgage market; (iii) how shocks to bank mortgage origination spills over to deposits, computed using the shift-share IV in Section 2. We now describe how we construct these moments.

In the deposit market, recall equation (7) implies that the deposit market share can be written as

$$\begin{aligned} s^d_{j,t} = & \sum_{k\in\mathcal{J}} \frac{\exp\left(\alpha^d r^d_{j,t} + q^d_{j,t} + \gamma\mathbb{I}(k=j)\right)}{1+\exp(\alpha^d r^d_{k,t} + q^d_{k,t} + \gamma) + \sum_{h\in\mathcal{J}\backslash k}\exp(\alpha^d r^d_{h,t} + q^d_{h,t})} \cdot s^m_{k,t-1} \\ & + \frac{\exp(\alpha^d r^d_{j,t} + q^d_{j,t})}{1+\sum_{k\in\mathcal{J}}\exp(\alpha^d r^d_{k,t} + q^d_{k,t})}\left(1 - \sum_{k\in\mathcal{J}} s^m_{k,t-1}\right), \end{aligned}$$

where $q^d_{j,t} = \beta^d X^d_{j,t} + \xi^d_{j,t}$ in the perceived quality of choosing option j. In each period t, we observe deposit rates $r^d_{j,t}$, non-rate characteristics $X^d_{j,t}$, and lagged mortgage market shares $s^m_{j,t-1}$ for all banks j. There are also strictly positive shares of households who choose to invest in money market funds or the outside option (cash), and the shares are both directly observed in the data. Given the rate and non-rate sensitivity parameters and the complementarity parameter γ, this system delivers a one-to-one mapping between deposit market shares $\{s^d_{j,t}\}_{j\in\mathcal{J}\cup\{J+1\}}$ and unobserved deposit product qualities $\{\xi^d_{j,t}\}_{j\in\mathcal{J}\cup\{J+1\}}$. Therefore, we can invert the observed deposit market shares to recover the unobserved qualities, following Berry, Levinsohn, and Pakes (1995).

A common challenge in demand estimation is that prices, in this case, deposit rates, might be endogenous. If a bank offers lower deposit rates on deposit products with higher unobserved quality, prices will be endogenous to unobserved quality, and this could bias our estimate of depositors' sensitivity to rates downward. Therefore, we instrument deposit rates with standard cost shifters commonly used in the literature: salaries and noninterest expenses related to the use of fixed assets (see Dick, 2007; Ho and Ishii, 2011; Wang et al., 2022). We denote the cost shifters by $Z_{j,t}$. The identifying assumption is that these cost shifters influence banks' supply of deposits and are orthogonal to unobserved demand shocks $\xi^d_{j,t}$. This yields the first moment condition: $\mathbb{E}(Z_{j,t}\xi^d_{j,t}) = 0$.

Similarly, in the mortgage market, equation (10) implies that the mortgage market share can be written as

$$s^m_{j,t} = \mu \sum_{k\in\mathcal{J}} \frac{\exp\left(q^m_{j,t} - \alpha^m r^m_{j,t} + \gamma\mathbb{I}(k=j)\right)}{1 + \exp(q^N_t - \alpha^m r^N_t) + \exp(q^m_{k,t} - \alpha^m r^m_{k,t} + \gamma) + \sum_{h\in\mathcal{J}\setminus k}\exp(q^m_{h,t} - \alpha^d r^m_{h,t})} \cdot s^d_{k,t}$$
$$+ \mu \frac{\exp(q^m_{j,t} - \alpha^m r^m_{j,t})}{1 + \sum_{h\in\mathcal{J}\cup J+1}\exp(q^m_{h,t} - \alpha^d r^m_{h,t})} \cdot \left(1 - \sum_{k\in\mathcal{J}} s^d_{k,t}\right) + (1-\mu)s^m_{j,t-1}.$$

Therefore, we can invert the mortgage market shares to obtain unobserved quality for mortgage products $\{\xi^m_{j,t}\}_{j\in\mathcal{J}}$. We use the same cost shifters to instrument for mortgage rates and construct the second moment condition: $\mathbb{E}(Z_{j,t}\xi^m_{j,t}) = 0$.

A key parameter in the demand system is the demand complementarity γ, which measures the premium households place on concentrating their transactions within a single bank. An intuitive way to identify γ would be to look at the proportion of households that deposit money and take mortgages from the same bank. However, this method cannot effectively identify γ, as the estimate might be confounded by households' correlated idiosyncratic preferences for deposits and mortgages, i.e., by correlation between $\epsilon^d_{i,j,t}$ and $\epsilon^m_{i,j,t}$. Therefore, to identify the household's complementary preference, we introduce a third set of moments leveraging the identified impact of changes in CLL on banks' deposits and mortgages in Section 2. Specifically, we exploit exogenous variation in mortgage origination induced by CLL changes through our Bartik shift-share instrument, estimating the local projection in equation (3) and tracing the extent to which these effects spill over to banks' deposit inflows.

Next, we estimate nine additional supply-side parameters to match the following moments of banks' balance sheets. First, we use banks' average deposit spreads and mortgage spreads to identify the marginal costs of servicing deposits, c^d, and originating mortgages, c^m. Higher marginal costs translate into higher spreads charged by banks. Similarly, we use the shadow banks' average mortgage spread to identify their cost of originating mortgages.[4] Finally, we use banks' average wholesale funding as a fraction of deposits to identify the cost of wholesale funding, ϕ.

Next, we use the mean, standard deviation, and persistence of banks' interest income to identify their productivity process. We use the mean and standard deviation of banks' share of risky assets to identify the degree of returns to scale in holding risky assets. When decreasing returns to scale are weak, the share of risky assets at the firm level should be more volatile, as it responds more strongly to underlying productivity shocks. We then use average net non-interest expenses (scaled by assets) and banks' market-to-book ratios to identify fixed operating costs. Targeting banks' market-to-book ratio directly also helps ensure that the model reasonably captures bank valuation, making it a suitable framework for analyzing counterfactuals related to synergies and bank value.

