# Market Power in Mortgage Lending and the Transmission of Monetary Policy*

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## Abstract

We present evidence that high concentration in mortgage lending reduces the sensitivity of mortgage rates and refinancing activity to mortgage-backed security (MBS) yields. We isolate the direct effect of concentration in two ways. First, we use a matching procedure to compare high- and low-concentration counties that are very similar on observable characteristics and find similar results. Second, we examine counties where bank mergers increase concentration in mortgage lending. Within a county, sensitivities to MBS yields decrease after a concentration-increasing merger. Our results suggest that the strength of monetary policy transmission through the mortgage market varies in the cross section.

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## I. Introduction

Housing is a critical channel for the transmission of monetary policy to the real economy. As shown by Bernanke and Gertler (1995), residential investment is the component of GDP that responds most strongly and immediately to monetary policy shocks. In addition, housing can be an important channel through which monetary policy affects consumption. An easing of monetary policy can reduce mortgage rates, enabling households to refinance their mortgages at lower rates and reduce their payments. If borrowers have higher marginal propensities to consume than lenders, as would be the case if borrowers are more liquidity constrained, then refinancing can boost aggregate consumption.

Using monetary policy to support housing credit has been a particular focus of the Federal Reserve during the Great Recession. The Federal Reserve's purchases of mortgage-backed securities (MBS) in successive rounds of quantitative easing have had the explicit goal of supporting the housing market. One of the aims of quantitative easing was to lower mortgage rates by reducing financing costs for mortgage lenders (Bernanke 2009, 2012). However, the widespread use of fixed rate mortgages introduces several frictions that may impede the transmission of these low rates to borrowers. For instance, it has been argued that the efficacy of monetary policy may be hampered by the high indebtedness of households with fixed rate mortgages (Campbell, 2012; Calza, Monacelli, and Stracca, 2013). "Underwater" households whose mortgage balances exceed the values of their homes have been unable to refinance, potentially reducing the impact of low interest rates on the economy.

Others have noted that the reduction in MBS yields from quantitative easing has only been partially passed through to borrowers, leading to historically high values of the so-called "primary-secondary spread" – the spread between mortgage rates and MBS yields (Dudley, 2012). Fuster, et al. (2012) consider a number of explanations for the increase in spreads, including greater costs of originating mortgages, capacity constraints, and market concentration, but ultimately do not identify a single factor as driving the increase.

In this paper, we explore in more detail whether market power in mortgage lending can impede the transmission of monetary policy to the housing sector. We build on the literature arguing that cost "pass-through" is lower in concentrated markets than in competitive markets –

when production costs fall, prices fall less in concentrated markets than they do in competitive markets because producers use their market power to capture larger profits (e.g., Rotemberg and Saloner, 1987). In the context of mortgage lending, this suggests that when the Federal Reserve lowers interest rates, mortgage rates will fall less in concentrated mortgage markets than in competitive markets. This could dampen the effects of monetary policy in locations where mortgage lending is more concentrated.

In this paper, we use panel data to examine the effects of mortgage market concentration at the county level. Rather than focus on the level of the spread between mortgage rates and MBS yields, we instead study the relationship between concentration and the pass-through from MBS yields to mortgage rates. We provide evidence that increases in mortgage market concentration are associated with decreased pass-through at the county level.

Using the yield on GSE-guaranteed MBS as a proxy for the costs of mortgage financing, we find that mortgage rates are less sensitive to costs in concentrated mortgage markets. A one-standard deviation increase in county concentration reduces the impact of a decrease in MBS yields on mortgage rates by 17%. Moreover, when MBS yields fall, the quantity of refinancing increases in the aggregate. However, a one-standard deviation increase in county concentration reduces the impact of a decline in MBS yields on the quantity of refinancing by 15%. The effects on mortgage rates and the quantity of refinancing compound each other. In a high-concentration county, fewer borrowers refinance, meaning that fewer households see their mortgage rates reduced at all. And of the borrowers that do refinance, the rates they are paying fall less on average. The magnitude of the combined effect is substantial: a one-standard deviation increase in concentration reduces total monetary policy transmission through the mortgage market by 29%.

Of course, mortgage market concentration is not randomly assigned, so it is difficult to ascribe causality to these results. We address endogeneity concerns in a variety of ways. First, we follow Hurst, Keys, Seru, and Vavra (2016) and use a nonparametric approach to purge mortgage rates of variation due to credit scores and loan-to-value ratios. In addition, our basic results are robust to a battery of controls including county and time fixed effects, population, wages, house prices, and county demographics. Moreover, we control for the interaction of changes in MBS yields with these characteristics. Thus, our results show that market concentration reduces the sensitivity of mortgage rates to MBS yields even after controlling for the possibility that this sensitivity can vary with county characteristics. Second, we use a matching procedure to ensure that the counties we study are similar on observable dimensions. This does not affect the results.

Third, we use bank mergers as an instrument for mortgage market concentration. Specifically, we examine a sample of counties where mortgage lending concentration is increased by bank mergers, but the counties in the sample were not the key motivation for the merger. In particular, we focus on counties where the banks involved in a merger have a substantial presence, but the county itself makes up only a small fraction of the banks' operations. Mergers increase the concentration of mortgage lending in such counties. However, because the county makes up a small fraction of each of the bank's operations, it is unlikely that the county was an important driver of the merger. In this sample of counties, we show that the sensitivity of refinancing activity and mortgage rates to MBS yields falls after the merger, consistent with the idea that increased concentration causes less pass-through. The exclusion restriction here is that bank mergers affect the sensitivity of refinancing and mortgage rates to MBS yields within a county only through their effect on market concentration in that county. For the exclusion restriction to be violated, it would have to be the case that bank mergers are anticipating changing county characteristics that explain our results, which seems unlikely. In examining observable county characteristics, we find no evidence of changes around mergers.

Our paper is related to the broader literature examining the pass-through of monetary policy to consumer borrowing rates. Hannan and Berger (1991) and Neumark and Sharpe (1992) show that pass-through is lower in more concentrated deposit markets. In addition, Scholnick (1996), Mojon (2000), Van Leuvensteijn, Kok Sørensen, Bikker and Van Rixtel (2013), find similar results on pass-through to both deposit and credit interest rates. Ausubel (1990) documents the impact of inertial consumer behavior on the effective level of competition in the credit card market, while Kahn, Pennacchi, and Sopranzetti (2005) examine the effect of competition on personal and automobile loan rates. Our paper builds on this literature by focusing on the transmission of monetary policy through the mortgage market. Our key contribution is to identify substantial cross-sectional variation in the pass-through of MBS yields to mortgage rates. Our paper is also related to Agarwal, Amromin, Chomsisengphet, Piskorski, Seru, and Yao (2015). They study the Home Affordable Refinance Program (HARP) program, using a program feature that gave borrowers a strong incentive to refinance with their existing lenders, to cleanly identify a market power effect.

Our paper shows that these kinds of market power effects persist even when consumers do not have a strong contractual reason to refinance with their existing lender.

The remainder of this paper is organized as follows. Section II provides some background on the mortgage market, and Section III describes the data. Section IV presents our results on mortgage rates, and Section V presents our results on the quantity of refinancing. Section VI concludes.

## II. Background

### *A. The Conforming Mortgage Market*

We begin with a brief review of the structure of the mortgage market. Our analysis focuses on prime, conforming loans, which are eligible for credit guarantees from the government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac. Such mortgages may be put into MBS pools guaranteed by the GSEs. The GSEs guarantee investors in these MBS that they will not suffer credit losses. If a mortgage in a GSE-guaranteed pool defaults, the GSE immediately purchases the mortgage out of the pool at par, paying MBS investors the outstanding balance of the mortgage. Thus, investors in GSE MBS bear no credit risk except for the GSEs' credit risk, which is generally small. In return for their guarantee, the GSE charges investors a guarantee fee. In addition to the fees charged by the GSEs, borrowers also pay mortgage lenders origination and servicing fees.

Conforming mortgages must meet certain criteria. For instance, their sizes must be below the so-called conforming loan limit, which is set by the Federal Housing Finance Agency. In addition, the mortgages must meet basic GSE guidelines on loan-to-value ratios (LTVs), credit (FICO) scores, and documentation.

An important fact for our empirical analysis is that GSE guarantee fees do not vary geographically. Indeed, until 2008, the GSEs charged a given lender the same guarantee fee for any loan they guaranteed, regardless of borrower (e.g., income, FICO), mortgage (e.g., LTV, loan type), and collateral (e.g., home value) characteristics.[1] In 2008 the GSEs began to charge fees that vary by FICO score, LTV, and loan type, but do not vary by geography or any other borrower

[1] However, there is some relatively minor variation in fees charged across lenders.

characteristics.[2] Thus, for the loans we focus on in our analysis, the only two dimensions of credit quality that should materially affect rates on GSE-guaranteed mortgages are FICO and LTV.[3,4] As we discuss further below, our empirical methodology nonparametrically controls for FICO and LTVs, ensuring that differences in borrower characteristics are not driving our results. Moreover, our results hold in the period prior to 2008, suggesting that borrower-level variation in GSE guarantee fees are not driving the results.

### B. *Definition of the Local Mortgage Market*

A key assumption underlying our empirical analysis is that competition in the mortgage market is local. Specifically, we are assuming that county-level measures of concentration are good proxies for the degree of competition in a local mortgage market. The advent of Internet-based search platforms like Bankrate.com and LendingTree.com has certainly improved the ability of borrowers to search for the best mortgage terms. However, it has been shown that there is still pricing heterogeneity for homogeneous products listed on the Internet (Dinerstein, Einav, Levin, and Sundaresan, 2014). Moreover, there is substantial evidence that many borrowers still shop locally for their mortgages. Analyzing data from the Survey of Consumer Finances, Amel, Kennickell, and Moore (2008) find that the median household lived within four miles of its primary financial institution in 2004. They find that 25% of households obtained mortgages from this primary financial institution, while over 50% of households obtained mortgages from an institution less than 25 miles away.

In addition, borrowers report that they exert little effort in shopping for lower mortgage rates. According to Lacko and Pappalardo (2007), in a survey conducted by the Federal Trade Commission, the average borrower considered only two loans while shopping. Thus, it is likely that local market competition could affect loan terms like rates and points charged upfront. It could

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[2] Fannie Mae publishes their guarantee fee matrix online at: https://www.fanniemae.com/content/pricing/llpa-matrix.pdf

[3] Loan type does not affect our analysis of mortgage rates because we restrict our sample to 30-year fixed rate, full documentation loans.

[4] Other determinants of credit quality may have a small effect on the rates of GSE-guaranteed mortgages due to prepayment risk. When a GSE-guaranteed mortgage defaults, the GSEs immediately pay investors the remaining principal and accrued interest. From an investor's perspective, it is as though the loan prepays. If defaults correlate with the stochastic discount factor, which is likely, this risk will be priced by investors. However, since prepayments induced by default are much smaller than prepayments induced by falling mortgage rates, this effect will be very small.

also manifest itself in other ways. For instance, lenders may advertise more in more competitive markets, leading to greater borrower awareness of lower mortgage rates and increased refinancing activity. Indeed, Gurun, Matvos, and Seru (2013) find evidence that local advertising affects consumer mortgage choices, suggesting that local competition is important.

Data from RateWatch, a vendor that surveys lenders about the mortgage rates they charge, provides more direct evidence that mortgage markets are partially local. RateWatch surveys different branches of the same lender and, crucially, keeps track of how many rate-setting locations a particular lender has. For instance, if the lender sets one national rate, it will have one rate-setting location. In contrast, if each branch has the authority to set its own mortgage rates, RateWatch will record each branch as a rate-setting location. Of the 63,615 surveyed branches, 31,086 (49%) have rate-setting locations in the same MSA. The median rate-setting location covers just four branches, while the average rate-setting location covers 16 branches. While some large lenders set a single rate nationally, the median rate-setting location covers a single MSA, and the average rate-setting location covers two. Within the median MSA, there are eight rate-setting locations, and the average MSA has 18 rate-setting locations.

Thus, there are good reasons to believe that competition in the mortgage market is local. In the data, county-level concentration is strongly autocorrelated over time. A simple regression of our main measure of concentration (the market share of the top 4 lenders in a county) yields an annual autoregressive coefficient of 0.87. This implies that a one-standard deviation increase in Top 4 dissipates after eight years. Entry and competition do operate in this market, but at relatively low frequencies. This slow adjustment may be the product of barriers to entry in mortgage lending. Specifically, mortgage origination requires balance sheet capacity for warehousing loans before they are securitized. In addition, regulatory frictions may play an important role. Mortgage lenders must comply with a variety of regulations, including the Home Mortgage Disclosure Act and the Community Reinvestment Act.

## III. Data

The data in the paper come primarily from two sources. The first is the loan application register data required by the Home Mortgage Disclosure Act (HMDA) of 1975. The data contain every loan application made in the United States to lenders above a certain size threshold. Of primary interest in this paper, the data contain information on whether the loan application was for a refinancing or a new home purchase, whether the loan application was granted, a lender identifier, as well as loan characteristics including year, county, dollar amount, and borrower income. We construct an annual, county-level sample of mortgage refinancing using this data over 1990-2014. To ensure that we are focusing on comparable markets, we restrict the sample to the top 500 counties by population.

Since the HMDA database includes lender identifiers, we can use it to construct county-level measures of competition in mortgage lending. The measure of concentration we use in all our baseline specifications is the share of each county's market served by the top 4 mortgage lenders in the county. In the Internet Appendix, we establish that the results are robust to alternative measures of concentration, including using the Hirschman-Herfindahl Index of concentration calculated using the same HMDA database and conducting our analysis at the MSA level rather than the county level. While these measures of concentration are surely imperfect proxies for the level of local competition, it is only important for our analysis that they capture some of the variation in local competition.[5]

Fig. 1 shows the geographic distribution of top 4 concentration, both for the entire nation and for our sample of the top 500 counties. To give concrete examples of high and low concentration counties, Fig. 2 lists the highest and lowest concentration counties in our sample in 2010. The identities of the top lenders, and their dominance across markets, has changed over time. For example, in 2000, the top national lender was Bank of America, which appeared among the top 4 lenders in 168 of the top 500 counties. In 2010, the top national lender was Wells Fargo, which appeared among the top 4 lenders in 427 of the top 500 counties. Beyond the biggest banks, over 4,000 institutions appear in the top 4 in one of the counties in our sample at least once. For these institutions, the median number of counties in which they appear in the top 4 is one, the mean is five, and the 95th percentile is 10.

[5] In addition, in the Internet Appendix results, we show that the results are similar when we exclude county-years where the fraction of loans originated by brokers and correspondents is high. Because HMDA may not account for sales through brokers and correspondents properly, the scope for mismeasuring concentration is greater in these counties. The robustness of our results to the exclusion of these counties shows that such measurement error is unlikely to be driving our results.

To supplement the HMDA data and analyze the determinants of mortgage rates, we use Fannie Mae's Single Family Loan Performance Data. The data includes the borrower's credit (FICO) score, the date of origination, the loan size, the loan size relative to the house value (LTV ratio), whether the loan is originated for purchase or refinancing, the three-digit zip code of the property, and the interest rate on the mortgage. To ensure the loans we study are maximally comparable, we restrict the sample to loans for refinancing that are 30-year, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages with FICO scores above 660 guaranteed by the GSEs between 1999 and 2014. We use the USPS/HUD Crosswalk files to map three-digit zip codes to counties and restrict the sample to the 500 largest counties by population.

To purge mortgage rates of geographical differences in borrower and loan characteristics that may be correlated with market concentration, we follow the procedure used in Hurst, Keys, Seru, and Vavra (2016). Specifically, we run the regression

$$Rate_{ikm} = \alpha_{0,m} + \alpha_{1,m}\mathbf{X}_{im} + \eta_{ikm},$$

where $Rate_{ikm}$ is the loan-level mortgage rate on a loan to borrower *i* in county *k* in month *m*, and $\mathbf{X}_{im}$ is a series of FICO dummies (620-639, 640-659, …. 780-799, etc.) and a series of LTV dummies (50-54, 55-59, ….80-84, ….95-99, etc.). Note that regression includes time dummies $\alpha_{0,m}$ and time-varying coefficients on the controls $\alpha_{1,m}$. Thus, the regression allows for time-varying distributions and pricing of borrower FICOs and LTVs. This is important because, as described above, the GSEs began to charge fees varying by FICO score and LTV in 2008, and these price schedules have varied over time.

We aggregate the residuals by county-quarter, adding back the time dummies so that we can estimate the average degree of pass-through across all counties. Specifically, we construct

$$R_{kt} = \frac{1}{N_{kt}} \sum_{(i,m)\in\{k,t\}} \left(\alpha_{0,m} + \eta_{ikm}\right)$$

for each quarter *t* and county *k*. $R_{k,t}$ is the average residual rate faced by all individuals in quarter *t* and county *k*. It is our main dependent variable when we study pass-through of MBS yields into mortgage rates.

Finally, we supplement these data sources with county-level demographic and wage statistics from the Census Bureau and historical yields on current coupon Fannie Mae MBS, which we obtain from Bloomberg.

Table 1 provides summary statistics. The average residualized rate in our sample is 5.98% (it is not zero on average because we add back the time dummies $\alpha_{0,m}$). The average change in the residualized rate is on average close to zero, as is the average change in MBS yield. The average county in our sample has a population of 283,000, with an average wage of $38,000 per year and an average home price of $157,000.

## IV. Mortgage Rates Results

### *A. Baseline Results*

We now turn to the results. We begin by studying the pass-through of MBS yields into local mortgage rates. We regress the change in our residualized rates on the change in 30-year Fannie Mae current coupon MBS yields over the quarter,[6] county-level top-4 concentration lagged one year, and the interaction of the two. Formally, we run:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

We weight the regression by the quantity (volume) of loans originated in county $k$ at time $t$. Standard errors are clustered by county and time. The coefficient of interest is $\beta_3$, which measures the extent to which sensitivities to MBS yields depend on county concentration.

