Competition with Multidimensional Contracts*

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June 2, 2025

Abstract

How do lenders charge markups when setting interest rates and upfront fees? Using variation from bank mergers and lender failures, we find that local concentration increases fees in prepayable mortgages but rates in expensive-to-prepay mortgages. We estimate a structural model of multidimensional pricing. Differences in time-preferences create gains from intertemporal trade that favor rate markups, but lenders instead markup fees to reduce prepayment risk. The model rationalizes observed markups across markets and contract types. Optimal regulation caps fees, as prepayment risk limits lenders' ability to charge offsetting rates. In contrast, rate caps induce socially inefficient fees and reduce borrower welfare.

Keywords: Mortgages, market structure, local competition, bank merger policy, contract design.
JEL Classification Codes: G2, L5

*We thank Manuel Adelino, Neil Bhutta (discussant), John Cochrane, James Conklin (discussant), Kristle Cortés (discussant), Anthony DeFusco, Mark Egan, Marco Giacoletti (discussant), João Granja (discussant), Lars Peter Hansen, Erik Hurst, Erica Jiang (discussant), Arvind Krishnamurthy, Eric Posner, Benjamin Roth (discussant), Amit Seru, Philip Strahan, Amir Sufi, Robert Townsend, Paul Willen (discussant), and Anthony Lee Zhang (discussant), as well as numerous seminar participants at AREUEA, ASSA, Boston College, BFI Macro Finance Conference, Chicago Booth Household and Corporate Lending Conference, Colorado Finance Summit, Community Banking in the 21st Century: Research and Policy Conference, Conference on Market-Based Solutions for Reducing Wealth Inequality, Duke Fuqua, EFA, Federal Housing Finance Agency, MLEA, CLEA, ITAM, Michigan Young Scholars' Conference, Philadelphia Fed Conference on Credit Markets and the Macroeconomy, UConn Finance Conference, and WFA for their thoughtful comments and suggestions. We thank Awanti Acharya, Mitch Abdon, Daniel Bonneau, Jiajie Xu, and Song Zhang for excellent research assistance. We gratefully acknowledge funding from the Alfred P. Sloan Foundation, the Washington Center for Equitable Growth, and the Boston College Ignite Program.

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A vast body of work has documented a rise in market concentration and studied its impact on prices and markups (Autor et al., 2020; De Loecker, Eeckhout and Unger, 2020; Barkai, 2020). The literature typically abstracts away from heterogeneity in relation to pricing: most studies assume that each product has a one-dimensional price. While this is a reasonable assumption for soda or cereal, it is frequently violated in financial markets, where contracts often feature multidimensional pricing (e.g., having both an interest rate and an origination fee). Additionally, pricing dimensions interact with other contract features. For example, in loans with embedded optionality, such as prepayable mortgages and callable bonds, interest payments cease upon prepayment, and higher interest rates can, in turn, increase the risk of prepayment. In contrast, upfront fees are not subject to prepayment dynamics, since they are paid upfront. This raises the question of how lenders design multidimensional pricing contracts to strategically respond to variation in both local competition and prepayment risk.

We study this question in the context of the U.S. mortgage market. The Federal Reserve, which regulates mortgage market competition through merger approvals, has found little to no relationship between local mortgage market concentration and interest rates on standard fixed-rate mortgages with no prepayment restrictions. Consequently, it regards the market to be national in scope. As a result, its antitrust analysis treats local mortgage lending concentration as irrelevant for market power.[1] However, this prevailing approach focuses narrowly on interest rates and prepayable mortgages, and overlooks a longstanding idea in the theoretical literature: that more complex contract design can enable rent extraction (DellaVigna and Malmendier, 2004; Gabaix and Laibson, 2006; Bordalo, Gennaioli and Shleifer, 2013).

Our main result is that, contrary to a broad consensus among policymakers and in the academic literature, local mortgage concentration has a significant impact on mortgage pricing. In line with past studies, we find no consistent relationship between concentration and interest rates among standard, prepayable loans. However, we document a robust and economically meaningful relationship between concentration and upfront fees. The pattern reverses in loans with prepayment penalties that make prepayment more costly. Here, rates,

[1]Prior to 2008, the Federal Reserve considered mortgage markets to be geographically local. However, with the approval of Bank of America's acquisition of Countrywide, it declared the mortgage market to be "national in scope" (Federal Reserve System, 2008). The Fed reaffirmed this position in a later analysis of interest rates, stating: "we test for an empirical relationship between the local concentration of mortgage lending and changes in mortgage rates and find essentially no correlation," concluding that "local mortgage markets appear too unconcentrated . . . for the participants to have market power and the individual ability to affect prices" (Amel et al., 2018).

not fees, rise with local concentration. These findings are robust across multiple empirical strategies and confirmed using two independent instrumental variable (IV) approaches that capture both cross-sectional and time-series variation. Moreover, we find that the results are driven by lender-collected upfront charges, such as application and underwriting fees, that are unrelated to the rate-point pricing menu.

The empirical findings reveal a fundamental tradeoff in multidimensional loan pricing: lenders must balance intertemporal gains from trade against exposure to prepayment risk. The gains from trade arise because borrowers discount future payments more heavily than lenders or the ultimate investors. A higher interest rate (and lower fee) increases these gains, but also raises the likelihood that the borrower will refinance. Conversely, a higher upfront fee (and lower rate) reduces prepayment risk but limits the gains from trade.

With this tradeoff in mind, we build and estimate a dynamic structural model in which lenders with market power endogenously set rates and fees to maximize profits, subject to borrower prepayment risk. The model delivers equilibrium pricing regimes consistent with our empirical findings: when prepayment is cheap, lenders extract markups through fees; when prepayment is costly, markups shift to rates. Our estimated parameters suggest that the standard U.S. fixed-rate prepayable mortgages lie in an intermediate regime, where both dimensions are marked up. In this region, fee markups respond to local concentration, while rate markups respond only to variation in expected refinancing. The model thus rationalizes our reduced-form findings across loan types. It also clarifies that even when rates do not vary with local concentration, lenders still impose positive markups at the national level. We use the model to evaluate counterfactual pricing regulations. An interest rate cap—a common tool among regulators (Cuesta and Sepúlveda, 2021; Cherry, 2024)—inhibits intertemporal gains from trade, causes lenders to extract markups through higher fees, and reduces borrower welfare. In contrast, when fees are capped at marginal origination costs, lenders reallocate markups to interest rates. Because rates are a more competitive margin, disciplined by both competition and prepayment risk, total markups decline, and borrower welfare increases by approximately $250 per loan.

We begin our analysis with a simple ordinary least squares (OLS) framework to estimate how interest rates and upfront fees vary with local market concentration in standard fixed-rate prepayable mortgages. Our primary data source is the Home Mortgage Disclosure Act (HMDA), with the analysis relying critically on newly available information on upfront fees, which has been collected since 2018. Consistent with prior work, we find no systematic relationship between concentration and interest rates: the estimated coefficients are small, fluctuate in sign, and are economically negligible across specifications. That is, although lenders may earn markups on rates, those markups do not vary with local market power in prepayable loans. In contrast, we find a strong and robust relationship between market concentration and fees. Borrowers in more concentrated counties pay significantly higher upfront fees, even after controlling for detailed loan characteristics and including both lender and county fixed effects. For example, comparing the top and bottom deciles of the concentration distribution, average fees are 16 basis points higher, corresponding to more than $500 in additional costs for a typical loan in 2023.

We then examine loans with prepayment penalties, where prepayment is much less likely because refinancing entails a substantial cost for the borrower. In this setting, we observe a reversal in pricing behavior: local market concentration is associated with significantly higher interest rates, while the relationship with fees disappears. These results appear in our main HMDA sample, where loans with prepayment penalties are present but unusual after 2018. To strengthen this evidence, we turn to the Black Knight McDash dataset, which provides broader historical coverage and includes a much larger sample of loans with prepayment restrictions. In this sample, local concentration is associated with higher interest rates for mortgages with prepayment penalties, but not for standard prepayable mortgages. Together, we find that market concentration raises fees when prepayment is easy, and raises rates when prepayment is costly. This pattern suggests that the way lenders price mortgages depends not only on market structure but also on contractual features that affect a borrower's ability to refinance.

At its core, our analysis examines whether lenders exercise market power by charging rates or fees above marginal costs, and whether such markups vary systematically with market concentration. We observe the prices paid but not the marginal costs, and since price equals markup plus marginal cost, interpreting our regressions of prices on concentration as evidence of market power requires the assumption that concentration is conditionally uncorrelated with unobserved marginal costs. This is the key identification challenge: if marginal costs covary with concentration, then the estimated relationship between concentration and prices may attribute changes in unobserved costs to changes in markups. Our OLS specification controls for detailed loan characteristics, as well as lender, county, and time fixed effects. These absorb potential sources of bias such as differential lender entry into high-risk markets, targeting of specific borrower segments, or mechanical co-movement between aggregate interest rates and concentration. We further assess robustness using a merged HMDA-GSE sample that includes borrower FICO scores and the exact month of origination, both of which we control for directly. While we view the OLS evidence as credible, we complement it with two IV strategies to address any remaining endogeneity concerns: one that generates cross-sectional variation across counties and another that generates panel variation within counties over time.

Our first IV strategy, which is novel to the literature, exploits variation in the 2007 market share of lenders that failed during the 2008 financial crisis. Although many of these lenders were later acquired, their failures led to persistently lower market concentration, as successor firms never fully regained lost share. We show that even a decade later, counties with high failed-lender exposure remain significantly less concentrated than comparable markets, and that the induced differences in concentration are unlikely to be correlated with unobserved differences in marginal cost. Our second IV strategy uses bank mergers to capture changes in concentration. Following Dafny, Duggan and Ramanarayanan (2012) and Scharfstein and Sunderam (2016), we focus on counties where the merger had a meaningful local impact—because the merging banks held sizeable ex-ante market shares in that county—but that were unlikely to have driven the merger decision, because they accounted for only a small share of each bank's total lending. While the mergers themselves are endogenous, these local concentration changes are plausibly orthogonal to marginal cost. The panel structure of the instrument also permits the inclusion of county fixed effects, addressing residual concerns about unobserved geography-specific factors.

Both IV strategies yield results that reinforce our core empirical finding: the effect of market concentration on mortgage pricing depends on the prepayment risk embedded in the contract. For standard prepayable loans, we find no consistent relationship between concentration and interest rates, but a strong and statistically significant relationship with fees. In contrast, for loans with prepayment penalties—where prepayment is costlier and thus less likely—the pattern reverses, and concentration is associated with higher interest rates but not higher fees.

Motivated by these empirical findings, we build and estimate a dynamic structural model of multi-dimensional mortgage pricing with endogenous prepayment. We use the model to rationalize our reduced form findings and study the equilibrium impacts of counterfactually reducing pricing dimensionality. The model follows a borrower, who in the first period obtains a mortgage from imperfectly competitive lenders that set rates and fees to maximize expected profit. Without prepayment risk, lenders prefer to markup rates because they value future cash flows more than borrowers do. However, in subsequent periods the borrower can prepay the mortgage and terminate interest payments. In this case, a higher rate increases the likelihood of refinancing, while fees are realized immediately and do not affect refinancing. Endogenous prepayment risk therefore tilts optimal markups toward fees.

Borrower refinancing behavior is summarized by the "s-curve," which relates the contracted versus current rate differential to the probability of refinancing. A steep s-curve means that borrowers are more responsive to rate differentials, thus making rate setting more competitive from the lender's perspective. This slope is pinned down in our model by the fixed cost of refinancing and borrowers' rate sensitivity. We estimate these parameters by matching the model-implied s-curve to the empirical s-curve, matching it almost exactly. Remaining demand parameters come from the literature and mortgage-shopping data; lender marginal costs are recovered from the first-order pricing conditions.

We first use the estimated model to reconcile the contrasting patterns across standard prepayable mortgages and those with prepayment penalties. When the fixed refinancing cost is high, as with loans carrying prepayment penalties, refinancing is rare, and lenders extract rents almost entirely through higher rates. Local concentration therefore raises rates but leaves fees unchanged. With standard prepayable mortgages, the fixed cost is relatively low. In this pricing regime, both rates and fees are marked up. Rates are disciplined by their effect on future refinancing, while total markups inclusive of fee and rate income are disciplined by local concentration. As local concentration increases, the tradeoff on rate setting is unchanged, while optimal total markups increase. Therefore, lenders respond by increasing fees but leaving rates unchanged, mirroring the reduced-form results.

Next, we compare two counterfactual contract designs that cap fees to marginal origination costs (and allow rate markups), or cap rates to marginal funding costs (and allow fee markups). When capping fees, fees fall by roughly 75 basis points (bps) while rates rise by roughly 20 bps. This is not an innocuous shift, however. When marking up rates rather than fees, lenders face a more competitive dimension of pricing because higher rates increase borrowers' refinancing incentives. In consequence, annual refinance probabilities rise by roughly 2 percentage points, and effective lender markups fall by roughly 12% relative to the baseline. Consumer welfare increases by roughly \$250 for an average loan.[2] In contrast, when capping rates, markups shift to fees, refinancing falls, effective markups remain constant, and borrower welfare declines because intertemporal gains from trade are lost. Thus, our model emphasizes that there are potential gains to consumer welfare for reducing pricing

[2]Our welfare calculation is only on the intensive margin of lending and likely understates the effect due to changes in the extensive margin of period-one lending. As the policy leads to lower effective price (in utility terms), and the quantity effect can be large even for small changes in prices, as shown by Defusco, Johnson and Mondragon (2019), the all-in effect could be even larger.

dimensionality by increasing competition. However, the dimension on which lenders are allowed to compete matters: Rates are a consumer-welfare improving dimension because they facilitate gains from trade and are a more competitive pricing margin.

In the final part of our paper, we evaluate the political and regulatory implications of our results. In the U.S. mortgage market, the Federal Reserve has fairly direct control over local mortgage lender concentration, as existing banking regulations allow them to approve or deny bank mergers. Our analysis shows that lender concentration is a significant factor in mortgage pricing, with high concentration enabling large transfers from borrowers to lenders. Taken together, our results imply that it is critical for policymakers to account appropriately for lender concentration in local mortgage markets.[3]

Currently, however, the role of local concentration is neglected in the regulation of the U.S. mortgage market. That is, when evaluating a merger between two financial institutions, regulators do not consider whether the merger will increase concentration in local mortgage markets. There are two reasons for this. First, the prevailing view among both academics and regulators is that local concentration has no significant influence on mortgage pricing. This view is based on a long literature studying mortgage interest rates for standard prepayable mortgages. However, as we emphasize in this paper, mortgage pricing is multidimensional and the choice of markups across pricing dimensions interact with the contractual features of the mortgages.

The second reason for the neglect of local concentration is the widespread view that deposit market concentration and mortgage market concentration are correlated, so that regulations policing the former will automatically control the latter (Federal Reserve System, 2021). This view is based on the assumption that financial institutions cleanly "bundle" their products—that is, that for banks offering multiple products (such as deposits and mortgage lending), it suffices to evaluate concentration in just one of the product markets. The bundling assumption was reasonable in the early and mid-1990s; however, as we show in this paper, local deposit markets and local mortgage markets have since diverged, and there is no longer any strong relationship between their concentrations.

Thus, our results highlight an important academic and regulatory gap: local mortgage concentration *does* affect mortgage pricing, but along dimensions that previous studies have

[3] We find that high lender concentration disproportionately increases costs for unsophisticated borrowers (in particular, for low income borrower and those with low credit scores) is of particular interest as the Federal Reserve begins to consider its policies in terms of their impact on inequality. See, for example, the speech "Monetary policy and inequality" by Ben S. Bernanke, former Chairman of the Federal Reserve (https://www.brookings.edu/blog/ben-bernanke/2015/06/01/monetary-policy-and-inequality/).

overlooked. Specifically, we show that the effect of concentration depends on the prepayment risk embedded in the contract. For standard prepayable loans, local market power manifests through higher fees, while interest rates remain unaffected. In contrast, when prepayment is costly–as in loans with prepayment penalties–concentration is associated with higher rates, not higher fees. Moreover, the regulation of deposit market concentration no longer adequately addresses mortgage market concentration, as deposit and mortgage markets are now largely unbundled. Local mortgage concentration therefore needs to be a first-order consideration in both the study and the regulation of mortgage lending in the United States.

Relationship to the Literature

The main contribution of our paper is to examine how firms use multidimensional pricing to exert market power when facing both market competition and contractual prepayment risk. We study this question in the context of the U.S. mortgage market, and our paper is closely related to a set of papers studying the impact of lenders' market power. It has been documented that lenders exercise market power to set mortgage interest rates; see, e.g., Bhutta, Fuster and Hizmo (2024) (which examines price dispersion) and Buchak et al. (2024) (which provides structural estimates of rate markups). Lender markups translate into significant costs for borrowers: Fuster, Lo and Willen (2024) estimate that the price of residential mortgage intermediation was roughly 142 basis points between 2008 and 2014, and market power has important implications for the transmission of monetary policy; see, e.g., Xiao (2020) and Wang et al. (2022).

While there appear to be lender markups on interest rates *in aggregate*, as noted earlier, *local variation in concentration* is seen by regulators and policy makers as largely irrelevant in contributing to mortgage lenders' market power. Specifically, the Federal Reserve considers mortgage markets to be national in scope because they find little to no relationship between local concentration and interest rates (Federal Reserve System, 2008; Amel et al., 2018). The assumption that mortgage markets are national in scope aligns with prior work in the academic literature on standard prepayable mortgages, where estimates of the relationship between local concentration and interest rates range from no effect to a small, positive relationship.[4]

[4]For example, Fuster et al. (2013) study the gap between primary and secondary mortgage rates and argue that overall concentration in the national market alone seems unlikely to explain profits; Scharfstein and Sunderam (2016) have found that increased local concentration leads to reduced pass-through of MBS rates to origination rates for consumers, while Amel et al. (2018) argue that there are no differences. Bhutta, Fuster and Hizmo (2024) study a sample of *locked* mortgages and find a positive relationship when interacting

Our central contribution, and departure from prior work, is to move beyond interest rates and examine how lenders use upfront fees to exert market power—and how the choice between pricing margins varies with prepayment risk. The data necessary to examine fees at large scale in the U.S. mortgage market has only recently become available, so few papers have addressed this topic. Two related papers, those of Liu (2019) and Benetton, Gavazza and Surico (2025), examine lender pricing strategies across both fees and rates in the U.K. mortgage market. These papers, like ours, find a non-trivial tradeoff in setting rates and fees, although due to the structure of the U.K. market, they do not specifically tackle the question of local market concentration in relation to pricing.[5]

Our empirical and theoretical analyses show that contractual prepayment risk plays a central role in determining the margin—rates or fees—along which lenders exercise market power. This finding builds on a growing literature demonstrating that contractual variation in mortgage design can influence both borrower behavior and broader macroeconomic dynamics. For example, Mayer, Piskorski and Tchistyi (2013) show that prepayment penalties can improve welfare for risky borrowers by lowering interest rates and reducing defaults, while Beltratti, Benetton and Gavazza (2017) document how prepayment penalties affect prepayment, pricing, and borrower selection in the Italian mortgage market.

In addition to contractual differences, prepayment risk is often related to the borrowers' (lack of) financial sophistication (Woodward and Hall, 2012; Agarwal, Rosen and Yao, 2016; Keys, Pope and Pope, 2016; Agarwal, Ben-David and Yao, 2017; Andersen et al., 2020; Jørring, 2024), and a set of recent papers illustrates how firms across various financial markets often tailor their products to exploit consumers' lack of financial sophistication (Gurun, Matvos and Seru, 2016; Agarwal, Chomsisengphet and Lim, 2017; Célérier and Vallée, 2017; Egan, 2019). (We capture this effect in our model by allowing for differential salience of

concentration with a measure of sophistication, suggesting that local competition is helpful primarily for sophisticated borrowers. Fuster, Lo and Willen (2024) study rate sheet data from 2008 to 2014 and find that, within a specific market, interest rates do not vary with time-series variation in local concentration. In contrast, Ratnadiwakara and Yerramilli (2020) argue that local concentration does matter for interest rates, finding that following bank mergers, acquiring banks increase their interest rates. Relatedly, Hurst et al. (2016) show that interest rates for conforming loans do not vary with regional differences in credit risk and Granja and Paixão (2019) find that banks price deposits uniformly across branches.

[5] Another strand of the literature has examined the interaction between market concentration and non-price attributes and outcomes, even outside the primary market; see, e.g., Cetorelli and Strahan (2006) (firm entry), Ho and Ishii (2011) (branch network and distance traveled), Sharpe and Sherlund (2016) (lending capacity constraints), Favara and Giannetti (2017) (liquidation of collateralized debt), Di Maggio, Kermani and Korgaonkar (2019) (prepayment penalty terms), Begley and Purnanandam (2020) (product quality, incidence of fraud), Saidi and Streitz (2020) (markups in product markets), and Yannelis and Zhang (2021) (the interaction of loan screening and competition).

rates and fees.) Relatedly, a number of recent papers study the effect of competition and consumer sophistication in the auto-loan market (Low et al., 2020; Hankins, Momeni and Sovich, 2023; Momeni, 2024). Finally, while our findings are not driven by the rate–point menu, prior work—including Stanton and Wallace (1998), Bhutta and Hizmo (2020), Willen and Zhang (2022), and Zhang (2024)—has shown that this margin plays an important role in shaping borrower outcomes and distributional effects.

Our paper proceeds as follows. In Section 1, we describe our datasets and key variables. Section 2 presents our reduced-form methodology and results. In Section 3, we build, estimate, and apply our structural model. In Section 4 we discuss the regulatory implications of our results, and Section 5 concludes.

1 Data and Key Variables

We combine several standard datasets used in the mortgage and banking literature. In this section, we present these datasets and describe how we measure the key variables for our analysis: mortgage lender concentration, interest rates, and fees.

1.1 Data

Home Mortgage Disclosure Act: Our main data source is the mortgage-level application and acceptance data collected under the Home Mortgage Disclosure Act (HMDA), which covers the near universe of U.S. mortgage applications. The HMDA data, used extensively in the literature, includes lender identification, application outcome, and loan type, purpose, size, year of origination, and location at the census tract level. Since 2018, HMDA has recorded several further variables that are key in our analysis: loan interest rate, non-interest-rate charges (including origination charges, discount points, and lender credits), loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio. Consequently, our study centers on the years 2018 to 2023. Table 1 presents high-level summary statistics.[6]

[6] In our baseline sample, we follow the literature and restrict attention to 30-year, conventional, first-lien mortgages originated for the purchase of owner-occupied single-family homes. We exclude government-insured loans—such as FHA, VA, FSA, and RHS mortgages—as well as mortgages with "exotic" features, including reverse mortgages, open-end lines of credit (e.g., HELOCs), interest-only structures, prepayment penalties, introductory-rate periods, balloon payments, or other non-amortizing terms. These restrictions ensure that our sample is comparable to those used in prior studies. By focusing on conforming loans—those eligible for credit guarantees from the GSEs (Fannie Mae and Freddie Mac)—we also avoid concerns about unobserved heterogeneity in borrower credit quality driving pricing differences. In subsequent analyses, we relax these restrictions as needed: for instance, we include loans with prepayment penalties when studying

Fannie Mae and Freddie Mac single-family loan origination and performance data: Fannie Mae and Freddie Mac provide information on the GSEs' portfolios of 30-year single-family conforming fixed-rate mortgages. As with the HMDA sample, we restrict the sample to 30-year mortgages originated for purchases of owner-occupied homes. These loans are fully amortizing, prepayable, and have full documentation. The loan-level origination dataset provides interest rates, FICO scores, LTVs, and DTIs, as well as loan size, type, purpose, and location. It also identifies the originator that sold the loan to the GSE in cases where the originator had sufficiently high origination market share in the reporting period.