The algorithm proceeds as follows: we (i) compute the moments in the data, stacking the demand-side moment conditions with the moments constructed from banks' balance sheet behaviors. (ii) for a given set of model parameters, simulate banks' behavior using the equilibrium criteria described in Section 4.5; (iii) compute the same moments using the simulated data and compute the distance between the simulated moment and the data moment; (iv) iterate (ii) and (iii) until we find model parameters that minimize the distance between the simulated and data moments.

Overall, the model fits the data well. Table 2 presents the data moments and the simulated moments used in estimation.

[4] Since we assume shadow banks securitize all mortgages, their marginal cost c^s combines the costs of mortgage origination and securitization.

Table 2: Moment Conditions

	Actual	Simulated
(1) Deposit Market share for banks	0.710	0.735
(2) Deposit Market share for MMF	0.237	0.235
(3) Mortgage market share for banks	0.582	0.476
(4) Deposit rate sensitivity	0.968	0.828
(5) Mortgage rate sensitivity	-1.462	-1.429
(6) Banks' deposit-mortgage sensitivity	0.047	0.039
(7) Average bank deposit spread	0.013	0.014
(8) Average bank mortgage spread	0.017	0.016
(9) Average shadow bank mortgage spread	0.020	0.020
(10) Wholesale funding deposit ratio	0.214	0.208
(11) Average interest income	0.031	0.030
(12) Dispersion in interest income	0.022	0.024
(13) Auto-correlation of interest income	0.802	0.651
(14) Share of risky assets	0.689	0.791
(15) Dispersion in risky asset share	0.212	0.478
(16) Net non-interest expenses	0.019	0.016
(17) Market-to-book	1.616	1.300

Note: In this table, we report the moment conditions targeted in our simulated method of moments estimation. The actual moments are calculated using the observed data. The simulated moments are computed from model-simulated data using the parameter values reported in Table 3.

The estimation results are reported in Table 3. We find that banks possess market power in both the deposit and mortgage markets, as evidenced by downward-sloping demand on both sides. Consumers also exhibit strong complementary preferences. The estimate of $\gamma = 0.414$ implies that, all else equal, an existing relationship with a bank raises the probability that a consumer chooses an additional service from the same bank by roughly 40 percent percent relative to having no prior relationship with any bank. On the supply side, banks' productivity in risky asset investment is fairly persistent and exhibits substantial variation. Risky investment is subject to only a modest degree of decreasing returns to scale, consistent with the evidence in Egan et al. (2022).

Table 3: Parameter Estimates

Panel A: Demand Parameters		
α^d	Depositors' sensitivity to deposit rates	0.831
α^m	Borrowers' sensitivity to mortgage rates	-1.372
$\bar{q}^d_{j,j\in\mathcal{J}}$	Mean quality of banks' deposits	2.308
$\bar{q}^d_{J+1}$	Mean quality of holding MMF	0.010
$\bar{q}^m_{j,j\in\mathcal{J}}$	Mean quality of banks' mortgages	-0.044
γ	Demand complementarity	0.414
Panel B: Supply Parameters		
c^d	Bank's marginal cost of taking deposits	0.005
c^m	Bank's marginal cost of originating mortgages	0.001
ϕ	Quadratic cost of wholesale funding	0.005
c^s	Shadow bank's marginal cost of originating mortgages	0.007
μ_ω	Mean of log productivity from holding risky assets	-3.291
ρ_ω	Auto-correlation log productivity from holding risky assets	0.675
σ_ω	Std of log productivity from holding risky assets	0.186
θ	Returns to scale from holding risky assets	0.936
χ	Fixed operating cost	0.177

Note: This table reports the model parameter estimates. Panel A presents the parameters governing consumer demand, while Panel B reports the parameters governing bank and shadow bank operations.

6. Implications

6.1. Value of demand complementarity

In this section, we use the estimated model as a laboratory to quantify the value banks derive from consumers' complementary demand. Intuitively, such complementarities create opportunities for banks to deepen customer relationships. As customers jointly demand deposits and mortgages, banks can differentiate their products from competitors through these relationships, thereby increasing their effective market power. Banks can then exploit this market power by charging higher markups, which raises their overall value.

To quantify this effect, we conduct a counterfactual exercise in which we shut down complementary demand by setting $\gamma = 0$, so that consumers choose deposits and mortgages independently. We then resolve the model and compare banks' market values in this counterfactual to the baseline, which we normalize to 100%. In the counterfactual, bank value declines by 2.49%, implying that the ability to leverage consumers' complementary demand contributes 2.49% to bank value.

Table 4: Value of demand complementarity

	Value component	% value of demand complementarity
Bank (total)	100.0%	2.49%
Deposit franchise	45.87%	5.43%
Mortgage business	18.55%	13.43%

Note: This table reports the value banks derive from leveraging customers' complementary demand, expressed as a percentage of three components: (i) banks' total market value, (ii) the value of the deposit franchise, and (iii) the value of the mortgage business. The deposit-franchise value is computed as the present value of banks' per-period deposit profits (the deposit spread multiplied by total deposits). The mortgage-business value is defined as the present value of banks' per-period mortgage profits, net of securitization costs when loans are sold. Calculations use the parameter estimates reported in Table 3.

To put this magnitude in perspective, we decompose bank value in the baseline model. We first compute the value of the deposit franchise, defined as the present value of deposit spreads times the deposit base, scaled by total bank value. We find that the value of complementary demand amounts to 5.43% of the deposit franchise.