Table 2 shows the results. The coefficient $\beta_1$ shows that there is positive pass-through of MBS yields to borrowers. When MBS yields rise, mortgage rates rise as well. The coefficient $\beta_3$ on the interaction between MBS yields and concentration implies that high concentration reduces the pass-through of MBS yields to borrowers. Fig. 3 presents this result graphically, plotting the change in residualized rates for high- (top decile) and low- (bottom decile) concentration counties

[6] The current coupon MBS yield is meant to represent the yield on newly issued MBS. It is derived from prices in the forward market for GSE MBS, called the to-be-announced or TBA market, on MBS to be delivered in the current month. In the Internet Appendix, we also find that our results are robust to using the 10-year Treasury yield as a proxy for funding costs. In addition, in the Internet Appendix, we show that our results are robust to replacing the change in the MBS yield with the change in the incentive to refinance, measured as the difference between the average coupon on existing MBS and the current coupon MBS yield.

as a function of the change in MBS yields. Fig. 3 also highlights how our results relate to Hurst, Keys, Seru, and Vavra (2016). They show that the average mortgage rate does not vary systematically across county characteristics, including concentration. Fig. 3 shows that this is because mortgage rates fall more in low concentration counties when MBS yields fall, but also rise more in low concentration counties when MBS yields rise. Since the change in MBS yields nets out to approximately zero over time, there is no relationship between rates and concentration on average.

Recall that the dependent variable has already been residualized nonparametrically with respect to borrower FICO and LTV. However, one may still wonder whether the differences in pass-through we are finding are driven by county characteristics other than market concentration. For instance, if some counties have more sophisticated borrowers than others, and these differences are not captured by FICO and LTV, these counties might experience a larger increase in refinancing demand when MBS yields fall and thus see their mortgage rates fall less.

To examine this possibility, Fig. 4 plots various county characteristics as a function of concentration. The first panel of Fig. 4 plots demographic characteristics: population, percentage of the population under 18, percentage of the population over 65, percentage of the population that is black, percentage of the population with a high school degree, and the homeownership rate. To give a sense of economic magnitudes, the range of the y-axis is set to be the $10^{th}$-$90^{th}$ percentile of the dependent variable. As the figure shows, there is not a strong relationship between market concentration and homeownership or high school graduation rate. For the other measures, there are relationships between concentration and demographics. However, many of the relationships are relatively small, both in economic terms and relative to the overall amount of variation in the demographic variable. For instance, as top 4 concentration ranges from 20% to 50%, a change of 2.5 standard deviations, the percentage of the population that is under 18 drops from 24% to 22.7%.

The second panel of Fig. 4 plots financial variables as a function of market concentration. We plot average wage, loan LTV, borrower FICO, and average house price. There are again relationships between these variables and market concentration, though with the exception of FICO, they are not economically large. Table 3 formalizes the results in Fig. 4 using regressions. Specifically, we run univariate panel regressions of demographic variables on concentration. We include year fixed effects so that we isolate the cross-sectional relationships between the variables.

To ensure that differences in county characteristics are not confounding our results, we include a variety of additional controls across specifications in Table 2. We start by adding county and year fixed effects in the second and third columns of the table. Note that because $Top4_{k,t}$ is measured annually (because it is from the HMDA data), we only need to add year rather than year-quarter fixed effects to control for any time trends in concentration.

In our most stringent specification, we also include a host of controls $\mathbf{X}_{k,t}$, which include all the county characteristics discussed above as well as their interactions with the change in MBS yields. This allows the response of mortgage rates to MBS yields to vary across counties for reasons other than market concentration. This specification is presented in the fourth column of Table 2. For compactness, the levels of the controls are suppressed in the table, but their interactions with the change in MBS yields are shown. The fourth column of Table 2 shows that our main result survives these saturated controls, with the magnitude and significance of the interaction between market concentration and the change in MBS yields unchanged.[7] This suggests that county characteristics other than concentration are not driving our results.

One may still worry that time-varying borrower selection could explain these results. In other words, a high-concentration county may have similar demographic characteristics to a low-concentration county, but different types of borrowers might take out mortgages in the high-concentration county when MBS yields fall. In the Internet Appendix, we examine this hypothesis by running our baseline specifications but using borrower characteristics, including FICO, LTV, and debt-to-income ratio, as the dependent variable. We find no evidence that these variables respond differently in high- versus low-concentration counties to changes in MBS yields. In addition, we find no evidence that the share of adjustable rate mortgages changes differentially in high- versus low-concentration as MBS yields change.

The final column of Table 2 shows that our results persist when we restrict the sample to the pre-crisis period, 1999-2007. Thus, the results we document here are not solely driven by the

[7] Our house price data is from Zillow and is restricted to a limited number of MSAs starting in 1996, which explains the sharp decrease in the number of observations. The results are robust to using MSA house price data from the Federal Housing Finance Agency.

period during and after the financial crisis. The statistical evidence is somewhat weaker here because the time dimension of our data is relatively short.

The magnitudes of the effects in Table 2 are large. For instance, take the estimates from the regression with county and time fixed effects in the third column. These estimates imply a one-standard deviation increase in concentration decreases the pass-through of a 100 basis point reduction in MBS yields on mortgage rates by 17%.[8]

*B. Addressing Endogeneity Concerns: Matched Samples*

While the results above are quite robust to a variety of controls, one may still be concerned that our controls only absorb linear effects of observable characteristics, except for FICO and LTV, where our procedure for generating residualized rates accommodates nonlinearities in mortgage pricing. We address these concerns by employing a propensity score matching procedure to ensure that we are comparing counties that are very similar along observable dimensions. In particular, it ensures that the distributions of the covariates we control for are very similar for high-concentration and low-concentration counties.

We follow the procedure recommended by Imbens (2015). For each quarter, we estimate the probability that a county has high concentration (top quartile for that quarter) based on observable characteristics. Specifically, we run a logit regression of an indicator that the county has high concentration on the same vector of controls we use above (population, percentage of the population under 18, percentage of the population over 65, percentage of the population that is black, percentage of the population with a high school degree, and the homeownership rate, wage and local house prices) and their squares. Panel A of Table 4 shows the estimated propensity score.

We then match each high-concentration county to the county with low concentration (bottom quartile for the quarter) that is its nearest neighbor in terms of propensity score. We restrict the sample in two ways. We first exclude counties where the estimated propensity score is close to zero (specifically less than 0.2) or close to one (specifically greater than 0.8). This excludes

[8] The standard deviation of concentration is 0.12, while the coefficient on the change is MBS yields is 0.677, and the coefficient on the interaction term is -0.932. Thus, a one-standard deviation increase in concentration reduces the effect of a change in MBS yields by -0.932 * 0.12 / 0.677 = 17%. We use the third column of Table 2 for this calculation because the fourth column interacts MBS yields with other controls, which distorts the baseline coefficient on the change in MBS yields (since the variables interacted with MBS yields have non-zero means). The fourth column implies similar magnitudes.

counties where the overlap assumption for the covariates is unlikely to hold. We also exclude counties where the difference in propensity score between the county and its nearest neighbor in terms of propensity score is more than 0.06. This is one quarter of the standard deviation of the estimate propensity score in sample, so we are left with a sample where each county has a close propensity score match in both absolute and relative terms.

We then run our baseline specifications in the matched sample, replacing market concentration with a dummy indicating that the county was treated (i.e. had high concentration). Specifically, we run the regression

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Treated_{k,t} + \beta_3 \cdot \Delta MBS\ Yield_t \times Treated_{k,t} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

Panel B of Table 4 shows the results. The first two columns examine the full matched sample. They show that the pass-through of changes in MBS yields is lower in treated counties than in control counties. The remaining columns break the sample into blocks by propensity score, as recommended by Imbens (2015). That is, we estimate the baseline regression, restricting the sample to counties whose propensity score is in the range specified in the column heading. The results are qualitatively similar in each propensity score block and quantitatively strongest for propensity scores between 0.4 and 0.6. This indicates that the treatment effect exists, and is similar in magnitude, across the distribution of counties in our sample.

Finally, Panel C of Table 4 shows that covariates are well-balanced in our matched sample. We run regressions of demographic variables on a dummy indicating treatment (high concentration). The only variable that treatment is significantly correlated with is market concentration.

### *C. Addressing Endogeneity Concerns: Bank Mergers*

The second way we address endogeneity concerns uses bank mergers to create variation in mortgage market concentration that is plausibly unrelated to county characteristics. We construct a sample of counties affected by bank mergers, where the counties in the sample were not the key motivation for the merger.[9] Specifically, mergers are identified using the list of bank mergers

[9] We must measure the impact of bank mergers using deposits, not mortgage loans, because we cannot link bank identifiers to HMDA identifiers. HMDA provides links to bank identifiers consistently starting in 2010. Prior to 2010,

provided by the Federal Reserve Bank of Chicago. We exclude FDIC-assisted mergers of failed banks. Using the FDIC's *Summary of Deposits* to identify the county-level locations of bank operations, we focus on counties where each bank involved in a merger makes up more than 10% of the total deposits in the county, but the county itself makes up no more than 2% of each bank's total deposits.[10] The idea is to isolate counties where the banks involved in the merger each have a relatively large market share as measured by the fraction of the total deposits in the county. This means that the merger is likely to have an effect on mortgage market concentration. However, we also require that the county is not a large part of the bank's total business; the county must contain only a small fraction of the bank's total deposits. This helps to ensure that the characteristics of the county were not a key driver of the merger. Garmaise and Moskowitz (2006) use a similar approach to study the effects of credit availability on crime.[11] Within the sample, we examine how the sensitivity of refinancing and mortgage rates to MBS yields changes after the merger takes place.

There are 611 mergers that meet the criteria for inclusion in our sample.[12] The average merger involves banks totaling $6 billion in deposits with branches in 70 counties across two states. About 80% of the counties in our sample are involved in such a merger at some point in the sample. Fig. 5 gives the geographic distribution of the merger counties. Merger counties are distributed across the country.

As shown in Table 5, Panel A, these merger counties are somewhat different from counties not involved in mergers. In the table, we run regressions of the form:

$$y_{k,t} = \alpha_t + Merger_k + \varepsilon_{k,t},$$

where $y_{k,t}$ is a characteristic of county *k* at time *t*, and $Merger_k$ is a dummy for whether the county is ever involved in a merger satisfying our cutoff requirements. The specification has time fixed

in our data, the only years HMDA can be linked to bank identifiers are 2004-2006, too short a timespan for our analysis.

[10] The cutoffs capture 25% of bank-counties along each dimension. Specifically, 25% of bank shares of total county deposits are above 10%, and 25% of county shares of total bank deposits are below 2%.

[11] Dafny, Duggan, and Ramanarayanan (2012) take a somewhat similar approach in studying the effects of health insurer mergers.

[12] Some counties experience more than one qualifying merger. In these cases, we use the date of the first merger to define when the county has experienced a merger.

effects, so we are essentially asking whether merger counties are different from non-merger counties, controlling for national time trends. The table shows that merger counties tend to have smaller populations and lower wage levels but higher homeownership rates.

For this reason, we exclude non-merger counties from our sample.[13] We instead use an IV strategy where we only compare the pass-through of MBS yields before and after a merger within the same county. The exclusion restriction in this case is that bank mergers affect the sensitivity of refinancing and mortgage rates to MBS yields within a county only through their effect on market concentration in that county. Of course, bank mergers are not random. However, for the exclusion restriction to be violated, it would have to be the case that bank mergers are anticipating changing county characteristics that explain our results. For instance, if the alternative is that our results reflect high mortgage market concentration in counties with unsophisticated borrowers, bank mergers would have to anticipate declining sophistication within a county. This seems unlikely. In Table 5, Panel B, we show the evolution of observable characteristics within a county around a merger. Specifically, we run

$$y_{k,t} = \alpha_k + \alpha_t + \sum_{j=-3}^{3} Merger_{k,t+j} + \varepsilon_{k,t},$$

where $y_{k,t}$ is a characteristic of county *k* at time *t*, $Merger_{k,t+j}$ indicates that a merger takes place in county *k* at time *t-j*. The specification includes both time and county fixed effects and thus traces out the evolution the characteristic *y* in event time around the merger. Because changing characteristics that drive bank mergers are likely to be slow moving, we collapse the data to the county-year level so that we are looking at the period three years before and three years after the merger. The table shows that there is not much change in county characteristics associated with mergers. While the exclusion restriction cannot be directly tested, this does give us some comfort that changing county characteristics are not driving both mergers and the change in pass-through.

We next turn to our IV estimates in Table 6. In the first two columns, we examine the first stages, regressing $Top\ 4_{i,t}$ and $\Delta MBS\ Yield_t \times Top\ 4_{i,t}$ on a post-merger indicator and the change in MBS yields interacted with the post-merger indicator. The specifications include county and

[13] The alternative would be to run a differences-in-differences specification where we use non-merger counties as the control group for merger counties. But given the differences in characteristics between merger and non-merger counties, the parallel trends assumption is unlikely to hold.

time fixed effects, so the results are not driven by trends in concentration over time, or by the tendency for mergers to occur in concentrated counties. The coefficient is identified off variation within a given county after a merger relative to the experience of other counties that did not experience mergers at the same time. Each merger is associated with an increase in mortgage market concentration of 0.6%.[14]

We then use mergers as an instrument for concentration. Specifically, we run an instrumental variables regression where $Top\ 4_{i,t}$ and $\Delta MBS\ Yield_t \times Top\ 4_{i,t}$ are instrumented for using the post-merger indicator and the post-merger indicator interacted with the change in MBS yields. Only counties that experience a merger are in the sample.

The results show that the sensitivity of mortgage rates to MBS yields decreases with top 4 concentration when instrumented by the post-merger indicator. The sensitivity of rates to MBS yields decreases after a merger at the same time that mortgage market concentration is increasing. Table 6 also shows the reduced form for the results, which makes the interpretation clearer. The results show that the sensitivity of rates to MBS yields drops after a merger. Since the specification contains county fixed effects, the results show that the sensitivity of refinancing to MBS yields decreases *within a given county* after a merger that increases mortgage market concentration in that county.

Note that the magnitudes of the coefficients are larger here than in Tables 2 and 4. The reason is that instrumenting substantially reduces the amount of variation in concentration. While the magnitude of the effect in the first stage is statistically significant, it is small relative to the total variation we observe in concentration in the full sample.[15] As the reduced form makes clear, for each county we are simply comparing the sensitivity to MBS yields before and after the merger. However, the economic magnitudes are similar to those in our earlier results. A one-standard deviation increase in concentration decreases the pass-through of MBS yields by about 25%.

[14] The first stage effect is relatively small because we are selecting mergers based on deposit concentration but then looking at the effects on mortgage lending concentration. When we examine the effect of the same mergers on deposit concentration, we find larger effects. In untabulated results, we also find that we obtain similar results doing full IV analysis measuring concentration in terms of deposits.
[15] However, the overall Kleibergen-Paap F-statistic for the joint first stages is above the Stock-Yogo (2005) 10% maximal IV size critical value.

*D. Timing*

While our refinancing analysis below is conducted at the annual level, the mortgage rate analysis in this section is conducted at the quarterly level. It is possible that concentration affects the speed of pass-through in rates, although not the ultimate magnitude of pass-through. In the Internet Appendix we show that this is not the case. The results indicate that the differences in pass-through we document at the one-quarter frequency persist for longer horizons. Specifically, if we redo our analysis with a two-quarter or three-quarter horizon, we obtain very similar results. At the four-quarter horizon, we start to lose statistical significance, though the point estimate on interaction of MBS yields and market concentration is still large. This indicates that there are persistent differences across counties in the pass-through of MBS yields to mortgage rates.

## Mortgage Refinancing Results

*A. Baseline Results: Quantity of Refinancing*

We next examine the effect of mortgage market concentration on the frequency of refinancing. In the HMDA sample, we measure refinancing activity for each county by the number of mortgages refinanced in a given year, normalized by the county's population in that year.[16] We regress the change in this measure on the change in 30-year Fannie Mae current coupon MBS yields over that year, county-level top 4 concentration lagged one year, and the interaction of the two. Formally, we run:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

We weight the regression by the population of county $k$ at time $t$. The coefficient of interest is $\beta_3$, which measures the difference in sensitivities to MBS yields between high- and low-concentration counties.

[16] Similar results are obtained using dollar loan volume as a measure of the quantity of refinancing, rather than the number of refinancing transactions. In addition, the results are robust to normalizing the number of refinancing transactions by the number of owner-occupied housing units in the county, which were obtained from the Census Bureau's American Community Survey. Thus, differences in homeownership rates across counties cannot account for our results.

Note that the dependent variable is the change in refinancing, rather than the level. We use the change in refinancing rather than its level because we are interested in the stimulative effect of MBS yield reductions. The stimulative effect of a change in MBS yields relative to the previous period is determined by the change in behavior relative to the previous period.

Table 7 shows the results. The first column shows that a 100 bps decrease in MBS yields increases the quantity of refinancing per person by 1.3% (percentage points) in a county with an average level of mortgage market concentration (33%). Relative to the standard deviation of refinancing per capita of 1.2%, this is a large effect. The positive coefficient on the interaction of MBS yields and concentration implies that higher mortgage market concentration mitigates this effect. A one-standard deviation increase in concentration decreases the effect of MBS yields by 15%.[17] Fig. 6 presents this result graphically, plotting the change in refinancing per capita for high- (top decile) and low- (bottom decile) concentration counties as a function of the change in MBS yields.

The remaining columns show that the results are robust to the battery of additional controls that we used in Table 2, including county-level log population, average wages, debt-to-income ratios,[18] house prices, elderly population, children, race, and education, as well as the interaction of changes in MBS yields with these characteristics (again, the direct effects of the controls are suppressed for compactness). It is reassuring to note that the coefficients across specifications and controls are very consistent. While these specifications cannot completely account for unobservable differences between counties, they do suggest that our results are not driven by a variety of observable county characteristics.

An additional concern with our results could be that our concentration measures are proxies for the type of lender, and different types of lenders have different sensitivities to MBS yields. In particular, it is possible that small localized lenders are more likely to hold loans on their balance sheet rather than securitize them (Loutskina and Strahan, 2011). In contrast, large lenders are likely

[17] The baseline effect of a decrease in MBS yields is a 1.3% increase in refinancing. The coefficient on the interaction term is -0.016, and the standard deviation of concentration is 12%. Thus, a one-standard deviation increase in concentration reduces the 0.016 * .12 / .013 = 0.15.

[18] The debt-to-income ratios used here are from HMDA and thus reflect the ratio of mortgage debt to income for mortgage borrowers. Our results are also robust on controlling for the ratio of total debt to income at the county level, which is studied by Mian, Rao, and Sufi (2012).

to securitize their loans and thus may not display geographical variation in their sensitivity to MBS yields.