In part of our analysis, we merge the HMDA dataset with the GSE dataset. For this merged sample, we observe the credit score and month of origination. We match the HMDA and GSE datasets using the following conservative procedure. We first restrict the GSE loans to those matching the criteria listed above for the HMDA loans (i.e., loans for the purchase of owner-occupied homes, etc.). We then match loans on location (state, metropolitan statistical area, and ZIP Code), the exact loan amount and interest rate, and the purchaser type (i.e., Fannie Mae or Freddie Mac). To ensure the highest-quality match, we exclude all loans with duplicate observations, and we match without replacement.

Black Knight McDash Analytics: Black Knight is a private company that has created a loan-level mortgage dataset covering loans serviced by the ten largest mortgage servicers in the United States. This dataset is similar to the GSE dataset in content (it includes similar loan-level origination and performance variables). The Black Knight dataset complements the HMDA and GSE datasets chiefly by providing borrower FICO scores and performance measures for markets beyond conforming agency loans. Specifically, for our analysis it complements the GSE dataset by providing data on mortgages with prepayment penalties.

Supplemental data: We supplement the datasets on mortgages with a number of additional data sources that are commonly used in the literature. At the county-year level, we collect demographic variables, unemployment rates, and conforming mortgage loan limits from the American Community Survey, the Bureau of Labor Statistics, and the Federal Housing Finance Agency, respectively. At the lender-year level, we collect RSSD lender identifiers from the Federal Reserve Board, bank branch deposit data from the FDIC's Summary of Deposits, and bank merger data from the Federal Financial Institutions Examination Council. Finally, we use spatial crosswalks provided by the Department of Housing and Urban Development.

prepayment risk, and we incorporate FHA loans and refinances when examining heterogeneity across loan types.

1.2 Key Variables

Having described our data, we now describe how we measure the key variables for our empirical analysis: mortgage lender concentration, interest rates, and non-interest-rate origination fees. In the Online Appendix Section C we present aggregate facts and time-series trends concerning these variables.

Concentration: We use two standard measures of concentration: the Herfindahl–Hirschman index (HHI) and the concentration ratio of the top τ lenders in a market (CRτ). Markets are considered at the county-year level. With s_{jct} denoting the market share of lender j in county c at year t, the HHI and the CRτ are defined as

$$HHI_{ct} = \sum_{j \in J(c,t)} s_{jct}^2, \tag{1}$$

$$CR\tau_{ct} = \sum_{j \in J^\tau(c,t)} s_{jct}, \tag{2}$$

where $J(c,t)$ is the set of lenders that originated a loan in county c in year t, and $J^\tau(c,t)$ is the set of the top τ lenders by origination market share. In our baseline analysis, we follow the literature and set $\tau = 4$ (in unreported results, we find consistent estimates for $\tau = 2$, 6, and 8). In the Online appendix Section C.I we describe time-series and cross-sectional patterns of mortgage concentration.

Interest Rates: The interest rate on the mortgage loan is observed in the HMDA data from 2018 and onwards. In the Online Appendix Section C.II we describe aggregate facts on the distribution of interest rates.

Non-interest Fees: The HMDA dataset includes data on multiple sources of non-interest fees that borrowers pay up front as part of the closing process. A portion is paid to the lender, while the rest goes to third parties (e.g., appraisals and title insurance). Fee data is collected on a standardized form, mandated by the Consumer Financial Protection Bureau (CFPB), that lenders must fill out after loan origination. (See Figure A3 for an example.) Our measurement uses four underlying variables: Origination charges, Discount points, Lender credits (essentially negative points, which are reported separately from other quantities), and Total loan costs. Non-interest fees that accrue to the lender are Origination charges less lender credits;[7] Non-interest fees that accrue to third-parties are Total loan costs

[7] Origination charges already include discount points. We subtract lender credits as they reduce the fee that the borrower pays.

less Origination charges:[8]

$$\text{Lender fees} = \text{Origination charges} - \text{Lender credits}. \tag{3}$$

$$\text{Third-party fees} = \text{Total loan costs} - \text{Origination charges}. \tag{4}$$

In part of the analysis, we follow Bhutta, Fuster and Hizmo (2024) and restrict our sample by only studying fees for loans with zero discount points and zero lender credits.[9]

2 Reduced Form Evidence

In this Section, we describe our empirical methodology and present our reduced form evidence on the impact of local concentration on mortgage pricing.

2.1 Empirical Design

We are interested in whether local lender concentration leads to higher markups on rates and/or fees. We observe prices but not markups or marginal costs, so interpreting regressions of prices on concentration as informative about markups requires that concentration be conditionally uncorrelated with unobserved costs. Our central identification concern is therefore isolating variation in concentration that is orthogonal to marginal costs.

2.1.1 Baseline OLS Specification

In our main specification, we regress interest rates and fees on measures of concentration at the loan level as follows:

$$Y_{ibct} = \beta Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_b + \gamma_c + \gamma_t + \epsilon_{ibct}, \tag{5}$$

where $Concentration_{ct-1}$ is the one-year lagged county-year measure of concentration, either $CR4_{ct-1}$ or HHI_{ct-1}, and the rest of the model is as specified earlier. The coefficient of interest is β, which captures the effect of an increase in the lagged concentration for loans

[8] We do not subtract Lender credits because they are not included in either Total loan costs or Origination charges. Note also that the HMDA dataset includes a fifth variable, called "Total Points and Fees," which appears to be a legacy variable unrelated to the standard CFPB closing cost disclosure form. We have excluded this variable from the analysis, because it is missing from more than 99.7% of the observations.

[9] Section C.III in the Online Appendix provides details on the distribution of fees for the full sample and for the sample of loans wit zero points and credits.

with similar credit risk, originated by the same lender, in the same county, and in the same year.

The loan-, county-, and year-level controls, together with the set of fixed effects in (5), capture many concerns related to differences in observable loan costs. Any remaining contaminating variation would have to reflect within-county, across-time differences in costs that are correlated with lender concentration. One possibility is that higher variable costs of serving borrowers lead fewer—or more specialized—lenders to enter, who then charge similar markups but higher rates over a baseline of higher marginal cost. This would bias the OLS estimates upward. Another possibility is that markups vary across lenders, and that low-cost lenders gain larger market shares while charging similar markups. In this case, concentration would be mechanically higher in low-cost markets, biasing the OLS coefficients downward. A priori, it is not obvious which direction the bias would go. To address these concerns, we implement two IV strategies that generate variation in lender concentration plausibly orthogonal to unobserved marginal costs.

2.1.2 IV Specifications

We implement two independent instruments for lender market concentration: the 2007 market share of certain lending institutions that failed in the 2008 financial crisis, and the occurrence of bank mergers. The first instrument generates cross-sectional variation across counties, and the latter generates panel variation. As we will show, while exploiting conceptually distinct sources of variation, the instruments are both highly relevant and deliver consistent results.

Failed Lenders: Our first IV design, which is novel to the literature, uses the market share of lenders that failed 2007 as an instrument for variation in concentration. The IV specification mirrors our baseline OLS specification:

$$Y_{ibct} = \beta \widehat{Concentration}_{ct-1}^{Failed\ Share} + \eta' X_i + \mu' X_{ct} + \gamma_b + \gamma_t + \gamma_s + \epsilon_{ibct}. \tag{6}$$

The failed lender instrument is relevant because the market shares of *other* lenders are highly sticky. Although many of the failed lenders were eventually acquired by competitors, their failures resulted in persistently lower market concentration, as successor firms never fully regained lost market share. The F-statistics in our regressions confirm this persistent effect.[10]

Instrument exogeneity relies on the fact that the economic forces that drove the 2008 failures are not related to unobserved variation in lender marginal costs during our sample period. Given the dramatic structural changes in credit provision following the crisis, such as the collapse of private-label securitization, these induced differences in lender concentration are unlikely to be correlated with unobserved differences in marginal cost a decade later. Indeed, we find that the 2007 failed lender shares are uncorrelated with the presence of contractual features typical of pre-financial crisis mortgage origination in our sample period.

To further address potential concerns that failed-lender shares may be correlated with unobserved borrower characteristics, in our baseline analysis, we focus on the 2007 market share of a single institution: Wachovia. As documented by Mondragon (2020), Wachovia was a healthy lender before the crisis that failed due to provisions and expected losses from the acquisition of Golden West Financial Corporation—a lender with a large portfolio of toxic option adjustable-rate mortgages (ARMs). Consistent with the predictions of Mondragon (2020), we find no correlation between Wachovia's 2007 market share and the share of high-risk borrowers in that year—and, importantly for our identification strategy, no correlation with high-risk borrower shares during our sample period (see Figure A5).

Finally, to ensure there is nothing special about Wachovia driving our results and affecting external validity, we also employ our Failed Lender IV using two other lenders who failed during the financial crisis: Countrywide and Washington Mutual. In contrast with Wachovia, both Countrywide and Washington Mutual failed precisely because of low credit standards.[11]

Incidental Bank Mergers: Our second IV analysis uses bank mergers in non-central markets as an instrument for market concentration. The IV specification is:

$$Y_{ibct} = \beta \widehat{Concentration}_{ct-1}^{Merger} + \eta' X_i + \mu' X_{ct} + \gamma_b + \gamma_c + \gamma_t + \epsilon_{ibct}. \tag{7}$$

Notice that for this instrument (unlike the failed lender instrument) we include a county fixed effect. This means we are estimating the effects of concentration using panel variation in within-county concentration.

The key empirical challenge is that mergers are not random. We therefore follow the

[10]For this instrument we cannot include a county fixed effect, since the failed lender share is constant for each county. We do, however, include a state fixed effect, γ_s. In other words, we are estimating the effect based on cross-sectional variation within each state.

[11]See Figures A6 and A7 for Countrywide and WaMu correlations, and see Section E.II for robustness tests showing that the estimates are consistent across varying thresholds and specifications.

procedure of Dafny, Duggan and Ramanarayanan (2012) and Scharfstein and Sunderam (2016) to construct a sample of counties that have been affected by bank mergers, but that are unlikely to have been the key motivation for the mergers. Our approach is as follows.

We start with the list of bank mergers provided by the National Information Center at the Federal Financial Institutions Examination Council. We exclude government-assisted bank failures and keep only mergers or acquisitions in which the predecessor transferred all of its assets to the successor. For each merger involving two financial institutions that originate mortgages, we identify the counties in which both parties had a non-zero market share in the year prior to the merger. (More than 95% of the counties in the sample appear in at least one merger.) Then we isolate counties where the merger increased concentration, but where this increase, while substantial, would likely have been *incidental* (and not a key motivation for the merger).[12] In total, we identify 144 counties where a merger incidentally increased concentration. For these counties, we estimate the difference between fees paid before the merger and fees paid afterward, as a function of the change in concentration (conditional on other observable characteristics).[13]

2.2 OLS Results

We begin by confirming that, as established in the prior literature, there is little to no relationship between local concentration and interest rates for standard prepayable loans.

Table 2, Panel A, presents OLS regressions of interest rates on local concentration. We estimate four sample variations: (i) full HMDA, (ii) merged HMDA-GSE, (iii) zero-point loans, and (iv) a merged and restricted sample. In seven of eight cases, the coefficient on concentration is statistically insignificant and economically small. The only exception is a negative estimate in the full HMDA sample using CR4. The model places tight bounds on the effect of concentration on interest rates. In the most saturated specification, a one-standard-deviation increase in CR4 is associated with a change in rates between -0.007 and $+0.007$ percentage points at the 95% confidence level. A similar range holds when using HHI

[12] Specifically, following Scharfstein and Sunderam (2016), we identify counties where each of the banks involved in the merger was responsible for more than 1% of the total mortgage originations in the county, but the county itself contributed no more than 2% of each bank's mortgage originations in the year before the merger. They use deposit concentration to measure the impact of mergers because they cannot link bank mergers to HMDA identifiers prior to 2010, but this is not a problem in our setting since the CFPB provides bank identifiers from 2018 onwards. In Section E, we show that our results are robust to changing the thresholds.

[13] Section E.I provides an illustrative example.

as the concentration measure.[14]

We now turn to our main result, on upfront fees. As reported in Table 2, Panel B, while there is essentially no relationship between concentration and interest rates, we find a large and significant relationship between concentration and fees. The coefficient in Column (7) of Panel B, which corresponds to the most saturated model, implies that an increase in CR4 from 0 to 1 leads to a 0.15-percentage-point increase in fees. (Or, equivalently, every one-percentage-point increase in CR4 leads to a 0.15-basis-point increase in fees.)

Figure 1 shows the main results graphically in a binned scatterplot. The y-axis gives the interest rate residual (in Panels A and B) and fees residual (Panels C and D), while the x-axis gives lagged market concentration residual. The first row corresponds to Columns (3) and (7) in Table 2 Panel A, while the second row corresponds to Columns (3) and (7) in Table 2 Panel B. Observe that the relationship between concentration and fees is much stronger than the relationship between concentration and interest rates; moreover, the relationship does not appear to be driven specifically by points.[15]

2.3 IV Results

Table 3 reports results from our two IV strategies: failed lender exposure (Cols. 1–4) and incidental bank mergers (Cols. 5–8). Both instruments are strong predictors of market concentration. In the first stage, a one-percentage-point increase in Wachovia's 2007 market share predicts a 0.23-point drop in CR4 (F-statistics: 25 and 19 for CR4 and HHI), while an incidental merger increases CR4 by four percentage points (F-statistics: 20 and 31). In the second stage, none of the four specifications reveal a significant relationship between concentration and interest rates—two coefficients are positive, two are negative, and all are statistically indistinguishable from zero. As discussed above, these findings are consistent with prior literature that finds no consistent evidence (Amel et al., 2018; Fuster, Lo and Willen, 2024; Ratnadiwakara and Yerramilli, 2020; Bhutta, Fuster and Hizmo, 2024), and

[14]These bounds are based on Column (7), where the coefficient is 0.001 and the standard error is 0.019. Applying ± 2 standard errors and multiplying by the standard deviation of CR4 (0.18) yields a range of [–0.0067, 0.0070]. For HHI, the corresponding range is [–0.0013, 0.0107].

[15]Borrowers often trade discount points or lender credits for interest rate adjustments (Stanton and Wallace, 1998; Bhutta and Hizmo, 2020; Willen and Zhang, 2022; Zhang, 2024), but this tradeoff does not drive our main results. Estimates remain similar when restricting to loans with exactly zero points and credits, as in Bhutta, Fuster and Hizmo (2024). We provide additional evidence in the Online Appendix by controlling directly for rate–point combinations (Sections D.I and D.IV). Separately, a placebo test shows that local concentration has no effect on third-party fees, indicating that our results are not driven by broader geographic or borrower-specific pricing differences (Section D.II).

reinforce our conclusion: for standard prepayable loans, local concentration does not materially affect interest rates.

Turning to upfront fees, we find that local concentration has a large and statistically significant effect across both instruments. A one-percentage-point increase in instrumented CR4 raises fees by 2.8 basis points using the failed lender instrument and by 1.1 basis points using the bank merger instrument, with similar results when using HHI.[16] Translating these effects, a one-standard-deviation increase in CR4 or HHI raises average fees by 19 and 47 basis points, respectively—implying \$650 to \$1,600 in additional costs per borrower. As a back-of-the-envelope aggregation, this corresponds to an annual transfer of \$6 to \$14 billion from borrowers to lenders.[17] We also estimate the impact on lenders' total expected returns: using the merger IV, a one-standard-deviation increase in CR4 increases the present value of lender profits by 24 basis points per dollar lent, with over three-quarters of the gain driven by higher fees.[18]

2.4 Does Mortgage Pricing Depend on Prepayment Risk?

Having established that local market concentration raises fees but not rates for standard prepayable mortgages, we now examine the economic mechanism behind this result. First, we show in the HMDA data that the pattern reverses for mortgages with prepayment penalties: concentration increases interest rates, while the relationship with fees disappears. Second, we show that this difference in pricing behavior is statistically significant, using both OLS and IV specifications. Finally, we confirm the result using the McDash dataset, which contains a much larger sample of loans with prepayment penalties.

The Effect of Concentration on Mortgages with Prepayment Penalties: Panel A of Table 4 shows OLS estimates for loans with prepayment penalties. To mirror the analysis of prepayable loans, Columns (1)–(4) use the full sample; Columns (5)–(8) restrict to loans with zero points and credits. Across both samples, we find a consistent shift in pricing behavior relative to standard prepayable loans: concentration is positively and significantly associated with interest rates (Cols. 1–2, 5–6), but shows no significant relationship with fees (Cols. 3–4, 7–8). These results suggest that when prepayment is contractually limited,

[16] The IV coefficients exceed their OLS counterparts, consistent with measurement error attenuation or endogenous concentration being associated with unobservably low-cost markets. Both IV strategies help address these concerns. See Appendix E for additional robustness checks.

[17] CR4: $0.18 \times 1.080 \times 3.07$T=6.0B. HHI: $0.10 \times 4.735 \times 3.07$T=14.6B.

[18] See Appendix D.III for the total return calculations.

lenders in concentrated markets extract markups through rates rather than fees—reversing the pattern found in prepayable mortgages.

Comparing The Effect of Concentration by Prepayment Risk: In Panel B of Table 4, we present the results from a formal test of whether the effect of local market concentration differs by prepayment risk. The sample pools loans with and without prepayment penalties and estimates a difference-in-differences (DID) specification that includes both a dummy for the presence of a prepayment penalty and its interaction with the concentration measure (CR4 or HHI). The estimating equation is:

$$\begin{aligned} Y_{ibct} = {} & \beta_1 Concentration_{ct-1} + \beta_2 Penalty_i + \beta_3 (Concentration_{ct-1} \times Penalty_i) \\ & + \eta' X_i + \mu' X_{ct} + \gamma_b + \gamma_c + \gamma_t + \epsilon_{ibct} \end{aligned} \tag{8}$$

where $Penalty_i$ is an indicator for whether loan i includes a prepayment penalty. The rest of the notation follows the baseline OLS specification in Equation (5).

Columns (1)–(4) of Table 4 report OLS estimates; Columns (5)–(8) report IV estimates. In both sets of regressions, the interaction terms show a consistent pattern: concentration has a significantly stronger effect on interest rates (Cols. 1–2, 5–6) and a weaker effect on fees (Cols. 3–4, 7–8) when prepayment penalties are present. These results confirm that the pricing margin through which lenders exercise market power depends on prepayment risk.

Extending the Analysis using Historical Data: Recognizing that mortgages with prepayment penalties are relatively rare in our baseline HMDA sample (2018–2023), and that this may lead to unstable estimates, we turn to the Black Knight McDash dataset to validate our findings in a larger and more historically representative sample. Panel C of Table 4 reports estimates from both the baseline OLS specification and the difference-in-differences model. Columns (1)–(2) show that for loans without prepayment penalties, concentration has no significant effect on interest rates. In contrast, Columns (3)–(4) show a strong and significant positive effect for loans with prepayment penalties. Columns (5)–(6), which pool both groups and estimate the DID model, confirm this contrast: the interaction terms are positive and significant, indicating that the effect of concentration on pricing is substantially larger when prepayment is contractually limited. These results replicate the HMDA patterns and reinforce the conclusion that lenders adjust the pricing margin in response to both market structure and the borrower's ability to refinance.

3 A Structural Model of Multi-Dimensional Pricing

Motivated by the facts above, we build and estimate a dynamic structural model of multidimensional mortgage pricing. We use the model for two purposes. First, we rationalize the empirical finding that greater lender concentration increases fees but not rates for standard prepayable mortgages, while doing the opposite when prepayment penalties apply. Second, we measure the welfare and distributional effects of counterfactually simplifying mortgage contracts by capping rates or fees. The remainder of this section proceeds as follows: we describe the model, outline the estimation approach, highlight the key economic forces, and conclude with counterfactual simulations.

3.1 Model description

In period one, a borrower chooses among J differentiated lenders, each offering a (nominally) perpetual, fixed rate, prepayable mortgage characterized by an interest rate and a one-time origination fee. In subsequent periods, the borrower has the ability to refinance to a new mortgage, and may do so repeatedly. The rate to which he can refinance is stochastic, and the borrower incurs a fixed cost each time he refinances. The J period-one lenders engage in differentiated Bertrand competition, choosing rates and fees to maximize lifetime expected profits while anticipating competition from other lenders and future refinancing. We do not explicitly consider lender entry/exit, but in robustness checks we show that this margin is unlikely to be quantitatively important in our results. As our setting primarily concerns GSE-guaranteed mortgages, the lender (and implicitly, the purchaser of the originated mortgage) faces prepayment risk, but not credit risk. Our focus is on the period-one fee and rate setting decision and how it shapes later refinancing and borrower welfare. We map the model to our reduced-form results by varying the refinance cost and market structure, and consider counterfactuals that cap fees or rates.

We first solve the borrower's problem and then characterize the period-one lender pricing problem. Appendix Section F shows derivations of key equations.

3.1.1 Borrower's problem

The borrower is risk neutral, lives forever, discounts the future at $\beta \in (0, 1)$, and obtains an infinite-maturity, fixed-rate, prepayable mortgage.[19] All monetary amounts are expressed

[19]Most mortgages have a 30-year term. In reality, nearly all are refinanced well before maturity. Treating the contract as perpetual is therefore innocuous and simplifies the model.

as a share of mortgage principal. We work backwards from the refinancing decision.

Period two+ refinancing decision: The borrower enters each period after the first with rate r_0. With probability μ he prepays for non-rate reasons (e.g., moving or cash-out) and exits the model. Otherwise, with probability ϕ he considers refinancing, and with probability $1-\phi$ he pays r_0 and continues to the next period. $\phi < 1$ captures behavioral reasons for not considering refinance, such as a lack of attention.[20] Flow utility from paying r_0 is $-\alpha r_0$, where $\alpha > 0$ measures sensitivity to rate payments.

