Do Mortgage Lenders Compete Locally? Implications for Credit Access*

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Abstract

We study the impact of mortgage lender concentration on household credit access. An extensive literature has found little to no relationship between local lender concentration and mortgage interest rates; consequently, federal regulators regard mortgage markets as national and view their local concentration as irrelevant to financial regulation and monetary policy. We argue that this view is incomplete, showing that although local concentration has no influence on interest rates, it strongly affects lending standards and upfront fees. In more concentrated areas, mortgage application rejection rates are higher (this effect is particularly pronounced for low-income, female, and racial-minority applicants), and the pool of originated mortgages is less risky in terms of both ex-ante credit scores and ex-post default. On the intensive margin, lenders charge higher fees in more concentrated markets: non-interest fees are on average 35 basis points higher in the 10% most concentrated markets than in the 10% least concentrated markets. Again, these effects are strongest among minority applicants. Our findings suggest that contrary to current policy, regulators concerned with credit access should regard mortgage markets as local when making policy decisions such as bank merger approvals.

Keywords: Mortgage market structure, bank merger policy, household finance.

JEL Classification Codes: G2, L5

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1 Introduction

The United States residential mortgage market is the largest consumer finance market in the world. Trillions of dollars in loans are originated annually to finance new home purchases or to refinance existing mortgages. These loans constitute most households' largest liability and finance their largest asset. Given its enormous size, even small price increases in this market can lead to large aggregate transfers from borrowers to lenders and large welfare losses stemming from reduced lending quantities. It is therefore of tremendous policy and academic interest to understand how much market power mortgage lenders have, and how this market power impacts access and prices.

Lender market power can arise from many causes. For example, large price dispersion is generated by frictions such as borrower search costs, borrowers' lack of sophistication, the structure of bank branch networks, and lender bundling (e.g., of deposit services or other transaction services). Such price dispersion can imply significant markups. More directly, high local concentration can allow a small number of lenders to compete oligopolistically, exercising market power even when products are only slightly differentiated or search costs are low.

This paper asks how local concentration affects mortgage access and pricing. In the context of mortgage lending, local concentration is an especially important source of market power to study because it is a factor over which regulators have direct control: existing banking regulation allows them to approve or deny bank mergers. In particular, the connection between concentration and credit access for low-income, female, and minority borrowers is becoming increasingly relevant as the Federal Reserve reconsiders its policies in terms of their impact on inequality.[1]

The prevailing view among academics and regulators is that lenders' local market power has no significant influence on prices in the U.S. residential mortgage market. Consequently, when evaluating a merger between two financial institutions, regulators currently do not take into account whether the merger will increase concentration in the local mortgage market.[2] Since 2008, for example, the Federal Reserve (which oversees regulation of mortgage lenders) has designated the market for mortgage origination as

[1]The President of the Atlanta Fed, for example, has written: "I believe the Federal Reserve Bank of Atlanta, and the Federal Reserve more generally, can play an important role in helping to reduce racial inequities and bring about a more inclusive economy" (https://www.frbatlanta.org/about/feature/2020/06/12/bostic-a-moral-and-economic-imperative-to-end-racism).

[2]In contrast, the Federal Reserve Board does consider local concentration in *deposit markets* when evaluating mergers. See https://www.federalreserve.gov/bankinforeg/competitive-effects-mergers-acquisitions-faqs.htm.

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"national in scope" (Federal Reserve System, 2008). In a recent note, the Federal Reserve reaffirmed 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).

The view that local lending concentration does not drive mortgage prices is based on a long literature studying mortgage *interest rates*, e.g., Fuster et al. (2013) and Hurst et al. (2016). But mortgage pricing is multidimensional: borrowers pay significant non-interest-rate costs in the form of origination fees and points. In this paper, we strongly confirm the conclusion in the previous literature that local lending concentration does not affect interest rates; however, we show that high local concentration significantly increases non-interest-rate costs. We also find strong impacts on the extensive margin: borrowers in areas with high lender concentration are considerably more likely to have their mortgage applications rejected. Hence, while previous studies have correctly established that there is no relationship between concentration and interest rates, these null results mask economically significant effects on other, no less relevant, dimensions.

Our paper begins with a simple ordinary least squares (OLS) analysis on interest rates and non-interest-rate costs. We primarily use data collected under the Home Mortgage Disclosure Act (HMDA). Our analysis relies crucially on newly available points and fees data, which has been collected starting in 2018; thus, our main sample covers loans originated in 2018 and 2019. We first study interest rates across several market segments, time periods, and empirical settings. Regressing rates on two measures of lender concentration—the Herfindahl–Hirschman index (HHI) and the concentration ratio of the top four lenders in a market (CR4)—with controls for loan risk, we find essentially no relationship between rates and concentration. That is, while there may be markups in interest rates, these markups do not depend systematically on how concentrated lenders are in a given market. Our estimates are precise zeros: we establish tight bounds with low standard errors on any possible relationship. We confirm this finding in other samples and time periods using the Fannie Mae and Freddie Mac GSE datasets, as well as the Black Knight dataset, which includes non-agency mortgages.

However, the same OLS specification yields an economically significant relationship between concentration and fees, where borrowers in counties with greater lender concentration pay much higher fees. We find that, as a fraction of loan principal, non-interest fees are on average 35 basis points higher in the 10% most concentrated markets than in the 10% least concentrated markets. This corresponds to more than $1,200 in extra fees for the average borrower's loan size.

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This analysis is subject to a number of identification concerns. We would like to understand lenders' market power through their markups; however, since we do not directly observe marginal costs, we cannot rule out the possibility that higher prices are due to unobservably higher marginal costs that vary systematically with lender concentration, while markups do not.

The direction of the resulting biases is not ex-ante obvious. For example, borrowers in certain markets may be more costly to lend to—either because they are riskier or because origination is more difficult (e.g., they frequently lack documentation). Facing higher costs, fewer lenders might enter such markets, leading to both greater concentration and higher prices (due to higher marginal costs), but not necessarily higher markups. On the other hand, some lenders might be more productive than others, and might see lower costs and greater lending quantities as a result. This would lead to high concentration and low prices, implying a downward bias in our OLS coefficients; that is, concentration and price would again be correlated, but the high concentration would not be the cause of the low prices. Our null result for interest rates may suggest that the latter is happening, while our strong positive result for points and fees may suggest that the former is happening; without further analysis, the OLS results are difficult to interpret.

To address these identification concerns, we utilize the instrumental variables (IV) approach of Garmaise and Moskowitz (2006) and Scharfstein and Sunderam (2016). This approach uses bank mergers as an instrument for concentration. Bank mergers are not typically exogenous, as they are often motivated by lending opportunities or cost synergies in markets where the target has a significant market share. With this concern in mind, this approach looks for variations in concentration that occur in a given county, but only due to bank mergers that are unrelated to lending opportunities in that county.

The following scenario illustrates the approach. Suppose that Bank A operates mainly in Middlesex County but has a small mortgage lending business in nearby Plymouth County, while Bank B operates mainly in Norfolk County but also has a small mortgage lending business in Plymouth County. Bank A acquires Bank B. We interpret this merger as Bank A wanting to expand its lending business in Bank B's main county of operation, Norfolk County; Bank B's operation in Plymouth County is incidental. However, by virtue of the merger, lender concentration in Plymouth County increases; our bank merger instrument takes advantage of this variation. While unobserved differences in marginal costs in Norfolk County may have motivated the merger, we may assume that those in Plymouth County were orthogonal to the decision to merge.

Our IV analysis robustly leads to conclusions similar in direction and magnitude to

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those of the OLS analysis: we uniformly find precise zeros relating concentration to interest rates, but economically large and statistically significant relationships between concentration and points and fees. Quantitatively, we establish with 95% confidence that a one-standard-deviation increase in CR4 will not increase the interest rate by more than 0.39%. By contrast, a one-standard-deviation increase in CR4 will increase points and fees by between 1.1% and 9.2% (with 95% confidence). In terms of the aggregate mortgage market, a back-of-the-envelope calculation suggests that if the concentration ratio in all counties were at most equal to the current 25th-percentile ratio, the decrease in fees would amount to an annual net transfer of $2.2 billion from lenders to borrowers; this is not to mention welfare changes from expanding lending quantities. As additional robustness checks, we confirm these findings with two additional instruments for concentration: The staggered implementation of the Interstate Banking and Branching Efficiency Act (IBBEA), following Rice and Strahan (2010), and the pre-crisis market share of large failed lenders. These approaches yield qualitatively and quantitatively similar results.

To refine our understanding of the above results, we next ask how borrowers trade off fees against interest rates. That is, mortgage lenders typically offer a menu of interest rates together with upfront fees; in particular, borrowers have the option of paying for so-called discount points to obtain lower interest rates.[3] Is it possible that borrowers in more concentrated markets, who (our analysis has shown) pay more in fees, are getting correspondingly lower rates in exchange? The fact that our earlier analysis uncovered no relationship between interest rates and concentration suggests that the answer is no, but in order to examine this question more carefully, we study the relationship between concentration and non-interest-rate costs while conditioning on the interest rate.

We find that in a model with both concentration and interest rate as independent variables, both are positively associated with non-interest-rate costs. Furthermore, if we analyze discount points separately from other types of non-interest-rate costs, we do find a negative relationship between interest rates and discount points (i.e., borrowers do trade off lower rates for higher discount points). However, when local concentration increases, the entire menu of rates and points shifts outwards. In other words, we find that when concentration is higher, borrowers must pay more discount points to obtain a given interest rate.

We then consider the extensive margin of credit provision. Broadly, we find evidence that lenders in more concentrated markets are generally less willing to extend credit, and

[3] See Bhutta et al. (2020) for a detailed description of the relationship between discount points and mortgage interest rates.

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are especially unlikely to lend to risky borrowers. In particular, using the same OLS and IV methodologies described above, we show that rejection rates for mortgage applications rise significantly when lender concentration is higher. Moreover, the pool of originated mortgages in highly concentrated areas has higher FICO scores on average, lower loan-to-value (LTV) ratios, and lower debt-to-income (DTI) ratios. Ex-post, borrowers are significantly less likely to default on their mortgages in highly concentrated areas.

This point provides important context to our rates and fees results and allays a potential identification concern: that borrowers in high-concentration areas might be subject to higher fees because they are riskier. We find the opposite: borrowers in the most concentrated markets are significantly *less* risky than borrowers in the least concentrated markets.

Finally, we closely examine which groups of borrowers or potential borrowers are most affected by local concentration. We find that while greater concentration reduces credit access for all borrowers, the reduction is particularly large for low-income borrowers, female borrowers, and borrowers belonging to racial minorities. In other words, increases in local competition raise credit access the most for these historically excluded subsets of borrowers. This is true on both the extensive margin of loan approvals and the intensive margin of origination fees. Thus, our results show that local lender concentration is a particularly important policy consideration for regulators concerned with affordable credit access for these groups.

To summarize, our paper highlights how local market concentration affects a significant but overlooked dimension of mortgage pricing, namely non-interest-rate charges such as points and fees. We find that lenders aggressively exercise market power when setting points and fees. This contrasts with the view prevailing among academics and regulators, based on the null relationship between lender concentration and interest rates, that local market power has no effect on mortgage pricing. Our findings have important consequences for regulations targeting more equitable access to credit, bank regulatory policy, and particularly bank merger approval.

1.1 Related Literature

Our paper is closely related to a large literature on mortgage prices, market power, and its impact. It has been documented that lenders exercise market power to set mortgage interest rates; see, e.g., Bhutta et al. (2020) (which examines price dispersion) and Buchak et al. (2018) (which provides structural estimates of markups). Lender markups translate into significant costs for borrowers: Fuster et al. (2017) estimate that the price of

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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., Scharfstein and Sunderam (2016) and Xiao (2020).

As noted earlier, local concentration is widely seen as irrelevant to mortgage lenders' market power; policymakers consider mortgage markets to be national in scope. This is because, almost uniformly, the literature finds no relationship between local concentration and interest rates; see, e.g., Hurst et al. (2016), Fuster et al. (2013), and Amel et al. (2018).[4] Our paper strongly confirms this conclusion about interest rates across several settings and empirical designs.

Our primary contribution to and departure from the literature is the extension of this analysis beyond interest rates to other dimensions that may reflect lenders' market power, namely, upfront fees and the extensive margin of lending. The data necessary to examine fees at large scale in the U.S. mortgage market has only recently become available, and so few papers have examined mortgage fees in this setting. For the U.K. mortgage market, Benetton et al. (2019) and Liu (2019) examine lender pricing strategies across both fees and rates, although they do not specifically tackle the question of local market concentration. Rather, they highlight how lenders exploit borrowers' potential financial mistakes in trading off rates and fees, as Jørring (2020) does in the context of credit card companies.

Another related strand of the literature has examined the impact of market concentration and lending access on non-price attributes and outcomes, even outside the primary market, e.g., Begley and Purnanandam (2020) (product quality, incidence of fraud), Di Maggio et al. (2019) (prepayment penalty terms), Favara and Giannetti (2017) (liquidation of collateralized debt), Cetorelli and Strahan (2006) (firm entry), Sharpe and Sherlund (2016) (mortgage lending capacity constraints), and Saidi and Streitz (2020) (markups in product markets). Our paper extends this analysis to both fully non-price attributes (e.g., the extensive margin and the risk composition of borrowers) and non-standard price attributes (e.g., non-rate points and fees) in the residential mortgage market.

Finally, our paper connects to a large literature on racial and gender discrimination in mortgage lending, e.g., Holmes and Horvitz (1994), Tootell (1996), Ladd (1998), Charles and Hurst (2002), and Dobbie et al. (2018). While previous papers have identified per-

[4]Scharfstein and Sunderam (2016) have found that increased concentration leads to reduced pass-through of MBS rates to origination rates for consumers, although this finding is disputed in Amel et al. (2018). In the present paper, we use an instrumental variables approach similar to that of Scharfstein and Sunderam (2016) to study the effect of concentration on the *level* of interest rates.

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sistent gaps in approval rates between high- and low-income borrowers, white and black borrowers, and male and female borrowers, our paper contributes by examining how the provision of credit to these groups on the extensive margin varies with local concentration. In particular, we document that these gaps shrink as markets become less concentrated.

Our paper proceeds as follows. In Section 2 we describe our datasets and present some high-level facts about concentration and mortgage pricing in the United States. In Section 3 we introduce our empirical methodology and use it to examine the effects of local lender concentration on interest rates. Sections 4 and 5 comprise our main contribution, an analysis of the impact of local lender concentration on non-rate fees and on the extensive margin of lending. In section 6 we examine which borrower groups are most impacted along these margins. Section 7 provides a brief discussion of our results and concludes.

2 Data and Aggregate Facts

2.1 Data

Our paper combines several standard datasets in the mortgage and banking literature. We describe these datasets and their relevance to our analysis below.