Table 8 shows that large lenders respond to local mortgage market conditions in the same way as small lenders, for varying definitions of large. Each column reports results of the saturated specification from Table 7 but restricts the sample to lenders that operate in the number of counties given by the column header. For instance, the first column restricts the samples to loans made by lenders that operate one than one county.[19] We rescale the dependent variable by the national market share of these lenders in the sample to make the coefficients comparable to those in the Table 7. Thus, the coefficients can be interpreted as the sensitivity of refinancing to MBS yields, assuming all refinancing in the country was done by the lenders in our restricted sample.[20] For instance, the first column of Table 8 shows the sensitivity of refinancing to MBS yields, assuming all refinancing was performed by lenders that operate in more than one county. The results in Table 8 are uniform across lenders that operate in more than 1, 5, 10, 50, and 250 counties. Refinancing loans originated is less sensitive to MBS yields in more concentrated markets for lenders of all sizes. This suggests that geographic variation in the lender size and complexity is not driving our results.

### *B. Addressing Endogeneity Concerns: Matched Samples*

We now repeat our matching procedure for our refinancing results. As before, we estimate the probability that a county has high concentration (top quartile for that quarter) based on observable characteristics using a logit regression. We then match each high-concentration county to the county with low concentration that is its nearest neighbor in terms of propensity score. We again restrict the sample to exclude counties where the estimated propensity score is close to zero or one and counties where we cannot find a close match in terms of propensity score. We then run our baseline specifications in the matched sample, replacing market concentration with a dummy indicating that the county was treated (i.e. had high concentration).[21]

[19] At the beginning of our sample in 1990, the median lender operates in two counties. By 2010, the median lender operates in six counties.
[20] For instance, if lenders operating in more than one county have a 50% national market share, then we multiply the dependent variable by two. Thus, the results characterize behavior assuming all lending as done by those lenders.
[21] For compactness, we omit the estimated propensity score and covariate balance tests as they are quite similar to those reported in Table 4.

Table 9 shows the results. The first two columns examine the full matched sample and show that the pass-through of changes in MBS yields is lower in treated counties than in control counties. The remaining columns break the sample into blocks by propensity score, as recommended by Imbens (2015). The results are qualitatively similar in each propensity score block, though statistically weaker than the pooled results for the full sample.

### *C. Addressing Endogeneity Concerns: Bank Mergers*

We now repeat our IV procedure for our refinancing results. We again identify mergers where each bank involved in a merger makes up more than 10% of the total deposits in the county, but the county itself makes up no more than 2% of each bank's total deposits. Within the sample, we examine how the sensitivity of refinancing and mortgage rates to MBS yields changes after the merger takes place.

We report the results in Table 10. The first two columns report the first stages, regressing $Top\ 4_{i,t}$ and $\Delta MBS\ Yield_t \times Top\ 4_{i,t}$ on a post-merger indicator and the change in MBS yields interacted with the post-merger indicator. We then use mergers as an instrument for concentration, running an instrumental variables regression where $Top\ 4_{i,t}$ and $\Delta MBS\ Yield_t \times Top\ 4_{i,t}$ are instrumented for using the post-merger indicator and the post-merger indicator interacted with the change in MBS yields. Only counties that experience a merger are in the sample.

The results show that the sensitivity of refinancing to MBS yields decreases with top 4 concentration when instrumented by the post-merger indicator. The sensitivity of rates to MBS yields decreases after a merger at the same time that mortgage market concentration is increasing. Table 10 also shows the reduced form for the results, which makes the interpretation clearer. The results show that the sensitivity of rates to MBS yields drops after a merger. Because the specification contains county fixed effects, the results show that the sensitivity of refinancing to MBS yields decreases *within a given county* after a merger that increases mortgage market concentration in that county.

### *D. Mechanism*

The findings so far have established that concentration reduces the sensitivity of both refinancing and mortgage rates to MBS yields. In Table 11, we link the two sets of results, showing that in locations where mortgage rates are higher, refinancing activity should be lower. Table 11 regresses the change in annual county-level refinancing rates on the annual change in county level residualized mortgage rates. As predicted, Column 1 shows that there is a negative relationship between the two. The remaining columns add our standard set of controls. While the results get weaker when we add year and county fixed effects, they regain their economic and statistical significance once we add the full set of controls. While not establishing a causal link between price and quantity, these findings are consistent with the idea that low refinancing frequencies are affected by high mortgage rates.

### *E. Magnitudes*

What is the total economic magnitude of the effects of market concentration we are finding? Note that the effect of concentration on mortgage rates compounds with the effect on refinancing. In a high-concentration county, fewer borrowers refinance, meaning that fewer households see their mortgage rates reduced at all. And of the borrowers that do refinance, the rates they pay fall less on average. The results in Table 7 imply that a one-standard deviation increase in market concentration decreases the impact of a decline in MBS yields on the quantity of refinancing by 15%. For the households that do refinance, the results in Table 2 show that a one-standard deviation increase in county concentration reduces the impact of a decrease in MBS yields by 17%. Taken together, these imply that the effect of a decrease in MBS yields is only 29% smaller in the high-concentration county.

## V. Conclusion

We present evidence that high concentration in local mortgage lending reduces the sensitivity of mortgage rates and refinancing activity to MBS yields. A decrease in MBS yields is typically associated with greater refinancing activity and lower rates on new mortgages. However, this effect is dampened in counties with concentrated mortgage markets. Our estimates suggest that the impact of a 100 bps decrease in MBS yields is only 70% as large in a county with mortgage market concentration one standard deviation above the mean as it is in a county with average concentration.

We isolate the direct effect of mortgage market concentration and rule out alternative explanations based on borrower, loan, and collateral characteristics in two ways. First, we use a matching procedure to compare high- and low-concentration counties that are very similar on observable characteristics and find similar results. Second, we examine counties where concentration in mortgage lending is increased by bank mergers. We show that within a given county, sensitivities to MBS yields decrease after a concentration-increasing merger.

Our results suggest that the effectiveness of monetary policy transmission through the mortgage market varies in the cross section. Our baseline estimates suggest that the impact on local housing markets of the fall in MBS yields induced by a monetary easing varies substantially across counties. Though our analysis does not directly study the time series, it does suggest that consolidation in the mortgage market may reduce the effectiveness of monetary policy transmission through the mortgage market over time.

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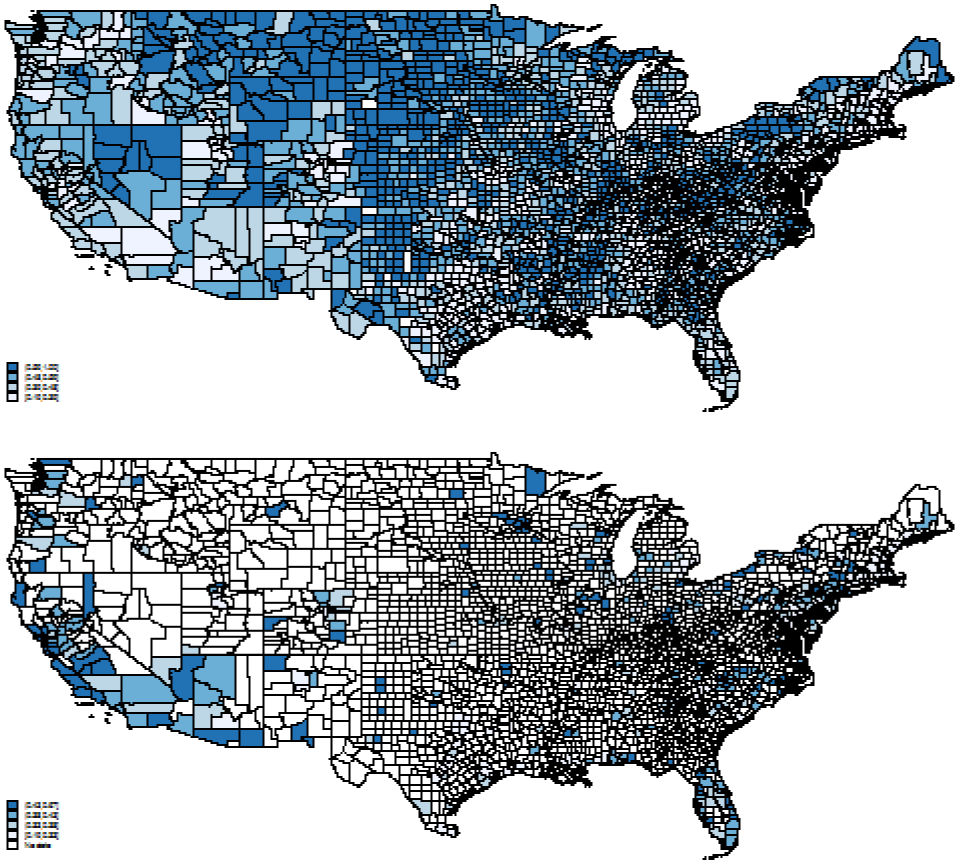

**Figure 1. Geographic distribution of market concentration in 2010**

This figure plots the geographic distribution of mortgage market concentration in 2010. The top panel shows the full nationwide distribution, while the bottom panel restricts the sample to the top 500 counties by population. Concentration is measured as the share of the top 4 lenders in each market.

| Top 10 Counties | Bottom 10 Counites |
|---|---|
| Morgan County, IL | Worcester County, MA |
| Coshocton County, OH | Plymouth County, MA |
| Cole County, MO | Essex County, MA |
| Ogle County, IL | York County, ME |
| Bureau County, IL | Hamden County, PA |
| Potter County, TX | Saginaw County, MI |
| Chemung County, NY | Tangipahoa Parish, LA |
| Grand Forks County, ND | Smith County, TX |
| Tioga County, PA | Milwaukee County, WI |
| Vigo County, Indiana | Travis County, TX |

**Figure 2. Highest and lowest concentration counties in 2010**

This lists the highest and lowest concentration counties in 2010. Concentration is measured as the share of the top 4 lenders in each county. The sample is limited to the top 500 counties by population.

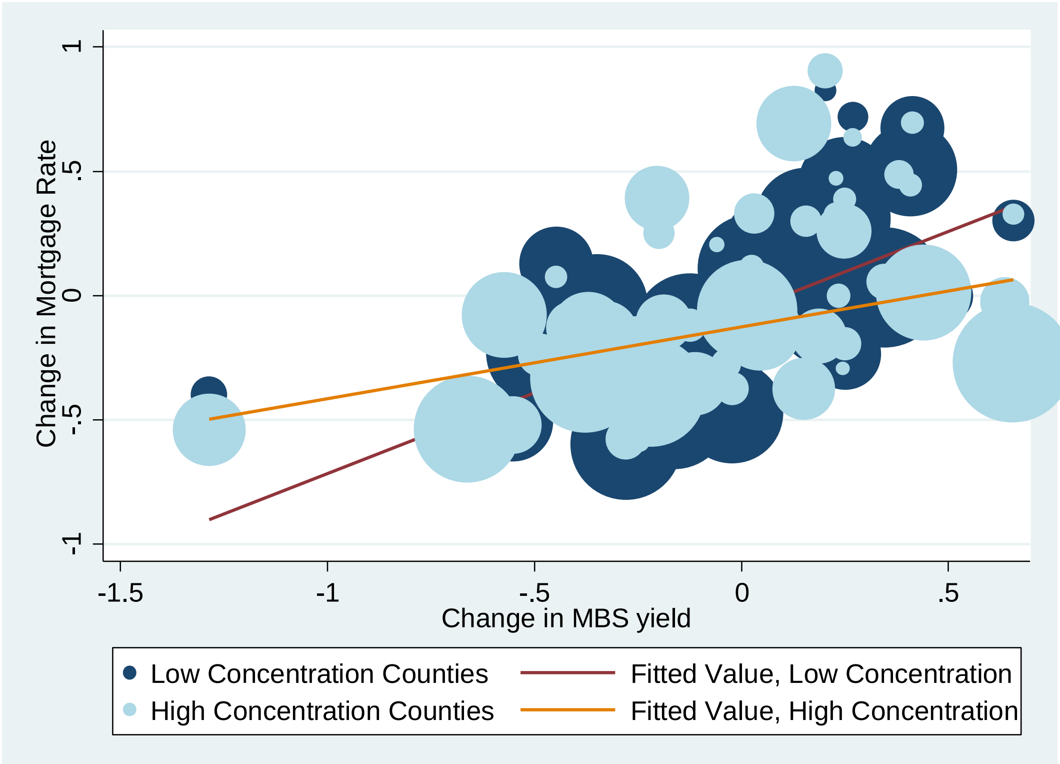


**Figure 3. Differences in pass-through**

This figure plots the relationship between the change in mortgage rates and the change in the MBS yields for high-concentration (top 10%) and low-concentration (bottom 10%) counties. Mortgage rates are residualized with respect to FICO and LTV each month. Concentration is measured as the share of the top 4 lenders in each county. The sample is limited to the top 500 counties by population, and observations are weighted by the quantity of loans in the county-quarter.

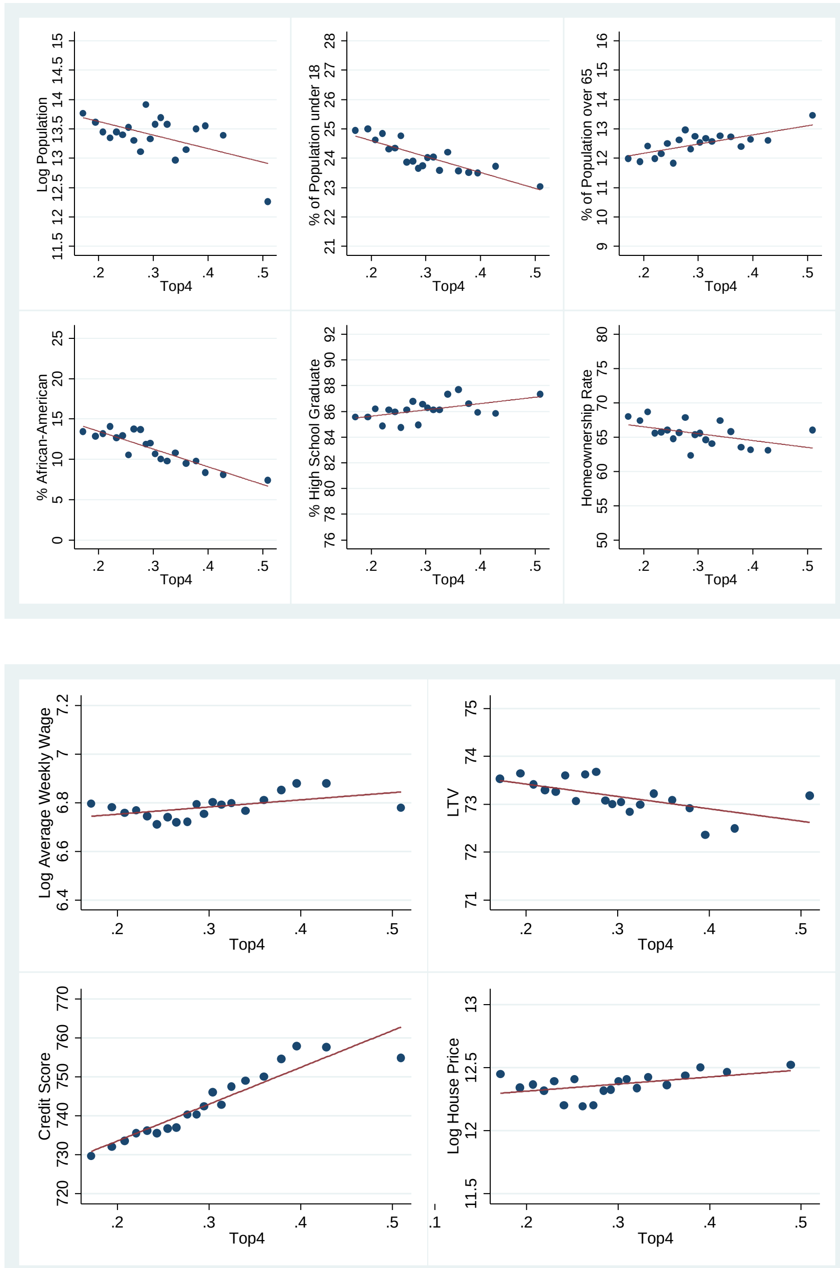


**Figure 4. Relationship between market concentration and county characteristics**

This figure plots the relationship between market concentration and county characteristics. The top panel plots demographic variables, and the bottom panel plots financial variables. Concentration is measured as the share of the top 4 lenders in each market.

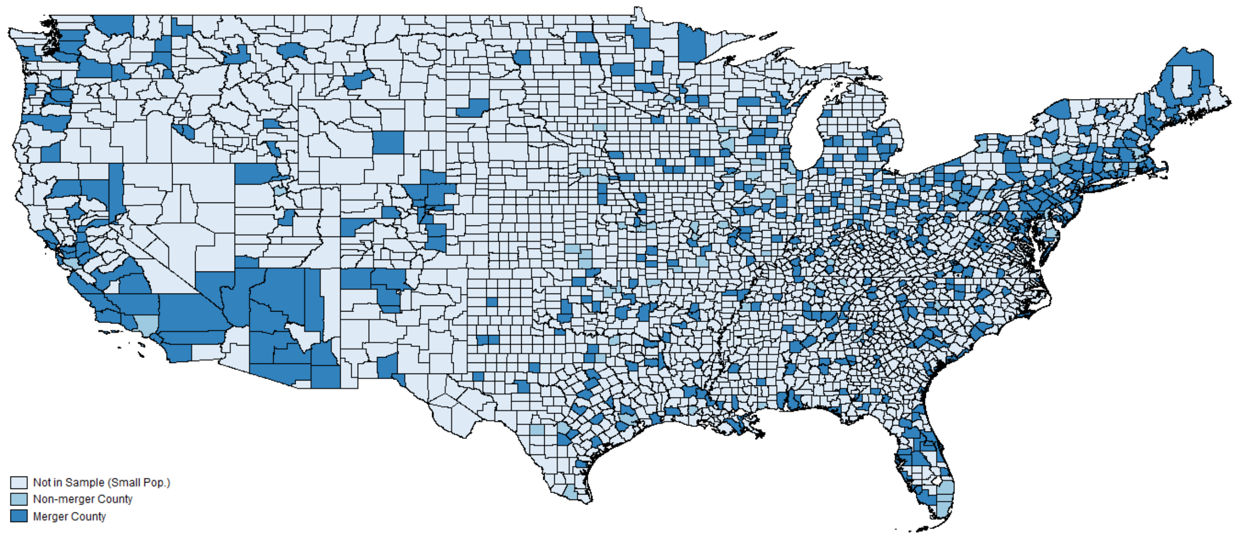


**Figure 5. Geographic distribution of merger counties.**

This figure shows the geographic distribution of merger counties used in our IV analysis.