If he considers refinancing, the borrower draws an exogenous rate $r \sim dr(r)$. If he refinances, his contract rate becomes r, and he incurs a utility cost c, which encompasses both origination charges and any non-monetary costs of the refinance process such as search costs or inconvenience.[21] Finally, he incurs an idiosyncratic utility shock ϵ_r, which captures time-borrower specific costs of refinancing, such as how busy the borrower is. If he declines to refinance, he keeps r_0 and draws ϵ_n, an idiosyncratic utility shock. The indirect utilities are

$$u_r(r) = -\alpha r - c + \beta E u(r) + \epsilon_r \tag{9}$$

$$u_n(r_0) = -\alpha r_0 + \beta E u(r_0) + \epsilon_n. \tag{10}$$

$Eu(r)$ denotes the continuation value given contracted rate r. The borrower takes the action with higher indirect utility. His beginning-of-period utility, before the shocks realize, is

$$Eu(r_0) = (1-\mu)\left[\underbrace{(1-\phi)\left(-\alpha r_0 + \beta E u(r_0)\right)}_{\text{does not consider refinance}} + \underbrace{\phi \int_{\epsilon, r} \max\left\{u_r(r), u_n(r_0)\right\} d\epsilon dr(r)}_{\text{considers refinance}}\right] + \underbrace{\mu \times 0}_{\text{exogenous prepayment}} \tag{11}$$

The integral runs over the idiosyncratic shocks and the draw of the new potential rate. Equation (11) implicitly defines the value function $Eu(r_0)$. The beginning-of-period probability

[20] This captures the "woodhead" behavior often referenced in the refinance literature, e.g., Campbell (2006), and broadly follows Andersen et al. (2020).

[21] We do not directly model the market structure that gives rise to r or c, which includes an origination fee. It is sufficient for the model to match an empirical refinance probability as a function of initial rate, $P(r_0)$. A deeper microfoundation would increase complexity without altering our conclusions.

of refinance given r_0 is,

$$P(r_0) = \underbrace{\mu}_{\text{exogenous refi}} + \underbrace{(1-\mu)\left[\phi \int_{r,\epsilon} \mathbf{I}(u_r(r) > u_n(r_0)) d\epsilon dr(r)\right]}_{\text{rate-driven refi}} \tag{12}$$

Period one borrowing decision: In period one, the borrower receives offers $j \in \{1, \ldots, J\}$, each with fee f_j, rate r_j, and an idiosyncratic borrower–lender shock ϵ_{ij}. The shock reflects non-price factors observed by the borrower but not by the lender (distance, advertising exposure, and so on). The borrower pays the fee up front and starts period two with rate r_j, after which the refinancing game begins. Indirect utility from offer j is

$$u_{ij}(f, r) = -\gamma f_j + \beta E u(r_j) + \epsilon_{ij}. \tag{13}$$

Parameter γ measures fee disutility. A natural benchmark has $\gamma = \alpha$, implying equal weight on fees and interest. We allow but do not impose $\gamma \neq \alpha$ to capture behavioral differences. The borrower must obtain a loan, so there is no outside option. He picks the offer with the highest indirect utility. From the lender's view, the probability of being chosen is

$$s_j(f, r) = \int_\epsilon \mathbf{I}(u_{ij}(f_j, r_j) > u_{ik}(f_k, r_k) | \forall k) d\epsilon, \tag{14}$$

where f and r collect all lenders' fees and rates. Finally, the borrower's ex-ante expected utility is

$$E u_0(f, r) = \int_\epsilon \max\left\{u_{ij}(f, r)\right\}_j d\epsilon. \tag{15}$$

3.1.2 Lender's problem

In period one, the J differentiated lenders set fees and rates in Bertrand competition to maximize profit given other lenders' prices. Loan origination carries an upfront origination cost mc_f and a per-period funding cost mc_r until it is refinanced. Conditional on making the loan, the lender's net income per dollar lent is

$$\mathcal{V}(f, r) = f - mc_f + \underbrace{\sum_{t=1}^{\infty} (r - mc_r) \left[\rho(1 - P(r))\right]^t}_{\equiv \mathcal{I}(r)}. \tag{16}$$

Here, $f - mc_f$ captures the fee income net of origination costs, and $\mathcal{I}(r)$ is the net present value of the interest income adjusted for refinancing. The lender discounts the future by ρ. Interpreting this in an originate-to-distribute setting, $\mathcal{I}(r)$ reflects the price that an outside investor would pay for the future cash flows.[22] Total profit is

$$\Pi(f, r) = s(f, r)\mathcal{V}(f, r). \tag{17}$$

We require that $f \geq mc_f$ and $r \geq mc_r$ so fees cover origination costs and rates cover funding costs.[23] With these restrictions, the lender solves

$$\max_{f \geq mc_f, r \geq mc_r} \Pi(f, r). \tag{18}$$

3.1.3 Equilibrium

In equilibrium: (i) borrowers refinance optimally, satisfying (12); (ii) borrowers choose loans optimally in period 1 as in (13)–(14); and (iii) lenders pick f, r to solve (18). Additionally, we impose a symmetric equilibrium where all lenders pick the same f, r. Solving the lender's problem yields three candidate profit-maximizing regimes:

$$f > mc_f, \quad r > mc_r, \quad \frac{\partial \Pi(f,r)}{\partial f} = 0, \quad \frac{\partial \Pi(f,r)}{\partial r} = 0 \qquad \text{(“Fee and rate markup”)}$$

$$f > mc_f, \quad r = mc_r, \quad \frac{\partial \Pi(f,r)}{\partial f} = 0, \quad \frac{\partial \Pi(f,r)}{\partial r} < 0 \qquad \text{(“Fee markup only”)}$$

$$f = mc_f, \quad r > mc_r, \quad \frac{\partial \Pi(f,r)}{\partial f} < 0, \quad \frac{\partial \Pi(f,r)}{\partial r} = 0 \qquad \text{(“Rate markup only”)}$$

We label these cases “fee and rate markup,” “fee-only markup,” where rates are set to the marginal funding cost, and “rate-only markup,” where fees are set to the marginal origination cost, and analyze them in the next sections.

[22] In the case of the lender selling the originated mortgage to an MBS investor, we are implicitly assuming that prepayment risk is correctly reflected in the price of the loan. This is consistent with Gabaix, Krishnamurthy and Vigneron (2007), who show that prepayment risk is priced in the MBS market. In more recent work, Chernov, Dunn and Longstaff (2017) find that prepayment risk caries a significant risk premium, and Boyarchenko, Fuster and Lucca (2019), who study MBS spreads, show that non-interest-rate prepayment risk (such as prepayment risk related to house prices) contribute to a pricing smile.

[23] $r < mc_r$ essentially means that the “borrower” is lending money to the “lender,” and so we rule this out. A microfounded financial constraint would give rise to this restriction.

3.2 Model estimation

We begin my making standard functional form assumptions, and then discuss the identification of the model's underlying parameters.

3.2.1 Functional form assumptions

First, we assume the ϵ shocks follow a Type-1 extreme-value distribution, giving closed-form choice probabilities and expected utilities (see Appendix F). This assumption yields quasi–closed-form first-order conditions, up to $Eu(r)$ and $P(r)$:

$$\mathcal{V}(f,r) = \left(\frac{1}{\gamma}\right)\left(\frac{1}{1-s(f,r)}\right) \tag{19}$$

$$\mathcal{V}(f,r) = \left(\frac{1}{\tilde{\alpha}}\right)\left(\frac{1}{1-s(f,r)}\right)\frac{\partial \mathcal{I}(r)}{\partial r} \tag{20}$$

$$\tilde{\alpha} = \alpha\left(\frac{\beta(1-P(r_j))}{1-\beta(1-P(r_j))}\right)$$

The interior fee condition is the usual logit markup: markups rise with fee sensitivity and period-one market share. The rate condition is richer because it also incorporates *future* competition through $\partial\mathcal{I}(r)/\partial r$ and as well as altering the borrower's effective rate sensitivity. Through the possibility of future refinancing, a lender effectively competes with both current and future rivals; this interaction shapes our results for how rates and fees vary with concentration and future refinance costs.

Given these functional form assumptions, the following parameters remain: On the *borrower side*: α (rate sensitivity), γ (fee sensitivity), β (discount factor), c (refinance cost), ϕ (refinance-consideration probability), and μ (exogenous prepayment probability). On the *lender side*: mc_f, mc_r (origination and funding costs), ρ (lender discount factor), and J (number of symmetric lenders). We assume that the refinance rate follows $r \sim \mathcal{N}(\mu_r, \sigma_r^2)$. Table 5 summarizes these parameters.

3.2.2 Externally calibrated parameters

For discount rates, we impose $1 > \rho > \beta$, so lenders value the future more than borrowers, consistent with savers funding mortgages. Similar to Iacoviello (2005)[24] we set $\rho = 0.96$ and $\beta = 0.92$ on an annualized basis. For the rate process over our time period, the historical

[24] Which in turn cites Lawrance (1991).

30-year mortgage rates have $\mu_r = 4.31$ and $\sigma_r = 1.34$. For the market structure, our baseline scenario has $J = 9$ symmetric lenders, matching our observed CR4.[25] We study comparative statics around J.

3.2.3 Parameters estimated through SMM

We recover α, c, ϕ, and μ by matching the empirical "s-curve." The s-curve relates the rate incentive, i.e., the difference between the borrower's current rate and a hypothetical refinance rate given current market conditions, to the probability of refinancing. While the estimation is done simultaneously, for expositional clarity we provide intuition around which parts of the s-curve identify which parameters. The rate of refinancing given a zero or negative rate incentive pins down μ, yielding $\mu = 5.9\%$. The refinance cost c controls the rate incentive at which point the borrower begins to respond. If c is very low, the borrower responds at low rate differentials; if c is very high, the rate differential must be large to induce refinance. We estimate that $c = 3.00\%$. Average observed fees are 1.84%, so our estimate implies a modest hedonic cost of refinancing above the refinancing fee.

Rate sensitivity α governs the slope of the curve; we obtain $\alpha = 1.28$, similar to estimates in the literature.[26] Finally, ϕ is identified by the refinancing rate when the rate incentive is very high. We estimate $\phi = 34\%$, consistent with other frictions such as LTV or income limits. As Figure A10 shows, our model closely reproduces the empirical s-curve.

Fee sensitivity γ measures the utility cost of paying upfront fees. A frictionless benchmark sets $\gamma = \alpha$, treating a dollar of fees like a dollar of interest. Empirical work, however, rejects this symmetry. Benetton, Gavazza and Surico (2025) show that mortgage applicants react less to fees than to rates, implying $\gamma < \alpha$. Guided by their finding, we write $\gamma = \omega\alpha$ and estimate ω from the National Survey of Mortgage Originations (NSMO). We take the share of borrowers who report being "very" familiar with closing costs and divide by the share "very" familiar with rates; the ratio is 0.86. Hence we set $\omega = 0.86$, so borrowers value a fee dollar about 14% less than an interest dollar.

With borrower parameters in hand we back out lender costs from observed equilibrium pricing, obtaining $mc_r = 4.24\%$ and $mc_f = 1.06\%$. Table 5, panel B, reports these estimates

[25] The average CR4 is 0.47. With equal shares CR4$= 4/J$, so $J \approx 4/0.47 \approx 9$.

[26] Buchak et al. (2024) estimate an average borrower's rate sensitivty as $\alpha = 1.65$. This α corresponds to our $\tilde{\alpha}$, as our α represents the structural per-period sensitivity to rate payments and their α represents the sensitivity to interest rates payments capitalized over the life of the mortgage. Accounting for the refinance probability and discount rate, their per-period sensitivity to rate payments is approximately 1.15, which is closely in line with our estimate.

with bootstraped standard errors.

3.3 Understanding the model's mechanisms

We first use the estimated model to illuminate its mechanisms and to interpret the reduced-form findings. The central question is where lenders place their markup: on rates, on fees, or on both. Borrowers discount future payments more than lenders do, which pushes lenders to prefer rate markups over fee markups. However, lenders face different degrees of competition in setting rates and fees. In setting fees, lenders compete only with contemporaneous lenders. In setting rates, lenders also compete with *future* lenders through the refinancing channel. In the extreme where refinancing is impossible, lenders prefer rate markups. On the other extreme where refinancing is near-costless, lenders prefer to extract markups through fees to avoid future competition. At intermediate refinancing costs, lenders mark up both such that fees reflect current competition and rates reflect future competition.

Figure 2 illustrates this tradeoff. Panels A and B show optimal rates and fees as the refinance cost c varies. The vertical dashed line indicates the estimated c. The solid red line shows the rate-markup-only outcome ($f = mc_o$), the dashed blue like shows the fee-markup-only outcome ($r = mc_r$), and the dotted black line shows the unconstrained profit-maximizing outcome.

Under the rate-only strategy (red) the optimal rate falls with c: A higher refinancing cost means borrowers choose to refinance less often, and so are endogenously more sensitive to period-one rates. This induces lenders to cut rates to better compete with other lenders in period-one. Under the fee-only strategy (blue), the optimal fee is marked up over marginal cost but does not vary with refinancing costs.

The profit-maximizing strategy (black) features fee-only markups when c is low and rate-only markups when c is high. In the low-c region, the refinance channel dominates, while in the high-c region, the discount rate differential channel dominates. In the intermediate region, both rates and fees are marked up. Lenders set rates to trade off greater interest income against greater refinance likelihood (competition with the future)[27] and set fees to trade off greater all-in income against lower market share (competition with the present). When c increases, refinance likelihood decreases, leading lenders to raise rates. They offset higher rates with lower fees to better compete with period-one lenders.

[27] Observe that by combining Equations (19) and (20), which both hold in this interior region, one observes immediately that rate dependence on local market share immediately drops out, leaving rates to depend only upon future refinance probability.

Panels C and D trace equilibrium rates and fees as market concentration changes. We plot three refinance-cost scenarios: baseline (black, estimated c), high cost $c = 15$ (red, prepayment-penalty loans), and low cost $c = 0$ (blue). Recall from above that the estimated model suggests that the baseline strategy is one of mixed-markups. In this baseline, fees rise with concentration while rates stay flat, matching the reduced-form evidence. This is because in the estimated region, fees are determined by current competition while rates are determined by future competition. Thus, cross-sectional variation in concentration moves the former but not the latter. Note that while our baseline model implies that rates are marked up over marginal cost, these markups are not econometrically detectable by using local variation in concentration. In the high-cost scenario, pricing follows the rate markup regime, and consistent with the reduced form results on loans with prepayment penalties, rates increase with concentration while fees do not. Finally, in the low-cost scenario, pricing follows the fee markup regime, with fees again increasing with concentration and rates remaining constant, albiet lower, than the mixed-markup regime.

3.4 Counterfactual mortgage contract design

We use the model to evaluate counterfactuals that restrict lenders to a *single* pricing dimension. We compare equilibrium rates, fees, refinancing probabilities, and borrower welfare under policies that restrict fees to the marginal origination cost or rates to the marginal funding cost to the baseline in which lenders can mark up along both dimensions. Figure 3 imposes *rate-only* markups, and Figure 4 imposes *fee-only* markups.

Consider the rate-only scenario in Figure 3. Panel A plots the change in rates and fees, B the change in refinance probabilities, C the change in borrower surplus, and D the change in effective lender markups, inclusive of net fee and rate income, all against the refinance cost c (where the vertical dashed line corresponds to the estimated c). When c is low or moderate, rates rise and fees fall because lenders are forced to shift non-zero fee markups into higher rates. At the estimated c, the model predicts a rate increase of about 20 bp and a fee decline of about 75 bp. For high c there is no impact because the profit-maximizing outcome already places the markup on rates.

Higher rates raise the incentive to refinance, and as Panel B shows, refinance probabilities rise by roughly 2 pp at the estimated c. Panel C shows borrower welfare gains of about \$250 per average loan. By forcing rate competition, the policy exposes lenders to both current competition and future competition from refinance, forcing them to reduce markups by roughly 12% relative to the profit-maximizing baseline, shown in Panel D.

The fee-only policy (Figure 4) does the opposite. Rates fall, fees rise, and refinance becomes less likely. Welfare drops by about $20 per loan at the estimated c. Borrowers prefer paying markups in rates because they can refinance later, so shifting the markup to fees-only directly reduces surplus. In this case, borrower welfare falls, even though effective markups do not increase, as the inability to markup rates eliminates welfare-improving gains from trade and thus total surplus. The welfare effect of capping rates is non-monotone in c because the underlying pricing regime switches. When both dimensions are marked up, the fee reflects current-period competition and the rate reflects future competition. Increasing the refinance cost in this region increases the profit-maximizing rate and reduces the fee. Thus, forcing lenders to keep rates at the marginal cost of funding has a larger local impact. When refinance costs are high enough to switch to the rate-only markup regime, marginally higher refinance costs make the borrower more sensitive to current-period interest rates, which reduces their willingness to pay for high rates, and lenders cannot offset this by offering lower fees. In consequence, higher refinance costs reduce profit-maximizing rates, and therefore the impact of capping them becomes smaller.

Falling lender markups in the case of capped fees suggest that in a model with fixed operating costs and lender entry/exit, some lenders would exit in response to the cap. To examine the robustness of our results to lender exit, we resimulate our counterfactuals with fewer lenders in the counterfactual relative to the baseline. In particular, we reduce the number of lenders by 10% and recalculate all of our outcome variables. As Figures A11 and A12 in the appendix show, our results are qualitatively unchanged, although consumer welfare decreases modestly in both cases as compared to the baseline results where the number of lenders is fixed.

In sum, multidimensional pricing enables lenders with market power to extract greater surplus from borrowers. Lenders typically face less competition in setting fees than in setting rates and thus prefer to mark up fees rather than rates. Therefore, a counterfactual contractual design that forces lenders to price along the more competitive dimension, rates, meaningfully increases consumer surplus.

4 Implications for Regulation and Policy

In this section, we discuss the implications of the results for mortgage contract design and antitrust concerns around bank merger approval. Our paper raises two implications.

First, regulators should regard local competition as relevant in mortgage pricing, and thus consider local mortgage lending concentration when evaluating bank mergers. Second, where possible, regulators should limit lenders' ability to markup fees and encourage competition in rates.

Regardling local lending competition, our paper shows that contrary to the concensus, local concentration does impact prices through fees as opposed to rate. This suggests that regulators should consider local lending concentration as relevant in questions around antitrust and market power. The common, and historically correct, intuition has been that financial products are offered as a bundle, i.e., mortgage lending and bank deposits, and therefore lending concentration is highly correlated with deposit concentration. Thus, while the Federal Reserve does not *directly* consider local mortgage market concentration when evaluating the competitive impact of mergers and acquisitions, the fact that it does consider local deposit market concentration (Federal Reserve System, 2021), means that lending market concentration will *indirectly* be limited.

However, mortgage markets and deposit markets have decoupled over the past 30 years. In Figure 5, we document this divergence. Panel A shows a scatterplot of local deposit market concentration and local mortgage market concentration in 1994. Here, the cross-sectional correlation between deposit and mortgage concentration is 0.66, and the R^2 value from a univariate regression using deposit concentration to predict mortgage concentration is 0.43. In other words, in 1994, the counties with high deposit concentration were on average the same as those with high mortgage concentration, so the bundling assumption was valid.[28]

By contrast, in the data for 2023 (shown in Panel B), this relationship is almost completely gone: the correlation is now 0.19, and the univariate R^2 is only 0.04. The bundling assumption is therefore no longer valid: regulatory decisions focusing on deposit concentration are likely to miss the markets with high mortgage concentration. In Panel C, we document how the relationship between deposit concentration and mortgage concentration has unraveled since 1994. The plot shows the R^2 value of mortgage CR4 regressed on deposit CR4, for each year from 1994 to 2023. The values are much lower in the 2010s and 20s than in the mid-1990s. This confirms that, to the extent that high mortgage market concentration enables lenders to exert market power, this market power can no longer be effectively curtailed by regulatory decisions based on deposit market concentration.

Regarding fees versus rates, our model suggests that in a multidimensional pricing setting,

[28] We thank João Granja for suggesting this analysis. The starting point of the analysis is 1994, since the Summary of Deposits dataset only goes back to 1994 (while the HMDA dataset goes back to 1990).

lenders will endogenously choose to markup the less competitive pricing margin, i.e., fees. Regulations that discourage—or directly forbid—fee markups have the effect of reducing total effective markups and therefore increase borrower welfare. Rate caps, in contrast, run the risk of reducing aggregate welfare by raising fees, which are set less competitively.

Taken together, our results highlight a regulatory gap. By overlooking fees, the Federal Reserve ignores a less competitive dimension of mortgage pricing and regards the mortgage markets as national in scope. Our findings suggest that once fees are accounted for, local market concentration plays a critical role in shaping borrower outcomes, as it enables lenders to extract markups more effectively.

5 Conclusion

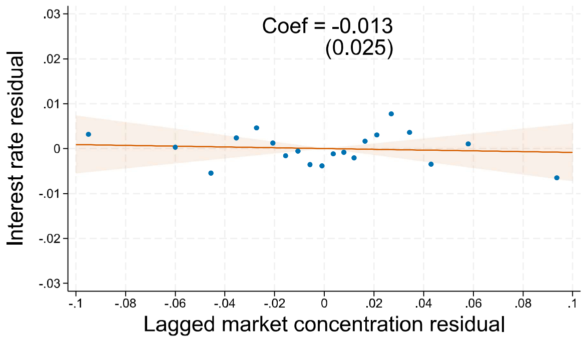
In this paper, we have shown that mortgage lenders use multidimensional pricing to exert market power in the presence of local competition and prepayment risk. Using variation from lender failures and bank mergers, we found that concentration raises fees but not rates for prepayable loans, with the pattern reversing when prepayment penalties apply. Using a dynamic structural model, we rationalized these findings and showed that, at the estimated parameters, lenders mark up both rates and fees, but higher local concentration endogenously affects only fees—the pricing margin less exposed to prepayment risk. In policy counterfactuals, we show that an interest rate cap, a common tool among regulators, inhibits intertemporal gains from trade and reduces borrower welfare. In contrast, in a counterfactual that caps fees, lenders reallocate markups to rates, reducing overall markups and increasing borrower welfare by approximately \$250 per loan.

The findings in this paper point to several implications for public policy and interesting areas for future research. First, our results highlight that regulators should factor local lender concentration into their policy decisions—for example, when assessing the consequences of potential bank mergers or the pass-through of monetary policy. Although regulators *do* take deposit market concentration into account in these decisions, our paper documents an increasing divergence between deposit market concentration and lending market concentration. This divergence implies that a deposit-market-focused regulatory regime is not sufficient to limit the exercise of market power in mortgage markets.

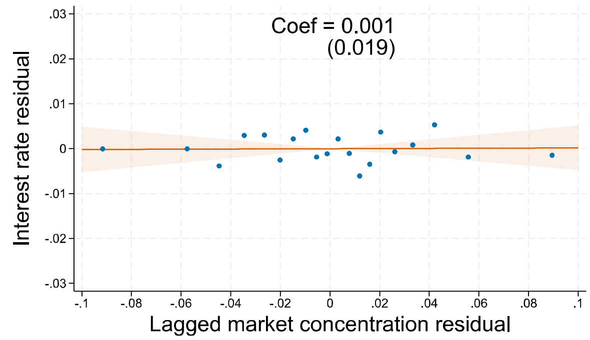
Second, the results in the paper speak to a nascent literature that challenges the standard assumptions of the consequences of competition in financial markets. For example, Wang (2023) studies competition among credit card payment networks and finds that increased entry (and decreased concentration) can lower consumer welfare in two-sided markets, and Koont (2023) studies deposit competition and finds that while digital banking increases competition it can pose risks to financial stability.