We then benchmark against the mortgage franchise, defined as the present value of banks' per-period profits from mortgage lending (net of securitization costs when loans are sold). Under this measure, the value of complementary demand corresponds to a sizable 13.43% of the mortgage franchise. The result suggests that a substantial portion of the value generated from mortgage lending materializes outside the focal market. Standard accounting of "originate-to-sell" mortgage income likely understates the true economic return from mortgages, as banks often retain servicing rights (Hamdi, Jiang, Lewis, Padi, and Pal, 2023), keeping customers within their orbits and increasing the opportunity of cross-selling additional products.

6.2. Cross-market pricing

We next examine how complementary demand, which links market shares and market power across deposit and loan markets, affects banks' pricing behavior in these markets. To this end, we compare the baseline model with a set of counterfactuals in which we vary the magnitude of γ. This allows us to study how banks adjust their strategic behavior across the two markets as demand complementarity changes.

In our model, an increase in γ generates two opposing forces on banks' pricing behavior. On the one hand, a higher γ implies that banks become more differentiated from consumers' perspective, effectively increasing their market power and allowing them to charge higher markups. On the other hand, a higher γ raises the benefit of expanding market share, since doing so also enhances banks' market power in the other market. This second channel induces banks to compete more aggressively and to lower their spreads in the focal market, anticipating cross-market spillovers. Consequently, the net effect of γ on banks' pricing behavior is ex-ante unclear and depends on the relative strength of these two forces.

Our results in Figure 5 show that the differentiation effect dominates in both deposit and mortgage markets: as the complementarity parameter increases, banks charge higher spreads in both markets as they have more market power. Meanwhile, the deposit market spread increases more than the mortgage market spread. In other words, cross-selling opportunities incentivize banks to redistribute their spreads between the two markets, extracting a higher fraction of their rents from depositors than mortgage borrowers.

The reason we observe these different patterns across the deposit and loan markets lies in the demand elasticities estimated from households' utility functions. Depositors exhibit a relatively lower rate sensitivity than mortgage borrowers. Given this asymmetry, banks optimally use the mortgage market not only as a source of interest income but also as a channel to build their customer base. In this sense, banks effectively subsidize the

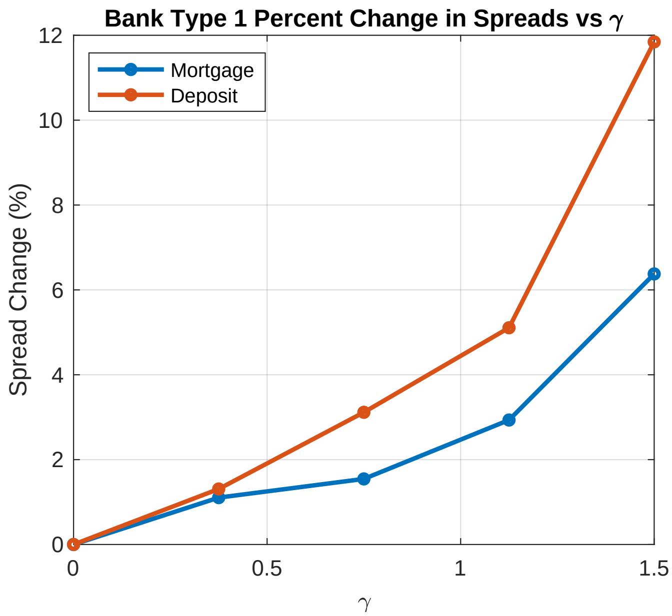

Figure 5: Demand Complementarity and Bank Cross-Market Subsidization
The graphs show how the markup that banks charge in the deposit and mortgage markets respond to changes in the demand complementarity parameter γ, which measures the additional utility households derive from obtaining deposit and mortgage services from the same bank. The changes in deposit and mortgage markups are expressed as percentage deviations from their average values under the baseline model.

larger increase in deposit spreads through a smaller increase in mortgage spreads: by competing more aggressively for mortgage borrowers, they attract customers who can subsequently be served in the relatively inelastic deposit market. Thus, although demand complementarities increase banks' market power in both markets, the increase in spreads is more amplified in the deposit market than in the mortgage market.

We are not the first to document such cross-market redistributive effects. A prominent example is Park and Pennacchi (2008), who analyze the pricing strategies of multimarket banks relative to single-market ones. Their mechanism operates through the supply side: single-market banks face tighter funding constraints due to frictions in accessing wholesale funding markets, and therefore subsidize deposits to relax these constraints.

Our mechanism is fundamentally different. Rather than arising from banks' funding constraints, the cross-market redistributive effects in our model are driven by demand-side forces. In particular, customers value obtaining deposit and mortgage services from the same bank, while exhibiting higher rate sensitivity in the mortgage market. As a result, banks optimally compress spreads in the mortgage market to expand their customer base and exploit demand complementarities across products. Our paper thus isolates a demand-based channel that complements the supply-side mechanisms emphasized in the existing literature.

6.3. Interconnectedness of Mortgages and Deposits

Previously, we showed that consumers' complementary demand creates incentives for banks to coordinate their behavior across markets in order to optimally profit from these demand features. Our final exercise builds on this mechanism by examining how such complementarities generate interconnectedness between deposit-taking and mortgage origination activities.

To this end, we conduct an additional set of counterfactual exercises in which we shock banks' mortgage business by lowering their marginal cost of originating mortgages. We fix the reduction at 5 basis points and compare banks' behavior across scenarios with and without complementary demand. In particular, we focus on how the expansion in mortgage origination spills over into deposit-taking activity.

Our model implies that a 5-basis-point reduction in mortgage origination costs increases a bank's steady-state mortgage holdings by 0.139 per year, corresponding to a 1.98% increase relative to the baseline. In the new steady state, each additional dollar of mortgage lending generates approximately 7.2 cents of deposit growth.