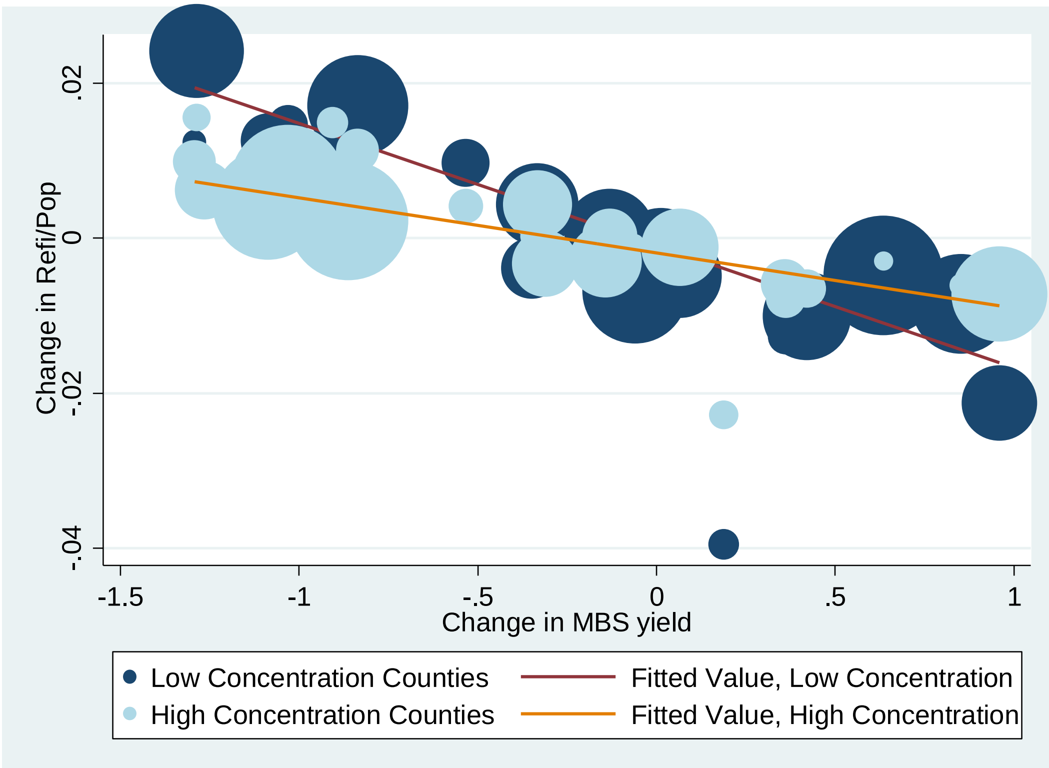


**Figure 6. Differences in propensity to refinance**

This figure plots the relationship between the change in refinancings per capita and the change in the MBS yields for high-concentration (top 10%) and low-concentration (bottom 10%) counties. Concentration is measured as the share of the top 4 lenders in each county. The sample is limited to the top 500 counties by population, and observations are weighted by population.

## Table 1
## Summary statistics

This table presents summary statistics. The unit of observation is county-quarter for the rates data and county-year for the refinancing data. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter. ΔMBS Yield is the change in the current-coupon Fannie Mae 30-year FRM MBS yield from quarter t to quarter t+1 from Bloomberg. Top 4 is the share of the top 4 mortgage originators in each county in HMDA. LTV is the loan-to-value ratio. FICO is the credit score. ln(Population) is the log population from the Census. ln(Wage) is the log average weekly wage in the county-year from the BLS's Quarterly Census of Employment and Wages. ln(Price) is the log average price in the county from Zillow. % Over 65 is the fraction of the population over 65 from the ACS. % Under 18 is the fraction of the population under 18. % Black is the fraction of the population that is African-American. % High school is the fraction of the population with a high school degree or more education. Homeowner is the homeownership rate. Refi/Population is the number of refinancings in a given county-year in HMDA divided by the population of that county in that year obtained from the Census. ΔRefi/Pop is the change in this ratio within the county from year t to year t+1. DTI is the loan-to-income ratio calculated for borrowers in HMDA.

| | N | Mean | Stdev | Min | Max |
|---|---|---|---|---|---|
| $R_{k,t}$ | 29463 | 5.98 | 1.14 | 3.22 | 9.73 |
| $\Delta R_{k,t}$ | 29463 | -0.04 | 0.37 | -1.96 | 1.97 |
| ΔMBS Yield$_t$ | 29463 | -0.05 | 0.36 | -1.28 | 0.66 |
| Top 4$_{k,t}$ | 29463 | 0.33 | 0.12 | 0.12 | 0.79 |
| $LTV_{k,t}$ | 29463 | 74 | 2.0 | 60 | 99 |
| $FICO_{k,t}$ | 29463 | 739 | 18 | 660 | 820 |
| ln(Population$_{k,t}$) | 29463 | 12.55 | 0.80 | 11.43 | 16.13 |
| ln(Wage$_{k,t}$) | 29463 | 6.60 | 0.24 | 5.90 | 8.08 |
| ln(Price$_{k,t}$) | 21760 | 11.97 | 0.55 | 10.59 | 15.90 |
| % Over 65$_{k,t}$ | 29463 | 13.83 | 3.43 | 3.80 | 32.50 |
| % Under 18$_{k,t}$ | 29463 | 23.53 | 2.86 | 13.40 | 36.30 |
| % Black$_{k,t}$ | 29463 | 11.43 | 12.81 | 0.00 | 70.10 |
| % High School$_{k,t}$ | 29463 | 85.74 | 5.43 | 57.7 | 97.5 |
| Homeowner$_{k,t}$ | 29463 | 68.00 | 8.65 | 19.1 | 88.5 |
| Refi/Population$_{k,t}$ | 11943 | 0.018 | 0.015 | 0.000 | 0.130 |
| ΔRefi/Population$_{k,t}$ | 11943 | 0.000 | 0.012 | -0.075 | 0.078 |
| $DTI_{k,t}$ | 11943 | 1.91 | 0.49 | 0.65 | 3.36 |

**Table 2**
**Mortgage rates and concentration**

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs quarterly 1999-2014. Observations are weighted by the quantity of loans in the county-quarter. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The final column restricts the sample to the years before the financial crisis, 1999-2007. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | 0.808 | 0.676 | 0.677 | 2.545 | 0.925 |
| | [4.01] | [3.70] | [3.66] | [3.27] | [0.89] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **-1.288** | **-0.926** | **-0.932** | **-0.957** | **-1.044** |
| | **[-2.34]** | **[-2.09]** | **[-2.08]** | **[-2.04]** | **[-1.74]** |
| Top 4$_{k,t-1}$ | -0.199 | -0.026 | 0.001 | -0.005 | -0.057 |
| | [-0.94] | [-0.48] | [0.05] | [-0.17] | [.] |
| Δ MBS Yield$_t$ | | | | 0.007 | -0.042 |
| x ln(Population$_{k,t-1}$) | | | | [0.49] | [-1.32] |
| Δ MBS Yield$_t$ | | | | -0.338 | 0.232 |
| x ln(Wage$_{k,t-1}$) | | | | [-2.02] | [1.08] |
| Δ MBS Yield$_t$ | | | | 0.05 | -0.058 |
| x ln(Price$_{k,t-1}$) | | | | [0.97] | [-1.61] |
| Δ MBS Yield$_t$ | | | | -0.005 | -0.001 |
| x % Over 65$_{k,t-1}$ | | | | [-0.88] | [-0.19] |
| Δ MBS Yield$_t$ | | | | -0.001 | 0.009 |
| x % Under 18$_{k,t-1}$ | | | | [-0.38] | [1.24] |
| Δ MBS Yield$_t$ | | | | 0.000 | -0.002 |
| x % Black$_{k,t-1}$ | | | | [0.55] | [-2.87] |
| Δ MBS Yield$_t$ | | | | -0.001 | -0.004 |
| x % High School$_{k,t-1}$ | | | | [-0.22] | [-0.45] |
| Δ MBS Yield$_t$ | | | | -0.001 | -0.002 |
| x Homeowner$_{k,t-1}$ | | | | [-0.54] | [-0.51] |
| $R^2$ | 0.266 | 0.329 | 0.318 | 0.329 | 0.518 |
| N | 29463 | 29463 | 29463 | 21760 | 12438 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

**Table 3**
**Concentration and county characteristics**

This table reports the relationship between market concentration and county characteristics. Observations are weighted by the quantity of loans in the county-quarter to match Table 2. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets. The bottom panel gives the weighted mean and standard deviation of each characteristic in the sample.

| | Ln(Pop$_{k,t}$) | Under 18$_{k,t}$ | Over 65 $_{k,t}$ | Black $_{k,t}$ | High School $_{k,t}$ | Homeowner $_{k,t}$ | Ln(Wage $_{k,t}$) | LTV $_{k,t}$ | FICO $_{k,t}$ | Ln(Price $_{k,t}$) |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 4$_{k,t-1}$ | -3.927 | -4.911 | 4.392 | -28.061 | -0.795 | -5.568 | -0.456 | -0.097 | 13.615 | 0.387 |
| | [-3.35] | [-2.47] | [2.20] | [-3.56] | [-0.18] | [-0.74] | [-1.79] | [-0.07] | [4.04] | [0.62] |
| $R^2$ | 0.054 | 0.077 | 0.044 | 0.031 | 0.108 | 0.029 | 0.277 | 0.12 | 0.84 | 0.072 |
| N | 29463 | 29463 | 29463 | 29463 | 29463 | 29463 | 29463 | 29463 | 29463 | 21760 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Mean | 12.55 | 23.53 | 13.83 | 11.43 | 85.74 | 68.00 | 6.60 | 74 | 739 | 11.97 |
| SD | 0.80 | 2.86 | 3.43 | 12.81 | 5.43 | 8.65 | 0.24 | 2 | 18 | 0.55 |

## Table 4
## Mortgage rates matching results

This table presents results from our matching methodology. The county-level sample runs quarterly 1999-2014. Panel A presents our estimated propensity score. We designate as treated counties those in the top quartile of concentration in a given quarter and designate as untreated counties those in the bottom quartile of concentration. The propensity score is estimated by running a logit regression of a dummy indicating the county is treated on characteristics. Panel B presents the estimated treatment effect for the full sample and more subsamples based on the estimated propensity score. Observations are weighted by the quantity of loans in the county-quarter. The dependent variable is the change in average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The levels of the controls are suppressed for compactness but included in the regressions. Panel C shows covariate balance by regressing demographics on the treatment dummy. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| Panel A: Estimated Propensity Score | | |
|---|---|---|
| | Coefficient | t-statistic |
| $\ln(Population_{k,t})$ | -3.612 | [-3.15] |
| $\ln(Wage_{k,t})$ | 2.916 | [0.32] |
| $\ln(Price_{k,t})$ | -9.995 | [-1.72] |
| % Over 65 $_{k,t}$ | 0.049 | [0.53] |
| % Under 18 $_{k,t}$ | -0.090 | [-0.33] |
| % Black $_{k,t}$ | -0.031 | [-2.02] |
| % High School $_{k,t}$ | -0.487 | [-1.72] |
| Homeowner $_{k,t}$ | 0.155 | [2.60] |
| $\ln(Population_{k,t})^2$ | 0.120 | [2.69] |
| $\ln(Wage_{k,t})^2$ | -0.216 | [-0.32] |
| $\ln(Price_{k,t})^2$ | 0.404 | [1.69] |
| % Over $65^2_{k,t}$ | 0.002 | [0.61] |
| % Under $18^2_{k,t}$ | 0.003 | [0.48] |
| % $Black^2_{k,t}$ | 0.000 | [0.65] |
| % High $School^2_{k,t}$ | 0.003 | [1.79] |
| $Homeowner^2_{k,t}$ | -0.002 | [-3.80] |
| $R^2$ | 0.099 | |
| N | 21760 | |

| Panel B: Estimated treatment effect | | | | | |
|---|---|---|---|---|---|
| | Full matched sample | | P-score [.2, .4] | P-score [.4, .6] | P-score [.6, .8] |
| Δ MBS Yield$_t$ | 0.394 | 2.513 | 2.737 | 2.397 | 2.395 |
| | [5.10] | [3.07] | [1.35] | [2.05] | [2.70] |
| Δ MBS Yield$_t$ x Treated$_{k,t}$ | **-0.052** | **-0.055** | **-0.047** | **-0.094** | **-0.054** |
| | **[-1.84]** | **[-1.85]** | **[-0.64]** | **[-2.39]** | **[-1.70]** |
| Treated$_{k,t}$ | 0.015 | 0.013 | 0.018 | 0.015 | 0.016 |
| | [1.06] | [0.82] | [0.50] | [14.70] | [0.60] |
| Δ MBS Yield$_t$ | | 0.033 | 0.153 | 0.067 | 0.03 |
| x ln(Population$_{k,t-1}$) | | [2.48] | [7.21] | [5.76] | . |
| Δ MBS Yield$_t$ | | -0.465 | -0.241 | -0.471 | -0.525 |
| x ln(Wage $_{k,t-1}$) | | [-2.28] | [-0.69] | [-2.06] | [-2.44] |
| Δ MBS Yield$_t$ | | 0.067 | -0.013 | 0.065 | 0.1 |
| x ln(Price $_{k,t-1}$) | | [1.14] | [-0.13] | [1.01] | [1.44] |
| Δ MBS Yield$_t$ | | -0.01 | -0.057 | -0.025 | -0.009 |
| x % Over 65 $_{k,t-1}$ | | [-1.13] | [-1.30] | [-1.92] | [-0.98] |
| Δ MBS Yield$_t$ | | -0.008 | -0.053 | -0.023 | -0.004 |
| x % Under 18 $_{k,t-1}$ | | [-1.17] | [-1.18] | [-1.71] | [-0.85] |
| Δ MBS Yield$_t$ | | 0.002 | -0.003 | 0.003 | 0.003 |
| x % Black $_{k,t-1}$ | | [1.31] | [-2.03] | [4.90] | [1.60] |
| Δ MBS Yield$_t$ | | -0.001 | -0.018 | 0 | -0.001 |
| x % High School $_{k,t-1}$ | | [-0.13] | [-0.77] | [0.03] | [-0.22] |
| Δ MBS Yield$_t$ | | 0.002 | 0.014 | 0.005 | 0.003 |
| x Homeowner $_{k,t-1}$ | | [0.68] | [1.54] | [1.49] | [0.83] |
| $R^2$ | 0.314 | 0.33 | 0.369 | 0.332 | 0.319 |
| N | 12684 | 12684 | 334 | 3408 | 8942 |
| County FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |

| Panel C: Covariate balance in matched pairs | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Top4_{k,t}$ | $Ln(Pop_{k,t})$ | Under $18_{k,t}$ | Over 65 $_{k,t}$ | Black $_{k,t}$ | High School $_{k,t}$ | Homeowner $_{k,t}$ | Ln(Wage $_{k,t}$) | LTV $_{k,t}$ | FICO $_{k,t}$ | Ln(Price $_{k,t}$) |
| $Treated_{k,t}$ | 0.084 | 0.092 | -0.108 | 0.281 | -0.532 | 0.615 | -0.006 | -0.02 | -0.006 | -0.002 | -0.02 |
| | [13.54] | [0.98] | [-0.31] | [1.00] | [-0.41] | [1.08] | [-0.01] | [-0.92] | [-0.01] | [-0.02] | [-0.33] |
| $R^2$ | 0.188 | 0.002 | 0.000 | 0.002 | 0.000 | 0.003 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 |
| N | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 | 12684 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |

**Table 5**
**Merger sample county characteristics**

This table reports characteristics of the counties used in the merger sample. Panel A reports the coefficient from running a regression of the specified variable on an indicator for whether the county is in the merger sample. The sample runs quarterly from 1999 to 2014. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets. Panel B reports characteristics of the counties used in the merger sample. It reports the coefficient from running a regression of the specified variable on an indicator for whether the county is in the merger sample:

$$y_{k,t} = \alpha_k + \alpha_t + \sum_{j=-3}^{3} Merger_{k,t+j} + \varepsilon_{k,t}.$$