Finally, our theoretical and empirical findings apply beyond the US residential mortgage context. Many loans, including other consumer loans as well as commercial and industrial loans, typically include similar prepayment options along with multidimensional pricing. Hence, our paper suggests that researchers and policymakers must examine fees and other one-time underwriting costs in addition to rates when looking for evidence of markups. Ignoring the multidimensional pricing aspect of the problem risks missing the key pricing dimension in which one should expect markups to manifest.

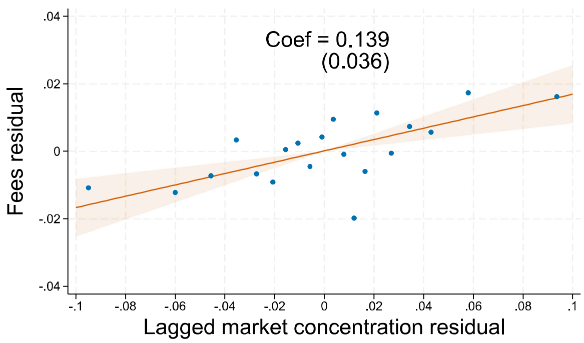
Figure 1: Interest rates, fees, and local concentration



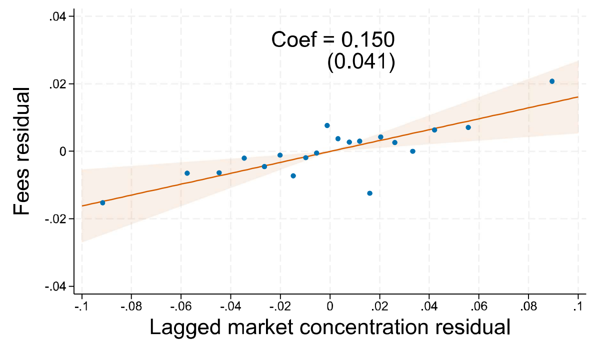
Panel A: Concentration and interest rates
(including loans with points)



Panel B: Concentration and interest rates
(only loans with zero points)



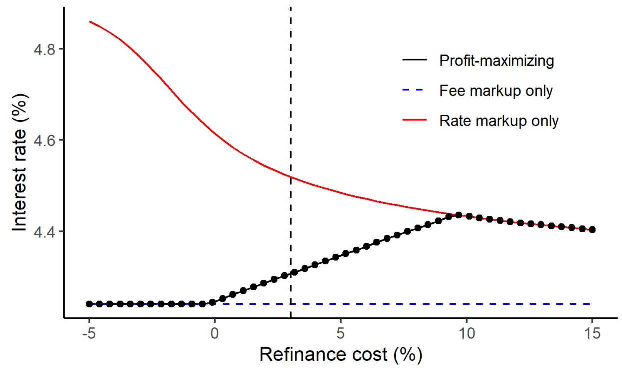
Panel C: Concentration and lender fees
(including loans with points)



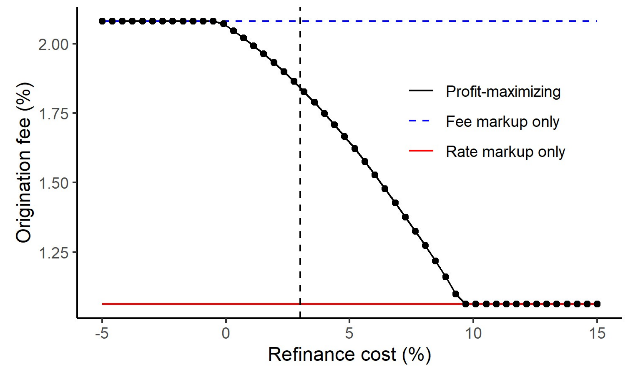
Panel D: Concentration and lender fees
(only loans with zero points)

Note: This figure shows the distribution of residualized interest rates and fees relative to local mortgage market concentration. Both panels show a binned scatterplot of either interest rates (Panels A and B) or fees (Panels C and D) residualized from Equation (21), where both variables are regressed on loan and county characteristics, and year, county, and lender fixed effects. In Panels A and C the sample includes all loans while in Panels B and D, the sample only includes loans with zero discount points and zero lender credits. In each panel, the dots represent 20 equal-sized bins based on the residualized one-year lagged county-level CR4. The solid line is a linear regression on the entire dataset, the transparent bars represent the 95% confidence interval, and the coefficients are displayed. The standard errors (in parentheses) are clustered at the county level.

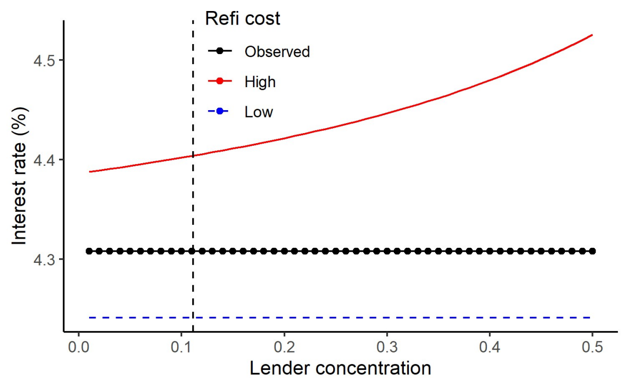
Figure 2: Rates, fees, refinance costs, and competition



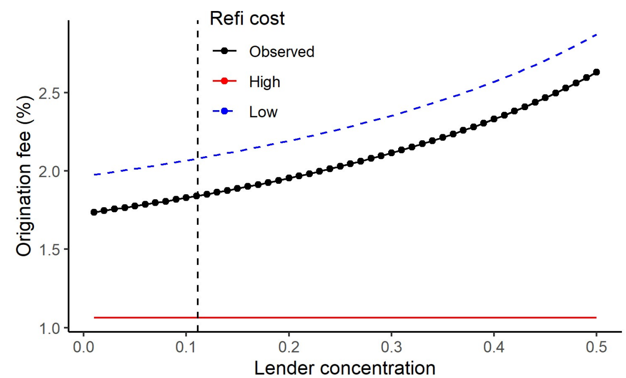
Panel A: Interest rates versus refinance cost



Panel B: Fees versus refinance cost



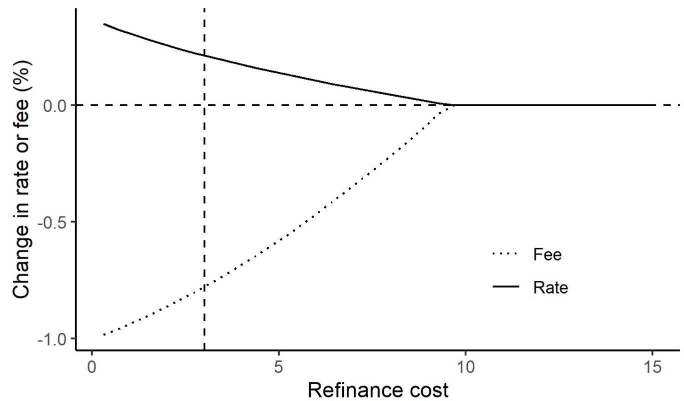
Panel C: Interest rates versus lender concentration



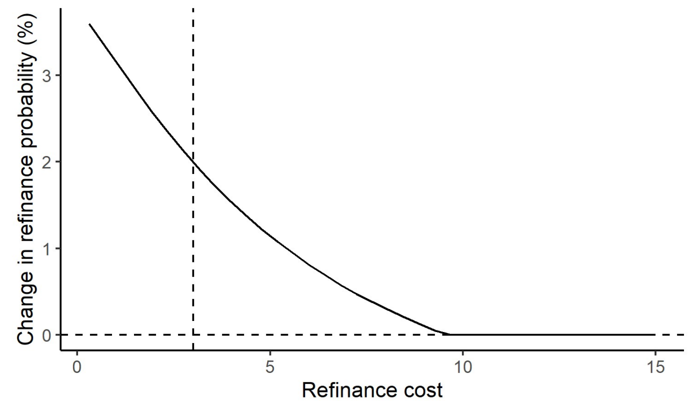
Panel D: Fees versus lender concentration

Note: This figure shows how rates, Panels A and C, and fees, B and D, vary with the hedonic refinance cost c, A and B, and lender concentration $1/J$, C and D. In panels A and B, the red line is the equilibrium interest rate or fee when lenders can markup rates but must set fees equal to the marginal cost of origination. The dashed blue line is the equilibrium interest rate or fee when lenders can markup fees but must set rates equal to the marginal cost of origination. The dotted black line is the lender's optimal pricing strategy given the choice of marking up rates only, fees only, or both under the constraint that rates and fees exceed their respective marginal costs. The dashed vertical line is the estimated refinance cost. In panels C and D, the dotted black line is the rate or fee when refinance costs are set to the estimated value, $c = 3.005$. The dashed blue line corresponds to low refi costs, $c = 0$, and the red line corresponds to high refi costs, $c = 15$. In these panels, the lender is following the profit-maximizing fee and rate strategy. The dashed vertical line is the calibrated market concentration.

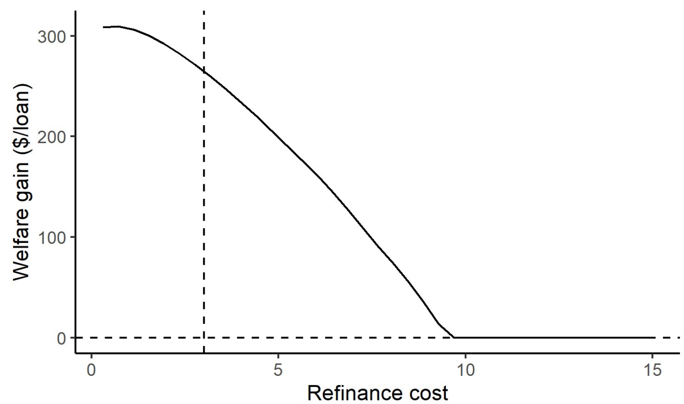
Figure 3: Counterfactual: Capping fees at marginal origination costs



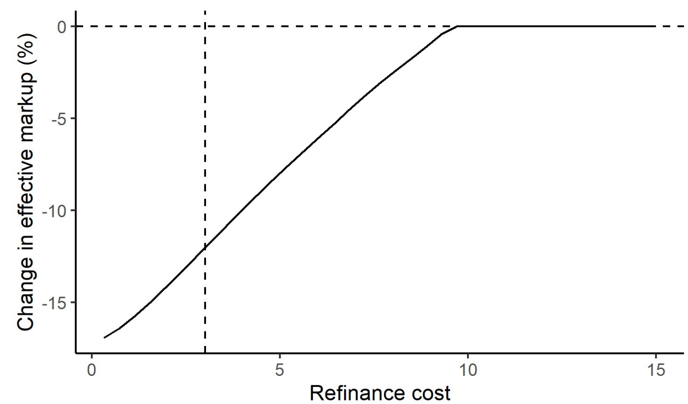
Panel A: Rates and fees



Panel B: Refinance probability



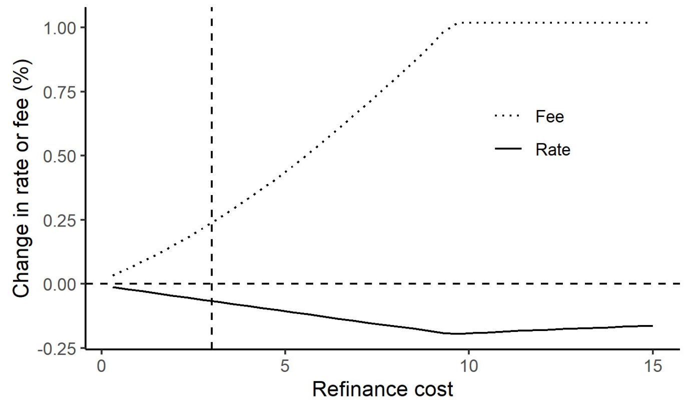
Panel C: Borrower welfare



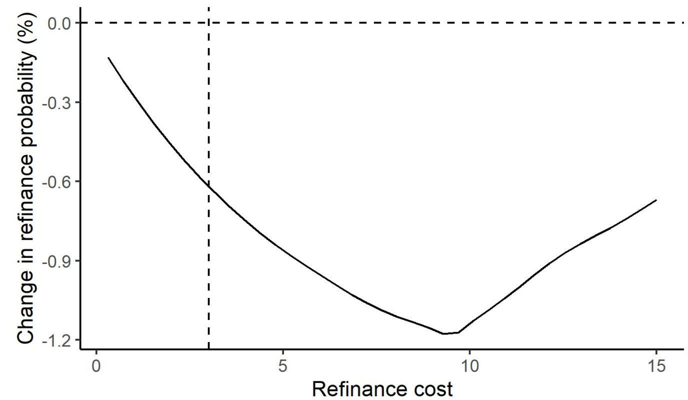
Panel D: Lender markups

Note: This figure studies the impact of a counterfactual where lenders are forced to set fees equal to the marginal cost of origination, mc_o, and only impose markups through rates. Each panel compares outcomes in the counterfactual "rate markup only" scenario to the estimated "profit-maximizing" scenario. These panels show the counterfactual impact versus the hedonic refinance cost c, with the dashed vertical line indicating the estimated value. Panel A shows the change in rates (solid) and fees (dotted). Panel B shows the change in annual refinance probability. Panel C shows the change in welfare, measured in dollar utility for a loan of average size. Panel D shows the change in lender markups, inclusive of net fee and rate income.

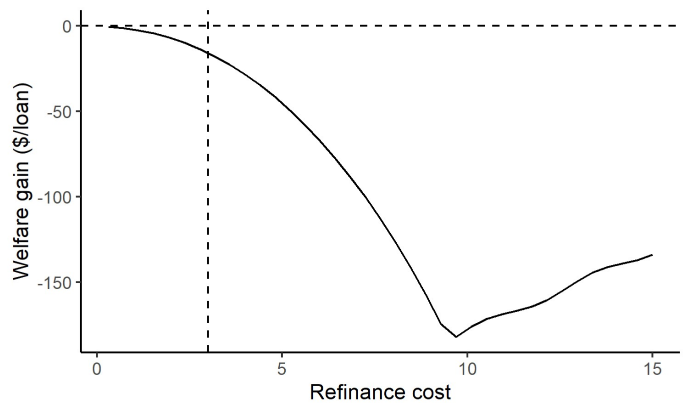
Figure 4: Counterfactual: Capping rates at marginal funding costs



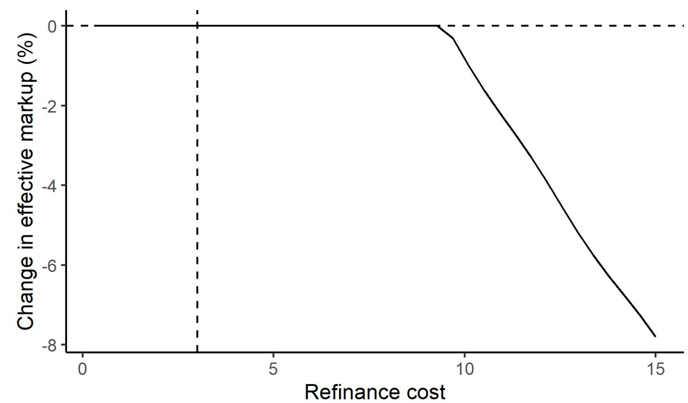
Panel A: Rates and fees



Panel B: Refinance probability



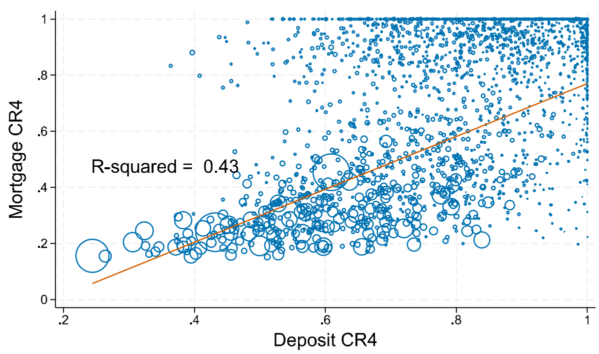
Panel C: Borrower welfare



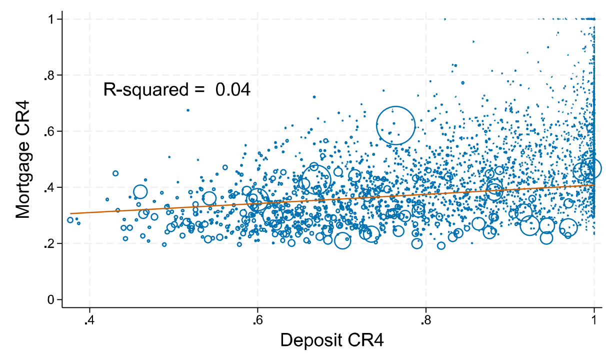
Panel D: Lender markups

Note: This figure studies the impact of a counterfactual where lenders are forced to set rates equal to the marginal cost of funding, mc_r, and only impose markups through fees. Each panel compares outcomes in the counterfactual “rate markup only” scenario to the estimated “profit-maximizing” scenario. These panels show the counterfactual impact versus the hedonic refinance cost c, with the dashed vertical line indicating the estimated value. Panel A shows the change in rates (solid) and fees (dotted). Panel B shows the change in annual refinance probability. Panel C shows the change in welfare, measured in dollar utility for a loan of average size. Panel D shows the change in lender markups, inclusive of net fee and rate income.

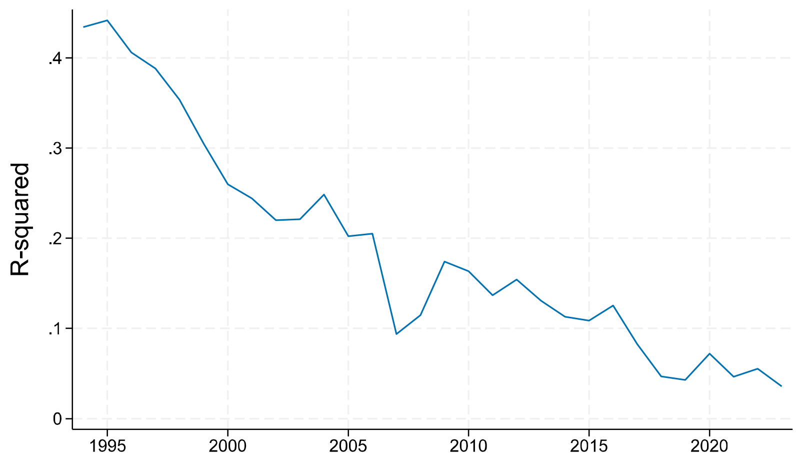
Figure 5: CORRELATION BETWEEN DEPOSIT AND MORTGAGE CONCENTRATION



Panel A: Market correlation in 1994



Panel B: Market correlation in 2023



Panel C: R^2 over time

Note: This figure shows cross-sectional correlation between county-level concentration in deposit markets and mortgage markets across time. The data sources are the 1994–2023 Summary of Deposits dataset and the 1994–2023 HMDA dataset. Panels A and B show scatterplots of local deposit market CR4 and local mortgage market CR4. Each circle represents a county in 1994 (Panel A) or 2023 (Panel B). The size of each circle is scaled by the amount of deposits in the county, the solid line represents the linear predicted values, and the R^2 is displayed. Panel C shows, for each year from 1994 to 2023, the R^2 from a univariate regression of local mortgage market CR4 on local deposit market CR4 (where each observation is weighted by the amount of deposits in the county-year).

Table 1: Summary Statistics

Panel A: Full HMDA sample

	N	Mean	Std. dev.	10%-tile	90%-tile
Loan amount ($)	12,434,662	336,859.49	236,104.36	135,000.00	575,000.00
Interest rate (percent)	12,419,816	4.31	1.34	2.88	6.38
Total loan costs ($)	12,264,511	5,163.60	13,629.59	2,156.20	9,154.45
Total loan costs (pct.)	12,264,511	1.84	1.53	0.67	3.34
Lender fees ($)	12,352,128	1,906.92	48,547.48	-25.42	4,995.32
Lender fees (pct.)	12,352,128	0.68	0.87	-0.01	1.76
Origination charge ($)	12,352,128	2,378.09	3,187.92	85.94	5,550.00
Origination charge (pct.)	12,352,128	0.83	0.81	0.03	1.91
Discount points ($)	4,902,120	2,744.64	3,809.45	276.67	6,412.50
Discount points (pct.)	4,902,120	0.83	0.83	0.12	1.93
Lender credits ($)	4,745,734	1,231.90	78,168.28	15.30	3,389.00
Lender credits (pct.)	4,745,734	0.39	0.71	0.00	1.04
Third-party fees ($)	12,352,128	2,734.94	13,089.55	1,212.55	4,480.00
Third-party fees (pct.)	12,352,128	1.00	1.02	0.40	1.71
Applicant income ($)	12,315,135	124.17	135.58	45.00	220.00
Combined loan-to-value ratio (pct.)	12,434,662	82.79	16.21	63.37	97.00
Debt-to-income ratio (pct.)	12,369,881	35.32	9.96	25.00	47.00

Panel B: Matched HMDA–GSE sample

	N	Mean	Std. dev.	10%-tile	90%-tile
Loan amount ($)	2,988,213	314,879.97	157,672.54	134,000.00	528,000.00
Interest rate (percent)	2,988,213	4.22	1.26	2.88	6.12
Total loan costs ($)	2,982,576	5,041.92	4,640.61	2,117.71	8,927.97
Total loan costs (pct.)	2,982,576	1.85	1.26	0.68	3.39
Lender fees ($)	2,981,697	1,878.78	2,898.19	-51.38	4,925.25
Lender fees (pct.)	2,981,697	0.69	0.88	-0.02	1.83
Origination charge ($)	2,981,697	2,358.49	2,778.06	0.00	5,607.50
Origination charge (pct.)	2,981,697	0.85	0.82	0.00	2.02
Discount points ($)	1,310,635	2,490.84	2,926.63	257.04	5,771.25
Discount points (pct.)	1,310,635	0.83	0.79	0.12	1.94
Lender credits ($)	1,133,546	1,264.59	2,235.84	15.00	3,744.00
Lender credits (pct.)	1,133,546	0.41	0.63	0.00	1.21
Third-party fees ($)	2,981,697	2,680.95	3,508.90	1,215.43	4,259.95
Third-party fees (pct.)	2,981,697	1.00	0.65	0.42	1.70
Applicant income ($)	2,956,814	113.84	86.86	46.00	197.00
Combined loan-to-value ratio (pct.)	2,988,213	83.19	14.70	64.10	96.91
Debt-to-income ratio (pct.)	2,987,349	35.65	9.79	25.00	47.00
FICO	2,986,139	753.70	42.81	692.00	803.00

Panel C: County-year statistics

	N	Mean	Std. dev.	10%-tile	90%-tile
Mortgage lenders	19,029	52.70	66.29	5.00	136.00
Herfindahl-Hirschman Index (HHI)	18,991	0.10	0.10	0.03	0.19
Market share for top 4 (CR4)	18,991	0.47	0.18	0.26	0.72
Unemployment rate	18,940	4.54	2.05	2.50	7.20

Note: This table reports the number of observations, the mean and standard deviation, and the 10th and 90th percentiles. Panel A gives summary statistics for the HMDA dataset. Panel B gives summary statistics for the HMDA–GSE matched sample. Panel C gives summary statistics for the county-year variables. See Subsection 1.1 for details on sample selection and matching procedures.