HMDA: 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. It also contains limited demographic information on applicants, notably race and income. 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 2018 and 2019, although in several analyses not requiring these values, we extend the sample back to 1990.

In order to study comparable mortgages, we follow the literature and restrict our sample to 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes. We exclude government-insured loans, such as FHA and VA loans; and we exclude mortgages with "exotic" features, such as reverse mortgages, mortgages with an open-end line of credit (e.g. HELOCs), interest-only mortgages, and mortgages with prepayment penalties, intro-rate periods, balloon payments, or other non-

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amortizing features.[5]

Table 1 Panel A presents high-level summary statistics for the 2018–2019 HMDA loan-level dataset. The average loan size in the sample is $267,401, with a standard deviation of $173,909. The average interest rate is 4.48%, with a standard deviation of .59%. The 25th and 75th percentiles are 4.0% and 4.9%, respectively. In dollar terms, the average sum of all non-interest costs is $5,183, while the 25th and 75th percentiles for total non-interest costs are respectively $3,066 and $6,762. Origination charges, discount points, and lender credits make up on average $1,673, $578, and $432, respectively. The average combined LTV ratio is 89%, and the average DTI ratio is 38%.

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 primary residence homes. These loans are fully amortizing 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 Fannie Mae and Freddie Mac (GSE) dataset. For this merged sample, we observe the credit score at origination and track loan performance over time (to gather information on delinquencies). We match the HMDA and the 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, MSA, and ZIP), 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), but it also covers non-conforming jumbo loans. To ensure comparability with the HMDA and GSE samples, we

[5]In part of the analysis, we extend the time period and analyze mortgage applications from HMDA going back to 1990. Not all variables are available in the earlier periods, and for this part of the analysis, we restrict the sample to conventional mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans.

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restrict the Black Knight sample to 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. The results from the Black Knight dataset complement the HMDA and GSE datasets chiefly by providing borrower FICO scores and performance measures for markets beyond conforming agency loans, both of which are absent from HMDA.[6]

Supplemental data: We complement the datasets on mortgages with a number of additional data sources that are common 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 and bank mergers from the Federal Financial Institutions Examination Council. Finally, we use spatial crosswalks provided by the Department of Housing and Urban Development.

2.2 Aggregate Facts

Having described our data, we now present some aggregate facts and trends concerning lender concentration, interest rates, and non-interest-rate origination fees. Overall, we document significant market-level variation in all three quantities. In subsequent sections, we explore the relationships between them in order to identify the causal impact of competition on the two facets of pricing.

To measure concentration, we use two standard competition measures: the Herfindahl–Hirschman index (HHI) and the concentration ratio of the top four lenders in a market (CR4). 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 CR4 are defined as

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

$$CR4_{ct} = \sum_{j \in J^4(c,t)} s_{jct}, \tag{2}$$

where $J(c,t)$ is the set of lenders that originated a loan in county c in year t, and $J^4(c,t)$ is the set of the top four lenders by origination market share.

Table 1 Panel C shows summary statistics at the market level for the lender and

[6] Unlike with the GSE data, we do not perform a loan-level merge between the Black Knight data and either the HMDA data or GSE data.

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concentration variables. On average, there are 62 unique lenders in a county-year, but this large number masks significant variation: the interquartile range is from 19 to 80 unique lenders. The mean HHI at the county-year level is 8.0%, with an interquartile range of 3.7% to 9.4%. Similarly, the mean CR4 is 41.8%, with an interquartile range of 29.6% to 51.1%.

Although we focus our analysis on 2018 and 2019, in order to provide more context, we first present some aggregate trends in market concentration over time and across geographies. Figure 1 Panel A shows the origination-weighted county average HHI (yellow), CR4 (blue), and CR10 (red) between 1990 and 2019.[7] After a slight decrease from 1990 to 1992, all three measures of concentration have been fairly stable across the following three decades—with a slight increase from 2006 to 2009, and a reversal from 2010 to 2012.

Apart from time-series variation, there is also significant geographical variation in concentration. To provide a sense of this variation, Figure 1 Panel B shows the nationwide distribution of CR4 in 2018 across all counties in the United States. These CR4 values range from 13% to 100%, with the highest concentration in the most rural counties. Even among highly populated counties there is significant variation. Panel C shows the distribution for the 1,000 most populous counties in 2018. Here, the values range from 13% to 74%.

We turn now to interest rates and non-interest-rate fees. Broadly, we note that there is significant variation in both rates and fees, which is itself suggestive of variation in market power, though not necessarily at a local level. Figure 2 Panel A shows a histogram of interest rates for 2018 and 2019, while Panel B shows the histogram for non-interest fees as a fraction of the loan amount over the same time period. The raw values in Figure 2 show significant variation; however, this could arise from differences in lenders' marginal costs—for example, the costs of lending to riskier borrowers. We therefore residualize these rates and fees with the following specification:

$$Y_{ict} = \mathbf{X}_i'\beta + \mathbf{X}_c'\eta + \epsilon_{ict}, \tag{3}$$

where $\mathbf{X}_i$ is a vector of loan-level controls and $\mathbf{X}_c$ is a vector of census-tract-level controls. Loan-level controls include the size and type of the loan (conforming or jumbo), the purpose of the loan (home purchase or refinance), and bins for LTV and DTI ratios. The census-tract-level controls include the percentage of minority population and the ratio of the median family income in the census tract to the median family income in the

[7] CR10 is defined analogously to CR4: the market share of the top-10 lenders.

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MSA. This regression removes differences in interest rates that are attributable to, for example, differences in risk explainable by individual or geographical factors. We plot the residualized rates and fees in Figure 2 Panels C and D, respectively. These plots show that even after differences due to risk are removed, there remains a significant amount of dispersion in both rates and fees. The following sections ask, in effect, whether this dispersion can be partially explained by lender concentration.

3 Rates and Competition

We now turn to our strategy for identifying the impact of competition on rates and fees. The interest rate is, definitionally, the marginal cost plus a markup:

$$InterestRate_{ict} = Markup_{ict} + MC_{ict}.$$

Typical models of oligopolistic competition deliver the prediction that markups are increasing in lender concentration.[8] To examine whether lenders exploit local market power, we would ideally regress markups (as opposed to interest rates or fees) on regional concentration:

$$Markup_{ict} = \beta_0 + \beta_1 Concentration_{ct} + \epsilon_{ict}. \tag{4}$$

Unfortunately, we do not observe marginal costs and therefore cannot measure markups directly. Rather, we observe only interest rates, which are the sum of markups and unobserved marginal costs. This observation motivates our OLS specification and highlights the primary identification concerns, which we discuss below.

[8]For example, a standard logit model of demand has lenders optimally setting rates as

$$r = \underbrace{\frac{1}{\alpha}\frac{1}{1-s}}_{\text{markup}} + MC,$$

where α is the borrower's price sensitivity and s is the lender's market share. Clearly markups are increasing in lender market share, i.e., in concentration.

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3.1 Baseline OLS Specification

Our main specification regresses interest rates on measures of competition at the loan level as follows:

$$InterestRate_{ilctd} = \beta Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict}, \tag{5}$$

where $InterestRate_{ilctd}$ is the fixed interest rate, expressed in percent, for loan i, originated by lender l, in county c, in year t. (In the matched HMDA–GSE sample, we further see the origination date d.) $Concentration_{ct-1}$ is the one-year lagged county-year measure of concentration, either HHI_{ct-1} or $CR4_{ct-1}$. X_i is a vector of loan-level controls, including mortgage size and type (conforming or jumbo) and measures of individual credit risks, with bins for the LTV and DTI ratios (and credit score in the matched sample). X_{ct} is a vector of county-year–level controls, including the percentage of minority population and the ratio of the median family income in the census tract to the median family income in the MSA. Finally, γ_l is a lender fixed effect, and γ_d is an origination-date fixed effect.

Table 2 Panel A shows the regression results. Columns (1)–(5) regress interest rates on CR4 with an increasingly broad set of controls and fixed effects. Column (5), which includes loan and county controls and lender fixed effects, finds a small positive and statistically insignificant relationship between concentration and interest rates. Given the estimate and standard errors, we can conclude with 95% confidence that a one-standard-deviation change in CR4 is associated with an increase in the interest rate of no greater than 0.01 percentage points. We find similar results using HHI as the measure of concentration in Column (6).

We next examine subsamples of loans: jumbo loans and conforming loans in Columns (7) and (8), and the HMDA–GSE sample—which includes both the credit score and an origination-date fixed effect—in Columns (9) and (10). We find that the results are statistically insignificant for conforming loans and the matched sample, and significant for jumbo loans.[9]

Figure 3 shows binned scatterplots of these results, in order to rule out any nonlinearities in the data that are masking a positive relationship. The x-axes of Panels A and B show equal-sized bins of lender concentration, and the y-axes show interest rates. Panel A shows raw values; Panel B shows residualized values. In both cases, we confirm the regression results, finding no relationship between concentration and interest rates.

[9]In the regression for jumbo loans, the measure of concentration is calculated based only on jumbo loans.

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To interpret these results correctly, we need to address potential identification concerns. Recall that while we would like to analyze market power via markups, we are able to observe only interest rates: the sum of markups and unobserved marginal costs. Average marginal costs may vary geographically for many reasons. For example, borrowers in a given county may be riskier than average (more likely to default) or more expensive to service. Origination costs may vary systematically with local economic or demographic characteristics such as average income, wealth, or race. Lenders in a certain area may be more efficient at originating mortgages.

The identification concern is the possibility that unobserved marginal costs are correlated with concentration. Consider several reasons that could occur. To the extent that higher marginal costs cannot be passed on to borrowers, lending in high-marginal-cost areas is less profitable, conditional on entry. In consequence, fewer lenders may enter these areas, so that equilibrium concentration will be higher, leading to upward biases in the OLS coefficients. On the other hand, if lenders differ in productivity (e.g., if some possess automated origination or underwriting technology), the most productive lenders will expand market share while having lower average marginal costs. In this case, the OLS coefficients will be biased downwards.

The loan- and county-level controls, together with the set of fixed effects in (5), capture many of the concerns related to differences in the observable risks or costs of loans. Of course, further correlation could remain after conditioning on these observables. To address this potential problem, we adopt an instrumental variables strategy in order to generate variation in lender concentration orthogonal to unobserved differences in marginal costs. Motivated by the previous discussion, we are looking for, at a high level, a cause of variation in concentration unrelated to lenders' endogenous entry, exit, or expansion. We detail this instrument in the following section.

3.2 IV Analysis

Our instrumental variables (IV) strategy uses bank mergers in non-central markets as an instrument for market concentration. The key empirical challenge is that mergers are, of course, not random.[10] To address this challenge, we follow Scharfstein and Sunderam (2016) and construct a sample of counties that have been affected by bank mergers, but where those counties were unlikely to be the key motivation for the mergers.[11] Specifically,

[10]A growing body of work uses bank mergers as instruments for market concentration (Garmaise and Moskowitz, 2006; Favara and Giannetti, 2017; Giannetti and Saidi, 2019; Saidi and Streitz, 2020).

[11]Dafny et al. (2012) use a similar method when studying the effect of mergers between health insurers.

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we construct the merger IV using the following three-step algorithm.

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 where 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 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, to study counties where the merger *incidentally* increased market concentration, we exclude counties where the mortgage origination for either party in the merger made up more than 2% of the origination in that county in the year prior to the merger. We also exclude counties where either financial institution had more than 10% of the market share. Finally, we limit the time-series sample to the five years before and after the merger. That is, the IV is a dummy variable taking the value of zero in the five years prior to the merger, and the value of one in the five years following the merger (including the merger year).

Figure A2 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. Figure A2 describes 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 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 both also have lending 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.

The first stage regression is as follows:

$$Concentration_{ct} = \phi Merger_{ct} + \eta' X_{ct} + \gamma_t + \gamma_c + \zeta_{ct} \tag{6}$$

Here, $Concentration_{ct}$ is the concentration ratio, CR4, in county c at year t. $Merger_{ct}$ is the instrument: a zero-one indicator for whether a relevant merger "accidentially" occurred in the county in five years leading up to time t, as described above. X_{ct} is the vector of county-level controls used earlier; γ_t and γ_c are time and county fixed effects. For specifications using only the 2018-2019 HMDA sample, given the short time period,

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we omit the county fixed effect. In those cases, the identifying variation is essentially cross-sectional, comparing counties that had relevant mergers in the five years prior to 2018 to those that did not.

The instrumented concentration measure, the IV specification, and the reduced form specifications are standard:

$$\hat{Concentration}_{ct} \equiv \hat{\phi} Merger_{ct} + \hat{\eta}' X_{ct} + \hat{\gamma}_t + \hat{\gamma}_c \tag{7}$$

$$InterestRate_{ilctd} = \beta \hat{Concentration}_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{8}$$

$$InterestRate_{ilctd} = \beta Merger_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{9}$$

We show the results in Table 2 Panel B. Columns (1)—(3) show the first stage, (4)—(6) showing the IV, and (7)—(9) showing the reduced form. Columns (1), (2), (4), (5), (7), and (8) use the full HMDA dataset; the remaining columns use the merged HMDA-GSE dataset. All columns include loan and county controls, columns (2), (5), and (8) include lender fixed effects, and (3), (6), and (9) include month fixed effects and FICO score, which is observable in the matched sample.

The first-stage results are strongly positive with highly significant F-statistics. (The F-statistics on the merger variable are 96, 137, and 79, respectively, in the three specifications.) However, consistently across the IV and reduced form results, we find economically small and statistically insignificant results. The reduced form results provide easily interpretable quantities: in the HMDA sample (Columns (7) and (8)), counties with a merger see an increase in their interest rates of 5 and 7 basis points, in the models without and with lender fixed effects, respectively. In the most saturated model, with month fixed effects and credit scores (the HMDA–GSE sample in Column (9)), counties in which a bank merger occurred see interest rates that are an economically small and statistically insignificant 0.007 basis points *lower* than other counties.[12]

This section served as an introduction to our empirical design, presenting the baseline OLS, potential identification issues, and an instrument to address those issues. We applied this methodology to interest rates and confirmed, with high precision, results known in the academic literature as well as to policymakers: that geographical concentration does not drive differences in interest rates. If we were to stop here, we might conclude, as regulators and policymakers have, that mortgage lenders do not have market power stemming from

[12]As additional robustness checks, we confirm these findings with two additional instruments for concentration: The staggered implementation of the IBBEA, following the approach in Rice and Strahan (2010), and the pre-crisis market share of large failed lenders. These approaches, reported in Appendix Section A.1, yield qualitatively similar results.

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local concentration. However, as we noted in the introduction, lenders can exercise market power through other dimensions of mortgage pricing. In the rest of the paper we examine the effects of concentration on two of these dimensions: points and fees (Section 4) and lending standards (Section 5).