The sample runs annually from 1999 to 2014. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| Panel A: Merger county characteristics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ln(Pop$_{k,t}$) | Under 18$_{k,t}$ | Over 65 $_{k,t}$ | Black $_{k,t}$ | High School $_{k,t}$ | Homeowner $_{k,t}$ | Ln(Wage $_{k,t}$) | LTV $_{k,t}$ | FICO $_{k,t}$ | Ln(Price $_{k,t}$) |
| Merger$_k$ | -0.65 | -0.054 | 0.501 | -1.384 | 0.305 | 4.217 | -0.128 | 0.215 | -0.407 | -0.221 |
| | [-3.67] | [-0.13] | [1.19] | [-0.89] | [0.42] | [3.15] | [-3.78] | [1.19] | [-0.63] | [-2.19] |
| $R^2$ | 0.04 | 0.029 | 0.03 | 0.001 | 0.073 | 0.032 | 0.295 | 0.029 | 0.529 | 0.088 |
| N | 29466 | 29466 | 29466 | 29466 | 29466 | 29466 | 29466 | 29466 | 29466 | 21760 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |

| Panel B: Evolution of merger county characteristics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ln($Pop_{k,t}$) | Under 18$_{k,t}$ | Over 65 $_{k,t}$ | Black $_{k,t}$ | High School $_{k,t}$ | Homeowner $_{k,t}$ | Ln(Wage $_{k,t}$) | LTV $_{k,t}$ | FICO $_{k,t}$ | Ln(Price $_{k,t}$) |
| $Merger_{k,t-3}$ | -0.006 | 0.041 | -0.019 | 0.12 | -0.066 | 0.062 | -0.004 | 0.212 | -0.436 | -0.045 |
| | [-0.92] | [0.71] | [-0.36] | [1.03] | [-0.73] | [0.61] | [-1.13] | [2.51] | [-0.71] | [-2.87] |
| $Merger_{k,t-2}$ | -0.005 | 0.048 | 0.002 | 0.101 | -0.12 | -0.053 | -0.004 | -0.021 | 0.452 | -0.03 |
| | [-0.88] | [1.01] | [0.04] | [0.97] | [-1.40] | [-0.43] | [-1.55] | [-0.20] | [0.77] | [-1.56] |
| $Merger_{k,t-1}$ | 0.000 | 0.024 | -0.031 | 0.066 | -0.022 | 0.046 | -0.004 | -0.171 | 0.17 | -0.022 |
| | [0.07] | [0.65] | [-0.81] | [0.70] | [-0.40] | [0.60] | [-1.00] | [-1.30] | [0.33] | [-1.03] |
| $Merger_{k,t}$ | 0.000 | -0.01 | -0.034 | 0.106 | -0.237 | 0.047 | -0.002 | -0.238 | -0.044 | -0.02 |
| | [0.03] | [-0.24] | [-0.83] | [1.20] | [-1.47] | [0.48] | [-0.50] | [-1.79] | [-0.08] | [-1.10] |
| $Merger_{k,t+1}$ | 0.000 | 0.164 | -0.099 | -0.029 | -0.243 | 0.085 | 0.000 | -0.139 | -0.561 | -0.007 |
| | [-0.05] | [1.56] | [-1.38] | [-0.40] | [-1.43] | [0.67] | [-0.11] | [-1.55] | [-0.67] | [-0.38] |
| $Merger_{k,t+2}$ | -0.004 | 0.128 | 0.004 | -0.074 | -0.077 | 0.105 | -0.001 | -0.121 | -0.727 | 0.013 |
| | [-0.75] | [1.75] | [0.07] | [-0.92] | [-0.89] | [0.95] | [-0.20] | [-1.04] | [-1.53] | [0.61] |
| $Merger_{k,t+3}$ | -0.003 | 0.089 | 0.016 | -0.024 | 0.073 | 0.186 | -0.002 | -0.174 | -0.076 | 0.016 |
| | [-0.65] | [1.98] | [0.22] | [-0.41] | [0.94] | [2.41] | [-0.64] | [-1.83] | [-0.10] | [0.72] |
| $R^2$ | 0.998 | 0.969 | 0.979 | 0.998 | 0.963 | 0.984 | 0.967 | 0.396 | 0.713 | 0.95 |
| N | 7196 | 7196 | 7196 | 7196 | 7196 | 7196 | 7196 | 7196 | 7196 | 5247 |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |

## Table 6
## Mortgage rates IV estimates

This table reports results where we estimate the regression

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t},$$

using bank mergers as an instrument for concentration. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Observations are weighted by the quantity of loans in the county-quarter. We examine the effect of the merger on the county's mortgage market concentration in the first column. Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield. Standard errors are clustered by county and quarter, with t-statistics reported in brackets.

| | First Stage (Joint F = 7.6) | | IV | | Reduced Form | |
|---|---|---|---|---|---|---|
| | Top 4 | Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | | | | |
| Post$_{k,t}$ | **0.005** | 0.026 | | | -0.005 | -0.003 |
| | **[5.51]** | [1.56] | | | [-0.14] | [-0.02] |
| Δ MBS Yield$_t$ | 0.000 | **0.311** | | | **-0.09** | **-0.103** |
| x Post$_{k,t}$ | [0.84] | **[28.74]** | | | **[-1.62]** | **[-1.86]** |
| Δ MBS Yield$_t$ | | | 1.132 | 2.732 | 0.456 | 2.591 |
| | | | [3.05] | [3.13] | [5.34] | [3.21] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | | | **-2.382** | **-6.739** | | |
| | | | **[-2.10]** | **[-2.26]** | | |
| Top4$_{k,t-1}$ | | | -0.299 | -1.709 | | |
| | | | [-0.08] | [-0.52] | | |
| Δ MBS Yield$_t$ | | | | -0.16 | | 0.005 |
| x ln(Population$_{k,t-1}$) | | | | [-2.10] | | [1.02] |
| Δ MBS Yield$_t$ | | | | 0.336 | | -0.419 |
| x ln(Wage$_{k,t-1}$) | | | | [1.45] | | [-2.26] |
| Δ MBS Yield$_t$ | | | | -0.051 | | 0.064 |
| x ln(Price$_{k,t-1}$) | | | | [-0.72] | | [1.19] |
| Δ MBS Yield$_t$ | | | | 0.022 | | -0.008 |
| x % Over 65$_{k,t-1}$ | | | | [1.32] | | [-0.93] |
| Δ MBS Yield$_t$ | | | | 0.025 | | -0.001 |
| x % Under 18$_{k,t-1}$ | | | | [1.34] | | [-0.09] |
| Δ MBS Yield$_t$ | | | | -0.01 | | 0.002 |
| x % Black$_{k,t-1}$ | | | | [-2.06] | | [1.63] |
| Δ MBS Yield$_t$ | | | | 0.012 | | -0.003 |
| x % High School$_{k,t-1}$ | | | | [1.15] | | [-0.30] |
| Δ MBS Yield$_t$ | | | | -0.025 | | 0.002 |
| x Homeowner$_{k,t-1}$ | | | | [-1.84] | | [0.57] |
| $R^2$ | 0.835 | 0.771 | 0.301 | 0.075 | 0.314 | 0.327 |
| N | 26105 | 26105 | 25682 | 19143 | 25682 | 19143 |
| County FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |

## Table 7
## Refinancing and concentration

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2007. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | -0.018 | | | | |
| | [-5.13] | | | | |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **0.016** | **0.015** | **0.015** | **0.018** | **0.022** |
| | **[1.91]** | **[4.27]** | **[4.25]** | **[3.26]** | **[2.91]** |
| Top 4$_{k,t-1}$ | -0.006 | 0.006 | 0.008 | 0.001 | -0.005 |
| | [-1.08] | [3.16] | [2.00] | [0.14] | [-0.54] |
| Δ MBS Yield$_t$ | | | | -0.005 | -0.009 |
| x DTI$_{k,t-1}$ | | | | [-2.77] | [-2.69] |
| Δ MBS Yield$_t$ | | | | 0.002 | 0.003 |
| x ln(Population$_{k,t-1}$) | | | | [3.77] | [2.72] |
| Δ MBS Yield$_t$ | | | | -0.014 | -0.012 |
| x ln(Wage$_{k,t-1}$) | | | | [-3.63] | [-2.31] |
| Δ MBS Yield$_t$ | | | | 0.001 | 0.00 |
| x ln(Price$_{k,t-1}$) | | | | [0.63] | [0.06] |
| Δ MBS Yield$_t$ | | | | 0.00 | 0.00 |
| x % Over 65$_{k,t-1}$ | | | | [1.16] | [0.06] |
| Δ MBS Yield$_t$ | | | | 0.00 | 0.00 |
| x % Under 18$_{k,t-1}$ | | | | [-0.80] | [-1.89] |
| Δ MBS Yield$_t$ | | | | 0.00 | 0.00 |
| x % Black$_{k,t-1}$ | | | | [4.99] | [3.33] |
| Δ MBS Yield$_t$ | | | | 0.18 | 0.00 |
| x % High School$_{k,t-1}$ | | | | [-0.21] | [-1.89] |
| Δ MBS Yield$_t$ | | | | 0.18 | 0.00 |
| x Homeowner$_{k,t-1}$ | | | | [-0.21] | [-1.89] |
| $R^2$ | 0.5 | 0.78 | 0.77 | 0.831 | 0.841 |
| N | 11942 | 11942 | 11942 | 7775 | 4673 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Table 8
## Lender breakdown of refinancing results

This table examines the behavior of different types of lenders. It presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t},$$

restricting the sample to lenders that operate in the number of counties shown in the column heading. For instance, the first column examines refinancing mortgages originated by lenders that operate in more than one county. In each column, we rescale by the national market share of the type of lender we are focusing on. The county-level sample runs annually 1990-2014. Refi/Pop is the number of refinancings divided by the population; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| | > 1 | > 5 | > 10 | > 50 | > 250 |
|---|---|---|---|---|---|
| Δ MBS Yield $_t$ x Top4$_{k,t-1}$ | **0.018** | **0.019** | **0.018** | **0.016** | **0.019** |
| | **[3.31]** | **[3.34]** | **[3.20]** | **[2.66]** | **[2.79]** |
| Top4$_{k,t-1}$ | 0.001 | 0.001 | 0.000 | -0.002 | -0.002 |
| | [0.17] | [0.15] | [0.02] | [-0.32] | [-0.33] |
| Δ MBS Yield $_t$ | -0.005 | -0.005 | -0.005 | -0.006 | -0.006 |
| x DTI$_{k,t-1}$ | [-2.77] | [-2.75] | [-2.73] | [-2.78] | [-2.89] |
| Δ MBS Yield $_t$ | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| x ln(Population$_{k,t-1}$) | [3.77] | [3.77] | [3.73] | [3.41] | [2.78] |
| Δ MBS Yield $_t$ | -0.014 | -0.014 | -0.014 | -0.014 | -0.013 |
| x ln(Wage $_{k,t-1}$) | [-3.63] | [-3.63] | [-3.63] | [-3.46] | [-3.13] |
| Δ MBS Yield $_t$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| x ln(Price $_{k,t-1}$) | [0.63] | [0.61] | [0.60] | [0.54] | [0.32] |
| Δ MBS Yield $_t$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| x % Over 65 $_{k,t-1}$ | [1.15] | [1.20] | [1.24] | [1.28] | [0.65] |
| Δ MBS Yield $_t$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| x % Under 18 $_{k,t-1}$ | [-0.81] | [-0.86] | [-0.98] | [-1.23] | [-1.56] |
| Δ MBS Yield $_t$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| x % Black $_{k,t-1}$ | [4.98] | [4.96] | [4.87] | [4.53] | [4.24] |
| Δ MBS Yield $_t$ | 0.001 | -0.001 | 0.001 | -0.001 | -0.001 |
| x % High School $_{k,t-1}$ | [0.72] | [-0.41] | [0.72] | [-0.41] | [-0.41] |
| Δ MBS Yield $_t$ | -0.003 | -0.006 | -0.003 | -0.006 | -0.006 |
| x Homeowner $_{k,t-1}$ | [-2.39] | [-3.04] | [-2.39] | [-3.04] | [-3.04] |
| $R^2$ | 0.764 | 0.757 | 0.747 | 0.723 | 0.709 |
| N | 11943 | 11943 | 11943 | 11943 | 11943 |
| County FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |

## Table 9
## Refinancing matching results

This table presents results for the quantity of refinancing from our matching methodology. The county-level sample runs annually 1990-2014. The table presents the estimated treatment effect for the full sample and more subsamples based on the estimated propensity score. Observations are weighted by population. The dependent variable is the change in refinancing per capita; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| | Full matched sample | | P-score [.2, .4] | P-score [.4, .6] | P-score [.6, .8] |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | | | | | |
| Δ MBS Yield$_t$ x Treated$_{k,t}$ | **0.012** | **0.008** | **0.017** | **0.006** | **0.009** |
| | **[2.16]** | **[2.71]** | **[1.55]** | **[1.17]** | **[2.42]** |
| Treated$_{k,t}$ | 0.001 | -0.007 | 0.004 | -0.004 | -0.008 |
| | [0.22] | [-1.35] | [0.41] | [-0.84] | [-1.25] |
| Δ MBS Yield$_t$ | | -0.001 | -0.016 | -0.005 | 0 |
| x DTI$_{k,t-1}$ | | [-0.83] | [-2.50] | [-2.05] | [-0.06] |
| Δ MBS Yield$_t$ | | 0.002 | 0.002 | 0.002 | 0.002 |
| x ln(Population$_{k,t-1}$) | | [3.34] | [1.45] | [2.62] | [3.82] |
| Δ MBS Yield$_t$ | | -0.009 | -0.006 | -0.011 | -0.012 |
| x ln(Wage$_{k,t-1}$) | | [-3.16] | [-0.98] | [-2.81] | [-3.84] |
| Δ MBS Yield$_t$ | | -0.005 | 0.004 | -0.003 | -0.006 |
| x ln(Price$_{k,t-1}$) | | [-2.28] | [0.62] | [-1.26] | [-2.26] |
| Δ MBS Yield$_t$ | | 0.00 | 0.00 | 0.00 | 0.00 |
| x % Over 65$_{k,t-1}$ | | [2.10] | [0.85] | [1.13] | [0.86] |
| Δ MBS Yield$_t$ | | 0.00 | 0.00 | 0.00 | 0.00 |
| x % Under 18$_{k,t-1}$ | | [-0.52] | [-0.27] | [-1.10] | [-0.54] |
| Δ MBS Yield$_t$ | | 0.00 | 0.00 | 0.00 | 0.00 |
| x % Black$_{k,t-1}$ | | [4.48] | [2.61] | [3.38] | [4.62] |
| Δ MBS Yield$_t$ | 0.779 | 0.831 | 0.867 | 0.837 | 0.834 |
| x % High School$_{k,t-1}$ | 6794 | 6762 | 379 | 2518 | 3865 |
| Δ MBS Yield$_t$ | -0.011 | 0.08 | -0.031 | 0.075 | 0.101 |
| x Homeowner$_{k,t-1}$ | [-7.19] | [2.75] | [-0.55] | [2.12] | [3.09] |
| $R^2$ | 0.012 | 0.008 | 0.017 | 0.006 | 0.009 |
| N | [2.16] | [2.71] | [1.55] | [1.17] | [2.42] |
| County FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |

## Table 10
## Refinancing IV estimates

This table reports results where we estimate the regression

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t},$$

using bank mergers as an instrument for concentration. The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population. We examine the effect of the merger on the county's mortgage market concentration in the first column. Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield. Standard errors are clustered by county and year, with t-statistics reported in brackets.

| | First Stage (Joint F = 7.6) | | IV | | Reduced Form | |
|---|---|---|---|---|---|---|
| | Top 4 | Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | | | | |
| Post$_{k,t}$ | **0.006** | 0.026 | | | 0.000 | 0.000 |
| | **[5.51]** | [1.56] | | | [0.72] | [0.50] |
| Δ MBS Yield$_t$ | 0.000 | **0.311** | | | **0.002** | **0.001** |
| x Post$_{k,t}$ | [0.84] | **[8.74]** | | | **[2.51]** | **[2.01]** |
| Δ MBS Yield$_t$ | | | | | | |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | | | **0.083** | **0.715** | | |
| | | | **[2.78]** | **[0.38]** | | |
| Top4$_{k,t-1}$ | | | 0.003 | 0.01 | | |
| | | | [0.05] | [0.02] | | |
| Δ MBS Yield$_t$ | | | | 0.013 | | 0.001 |
| x ln(Population$_{k,t-1}$) | | | | [0.41] | | [2.67] |
| Δ MBS Yield$_t$ | | | | 0.008 | | -0.009 |
| x ln(Wage$_{k,t-1}$) | | | | [0.19] | | [-3.10] |
| Δ MBS Yield$_t$ | | | | -0.023 | | -0.001 |
| x ln(Price$_{k,t-1}$) | | | | [-0.34] | | [-0.59] |
| Δ MBS Yield$_t$ | | | | 0.022 | | -0.006 |
| x % Over 65$_{k,t-1}$ | | | | [0.29] | | [-2.46] |
| Δ MBS Yield$_t$ | | | | 0.001 | | 0.000 |
| x % Under 18$_{k,t-1}$ | | | | [0.51] | | [2.00] |
| Δ MBS Yield$_t$ | | | | 0.003 | | 0.000 |
| x % Black$_{k,t-1}$ | | | | [0.39] | | [-0.92] |
| Δ MBS Yield$_t$ | | | | 0.007 | | 0.002 |
| x % High School$_{k,t-1}$ | | | | [1.29] | | [1.01] |
| Δ MBS Yield$_t$ | | | | -0.028 | | 0.000 |
| x Homeowner$_{k,t-1}$ | | | | [-1.84] | | [-0.61] |
| $R^2$ | 0.634 | 0.642 | 0.701 | 0.724 | 0.765 | 0.829 |
| N | 8831 | 8831 | 8831 | 6929 | 8831 | 6929 |
| County FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |

## Table 11
## Refinancing and mortgage rates

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta R_{k,t} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs annually 2000-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2006. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| $\Delta R_{k,t}$ | **-0.016** | **-0.001** | **-0.001** | **-0.006** | **-0.007** |
| | **[-4.66]** | **[-0.42]** | **[-0.44]** | **[-2.25]** | **[-2.10]** |
| Δ MBS Yield $_t$ | | | | -0.003 | -0.005 |
| x $DTI_{k,t-1}$ | | | | [-1.42] | [-1.33] |
| Δ MBS Yield $_t$ | | | | 0.001 | 0.001 |
| x ln(Population$_{k,t-1}$) | | | | [2.61] | [1.95] |
| Δ MBS Yield $_t$ | | | | -0.012 | -0.01 |
| x ln(Wage $_{k,t-1}$) | | | | [-3.23] | [-2.00] |
| Δ MBS Yield $_t$ | | | | -0.001 | -0.003 |
| x ln(Price $_{k,t-1}$) | | | | [-0.52] | [-1.15] |
| Δ MBS Yield $_t$ | | | | 0.000 | 0.000 |
| x % Over 65 $_{k,t-1}$ | | | | [1.08] | [0.01] |
| Δ MBS Yield $_t$ | | | | 0.000 | 0.000 |
| x % Under 18 $_{k,t-1}$ | | | | [-1.15] | [-2.14] |
| Δ MBS Yield $_t$ | | | | 0.000 | 0.000 |
| x % Black $_{k,t-1}$ | | | | [4.13] | [2.65] |
| Δ MBS Yield $_t$ | | | | 0.001 | -0.001 |
| x % High School $_{k,t-1}$ | | | | [0.72] | [-0.41] |
| Δ MBS Yield $_t$ | | | | -0.003 | -0.006 |
| x Homeowner $_{k,t-1}$ | | | | [-2.39] | [-3.04] |
| $R^2$ | 0.432 | 0.776 | 0.761 | 0.821 | 0.829 |
| N | 5183 | 5183 | 5183 | 4524 | 2374 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

# Internet Appendix for "Market Power in Mortgage Lending"

## I. Model

We now briefly present a simple model of competition in the market for mortgage refinancing. The model is purely illustrative – it is meant only to demonstrate that our findings can be rationalized in a model where differences in market competition are the driving force. The model features Cournot competition with capacity constraints; it is a multi-firm version of the Monti-Klein model of deposit pricing (Monti (1972), Klein(1971)). There are two main results. First, the pass-through of MBS yields to mortgage rates is larger in markets with more competing lenders. Second, differences in pass-through between high- and low-concentration markets are highest when yields are falling because of the impact of capacity constraints.