Table 2: Local Concentration and Mortgage Pricing (OLS)

Panel A: Interest Rates

	Including points				Zero points			
	HMDA		HMDA-GSE		HMDA		HMDA-GSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR4	-0.266***		-0.013		-0.123		0.001	
	(0.084)		(0.025)		(0.080)		(0.019)	
HHI		-0.275		0.014		0.057		0.047
		(0.222)		(0.031)		(0.161)		(0.030)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
Month FE			✓	✓			✓	✓
FICO bin FE			✓	✓			✓	✓
N	12,340,058	12,340,058	2,984,503	2,984,503	3,559,034	3,559,034	734,445	734,445
R^2	0.79	0.79	0.93	0.93	0.80	0.80	0.94	0.94

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Lender Fees

	Including points				Zero points			
	HMDA		HMDA-GSE		HMDA		HMDA-GSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR4	0.314***		0.139***		0.090**		0.150***	
	(0.038)		(0.036)		(0.039)		(0.042)	
HHI		0.967***		0.203***		0.327***		0.248***
		(0.120)		(0.060)		(0.095)		(0.064)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
Month FE			✓	✓			✓	✓
FICO bin FE			✓	✓			✓	✓
N	12,274,206	12,274,206	2,978,006	2,978,006	3,516,873	3,516,873	731,557	731,557
R^2	0.25	0.25	0.28	0.28	0.47	0.47	0.33	0.33

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results from equation (5). In Panel A, the dependent variable is the interest rate, and in Panel B, the amount of lender fees. Standard errors (in parentheses) are clustered at the county level. In Columns (1) and (2), the sample is the full HMDA dataset. In Columns (3) and (4) the sample is the merged HMDA-GSE dataset. In Columns (5) and (6), the sample is restricted to loans from the HMDA dataset with zero discount points and zero lender credits. In Columns (7) and (8), the sample is restricted to loans from the HMDA-GSE dataset with zero discount points and zero lender credits. See Subsection 1.1 for details on sample selection.

Table 3: Local Concentration and Mortgage Pricing (IV)

Panel A: Interest Rates

	Failed Lender IV				Incidental Merger IV			
	First stage		IV		First stage		IV	
	(1) CR4	(2) HHI	(3) Rates	(4) Rates	(5) CR4	(6) HHI	(7) Rates	(8) Rates
Share failed	-0.228***	-0.048***						
	(0.045)	(0.011)						
CR4			0.315				-0.398	
			(0.285)				(0.317)	
HHI				1.483				-1.744
				(1.347)				(1.389)
Incidental merger					0.040***	0.009***		
					(0.009)	(0.002)		
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓				
County FE					✓	✓	✓	✓
N	12,061,303	12,061,303	12,047,410	12,047,410	215,744	215,744	215,576	215,576
R^2	0.45	0.42	0.00	0.00	0.93	0.91	0.00	0.00
F-stat	25	19			20	31		

Panel B: Lender Fees

	Failed Lender IV				Incidental Merger IV			
	First stage		IV		First stage		IV	
	(1) CR4	(2) HHI	(3) Fees	(4) Fees	(5) CR4	(6) HHI	(7) Fees	(8) Fees
Share failed	-0.228***	-0.048***						
	(0.045)	(0.011)						
CR4			2.802***				1.080**	
			(0.730)				(0.497)	
HHI				13.156***				4.735**
				(3.727)				(1.856)
Incidental merger					0.040***	0.009***		
					(0.009)	(0.002)		
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓				
County FE					✓	✓	✓	✓
N	12,061,303	12,061,303	11,983,059	11,983,059	215,744	215,744	214,576	214,576
R^2	0.45	0.42	-0.00	-0.03	0.93	0.91	0.03	0.03
F-stat	25	19			20	31		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results from the IV specifications. In Panel A, the dependent variable is the interest rate, and in Panel B, the amount of lender fees. Columns (1) and (2) show the first stage and Columns (3) and (4) the second stage for the Failed Lender IV (equation 6). Columns (5) and (6) show the first stage and Columns (7) and (8) the second stage for the Incidental Merger IV (equation 7). Standard errors (in parentheses) are clustered at the county level.

Table 4: Pricing of Mortgages by Prepayment Risk

Panel A: HMDA (Only loans with prepayment penalties)

	Including points				Zero points			
	(1) Rates	(2) Rates	(3) Fees	(4) Fees	(5) Rates	(6) Rates	(7) Fees	(8) Fees
CR4	1.210***		-0.173		1.313***		-0.163	
	(0.157)		(0.268)		(0.207)		(0.156)	
HHI		3.961***		-0.091		4.115***		-0.009
		(0.402)		(0.682)		(0.494)		(0.365)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	24,915	24,915	22,905	22,905	8,383	8,383	6,466	6,466
R^2	0.81	0.81	0.39	0.39	0.78	0.78	0.79	0.79

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: HMDA (Loans with and without prepayment penalties)

	OLS				IV			
	(1) Rates	(2) Rates	(3) Fees	(4) Fees	(5) Rates	(6) Rates	(7) Fees	(8) Fees
CR4	-0.265***		0.315***		-0.393***		1.078***	
	(0.006)		(0.007)		(0.145)		(0.173)	
HHI		-0.269***		0.966***		-1.713***		4.713***
		(0.021)		(0.026)		(0.636)		(0.757)
Penalty	0.008	0.024***	0.103***	0.033***	-2.343*	-0.619	4.094***	1.630***
	(0.015)	(0.009)	(0.019)	(0.011)	(1.288)	(0.427)	(1.295)	(0.460)
CR4 X Penalty	0.189***		-0.437***		5.945**		-9.220***	
	(0.041)		(0.051)		(2.824)		(2.857)	
HHI X Penalty		0.928***		-1.576***		10.336**		-18.029***
		(0.146)		(0.183)		(4.367)		(4.681)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	12,365,342	12,365,342	12,297,482	12,297,482	215,820	215,820	214,810	214,810
R^2	0.79	0.79	0.25	0.25	0.00	0.00	0.03	0.03

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Pricing of Mortgages by Prepayment Risk (cont'd)

Panel C: Black Knight

	No penalty		Prepayment penalty		Full sample	
	(1) Rates	(2) Rates	(3) Rates	(4) Rates	(5) Rates	(6) Rates
CR4	0.059		0.730***		0.002	
	(0.131)		(0.222)		(0.124)	
HHI		0.377		2.415***		0.219
		(0.266)		(0.522)		(0.265)
Penalty					0.125**	0.253***
					(0.055)	(0.029)
CR4 X Penalty					0.838***	
					(0.153)	
HHI X Penalty						3.227***
						(0.398)
Loan controls	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
FICO bin FE	✓	✓	✓	✓	✓	✓
N	2,610,590	2,610,590	514,399	514,399	3,125,243	3,125,243
R^2	0.51	0.51	0.35	0.35	0.49	0.49

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results from the OLS and IV specifications used to estimate the effect of local market concentration on mortgage pricing, separately by prepayment risk. In Panel A, the regressions are estimated using only loans with prepayment penalties. Columns (1)–(4) use the full sample (including loans with non-zero points and credits), while Columns (5)–(8) restrict to loans with exactly zero points and credits. In Panel B, the sample includes all loans and estimates a difference-in-differences specification (equation 8) that interacts the concentration measure with a dummy for whether the loan includes a prepayment penalty. Columns (1)–(4) report OLS estimates, and Columns (5)–(8) report IV estimates. Panel C replicates both the baseline specification (equation 5) and the difference-in-differences specification (equation 8) using the Black Knight dataset. Columns (1)-(2) and (3)-(4) estimate the effect of concentration separately for loans without and with prepayment penalties. Columns (5) and (6) pool both groups and include an interaction between concentration and a prepayment penalty indicator.

Table 5: Structural estimation

Panel A: Externally Calibrated Parameters

Parameter	Description	Value	Source
Borrower parameters			
β	Borrower discount factor	0.92	Iacoviello (2005)
Lender parameters			
ρ	Lender discount factor	0.96	Iacoviello (2005)
Rate process			
μ_r	Rate mean	4.31	Data 2018-2023
σ_r	Rate volatility	1.34	Data 2018-2023

Panel B: Parameters estimated through SMM

Parameter	Description	Estimate	SE	Source
Borrower parameters				
α	Rate sensitivity	1.279	(0.180)	S-curve
γ	Fee sensitivity	1.105	(0.155)	Fee/rate familiarity
c	Refi cost	3.005	(0.354)	S-curve
ϕ	Refi consideration	0.340	(0.070)	S-curve
μ	Exogenous prepayment	0.059	(0.008)	S-curve
Lender parameters				
mc_f	Origination cost	1.063	(0.236)	Lender FOC
mc_r	Funding cost	4.241	(0.014)	Lender FOC

Panel C: SMM target moments

Moment	Data	Model moment
S-curve	See Figure A10	
Average rate	4.31	4.31
Average fee	1.84	1.84

Note: This table provides the details of the structural estimation. Panel A shows the externally calibrated parameters, which are calibrated from a combination of papers in the literature as well as a direct estimation of the interest rate process. Panel B shows the parameters estimated through the simulated method of moments, where the first column shows the parameter, the second column describes the parameter, the third column shows the estimate, the fourth column shows the bootstrapped standard error, and the last column describes what identifies the parameter. Panel C shows the target moments. Note that there are four parameters calibrated with 12 separate moments from the s-curve (the rate incentive curve plotted in Figure A10).

Declaration of generative AI and AI-assisted technologies in the writing process
During the preparation of this work the author(s) used ChatGPT in order to assist in proof-reading the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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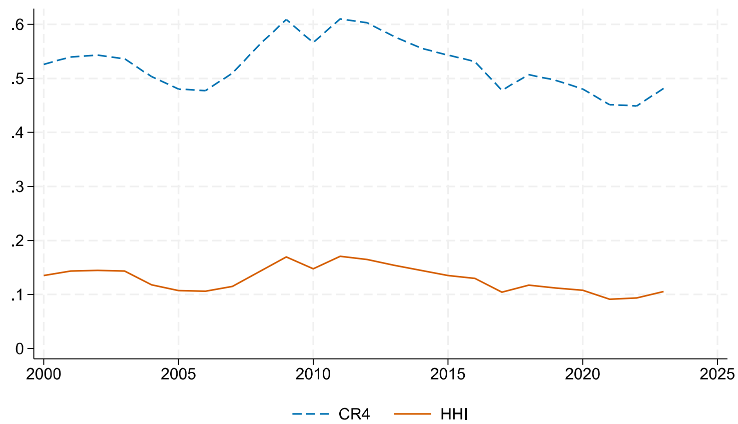
Appendix for Online Publication

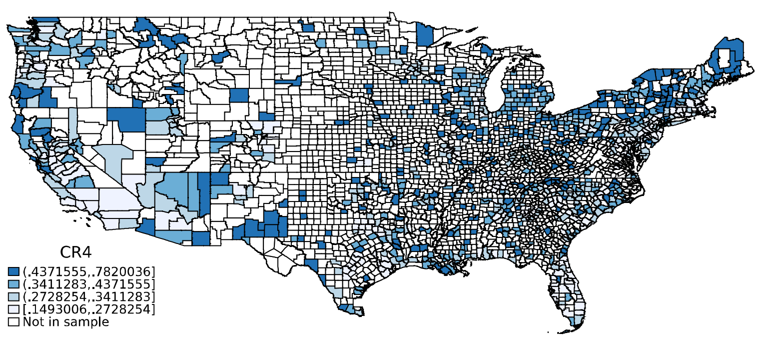
Contents

A Additional Figures

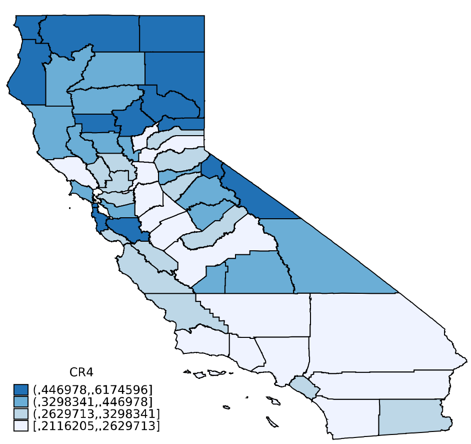
Figure A1: Local Mortgage Concentration



Panel A: Local mortgage concentration over time



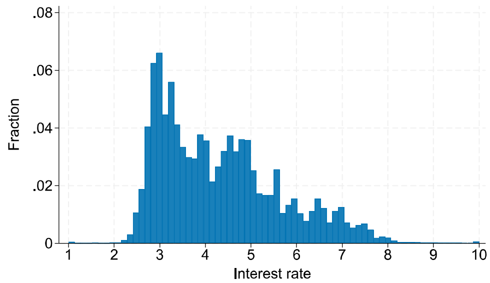
Panel B: National distribution of mortgage concentration



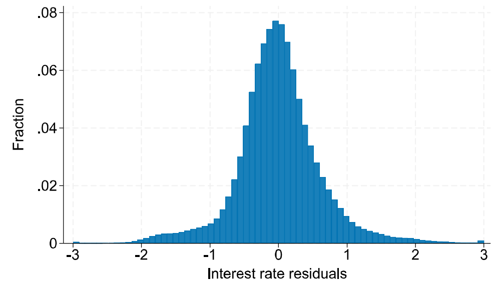
Panel C: Mortgage concentration in California

Note: This figure shows the distribution of local concentration across time and space. The data source is the HMDA dataset. Panel A shows the average county-level (dotted blue line) and HHI (solid orange line) for originated mortgages. Panel B shows the nationwide distribution of county-level mortgage market CR4 for the top 1,000 counties based on population in 2018. Panel C shows the 2018 distribution of county-level mortgage market CR4 in California.

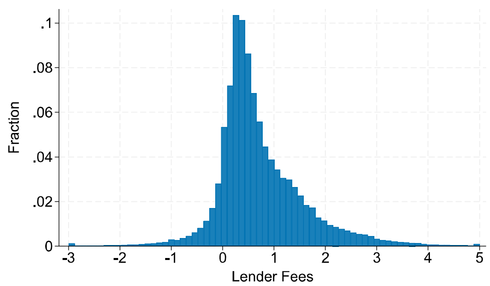
Figure A2: Distribution of Interest Rates and Fees



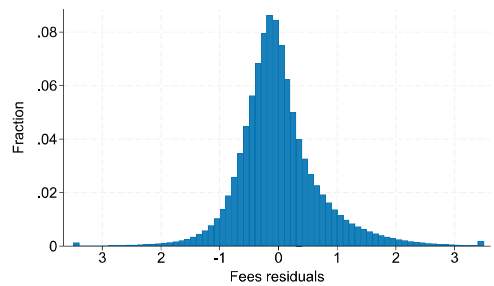
Panel A: Interest rates



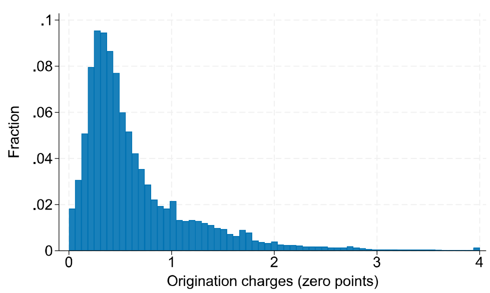
Panel B: Interest rate residuals



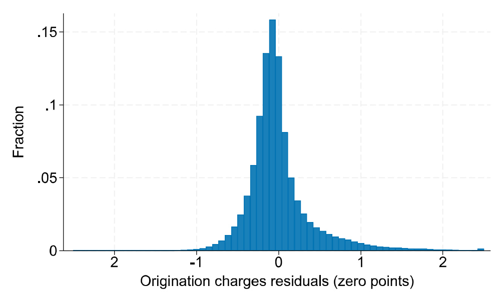
Panel C: Lender fees



Panel D: Lender fee residuals



Panel E: Lender fees (at zero points)



Panel F: Lender fees residuals (at zero points)

Note: This figure shows the distribution of mortgage interest rates and non-interest lender fees. The data source is the HMDA dataset. Panels A, C, and E show the distribution of interest rates, lender fees for all loans, and lender fees for loans with zero discount points and zero lender credits, respectively. Panels B, D, and F show the residuals from Equation (21) where the dependent variable is either interest rates, lender fees for all loans, and lender fees for loans with zero discount points and zero lender credits, respectively.

Figure A3: CFPB Mortgage Closing Cost Disclosure Form

Closing Cost Details

Loan Costs		Borrower-Paid		Seller-Paid		Paid by Others
		At Closing	Before Closing	At Closing	Before Closing	
A. Origination Charges		**$1,802.00**				
01 0.25 % of Loan Amount (Points)		$405.00				
02 Application Fee		$300.00				
03 Underwriting Fee		$1,097.00				
04						
05						
06						
07						
08						
B. Services Borrower Did Not Shop For		**$236.55**				
01 Appraisal Fee	to John Smith Appraisers Inc.					$405.00
02 Credit Report Fee	to Information Inc.		$29.80			
03 Flood Determination Fee	to Info Co.	$20.00				
04 Flood Monitoring Fee	to Info Co.	$31.75				
05 Tax Monitoring Fee	to Info Co.	$75.00				
06 Tax Status Research Fee	to Info Co.	$80.00				
07						
08						
09						
10						
C. Services Borrower Did Shop For		**$2,655.50**				
01 Pest Inspection Fee	to Pests Co.	$120.50				
02 Survey Fee	to Surveys Co.	$85.00				
03 Title – Insurance Binder	to Epsilon Title Co.	$650.00				
04 Title – Lender's Title Insurance	to Epsilon Title Co.	$500.00				
05 Title – Settlement Agent Fee	to Epsilon Title Co.	$500.00				
06 Title – Title Search	to Epsilon Title Co.	$800.00				
07						
08						
D. TOTAL LOAN COSTS (Borrower-Paid)		**$4,694.05**				
Loan Costs Subtotals (A + B + C)		$4,664.25	$29.80			

Other Costs		Borrower-Paid At Closing	Borrower-Paid Before Closing	Seller-Paid At Closing	Seller-Paid Before Closing	Paid by Others
E. Taxes and Other Government Fees		**$85.00**				
01 Recording Fees	Deed: $40.00 Mortgage: $45.00	$85.00				
02 Transfer Tax	to Any State			$950.00		
F. Prepaids		**$2,120.80**				
01 Homeowner's Insurance Premium (12 mo.) to Insurance Co.		$1,209.96				
02 Mortgage Insurance Premium (mo.)						
03 Prepaid Interest ($17.44 per day from 4/15/13 to 5/1/13)		$279.04				
04 Property Taxes (6 mo.) to Any County USA		$631.80				
05						
G. Initial Escrow Payment at Closing		**$412.25**				
01 Homeowner's Insurance $100.83	per month for 2 mo.	$201.66				
02 Mortgage Insurance	per month for mo.					
03 Property Taxes $105.30	per month for 2 mo.	$210.60				
04						
05						
06						
07						
08 Aggregate Adjustment		– 0.01				
H. Other		**$2,400.00**				
01 HOA Capital Contribution	to HOA Acre Inc.	$500.00				
02 HOA Processing Fee	to HOA Acre Inc.	$150.00				
03 Home Inspection Fee	to Engineers Inc.	$750.00			$750.00	
04 Home Warranty Fee	to XYZ Warranty Inc.			$450.00		
05 Real Estate Commission	to Alpha Real Estate Broker			$5,700.00		
06 Real Estate Commission	to Omega Real Estate Broker			$5,700.00		
07 Title – Owner's Title Insurance (optional)	to Epsilon Title Co.	$1,000.00				
08						
I. TOTAL OTHER COSTS (Borrower-Paid)		**$5,018.05**				
Other Costs Subtotals (E + F + G + H)		$5,018.05				
J. TOTAL CLOSING COSTS (Borrower-Paid)		**$9,712.10**				
Closing Costs Subtotals (D + I)		$9,682.30	$29.80	$12,800.00	$750.00	$405.00
Lender Credits						

CLOSING DISCLOSURE

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Note: Figure shows page 2 of the CFPC example closing cost disclosure form. Source: https://files.consumerfinance.gov/f/201311_cfpb_kbyo_closing-disclosure.pdf.

Figure A4: The Menu of Discount Points and Interest Rates

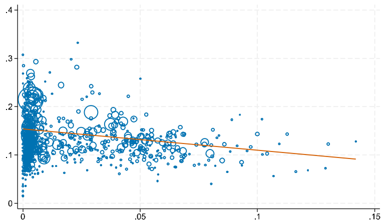
BANK OF AMERICA

Loan amount: $200,000

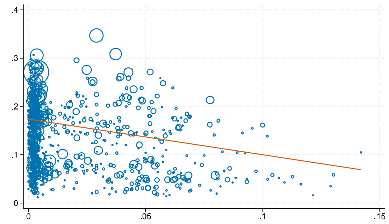
	No points	1 point	2 points
Cost per point(s)	0	$2,000	$4,000
APR*	4.5%	4.25%	4%
Monthly payment**	$1,013.37	$983.88	$954.83
Monthly payment savings	N/A	$29.49	$58.54
Break even (time to recover point costs)	N/A	68 months	68 months
Total payment savings on a 30-year loan	N/A	$10,616.40	$21,074.40

Note: Figure shows an example of how interest rates and discount points are presented from Bank of America. Source: https://bettermoneyhabits.bankofamerica.com/en/home-ownership/buying-mortgage-points-lower-rate

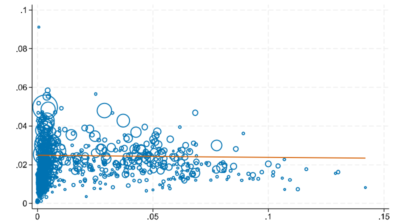
Figure A5: Failed Lender IV - Correlations: Wachovia



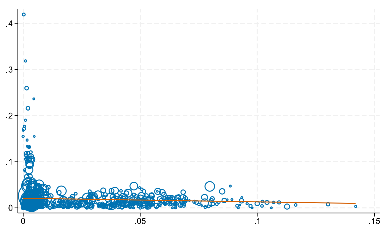
Panel A: NINJA loans (2007)



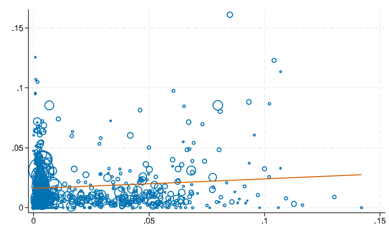
Panel B: Pre-payment penalty (2007)



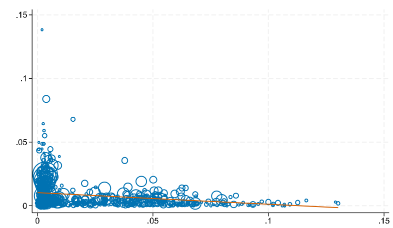
Panel C: Private label (2007)



Panel D: NINJA loans (2017)



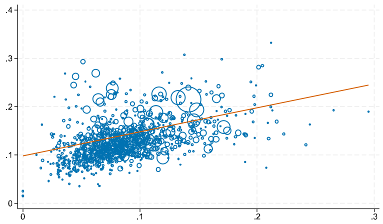
Panel E: Pre-payment penalty (2017)



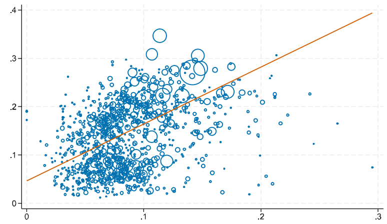
Panel F: Private label (2018)

Note: This figure shows scatter plots of the 1,000 largest counties (by number of mortgages). For each circle, the x-axis is the market share of Wachovia in 2007, and the y-axis is the fraction of mortgages with a specific attribute. Panels A and D show the fraction of NINJA (No Income No Job or Assets) mortgages in 2007 and 2017, respectively. Panels B and E mortgages with a pre-payment penalty in 2007 and 2017. (For these four panels, the data source is Black Knight.) Panels C and F mortgages securitized by private-label firms in 2007 and 2018. (For these two panels, the data source is HMDA.) In each panel, the solid line is the weighted univariate OLS predicted values.