4 Fees and Competition

In this section, we apply the methodology introduced in Section 3 to analyze newly available data on points and fees. We show that in contrast to interest rates, points and fees on otherwise similar loans vary strongly with exogenous differences in local lender concentration.

We begin with the same steps as in Section 3: we first show suggestive correlative evidence through OLS (Subsection 4.1), then make the causal case with our instrument (Subsection 4.2). Finally, in Subsection 4.3, we confirm that although lenders and borrowers do trade off discount points and fees against interest rates, differences in concentration shift the entire point–rate menu rather than moving borrowers along it.

4.1 Baseline OLS Specification

Having already detailed the empirical design in Section 3, we proceed immediately to the specifications and results. Our main specification for points and fees is similar to that of Subsection 3.1 for interest rates. Using the 2018–2019 HMDA data, we regress points and fees on measures of competition at the loan level as follows:

$$Fees_{ilctd} = \beta Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict}, \tag{10}$$

where $Fees_{ilctd}$ is the sum of points and fees for loan i (expressed as a percentage of the loan principal), originated by lender l, in county c, at time t. (In the matched HMDA–GSE sample, we further see the origination date d.) $Concentration_{ct-1}$ is the one-year lagged county-year measure of concentration, either HHI_{ct-1} or $CR4_{ct-1}$. X_i is a vector of loan-level controls, including mortgage size and type (conforming or jumbo) and measures of individual credit risks, with bins for LTV and DTI ratios (and credit score in the matched sample). X_{ct} is a vector of county-year–level controls, including the percentage of minority population and the ratio of the median family income in the census tract to the median family income in the MSA. Finally, γ_l is a lender fixed effect, and γ_d is an origination-date fixed effect.

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Table 3 Panel A shows the regression results. Columns (1)–(5) include progressively richer controls over the full HMDA sample, with Column (5) showing the most saturated specification, with loan and county controls and lender fixed effects. Across these specifications, we observe that the introduction of controls or fixed effects has little effect on the parameter estimates.

In Column (5), the most saturated specification, we find an economically and statistically significant correlation: a 1-percentage-point increase in CR4 is associated with a 1.11-percentage-point increase in upfront fees as a fraction of loan balance. Column (6), which uses HHI rather than CR4 as the measure of concentration, finds a similarly large correlation.

Figure 3 Panels C and D show these results graphically with binned scatterplots, with Panel C showing raw fees and Panel D showing residualized fees. These plots reveal a strong and consistent relationship between lender concentration and fees at all fee levels.

We next examine subsamples of loans: jumbo loans and conforming loans from the full HMDA sample in Columns (7) and (8), and conforming loans from the HMDA–GSE matched sample in Columns (9) and (10). The matched sample allows us to include month fixed effects and credit scores as controls, at the cost of significantly reducing the number of observations. Except in the case of jumbo loans, we find a robust and consistently positive relationship between lender concentration and points and fees. We emphasize in particular Columns (9) and (10), which correspond to the HMDA–GSE matched sample with and without the credit score control. Including the borrower credit score has essentially no impact on the estimated coefficient, which is also quantitatively similar to the estimate from the full HMDA sample.

The same identification concerns that applied to the analysis of interest rates apply here as well. Briefly, for the reasons discussed in the introduction and in Subsection 3.1, unobserved marginal costs could be either positively or negatively correlated with concentration. If the former, we would be overestimating the causal relationship between concentration and fees; if the latter, we would be underestimating it. To account for these potential confounding effects, we now apply the same IV strategies as in Subsection 3.2.

4.2 Instrumental Variables Approaches

As before, our main IV specification utilizes bank mergers as an exogenous shock to lending concentration. This analysis includes the same first-stage regression as that of Subsection 3.2, so we proceed immediately to the reduced form and two-stage least

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squares approaches. The specifications are as follows:

$$Fees_{ilctd} = \beta Concen\hat{t}ration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict}, \tag{11}$$

$$Fees_{ilctd} = \beta Merger_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict}. \tag{12}$$

The results are shown in Table 3 Panel B. The columns are the same as for interest rates: Columns (1)–(3) give the first-stage results, Columns (4)–(6) give the IV results, and Columns (7)–(9) give the reduced form results. Columns (3), (6), and (9) use the merged HMDA–GSE dataset, while the remaining columns use the full HMDA dataset. All columns include loan and county controls; Columns (2), (5), and (8) include lender fixed effects, and Columns (3), (6), and (9) include month fixed effects and FICO scores, which are observable in the matched sample.

As before, the first-stage results are positive and highly significant across the three specifications. The IV results, shown in Columns (4)–(6), are very similar to the OLS results: in the HMDA sample with lender fixed effects (Column (5)), a 1-percentage-point increase in concentration ratio induced by a bank merger causes roughly a 1.2-percentage-point increase in points and fees. Similarly, for the HMDA–GSE sample with FICO controls (Column (6)), we find that a 1-percentage-point increase in concentration ratio leads to a 1.32-percentage-point increase in points and fees.

We obtain interpretable magnitudes from the reduced form, which shows that in the complete HMDA sample with lender fixed effects (Column (8)), lenders in a county with a bank merger increase fees by roughly 19 basis points. In the HMDA–GSE matched sample (Column (9)), we find a nearly statistically identical difference of 22 basis points.

In contrast to our findings on interest rates, the findings here on fees are statistically and economically significant: areas with more concentrated mortgage origination see considerably higher fees. We find that, as a fraction of loan principal, non-interest fees are on average 35 basis points higher in the 10% most concentrated markets than in the 10% least concentrated markets. This corresponds to more than $1,200 in extra fees for the average borrower. For the IV estimates, the 95% confidence interval implies that a one-standard-deviation increase in CR4 will increase points and fees by between 1.1% and 9.2%. As mentioned in the introduction, these numbers imply that if the concentration ratio in all markets were brought down to at most the current 25th-percentile ratio, the resulting decrease in fees would constitute an annual net transfer of $2.2 billion from lenders to borrowers; this is not to mention welfare changes from expanding lending

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quantities.[13]

4.3 The Menu of Interest Rates and Points

Mortgage offers typically appear as a menu of interest rates together with upfront fees, including so-called discount points; an example is shown in Figure A1 in the appendix. Borrowers' mortgage choices fall somewhere on this menu: they can choose to pay more for discount points to obtain lower interest rates. To study this trade-off in detail, we follow Bhutta et al. (2020) and regress discount points on the interest rate spread deciles using the merged HMDA–GSE dataset. 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. Additionally, we control for DTI ratio, LTV ratio, income deciles, 23 credit score bins, and lender and origination-date fixed effects.

Figure 4 Panel A illustrates the trade-off with a plot of predicted values from the regression. We see a clear negative relationship between the price that the lender receives up front (the discount points) and the revenue that the lender receives over time (the interest rate minus funding costs).

This suggests that when studying mortgage pricing, it is important to consider rates and fees simultaneously. In particular, we need to check whether borrowers in more concentrated markets, who we have seen pay more in fees, are getting correspondingly lower interest rates in exchange—that is, whether they are simply making different choices on the same menu of rates and fees offered in less concentrated markets. In that case, the differences we have observed would be due to borrower choice rather than the exercise of lender market power.

The results of the previous sections already provide a rough argument against this possibility. We have demonstrated that there is essentially no relationship between concentration and interest rates (Section 3), while there is a strong positive relationship between concentration and fees (Subsections 4.1–4.2). But if concentration were driving borrowers to choose differently from identical menus, then we would expect it to influence rates and fees in opposite directions.

We now address this question more carefully. We find that in fact, the menu of discount points and interest rates differs significantly between low- and high-concentration markets.

[13] As we did in the case of interest rates, we confirm these findings with two additional instruments for concentration: The staggered implementation of the IBBEA, following the approach in Rice and Strahan (2010), and the pre-crisis market share of large failed lenders. These approaches, reported in Appendix Section A.1, yield qualitatively similar results.

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Figure 4 Panel B presents graphical evidence of this difference, recreating the point–rate 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. The menu for high-concentration markets (those in the top quartile by CR4) is uniformly 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 10 basis points more in a top-quartile market than in a bottom-quartile market.

To formalize this observation, we rerun the set of OLS and IV regressions from earlier, but this time including a control for the loan interest rate, so that we are comparing loans in differently concentrated markets that have the same interest rate. That is, we are examining whether increased concentration causes an upward shift in fees even when the interest rate is fixed.

The results of these regressions are shown in Table A1 in the appendix. Panel A gives the OLS results, with Columns (1)–(4) showing total points and fees and Columns (5)–(8) showing discount points alone. Note that the inclusion of the interest rate as a control does not alter the results

Interestingly, when looking at *total* points and fees, we do not recover the inverse relationship between fees and interest rates that we observed in Figure 4. Rather, this relationship holds only for the discount points portion of the total fee (Columns (5)–(8)). Here, for a fixed interest rate we again find a statistically significant relationship between discount points paid and concentration. For the most controlled specification, a 1-percentage-point increase in the concentration ratio is associated with an upward shift of roughly 25 basis points in the point–rate menu.

Panel B of Table A1 gives the results of the IV analysis with the interest rate control for total points and fees, and Panel C for discount points. Both are nearly identical to those without the control. Together, the results in Table A1 show that in higher-concentration areas, the entire point–rate schedule shifts towards higher fees for a given interest rate. This confirms that overall mortgage pricing is indeed higher in high-concentration areas.

5 The Extensive Margin of Lending

The previous sections showed that local lender concentration does not affect interest rates, but has a significant impact on the upfront fees that borrowers pay to lenders. This

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finding suggests that we should explore other, non-interest-rate margins through which local concentration might affect mortgage origination.

In this section, we examine the extensive margin of credit provision; that is, we ask how local concentration influences which borrowers obtain credit in the first place. This question is closely related to that of pricing: at a high level, according to many models with incomplete information (e.g., Stiglitz and Weiss, 1981), lenders often ration credit on the extensive margin as an alternative to increasing prices (which could endogenously increase loan risk).

We start by studying loan application approval rates, then analyze borrower and loan composition for approved loans. The methodology closely follows that of previous sections: we begin with the OLS analysis, then verify its conclusions using our previously established IV strategies. As detailed below, we find strong evidence that greater concentration leads lenders to approve fewer loans. Moreover, the pool of approved loans has lower risk both ex ante (exhibiting higher FICO scores and lower DTI and LTV) and ex post (exhibiting lower delinquency rates).

5.1 Loan Approval

Our main specification mirrors (4), but each observation is now a loan application from the HMDA dataset, rather than an originated loan. (Note that because the GSE dataset includes only approved loans, there is no matched sample that allows us to control for credit score.) The main specification is

$$Rejection_{ict} = \beta Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict}. \tag{13}$$

Here, $Rejection_{ict}$ is a zero–one dummy for whether the loan application is rejected, and β is the coefficient of interest on $Concentration_{ct-1}$, which is either the observed concentration measure HHI_{ct} or $CR4_{ct}$ (one-year lagged), or the instrumented measure using bank mergers. X_i is the same vector of loan controls as before, X_{ct} is the same vector of county-year controls, and γ_c and γ_t are county and year fixed effects. We use our bank merger instrument to resolve identification concerns similar to those of the previous sections (e.g., that lending to borrowers in more concentrated counties could be unobservably more or less costly).

Table 4 Panel A shows the results. To maintain continuity with the fees analysis (Section 4), Columns (1)–(5) focus on the 2018–2019 sample. We find that there is consistently a large positive relationship between concentration and rejection rates. Column (5), which

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corresponds to the most saturated specification, shows that a 1-percentage-point increase in CR4 is associated with a 0.081-percentage-point increase in the likelihood that an application is rejected. Columns (6)–(9), which cover 1991–2019, find similar (though slightly larger) effects. Figure 5 Panel A shows these results graphically in a binned scatterplot, with rejection rates on the y-axis and the one-year lagged market concentration on the x-axis. Panel B shows rejection rates on the y-axis and market concentration on the x-axis, both residualized by county and year fixed effects. In both panels, we see a robust linear relationship at all levels of market concentration.

These results are strongly consistent with the idea that greater lender concentration leads to more credit rationing on the supply side. It is natural to ask why a lender would accept a given application in a less concentrated market but reject a similar application in a more concentrated market, especially in the context of loans that will be sold to GSEs. Without investigating deeply, we offer two mechanisms. First, many borrowers approach lenders with incomplete applications or missing documentation. In less concentrated areas, loan officers may face greater competitive pressure to originate loans, so they may invest more time in helping these borrowers complete their applications. Second, in more concentrated areas there may simply be fewer loan officers; labor shortages may mean lenders are able to originate fewer loans. This is similar to the mechanism identified in Sharpe and Sherlund (2016).

We next implement the same IV strategy as earlier. Turning directly to the IV and reduced form specifications, the regressions are as follows:

$$Rejection_{ict} = \beta \hat{Concentration}_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict}, \tag{14}$$

$$Rejection_{ict} = \beta Merger_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict}. \tag{15}$$

Table 4 Panel B shows the results. Columns (1)–(3) give the first-stage results, Columns (4)–(6) the IV results, and Columns (7)–(8) the reduced form results. As before, the instrument is highly relevant for CR4 (Columns (1) and (3)) and HHI (Column (2)). The IV results similarly show a positive and statistically significant relationship between concentration and rejection rates, roughly in line with the OLS estimates. To offer interpretable magnitudes, counties with a bank merger see rejection rates increase by roughly 1.5 to 2 percentage points depending on the specific fixed effects included.

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5.2 Originated Loan Composition

Next, among originated loans, we examine the borrower composition along four measures of risk. We look at three ex-ante measures—FICO score, DTI ratio, and LTV ratio—as well as ex-post delinquency. Our analysis uses three separate sources of data: the 2018–2019 HMDA data, which includes information on DTI and LTV; the GSE data, which includes information on DTI, LTV, FICO scores, and delinquency for the universe of securitized conforming loans; and the Black Knight data, which includes information on DTI, LTV, FICO scores, and delinquency for a servicer-reported sample of all loans (including non-conforming loans).

The baseline loan-level specification is as follows:

$$Risk_{ict} = \beta Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict}, \tag{16}$$

where $Risk_{ict}$ is either an ex-ante measure of loan risk (FICO score, LTV, or DTI), or ex-post delinquency. Delinquency is measured by an indicator variable equal to one if the loan becomes at least 60 days delinquent within the first four years after origination. The rest of the specification exactly mirrors the specifications in the prior analyses.

Table 5 Panel A shows the OLS results. Consistently across all samples, we find that greater concentration is associated with lower risk, both ex ante and ex post. Columns (1)–(3) show that an increased concentration ratio is associated with significantly lower LTVs. This effect is somewhat muted in the GSE sample, whose conforming guidelines already impose fairly tight bounds on allowable LTVs. In the more representative Black Knight data, we find that a 1-percentage-point increase in CR4 is associated with an average LTV 17 points lower. That is, in more concentrated markets, borrowers take on less leverage.