Suppose borrowers face fixed costs of refinancing, $f$, distributed uniformly on the interval $[x\text{-}\Delta/2,\ x+\Delta/2]$. For simplicity, these fixed costs are expressed in flow units, so that they are comparable to mortgage rates. The support of the fixed cost distribution is taken to be large enough that the model solution is always interior.[1] Further suppose for simplicity that all borrowers are paying the same rate on their existing mortgage, $r_{t-1}$. Then an individual borrower has an incentive to refinance when

$$r_{t-1} - r_t > f.$$

Thus, we can write the demand for refinancing as

$$Q(r_t - r_{t-1}) = \Pr(r_{t-1} - r_t > f) = \frac{a}{b} - \frac{1}{b}(r_t - r_{t-1})$$

or equivalently

$$r_t(Q_t) = a + r_{t-1} - bQ_t$$

where $r_t(Q)$ is the mortgage rate corresponding to demand of $Q$ in the local area, $b = \Delta$, and $a = \Delta/2\text{-}x$.

[1] To generate positive demand for refinancing when rates are increasing requires negative fixed costs. This cannot literally be true, but can proxy from other benefits for households (e.g., liquidity) that arise from refinancing at such times.

Each mortgage originator is assumed to have pre-existing production capacity $\bar{q}$. When production is below the pre-existing capacity, the only costs of mortgage production are the costs of funding the loan, given by the MBS yield, $y_t$. Thus, we are effectively normalizing other production costs associated with mortgage origination to zero when production is below pre-existing capacity. However, if a lender wishes to produce more than its pre-existing capacity, it faces increasing, convex production costs, which capture the idea that it is costly to produce above pre-existing capacity. For instance, one could think of these convex costs as capturing loan officer overtime, strain on back-office capabilities, and other short-run costs of very high production. Formally, production costs are given by

$$C_t\left(q\right) = \begin{cases} y_t q & \text{if } q \le \bar{q} \\ y_t q + \frac{1}{2} c\left(q - \bar{q}\right)^2 & \text{if } q > \bar{q} \end{cases} .$$

We assume Cournot competition,[2] so firms solve the following maximization problem:

$$\max_{q_t} \; r_t\left(Q_t\right) q_t - C_t\left(q_t\right).$$

We solve for the symmetric Nash equilibrium, labeling optimal production of individual lenders $q^*$ and total equilibrium production $Q^* = nq^*$.

***Proposition 1.*** *Total equilibrium production depends on the difference between the MBS yield $y_t$ and the existing mortgage rate $r_{t-1}$:*

$$Q_t^*\left(y_t - r_{t-1}\right) = \begin{cases} Q_{t,1}^*\left(y_t - r_{t-1}\right) & \text{if } \; y_t - r_{t-1} \ge \bar{z} \\ Q_{t,2}^*\left(y_t - r_{t-1}\right) & \text{if } \; y_t - r_{t-1} < \bar{z} \end{cases} ,$$

*where*

$$Q_{t,1}^* = \frac{\left(a - \left(y_t - r_{t-1}\right)\right)N}{b\left(N+1\right)}, \; Q_{t,2}^* = \frac{\left(a - \left(y_t - r_{t-1}\right)\right)N}{b\left(N+1\right)+c}$$

*and* $\bar{z} = a - \bar{q}b\left(N+1\right)$.

[2] While it is more natural to model mortgage market competition as Bertrand, as argued by Kreps and Scheinkman (1983), Bertrand competition with capacity constraints is similar to Cournot competition under certain conditions. Furthermore, the model is merely meant to be illustrative, and Cournot competition simplifies the analysis considerably.

All proofs are given in the Appendix. The equilibrium depends on the MBS yield $y_t$ and the existing mortgage rate $r_{t-1}$. When the MBS yield is high relative to existing mortgage rates, the cost of producing loans is high, and lenders will produce few mortgages using existing capacity. In contrast, if MBS yields are low relative to existing mortgage rates, lenders will wish to produce many mortgages and will "add capacity" – moving up the marginal cost curve – to do so.

We can now study pass-through, the sensitivity of mortgage rates and quantities to changes in MBS yields, in each region of the equilibrium. Since we are interested in the behavior of pass-through as the number of competing lenders changes, it is useful to normalize pre-existing capacity so that it is fixed at the industry level. Specifically, let $\bar{q} = \frac{\bar{Q}}{N+1}$ where $\bar{Q}$ is aggregate industry capacity. Thus, as we vary $N$, the threshold point $\bar{z}$ is fixed.

The following proposition describes how the aggregate sensitivities of quantities and prices to changes in MBS yields vary with the degree of competition.

***Proposition 2***. *Mortgage quantities rise when MBS yields fall:* $\partial Q_t^* / \partial \left( y_t - r_{t-1} \right) < 0$. *In addition, mortgage rates fall when MBS yields fall:* $\partial r_t \left( Q_t^* \right) / \partial \left( y_t - r_{t-1} \right) > 0$. *Finally, these sensitivities are larger in magnitude when there are more lenders:* $\partial^2 Q_t^* / \partial \left( y_t - r_{t-1} \right) \partial N < 0$, $\partial^2 r_t \left( Q_t^* \right) / \partial \left( y_t - r_{t-1} \right) \partial N > 0$.

When MBS yields fall relative to existing mortgage rates $r_{t-1}$, the marginal cost of lending falls. Therefore, lenders produce more mortgages, and the market clearing price is lower. This is true even in the region of the parameter space where lenders must add more capacity. If MBS yields fall, the profits from producing more mortgages will be high enough that it is worthwhile for lenders to move up the marginal cost curve. The second part of the proposition is the key for our empirics. As the number of lenders increases, each has less effective market power, so more of the benefit of falling MBS yields is passed through to borrowers.[3] Thus, pass-through is higher in low-concentration areas than in high-concentration areas.

When are these differences in pass-through between low- and high-concentration areas largest? The following proposition shows that under certain conditions, the differences will be larger when MBS yields fall more relative to existing mortgage rates.

***Proposition 3.*** *Differences in pass-through between low- and high-concentration areas are larger when MBS yields fall relative to when they rise, provided* $b\left(N^2-1\right)>c$ *and* $y_t - r_{t-1} = \bar{z}$ *initially. Under this condition, we have* $\frac{\partial^2 Q^*_{t,2}}{\partial\left(y_t - r_{t-1}\right)\partial N} < \frac{\partial^2 Q^*_{t,1}}{\partial\left(y_t - r_{t-1}\right)\partial N}$ *and* $\frac{\partial^2 r_t\left(Q^*_{t,2}\right)}{\partial\left(y_t - r_{t-1}\right)\partial N} > \frac{\partial^2 r_t\left(Q^*_{t,1}\right)}{\partial\left(y_t - r_{t-1}\right)\partial N}$ .

The condition $b\left(N^2-1\right)>c$ will hold for sufficiently large *N*, sufficiently large *b*, or sufficiently small *c*. We interpret the condition that $y_t - r_{t-1} = \bar{z}$ initially as saying that the industry starts at capacity. Essentially, if the cost of adding capacity *c* is too high, then no lenders will add capacity when MBS yields fall relative to existing mortgage rates. In this case, capacity decisions will not contribute to the difference between high- and low- concentration counties. However, for more moderate values of *c*, lenders in low-concentration areas will add more capacity than lenders in high-concentration areas when MBS yields fall relative to existing mortgage rates. These differences in capacity decisions will amplify the differences in pass-through between high- and low-concentration areas.

[3] It is worth noting that low pass-through can be a symptom of high market power, but it need not be (Bulow and Pfleiderer, 1983). The model is meant for illustrative purposes, and the results are sensitive to functional form assumptions. Ultimately the relationship between pass-through and market power is an empirical question.

## Appendix

**Proof of Proposition 1.** If we are below $\bar{q}$, each firm has first order condition

$$0 = a - bQ_t - bq_t - y_t + r_{t-1}.$$

In a symmetric equilibrium, we have $Q = Nq$ which implies that

$$q^*_{t,1} = \frac{a - \left(y_t - r_{t-1}\right)}{b\left(N+1\right)}.$$

When we are above $\bar{q}$, the first order condition is

$$0 = a - bQ_t - bq_t - y_t + r_{t-1} - cq_t.$$

In a symmetric equilibrium, this implies that

$$q^*_{t,2} = \frac{a - \left(y_t - r_{t-1}\right)}{b\left(N+1\right) + c}.$$

To find the bounds, we can plug in to find the values that yield $\bar{q}$ in each of these expressions:

$$\bar{q} = q^*_1 = \frac{a - \bar{z}}{b\left(N+1\right)} \ .$$

**Proof of Proposition 2.** Differentiating gives the pass-through result:

$$\frac{\partial Q^*_{t,1}}{\partial\left(y_t - r_{t-1}\right)} = \frac{-N}{b\left(N+1\right)} < 0, \quad \frac{\partial Q^*_{t,2}}{\partial\left(y_t - r_{t-1}\right)} = \frac{-N}{b\left(N+1\right) + c} < 0.$$

Differentiating with respect to *N* gives the change with the number of lenders

$$\frac{\partial^2 Q^*_{t,1}}{\partial\left(y_t - r_{t-1}\right)\partial N} = \frac{-1}{b\left(N+1\right)^2} < 0, \quad \frac{\partial^2 Q^*_{t,2}}{\partial\left(y_t - r_{t-1}\right)\partial N} = \frac{-\left(b+c\right)}{\left(b\left(N+1\right)+c\right)^2} < 0$$

**Proof of Proposition 3.** We want to find conditions so that $\frac{\partial^2 Q^*_{t,1}}{\partial\left(y_t - r_{t-1}\right)\partial N} < \frac{\partial^2 Q^*_{t,2}}{\partial\left(y_t - r_{t-1}\right)\partial N}$.

Plugging in the values for these cross-partials from above, we have

$$\frac{-\left(b+c\right)}{\left(b\left(N+1\right)+c\right)^2} < \frac{-1}{b\left(N+1\right)^2}.$$

Rearranging, we have $b\left(N^2 - 1\right) > c$. The asymmetry stated in the proposition only applies if our starting point is the boundary between $Q^*_{t,1}$ and $Q^*_{t,2}$, that is, if $y_t - r_{t-1} = \bar{z}$.

## II. Additional Results

### Appendix Table 1
### Time-Varying Borrower Characteristics

In this table, we present results using changes in borrower characteristics as the dependent variable. Specifically, we run regression specifications of the form

$$\Delta Borrower\ Characteristic_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{i,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{i,t-1} + \varepsilon_{i,t}.$$

In Panel A, the borrower characteristic used as the dependent variable is the debt-to-income ratio from HMDA. In specifications with interactions between controls and changes in MBS yields, the levels and differences of the controls are suppressed for compactness but included in the regressions. The county-level sample runs annually 1990-2014. Standard errors are clustered by county and year, and t-statistics are reported in the brackets. In Panel B, the characteristics are FICO and LTV from Fannie Mae's Single Family Loan Performance Data and Freddie Mac's Single Family Loan-Level Data Set. The county-level sample runs quarterly from 1999 to 2014. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| Panel A: DTI from HMDA | | |
|---|---|---|
| $DTI_{k,t-1}$ | -1.028 | -0.707 |
| | [-30.11] | [-9.01] |
| Δ MBS Yield $_t$ x Top4$_{k,t-1}$ | 0.263 | 0.086 |
| | [1.55] | [1.17] |
| Top 4$_{k,t-1}$ | 0.03 | -0.04 |
| | [0.43] | [-0.55] |
| Δ MBS Yield $_t$ | | 0.035 |
| x $DTI_{k,t-1}$ | | [0.61] |
| Δ MBS Yield $_t$ | | -0.009 |
| x ln(Population$_{k,t-1}$) | | [-1.11] |
| Δ MBS Yield $_t$ | | 0.04 |
| x ln(Wage $_{k,t-1}$) | | [0.94] |
| Δ MBS Yield $_t$ | | -0.001 |
| x ln(Price $_{k,t-1}$) | | [-0.01] |
| Δ MBS Yield $_t$ | | -0.001 |
| x % Over 65 $_{k,t-1}$ | | [-0.48] |
| Δ MBS Yield $_t$ | | -0.003 |
| x % Under 18 $_{k,t-1}$ | | [-1.70] |
| Δ MBS Yield $_t$ | | 0 |
| x % Black $_{k,t-1}$ | | [0.51] |
| Δ MBS Yield $_t$ | | 0.273 |
| x % High School $_{k,t-1}$ | | [4.28] |
| Δ MBS Yield $_t$ | | -0.092 |
| x Homeowner $_{k,t-1}$ | | [-1.25] |
| $R^2$ | 0.764 | 0.823 |
| N | 11943 | 7775 |
| County FE | Y | Y |
| Year FE | Y | Y |

| Panel B: FICO and LTV from Loan-Level data | | | | |
|---|---|---|---|---|
| | FICO | | LTV | |
| Δ MBS Yield$_t$ | -7.319 | -6.38 | 0.143 | -0.321 |
| | [-4.54] | [-0.55] | [0.76] | [-0.22] |
| Δ MBS Yield $_t$ x Top4$_{k,t-1}$ | -0.974 | -1.399 | 0.089 | 0.392 |
| | [-0.26] | [-0.36] | [0.21] | [0.92] |
| Top 4$_{k,t-1}$ | 1.081 | 1.45 | 0.454 | 0.407 |
| | [0.83] | [0.85] | [2.43] | [2.07] |
| Δ MBS Yield $_t$ | | 0.07 | | 0.029 |
| x ln(Population$_{k,t-1}$) | | [0.30] | | [0.71] |
| Δ MBS Yield $_t$ | | 0.033 | | -0.249 |
| x ln(Wage $_{k,t-1}$) | | [0.01] | | [-0.79] |
| Δ MBS Yield $_t$ | | 0.62 | | 0.038 |
| x ln(Price $_{k,t-1}$) | | [0.97] | | [0.29] |
| Δ MBS Yield $_t$ | | -0.067 | | 0.017 |
| x % Over 65 $_{k,t-1}$ | | [-0.74] | | [2.90] |
| Δ MBS Yield $_t$ | | -0.239 | | 0.036 |
| x % Under 18 $_{k,t-1}$ | | [-2.95] | | [3.38] |
| Δ MBS Yield $_t$ | | -0.014 | | -0.001 |
| x % Black $_{k,t-1}$ | | [-0.90] | | [-0.38] |
| Δ MBS Yield $_t$ | | -0.069 | | 0.003 |
| x % High School $_{k,t-1}$ | | [-0.95] | | [0.41] |
| Δ MBS Yield $_t$ | | 0.048 | | -0.001 |
| x Homeowner $_{k,t-1}$ | | [1.27] | | [-0.43] |
| $R^2$ | 0.221 | 0.247 | 0.009 | 0.017 |
| N | 29892 | 22112 | 29895 | 22115 |
| County FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |

## Appendix Table 2
## Analyzing Counties with Low Broker Share

This table presents our results, restricting the sample to counties where the share of loan originations by brokers and correspondents is low. The column headers also show the cutoff we use for the share of brokers and correspondents. In specifications with interactions between controls and changes in MBS yields, the levels and differences of the controls are suppressed for compactness but included in the regressions. Panel A presents the results for the quantity of refinancing; the county-level sample runs annually 1990-2014. Standard errors are clustered by county and year, and t-statistics are reported in the brackets. Panel B presents the results for average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; the county-level sample runs quarterly 1999-2014. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| Panel A: HMDA Refinancing Results | | | | |
|---|---|---|---|---|
| | Broker Share < 0.25 | | Broker Share < 0.10 | |
| Δ MBS Yield $_t$ x Top4$_{k,t-1}$ | **0.019** | **0.013** | **0.019** | **0.011** |
| | **[6.32]** | **[2.74]** | **[6.17]** | **[2.32]** |
| Top 4$_{k,t-1}$ | 0.007 | -0.004 | 0.007 | -0.004 |
| | [1.69] | [-0.80] | [1.70] | [-0.68] |
| Δ MBS Yield $_t$ | | -0.003 | | -0.004 |
| x DTI$_{k,t-1}$ | | [-1.30] | | [-1.53] |
| Δ MBS Yield $_t$ | | 0.002 | | 0.002 |
| x ln(Population$_{k,t-1}$) | | [3.52] | | [3.38] |
| Δ MBS Yield $_t$ | | -0.01 | | -0.009 |
| x ln(Wage $_{k,t-1}$) | | [-3.25] | | [-2.94] |
| Δ MBS Yield $_t$ | | -0.003 | | -0.002 |
| x ln(Price $_{k,t-1}$) | | [-1.24] | | [-1.04] |
| Δ MBS Yield $_t$ | | 0 | | 0 |
| x % Over 65 $_{k,t-1}$ | | [1.81] | | [2.32] |
| Δ MBS Yield $_t$ | | 0 | | 0 |
| x % Under 18 $_{k,t-1}$ | | [-1.09] | | [-0.35] |
| Δ MBS Yield $_t$ | | 0 | | 0 |
| x % Black $_{k,t-1}$ | | [4.22] | | [4.22] |
| Δ MBS Yield $_t$ | | 0.273 | | 0.273 |
| x % High School $_{k,t-1}$ | | [4.28] | | [4.28] |
| Δ MBS Yield $_t$ | | -0.092 | | -0.092 |
| x Homeowner $_{k,t-1}$ | | [-1.25] | | [-1.25] |
| $R^2$ | 0.766 | 0.826 | 0.774 | 0.83 |
| N | 10725 | 7713 | 9194 | 6723 |
| County FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |

| Panel B: Residualized Rates from Loan-Level data | | | | |
|---|---|---|---|---|
| | Broker Share < 0.25 | | Broker Share < 0.10 | |
| Δ MBS Yield$_t$ | 0.677 | 2.545 | 0.679 | 3.369 |
| | [3.66] | [3.27] | [3.56] | [3.36] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **-0.933** | **-0.958** | **-0.954** | **-1.078** |
| | **[-2.08]** | **[-2.04]** | **[-2.01]** | **[-2.20]** |
| Top 4$_{k,t-1}$ | 0 | -0.005 | 0.009 | 0.019 |
| | [0.02] | [-0.18] | [0.49] | [0.85] |
| Δ MBS Yield$_t$ | | 0.007 | | 0.024 |
| x ln(Population$_{k,t-1}$) | | [0.49] | | [1.41] |
| Δ MBS Yield$_t$ | | -0.338 | | -0.432 |
| x ln(Wage$_{k,t-1}$) | | [-2.02] | | [-2.18] |
| Δ MBS Yield$_t$ | | 0.05 | | 0.026 |
| x ln(Price$_{k,t-1}$) | | [0.97] | | [0.56] |
| Δ MBS Yield$_t$ | | -0.005 | | -0.011 |
| x % Over 65$_{k,t-1}$ | | [-0.88] | | [-1.54] |
| Δ MBS Yield$_t$ | | -0.001 | | -0.006 |
| x % Under 18$_{k,t-1}$ | | [-0.38] | | [-1.20] |
| Δ MBS Yield$_t$ | | 0 | | 0.001 |
| x % Black$_{k,t-1}$ | | [0.56] | | [0.82] |
| Δ MBS Yield$_t$ | | -0.001 | | -0.001 |
| x % High School$_{k,t-1}$ | | [-0.22] | | [-0.21] |
| Δ MBS Yield$_t$ | | -0.001 | | 0 |
| x Homeowner$_{k,t-1}$ | | [-0.54] | | [0.14] |
| $R^2$ | 0.319 | 0.33 | 0.322 | 0.336 |
| N | 28317 | 21681 | 23837 | 18043 |
| County FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |

## Appendix Table 3
## Using 10-Year Treasury Yields

This table shows that our results are robust using the 10-year Treasury yield as a proxy for MBS yields. In specifications with interactions between controls and changes in Treasury yields, the levels and differences of the controls are suppressed for compactness but included in the regressions. Panel A presents the results for the quantity of refinancing; the county-level sample runs annually 1990-2014. Standard errors are clustered by county and year, and t-statistics are reported in the brackets. Panel B presents the results for average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; the county-level sample runs quarterly 1999-2014. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| Panel A: HMDA Refinancing Results | | | | | |
|---|---|---|---|---|---|
| Δ Treasury10$_t$ | -0.02 | | | | |
| | [-4.28] | | | | |
| Δ Treasury10$_t$ x Top4$_{k,t-1}$ | **0.02** | **0.019** | **0.019** | **0.016** | **0.017** |
| | **[2.78]** | **[10.40]** | **[10.05]** | **[2.51]** | **[2.03]** |
| Top 4$_{k,t-1}$ | 0.003 | 0.005 | 0.006 | -0.003 | -0.009 |
| | [0.60] | [3.49] | [1.46] | [-0.48] | [-1.00] |
| Δ Treasury10$_t$ | | | | -0.001 | -0.006 |
| x DTI$_{k,t-1}$ | | | | [-0.23] | [-1.29] |
| Δ Treasury10$_t$ | | | | 0.002 | 0.002 |
| x ln(Population$_{k,t-1}$) | | | | [3.05] | [2.77] |
| Δ Treasury10$_t$ | | | | -0.013 | -0.013 |
| x ln(Wage $_{k,t-1}$) | | | | [-2.85] | [-2.55] |
| Δ Treasury10$_t$ | | | | -0.005 | -0.006 |
| x ln(Price $_{k,t-1}$) | | | | [-1.30] | [-1.31] |
| Δ Treasury10$_t$ | | | | 0 | 0 |
| x % Over 65 $_{k,t-1}$ | | | | [2.10] | [1.17] |
| Δ Treasury10$_t$ | | | | 0 | 0 |
| x % Under 18 $_{k,t-1}$ | | | | [-1.21] | [-1.70] |
| Δ Treasury10$_t$ | | | | 0 | 0 |
| x % Black $_{k,t-1}$ | | | | [3.83] | [3.85] |
| Δ Treasury10$_t$ | | | | 0 | 0 |
| x % High School $_{k,t-1}$ | | | | [1.81] | [1.81] |
| Δ Treasury10$_t$ | | | | 0 | 0 |
| x Homeowner $_{k,t-1}$ | | | | [-1.09] | [-1.09] |
| $R^2$ | 0.408 | 0.772 | 0.761 | 0.815 | 0.839 |
| N | 11943 | 11943 | 11943 | 7775 | 4673 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

| Panel B: Residualized Rates from Loan-Level data | | | | | |
|---|---|---|---|---|---|
| Δ Treasury10$_t$ | 0.65 | 0.586 | 0.587 | 2.267 | 0.354 |
| | [3.64] | [3.51] | [3.46] | [2.81] | [0.38] |
| Δ Treasury10$_t$ x Top4$_{k,t-1}$ | **-1.01** | **-0.773** | **-0.78** | **-0.813** | **-0.156** |
| | **[-2.13]** | **[-1.77]** | **[-1.96]** | **[-2.07]** | **[-0.31]** |
| Top 4$_{k,t-1}$ | -0.329 | 0.016 | 0.06 | 0.097 | 0.009 |
| | [-1.40] | [0.27] | [0.27] | [0.75] | [0.09] |
| Δ Treasury10$_t$ | | | | 0.005 | -0.041 |
| x ln(Population$_{k,t-1}$) | | | | [0.30] | [-1.41] |
| Δ Treasury10$_t$ | | | | -0.324 | 0.193 |
| x ln(Wage $_{k,t-1}$) | | | | [-1.76] | [1.00] |
| Δ Treasury10$_t$ | | | | 0.051 | -0.008 |
| x ln(Price $_{k,t-1}$) | | | | [0.96] | [-0.22] |
| Δ Treasury10$_t$ | | | | -0.005 | -0.002 |
| x % Over 65 $_{k,t-1}$ | | | | [-1.08] | [-0.57] |
| Δ Treasury10$_t$ | | | | -0.002 | 0.007 |
| x % Under 18 $_{k,t-1}$ | | | | [-0.66] | [1.50] |
| Δ Treasury10$_t$ | | | | 0.001 | -0.001 |
| x % Black $_{k,t-1}$ | | | | [0.70] | [-0.68] |
| Δ Treasury10$_t$ | | | | 0.001 | -0.007 |
| x % High School $_{k,t-1}$ | | | | [0.10] | [-0.89] |
| Δ Treasury10$_t$ | | | | -0.002 | 0 |
| x Homeowner $_{k,t-1}$ | | | | [-0.88] | [0.18] |
| $R^2$ | 0.22 | 0.335 | 0.322 | 0.34 | 0.506 |
| N | 29463 | 29463 | 29463 | 21760 | 12438 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 4
## Using HHI to Measure Concentration: Refinancing

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot HHI_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times HHI_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; HHI is the Herfindahl-Hirshmann index of concentration (the sum of market shares squared) among mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2007. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and year.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | -0.015 | | | | |
| | [-6.12] | | | | |
| Δ MBS Yield$_t$ x HHI$_{k,t-1}$ | **0.046** | **0.045** | **0.046** | **0.053** | **0.07** |
| | **[3.24]** | **[10.15]** | **[9.70]** | **[2.66]** | **[2.92]** |
| HHI$_{k,t-1}$ | 0.008 | 0.019 | 0.022 | -0.017 | -0.069 |
| | [0.69] | [6.26] | [3.48] | [-0.81] | [-1.50] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.005 |
| x DTI$_{k,t-1}$ | | | | [-1.23] | [-1.41] |
| Δ MBS Yield$_t$ | | | | 0.002 | 0.002 |
| x ln(Population$_{k,t-1}$) | | | | [3.44] | [2.69] |
| Δ MBS Yield$_t$ | | | | -0.01 | -0.009 |
| x ln(Wage$_{k,t-1}$) | | | | [-3.27] | [-2.35] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.004 |
| x ln(Price$_{k,t-1}$) | | | | [-1.27] | [-1.35] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Over 65$_{k,t-1}$ | | | | [1.84] | [1.13] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Under 18$_{k,t-1}$ | | | | [-1.11] | [-1.65] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Black$_{k,t-1}$ | | | | [4.18] | [3.13] |
| Δ MBS Yield$_t$ | | | | 0.001 | -0.001 |
| x % High School$_{k,t-1}$ | | | | [0.72] | [-0.41] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.006 |
| x Homeowner$_{k,t-1}$ | | | | [-2.39] | [-3.04] |
| $R^2$ | 0.495 | 0.771 | 0.761 | 0.824 | 0.834 |
| N | 11943 | 11943 | 11943 | 7775 | 4673 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 5
## Using HHI to Measure Concentration: Mortgage rates

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot HHI_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times HHI_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs quarterly 1999-2014. Observations are weighted by the quantity of loans in the county-quarter. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; HHI is the Herfindahl-Hirshmann index of concentration (the sum of market shares squared) among mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The final column restricts the sample to the years before the financial crisis, 1999-2007. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | 0.586 | 0.511 | 0.51 | 2.396 | 0.683 |
| | [4.59] | [4.32] | [4.26] | [3.31] | [0.65] |
| Δ MBS Yield$_t$ x HHI$_{k,t-1}$ | **-4.392** | **-3.053** | **-3.07** | **-3.137** | **-3.996** |
| | **[-2.06]** | **[-1.86]** | **[-1.94]** | **[-1.87]** | **[-1.71]** |
| HHI$_{k,t-1}$ | -0.715 | -0.122 | 0.043 | 0.086 | 0.223 |
| | [-0.89] | [-0.67] | [0.80] | [0.96] | [0.80] |
| Δ MBS Yield$_t$ | | | | 0.008 | -0.043 |
| x ln(Population$_{k,t-1}$) | | | | [0.57] | [-1.33] |
| Δ MBS Yield$_t$ | | | | -0.35 | 0.246 |
| x ln(Wage$_{k,t-1}$) | | | | [-2.10] | [1.11] |
| Δ MBS Yield$_t$ | | | | 0.049 | -0.061 |
| x ln(Price$_{k,t-1}$) | | | | [0.95] | [-1.69] |
| Δ MBS Yield$_t$ | | | | -0.006 | -0.002 |
| x % Over 65$_{k,t-1}$ | | | | [-1.00] | [-0.34] |
| Δ MBS Yield$_t$ | | | | -0.003 | 0.009 |
| x % Under 18$_{k,t-1}$ | | | | [-0.67] | [1.33] |
| Δ MBS Yield$_t$ | | | | 0.001 | -0.002 |
| x % Black$_{k,t-1}$ | | | | [1.08] | [-2.95] |
| Δ MBS Yield$_t$ | | | | -0.001 | -0.005 |
| x % High School$_{k,t-1}$ | | | | [-0.18] | [-0.46] |
| Δ MBS Yield$_t$ | | | | 0 | -0.001 |
| x Homeowner$_{k,t-1}$ | | | | [-0.11] | [-0.25] |
| $R^2$ | 0.26 | 0.326 | 0.315 | 0.327 | 0.516 |
| N | 29463 | 29463 | 29463 | 21760 | 12438 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 6
## MSA-level Analysis: Refinancing

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The MSA-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2007. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by MSA and year.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | -0.017 | | | | |
| | [-4.85] | | | | |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **0.015** | **0.015** | **0.015** | **0.013** | **0.003** |
| | **[2.70]** | **[5.78]** | **[5.39]** | **[2.92]** | **[0.78]** |
| Top 4$_{k,t-1}$ | 0.001 | 0.005 | 0.004 | -0.008 | -0.01 |
| | [0.18] | [3.11] | [1.23] | [-1.81] | [-1.32] |
| Δ MBS Yield$_t$ | | | | 0 | -0.002 |
| x DTI$_{k,t-1}$ | | | | [-0.29] | [-1.18] |
| Δ MBS Yield$_t$ | | | | 0.001 | 0.001 |
| x ln(Population$_{k,t-1}$) | | | | [2.54] | [2.10] |
| Δ MBS Yield$_t$ | | | | -0.009 | -0.01 |
| x ln(Wage$_{k,t-1}$) | | | | [-2.42] | [-2.69] |
| Δ MBS Yield$_t$ | | | | -0.008 | -0.009 |
| x ln(Price$_{k,t-1}$) | | | | [-3.54] | [-3.75] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Over 65$_{k,t-1}$ | | | | [0.10] | [-1.00] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Under 18$_{k,t-1}$ | | | | [0.45] | [-0.52] |
| Δ MBS Yield$_t$ | | | | 0 | 0 |
| x % Black$_{k,t-1}$ | | | | [4.20] | [3.76] |
| Δ MBS Yield$_t$ | | | | 0.001 | -0.001 |
| x % High School$_{k,t-1}$ | | | | [0.72] | [-0.41] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.006 |
| x Homeowner$_{k,t-1}$ | | | | [-2.39] | [-3.04] |
| $R^2$ | 0.48 | 0.764 | 0.753 | 0.828 | 0.844 |
| N | 7589 | 7589 | 7589 | 4102 | 2986 |
| MSA FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 7
## MSA-level Analysis: Mortgage rates

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The MSA-level sample runs quarterly 1999-2014. Observations are weighted by the quantity of loans in the county-quarter. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The final column restricts the sample to the years before the financial crisis, 1999-2007. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by MSA and quarter, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | 0.813 | 0.686 | 0.688 | 2.135 | -0.468 |
| | [4.19] | [3.97] | [3.93] | [2.55] | [-0.30] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **-1.28** | **-0.931** | **-0.937** | **-0.927** | **-0.915** |
| | **[-2.41]** | **[-2.25]** | **[-2.23]** | **[-2.06]** | **[-1.62]** |
| Top 4$_{k,t-1}$ | -0.218 | -0.067 | -0.022 | -0.044 | -0.188 |
| | [-1.11] | [-1.58] | [-0.20] | [-0.08] | [-1.11] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.055 |
| x ln(Population$_{k,t-1}$) | | | | [-0.18] | [-1.66] |
| Δ MBS Yield$_t$ | | | | -0.398 | 0.291 |
| x ln(Wage$_{k,t-1}$) | | | | [-1.96] | [0.91] |
| Δ MBS Yield$_t$ | | | | 0.093 | -0.009 |
| x ln(Price$_{k,t-1}$) | | | | [1.38] | [-0.25] |
| Δ MBS Yield$_t$ | | | | -0.005 | -0.001 |
| x % Over 65$_{k,t-1}$ | | | | [-0.89] | [-0.19] |
| Δ MBS Yield$_t$ | | | | 0.003 | 0.015 |
| x % Under 18$_{k,t-1}$ | | | | [1.33] | [1.78] |
| Δ MBS Yield$_t$ | | | | 0 | -0.002 |
| x % Black$_{k,t-1}$ | | | | [0.36] | [-1.24] |
| Δ MBS Yield$_t$ | | | | 0.003 | -0.002 |
| x % High School$_{k,t-1}$ | | | | [0.55] | [-0.20] |
| Δ MBS Yield$_t$ | | | | -0.002 | 0.001 |
| x Homeowner$_{k,t-1}$ | | | | [-0.84] | [0.30] |
| $R^2$ | 0.287 | 0.347 | 0.337 | 0.35 | 0.535 |
| N | 20511 | 20511 | 20511 | 12424 | 7119 |
| MSA FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 8
## Mortgage Rates and Concentration, Lags

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs 1999-2014. In each column, we pool the quarterly sample to study pass-through over a different horizon, which is given by the column header. Observations are weighted by the quantity of loans in the county-time period. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and time period, and t-statistics are reported in the brackets.

| | 1 qtr | 2 qtrs | 3 qtrs | 4 qtrs |
|---|---|---|---|---|
| Δ MBS Yield$_t$ | 2.082 | 2.889 | 2.995 | 4.159 |
| | [1.77] | [3.00] | [3.76] | [4.14] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **-1.22** | **-1.021** | **-0.951** | **-0.655** |
| | **[-2.09]** | **[-1.87]** | **[-2.81]** | **[-1.52]** |
| Top 4$_{k,t-1}$ | 0.263 | 0.05 | -0.288 | -0.092 |
| | [0.39] | [0.07] | [-0.37] | [-0.12] |
| Δ MBS Yield$_t$ | -0.005 | 0.008 | 0.011 | 0.056 |
| x ln(Population$_{k,t-1}$) | [-0.22] | [0.38] | [0.47] | [4.60] |
| Δ MBS Yield$_t$ | -0.299 | -0.428 | -0.416 | -0.76 |
| x ln(Wage $_{k,t-1}$) | [-1.34] | [-1.85] | [-2.04] | [-4.15] |
| Δ MBS Yield$_t$ | 0.06 | 0.102 | 0.035 | 0.074 |
| x ln(Price $_{k,t-1}$) | [0.90] | [2.15] | [0.44] | [1.15] |
| Δ MBS Yield$_t$ | 0.002 | -0.015 | -0.009 | -0.014 |
| x % Over 65 $_{k,t-1}$ | [0.16] | [-2.37] | [-0.93] | [-1.88] |
| Δ MBS Yield$_t$ | 0.006 | -0.008 | -0.006 | -0.013 |
| x % Under 18 $_{k,t-1}$ | [0.65] | [-1.41] | [-0.95] | [-1.55] |
| Δ MBS Yield$_t$ | 0 | 0.002 | 0.002 | 0.003 |
| x % Black $_{k,t-1}$ | [0.12] | [1.47] | [1.35] | [2.51] |
| Δ MBS Yield$_t$ | 0.002 | -0.003 | 0.003 | 0.005 |
| x % High School $_{k,t-1}$ | [0.35] | [-0.48] | [0.36] | [0.95] |
| Δ MBS Yield$_t$ | -0.005 | 0.003 | 0.001 | 0.003 |
| x Homeowner $_{k,t-1}$ | [-1.09] | [0.93] | [0.38] | [1.04] |
| $R^2$ | 0.158 | 0.644 | 0.647 | 0.83 |
| N | 22446 | 11163 | 7476 | 5624 |
| County FE | Y | Y | Y | Y |
| Year FE | N | N | N | N |

## Appendix Table 9
## ARM share and concentration

This table presents regressions of the form:

$$\Delta ARM\ Share_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{i,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{i,t-1} + \varepsilon_{i,t}.$$