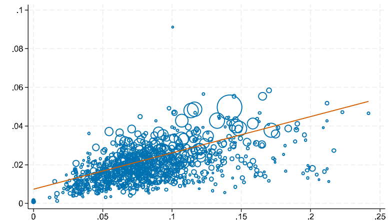
Figure A6: FAILED LENDER IV - CORRELATIONS: COUNTRYWIDE



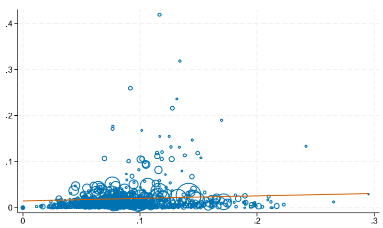
Panel A: NINJA loans (2007)



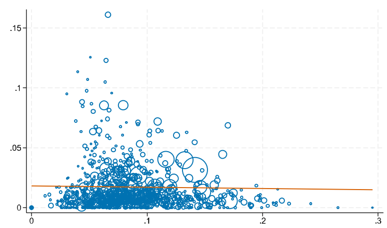
Panel B: Pre-payment penalty (2007)



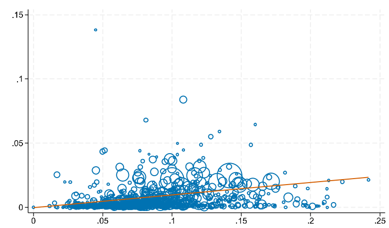
Panel C: Private label (2007)



Panel D: NINJA loans (2017)



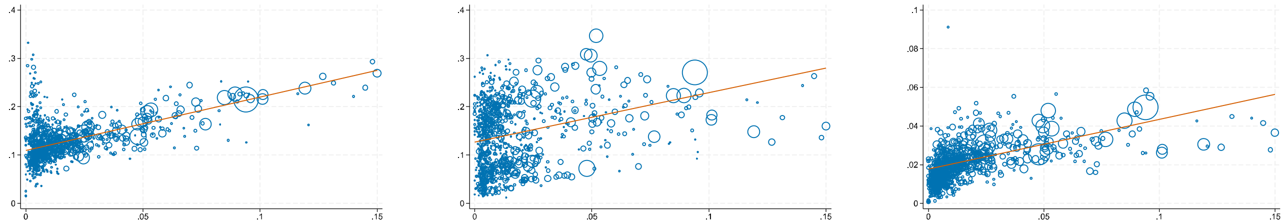
Panel E: Pre-payment penalty (2017)



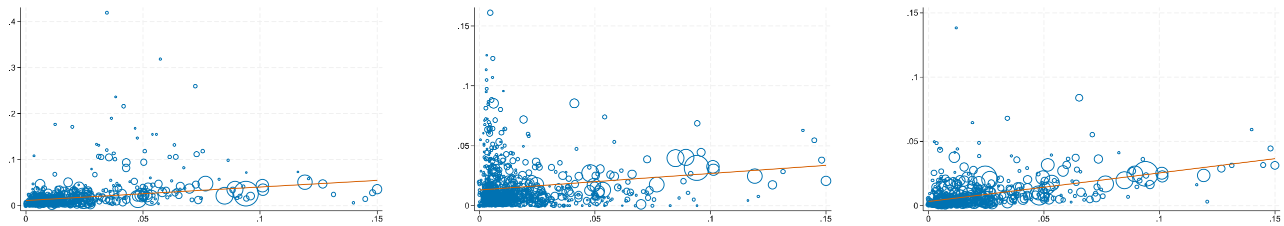
Panel F: Private label (2018)

Note: This figure shows scatter plots of the 1,000 largest counties (by number of mortgages). For each circle, the x-axis is the market share of Countrywide in 2007, and the y-axis is the fraction of mortgages with a specific attribute. Panels A and D show the fraction of NINJA (No Income No Job or Assets) mortgages in 2007 and 2017, respectively. Panels B and E mortgages with a pre-payment penalty in 2007 and 2017. (For these four panels, the data source is Black Knight.) Panels C and F mortgages securitized by private-label firms in 2007 and 2018. (For these two panels, the data source is HMDA.) In each panel, the solid line is the weighted univariate OLS predicted values.

Figure A7: Failed Lender IV - Correlations: Washington Mutual



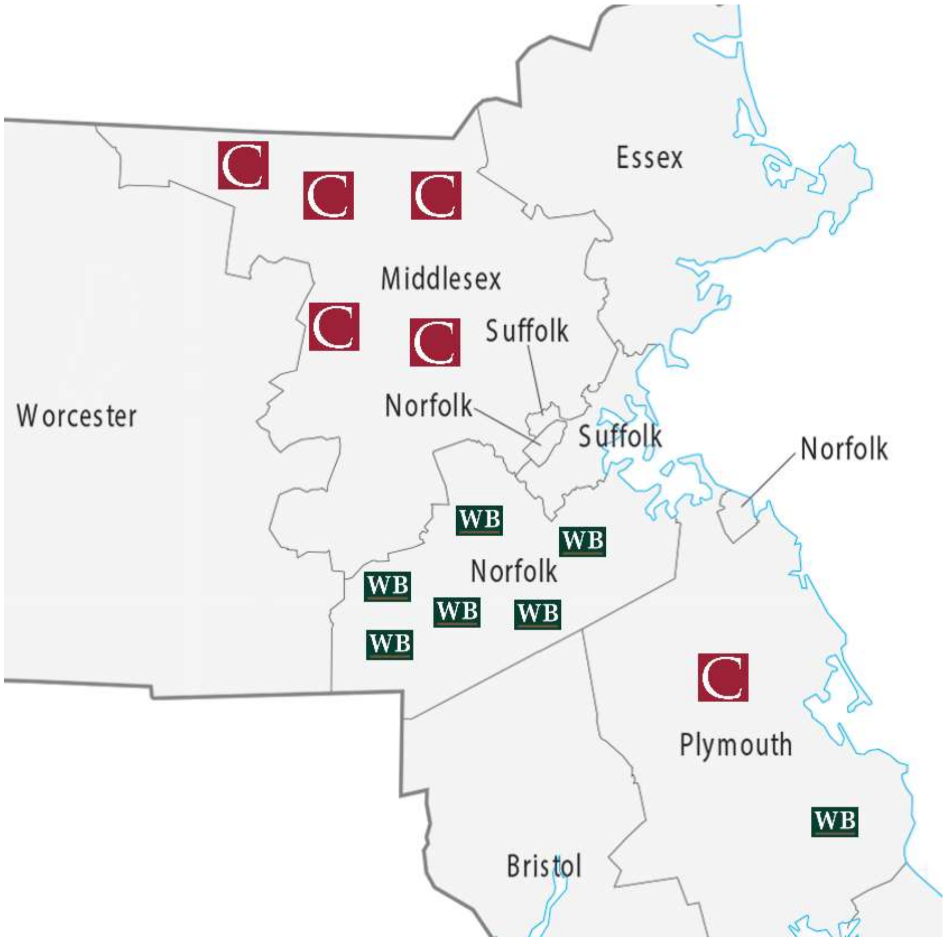
Panel A: NINJA loans (2007) Panel B: Pre-payment penalty (2007) Panel C: Private label (2007)



Panel D: NINJA loans (2017) Panel E: Pre-payment penalty (2017) Panel F: Private label (2018)

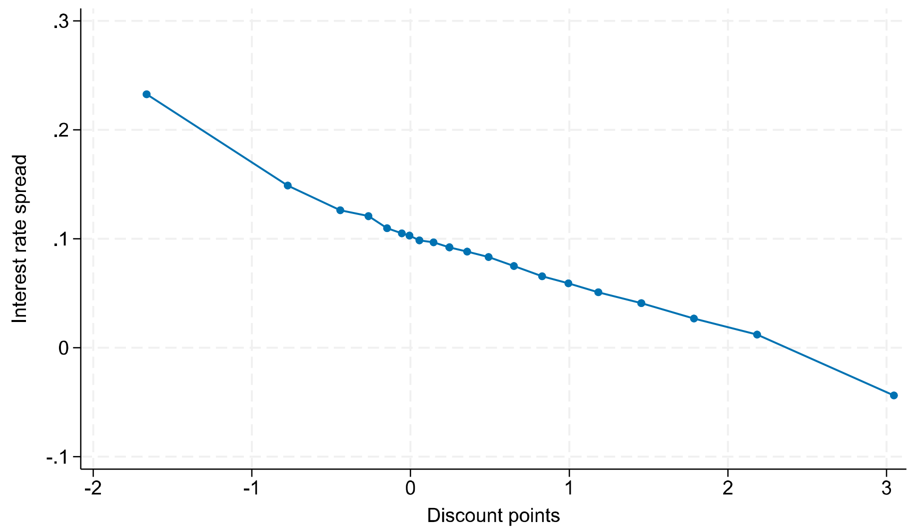
Note: This figure shows scatter plots of the 1,000 largest counties (by number of mortgages). For each circle, the x-axis is the market share of Washington Mutual in 2007, and the y-axis is the fraction of mortgages with a specific attribute. Panels A and D show the fraction of NINJA (No Income No Job or Assets) mortgages in 2007 and 2017, respectively. Panels B and E mortgages with a pre-payment penalty in 2007 and 2017. (For these four panels, the data source is Black Knight.) Panels C and F mortgages securitized by private-label firms in 2007 and 2018. (For these two panels, the data source is HMDA.) In each panel, the solid line is the weighted univariate OLS predicted values.

Figure A8: Bank Merger Instrument Construction

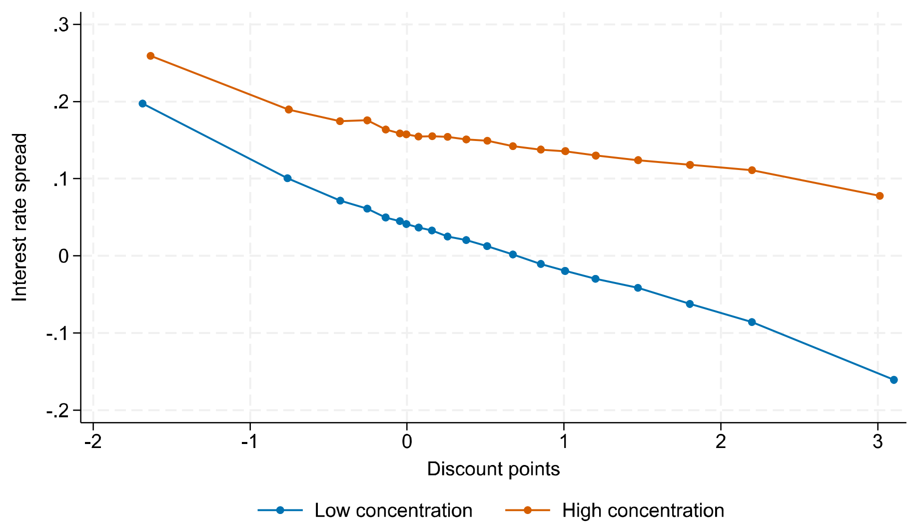


Note: Figure shows the construction and intuition of the merger instrument. In this hypothetical example, Cambridge Trust, primarily active in Middlesex County, purchases Wellesley Bank, primarily active in Norfolk County. The economic motivation for Cambridge Trust's purchase is to acquire branches in Norfolk. However, by virtue of the fact that Cambridge Trust and Wellesly Bank both have branches in Plymouth County, concentration in Plymouth County increases following the merger.

Figure A9: Discount points menu



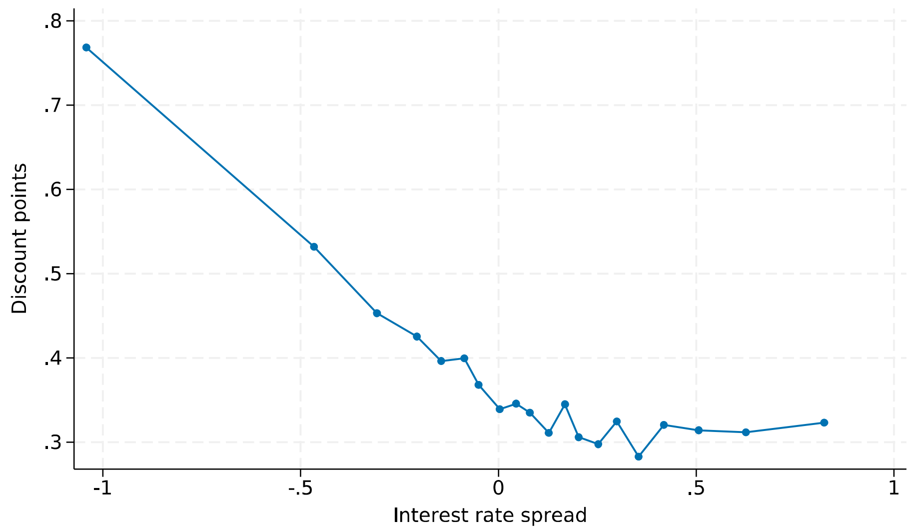
Panel A: Interest rates versus discount points



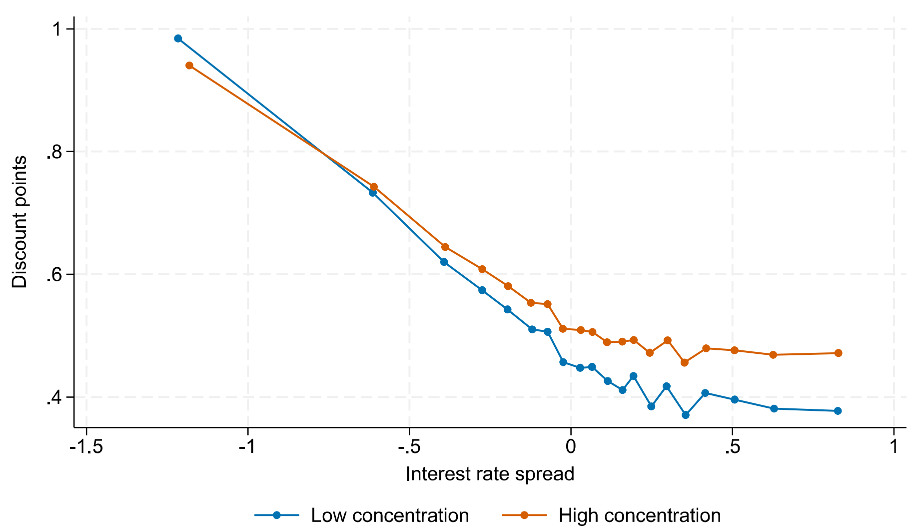
Panel B: Rates versus points (by concentration)

Note: The figure plots the relationship between discount points and interest rates. The data source is the merged HMDA-GSE dataset. Panel A plots a binned scatter plot of predicted values from a regression of interest rate spreads on loan-to-value and debt-to-income times FICO bins. Panel B plot predicted values from the same regression interacted with quartiles of the one-year lagged county-level CR4. Only the top and bottom quartile are included in Panel B. Interest rate spreads are calculated as the interest rate relative to the prime mortgage rate reported in Freddie Mac's weekly Primary Mortgage Market Survey (PMMS) and filtered for observations with more than a 1-percentage point positive spread.

Figure A9: Discount points menu (cont'd)



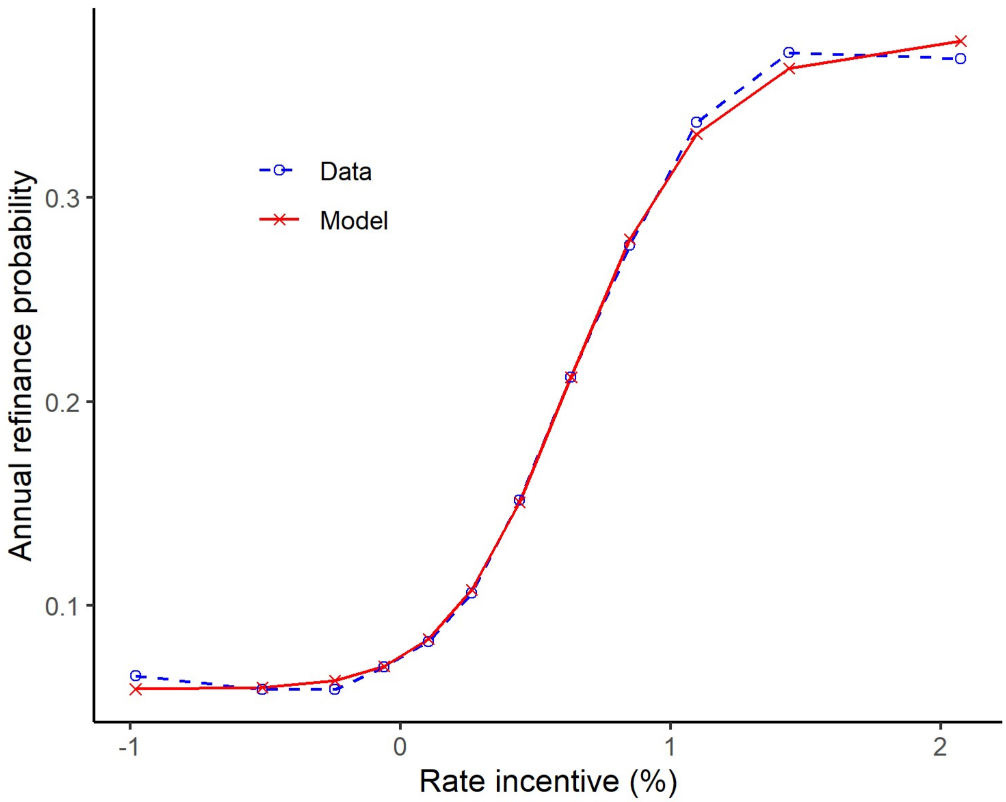
Panel C: Discount points versus interest rates



Panel D: Points versus rates (by concentration)

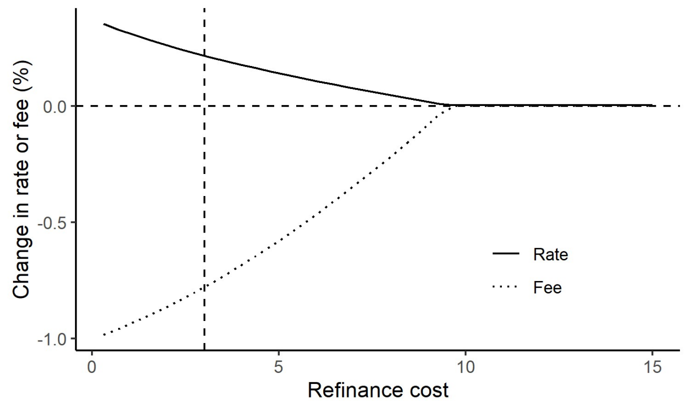
Note: The figure plots the relationship between interest rate spreads and discount points. The data source is the merged HMDA-GSE dataset. Panel A plots a binned scatter plot of predicted values from a regression of discount points on interest rate spreads and loan-to-value and debt-to-income times FICO bins. Panel B plot predicted values from the same regression interacted with quartiles of the one-year lagged county-level CR4. Only the top and bottom quartile are included in Panel B. Interest rate spreads are calculated as the interest rate relative to the prime mortgage rate reported in Freddie Mac's weekly Primary Mortgage Market Survey (PMMS) and filtered for observations with more than a 1-percentage point positive spread.

Figure A10: Empirical and model-implied s-curve

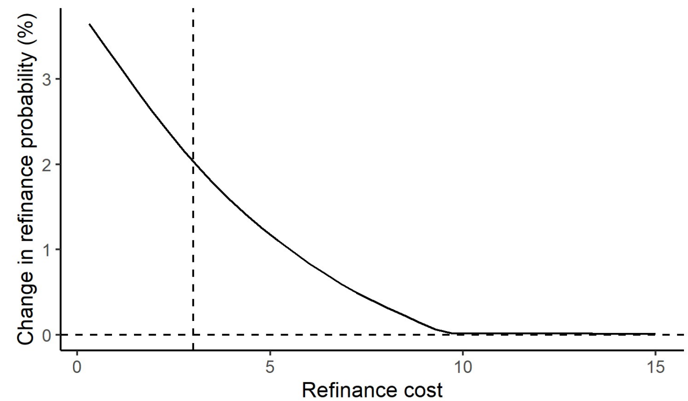


Note: This figure shows the empirical (blue) and model-implied (red) "s-curve." The x-axis is the rate incentive, i.e., the difference between a mortgage's current rate and prevailing rates at the time of observation. The y-axis is the annualized probability of refinancing.