In Columns (4)–(6) we find similar results for DTI: across the samples, borrowers' DTI is lower in more concentrated markets. In the Black Knight sample, a 1-percentage-point increase in CR4 is associated with an 8.8-percentage-point decrease in average DTI of originated loans. In Columns (7) and (8) we find that greater concentration is also associated with higher FICO scores of originated loans. Finally, Columns (9) and (10) show that delinquency rates are lower in more concentrated markets.

Figure 5 Panel C shows these results graphically. The figure plots the regression coefficients from a non-parametric regression, regressing a loan characteristic (the credit score, DTI, or LTV) or a loan outcome (loan default) on a dummy variable indicating whether the lender concentration was in the top quartile (the omitted variable is the bottom quar-

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tile). The bars indicate the point estimates, and the lines indicate the 95% confidence interval. The regressions includes county and year fixed effects, and the standard errors are double-clustered at the county and year levels. Comparing the top quantile to the bottom quantile, we find that FICO scores are 1% higher, DTIs are 6% lower, and LTV ratios are 1.8% lower in the most concentrated markets. Finally, the ex-post default rates are 5 percentage points lower, a difference of immense economic magnitude, given that the unconditional default rate is 10%. These findings are all strongly consistent with the hypothesis that in more competitive markets, lenders are more willing to originate loans that appear riskier ex ante.

We next implement the same IV strategy as before. The loan level IV and reduced form specifications are as follows:

$$Risk_{ict} = \beta Conce\hat{n}tration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict} \tag{17}$$

$$Risk_{ict} = \beta Merger_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_c + \gamma_t + \epsilon_{ict} \tag{18}$$

Table 5 Panel B shows the results. In this analysis, we focus on the Black Knight data as it covers the greatest number of observables and is most representative across the universe of mortgage products. Column (1) confirms that the first stage is significant in this subsample. Columns (2)–(5) show the IV results, while Columns (6)–(9) show the reduced form results. In direction and magnitude, the IV results are similar to the OLS results, although only the DTI result remains statistically significant. Quantitatively, we find that a county with a bank merger sees LTVs decrease by roughly 1 percentage point, DTIs decrease by roughly 1 percentage point, FICO scores increase by roughly 3 points, and delinquency rates decrease by roughly 33 basis points.

We note that this analysis provides important context for the earlier results on points and fees. As described in the introduction and in Section 3, a potential confounding factor in interpreting those results was that loans originated in more concentrated areas might be more costly for lenders because they are riskier, which means higher points and fees would not necessarily reflect higher markups. Our findings in this section help rule out this channel: loans made in more concentrated areas are, in fact, less risky, both ex ante and ex post. Thus, evaluations of the effects of concentration on lenders' market power should take into account that points and fees on loans made in concentrated areas are significantly higher even though the loans are less risky on both observable and unobservable characteristics.

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6 Credit Access for Marginal Borrowers

The previous sections showed that local lender concentration affects both the intensive margin of credit pricing and the extensive margin of credit provision. These findings highlight that contrary to the assumptions informing current policy, concentration does influence credit access. An important further question is which demographic groups are most affected by changes in concentration.

In this section, we examine the effects of lender concentration for marginal borrowers, those who have historically been excluded from credit markets: borrowers belonging to racial minorities, female borrowers, and low-income borrowers. As we mentioned in the introduction, the connection between concentration and credit access for marginal borrowers is becoming particularly relevant now as the Federal Reserve begins to consider how its policies impact inequality.

We start by studying how the three components of credit pricing and access—interest rates, points and fees, and loan approval—vary with borrower race, sex, and income. As detailed below, we find that marginal borrowers suffer on every component, facing higher rates, fees, and rejection probabilities. We then examine how the local lender concentration affects credit access across borrower groups. We find that while greater concentration reduces credit access for all borrowers, the effect is particularly strong for borrowers belonging to racial minorities, female borrowers, and low-income borrowers.

Our methodology mirrors that of previous sections: we begin with an OLS analysis, evaluate potential nonlinear effects using binned scatterplots, and finally verify the conclusions using the previously established IV strategies. Our OLS specification is as follows:

$$\begin{aligned} MortgagePrice_{ict} = \beta_1 BorrowerCharacteristic_i + \beta_2 Concentration_{ct-1} + \\ \beta_3 BorrowerCharacteristic_i \times Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \epsilon_{ictl}. \end{aligned} \tag{19}$$

Here, $MortgagePrice_{ict}$ is either the interest rate, the points and fees, or a zero-one dummy for whether the loan application is rejected.[14] $BorrowerCharacteristic_i$ comes in three different forms: (1) a zero-one dummy indicating whether the borrower is either "non-Hispanic white" or "Black or African American";[15] (2) a zero-one dummy indicating

[14] As with the specifications in the earlier sections, when we study interest rates and points and fees the sample includes all originated loans. When we study loan rejections the sample includes all loan applications.

[15] For ease of reading, we exclude other races and ethnic groups. The online appendix contains a specification which includes the full set of races and ethnic groups.

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whether the borrower is female or male; and (3) a vector of dummy variables indicating the borrower's income quartile. As before, $Concentration_{ct-1}$ is the concentration ratio, CR4, in county c, one-year lagged at year $t-1$. The coefficient of interest is β_3 on the interaction, which highlights whether the effect of concentration differs across borrower groups. X_i and X_{ct} are the vectors of applicant-level and county-level controls used earlier.[16]

Table 6 presents the results. Columns (1)–(3) present the results where the dependent variable is the interest rate. As discussed earlier, we do not see a consistent relationship between concentration and interest rates. In particular, although white and high-income borrowers obtain lower interest rates on average, concentration has no statistically significant effect on interest rates for any borrower group; there is no differential impact by race, sex, or income.

Columns (4)–(6) present the results where the dependent variable is points and fees. Consistent with our previous results, we see a strong relationship between concentration and points and fees across all three specifications. As was the case with rates, we find that white borrowers, male borrowers, and high-income borrowers pay lower points and fees. For example, black borrowers pay 16 basis points more in points and fees than white borrowers, and low-income borrowers (those in the bottom quartile) pay almost 2 percentage points more than high-income borrowers (those in the top quartile). Evaluating the effects of concentration on points and fees across borrower groups, we find that these effects are stronger for female and low-income borrowers than for male and high-income borrowers, respectively. In other words, while female and low-income borrowers pay higher fees on average, the fee differential shrinks in more competitive local markets. On the other hand, we do not find any difference between the effects of concentration for white and black borrowers.

Columns (7)–(8) present the results for loan rejection. As before, we see a strong positive relationship between concentration and rejection rates. Comparing borrower groups, we find that black applicants, female applicants, and low-income applicants all have higher loan rejection rates. As with fees, we find that concentration has a larger impact on the rejection rates of marginal borrowers: the differential rejection probability for a black, female, or low-income borrower is greater when local markets are more concentrated.

Figure 6 illustrates these results graphically with binned scatterplots, in order to rule out any nonlinearities. In each panel, the x-axis shows equal-sized bins of CR4 values,

[16]In Table A4 in the online appendix we present results that include lender fixed effects. The conclusions are similar to those in this section.

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and the y-axis shows loan rejection rates. Panels A, C, and E show the relationship between concentration and rejection rates for each applicant group, and Panels B, D, and F show the relationship between concentration and the rejection rate *gap* for each pair of applicant groups. In all three cases, we confirm the regression results, that an increase in lender concentration is associated with a differentially higher rejection rate for marginal loan applicants.

Next, we implement the bank merger IV strategy from before. The instrumented concentration and interaction term, the IV specification, and the reduced form regression specification are standard:

$$\begin{aligned} \widehat{Concentration}_{ct} \equiv \hat{\phi} Merger_{ct} + \hat{\zeta} BorrowerCharacteristic_i \\ + \hat{\eta}' X_i + \hat{\mu}' X_{ct} \end{aligned} \tag{20}$$

$$\begin{aligned} \widehat{BorrowerCharacteristic_i} \times Concentration_{ct} \equiv \hat{\phi} Merger_{ct} \\ + \hat{\zeta} BorrowerCharacteristic_i \times Concentration_{ct-1} + \hat{\eta}' X_i + \hat{\mu}' X_{ct} \end{aligned} \tag{21}$$

$$\begin{aligned} Rejection_{ict} = \beta_1 BorrowerCharacteristic_i + \beta_2 \widehat{Concentration}_{ct-1} \\ + \beta_3 \widehat{BorrowerCharacteristic_i} \times Concentration_{ct-1} + \eta' X_i + \mu' X_{ct} + \epsilon_{ictl} \end{aligned} \tag{22}$$

$$\begin{aligned} Rejection_{ict} = \beta_1 BorrowerCharacteristic_i + \beta_2 Merger_{ct} \\ + \beta_3 BorrowerCharacteristic_i \times Merger_{ct} + \eta' X_i + \mu' X_{ct} + \epsilon_{ictl} \end{aligned} \tag{23}$$

Table 7 shows the results. We focus here on how rejection rate differentials by log borrower income vary with lender concentration. Columns (1)–(2) present the OLS results with and without lender fixed effects. Columns (3)–(4) present the first-stage results, Columns (4)–(6) the IV results, and Columns (7)–(8) the reduced form results. As before, the instrument is highly relevant, with a joint F-statistic (for both the level and the interaction) above 300. The IV results similarly show a positive and statistically significant coefficient on the interaction term. In line with the OLS estimates, the effect of concentration on credit access is stronger for low-income borrowers. In other words, while low-income borrowers are rejected more on average, the rejection rate gap narrows significantly when local lending markets become more competitive.

Combined, these results highlight that mortgage lenders often compete by increasing the supply and decreasing the price of credit to marginal borrowers. This suggests that policies that encourage competition between mortgage lenders will particularly benefit

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racial-minority, female, and low-income borrowers, through lower points and fees and higher application acceptance rates.

7 Conclusion

In this paper, we showed that contrary to a broad consensus among policymakers and in the academic literature, local lender concentration has significant impacts on mortgage prices and credit access. Past studies have correctly identified that there is no relationship between concentration and mortgage interest rates, a result that we confirm. However, we find that increases in concentration are strongly correlated with increases in upfront fees. Our findings are robust across several data constructions and specifications. Moreover, we verify that high concentration does not simply shift borrowers' choices along the menu of rates and discount points; instead, it shifts the entire menu towards higher prices. These effects are particularly strong among historically marginal borrowers.

We also find strong impacts on the extensive margin. In highly concentrated areas, mortgage applications are rejected at higher rates, and the pool of approved applications is less risky by both ex-ante and ex-post measures, with higher FICO scores, lower LTV and DTI ratios, and lower delinquency rates. These results are particularly strong among low-income and minority borrowers, suggesting that considering local lender concentration is particularly important when it comes to questions of credit access to traditionally under served borrowers.

Taken together, our results highlight that regulators should factor local lender concentration into their decisions on policies such as bank mergers and the pass-through of monetary policy. An interesting problem for future work would be to evaluate the economic impact of the standard assumption that local concentration is irrelevant, by analyzing equilibrium market shares, lending quantities, and lending standards in a counterfactual world in which regulators enforced policy based on local lender concentration.

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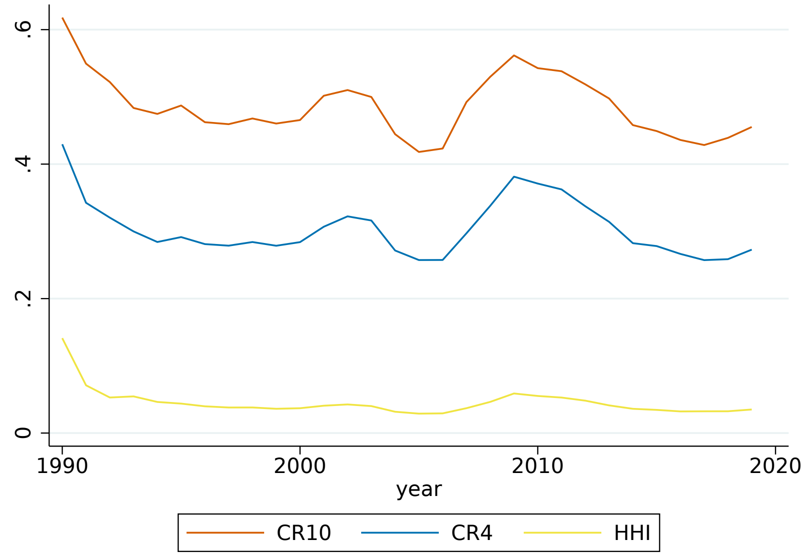
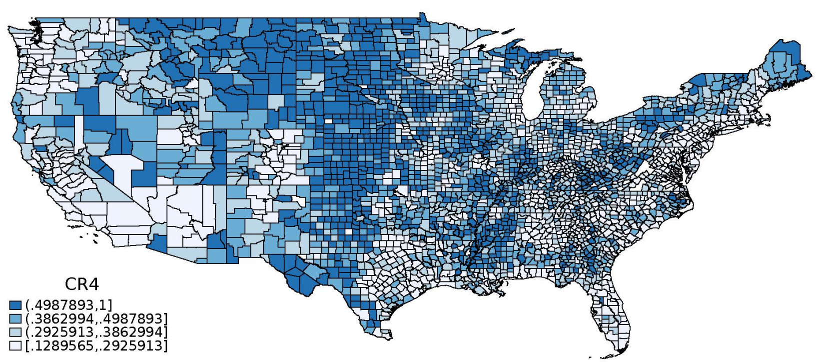
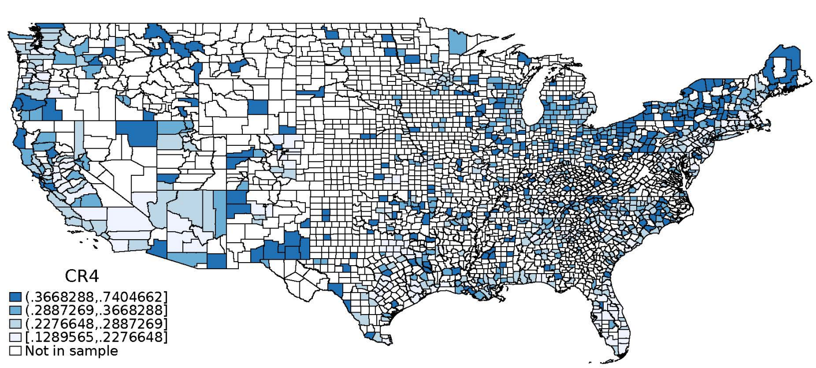
Figure 1: Local Mortgage Lending Concentration in the U.S.