This effect reflects a combination of forces. First, it captures the direct effect of demand complementarities, as governed by γ. Second, it incorporates banks' endogenous responses to customers with complementary demand. In particular, banks optimally adjust their strategic decisions in both deposit and loan markets when serving such customers, including adjustments that directly affect deposit supply. Finally, it also reflects pure supply-side effects arising from funding constraints or regulation, as emphasized in the literature (Gilje, Loutskina, and Strahan, 2016; Whited, Wu, and Xiao, 2022).

Quantitatively, when we shut down demand-side interconnectedness by setting the complementarity parameter $\gamma = 0$, the comovement between deposits and lending declines substantially. In this counterfactual, a one-dollar increase in mortgage origination raises deposits by only 2.2 cents, capturing the pure supply-side effect. This estimate is smaller than that documented in prior work, which is intuitive given that banks securitize a substantial fraction of the mortgages they originate. It is also much smaller relative to the baseline effect, indicating that demand complementarities and banks' endogenous responses to them are the primary drivers of the interconnectedness banks' between deposit-taking and mortgage lending activities.

Importantly, the deposit–mortgage spillover quantified in this exercise captures a fundamentally different concept from that estimated in the reduced-form analysis in Section 3.3. Below, we highlight the key conceptual differences between the two:

First, the reduced-form setting identifies a micro elasticity: it captures how a given bank's deposits respond when that bank gains mortgage market share relative to its peers. In contrast, this counterfactual exercise identifies a macro elasticity: it evaluates how aggregate bank behavior responds when all banks simultaneously expand mortgage lending, and how demand complementarities shape equilibrium outcomes.

Second, the reduced-form specification compares how changes in CLL affect mortgages and deposits across branches within the same parent bank by including parent bank–year fixed effects. It therefore captures an equilibrium outcome in which the effects are mediated by the bank's supply-side responses. Our quantification of deposit-mortgage spillover explicitly accounts for these endogenous responses, which can generate important strategic behavior, as we show in Section 6.2, and can be a key driver of the observed interconnectedness.

Lastly, the Bartik instrument used in the reduced-form analysis is well-suited for identifying short-run causal effects of changes in mortgage market share on deposit growth. However, its power diminishes over longer horizons as noise accumulates. We use simulated data to match these short-run effects, anchoring the model to the empirical evidence. The model then allows us to conduct counterfactual and compare outcomes across steady states.

6.4. Discussions

Overall, the results in this section suggest that banks can leverage customers' complementary preferences to expand their customer base and build greater effective market power. Institutions that specialize solely in either deposits or lending cannot exploit these cross-market complementarities. In contrast, multimarket banks benefit from synergies by jointly offering both services and internalizing demand complementarities. Importantly, these synergies persist even in the absence of internal agency or financing frictions, distinguishing them from traditional explanations for joint deposit–lending provision (Diamond and Rajan, 2000; Piazzesi and Schneider, 2020). Moreover, these strategies induce stronger comovement in banks' activities across markets. Expansion in one segment increases a bank's attractiveness in others, as perceived by its customer base. This form of interconnectedness also differs from the deposit–lending linkages emphasized in the existing literature, which primarily focus on funding frictions or costs associated with liquidity management within banks. Our paper thus provides a complementary explanation for the existence of multimarket banks, highlighting the quantitative importance of demand complementarities.

Another contribution of our paper lies in combining a reduced-form and structural approach to quantify and interpret demand complementarities. We first use a Bartik instrument to identify the strength of demand complementarities among consumers in the data. We then embed this empirically identified demand structure into a structural model that jointly incorporates consumer demand and banks' supply-side decisions. This framework allows us to evaluate the aggregate implications of demand complementarities for banks' behavior and valuation. This approach not only provides insight into key economic primitives that are difficult to directly isolate in reduced-form settings, such as the synergies and interconnectedness of multimarket banks, but it also offers a tractable framework for policy analysis.

For example, in April 2024, Governor Michelle Bowman noted that regulators are considering policies to encourage banks to expand their role in mortgage origination and servicing, including through more favorable capital requirements. She emphasized that these activities are valuable not only for generating revenue but also for strengthening customer relationships, which may improve bank performance and resilience at the aggregate level. Her comments highlight the importance of understanding how banks leverage customer relationships across markets and how cross-selling shapes aggregate outcomes for the banking industry. Our analysis in this section directly quantifies these mechanisms and provides a tool for evaluating such policy interventions[5].

7. Conclusion

In conclusion, we document that consumers display complementary demand across deposits and mortgages, and that banks rationally design their cross-selling strategies to monetize this preference. Such complementarities grant banks incremental market power across, rather than within, markets. Although our analysis focuses on retail banking, anecdotal evidence suggests that banks are actively exploring similar cross-selling practices in commercial lending and investment banking. Taken together, these pieces of evidence shed light on important policy implications: regulation aimed at curbing bank market

[5]Governor Bowman commented: "Customers with strong bank connections naturally turn to that bank for other financial needs, from checking accounts to investment services," Bowman said. "[G]ood customer service in the mortgage business can lead to a stronger relationship with customers and result in improved bank financial resiliency." See additional details of her comments here: https://www.bankingdive.com/news/fed-consider-changes-mortgage-lending-rules-bowman/812340/.

power should consider not only concentration in a single market but also banks' ability to leverage demand across markets, and policies or technologies that unbundle financial services may erode this source of bank value.