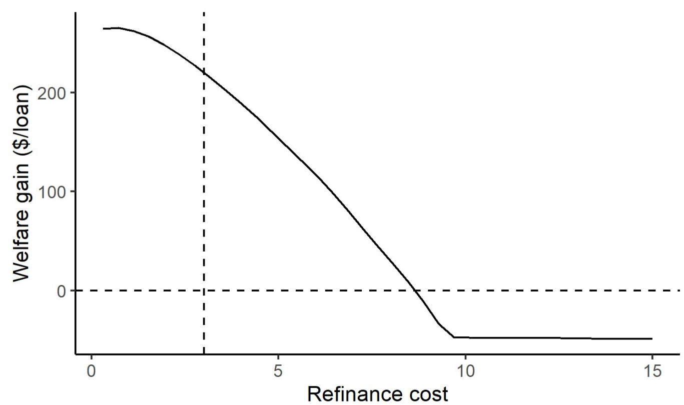
Figure A11: COUNTERFACTUAL ROBUSTNESS TO LENDER EXIT: CAPPING FEES AT MARGINAL ORIGINATION COSTS



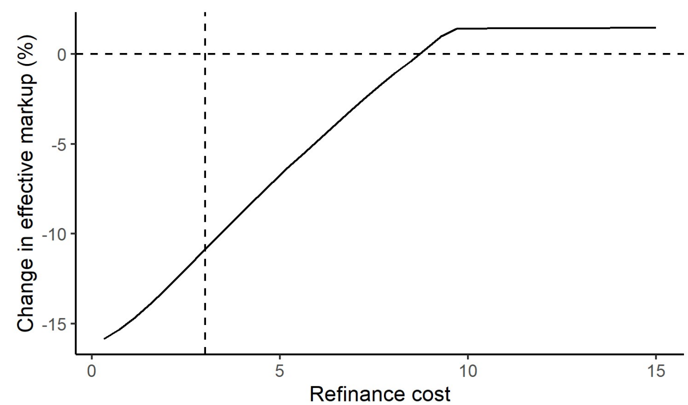
Panel A: Rates and fees



Panel B: Refinance probability



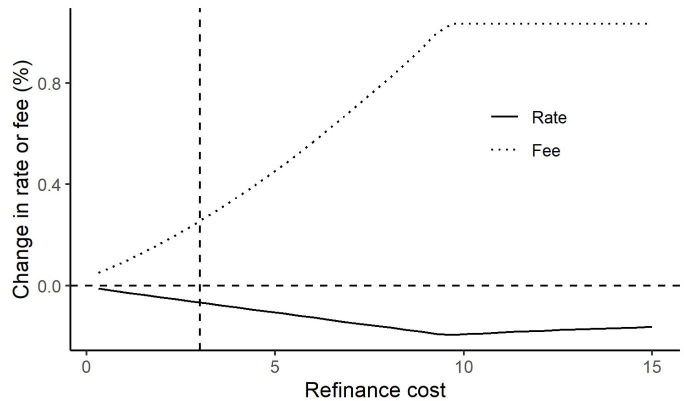
Panel C: Borrower welfare



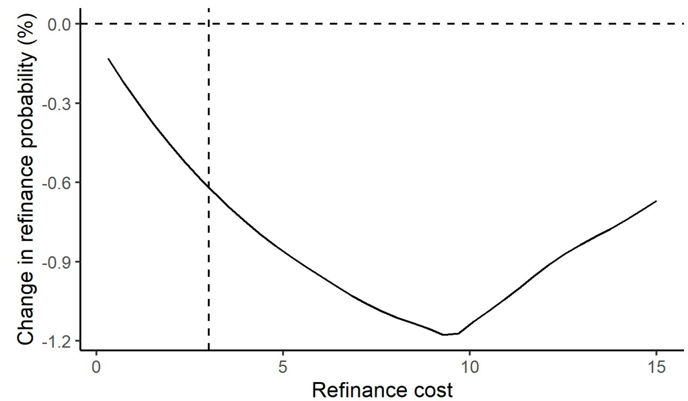
Panel D: Lender markups

Note: This figure studies the impact of a counterfactual where lenders are forced to set fees equal to the marginal cost of origination, mc_o, and only impose markups through rates. We assume in the counterfactual scenario, the number of lenders falls by 1 (roughly 10% relative to baseline). Each panel compares outcomes in the counterfactual "rate markup only" scenario to the estimated "profit-maximizing" scenario. These panels show the counterfactual impact versus the hedonic refinance cost c, with the dashed vertical line indicating the estimated value. Panel A shows the change in rates (solid) and fees (dotted). Panel B shows the change in annual refinance probability. Panel C shows the change in welfare, measured in dollar utility for a loan of average size. Panel D shows the change in lender markups, inclusive of net fee and rate income.

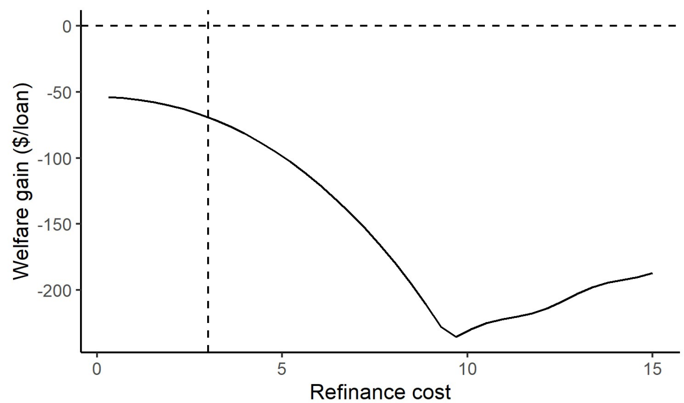
Figure A12: COUNTERFACTUAL ROBUSTNESS TO LENDER EXIT: CAPPING RATES AT MARGINAL FUNDING COSTS



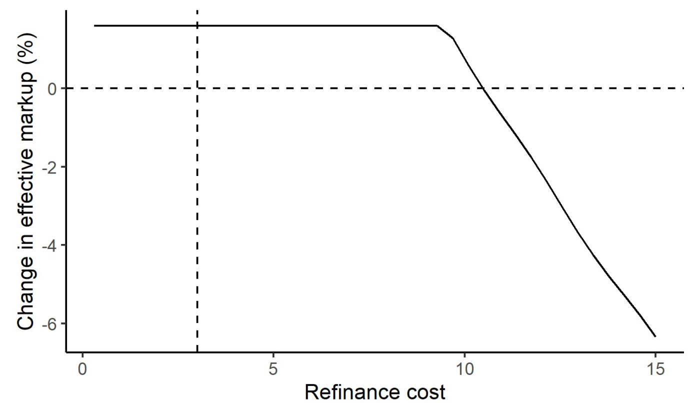
Panel A: Rates and fees



Panel B: Refinance probability



Panel C: Borrower welfare



Panel D: Lender markups

Note: This figure studies the impact of a counterfactual where lenders are forced to set rates equal to the marginal cost of funding, mc_r, and only impose markups through fees. We assume in the counterfactual scenario, the number of lenders falls by 1 (roughly 10% relative to baseline). Each panel compares outcomes in the counterfactual "rate markup only" scenario to the estimated "profit-maximizing" scenario. These panels show the counterfactual impact versus the hedonic refinance cost c, with the dashed vertical line indicating the estimated value. Panel A shows the change in rates (solid) and fees (dotted). Panel B shows the change in annual refinance probability. Panel C shows the change in welfare, measured in dollar utility for a loan of average size. Panel D shows the change in lender markups, inclusive of net fee and rate income.

B Additional Tables

Table A1: OLS robustness: Controlling for interest rates

	Including points				Zero points			
	HMDA		HMDA-GSE		HMDA		HMDA-GSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR4	0.312***		0.134***		0.097**		0.150***	
	(0.038)		(0.038)		(0.039)		(0.041)	
Interest rate	-0.006**	-0.006**	-0.399***	-0.399***	0.053***	0.053***	0.017***	0.017***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)
HHI		0.965***		0.209***		0.325***		0.247***
		(0.120)		(0.062)		(0.096)		(0.064)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓			✓	✓		
Month FE			✓	✓			✓	✓
FICO bin FE			✓	✓			✓	✓
N	12,260,411	12,260,411	2,978,006	2,978,006	3,511,441	3,511,441	731,557	731,557
R^2	0.25	0.25	0.30	0.30	0.48	0.48	0.33	0.33

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results from a modified version of equation (5), where the outcome variable is the amount of lender fees and the interest rate is included as an independent variable. Standard errors (in parentheses) are clustered at the county level. The sample is the 2018-2023 HMDA dataset.

Table A2: INSTRUMENT ROBUSTNESS I: CONTROLLING FOR INTEREST RATES

	Failed Lender IV				Incidental Merger IV			
	First stage		IV		First stage		IV	
	(1) CR4	(2) HHI	(3) Fees	(4) Fees	(5) CR4	(6) HHI	(7) Fees	(8) Fees
Share failed	-0.228***	-0.048***						
	(0.045)	(0.011)						
Interest rate	0.001***	0.000***	-0.005	-0.006	-0.001	-0.000	-0.011*	-0.011*
	(0.000)	(0.000)	(0.018)	(0.018)	(0.000)	(0.000)	(0.006)	(0.006)
CR4			2.793***				1.082**	
			(0.731)				(0.498)	
HHI				13.124***				4.746**
				(3.734)				(1.858)
Incidental merger					0.040***	0.009***		
					(0.009)	(0.002)		
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓				
County FE					✓	✓	✓	✓
N	12,047,410	12,047,410	11,969,502	11,969,502	215,576	215,576	214,417	214,417
R^2	0.45	0.42	-0.00	-0.03	0.93	0.91	0.03	0.03
F-stat	25	19			20	31		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results from a modified version of the IV specification that includes the interest rate as an independent variable. Columns (1) and (2) show the first stage and Columns (3) and (4) the second stage for the Failed Lender IV (equation 6). Columns (5) and (6) show the first stage and Columns (7) and (8) the second stage for the Incidental Merger IV (equation 7). Standard errors (in parentheses) are clustered at the county level.

Table A3: Instrument robustness II: Alternative lenders

	Countrywide & Washington Mutual				All Failed Lenders			
	First stage		IV		First stage		IV	
	(1) CR4	(2) HHI	(3) Fees	(4) Fees	(5) CR4	(6) HHI	(7) Fees	(8) Fees
Without Wachovia	-0.587***	-0.151***						
	(0.028)	(0.007)						
CR4			1.466***				1.534***	
			(0.192)				(0.189)	
HHI				5.695***				6.006***
				(0.746)				(0.734)
With Wachovia					-0.562***	-0.144***		
					(0.025)	(0.006)		
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
N	12,339,373	12,339,373	12,259,842	12,259,842	12,339,424	12,339,424	12,259,893	12,259,893
R^2	0.47	0.42	0.03	0.03	0.47	0.42	0.03	0.02
F-stat	448	463			522	535		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results from the Failed Lender IV specification using two other failed lenders instead of Wachovia: Countrywide and Washington Mutual. Columns (1) and (2) show the first stage and Columns (3) and (4) the second stage for the Failed Lender IV (equation 6). Columns (5) and (6) show the first stage and Columns (7) and (8) the second stage for the Incidental Merger IV (equation 6). Standard errors (in parentheses) are clustered at the county level.

Table A4: Instrument robustness III: Alternative samples

	Zero points				HMDA-GSE			
	First stage		IV		First stage		IV	
	(1) CR4	(2) HHI	(3) Fees	(4) Fees	(5) CR4	(6) HHI	(7) Fees	(8) Fees
Share failed	-0.539***	-0.140***			-0.285***	-0.184***		
	(0.028)	(0.007)			(0.044)	(0.024)		
CR4			1.151***				1.311***	
			(0.176)				(0.433)	
HHI				4.421***				2.025***
				(0.678)				(0.667)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓				
Month FE					✓	✓	✓	✓
FICO bin FE					✓	✓	✓	✓
N	3,561,690	3,561,690	3,514,090	3,514,090	2,984,147	2,984,147	2,977,650	2,977,650
R^2	0.52	0.48	0.11	0.10	0.35	0.24	0.06	0.07
F-stat	366	360			41	58		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results from the IV specifications. In Panel A, the dependent variable is the interest rate, and in Panel B, the amount of fees. Columns (1) and (2) show the first stage and Columns (3) and (4) the second stage for the Failed Lender IV (equation 6). Columns (5) and (6) show the first stage and Columns (7) and (8) the second stage for the Incidental Merger IV (equation 6). Standard errors (in parentheses) are clustered at the county level.

Table A5: Instrument robustness IV: Alternative threshold values

Panel A: Failed Lender IV

	First stage					IV				
	(1) CR4	(2) CR4	(3) CR4	(4) CR4	(5) CR4	(6) Fees	(7) Fees	(8) Fees	(9) Fees	(10) Fees
Share failed	-0.527***	-4.130***	-2.582***	-1.476***	-0.817***					
	(0.026)	(0.303)	(0.059)	(0.036)	(0.030)					
CR4						1.412***	0.329***	0.645***	1.066***	1.097***
						(0.179)	(0.109)	(0.081)	(0.123)	(0.150)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample filter	None	5%	10%	15%	20%	None	5%	10%	15%	20%
N	10,823,378	315,837	1,999,861	6,588,688	9,420,128	10,749,808	314,345	1,988,569	6,545,960	9,359,062
R^2	0.48	0.52	0.56	0.56	0.51	0.03	0.08	0.07	0.04	0.04
F-stat	409	186	1,895	1,708	716					

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Merger IV

	First stage						IV					
	(1) CR4	(2) CR4	(3) CR4	(4) CR4	(5) CR4	(6) CR4	(7) Fees	(8) Fees	(9) Fees	(10) Fees	(11) Fees	(12) Fees
Incidental merger	0.040***	0.038***	0.173***	0.021***	0.038***	0.173***						
	(0.009)	(0.012)	(0.019)	(0.007)	(0.012)	(0.019)						
CR4							1.080**	1.916**	0.973	1.954**	1.898**	0.973
							(0.497)	(0.775)	(0.989)	(0.752)	(0.767)	(0.989)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Filter 1	1%	2%	5%	1%	2%	5%	1%	2%	5%	1%	2%	5%
Filter 2	2%	2%	2%	5%	5%	5%	2%	2%	2%	5%	5%	5%
N	215,744	69,826	1,182	357,945	70,561	1,182	214,576	69,511	1,174	356,123	70,163	1,174
R^2	0.93	0.95	0.91	0.95	0.95	0.91	0.03	0.03	0.06	0.04	0.03	0.06
F-stat	20	10	88	9	10	88						

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the results from estimating the two instruments under different sample filters. Panel A reports the failed lender IV and Panel B the Merger IV. In Panel A, the "Sample Filter" row represents the threshold value for which counties to include in the sample. For example, in Columns (2) and (7) we include only counties where the failed lender share is between 0 and 5%. In Panel B, the two rows "Filter 1" and "Filter 2" refers to our sample filters. Filter 1 keeps only counties where each lender in the merger is involved in X percent of the total mortgage originations in the county. Filter 2 keep only counties where the county contributes no more than X percent of each lender's mortgage originations in the given year.

Table A6: Placebo & Robustness Analysis

Panel A: Effect of Concentration by Types of Fees

	(1) Origination charges	(2) Discount points	(3) Lender credits	(4) Third-party fees
CR4	0.235***	0.544***	-0.153***	0.053
	(0.038)	(0.097)	(0.025)	(0.039)
Loan controls	✓	✓	✓	✓
County controls	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	12,274,206	4,874,455	4,716,313	12,274,206
R^2	0.28	0.20	0.16	0.26

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Effect of concentration on Expected Present Value

	OLS	2SLS: 1st Stage		2SLS: 2nd stage	
		Failed lenders	Mergers	Failed lenders	Mergers
	(1) E[PV]	(2) CR4	(3) E[PV]	(4) CR4	(5) E[PV]
CR4	0.846***			1.877***	1.251
	(0.115)			(0.209)	(1.001)
Share failed		-1.489***			
		(0.109)			
Incidental merger			0.037***		
			(0.009)		
Year FE	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓
County FE			✓		✓
N	10,736,174	6,588,688	189,519	6,538,843	188,314
R^2	0.66	0.42	0.95	0.03	0.02
F-stat		186	18		

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results from the robustness and placebo analysis. Panel A shows the result from a modified version of the OLS and IV specifications that includes an imputed expected present value as the independent variable. Panel B shows the results from equation (5). In Column (1), the outcome variable is origination charges. In Column (2) and (3), the outcome variable is money paid for discount points and money received for lender credits, respectively. In Column (4), the outcome variable is third-party fees. Standard errors (in parentheses) are clustered at the county level.

Table A7: Familiar with Upfront Fees?

	Familiar with money at closing		
	(1)	(2)	(3)
High school graduate	-0.005		
	(0.035)		
Technical school	0.003		
	(0.038)		
Some college	0.005		
	(0.032)		
College graduate	0.027		
	(0.031)		
Postgraduate studies	0.020		
	(0.030)		
Education Level		0.007***	
		(0.002)	
Credit Score			0.031***
			(0.005)
Year FE	✓	✓	✓
Demographics FE	✓	✓	✓
N	21,621	21,621	21,621
R^2	0.08	0.08	0.09

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results an OLS using the NSMO database. The dependent variable is a dummy variable indicating whether the borrower is either *very familiar* or *somewhat familiar* with the money needed at closing. (This corresponds to question *x05g* taking the values 1 or 2.) In Column (1), the main independent variables are dummy variables indicating the level of education, where the omitted group is the lowest level of education ("Some Schooling"). In Column (2), the independent variable is the education level. In Columns (3), the independent variable is the borrowers VantageScore at origination, where the coefficient is scaled to represent the effect of a one-standard-deviation change in the credit score. Each regression includes a year fixed effect and the following demographic control variables: age, age-squared, a dummy variable indicating whether this is the first mortgage, marital status, sex, ethnicity, and race. Standard errors (in parentheses) are clustered at the survey-wave level.

Table A8: Mortgage Shopping Behavior

	Number of brokers/lenders			More than one broker/lender		
	(1)	(2)	(3)	(4)	(5)	(6)
High school graduate	0.134**			0.079**		
	(0.051)			(0.036)		
Technical school	0.229***			0.137***		
	(0.045)			(0.029)		
Some college	0.223***			0.147***		
	(0.049)			(0.032)		
College graduate	0.331***			0.209***		
	(0.045)			(0.030)		
Postgraduate studies	0.417***			0.244***		
	(0.047)			(0.030)		
Education Level		0.074***			0.043***	
		(0.007)			(0.004)	
Credit Score			0.077***			0.038***
			(0.012)			(0.006)
Year FE	✓	✓	✓	✓	✓	✓
Demographics FE	✓	✓	✓	✓	✓	✓
N	21,621	21,621	21,621	21,621	21,621	21,621
R^2	0.03	0.03	0.02	0.03	0.02	0.02

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results an OLS using the NSMO database. In Columns (1)–(3), the dependent variable is the number of brokers or lenders that the borrower seriously considered. (This corresponds to question *x11*.) In Columns (4)–(6), the dependent variable is a dummy variable taking the value one if the borrower considered more than one broker/lender. In Columns (1) and (4), the main independent variables are dummy variables indicating the level of education, where the omitted group is the lowest level of education (”Some Schooling”). In Columns (2) and (5), the independent variable is the education level. In Columns (3) and (6), the independent variable is the borrowers VantageScore at origination, where the coefficient is scaled to represent the effect of a one-standard-deviation change in the credit score. Each regression includes a year fixed effect and the following demographic control variables: age, age-squared, a dummy variable indicating whether this is the first mortgage, marital status, sex, ethnicity, and race. Standard errors (in parentheses) are clustered at the survey-wave level.

Table A9: Heterogeneity by Types of Borrowers

	Income			Credit Risk		
	Low Income	High Income	All	Low FICO	High FICO	All
	(1)	(2)	(3)	(4)	(5)	(6)
CR4	0.381***	0.326***	0.612***	0.428***	0.374***	0.441***
	(0.033)	(0.039)	(0.038)	(0.073)	(0.065)	(0.070)
High Income			-0.073***			
			(0.010)			
CR4 X High Income			-0.244***			
			(0.026)			
High FICO						-0.047***
						(0.011)
CR4 X High FICO						-0.074***
						(0.021)
Year FE	✓	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓
N	6,122,720	6,046,042	12,168,926	1,508,554	1,469,327	2,978,053
R^2	0.27	0.24	0.25	0.27	0.24	0.25

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results from equation (5). Standard errors (in parentheses) are clustered at the county level. In Columns (1) and (2), the sample is borrowers with either below or above median income, respectively. In Column (3), the sample is the full baseline sample. The variable "High Income" is a dummy variable indicating if the borrower has an above-median income. In Column (4) and (5), the sample is the matched HMDA-GSE sample with either below or above FICO score, respectively. In Column (6), the sample is the full HMDA-GSE sample. The variable "High FICO" is a dummy variable indicating if the borrower has an above-median FICO score.

Table A10: Heterogeneity by Types of Loans and Lenders

Panel A: Loan Types

	Refi	Cash-out	FHA
	(1)	(2)	(3)
CR4	0.364***	0.638***	0.558***
	(0.093)	(0.075)	(0.032)
Year FE	✓	✓	✓
Loan controls	✓	✓	✓
Lender FE	✓	✓	✓
N	6,030,184	4,161,576	3,878,182
R^2	0.30	0.35	0.29

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Lender Types

	Banks	Non-banks	FinTechs	Small	Large
	(1)	(2)	(3)	(4)	(5)
CR4	0.486***	0.539***	0.910***	0.384***	0.604***
	(0.036)	(0.046)	(0.094)	(0.050)	(0.034)
Year FE	✓	✓	✓	✓	✓
Loan controls	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓
N	5,806,067	6,468,127	994,209	5,640,704	6,633,363
R^2	0.28	0.23	0.25	0.24	0.24

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results from equation (5). Standard errors (in parentheses) are clustered at the county level. In Panel A Column (1), the sample is non-cash-out refinances. In Column (2), the sample is cash-out refinances. In Column (3), the sample is FHA loans. In Panel B Column (1) we restrict the sample to include only Banks, in Column (2) the sample includes only Non-banks, and in Column (3) the sample includes Non-banks that rely primarily on technology (so-called "FinTechs"). Columns (4) and (5) restrict the sample to lenders with below and above median size, respectively.

C Aggregate Facts

In this Section, we present aggregate facts and trends concerning mortgage lender concentration, interest rates, and non-interest-rate origination fees. Overall, we document significant market-level variation in all three quantities, which is itself suggestive of variation in market power, though not necessarily at a local level.

C.I Concentration

Although we focus our analysis on 2018–2023, in order to provide more context, we present some aggregate trends in market concentration over time and across geographic regions. Figure A1, Panel A, shows the averages of CR4 (dotted blue) and HHI (solid orange) between 1990 and 2023. Both measures of concentration have been fairly stable across these three decades, with a slight increase in average mortgage concentration from 2006 to 2009, and a reversal from 2011 to 2023.

Apart from time-series variation, there is significant geographical variation in concentration. To provide a sense of this variation, Panel B of Figure A1 shows the nationwide distribution of CR4 in 2018 across the 1,000 most populous counties in the United States. The CR4 values for these counties range from 15% to 78%. Interestingly, the cross-sectional variation in concentration is not due solely to differences between urban and rural counties. Panel C illustrates this fact using data from California. Among urban counties in California, Los Angeles County and San Diego County have CR4 values in the bottom quartile, while Santa Clara County (where San Jose is located) and San Francisco County have CR4 values in the top quartile. On the other hand, while rural Alpine County is in the top quartile, rural Yuba County is in the bottom quartile.

C.II Interest Rates

We next turn to interest rates. Figure A2, Panel A, shows a histogram of interest rates for 2018 through 2023. The raw values in Figure A2 show significant variation; however, this could arise from differences in funding costs across time or from differences in lenders' marginal costs—for example, the costs of lending to riskier borrowers. We therefore residualize interest rates with the following specification:

$$Y_{ibct} = \eta' X_i + \mu' X_{ct} + \gamma_b + \gamma_c + \gamma_t + \epsilon_{ibct}, \tag{21}$$

where Y_{ibct} is the interest rate (in percent) for loan i originated by lender b in county c in year t; X_i is a vector of loan-level controls; X_{ct} is a vector of county-year-level controls; and γ_b, γ_c, and γ_t are lender, county, and year fixed effects. The loan-level controls include the loan amount and bins for LTV and DTI ratios, and the county-year-level controls include unemployment levels. This regression removes differences in interest rates that can be attributed, for example, to differences in risk explainable by individual or geographical factors.[29] We plot the residualized interest rates in Figure A2, Panel B. The plot shows that even after differences due to risk are removed, there remains significant dispersion in interest rates.

C.III Non-interest Fees

Finally, we turn to non-interest fees. Figure A2, Panel C, shows a histogram of lender fees as a fraction of the loan amount. The raw values in Figure A2 show significant variation. However, as with interest rates, this variation could arise from differences in lenders' marginal costs. We therefore residualize fees using equation (21). Figure A2, Panel D, shows a plot of the residualized fees. As in the case of interest rates, the plot shows that even after

[29] When using the merged HMDA-GSE dataset, we further control for the FICO score (using the LLPA grid bins) and the year-month of origination.

differences due to risk are removed, there remains significant dispersion in fee amounts.

Finally, in part of the analysis, we follow Bhutta, Fuster and Hizmo (2024) and restrict our sample by only studying fees for loans with zero discount points and zero lender credits. In this restricted sample, the only remaining fees are application fees and underwriting fees. Figure A2, Panels E and F show plots of the raw and residualized fees in this sample, respectively.

D Robustness Tests for OLS Analysis

D.I Controlling for interest rates

Our results on the relationship between local concentration and fees for standard prepayable loans does not appear to be driven by borrower's with high fees endogenously having lower interest rates. We provide evidence for this in Table A1, where we regress fees on local concentration while also controlling for the interest rate. In the full sample, which includes points and credits, the relationship between fees and rates is (mechanically) negative. Interestingly, in the restricted sample where points and credits are fixed at zero, the relationship between fees and rates is positive. Crucially, the relationship between fees and local concentration remains virtually unchanged when we include the interest rate as a control, suggesting that our results are not driven by the endogenous sorting of borrowers across the rate–points menu.

D.II Placebo Test

As a placebo test, we decompose the effect of local concentration by the type of fees. If the main results are indeed driven by lender's market power, it is natural to expect that only fees controlled by the originating lenders are sensitive to local concentration. In this subsection, we investigate this insight and decompose the effects of concentration on fees into the different components of fees.

We begin by decomposing the effect of changes in concentration on the components of fees set by the originating lender. Columns (1)–(3) of Table A6 Panel A show the effects of concentration on each of the three components: origination charges, discount points, and lender credits. We find that higher concentration is associated with higher revenue for lenders in every category. That is, it is associated with larger amounts paid for origination charges and discount points (which are borrower expenses) and smaller amounts paid for lender credits (which are lender expenses).

In comparison, as a placebo exercise, we analyze how concentration relates to fees that are not determined by the originating lender, such as appraisal, inspection, and title insurance fees. Column (4) reports the results. We do not find any statistically significant correlation between these fees and concentration; the coefficient is not statistically different from zero and it is an order of magnitude lower than the coefficients for the fee types considered in Columns (1)–(3). This indicates that our main results are not driven by spurious geographic or borrower-specific variation that leads to higher fees across the board.

D.III Expected Present Value

In this subsection, we conduct a back-of-the-envelope calculation to impute the expected present value of the revenue from each mortgage. We then estimate the relationship between local concentration and the expected present value of payment revenue.

The expected present value of future payments depends on several factors including the expected payments, the expected path of discount rates, and the future opportunity cost of capital (which may or may not be different than the future discount rate). To simplify calculations, we make the following simplifying assumption. We impute the expected present value of payments as

$$E[PV(\text{payments})] = \text{fee} + \sum_{t=1}^{T} \frac{\text{interest rate}}{1+r} \tag{22}$$

We set $T = 5$ years as the average prepayment period. This is based on the average prepayment frequency, which we calculate in the HMDA-GSE dataset, were the average number of months before prepayment is 61 months (and the median is 38 months). This is consistent with the average Conditional Prepayment Rate (CPR) reported by the FHFA. For example, in their Prepayment Monitoring Report from the First Quarter of 2023,[30] the FHFA reports that during our sample period the CPR fluctuates between 5% and 35%. A CPR of 15% means that over half of the MBS portfolio has been prepaid after five years: $(1 - 15\%)^5 = 44\%$. We assume a constant discount rate of 5%.

For each mortgage in the sample, we impute the expected present value of payments using equation (22). Next, we repeat the OLS and IV analysis. Table A6 report the results. Specifically, the table shows the results from a modified version of the OLS and IV specifications that includes an imputed expected present value as the independent variable. Column (1) shows the OLS coefficients, Column (2) and (4) show the first and second stage for the Failed Lender IV (equation 6), respectively. Columns (3) and (5) show the first and second stage for the Incidental Merger IV (equation 6), respectively.

As the expected present value imputed in equation (22) is simply a weighted average of the fee and the interest rate, the coefficients from the OLS and IV analyses are also consistent with the results from the main analysis. For example, we see that in both the OLS and IV analysis the coefficient on CR4 is positive. In the OLS and Failed Lender IV the coefficient is statistically significant at the 1-% level. For the Incidental Merger IV, the coefficient is between the two other coefficients, but the standard errors are so large that the coefficient

[30]See https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/Prepayment-Monitoring-Report_2023Q1.pdf.

is statistically indistinguishable from zero.

D.IV The Menu of Interest Rates vs. Discount Points

In this Section, we analyze the heterogeneous relationship between interest rates and two specific components of fees: discount points and lender credits (which combined make up just less than one quarter of total upfront fees). Since discount points and lender credits are paid (received) by the borrower in exchange for lower (higher) interest rates, there is a mechanical relationship between discount points, lender credits, and interest rates. To study how local concentration affects this relationship in detail, we follow Bhutta and Hizmo (2020) and regress the interest rate spread on the net amount of discount points (discount points minus lender credits) using the matched HMDA–GSE dataset.[31]

Figure A9, Panel A, illustrates the relationship with a plot of predicted values from the regression. We see a negative relationship between the revenue that the lender receives over time (the interest rate minus funding costs) and one part of the revenue that the lender receives up front (the discount points minus lender credits).

Next, we analyze this relationship relative to concentration. We find that, the relationship between interest rates and points and credits differs significantly between low- and high-concentration markets. Figure A9, Panel B, presents graphical evidence of this difference, recreating the rate–point menu of Panel A for subsets of the data corresponding to high- and low-concentration markets. We plot the predicted values from a regression of discount points on interest rate spread deciles interacted with quartiles of the one-year lagged county-level CR4.

We find that at each part of the menu, borrowers in more concentrated counties pay higher

[31] Only discount points and lender credits are offered as a menu relative to interest rates. Other fees, for example origination charges are not. The interest rate spread is calculated as the interest rate relative to the prime mortgage rate reported in Freddie Mac's weekly Primary Mortgage Market Survey, and we control for LTV and DTI-FICO bins.

points for the same level of interest rates. The rate-points schedule for high-concentration markets (those in the top quartile by CR4) is shifted upward relative to the menu for low-concentration markets (those in the bottom quartile by CR4). In other words, obtaining the same interest rate through discount points costs about 50 basis points more in a top-quartile market than in a bottom-quartile market. This result highlights that our main result is not simply driven by borrowers in some counties choosing a different point on the menu. Rather, we find that lenders with market power increase the amount of points and decrease the amount of lender credits they offer given the prevailing interest rate.

In a recent paper, Willen and Zhang (2022) build a structural model using pairwise domination that tests for racial discrimination in menus contracts. They recommend that researchers study the relationship in two ways, both 'natural' and with 'flipped' axis; i.e., using both rates and points on the y-axis (and points and rates on the x-axis, respectively.) They show, theoretically, that in some cases, a dominant relationship using one variable as the dependent variable will not survive when using the other variable as the dependent variable. Following their suggestion, we repeat our analysis, regressing net points on the interest rate, and here we also find that low-concentration counties have dominating menus across the entire range. We plot this result in Figure A9 Panels C and D.

E Robustness Tests for IV Analysis

In this section, we provide additional robustness analysis of the IV results. First, mirroring the OLS analysis, Table A2 reports IV estimates that control directly for the interest rate. As before, the results are virtually unchanged, highlighting that our findings are not driven by the endogenous sorting of borrowers across the rate–points menu.

E.I Example of Incidental Merger IV

How does the Incidental Merger instrument work? Figure A8 provides an illustrative example. In 2020, Cambridge Bancorp—the parent of Cambridge Trust, a mortgage lender in Cambridge, Massachusetts—completed its merger with Wellesley Bancorp Inc., another mortgage lender in Massachusetts. The figure presents a hypothetical situation in which Cambridge Trust is primarily active in Middlesex County, while Wellesley Bank is primarily active in Norfolk County. The assumption behind our IV analysis is that the economic motivation for Cambridge Trust's purchase is to expand its presence in Norfolk County. However, since both Cambridge Trust and Wellesley Bank are also active in Plymouth County, the market concentration in Plymouth County increases following the merger. That is, the merger incidentally increases concentration in overlapping markets that are not central to either party in the merger.

E.II Robustness of Failed Lender IV

In the baseline specification for the failed lender IV, we use Wachovia's market shares as the instrument. In Table A3, we show that the results are robust to using the market shares of Countrywide and Washington Mutual instead or using the combined markets shares of all three lenders as well.

In Panels A–C in Figures A6 and A7, we report the correlations between 2007 borrower characteristics and the market shares of Countrywide and Washington Mutual, respectively, and we find indeed strong positive correlations with 2007 mortgage lending patterns, and we confirm that this correlation has vanished by 2017. While Countrywide and Washington Mutual's 2007 market shares appear unrelated to differences in borrower characteristics, we nevertheless use Wachovia's shares as our primary instrument out of an abundance of caution. Nonetheless, in robustness checks, we find that including either Wachovia alone, Countrywide and Washington Mutual, or all three lenders together deliver similar results.

Next, to ensure that our results are not driven by features unique to Wachovia that may limit external validity, we replicate the Failed Lender IV using two other large lenders that failed during the financial crisis: Countrywide and Washington Mutual. Results are reported in Table A3. Given Countrywide's substantial market share in 2007, the resulting first-stage F-statistics are very large (448 and 463). The estimated effect on fees is smaller in magnitude than when using Wachovia alone, but is interestingly very close to the estimates obtained using the Merger IV. Then, in Table A4, we show that the IV results are consistent when using more granular sample restrictions, and in Table A5, we demonstrate that our findings are robust to a range of sample restrictions and, in the case of the Incidental Mergers IV, to alternative definitions of what constitutes an incidental merger.

Specifically, in Table A5 Panel A, we report the results from five alternative specifications. Specifically, the table reports the results from estimating the failed lender IV under different sample filters. Columns (1)–(5) present the first stage results and Columns (6)–(10) present the second stage results. In Columns (1) and (6) we do not filter the sample at all. That is, relative to the baseline sample, we include even counties where the failed lenders did not originate any mortgages. In Columns (2) and (7) we include only counties where the failed lender share is between 0 and 5%. In Columns (3) and (8) we include only counties where the failed lender share is between 0 and 10%. In Columns (3) and (8) we include only counties where the failed lender share is between 0 and 10%. In Columns (4) and (9) we include only counties where the failed lender share is between 0 and 15%. In Columns (5) and (10) we include only counties where the failed lender share is between 0 and 20%.

Across all the specifications, we find strong first stages with F-stats between 186 and 1,895. The second stage coefficients vary between 0.3 and 1.4. For all five of the alternative specifications, the second stage coefficient is statistically significant at the 1%-level.

E.III Robustness of Incidental Merger IV

When constructing the incidental merger IV, we follow Scharfstein and Sunderam (2016) and employ two filters. Under the first filter ("Filter 1"), we keep only counties where each of the lenders involved in the merger are responsible for more than 1% of the total mortgage originations in the county. This filter ensures that the merger had a sufficiently large effect on local concentration. Under the second filter ("Filter 2"), we keep only counties where the county itself contributes no more than 2% of each bank's mortgage originations in the given year. This filter ensures that the county was not a material consideration in the decision to undertake the merger.

In this section, we analyze how sensitive the results are to the exact thresholds in Filter 1 and Filter 2. In Table A5 Panel B, we report the results when running the model six times (the baseline plus five alternative specifications). Columns (1)–(6) present the first stage results and Columns (7)–(12) present the second stage results. We let the filter thresholds for Filter 1 vary between 1%, 2%, and 5%, and we let the filter threshold for Filter 2 vary between 2% and 5%. (Columns (1) and (7) correspond to the baseline specification reported in the main paper.)

Across the six specification we see consistent positive first stages and positive IV estimates. As the threshold for Filter 1 increases, the number of observations drastically decreases, and when the threshold is 5% the estimate is positive but no longer statistically significant.

Reassuringly, all the IV estimates are in the same order of magnitude. And the baseline estimate reported in the paper is, in fact, the lowest coefficient estimate out of the six different specifications.

F Appendix for the Structural Model

In this section, we provide derivations for the structural model not shown in the text.

F.I Refinance and period 2+ value functions

Using the type-one extreme-value assumption on (ϵ_r, ϵ_n), one has,

$$E\left[\max\left\{u_r(r), u_n(r_0)\right\}\right] = \log\left[\exp(-\alpha r - c + \beta Eu(r)) + \exp(-\alpha r_0 + \beta Eu(r_0))\right] \tag{23}$$

The probability that the borrower refinances given r, r_0, and that the borrower is considering refinance, $P(r_0, r|consider)$, is,

$$P(r_0, r|consider) = \frac{\exp(-\alpha r - c + \beta Eu(r))}{\exp(-\alpha r - c + \beta Eu(r)) + \exp(-\alpha r_0 + \beta Eu(r_0))}. \tag{24}$$

Then, the ex-ante per-period probability of refinance is,

$$P(r_0) = \mu + (1-\mu)\phi \int_r P(r_0, r|consider)dr(r) \tag{25}$$

Equation (25) can be computed for any r_0 given the value function $Eu(r_0)$, which is defined implicitly in Equation (24).

Two important quantities for optimal rate setting the derivatives of $Eu(r_0)$ and $P(r_0)$ with respect to r_0. Begin by taking derivatives implicitly of $Eu(r_0)$:

$$\begin{aligned}
\frac{\partial Eu(r_0)}{\partial r_0} =& (1-\mu)(1-\phi)\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right) \\
&+ (1-\mu)\phi\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right)\int_r \frac{\exp(-\alpha r - c + \beta Eu(r))}{\exp(-\alpha r - c + \beta Eu(r)) + \exp(-\alpha r_0 + \beta Eu(r_0))} dr(r|r_0) \\
=& (1-\mu)\left[(1-\phi)\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right) + \phi\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right)\int_r \left(1 - P(r_0, r|consider)\right) dr(r|r_0)\right] \\
=& (1-\mu)(1-\phi)\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right) + \left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right)\left(\phi - P(r_0) + \mu(1-\phi)\right) \\
=& \left(1 - P(r_0)\right)\left(-\alpha + \beta\frac{\partial Eu(r_0)}{\partial r_0}\right)
\end{aligned}$$

Solving for the derivative, we obtain,

$$\frac{\partial Eu(r_0)}{\partial r_0} = -\alpha\left(\frac{1 - P(r_0)}{1 - \beta(1 - P(r_0))}\right) \tag{26}$$

Next, take derivatives of $P(r_0)$:

$$\begin{aligned}\frac{P(r_0)}{\partial r_0} &= (1-\mu)\phi \int_r \frac{\partial P(r_0, r|consider)}{\partial r_0} dr(r) \\ &= (1-\mu)\phi\left(\alpha - \beta\frac{\partial Eu(r_0)}{\partial r_0}\right)\int_r P(r_0, r|consider)\left(1 - P(r_0, r|consider)\right) dr(r)\end{aligned} \tag{27}$$

F.II Borrower's choice of lender in period 1

With the type-one extreme value assumption, the probability (equivalently, market share) for lender j given all offers $k \in \{1, \ldots, J\}$ and ex-ante expected utility is,

$$s_j(f, r) = \frac{\exp(-\gamma f_j + \beta Eu(r_j))}{\sum_k \exp(-\gamma f_k + \beta Eu(r_k))} \tag{28}$$

$$Eu_0(f, r) = \log\left[\sum_k \exp\left(-\gamma f_k + \beta Eu(r_k)\right)\right] \tag{29}$$

An important quantity for optimal rate setting is the derivative of $s_j(f, r)$ with respect to both fees and rates,

$$\frac{\partial s_j(f, r)}{\partial f_j} = -\gamma s_j(f, r)(1 - s_j(f, r)) \tag{30}$$

$$\begin{aligned}\frac{\partial s_j(f, r)}{\partial r_j} &= \beta\frac{\partial Eu(r_j)}{\partial r_j} s_j(f, r)(1 - s_j(f, r)) \\ &= -\alpha\left(\frac{\beta(1 - P(r_j))}{1 - \beta(1 - P(r_j))}\right) s_j(f, r)(1 - s_j(f, r))\end{aligned} \tag{31}$$

F.III Lender's profit and optimal pricing

The lender's income per originated dollar of loan is,

$$\mathcal{V}(f,r) = f - mc_f + \underbrace{\sum_{t=1}^{\infty}(r - mc_r)\left[\rho(1-P(r))\right]^t}_{\equiv \mathcal{I}(r)} \tag{32}$$

Recognizing that $\mathcal{I}(r)$ is a geometric series,

$$\begin{aligned}
\mathcal{I}(r) &\equiv \sum_{t=1}^{\infty}(r - mc_r)\left[\rho(1-P(r))\right]^t \\
&= (r - mc_r)\left(\sum_{t=0}^{\infty}(r - mc_r)\left[\rho(1-P(r))\right]^t - 1\right) \\
&= (r - mc_r)\left(\frac{1}{1-\rho(1-P(r))} - 1\right).
\end{aligned}$$

The derivative of this with respect to r is,

$$\begin{aligned}
\frac{\partial \mathcal{I}(r)}{\partial r} &= \left(\frac{1}{1-\rho(1-P(r))} - 1\right) - (r - mc_r)\rho\frac{\partial P(r)}{\partial r}\left(\frac{1}{\left(1-\rho(1-P(r))\right)^2}\right) \\
&= \left(1 - \rho\frac{\partial P(r)}{\partial r}\left(\frac{r - mc_r}{1-\rho(1-P(r))}\right)\right)\left(\frac{1}{1-\rho(1-P(r))}\right) - 1
\end{aligned} \tag{33}$$

The lender's profit (including its endogenous market share) is,

$$\Pi(f,r) = s(f,r)\mathcal{V}(f,r) \tag{34}$$

Derivatives of the profit function with respect to fees and rates are,

$$\frac{\partial \Pi(f,r)}{\partial f} = \frac{\partial s(f,r)}{\partial f}\mathcal{V}(f,r) + s(f,r)$$
$$\frac{\partial \Pi(f,r)}{\partial r} = \frac{\partial s(f,r)}{\partial r}\mathcal{V}(f,r) + s(f,r)\frac{\partial \mathcal{I}(r)}{\partial r}$$

These values are defined and computed above.

F.IV Fee Salience

In our model, we assume that interest rates are more salient than fees. How reasonable is this assumption? In addition to the related literature cited in the main paper, we have two "datapoints" that support this assumption. First, according to survey data, borrowers say that they are less likely to consider or pay attention to the fess than the interest rate when choosing their mortgage. Second, the mortgage rate appears to be a very salient feature of American culture. For example, The New York Times recently published an article describing homeowners who are envious over the interest rates that their friends are paying, and the article highlights that comparing your mortgage rate is a typical conversation at dinner parties. (There was no mention of the upfront fees associated with obtaining a mortgage.)[32]

Moreover, we find that unsophisticated borrowers pay less attention to upfront fees and that unsophisticated borrowers have lower elasticities of demand. Specifically, using the NSMO database, we show that borrowers with lower levels of education and lower credit scores are less likely to be familiar with the upfront fees (Table A7), and that these borrowers are also less likely to consider multiple mortgage lenders when choosing their mortgage (Table

[32] According to survey data from the 2020 National Survey of Mortgage Originations (NSMO), while 98% of borrowers considered the interest rate when choosing their mortgage, only 81% of borrowers considered fees; see `https://www.fhfa.gov/sites/default/files/2023-10/NSMO-Select-Weighted-Tabulations-20230303.pdf`. The article from The New York Times is: "*Feeling Mortgage-Rate Envy? You're Not Alone*." `https://www.nytimes.com/2023/08/04/realestate/mortgage-rates-increase.html` (accesed on September 1, 2024).

A8).

G Heterogeneity Analysis

In this Section, we provide additional detail on our heterogeneity analysis.

G.I Borrower Types

We first ask how the effects of concentration differ across borrower types. Table A9 reports the results. In Columns (1) and (2) we split the sample by borrowers with below and above median income, respectively. We see that in the sample with only low-income borrowers, the effect is larger than in the sample with only high-income borrowers. Correspondingly, in Column (3) we see that high-income (i.e., above-median) borrowers on average pay less fees and that the effect of concentration is lower for for high-income borrowers. In Columns (4)–(6) we repeat the analysis and split borrowers by credit risk. Consistent with the results on income, we see that the effect of concentration is lower for borrowers with high (i.e., above-median) FICO scores than for borrowers with low (i.e., below-median) FICO scores. These results indicate that the marginal borrower who is affected by local concentration is a low-income low-credit-score borrower, who is less likely to be financially sophisticated. For this analysis, we use the matched HMDA–GSE sample, which includes borrowers' FICO scores.[33]

[33]In each of the the heterogeneity specifications, we analyze heterogeneity using the OLS specification that relies on cross-sectional variation, since this is where the effect are largest and it will be easiest to detect potential heterogeneities. When conducting the analysis using the time-series variation, we find similar qualitative differences, but since the overall power in the time-series analysis is lower, the quantitative differences are smaller.

G.II Loan Types

Next, we ask how the effects of concentration differ across various types of loans. Recall that our baseline sample includes only conventional loans originated for home purchases. However, a sizable share of mortgages are originated for refinances or for non-conventional loans, such as FHA mortgages. Table A10, Panel A, report the results of estimating equation (5) for a sample that includes regular refinances, cash-out refinances, and FHA loans, respectively. We see that in each case, the results are consistent with the baseline results: there is a statistically significant positive relationship between concentration and fees. Furthermore, we see that relative to the baseline sample, the effect of concentration is lower among regular refinances and higher for cash-out refinances and FHA mortgages. For example, the effect of a one-percentage-point increase in CR4 is 73% larger for cash-out refinances than for regular non-cash-out refinances.

G.III Lender Types

Table A10, Panel B, presents the effects of concentration on fees across different types of mortgage lenders. We find that the effect is 20% larger for non-deposit-taking lenders ("non-banks") than for regular deposit-taking banks. Within "fintech lenders", we find that the effect of concentration is even stronger. This is consistent with the idea that these fintech lenders use their technology to identify and lend to price insensitive borrowers who value the convenience of an online origination over the price of that origination. The effect is also 54% larger for large lenders (those of above-median size) than for small lenders (those of below-median size), highlighting that large lenders with high market shares have more pricing power than small lenders. As above, these results indicate that lenders with market power raise fees specifically for financially unsophisticated borrowers. For example, Berger et al. (2024) argue that borrowers who refinance to take advantage of lower interest rates (those taking out a regular refinanced mortgage) are more likely to be sophisticated, Jørring (2024) shows that borrowers taking out equity-extracting loans (e.g., cash-out refinances) are less likely to be sophisticated, and Buchak, Chau and Jørring (2023) find that non-banks, particularly "fintech" non-banks, specifically target unsophisticated borrowers.