Panel A: Lending concentration over time



Panel B: Nationwide distribution



Panel C: Top 1,000 counties by population

Note: The figure plots the distribution of local mortgage market concentration across time and space. The data source is the 2018-2019 HMDA dataset. Panel (a) plots the average county-level concentration-ratio of originated mortgages for the top-10 lenders (CR10), the concentration-ratio for the top-4 lenders (CR4), and the Herfindahl-Hirschman Index (HHI). For each year, the average is weighted by total amount. Panel B plots the nationwide distribution of county-level CR4 in 2018. Panel C plots the distribution for the top-1,000 counties in 2018, based on population.

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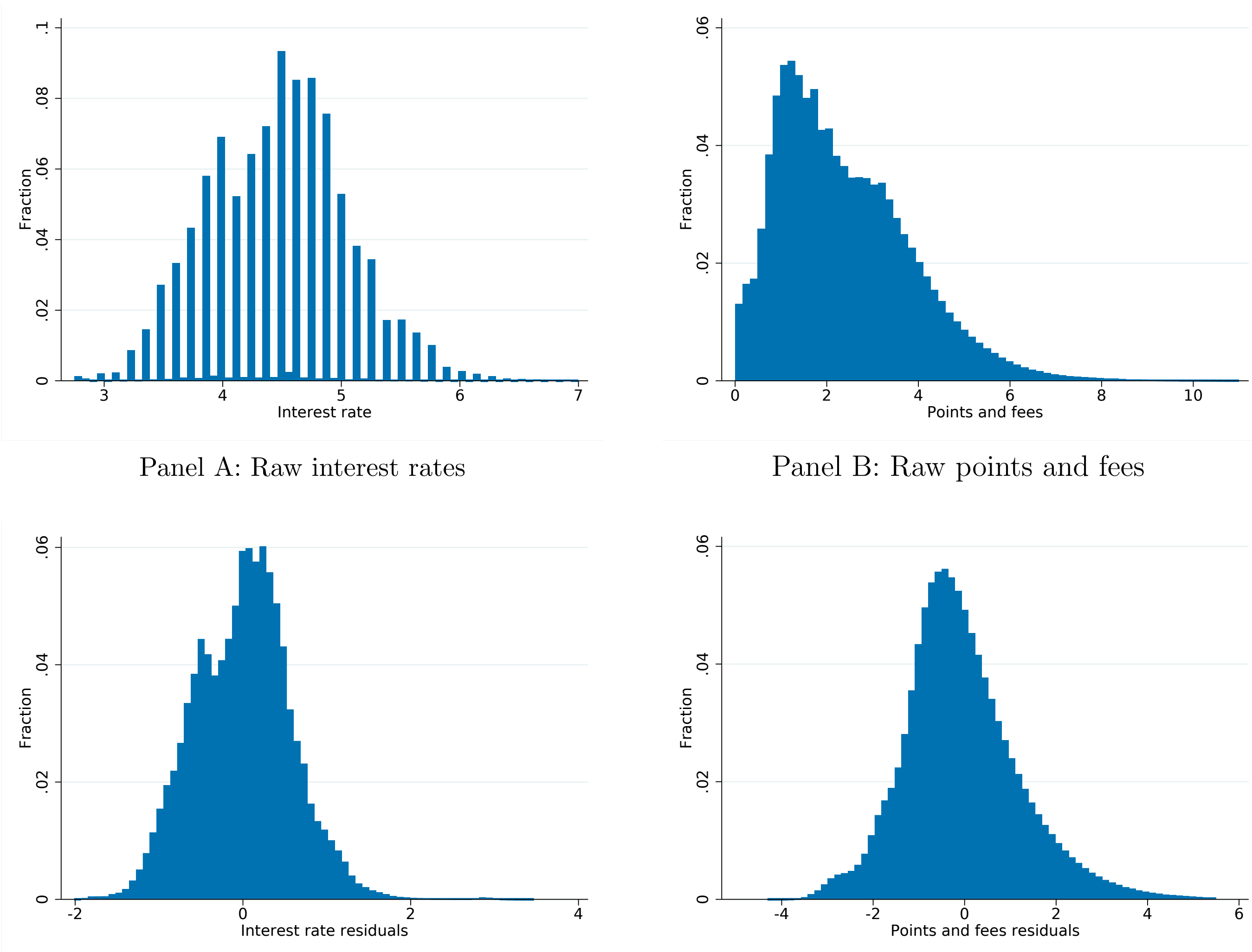
Figure 2: Distribution of Rates and Fees



Panel A: Raw interest rates

Panel B: Raw points and fees

Panel C: Interest rate residuals

Panel D: Points and fees residuals

Note: This figure shows the distribution of mortgage interest rates and non-interest fees. The data source is the 2018–2019 HMDA dataset. Panel A plots the distribution of interest rates. Panel B plots the distribution of the sum of all points and fees (as the percentage of the loan value). Panels C and D plot the residuals from Equation (3). Panel C plots the residuals when the dependent variable is the interest rate, and Panel D plots the residuals when the dependent variable is points and fees. In each regression, we control on loan characteristics (using loan size and loan type dummies and bins for the loan-to-value ratios and debt-to-income ratios) and census-tract-level characteristics (including the percentage of minority population and the ratio of the median family income in the census tract to the median family income in the MSA).

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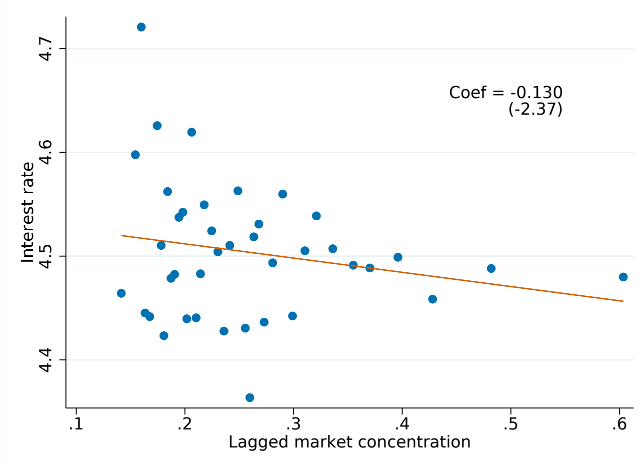
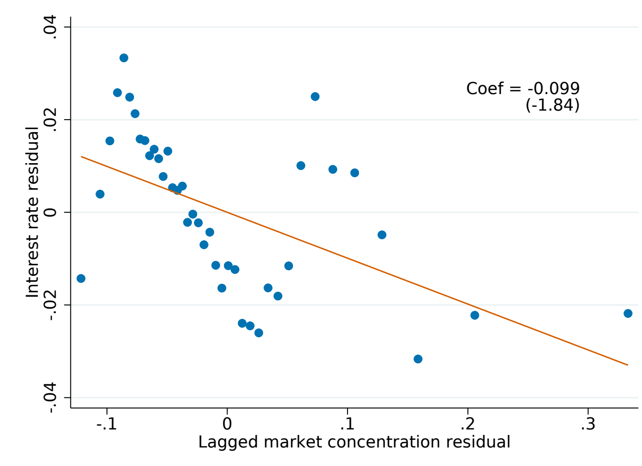
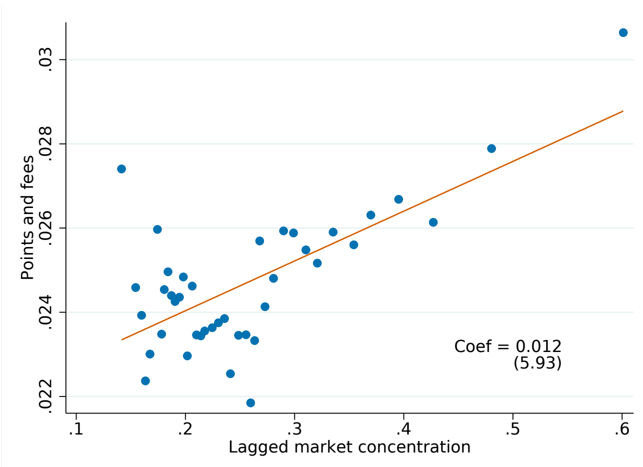
Figure 3: Interest rates, points and fees, and competition



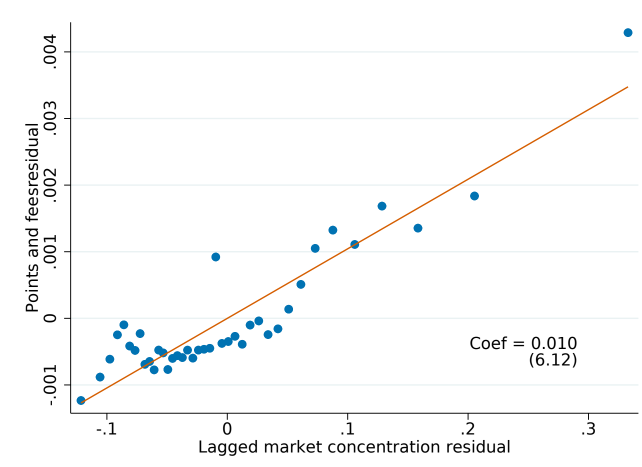
Panel A: Raw interest rates



Panel B: Interest rate residuals



Panel C: Raw points and fees



Panel D: Points and fees residuals

Note: The figure plots the distribution of interest rates and points and fees relative to local mortgage market concentration. The data source is the 2018-2019 HMDA dataset. Panel A shows a binned scatter plot of the mortgage interest rate. Panel B shows a binned scatter plots of interest rates residualized from regression equation (3), where interest rates are regressed on loan characteristics and census-tract level controls. Panel C plots a binned scatter plot of points and fees. Panel D plots a binned scatter plot of residualized points and fees. In all four panels, the dots represent 40 equal-sized bins based on the one-year lagged county-level CR4. The line is a linear regression on the entire dataset, with the coefficient displayed (and the t statistic in parentheses).

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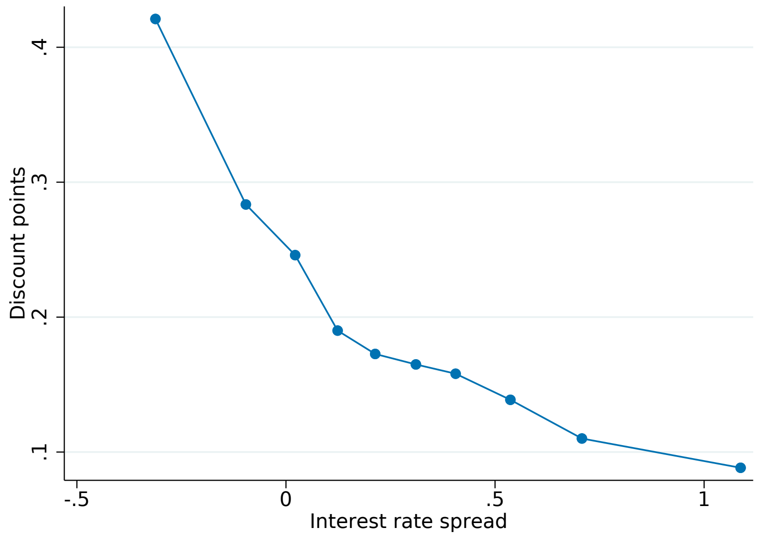
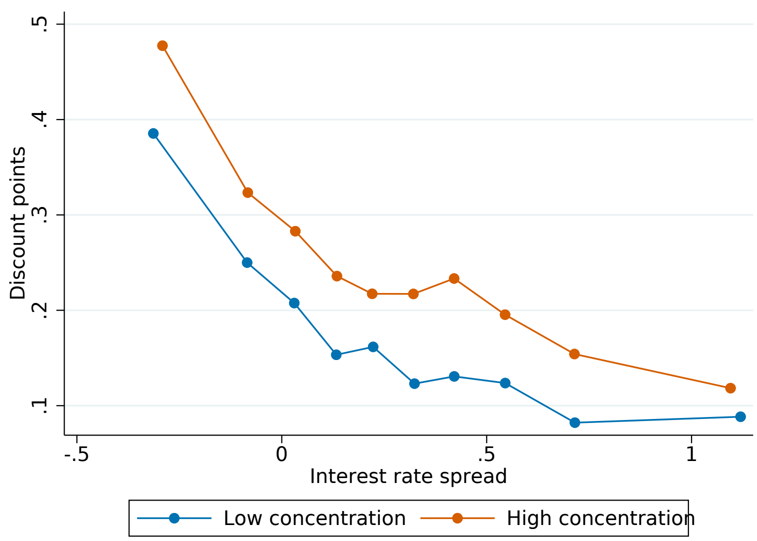
Figure 4: Discount points vs interest rates



Panel A: Points versus rates schedule



Panel B: Points versus rates by concentration

Note: The figure plots the relationship between discount points and interest rate spreads. The data source is the merged 2018-2019 HMDA-GSE dataset. Panel A plots predicted values from a regression of discount points on interest rate spread deciles. Panel B plots predicted values from a regression of discount points on interest rate spread deciles interacted with quartiles of the one-year lagged county-level CR4. Only the top and bottom quartile are included in the figure. For both panels, the controls include debt-to-income ratio, loan-to-value ratio, income deciles, 23 credit score bins, and lender and origination date fixed effects. 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).

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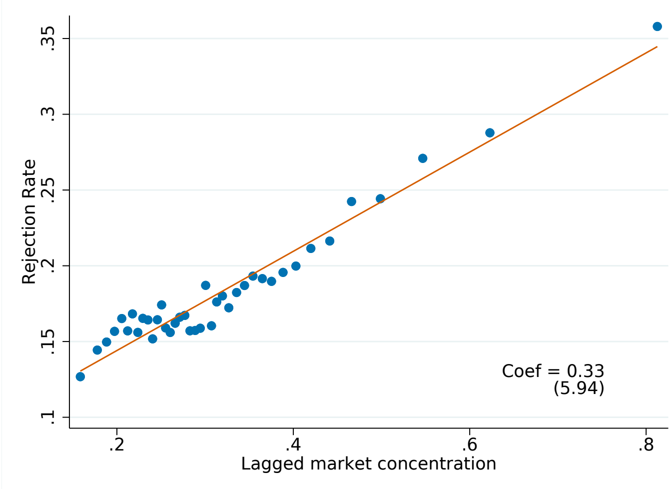
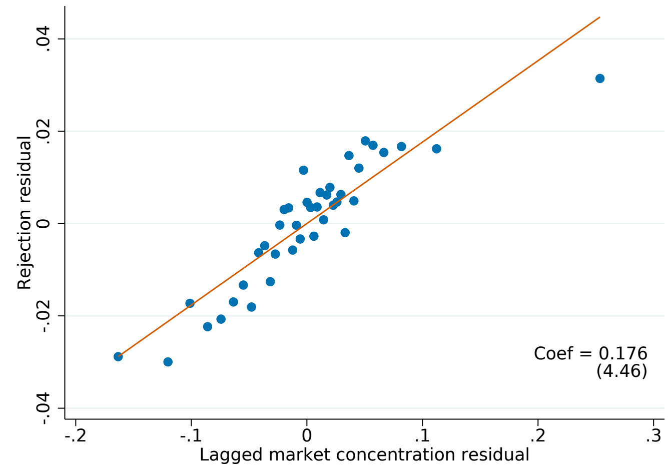
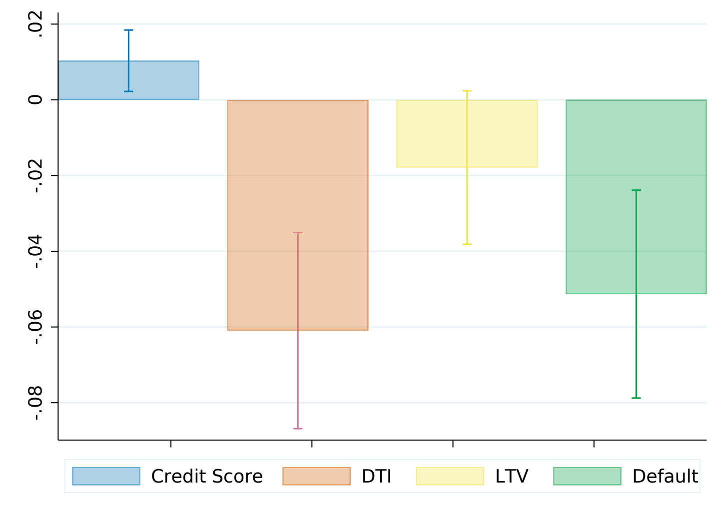
Figure 5: The Extensive Margin of Lending



Panel A: Raw rejection rates



Panel B: Rejection rates residuals



Panel C: Non-parametric estimates

Note: This figure shows the relationship between local lender concentration and the extensive margin of lending. The data source for Panels A and B is the full HMDA sample, and the data source for Panel C is the Black Knight dataset. Panel A shows a binned scatterplot of the rejection rates. Panel B shows a binned scatterplot of the residualized rejection rates, where loan rejection is regressed on loan and county-year controls and county and year fixed effects. In both panels, the dots represent 40 equal-sized bins based on the one-year lagged county-level CR4. The line is a linear regression on the entire dataset, with the coefficient displayed (and the t-statistic in parentheses). Panel C plots the regression coefficients from a non-parametric regression, regressing a loan characteristic (the credit score, debt-to-income ratio, or loan-to-value ratio) or a loan outcome (loan default) on a dummy variable indicating whether the lender concentration was in the top quartile (the omitted variable is the bottom quartile). The bars indicate the point estimates, and the lines indicate the 95% confidence interval. The regression includes county and year fixed effects, and the standard errors are double-clustered at the county and year levels.

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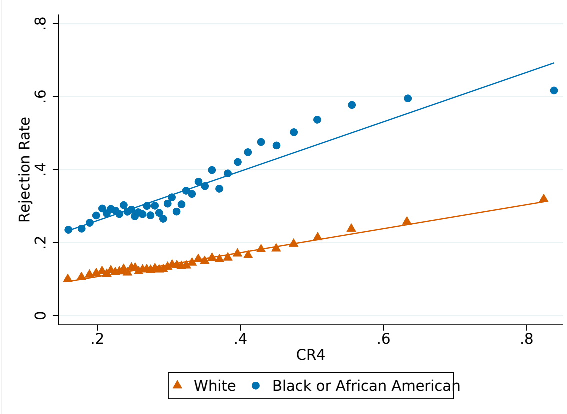
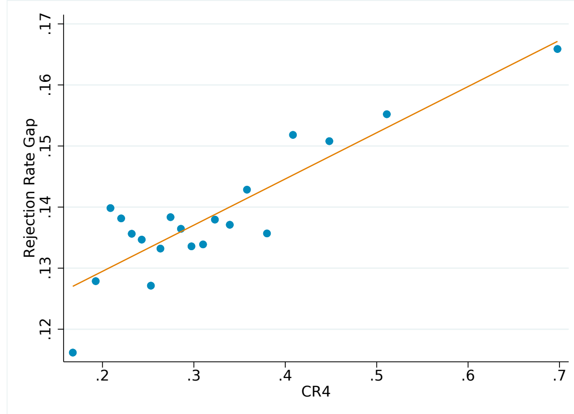
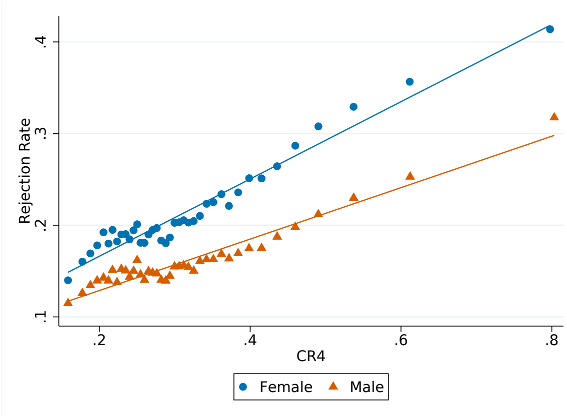
Figure 6: Local Concentration and Marginal Borrowers



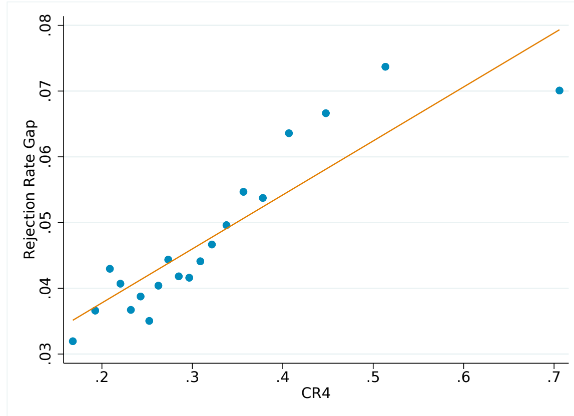
Panel A: Rejection rates by race



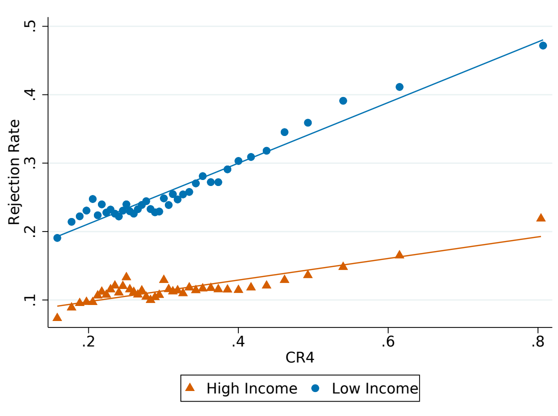
Panel B: Gap between white and black



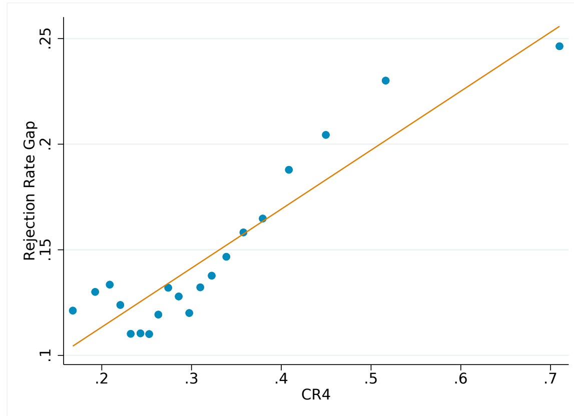
Panel C: Rejection rates by sex



Panel D: Gap between male and female



Panel E: Rejection rates by income quartile



Panel F: Gap between top and bottom income quartile

Note: This figure shows the relationship between local mortgage concentration (measured as the market share of the top four lenders, CR4) and loan rejection rates across different groups of applicants. Panels A, C, and E show the relationship for non-Hispanic white applicants and black or African American applicants, female and male applicants, and applicants from the top and bottom income quartiles, respectively. Panels B, D, and F show the relationship of local concentration and the gap in rejection rates between non-Hispanic white applicants and black or African American applicants, between male and female applicants, and between the bottom and the top income quartile, respectively. In each panel, the dots represent 20 equal-sized bins based on the one-year lagged county-level CR4, and the solid line is a linear regression on the entire dataset.

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Table 1: Summary Statistics

Panel A: Full HMDA sample

	N	Mean	Std. dev.	25%-tile	75%-tile
Loan amount ($)	6,219,040	267,401.11	173,908.90	165,000.00	325,000.00
Interest rate	6,196,808	4.48	0.59	4.00	4.88
Non-interest costs ($)	6,107,863	5,343.93	20,613.30	3,066.00	6,761.08
Origination charge ($)	6,096,393	1,672.75	2,616.79	673.80	2,000.00
Discount points ($)	6,219,023	577.90	2,022.76	0.00	460.55
Lender credits ($)	6,219,023	432.24	68,274.99	0.00	185.05
Applicant income ($)	6,171,847	107,717.43	1,114,142.09	54,000.00	118,000.00
Combined loan-to-value ratio	6,004,335	88.67	13.26	80.00	97.00
Debt-to-income ratio	6,168,664	37.89	10.61	33.00	45.00

Panel B: Matched HMDA-GSE sample

	N	Mean	Std. dev.	25%-tile	75%-tile
Loan amount ($)	111,255	240,749.13	115,807.53	155,000.00	315,000.00
Interest rate	111,255	4.65	0.39	4.38	4.88
Non-interest costs ($)	110,739	3,875.33	4,482.88	2,569.55	4,663.97
Origination charge ($)	110,132	1,577.07	1,723.72	770.00	1,848.86
Discount points ($)	111,254	534.37	1,240.38	0.00	473.48
Lender credits ($)	111,254	396.01	1,083.63	0.00	250.00
Applicant income ($)	110,107	95,038.35	65,634.73	55,000.00	118,000.00
Combined loan-to-value ratio	110,574	82.25	16.41	78.87	95.00
Debt-to-income ratio	110,899	35.79	10.00	25.00	44.00

Panel C: County-year statistics

	N	Mean	Std. dev.	25%-tile	75%-tile
Mortgage lenders	6,391	62.29	65.91	19.00	80.00
Herfindahl-Hirschman Index (HHI)	6,391	0.08	0.08	0.04	0.09
Market share for top 4 (CR4)	6,391	0.42	0.16	0.30	0.51
Market share for top 10 (CR10)	6,391	0.63	0.17	0.50	0.74
Census tract population	6,391	4,592.83	1,619.99	3,585.00	5,469.42
Percent minority population	6,391	22.58	21.57	6.67	31.85
Median family income for MSA-MD	6,391	63,558.23	14,222.59	54,500.00	69,680.89
Tract income to MSA-MD median	6,391	102.75	16.97	92.30	111.75

Note: The table reports number of observations, and the mean, standard deviation, and the 25th and 75th percentile. Panel A reports summary statistics for the 2018-2019 HMDA dataset of 30-year conventional, first-lien mortgages originated for home purchases of owner-occupied, single-family homes. We exclude government-insured loans, such as FHA and VA loans; and we exclude mortgages with "exotic" features, such as reverse mortgages, mortgages with an open-end line of credit (e.g. HELOCs), interest-only mortgages, and mortgages with prepayment penalties, intro-rate periods, baloon payments, or other non-amortizing features. Panel B reports summary statistics for the HMDA-GSE matched sample. Panel C reports summary statistics for the county-year dataset.

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Table 2: Interest rates and competition

Panel A: OLS Estimates

	All loans						Jumbo	Conforming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CR4	-0.10	-0.13	-0.11	0.046	0.034		0.42	0.051	0.12	0.012
	(-1.80)	(-2.31)	(-1.89)	(0.99)	(0.72)		(5.48)	(1.11)	(2.39)	(0.24)
HHI						0.22				
						(1.53)				
Loan controls		✓			✓	✓	✓	✓	✓	✓
County controls			✓		✓	✓	✓	✓	✓	✓
Lender FE				✓	✓	✓	✓	✓	✓	✓
Month FE										✓
Credit score										✓
Sample	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA-GSE	HMDA-GSE
N	6,191,113	5,963,877	6,191,113	6,189,403	5,962,467	5,962,467	268,408	5,693,598	111,472	111,375
R^2	0.00	0.03	0.01	0.12	0.14	0.14	0.24	0.13	0.13	0.44

Panel B: IV Estimates

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Merger	0.24	0.21	0.23				0.049	0.066	-0.000072
	(9.87)	(11.83)	(8.91)				(1.51)	(2.34)	(-0.00)
CR4				0.21	0.31	-0.00032			
				(1.59)	(2.38)	(-0.00)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,985,341	5,983,931	111,379	5,963,877	5,962,467	111,379	5,963,877	5,962,467	111,379
R^2	0.09	0.31	0.29	0.01	0.00	0.02	0.03	0.13	0.44
F-stat	96.10	137.70	79.34						

Note: This table shows the results from equations (5) (Panel A), (6), (8), and (9) (Panel B Columns (1)–(3), (4)–(6), and (7)–(9), respectively). Standard errors are clustered at the county level, t statistics in parentheses. "HMDA" denotes the the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "HMDA-GSE" denotes the matched sample, which only includes conforming loans. See Subsection 2.1 for details on sample selection and matching procedure.

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Table 3: Points, fees, and competition

Panel A: Total points and fees - OLS estimates

	All loans						Jumbo	Conforming		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CR4	1.24	0.93	1.25	1.45	1.11		-0.37	1.19	0.69	0.70
	(5.78)	(5.83)	(5.55)	(8.32)	(7.27)		(-3.46)	(8.01)	(3.08)	(3.13)
HHI						3.24				
						(5.82)				
Loan controls		✓			✓	✓	✓	✓	✓	✓
County controls			✓		✓	✓	✓	✓	✓	✓
Lender FE				✓	✓	✓	✓	✓	✓	✓
Month FE										✓
Credit score										✓
Sample	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA-GSE	HMDA-GSE
N	6,103,629	5,885,416	6,103,629	6,101,938	5,884,026	5,884,026	266,893	5,616,676	110,971	110,874
R^2	0.00	0.00	0.00	0.02	0.02	0.02	0.17	0.02	0.08	0.08

Panel B: Total points and fees - IV estimates

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Merger	0.19	0.16	0.17				0.14	0.19	0.22
	(11.61)	(10.98)	(8.62)				(1.88)	(3.96)	(3.28)
CR4				0.74	1.20	1.32			
				(1.83)	(3.82)	(3.33)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,985,341	5,983,931	110,263	5,885,416	5,884,026	109,765	5,885,416	5,884,026	109,765
R^2	0.13	0.33	0.31	0.00	0.00	0.01	0.00	0.02	0.08
F-stat	132.60	119.33	73.96						

Note: The This table shows the results from equations (10) (Panel A), (6), (11), and (12) (Panel B Columns (1)–(3), (4)–(6), and (7)–(9), respectively). Standard errors are clustered at the county level, t statistics in parentheses. "HMDA" denotes the the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "HMDA-GSE" denotes the matched sample, which only includes conforming loans. See Subsection 2.1 for details on sample selection and matching procedure.

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Table 4: The Extensive Margin of Lending

Panel A: Rejection Rates - OLS estimates

	2018–2019					1991–2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CR4	0.046	0.074	0.082	0.059	0.081	0.22	0.25	0.18	0.18
	(3.61)	(7.47)	(7.54)	(5.79)	(8.68)	(16.69)	(20.14)	(13.72)	(17.69)
Loan controls		✓			✓	✓	✓	✓	✓
County controls			✓		✓	✓	✓	✓	✓
County FE							✓		✓
Year FE								✓	✓
Lender FE				✓	✓				
N	11,879,908	10,996,996	11,879,908	11,876,751	10,994,666	88,047,473	88,047,473	88,047,473	88,047,473
R^2	0.00	0.16	0.01	0.13	0.25	0.05	0.08	0.07	0.09

Panel B: Rejection Rates - IV estimates

	First stage			IV			Reduced form	
	(1) CR4	(2) HHI	(3) CR4	(4)	(5)	(6)	(7)	(8)
Merger	0.22	0.089	0.057				0.020	0.014
	(11.31)	(5.40)	(16.53)				(4.73)	(3.29)
CR4				0.092		0.25		
				(3.95)		(3.44)		
HHI					0.22			
					(4.53)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓		✓	✓		✓	
County FE			✓			✓		✓
Year FE			✓			✓		✓
Sample	2018-2019	2018-2019	1991-2019	2018-2019	2018-2019	1991-2019	2018-2019	1991-2019
N	10,994,666	10,994,666	88,047,473	10,994,666	10,994,666	88,047,473	10,994,666	88,047,473
R^2	0.27	0.25	0.72	0.00	0.00	0.03	0.25	0.09
F-stat	127.93	29.13	273.13					

Note: This table shows the results from equations (13) (Panel A), (6), (14), and (15) (Panel B Columns (1)–(3), (4)–(6), and (7)–(8), respectively). Standard errors are clustered at the county level, t statistics in parentheses. "2018–2019" denotes the the 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "1991–2019" denotes the 1991–2019 HMDA sample, which includes conventional mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans. See Subsection 2.1 for details on sample selection.

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Table 5: The Composition of Loans

Panel A: OLS Estimates

	Loan-to-value			Debt-to-income			Credit Score		Default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CR4	-65.1	-2.54	-17.1	-3.90	-2.54	-8.84	12.4	53.2	-0.0084	-0.18
	(-1.15)	(-1.71)	(-4.65)	(-8.12)	(-5.70)	(-6.13)	(4.01)	(4.70)	(-3.58)	(-6.61)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Area controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓			✓						
MSA FE		✓			✓		✓		✓	
County FE			✓			✓		✓		✓
Year FE		✓	✓		✓	✓	✓	✓	✓	✓
Sample	HMDA	GSE	Black Knight	HMDA	GSE	Black Knight	GSE	Black Knight	GSE	Black Knight
Period	2018-2019	2010-2019	2010-2017	2018-2019	2010-2019	2010-2017	2010-2019	2010-2017	2010-2019	2010-2017
N	5,997,997	7,668,169	1,341,674	6,161,667	7,667,906	824,049	7,663,445	1,183,852	7,655,176	1,345,140
R^2	0.00	0.05	0.26	0.08	0.05	0.06	0.01	0.23	0.01	0.07

Panel B: IV Estimates

	First stage	IV				Reduced form			
	(1) CR4	(2) LTV	(3) DTI	(4) FICO	(5) Default	(6) LTV	(7) DTI	(8) FICO	(9) Default
Merger	0.034					-0.93	-0.91	2.89	-0.0033
	(5.26)					(-1.40)	(-5.10)	(1.34)	(-0.67)
CR4		-27.7	-28.4	86.8	-0.096				
		(-1.49)	(-5.03)	(1.47)	(-0.70)				
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sample	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight
Period	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017
N	1,345,140	1,341,674	824,049	1,183,852	1,345,140	1,341,674	824,049	1,183,852	1,345,140
R^2	0.90	0.00	-0.00	0.00	0.00	0.26	0.06	0.23	0.07
F-stat	27.66								

Note: This table shows the results from Equation (16) (Panel A) and Equations (6), (17), and (18) (Panel B Columns (1)–(3), (4)–(6), and (7)–(8), respectively). Standard errors are clustered at the county level, with t-statistics in parentheses. "HMDA" denotes the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "GSE" refers to the GSE 2010–2019 sample, which includes 30-year conforming, first-lien mortgages originated for purchases of owner-occupied single-family homes. "Black Knight" denotes the 2010–2017 Black Knight sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. See Subsection 2.1 for details on sample selection.

Table 6: Local Concentration and Marginal Borrowers - OLS Estimates

	Interest rates			Points and fees			Rejection rates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CR4	0.026	-0.12	-0.11	0.89	0.86	1.39	0.14	0.093	0.11
	(0.22)	(-2.21)	(-2.36)	(3.07)	(5.16)	(9.12)	(6.89)	(8.82)	(9.80)
White	-0.034			-0.16			-0.069		
	(-1.33)			(-2.62)			(-13.33)		
White X CR4	-0.11			0.016			-0.050		
	(-1.11)			(0.06)			(-2.53)		
Female		0.025			0.075			0.0055	
		(4.55)			(3.76)			(3.85)	
Female X CR4		-0.0029			0.55			0.0041	
		(-0.15)			(8.04)			(0.82)	
Income Q2			-0.027			-0.28			-0.038
			(-3.27)			(-8.32)			(-16.71)
Income Q3			-0.059			-0.42			-0.043
			(-5.65)			(-10.31)			(-12.68)
Income Q4			-0.049			-0.49			-0.048
			(-2.70)			(-7.32)			(-10.14)
Income Q2 X CR4			-0.039			-0.83			-0.021
			(-1.48)			(-8.40)			(-3.20)
Income Q3 X CR4			-0.030			-1.25			-0.059
			(-0.92)			(-10.06)			(-5.93)
Income Q4 X CR4			-0.14			-1.94			-0.11
			(-2.19)			(-8.44)			(-6.70)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	4,317,049	5,963,877	5,918,905	4,262,986	5,885,416	5,840,629	7,782,178	10,996,996	10,893,509
R^2	0.03	0.03	0.03	0.02	0.00	0.01	0.17	0.17	0.17

Note: This table shows the results from Equation (19). CR4 is the county-level market share of the top four lenders, lagged one year. "Income" is the natural logarithm of the applicant-level income. Standard errors are clustered at the county level, with t-statistics in parentheses. The sample includes the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. See Subsection 2.1 for details on sample selection.

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Table 7: Local Concentration and Marginal Borrowers - IV Estimates

Rejection rates

	OLS		First stage		IV		Reduced form	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			CR4	CR4 X Income				
CR4	0.42	0.41			0.21	0.20		
	(12.23)	(15.35)			(1.42)	(2.22)		
CR4 X Income	-0.082	-0.080			-0.046	-0.034		
	(-10.63)	(-13.75)			(-1.61)	(-2.09)		
Income	-0.017	-0.013			-0.028	-0.026	-0.040	-0.035
	(-7.27)	(-7.03)			(-3.49)	(-5.59)	(-36.59)	(-40.58)
Merger			0.25	0.051			0.049	0.047
			(13.45)	(0.42)			(1.41)	(2.30)
Merger X Income			-0.016	0.43			-0.011	-0.0084
			(-2.90)	(8.51)			(-1.56)	(-2.15)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓				✓		✓
N	10,831,976	10,829,650	10,831,976	10,831,976	10,831,976	10,829,650	10,831,976	10,829,650
R^2	0.17	0.25	0.09	0.16	0.01	0.01	0.17	0.25
F stat			308.80	308.80				

Note: This table shows the results from Equations (20)–(23). CR4 is the county-level market share of the top four lenders, lagged one year. "Income" is the natural logarithm of the applicant-level income. "Merger" is an indicator variable taking the value one if the county has had an "incidental" merger within the past five years. Standard errors are clustered at the county level, with t-statistics in parentheses. The sample includes the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. See Subsection 2.1 for details on sample selection.

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References

Amel, D. F., E. Anenberg, R. Jorgensen, et al. (2018). On the geographic scope of retail mortgage markets. *Board of Governors of the Federal Reserve System, FEDS Notes, June 15*.

Begley, T. A. and A. Purnanandam (2020). Color and Credit: Race, Regulation, and the Quality of Financial Services. SSRN Scholarly Paper ID 2939923, Social Science Research Network, Rochester, NY.

Benetton, M., A. Gavazza, and P. Surico (2019). Mortgage pricing and monetary policy. Technical report, working paper.

Bhutta, N., A. Fuster, and A. Hizmo (2020). Paying too much? Price dispersion in the US mortgage market.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018). The limits of shadow banks. Technical report, National Bureau of Economic Research.

Cetorelli, N. and P. E. Strahan (2006). Finance as a barrier to entry: Bank competition and industry structure in local us markets. *The Journal of Finance 61*(1), 437–461.

Charles, K. K. and E. Hurst (2002). The transition to home ownership and the black-white wealth gap. *Review of Economics and Statistics 84*(2), 281–297.

Dafny, L., M. Duggan, and S. Ramanarayanan (2012). Paying a Premium on Your Premium? Consolidation in the US Health Insurance Industry. *American Economic Review 102*(2), 1161–85.

Di Maggio, M., A. Kermani, and S. Korgaonkar (2019). Partial deregulation and competition: Effects on risky mortgage origination. *Management Science 65*(10), 4676–4711.

Dobbie, W., A. Liberman, D. Paravisini, and V. Pathania (2018). Measuring bias in consumer lending. Technical report, National Bureau of Economic Research.

Favara, G. and M. Giannetti (2017). Forced Asset Sales and the Concentration of Outstanding Debt: Evidence from the Mortgage Market. *The Journal of Finance 72*(3), 1081–1118.

Federal Reserve System (2008). Order Approving the Acquisition of a Savings Association and Other Nonbanking Activities. *Federal Reserve Board Notice June 05*.

Electronic copy available at: https://ssrn.com/abstract=3762250

Fuster, A., L. S. Goodman, D. O. Lucca, L. Madar, L. Molloy, and P. Willen (2013). The rising gap between primary and secondary mortgage rates. *Economic Policy Review 19*(2).

Fuster, A., S. Lo, and P. Willen (2017, August). The Time-Varying Price of Financial Intermediation in the Mortgage Market. Technical Report w23706, National Bureau of Economic Research, Cambridge, MA.

Garmaise, M. J. and T. J. Moskowitz (2006). Bank Mergers and Crime: The Real and Social Effects of Credit Market Competition. *The Journal of Finance 61*(2), 495–538.

Giannetti, M. and F. Saidi (2019, July). Shock Propagation and Banking Structure. *The Review of Financial Studies 32*(7), 2499–2540. Publisher: Oxford Academic.

Holmes, A. and P. Horvitz (1994). Mortgage redlining: Race, risk, and demand. *Journal of Finance*, 81–99.

Hurst, E., B. J. Keys, A. Seru, and J. Vavra (2016). Regional redistribution through the us mortgage market. *American Economic Review 106*(10), 2982–3028.

Jørring, A. (2020). Financial Sophistication and Consumer Spending. *Working Paper*.

Kroszner, R. S. and P. E. Strahan (1999). What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *The Quarterly Journal of Economics 114*(4), 1437–1467.

Ladd, H. F. (1998, June). Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives 12*(2), 41–62.

Liu, L. (2019). Non-salient fees in the mortgage market. *Available at SSRN 3437374*.

Rice, T. and P. E. Strahan (2010). Does credit competition affect small-firm finance? *The Journal of Finance 65*(3), 861–889.

Saidi, F. and D. Streitz (2020). Bank Concentration and Product Market Competition. Technical report.

Scharfstein, D. and A. Sunderam (2016). Market power in mortgage lending and the transmission of monetary policy. *Unpublished working paper. Harvard University*.

Sharpe, S. A. and S. M. Sherlund (2016). Crowding out effects of refinancing on new purchase mortgages. *Review of Industrial Organization 48*(2), 209–239.

Electronic copy available at: https://ssrn.com/abstract=3762250

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American economic review 71*(3), 393–410.

Tootell, G. M. (1996). Redlining in boston: Do mortgage lenders discriminate against neighborhoods? *The Quarterly Journal of Economics*, 1049–1079.

Xiao, K. (2020, June). Monetary Transmission through Shadow Banks. *The Review of Financial Studies 33*(6), 2379–2420.

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A Appendix

A.1 Alternate Instruments

In addition to the bank merger instrument, we consider two alternate instruments. The first instrument follows Kroszner and Strahan (1999) and Rice and Strahan (2010), utilizing the staggered implementation of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA), which while passed in 1994, was slowly rolled out across states. The act allowed out-of-state banks to set up branches in other states. States that implemented the act, or implemented the act sooner, see less local banking concentration. The identifying assumption is that the timing of the act's implementation was unrelated to local differences in the marginal costs of lending. Rice and Strahan (2010) created an index measuring the degree of deregulation ranging from zero to four. Specifically, they add one to the index: if a state imposes a minimum age of 3 or more years on target institutions of interstate acquirers; if a state does not permit de novo interstate branching; if a state does not permit the acquisition of individual branches by an out-of-state bank; and if a state imposes a deposit cap less than 30%.

The second instrument uses the pre-crisis share of three large mortgage lenders—Washington Mutual, Wachovia, and Countrywide—that failed during the crisis. The failure of these lenders and subsequent cannibalization of their market shares led to persistently lower lending concentration many years out, driven by the frictions associated with banks entering new markets. The identifying assumption for this instrument is that the forces that drove these lenders to operate in these counties in 2007 are orthogonal to unobserved economic conditions more than 10 years and a complete housing cycle later. To strengthen this assumption, we exclude counties where the failed lender had a market share of more than 20% of the market.

A.1.1 Bank Branching Regulation

We first use the staggered implementation of the Interstate Banking and Branching Efficiency Act. The first stage, second stage, and reduced form specifications are as follows:

$$\widehat{Concentration}_{ct} \equiv \hat{\phi} Index_{ct} + \hat{\eta}' X_{ct} + \hat{\gamma}_t + \hat{\gamma}_c \tag{24}$$

$$InterestRate_{ilctd} = \beta \widehat{Concentration}_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{25}$$

$$InterestRate_{ilctd} = \beta Index_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{26}$$

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The subsequent specifications mirror exactly those in the body of the text with the exception of the instrument. Table A2 Panel A shows the results for interest rates and Panel B shows the results for rejection rates. Since the bulk of the variation in interstate bank deregulation happened between the mid-1990s and the mid-2000s, we can only use this instrument for the samples that cover a long time period. Therefor, in Panel A (interest rates) we use the Black Knight sample from 1990-2017, and in Panel B (rejection rates) we use the HMDA sample from 1990-2019.

Across these specifications, the results are qualitatively similar to those we obtain using the main bank merger instrument. In Panel A Columns (5) and (6), we see that an instrumented increase in 1%-point in CR4 and HHI increases the interest rate by 0.013%-point and 0.055%-point, respectively. Both estimates are statistically insignificant, with t statistics of 0.75 and 0.74, respectively. In Panel B

A.1.2 Failed Banks

We next use the market share of three failed lenders in the financial crisis: Washington Mutual, Wachovia, and Countrywide. These lenders held large market shares in certain counties up until 2007, and following their failure lending concentration in these counties fell substantially. We use this to induce cross-sectional variation in concentration in 2018 and 2019.

The first stage, second stage, and reduced form specifications are as follows:

$$Concen\hat{t}ration_{ct} \equiv \hat{\phi} ShareFailed_{ct} + \hat{\eta}' X_{ct} + \hat{\gamma}_t + \hat{\gamma}_c \tag{27}$$

$$InterestRate_{ilctd} = \beta Concen\hat{t}ration_{ct-1} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{28}$$

$$InterestRate_{ilctd} = \beta ShareFailed_{ct} + \eta' X_i + \mu' X_{ct} + \gamma_l + \gamma_d + \epsilon_{ict} \tag{29}$$

As above, the IV and reduced form specifications exactly mirror those in the body of the text with the exception of the instrument. Table A3 Panel A shows the results for interest rates, Panel B shows the results for points and fees, and Panel C shows the results for rejection rates. Across these specifications, the results are qualitatively very similar to those we obtain using the main bank merger instrument.

Panel A Columns (4)-(9) show that there is no systematic evidence of competition affecting interest rates. On the other hand, in Panel B columns (4)-(9), confirms the prior results that higher concentration leads to statistically and economically higher points and fees. Recall, this instrument led to a decrease in concentration, hence the reduced form estimates are negative.

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A.2 Additional Tables and Figures

Figure A1: The Menu of Points, Fees, 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

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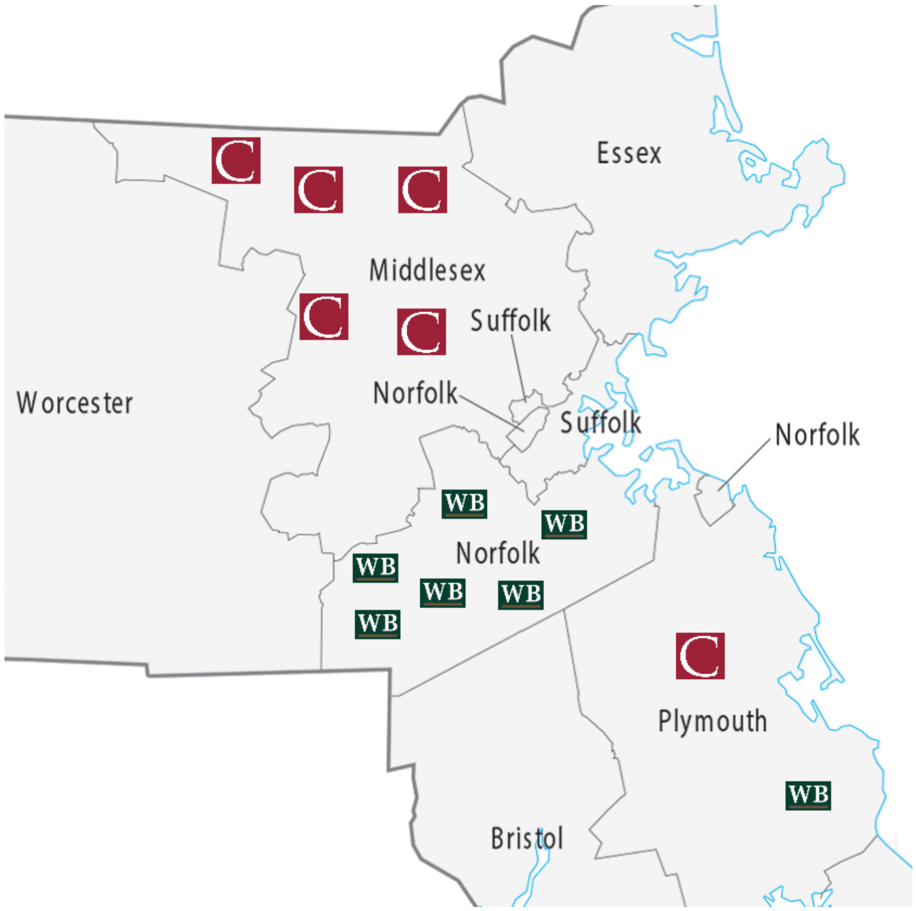
Figure A2: Bank Merger Instrument Construction



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.

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Table A1: Fees and competition: controlling for interest rates

Panel A: OLS estimates

	Total points and fees				Discount points			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR4	1.01	1.10	0.72	0.68	0.22	0.24	0.18	0.26
	(5.93)	(7.30)	(3.35)	(3.04)	(5.14)	(8.96)	(3.40)	(5.67)
Interest rate	0.18	0.060	0.24	0.13	-0.061	-0.10	-0.14	-0.21
	(17.37)	(7.20)	(14.65)	(7.62)	(-20.48)	(-40.32)	(-17.86)	(-27.93)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓		✓		✓		✓
Credit score			✓	✓			✓	✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA-GSE
N	5,864,141	5,862,751	111,013	110,888	5,963,870	5,962,460	111,506	111,379
R^2	0.00	0.02	0.03	0.08	0.01	0.13	0.01	0.16

Panel B: IV estimates - Points and fees

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Merger	0.24	0.21	0.23				0.20	0.23	0.25
	(9.79)	(11.72)	(8.91)				(3.19)	(3.40)	(2.37)
Interest rate	-0.0031	0.00049	0.00079	0.20	0.068	0.19	0.19	0.069	0.19
	(-2.22)	(0.49)	(0.25)	(17.11)	(7.88)	(6.94)	(16.53)	(7.72)	(6.83)
CR4				0.85	1.09	1.12			
				(3.18)	(4.37)	(2.57)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,963,877	5,962,467	111,379	5,864,141	5,862,751	110,888	5,864,141	5,862,751	110,888
R^2	0.09	0.31	0.29	0.00	0.00	0.01	0.00	0.02	0.08
F-stat	96.13	137.42	79.71						

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Table A1: Fees and competition: controlling for interest rates (cont'd)

Panel C: IV estimates - Discount points

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Merger	0.24	0.21	0.23				0.042	0.048	0.017
	(9.79)	(11.72)	(8.91)				(1.11)	(1.83)	(0.28)
Interest rate	-0.0031	0.00049	0.00079	-0.060	-0.10	-0.29	-0.060	-0.10	-0.29
	(-2.22)	(0.49)	(0.25)	(-19.15)	(-40.14)	(-28.96)	(-19.72)	(-39.58)	(-29.08)
CR4				0.18	0.22	0.075			
				(1.20)	(2.12)	(0.28)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,963,877	5,962,467	111,379	5,963,870	5,962,460	111,379	5,963,870	5,962,460	111,379
R^2	0.09	0.31	0.29	0.00	0.01	0.02	0.01	0.13	0.16
F-stat	95.79	137.42	79.41						

Note: This table shows the results from equations (10) (Panel A), (6), (11), and (12) (Panels B and C, Columns (1)–(3), (4)–(6), and (7)–(9), respectively), with the addition of the interest rate as a control. Panel A is the OLS estimate for total points and fees (Columns (1)–(4)) and discount points only (Columns (5)–(8)). Panel B is the IV estimate for total fees. Panel C is the IV estimate for discount points only. Standard errors are clustered at the county level, t statistics in parentheses. "HMDA" denotes the the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "HMDA-GSE" denotes the matched sample, which only includes conforming loans. See Subsection 2.1 for details on sample selection and matching procedure.

Table A2: Alternate Instruments: Bank Branching

Panel A: Interest rates

	OLS		First stage		IV		Reduced form
	(1)	(2)	(3) CR4	(4) HHI	(5)	(6)	(7)
CR4	-0.0048				0.013		
	(-1.30)				(0.75)		
HHI		-0.0077				0.055	
		(-0.86)				(0.74)	
IBBEA index			0.014	0.0032			0.00018
			(3.68)	(3.27)			(0.75)
Loan controls	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓
Sample	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight	Black Knight
N	3,882,255	3,882,255	2,671,337	2,671,337	2,670,490	2,670,490	2,670,490
R^2	0.09	0.09	0.14	0.09	0.06	0.05	0.13
Joint F-stat			13.57	10.67			

Panel B: Rejection rates

	OLS		First stage		IV		Reduced form
	(1)	(2)	(3) CR4	(4) HHI	(5)	(6)	(7)
CR4	0.27				0.42		
	(19.43)				(3.93)		
HHI		0.51				0.97	
		(17.74)				(3.91)	
IBBEA index			0.015	0.0066			0.0064
			(9.42)	(13.41)			(4.17)
Loan controls	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓
N	9,072,390	9,072,390	7,179,218	7,179,218	7,179,218	7,179,218	7,179,218
R^2	0.03	0.02	0.09	0.07	0.02	0.02	0.02
Joint F-stat			88.69	179.83			

Note: The Table shows the results of the IBBEA instrument. Panel A examines interest rates. Standard errors are clustered at the state level, t statistics in parentheses. "Black Knight" denotes the 2010–2017 Black Knight sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. In Panel B, the sample is the 1991–2019 HMDA sample, which includes conventional mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans. See Subsection 2.1 for details on sample selection.

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Table A3: Alternate Instruments: Failed Mortgage Lenders

Panel A: Interest rates

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share failed	-0.94	-0.76	-0.32				0.075	-0.29	-0.038
	(-14.61)	(-12.94)	(-5.16)				(0.87)	(-4.12)	(-0.43)
CR4				-0.079	0.38	0.12			
				(-0.88)	(3.84)	(0.42)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,265,473	5,264,484	111,378	5,247,420	5,246,431	111,378	5,247,420	5,246,431	111,378
R^2	0.20	0.36	0.29	0.01	0.00	0.02	0.03	0.13	0.44
F-stat	213.37	167.48	26.58						

Panel B: Points and fees

	First stage			IV			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share failed	-0.94	-0.76	-0.65				-2.35	-2.55	-2.33
	(-14.61)	(-12.94)	(-10.36)				(-5.02)	(-5.73)	(-4.48)
CR4				2.49	3.35	3.57			
				(5.01)	(5.49)	(4.21)			
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓	✓
Month FE			✓			✓			✓
Credit score			✓			✓			✓
Sample	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE	HMDA	HMDA	HMDA-GSE
N	5,265,473	5,264,484	97,414	5,180,937	5,179,964	96,988	5,180,937	5,179,964	96,988
R^2	0.20	0.36	0.34	0.00	0.00	0.00	0.02	0.08	0.08
F-stat	213.82	166.93	106.96						

Table A3: Alternate Instruments: Failed Mortgage Lenders (cont'd)

Panel C: Rejection rates

	First stage			IV			Reduced form	
	(1) CR4	(2) HHI	(3) CR4	(4)	(5)	(6)	(7)	(8)
Share failed	-0.91	-0.75	-0.18				-0.16	-0.18
	(-14.53)	(-12.88)	(-13.21)				(-5.49)	(-6.55)
CR4				0.17	0.24			
				(5.26)	(5.89)			
HHI						0.98		
						(5.98)		
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE		✓	✓		✓	✓		✓
Sample	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA	HMDA
N	9,287,682	9,285,971	9,285,971	9,287,682	9,285,971	9,285,971	9,287,682	9,285,971
R^2	0	0	0	0	0	0	0	0
F-stat	211	166	174					

Note: The Table shows the results of the failed lenders instrument. Panel A examines interest rates, Panel B examines points and fees, and Panel C examines rejection rates. Standard errors are clustered at the county level, t statistics in parentheses. "HMDA" denotes the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. "HMDA-GSE" denotes the matched sample, which only includes conforming loans. See Subsection 2.1 for details on sample selection and matching procedure.

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Table A4: Concentration and Marginal Borrowers - with Lender Fixed Effects

	Interest rates			Points and fees			Rejection rates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CR4	0.10	0.035	0.042	0.95	1.00	1.40	0.11	0.080	0.10
	(0.96)	(0.75)	(1.02)	(3.49)	(6.84)	(10.48)	(6.14)	(8.46)	(11.93)
White	-0.055			-0.22			-0.060		
	(-2.46)			(-4.08)			(-14.41)		
White X CR4	-0.041			0.34			-0.020		
	(-0.44)			(1.44)			(-1.21)		
Female		0.021			0.081			0.0091	
		(5.03)			(4.54)			(7.63)	
Female X CR4		-0.0028			0.49			0.0075	
		(-0.19)			(7.78)			(1.83)	
Income Q2			-0.016			-0.33			-0.032
			(-2.22)			(-10.70)			(-16.98)
Income Q3			-0.041			-0.49			-0.037
			(-4.58)			(-13.46)			(-13.75)
Income Q4			-0.034			-0.63			-0.035
			(-2.41)			(-13.82)			(-8.04)
Income Q2 X CR4			-0.040			-0.61			-0.022
			(-1.77)			(-6.78)			(-4.09)
Income Q3 X CR4			-0.021			-0.95			-0.050
			(-0.73)			(-8.86)			(-6.63)
Income Q4 X CR4			-0.075			-1.44			-0.11
			(-1.47)			(-8.19)			(-7.00)
Loan controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	4,315,973	5,962,467	5,917,495	4,261,925	5,884,026	5,839,238	7,780,398	10,994,666	10,891,183
R^2	0.12	0.14	0.14	0.08	0.02	0.02	0.25	0.25	0.25

Note: This table shows the results from Equation (19). CR4 is the county-level market share of the top four lenders, lagged one year. "Income" is the natural logarithm of the applicant-level income. Standard errors are clustered at the county level, with *t*-statistics in parentheses. The sample is the full 2018–2019 HMDA sample, which includes 30-year conventional, first-lien mortgages originated for purchases of owner-occupied single-family homes, excluding government-insured loans and loans with "exotic" features. See Subsection 2.1 for details on sample selection.