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A. Additional Tables and Figures

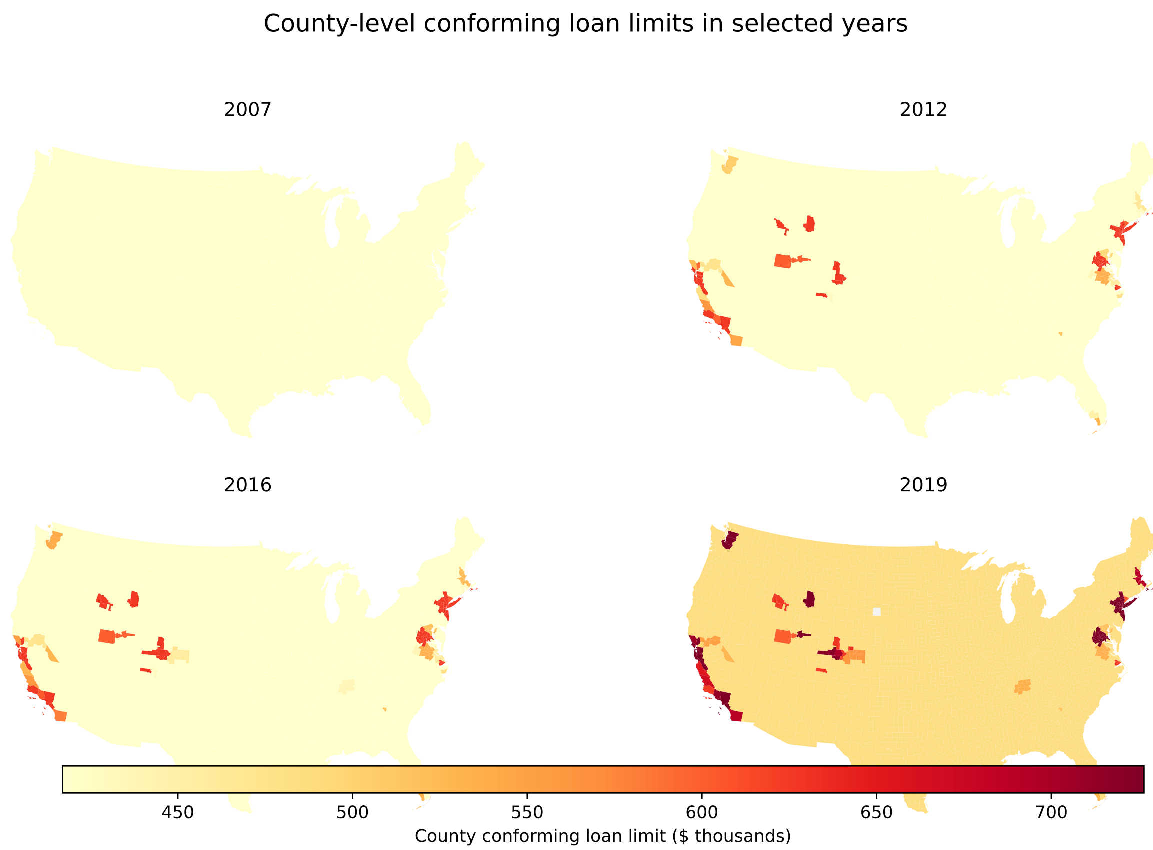

Figure A.1: County-level conforming loan limits in selected years

Notes. The figure shows how the county-level conforming-loan-limit schedule evolves from the pre-HERA uniform regime to the modern county-specific schedule, by mapping FHFA county-level conforming loan limits for selected years in the contiguous United States. The 2007 panel shows the largely uniform national regime before county-specific high-cost limits became widespread. Later panels show the county-specific schedule used in the modern period. Darker shading denotes higher conforming loan limits.

Table A.1: Annual distribution of county-level conforming loan limits

Year	Baseline	Median	P95	Max	High-cost (%)	Increase (%)
2007	\$417,000	\$417,000	\$417,000	\$417,000	0.0	0.0
2012	\$417,000	\$417,000	\$426,650	\$625,500	5.1	0.0
2013	\$417,000	\$417,000	\$426,650	\$625,500	5.1	0.0
2014	\$417,000	\$417,000	\$437,000	\$625,500	5.4	0.5
2015	\$417,000	\$417,000	\$437,000	\$625,500	6.2	1.5
2016	\$417,000	\$417,000	\$458,850	\$625,500	6.2	1.3
2017	\$424,100	\$424,100	\$466,900	\$636,150	6.3	97.4
2018	\$453,100	\$453,100	\$489,900	\$679,650	5.8	97.9
2019	\$484,350	\$484,350	\$506,920	\$726,525	5.1	98.6

Notes. The table reports annual cross-county distribution of FHFA CLL schedule for the contiguous United States. "Baseline" is the national CLL; "High-cost" is the share of counties above that baseline; and "Increase" is the share of counties whose limit rises relative to the previous year.

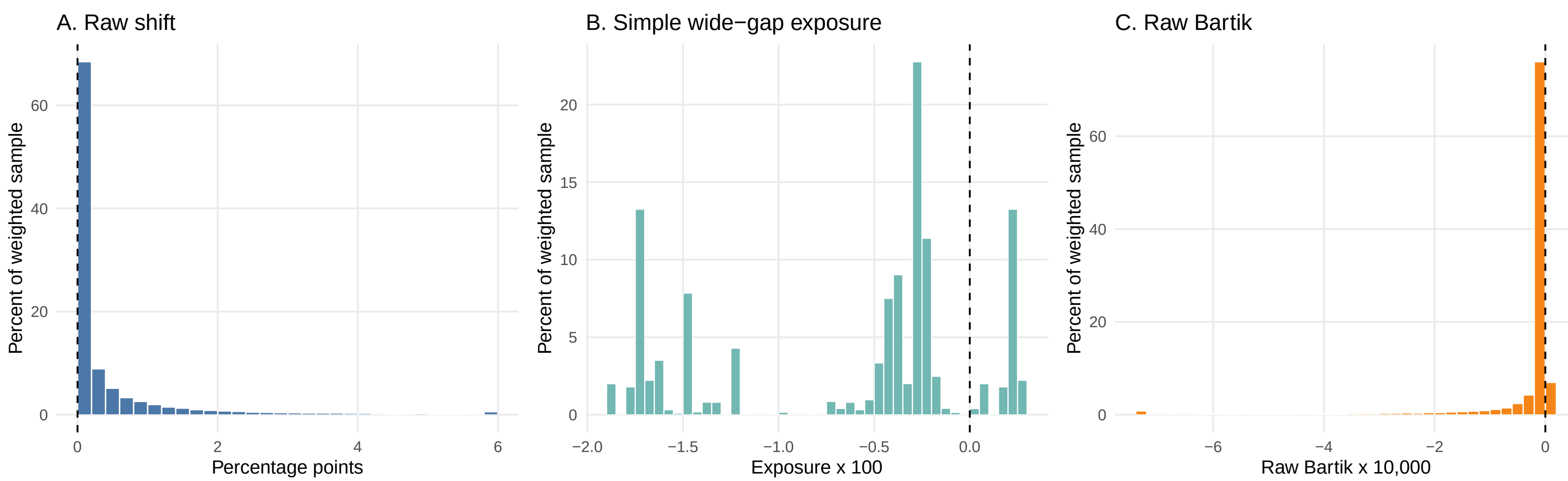

Figure A.2: Distribution of the Bartik instrument components

Notes. The figure plots the distribution of the local shift in Panel A, the simple bank exposure in Panel B, and the Bartik instrument in Panel C, weighted by lagged local mortgage loan count. The x-axes are restricted to be between the 0.5th and 99.5th percentiles for readability.

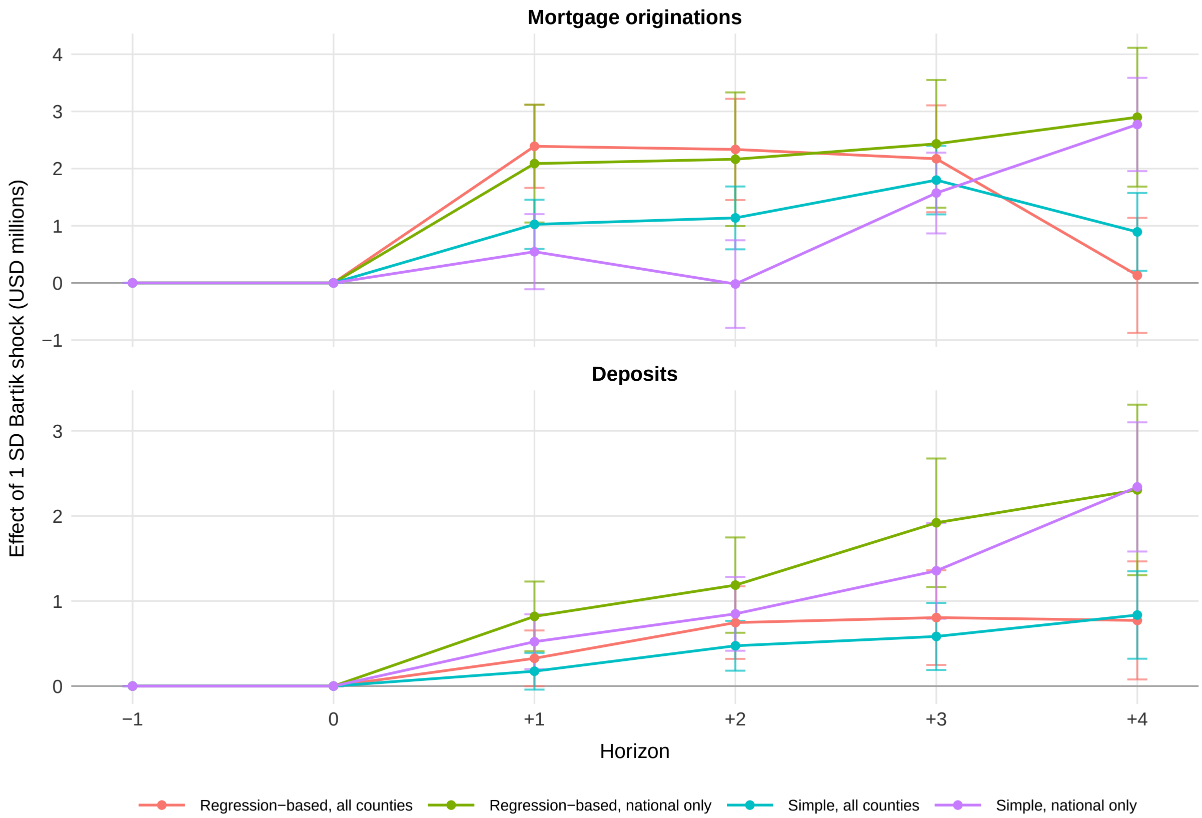

Figure A.3: Robustness: local projections with alternative bank exposure measure and sample

Notes. The figure plots the dollar response of mortgage origination volume and deposit volume to a one-standard-deviation increase in the Bartik instrument across four specifications. The specifications use the simple and regression-based exposure measures, each estimated in the all-counties sample and the national-only sample. All specifications use a five-mile radius to define the local mortgage market, restrict the estimating rows to 2017–2019, include bank-by-year and county-by-year fixed effects, use the benchmark VAR controls and lagged nearby loan-count weights, and cluster standard errors at the branch level. The simple all-counties series is our baseline specification. The point at horizon zero is normalized to zero and is plotted without a confidence interval. Error bars report 95 percent confidence intervals.

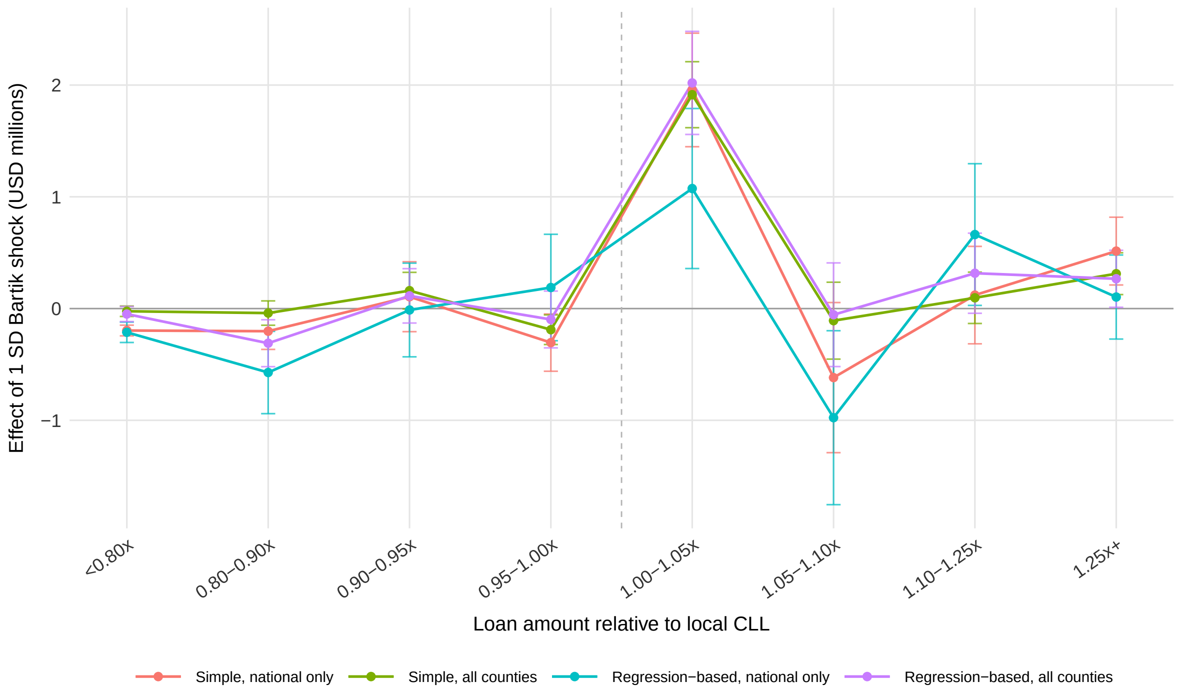

Figure A.4: Robustness: mortgage response is concentrated around the conforming threshold with alternative bank exposure measure and sample

Notes. The figure plots the dollar response of mortgage origination volume to a one-standard-deviation increase in the Bartik instrument across four robustness specifications. The four series combine two exposure measures, simple and regression-based, with two estimation samples, all-counties and national-only. In every specification, the outcome is the change in a bank's local lending share within loan-amount bins defined relative to the local CLL. All specifications use a five-mile radius to define the local mortgage market. The estimates restrict the sample to 2017–2019, include bank-by-year and county-by-year fixed effects, use the benchmark VAR controls and lagged nearby loan-count weights, and cluster standard errors at the branch level. The vertical dashed line marks the conforming threshold. Error bars report 95 percent confidence intervals.

Figure A.5: Pre-trend check in the national-only sample with alternative VAR lag specifications

Notes. The figure plots the dollar response of mortgage origination volume and deposit volume to a one-standard-deviation increase in the Bartik instrument. The horizontal axis reports the horizon of the outcome variable, mortgage or deposit growth, relative to the period of the Bartik instrument: negative horizons correspond to historical outcomes, while positive horizons correspond to future outcomes. Each specification includes the corresponding lagged VAR controls. The four colored series vary the number of lags included in the VAR controls. All specifications use the national-only sample, the simple bank exposure measure, a five-mile radius to define the local mortgage market, bank-by-year and county-by-year fixed effects, lagged nearby loan-count weights, and branch-level clustering. Error bars report 95 percent confidence intervals.

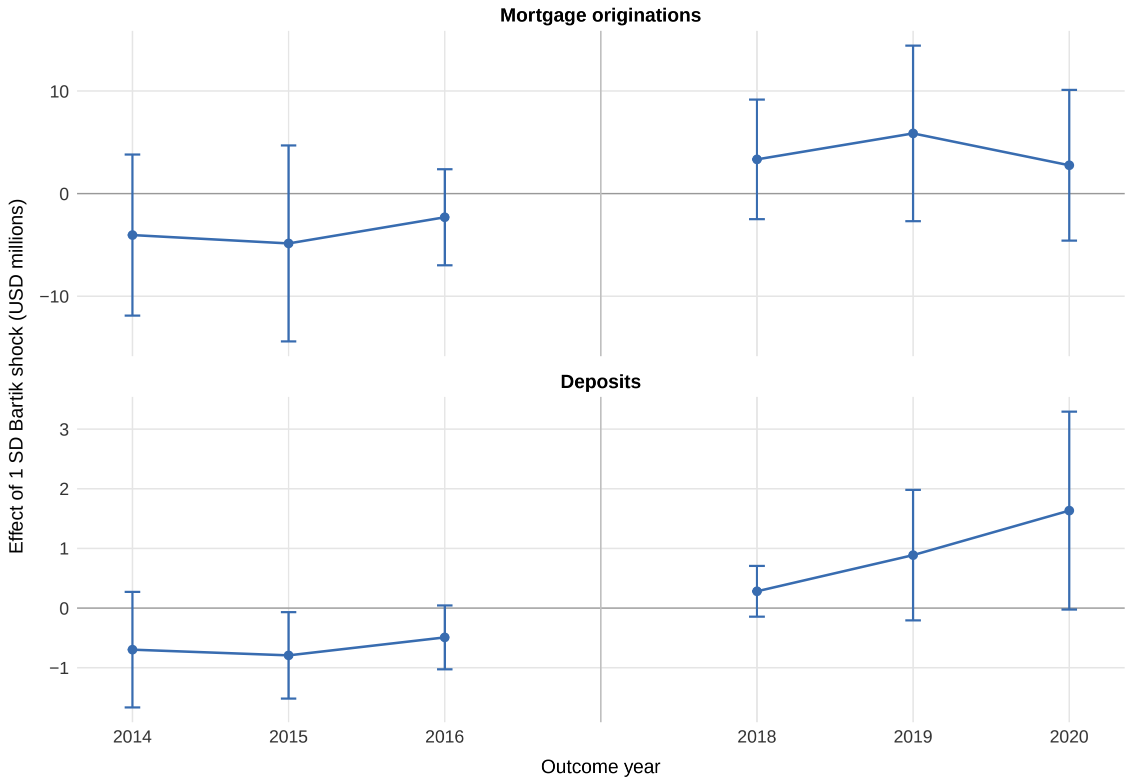

Figure A.6: Pre-trend check in the national-only sample with the 2017 Bartik instrument

Notes. The figure freezes the Bartik instrument at the 2017 level in the national-only sample and plots the dollar response of mortgage origination volume and deposit volume to a one-standard-deviation increase in the frozen Bartik instrument. The coefficients are estimated using the 2017 branch cross section, separately for pre-2017 placebo years, when the national CLL does not change, and post-2017 years, when the national CLL changes. The plotted series uses the regression-based bank exposure measure because it is more powerful than the simple bank exposure measure. The years before 2017 serve as placebo years before the national CLL starts to change. Error bars report 95 percent confidence intervals.

B. Data Construction

This appendix documents the data construction behind the benchmark reduced-form analysis. The benchmark combines a simple bank exposure measure with a leave-one-out local shift, uses the all-counties sample, and focuses on shock years 2017–2019 when the national CLL changes. The national-only sample is used as a comparison sample because its local loan-limit schedule is not tied to local high-cost formulas and because the flat national CLL from 2012 to 2016 provides natural placebo years.

B.1. Branch deposits and branch identifiers

Branch deposit balances come from the FDIC Summary of Deposits. The observation is a branch-year indexed by the FDIC branch identifier `uninumbr`. Deposits are measured as of June 30 and converted to dollars before taking logs. Annual deposit growth is the first difference of log branch deposits.

The canonical panel excludes any branch that ever records annual log deposit growth above 1.1 or below -0.5. These thresholds correspond to the 99th and the 1st percentiles of annual log deposit growth. The filter is intended to remove branches affected by mergers, sales, or internal bookkeeping changes rather than ordinary branch-level deposit variation. Because the screen is applied at the branch level, all observations for a flagged branch are dropped; this removes about 18 percent of branches and branch-year observations.

We do not impose minimum branch-deposit threshold. The filters are the branch-level deposit-growth screen described above, nonmissing branch, bank, local mortgage, CLL, and control variables needed for a given regression, and sufficient HMDA support outside the branch's own census division to construct the division-holdout exposure. Banks in the final sample are therefore large on average because multi-branch banks and banks with enough HMDA activity are more likely to survive the matching and exposure-support requirements.

B.2. HMDA mortgage originations

Mortgage originations come from HMDA. We use originated mortgage records and map HMDA lenders to RSSD identifiers so mortgage activity can be linked to Call Report banks and SOD branches. In pre-2018 HMDA files, the shift and outcome construction uses originated loans, one-to-four-family property records, and first or junior liens. In post-2018 files, it uses originated loans and purpose categories corresponding to purchase, home improvement, cash-out refinance, and non-cash-out refinance.

HMDA loan amounts are nominal dollars. Pre-2018 files report loan amounts in thousands, which we convert to dollars; post-2018 files report dollar amounts directly. The exposure measures use loan counts rather than loan volume. The mortgage outcomes in the local projections use the log of bank mortgage-origination volume around each branch.

B.3. Lender matching

For pre-2018 HMDA, respondent identifiers are mapped to RSSD identifiers using the HMDA lender crosswalk and, where available, an Avery-style pre-2018 mapping. When no direct crosswalk is available, respondent identifiers that appear to be RSSD identifiers are parsed as such. For post-2018 HMDA, lender LEIs are mapped to RSSD identifiers using the post-2018 lender file. The resulting RSSD is the bank identifier used in the bank×year fixed effects and Call Report merges.

B.4. Geographic construction of branch markets

HMDA does not identify the branch that originated a mortgage. Mortgage variables are therefore constructed as local bank-presence measures rather than branch-production measures. We use branch-ZIP crosswalks with branch-to-ZIP distance files for one-, two-, three-, four-, and five-mile radii. The benchmark uses the five-mile crosswalk. A ZIP can lie within five miles of multiple branches, so the same ZIP-level mortgage activity can enter multiple nearby branch markets. This construction matches the estimand, which is the deposit response at a branch associated with a lender's mortgage activity in the same local area, rather than a count of unique loans originated by that branch.

For the local shift construction, borrower tracts in HMDA are first normalized to a common tract vintage. Tract-year lending is then allocated through tract crosswalk weights and aggregated to branch markets through the branch-radius crosswalk. This construction yields both total nearby lending and focal-bank nearby lending for each branch-bank-year, which are then used to form leave-one-out measures.

B.5. Weights, fixed effects, and inference

All benchmark regressions use lagged local mortgage loan count as the regression weight. The preferred fixed effects are bank×year and county×year. Bank×year fixed effects absorb shocks common to all branches of a bank in a year. County×year fixed effects absorb county-level shocks and leave within-county differences across lenders. We cluster standard errors by branch.