The county-level sample runs quarterly 2000-2014. Observations are weighted by the quantity of loans in the county-quarter. Arm share is the fraction of loan originations in the county-quarter that are adjustable rate; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| | | | | |
|---|---|---|---|---|
| Δ MBS Yield$_t$ | 0.084 | | | |
| | [2.82] | | | |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | -0.075 | -0.028 | -0.026 | -0.012 |
| | [-1.25] | [-1.07] | [-0.96] | [-0.73] |
| Top 4$_{k,t-1}$ | 0.062 | -0.012 | -0.034 | -0.015 |
| | [2.29] | [-1.62] | [-1.87] | [-0.90] |
| Δ MBS Yield$_t$ | | | | 0.002 |
| x ln(Population$_{k,t-1}$) | | | | [1.05] |
| Δ MBS Yield$_t$ | | | | 0.008 |
| x ln(Wage$_{k,t-1}$) | | | | [0.75] |
| Δ MBS Yield$_t$ | | | | 0.035 |
| x ln(Price$_{k,t-1}$) | | | | [4.20] |
| Δ MBS Yield$_t$ | | | | 0 |
| x % Over 65$_{k,t-1}$ | | | | [-0.18] |
| Δ MBS Yield$_t$ | | | | 0.001 |
| x % Under 18$_{k,t-1}$ | | | | [1.25] |
| Δ MBS Yield$_t$ | | | | 0 |
| x % Black$_{k,t-1}$ | | | | [1.53] |
| Δ MBS Yield$_t$ | | | | 0.001 |
| x % High School$_{k,t-1}$ | | | | [1.13] |
| Δ MBS Yield$_t$ | | | | 0 |
| x Homeowner$_{k,t-1}$ | | | | [-0.31] |
| $R^2$ | 0.232 | 0.702 | 0.701 | 0.762 |
| N | 28010 | 28010 | 28010 | 20756 |
| County FE | N | N | Y | Y |
| YQ FE | N | Y | Y | Y |

## Appendix Table 10
## Mortgage rates and concentration: Driscoll-Kraay standard errors

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs quarterly 1999-2014. Observations are weighted by the quantity of loans in the county-quarter. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The final column restricts the sample to the years before the financial crisis, 1999-2007. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are Driscoll-Kraay with 5 lags, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | 0.808 | 0.676 | 0.677 | 2.621 | 1.036 |
| | [5.15] | [4.78] | [5.11] | [2.63] | [-0.23] |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **-1.288** | **-0.926** | **-0.932** | **-0.983** | **-1.093** |
| | **[-2.92]** | **[-2.61]** | **[-2.08]** | **[-2.19]** | **[-2.23]** |
| Top 4$_{k,t-1}$ | -0.199 | -0.026 | 0.001 | -0.023 | -0.05 |
| | [-1.31] | [-0.40] | [-0.08] | [0.05] | [-0.03] |
| Δ MBS Yield$_t$ | | | | 0.008 | -0.043 |
| x ln(Population$_{k,t-1}$) | | | | [0.51] | [-1.34] |
| Δ MBS Yield$_t$ | | | | -0.347 | 0.239 |
| x ln(Wage $_{k,t-1}$) | | | | [-2.08] | [1.13] |
| Δ MBS Yield$_t$ | | | | 0.052 | -0.054 |
| x ln(Price $_{k,t-1}$) | | | | [1.04] | [-1.50] |
| Δ MBS Yield$_t$ | | | | -0.006 | -0.002 |
| x % Over 65 $_{k,t-1}$ | | | | [-0.95] | [-0.34] |
| Δ MBS Yield$_t$ | | | | -0.002 | 0.007 |
| x % Under 18 $_{k,t-1}$ | | | | [-0.48] | [0.97] |
| Δ MBS Yield$_t$ | | | | 0 | -0.002 |
| x % Black $_{k,t-1}$ | | | | [0.62] | [-2.67] |
| Δ MBS Yield$_t$ | | | | -0.002 | -0.007 |
| x % High School $_{k,t-1}$ | | | | [-0.29] | [-0.67] |
| Δ MBS Yield$_t$ | | | | -0.001 | -0.001 |
| x Homeowner $_{k,t-1}$ | | | | [-0.46] | [-0.26] |
| $R^2$ | 0.266 | 0.329 | 0.318 | 0.327 | 0.513 |
| N | 29463 | 29463 | 29463 | 21760 | 12438 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 11
## Refinancing and concentration: Driscoll-Kraay standard errors

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; Top 4 is the share of the top 4 mortgage originators; ΔMBS Yield is the change in the Fannie Mae 30-year FRM MBS yield; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2006. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are Driscoll-Kraay with 4 lags, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| Δ MBS Yield$_t$ | -0.019 | | | | |
| | [-5.82] | | | | |
| Δ MBS Yield$_t$ x Top4$_{k,t-1}$ | **0.018** | **0.019** | **0.019** | **0.014** | **0.016** |
| | **[3.08]** | **[8.11]** | **[8.17]** | **[4.72]** | **[5.16]** |
| Top 4$_{k,t-1}$ | -0.001 | 0.006 | 0.007 | -0.003 | -0.007 |
| | [-0.18] | [3.33] | [2.05] | [-1.01] | [-1.64] |
| Δ MBS Yield$_t$ | | | | -0.002 | -0.004 |
| x DTI$_{k,t-1}$ | | | | [-0.82] | [-1.26] |
| Δ MBS Yield$_t$ | | | | 0.002 | 0.002 |
| x ln(Population$_{k,t-1}$) | | | | [3.50] | [2.89] |
| Δ MBS Yield$_t$ | | | | -0.009 | -0.008 |
| x ln(Wage $_{k,t-1}$) | | | | [-3.23] | [-2.24] |
| Δ MBS Yield$_t$ | | | | -0.004 | -0.006 |
| x ln(Price $_{k,t-1}$) | | | | [-1.56] | [-1.55] |
| Δ MBS Yield$_t$ | | | | 0.000 | 0.000 |
| x % Over 65 $_{k,t-1}$ | | | | [1.65] | [1.00] |
| Δ MBS Yield$_t$ | | | | 0.000 | 0.000 |
| x % Under 18 $_{k,t-1}$ | | | | [-1.56] | [-1.72] |
| Δ MBS Yield$_t$ | | | | 0.000 | 0.000 |
| x % Black $_{k,t-1}$ | | | | [4.22] | [3.11] |
| Δ MBS Yield$_t$ | | | | 0.001 | -0.001 |
| x % High School $_{k,t-1}$ | | | | [0.72] | [-0.41] |
| Δ MBS Yield$_t$ | | | | -0.003 | -0.006 |
| x Homeowner $_{k,t-1}$ | | | | [-2.39] | [-3.04] |
| $R^2$ | 0.501 | 0.775 | 0.764 | 0.823 | 0.831 |
| N | 11943 | 11943 | 11943 | 7775 | 4673 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 12
## Mortgage rates and concentration

This table presents regressions of the form:

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta Incentive_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta Incentive_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs quarterly 1999-2014. Observations are weighted by the quantity of loans in the county-quarter. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Top 4 is the share of the top 4 mortgage originators; ΔIncentive is the change in the current coupon Fannie Mae 30-year FRM MBS yield minus the average coupon paid on existing MBS; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price from Zillow. The final column restricts the sample to the years before the financial crisis, 1999-2007. In the fourth and fifth columns, the levels of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| $\Delta Incentive_t$ | 0.695 | 0.629 | 0.629 | -3.742 | -2.369 |
| | [3.49] | [3.46] | [3.42] | [-4.11] | [-2.95] |
| $\Delta Incentive_t$ x $Top4_{k,t-1}$ | **-1.119** | **-0.894** | **-0.897** | **-0.836** | **-1.175** |
| | **[-2.11]** | **[-2.01]** | **[-1.98]** | **[-1.89]** | **[-1.96]** |
| Top $4_{k,t-1}$ | -0.191 | 0.052 | 0.082 | 0.15 | 0.023 |
| | [-0.95] | [0.98] | [0.65] | [0.98] | [0.65] |
| $\Delta Incentive_t$ | | | | -0.023 | -0.058 |
| x ln($Population_{k,t-1}$) | | | | [-1.26] | [-1.99] |
| $\Delta Incentive_t$ | | | | 0.161 | 0.523 |
| x ln($Wage_{k,t-1}$) | | | | [0.97] | [2.92] |
| $\Delta Incentive_t$ | | | | 0.078 | -0.043 |
| x ln($Price_{k,t-1}$) | | | | [1.27] | [-1.13] |
| $\Delta Incentive_t$ | | | | 0.032 | 0.019 |
| x % Over $65_{k,t-1}$ | | | | [3.87] | [2.45] |
| $\Delta Incentive_t$ | | | | 0.058 | 0.038 |
| x % Under $18_{k,t-1}$ | | | | [5.73] | [4.65] |
| $\Delta Incentive_t$ | | | | 0.002 | -0.003 |
| x % $Black_{k,t-1}$ | | | | [1.05] | [-2.60] |
| $\Delta Incentive_t$ | | | | 0.015 | 0.002 |
| x % High $School_{k,t-1}$ | | | | [2.18] | [0.21] |
| $\Delta Incentive_t$ | | | | -0.007 | -0.005 |
| x $Homeowner_{k,t-1}$ | | | | [-2.74] | [-1.41] |
| $R^2$ | 0.199 | 0.299 | 0.288 | 0.475 | 0.599 |
| N | 29463 | 29463 | 29463 | 21760 | 12438 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 13
## Refinancing and concentration

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta Incentive_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta Incentive_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}.$$

The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population; Top 4 is the share of the top 4 mortgage originators; ΔIncentive is the change in the current coupon Fannie Mae 30-year FRM MBS yield minus the average coupon paid on existing MBS; ln(Wage) is the log average weekly wage; ln(Population) is the log population; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. The final column restricts the sample to the years before the financial crisis, 1990-2007. The levels and differences of the controls are suppressed for compactness but included in the regressions. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

| | | | | | |
|---|---|---|---|---|---|
| $\Delta Incentive_t$ | -0.021 | | | | |
| | [-6.57] | | | | |
| $\Delta Incentive_t$ x $Top4_{k,t-1}$ | **0.023** | **0.019** | **0.02** | **0.013** | **0.015** |
| | **[4.34]** | **[5.84]** | **[5.73]** | **[2.71]** | **[2.36]** |
| Top $4_{k,t-1}$ | 0.000 | 0.000 | 0.000 | -0.007 | -0.014 |
| | [0.08] | [0.16] | [0.10] | [-1.42] | [-1.57] |
| Δ $Incentive_t$ | | | | -0.003 | -0.005 |
| x $DTI_{k,t-1}$ | | | | [-1.27] | [-1.38] |
| $\Delta Incentive_t$ | | | | 0.002 | 0.002 |
| x ln($Population_{k,t-1}$) | | | | [3.38] | [2.59] |
| $\Delta Incentive_t$ | | | | -0.01 | -0.009 |
| x ln($Wage_{k,t-1}$) | | | | [-3.22] | [-2.29] |
| $\Delta Incentive_t$ | | | | -0.003 | -0.005 |
| x ln($Price_{k,t-1}$) | | | | [-1.26] | [-1.35] |
| $\Delta Incentive_t$ | | | | 0.000 | 0.000 |
| x % Over $65_{k,t-1}$ | | | | [1.71] | [0.94] |
| $\Delta Incentive_t$ | | | | 0.000 | 0.000 |
| x % Under $18_{k,t-1}$ | | | | [-1.19] | [-1.75] |
| $\Delta Incentive_t$ | | | | 0.000 | 0.000 |
| x % $Black_{k,t-1}$ | | | | [4.15] | [3.03] |
| $\Delta Incentive_t$ | | | | 0.001 | -0.001 |
| x % High $School_{k,t-1}$ | | | | [0.72] | [-0.41] |
| $\Delta Incentive_t$ | | | | -0.003 | -0.006 |
| x $Homeowner_{k,t-1}$ | | | | [-2.39] | [-3.04] |
| $R^2$ | 0.427 | 0.772 | 0.762 | 0.824 | 0.833 |
| N | 11942 | 11942 | 11942 | 7775 | 4673 |
| County FE | N | N | Y | Y | Y |
| Year FE | N | Y | Y | Y | Y |

## Appendix Table 14
## Mortgage rates IV estimates

This table reports results where we estimate the regression

$$\Delta R_{k,t} = \alpha + \beta_1 \cdot \Delta Incentive_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta Incentive_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t}\,,$$

using bank mergers as an instrument for concentration. R is the average of mortgage rates residualized with respect to FICO and LTV in the county-quarter; Observations are weighted by the quantity of loans in the county-quarter. We examine the effect of the merger on the county's mortgage market concentration in the first column. Top 4 is the share of the top 4 mortgage originators; ΔIncentive is the change in the current coupon Fannie Mae 30-year FRM MBS yield minus the average coupon paid on existing MBS. Standard errors are clustered by county and quarter, with t-statistics reported in brackets.

| | First Stage (Joint F = 7.6) | | IV | | Reduced Form | |
|---|---|---|---|---|---|---|
| | Top 4 | Δ Incentive$_t$ x Top4$_{k,t-1}$ | | | | |
| Post$_{k,t}$ | **0.005** | -0.001 | | | 0.003 | 0.002 |
| | **[5.49]** | [-0.09] | | | [0.15] | [0.15] |
| Δ Incentive$_t$ | 0 | **0.31** | | | **-0.084** | **-0.037** |
| x Post$_{k,t}$ | [0.57] | **[27.05]** | | | **[-1.55]** | **[-1.59]** |
| Δ Incentive$_t$ | | | 1.047 | -3.082 | 0.413 | -3.909 |
| | | | [3.09] | [-3.18] | [4.97] | [-4.35] |
| ΔIncentive$_t$ x Top4$_{k,t-1}$ | | | **-2.224** | **-2.665** | | |
| | | | **[-2.17]** | **[-0.77]** | | |
| Top4$_{k,t-1}$ | | | -0.784 | -0.562 | | |
| | | | [-0.24] | [-0.23] | | |
| ΔIncentive$_t$ | | | | -0.085 | | -0.023 |
| x ln(Population$_{k,t-1}$) | | | | [-1.05] | | [-1.92] |
| ΔIncentive$_t$ | | | | 0.383 | | 0.13 |
| x ln(Wage$_{k,t-1}$) | | | | [1.65] | | [0.71] |
| ΔIncentive$_t$ | | | | 0.017 | | 0.067 |
| x ln(Price$_{k,t-1}$) | | | | [0.34] | | [1.00] |
| ΔIncentive$_t$ | | | | 0.037 | | 0.031 |
| x % Over 65$_{k,t-1}$ | | | | [2.15] | | [3.60] |
| ΔIncentive$_t$ | | | | 0.06 | | 0.057 |
| x % Under 18$_{k,t-1}$ | | | | [3.79] | | [5.10] |
| ΔIncentive$_t$ | | | | -0.003 | | 0.002 |
| x % Black$_{k,t-1}$ | | | | [-0.50] | | [1.30] |
| ΔIncentive$_t$ | | | | 0.019 | | 0.016 |
| x % High School$_{k,t-1}$ | | | | [1.85] | | [2.25] |
| ΔIncentive$_t$ | | | | -0.014 | | -0.004 |
| x Homeowner$_{k,t-1}$ | | | | [-0.98] | | [-1.49] |
| $R^2$ | 0.835 | 0.775 | 0.266 | 0.447 | 0.284 | 0.467 |
| N | 26105 | 26105 | 25682 | 19143 | 25682 | 19143 |
| County FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |

## Appendix Table 15
## Refinancing IV estimates

This table reports results where we estimate the regression

$$\Delta\left(\frac{Refi}{Pop}\right)_{k,t} = \alpha + \beta_1 \cdot \Delta Incentive_t + \beta_2 \cdot Top\ 4_{k,t-1} + \beta_3 \cdot \Delta Incentive_t \times Top\ 4_{k,t-1} + \boldsymbol{\gamma}'\mathbf{X}_{k,t} + \varepsilon_{k,t},$$

using bank mergers as an instrument for concentration. The county-level sample runs annually 1990-2014. Observations are weighted by population. Refi/Pop is the number of refinancings divided by the population. We examine the effect of the merger on the county's mortgage market concentration in the first column. Top 4 is the share of the top 4 mortgage originators; ΔIncentive is the change in the current coupon Fannie Mae 30-year FRM MBS yield minus the average coupon paid on existing MBS. Standard errors are clustered by county and year with t-statistics reported in brackets.

| | First Stage (Joint F = 7.6) | | IV | | Reduced Form | |
|---|---|---|---|---|---|---|
| | Top 4 | Δ Incentive$_t$ x Top4$_{k,t-1}$ | | | | |
| Post$_{k,t}$ | **0.005** | -0.001 | | | 0 | 0 |
| | **[5.49]** | [-0.09] | | | [-0.49] | [-0.16] |
| Δ Incentive$_t$ | 0 | **0.31** | | | **0.002** | **0.001** |
| x Post$_{k,t}$ | [0.57] | **[27.05]** | | | **[2.73]** | **[1.87]** |
| Δ Incentive$_t$ | | | | | | |
| ΔIncentive$_t$ x Top4$_{k,t-1}$ | | | **0.093** | **0.629** | | |
| | | | **[3.97]** | **[1.71]** | | |
| Top4$_{k,t-1}$ | | | 0.024 | 0.164 | | |
| | | | [0.51] | [0.36] | | |
| ΔIncentive$_t$ | | | | 0.002 | | 0.001 |
| x ln(Population$_{k,t-1}$) | | | | [1.53] | | [2.97] |
| ΔIncentive$_t$ | | | | -0.006 | | -0.009 |
| x ln(Wage$_{k,t-1}$) | | | | [-1.16] | | [-3.12] |
| ΔIncentive$_t$ | | | | 0.002 | | -0.001 |
| x ln(Price$_{k,t-1}$) | | | | [0.21] | | [-0.77] |
| ΔIncentive$_t$ | | | | -0.005 | | -0.005 |
| x % Over 65$_{k,t-1}$ | | | | [-1.65] | | [-2.40] |
| ΔIncentive$_t$ | | | | 0 | | 0 |
| x % Under 18$_{k,t-1}$ | | | | [0.83] | | [2.13] |
| ΔIncentive$_t$ | | | | 0.004 | | 0 |
| x % Black$_{k,t-1}$ | | | | [0.34] | | [-1.44] |
| ΔIncentive$_t$ | | | | 0.007 | | 0.002 |
| x % High School$_{k,t-1}$ | | | | [1.29] | | [1.01] |
| ΔIncentive$_t$ | | | | -0.028 | | 0.000 |
| x Homeowner$_{k,t-1}$ | | | | [-1.84] | | [-0.61] |
| $R^2$ | 0.634 | 0.642 | 0.701 | 0.802 | 0.765 | 0.832 |
| N | 8831 | 8831 | 8831 | 6929 | 8831 | 6929 |
| County FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |