Concentration in Mortgage Lending, Refinancing Activity, and Mortgage Rates*

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Abstract

We present evidence that high concentration in local mortgage lending reduces the sensitivity of mortgage rates and refinancing activity to mortgage-backed security (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. 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 housing as a monetary policy transmission channel varies in both the time series and the cross section. Increasing concentration by one standard deviation above the mean reduces the overall impact of a decline in MBS yields by approximately 50%.

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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 is an important channel through which monetary policy may affect consumption. An easing of monetary policy allows households to refinance their mortgages at lower rates, reducing payments from borrowers to lenders. If borrowers have higher marginal propensities to consume than borrowers, they can then use the additional cash to finance other consumption, boosting aggregate consumption in the process. This would be the case if, for instance, borrowers are liquidity constrained. Indeed, refinancing is probably the most direct way in which monetary policy increases the disposable cash flow of liquidity constrained households (Hurst and Stafford 2004).

The importance of using monetary policy to support the housing sector has increased in recent years. In particular, 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. The aim of these policies was to lower mortgage rates to consumers by reducing the costs of financing for mortgage lenders (Bernanke 2009, 2012). Many have argued that the effectiveness of these policies has been hampered by the high indebtedness of many households (Eggertson and Krugman, 2012; Mian, Rao, and Sufi, 2012). According to these arguments, "underwater" households, whose remaining mortgage balance exceeds the value of their home, have been unable to refinance, reducing the impact of low interest rates on the economy.

In this paper, we explore a second friction that could impede the transmission of monetary policy to the housing sector: market power in mortgage lending. As shown in Figure 1, concentration in the mortgage lending industry increased substantially between 1994 and 2011.[1] A common idea in industrial organization is that cost "pass-through" is lower in concentrated

[1] Avery et. al. (2012) and Fuster et. al. (2012) argue that concentration has not risen much in recent years. The difference arises because Avery et. al. (2012) and Fuster et. al. (2012) focus on the market share of the top 10 lenders at the national level. In our data, the average value-weighted top 10 share across counties has increased over time, despite the fact that the national top 10 share has remained constant. This reflects increased geographical segmentation of lending. For instance, suppose there are two identical counties where two lenders each have a 50% market share. Then the average county market share and the aggregate share of each lender is 50%. However, if each lender concentrates in a different county, the average county-level share can go to 100% while their aggregate shares remain at 50%.

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

Evidence from the aggregate time series is broadly consistent with the idea that concentration in mortgage lending impacts mortgage rates. Figure 2 shows the average difference between the mortgage rate paid by borrowers and the yield on MBS for conforming loans guaranteed by the government-sponsored entity (GSE) Freddie Mac. [2] The yield on Freddie Mac MBS is the amount being paid to investors (savers) in the securities, who are providing financing for the loans, so the spread is a measure of the revenue going to mortgage originators and servicers. The spread rose substantially from 1994 to 2011. Moreover, as shown in Figure 3, the spread is highly correlated with mortgage market concentration. The correlation is 66% in levels and 59% in changes, so the correlation does not simply reflect the fact that both series have a positive time trend.

Of course, many other changes in the mortgage lending business took place over the sample period, so the time series evidence is not definitive. In this paper, we use panel data to examine the effects of mortgage market concentration. 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.

Using the yield on GSE-guaranteed MBS as a proxy for the costs of mortgage financing, we find that mortgage rates paid by borrowers are less sensitive to costs in concentrated mortgage markets. A decrease in MBS yields that reduces mortgage rates by 100 basis points (bps) in the mean county reduces rates only 73 bps in a county with concentration one standard deviation (18%) above the mean.

[2] Specifically, Figure 2 shows the time series of the borrowing rate reported in Freddie Mac's Weekly Primary Mortgage Market Survey minus the yield on current coupon Freddie Mac MBS minus the average guarantee fee charged by Freddie Mac on its loans.

Moreover, when MBS yields fall, the quantity of refinancing increases in the aggregate. However, the quantity of refinancing increases 35% less in the high-concentration county relative to the average county. These two effects 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. Taken together, they suggest that the housing channel of monetary policy transmission has approximately half the impact in the high-concentration county relative to the average county.

Of course, mortgage market concentration is not randomly assigned, so it is difficult to ascribe causality to these results. We attempt to address endogeneity concerns in a variety of ways. First, our basic results are robust to a battery of controls including county and time fixed effects, population, wages, house prices, and mortgage characteristics. 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 yield, even after controlling for the fact that this sensitivity can be different in counties with different 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 a bank involved in a merger is an important source of financing, but the county itself makes up only a small fraction of the bank's operations. Mergers increase the concentration of mortgage lending in such counties. However, because the county makes up a small fraction 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 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 refinancings 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.

Finally, using data on bank profits and employment, we provide evidence that market power is the mechanism behind the lower pass-through of MBS yields into mortgage rates. Interest and fee income from real estate loans, reported in the Call Reports banks file with the Federal Reserve, is typically positively correlated with MBS yields because interest income falls when yields fall. However, we show that interest and fee income is less sensitive to MBS yields in high-concentration counties. This suggests that banks in concentrated mortgage markets are able to use their market power to protect their profits when MBS yields fall. Similarly, employment in real estate credit is typically negatively correlated with MBS yields because refinancing demand decreases as MBS yields rise. However, the sensitivity is less negative (i.e., lower in absolute terms) in high-concentration counties. Taken together, while we cannot completely rule out alternative explanations, the evidence is consistent with the idea that mortgage market concentration decreases the transmission of monetary policy to the housing sector.

From the policy perspective, our results have both time series and the cross-sectional implications for the effectiveness of monetary policy. Specifically, the impact of monetary policy could be decreasing over time due to the increase in average mortgage market concentration documented in Figure 1. In addition, even in the absence of a time series trend, monetary policy could have different impacts across counties due to cross sectional variation in mortgage concentration across counties.

The remainder of this paper is organized as follows. Section II gives some relevant background on the mortgage market, and Section III presents a brief model to motivate our empirics. Section IV describes the data, and Section V presents the main results. 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. Conforming mortgages must meet certain qualifying characteristics. For instance, their sizes must be below the so-called conforming loan limit, which is set by the Federal Housing Finance Authority. In addition, borrowers eligible for conforming mortgages must have credit (FICO) scores above 620 and the mortgages must meet basic GSE guidelines in terms of loan-to-value ratios (LTVs) and documentation. Such mortgages may be put into MBS pools guaranteed by the GSEs. The GSEs guarantee investors purchasing 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. In return for their guarantee, the GSE charges investors a guarantee fee.

An important fact for our empirical analysis is that GSE guarantee fees do not vary geographically. Indeed, until 2008 the GSEs charged 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. From 2008 onwards, guarantee fees vary by FICO score, LTV, and loan type, but not geography or any other borrower characteristics.[3] 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.[4,5]

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

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

[5] 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 investors' 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.

B. Definition of the Local Mortgage Market

A key assumption of 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, 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.

Moreover, borrowers report that they exert little effort in shopping around 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 competition has effects on the local mortgage market. Competition could affect loan terms like rates and points charged upfront, but could 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.

III. Model

We now present a brief model of mortgage market competition to motivate our empirics. The model features Cournot competition with capacity constraints and delivers three main results. First, the pass-through of MBS yields to mortgage rates is larger in markets with more competing lenders. Second, pass-through is asymmetric: mortgage rates fall less when MBS yields fall than they rise when MBS yields rise. Third, this asymmetry disappears as there are more competing lenders in the market.

We assume linear demand for mortgages so that

$$p(Q) = a - bQ\,.$$

This can be motivated by assuming that there are fixed costs to refinancing and mortgage rates are initially uniformly distributed, but here we simply take it as given. Each lender producing mortgages 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, *r*. However, if a lender wishes to produce more than its pre-existing capacity, it faces convex adjustment costs, which capture the idea that it is costly to adjust capacity. Formally, production costs are given by

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

We assume Cournot competition, so firms solve the following maximization problem

$$\max_q \; p(Q)q - C(q).$$

We solve for the symmetric Nash equilibrium, which is described by the following proposition.

Proposition 1. *Optimal lender production decisions depend on the MBS yield r and are given by*

$$q^* = \begin{cases} q^*_{low} & \text{if } r \ge \bar{r} \\ \bar{q} & r \in \left[\underline{r}, \bar{r}\right] \\ q^*_{high} & \text{if } r < \underline{r} \end{cases}$$

where

$$q^*_{low} = \frac{a-r}{b(N+1)}, \; q^*_{high} = \frac{a-r}{b(N+1)+c}$$

and

$$\underline{r} = a - \bar{q}\left(b(N+1)+c\right), \; \underline{r} = a - \bar{q}b(N+1).$$

Proof*. All proofs are given in the Appendix.*

The equilibrium depends on the MBS yield *r*. When the MBS yield is high, the demand for loans will be low and can be met using existing capacity. In contrast, if MBS yields are lows, demand will be high, and lenders will add capacity to meet this demand. For intermediate values of MBS yields, the increase in marginal costs associated with adding capacity is too large and firms operate exactly at capacity.

We can now study pass-through, the sensitivity of prices 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 $\overline{q} = \overline{Q} / N$ where $\overline{Q}$ is aggregate industry capacity. Thus, as we vary *N*, aggregate industry capacity is fixed but become distributed among a larger number of lenders. Note that this normalization implies that both $\underline{r}$ and $\overline{r}$ approach $a - b\overline{Q}$ as *N* grows large. As the industry becomes very competitive, the range of MBS yields where lenders operate exactly at capacity vanishes.

The following proposition describes the aggregate sensitivities of quantities and prices to changes in MBS yields.

Proposition 2. *Let* $Q^*_{low} = Nq^*_{low}$ *and* $Q^*_{high} = Nq^*_{high}$ *be the total quantities produced. Then mortgage quantities rise when MBS yields fall:* $\partial Q^*_{low} / \partial r < 0$ *and* $\partial Q^*_{high} / \partial r < 0$. *In addition, mortgage rates fall when MBS yields fall:* $\partial P\left(Q^*_{low}\right) / \partial r > 0$ *and* $\partial P\left(Q^*_{high}\right) / \partial r > 0$. *Finally, these sensitivities are larger in magnitude when there are more lenders:* $\partial^2 Q^*_{low} / \partial r \partial N < 0$, $\partial^2 Q^*_{high} / \partial r \partial N < 0$, $\partial^2 P\left(Q^*_{low}\right) / \partial r \partial N > 0$, $\partial^2 P\left(Q^*_{high}\right) / \partial r \partial N > 0$.

When MBS yields fall, 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 are low enough, the demand for mortgages will be high enough that it is worthwhile for lenders to add capacity. As the number of lenders increases, each has less effective market power, so more of the benefit of low MBS yields is passed on to borrowers.

Finally, the model delivers asymmetric pass through, as the following proposition describes.

Proposition 3. *Pass-through is asymmetric. Mortgage rates are more sensitive to MBS yields when yields are high:* $\partial P\left(Q^*_{low}\right) / \partial r > \partial P\left(Q^*_{high}\right) / \partial r$. *Similarly, quantities are more sensitive to MBS yields when yields are high:* $\left|\partial Q^*_{low} / \partial r\right| > \left|\partial Q^*_{high} / \partial r\right|$. *This difference vanishes as the number of lenders grows large.*

The pass-through of changes in MBS yields is larger when yields are high and pre-existing capacity can be used to satisfy demand. When MBS yields are lower, additional capacity must be added to meet demand. The additional costs of adding capacity mean that mortgage rates to borrowers do not fall as much as MBS yields fall. However, with more lenders, this asymmetry vanishes. Each lender can make a small capacity adjustment, leading to a large increase in aggregate capacity.[6]

The model while simple serves to motivate our empirics, and shows that the intuitive link between pass through and market competition can be formalized. Moreover, the model underscores the link between industry capacity constraints and mortgage market competition. In markets with few lenders, lenders will be reluctant to add capacity to meet increased demand for mortgages.

IV. 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, the identity of the lender, as well as loan characteristics including year, county, dollar amount, and borrower income. Summary statistics for the sample of HMDA data we use are shown in Table 1 Panel A. Unfortunately, the data lack information on mortgage rates as well as FICO scores and loan-to-value ratios, which play a critical role in determining rates (Rajan, Seru, and Vig, 2012).

Since it contains lender identities, we can use the HMDA data 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 lenders in the county, though our results are robust to other measures such as the Herfindahl-Hirschman index (HHI). Figure 1 shows the time series of nation-wide top 4 concentration as well as the time series of the average county-level top 4 concentration.

[6] It is worth noting that asymmetric pass-through can be a symptom of high market power, but it need not be (Bulow and Pfleiderer, 1983). In general, the response of prices to costs depends on the curvature of the demand function as well as market structure (Dornbusch, 1987; Knetter, 1989; Bergin and Feenstra, 2001; Atkeson and Burstein, 2008).

To supplement the HMDA data, we use aggregates from the CoreLogic loan level servicing database. This database contains information on all the loans, including loans guaranteed by the GSEs, from a set of servicers that have data-sharing agreements with CoreLogic. This includes all large servicers, and loan volumes in the database range from 30-50% of loan volumes in HMDA. The data we work with are monthly aggregates at the county level for prime, full documentation, and fixed rate loans. The data contain mortgage rates, FICO scores, and LTVs.

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

V. Results

A. Baseline Results: Quantity of Refinancings

We now turn to the results. We begin by examining the frequency of refinancing in the HMDA sample. For each county we construct the number of mortgages refinanced in a given year, normalized by the county's population in that year. 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:

$$\Delta\left(\frac{Refi}{Pop}\right)_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{i,t} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{i,t} + \varepsilon_{i,t}.$$

The coefficient of interest is β_3, which measures the difference in sensitivities to MBS yields, between high and low concentration counties.

Table 2 Panel A shows the results. The first column shows that a 100 bps decrease in MBS yields (for reference, the standard deviation of MBS yields is 60 bps) increases the quantity of refinancings per person by 0.8% (percentage points) in a county with an average level of mortgage market concentration (46.4%). Relative to the standard deviation of refinancings per person of 1.2%, this is a large effect. Consistent with the predictions of the model in Section III, 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 (17.6%) decreases the effect of MBS yields by 35% (=.016 * 17.6%/0.8). The second column shows that the effects are stronger once we add county and year fixed effects. The time fixed effects show that the results are not simply due to changes in the sensitivity of refinancing to MBS yields over time. This shows that our results are unchanged when we isolate the cross-sectional variation in our data. Similarly, the third column shows that our results are equally strong if we restrict the sample to the period before the financial crisis, 1994-2006.

The fourth column shows that the lower sensitivity of refinancings per person to changes in MBS yields in high-concentration counties is particularly strong at times when MBS yields are falling. It is well known that in many markets prices fall more slowly in response to cost decreases than they rise in response to cost increases (Peltzman, 2000). As the model in Section III demonstrated asymmetric pass-through can be a symptom of high market power. Indeed, many studies in macroeconomics and industrial organization, take asymmetric pass-through as a sign of market power (e.g., Blinder ,1994; Blinder et al, 1998; Borenstein, Cameron, and Gilbert, 1997; Chenes, 2010; Jackson, 1997; Karrenbrock, 1991; Neumark and Sharpe, 1992).

The remaining columns show that the results are robust to a battery of additional controls including county-level population, average wages, loan size, debt-to-income ratios,[7] and house price appreciation.[8] In addition, Panel B of Table 2 shows that the results are robust to controlling for the interaction of changes in MBS yields with these characteristics. It is reassuring to note that the coefficients across specifications and controls are remarkably 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.

Finally, Panel C of Table 2 shows that that our results are not driven by differences in homeownership rates between high- and low-concentration counties. Specifically, it could be the case that high-concentration counties have low homeownership rates, and thus simply have less

[7] The debt-to-income ratios used here are from HMDA, and thus reflect the ratio of mortgage debt to income for mortgage borrowers. As shown in Table 4 below, our results are also robust on controlling for the ratio of total debt to income at the county level, which is studied Mian, Rao, and Sufi (2012).

[8] 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 smaller drops in observations in the earlier columns reflect data missing in HMDA.

scope for variation in refinancings per person since renters have no need to refinance. To address this concern, Panel C displays the same specifications as Panel B but uses as the dependent variable the change in refinancings normalized by owner-occupied housing units. We obtain county-level data on housing units from the Census Bureau's American Community Survey, which provides this information annually for counties with populations over 65,000.[9] The results are very similar to those in Panel B. Refinancings per owner-occupied housing unit increase when MBS yields fall, and the effect is smaller in high-concentration counties. Thus, differences in homeownership rates across counties cannot account for our results.

B. Baseline Results: Mortgage Rates

We next turn to the behavior of mortgage rates in the CoreLogic data. For each county-month, we take the average rate on prime, full-documentation, and fixed-rate loans. We restrict the sample to county-months with at least 5 loans, average FICO scores greater than 620, and average LTVs between 50 and 101. We regress the change in rates on the change in 30-year Fannie Mae current coupon MBS yields over the month, county-level top-4 concentration lagged one year, and the interaction of the two. Formally, we run:

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

Again, the coefficient of interest is β_3, which measures the difference in sensitivities to MBS yields, between high- and low-concentration counties.

Table 3 Panel A shows the results. The first column shows that a 100 bps decrease in MBS yields is associated with a 40 bps decrease in mortgage rates for borrowers in a county with an average level of mortgage market concentration. This is substantially less than a one-for-one relationship because of timing issues at the monthly level. Specifically, mortgages originated in a given month may have been agreed upon and locked in borrowing rates up to 6 weeks before the formal closing date. We obtain magnitudes closer to one-for-one for the average county if we aggregate the data up to the county-quarter or county-year level. However, the differential

[9] The ACS data begins in 2005. We backfill the number of owner-occupied housing units in each county for years before 2005 assuming the owner-occupancy rate is constant in earlier years. This preserves the cross-sectional variation in rates across counties, which is the most important dimension of variation in the data. The annual autocorrelation of county-level owner-occupancy rates is 0.96, so assuming a constant rate within county is a reasonable assumption.

sensitivity between high- and low-concentration counties, which is our main focus, is unaffected by such time aggregation. For robustness, Appendix Table 1 presents the same results as Table 3 but using data aggregated up to the county-quarter level.

Consistent with the model's predictions, the coefficient on the interaction between MBS yields and concentration implies that high concentration reduces the pass-through of MBS yields to borrowers. A one standard deviation increase in concentration decreases the effect of MBS yields on rates to borrowers by 27% (=.626 * 17.4%/40%). The second column in Table 3 Panel A adds county and year fixed effects, indicating that results are not driven solely by aggregate time trends or by fixed differences across counties. The third column shows that results persist when we restrict the sample to the pre-crisis period, 2000-2006. Though mortgage market concentration has grown substantially over recent years, the results we document here are not solely driven by the period during and after the financial crisis. The fourth column shows that the low sensitivity of mortgage rates to changes in MBS yields in high-concentration counties is particularly strong at times when MBS yields are falling. As discussed above, asymmetric pass-through can be a symptom of high market power. The statistical evidence is somewhat weaker here than in Table 2 because our mortgage rate data has a shorter time dimension (2000-2011) than our refinancing quantity data (1994-2011).

The remaining columns of Table 3 Panel A show that the results are robust to controlling for changes in LTV, changes in FICO, and house price appreciation. Panel B of Table 3 shows that the results are also robust to controlling for the interaction of changes in MBS yields with these characteristics. Again, it is reassuring to note that the coefficients across specifications and controls are remarkably consistent.

Unfortunately, our data does not contain information on points charged up front, fees, and closing costs. Thus, our results essentially assume that these costs do not covary with market concentration. In particular, if fees were lower in high-concentration areas, this may offset the smaller sensitivity to MBS yields we find in those counties. In untabulated results using data from the Monthly Interest Rate Survey (MIRS) conducted by the Federal Housing Finance Agency, we find that fees are on average higher in high-concentration counties, not lower. Moreover, fees are equally sensitive to MBS yields in high- and low-concentration counties.

C. *Assessing Magnitudes*

What is the total economic magnitude of the effects of market concentration we are finding? There are two different ways to answer this question. First, we can assess the relative effect across counties. 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 2 imply that a decrease in MBS yields has a 35% smaller effect on the quantity of refinancing in a county with concentration one standard deviation above the mean than in a county with average concentration. For the households that do refinance, the results in Table 3 show that a decrease in MBS yields has a 27% smaller effect on mortgage rates in the high-concentration county. Taken together, these imply that a decrease in MBS yields has a roughly 50% smaller effect in the high-concentration county.[10]

Table 4 provides a second way to assess the economic magnitude of our results. We can compare the effects of mortgage market concentration to the effects of various proxies for borrower credit quality. In general, having low credit quality can impede refinancing. For instance, Mian, Rao, and Sufi (2012) present evidence that high indebtedness has been an impediment to refinancing in the aftermath of the financial crisis. In the first four columns, we examine effects on the quantity of refinancings. The first column compares the effect of mortgage concentration to the effect of borrower debt-to-income (DTI) ratios. These DTIs are from HMDA, and thus reflect the ratio of mortgage debt to income for mortgage borrowers. The results show that over the full sample, the average level of DTI within a county had no effect on refinancing, while the interaction of DTI and MBS yields is negative. When MBS yields fall, borrowers are more likely to refinance in counties that have high DTIs. This is presumably because borrowers with high DTIs have a stronger incentive to refinance when MBS yields fall. The coefficients imply that a one standard deviation increase in market concentration reduces the sensitivity of refinancing to MBS yields as much as a 0.49 (= .014 * 17.6%/.005) decline in DTI, which corresponds to slightly more than one standard deviation of DTI.

[10] The frequency of refinancing is only 65% as high in the high-concentration county, and each refinancing reduces rates 73% as much. Thus the total effect is only 65%x73% = 48% as large in the high-concentration county.

The second column of Table 4 restricts the sample to the financial crisis period, 2007-2011. Now we see that the level of DTI has a negative effect on refinancing, consistent with Mian, Rao, and Sufi (2012). However, the interaction of MBS yields and DTI is still negative, implying that borrowers in high DTI areas are more likely to refinance when MBS yields fall. One interpretation of these results taken together is that many borrowers are underwater and cannot refinance in counties with high indebtedness. However, borrowers in those counties who are not underwater have strong incentives to refinance when MBS yields fall. The coefficient on the level of DTI implies that a one standard deviation increase in DTI in the crisis period decreases refinancings per capita by 0.1% (percentage points). A one standard deviation increase in concentration reduces the effect of a 100 bps drop in MBS yields by a similar amount in this specification. However, note that because DTI changes slowly within county, its effect on refinancings cumulates over several years. In contrast, a decline in MBS yields is a one-time event.

The third and fourth columns of Table 4 repeat the same exercise, but use a different measure of indebtedness. Specifically, we use county-level data on the ratio of total debt, not just mortgage debt, to income in 2007, as in Mian, Rao, and Sufi (2012). These specifications lack county fixed effects because we only have a single county-level observation for total debt-to-income. However, the coefficients and economic magnitudes are similar to those we obtained using DTIs from HMDA.

The final two columns of Table 4 examine the sensitivity of mortgage rates to changes in credit quality. The columns show that a one standard deviation increase in county-average LTV among mortgage borrowers in the CoreLogic dataset decreases mortgage rates by 5 bps. A one standard deviation decrease in FICO has a similar effect.[11] A one standard deviation increase in concentration reduces the effect of a 100 bps drop in MBS yields by about twice as much.

D. Discussion of Endogeneity Concerns

While the results above are quite robust to a variety of controls, one might still be concerned that market concentration is just a proxying for some other endogenous relationship,

[11] The relationships between rates and FICO scores and rates and LTVs are substantially stronger in levels than in differences. For example, in levels, a one standard deviation decrease in FICO increases rates by about 25 bps.

rather than the directly causing the observed effects through market power. That is, one may worry that our results are driven by unobservable differences between counties along dimensions other than mortgage market concentration. Of course, all our baseline specifications include county fixed effects, which absorb the average effect of any unobservable characteristics on changes in refinancings and mortgage rates. However, unobservable characteristics could still affect the *sensitivities* of the variables to MBS yields.

There are two broad types of confounds one may be concerned about. The first is confounds based on loan characteristics. For instance, as discussed above, low credit quality can impede refinancing when MBS yields fall. If high market concentration is correlated with poor credit quality, then households in high concentration counties may have trouble refinancing when MBS yields fall. However, as shown in Table 2 of the Appendix, we generally find that high concentration is associated with high, not low, credit quality. Moreover, our controls for county-level FICOs, LTVs, and house price appreciation in our results on mortgage rates (Table 3) should absorb such factors. Recall that our analysis focuses on conforming loans, which are eligible for GSE guarantees. Since GSE guarantee fees depend on only FICO scores, LTVs, and year of origination, controlling for these factors should absorb all priced differences in credit quality between conforming loans. Thus, any differences in the response of mortgage rates to MBS yields should not be driven by differences in the credit quality of loans in high- versus low-concentration counties. Indeed, as shown in Table 4, our results are robust to controlling for the measure of county-level indebtedness used by Mian, Rao, and Sufi (2012). Moreover, our results are equally strong if we restrict our sample to the years before the financial crisis, before the problems with high indebtedness emerged. Nonetheless, one may still be concerned that our controls only absorb linear effects of observable characteristics. Therefore, in the next section we use a matching procedure to ensure that our results are comparing counties that are very similar on observables.

The second type of confound that may raise concerns is based on demographic characteristics. Again, to the extent that such confounding demographic characteristics are observable, our controls are likely to absorb them. Nevertheless, there could be important borrower characteristics not fully captured by our controls. For instance, borrower sophistication is difficult to measure, and it could be the case that borrowers in high-concentration counties are less sophisticated than those in low-concentration counties. Thus, they could be slower to refinance when MBS yields fall and search less intensively for the best mortgage rate, leading us to observe less variation in borrowing rates as yields fall. However, it seems likely that such borrowers are more profitable from the lender perspective – unsophisticated borrowers who do not search for the best deal are likely to pay excessively high fees to originators. Thus, their presence would encourage more entry in the mortgage market and lower market concentration. For borrower sophistication to drive our results, it would have to be the case that unsophisticated borrowers are more costly to serve, so that fewer lenders enter areas where they predominate.

To address concerns about demographic confounds, in Section IV.D we examine variation in mortgage market concentration *within a given county* induced by bank mergers that are unlikely to be related to county characteristics. That is, we examine changes in mortgage market concentration in counties that are essentially an unintended consequence of a bank merger. Our results continue to hold when we restrict our attention to this merger-related variation in mortgage market concentration. Assuming that county characteristics are not simultaneously changing, this suggests that we are indeed isolating the effect of market power.

E. Addressing Endogeneity Concerns: Matched Samples

In this section, we try to address the endogeneity concerns discussed above in two ways. First, we employ a matching procedure to ensure that we are comparing counties that are very similar along observable dimensions. We start with the HMDA data. For each year, we try to match each county with a high concentration (above median for the year) to a county with low concentration along a variety of dimensions. We match to the county that is closest along those dimensions as measured by the Mahalobnis metric, which weights the distance between two counties along a given dimension by the inverse variance, properly accounting for the covariances between dimensions (Imbens, 2004; Rubin and Thomas, 1992). Matching along many dimensions can result in a nearest match that is poor along each individual dimension. Therefore, to ensure that each match is high quality, we require that each match is within 1/3 of a standard deviation along each dimension. We then run our baseline specifications in each matched sample.

The results for the HMDA sample are in Table 5 Panel A. The first two columns match on county population and average wages. The second two columns match on population, average wages, DTI, and loan size. The final two columns match on population, average wages, DTI, loan size, and house prices. Appendix Table 3 Panel A shows the quality of the matches along each dimension for each matched sample. While some differences remain when only matching on county population and wages, there are no statistically or economically significant differences in the other matched samples.

The results in Table 5 Panel A show that we obtain very similar results to the baseline in Table 2 when we use the matched samples. High mortgage market concentration is associated with a lower sensitivity of refinancings per capita to MBS yields, and the effect is particularly strong when MBS yields are falling.

The results for the CoreLogic sample are in Table 5 Panel B. The first two columns match on county population and average wages. The second two columns match on population, average wages, FICO, and LTV. The final two columns match on population, average wages, FICO, LTV, and house prices. Appendix Table 3 Panel B shows the quality of the matches along each dimension for each matched sample. As with the HMDA data sample, in the CoreLogic data some differences remain when only matching on county population and wages, but there are no statistically or economically significant differences in the other matched samples.

The results in Table 5 Panel B show that we obtain very similar results to the baseline in Table 3 when we use the matched samples. High mortgage market concentration is associated with a lower sensitivity of mortgage rates to MBS yields. There is some evidence that the effect is particularly strong when MBS yields are falling, though it is not consistent across samples.

F. Addressing Endogeneity Concerns: Bank Mergers

Our second attempt to address endogeneity concerns uses bank mergers to create variation in mortgage market concentration that is plausibly unrelated to county characteristics. Using the FDIC's *Summary of Deposits* to identify the county-level locations of bank operations, we construct a sample of counties affected by bank mergers, where the counties in the sample were not the key motivation for the merger. Specifically, we focus on counties where a bank involved in a merger is an important source of financing: the bank must make up a large 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. Within the sample, we examine how the sensitivity of refinancings and mortgage rates to MBS yields changes after the merger takes place.

Table 6 present the results for two such merger samples. Panel A presents our baseline sample of counties, where a bank involved in a merger makes up more than 15% of the total deposits in the county, but the county itself makes up no more than 2% of the bank's total deposits.[12] In the first column, we examine the effect of mergers on concentration:

$$Top\ 4_{i,t} = \alpha_t + \beta \cdot Post\ Merger_{i,t} + \varepsilon_{i,t}.$$

The results show that each merger is associated with an increase in mortgage market concentration of 3.1%. To the extent that we think of mergers as an instrument in this context, the instrument is relevant. Note that while the effect is statistically significant, it is small relative to the total variation we observe in concentration in the full sample.

We then use mergers as an instrument for concentration. Specifically, we run

$$\Delta\left(\frac{Refi}{Pop}\right)_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot \widehat{Top\ 4_{i,t}} + \beta_3 \cdot \Delta MBS\ Yield_t \times \widehat{Top\ 4_{i,t}} + \varepsilon_{i,t},$$

where $\widehat{Top\ 4_{i,t}}$ is the fitted value from the first stage regression of concentration on the post-merger indicator. Note that only counties that experience a merger that meets the criteria discussed above are in the sample. This means that the coefficients are essentially identified off the timing of the mergers, not the cross-sectional differences in concentration across counties. Moreover, the second stage exercise contains county fixed effects. Thus, the estimates can be interpreted as showing that the sensitivity of refinancings to MBS yields decreases *within a given county* after a merger that increases mortgage market concentration.

[12] The cutoffs capture 25% of bank-counties along each dimension. Specifically, 25% of bank shares of total county deposit are above 15%, and 25% of county shares of total bank deposits are below 2%.

The results show that the sensitivity of refinancings to MBS yields decreases with top 4 concentration when instrumented by the post-merger indicator. The sensitivity of refinancings to MBS yields decreases after a merger at the same time that mortgage market concentration is increasing. Note that the magnitudes of the coefficients are larger here than in Tables 2 and 3. The reason is that the fitted value $\widehat{Top\ 4}_{i,t}$ has less variation than the raw variable $Top\ 4_{i,t}$. Therefore, $\Delta MBS\ Yield_t$ x $\widehat{Top\ 4}_{i,t}$ is more collinear with $\Delta MBS\ Yield_t$ than is $\Delta MBS\ Yield_t \times Top\ 4_{i,t}$. However, the economic magnitudes are similar to those in our earlier results. A 100 bps decrease in MBS yields is associated with a 1.2% increase in refinancings in the average county, but only a 0.78% increase in a county with concentration one standard deviation above the mean. Thus, there is a 35% smaller increase in refinancings in the high-concentration county.

The remaining columns of Table 6 show the analogous results for changes in mortgage rates. Here, the lower power of the instrument comes into play. While the results show that the sensitivity of mortgage rates to MBS yields decreases with concentration as instrument by the post-merger indicators, the results are not statistically significant.

Panel B of Table 6 presents the results for our second merger sample. Here the sample consists of counties where a bank involved in a merger makes up more than 30% of the total deposits in the county, but the county itself makes up no more than 1% of the bank's total deposits. This is a more stringent requirement and therefore the sample in Panel B is much smaller than our first merger sample.

While we have far fewer observations, the benefit of studying this smaller sample is that the instrument is stronger. The first column of Panel B shows that the effect of a merger on mortgage market concentration is just as strong in this sample, both economically and statistically, as it is in the first sample. However, given that the sample is much smaller this means that mergers are a strong instrument in this sample. As argued by Staiger and Stock (1997), F-statistics are a good measure of the power of a set of instruments. The F-statistic of the post-merger dummy in the first sample (Panel A of Table 6) is 12.7, relatively close to Staiger and Stock's minimum recommended value of 10. The F-statistic of the post-merger dummy in the second sample (Panel B) is 19.3, indicating that the instrument is stronger here.

The results in Panel B of Table 6 show that high mortgage market concentration is associated with lower sensitivities to MBS yields. As in Panel A, the results are statistically significant for the number of refinancings. Unlike in Panel A, the results in Panel B are also statistically significant for mortgage rates, reflecting the stronger instrument.

Does our bank merger instrument satisfy the exclusion restriction? The exclusion restriction in this case is that bank mergers affect the sensitivity of refinancings 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.

G. Corroborating Evidence

Finally, we examine non-mortgage data for corroborating evidence of the mechanism. We first analyze the behavior of bank fees and interest income on real estate loans, which is obtained from the Call Reports. If market power in mortgage lending were really driving our results, one might expect that the revenues of lenders would be less sensitive to mortgage rates in high-concentration areas. Lenders in such areas, facing little competition, would have little incentive to offer lower rates when MBS yields fall and, thus, would be able to keep their revenues high.

To examine this prediction, we restrict the sample to banks completely located in one county according to the FDIC's *Summary of Deposits*. This ensures that we are picking up variation in local, county-level conditions. The first two columns of Table 7 show the results. A 100 bps decrease in MBS yields is associated with a 5.9% decrease in fee and interest income on real estate loans. However, this effect is mitigated in higher-concentration counties.

Next we examine employment in real estate credit, which we obtain from the Bureau of Labor Statistics *Quarterly Census of Employment and Wages*. Again, if market power in mortgage lending were really driving our results, one might expect that the employment by lenders in high concentration areas would be less sensitive to mortgage rates. As the model in Section III demonstrates, lenders in such areas, facing little competition, would have little incentive to increase their staff in response to increased demand. They could instead force borrowers wishing to refinance to wait for their staff to become available without fear of losing those borrowers to competitors. The last two columns of Table 7 show the results. Decreases in MBS yields are associated with increases in real estate credit employment, but again this effect is mitigated in higher-concentration counties.

Third, we examine the behavior of building permits using data from the Census's Building Permits Survey. This survey provides annual data on the number of building permits issued for single-family homes in each county. We examine both changes in percentage changes (the change in log permits issued) and changes in permits normalized by the number of existing housing units, which is a measure of investment in the housing stock. We present results both for the full sample, and the pre-2008 period in Table 8. In the pre-2008 period, a decrease in MBS yields is associated with an increase in permits issued. However, the effect is attenuated in high-concentration counties. Over the full sample, however, these relationships disappear. Figure 4 reveals the reason. For each year, the figure displays the 10^{th} percentile, median, and 90^{th} percentile of permits per housing unit across counties. The figure shows that both the median number of permits issued and cross-county variation in the number permits collapsed with the onset of the crisis in 2008. Essentially, permits drop to zero in all counties at the same time that MBS yields are falling, reversing the effects on yields and concentration that we find in the pre-crisis period.

VI. 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 half 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. Finally, we provide corroborating evidence based on banks' interest and fee income on real estate loans and employment in real estate credit that are consistent with the idea that we are isolating the effect of mortgage concentration.

Our results suggest that the effectiveness of housing as a monetary policy transmission channel varies in both the time series and 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. Moreover, given that the average county-level mortgage market concentration has risen over time, the impact of monetary policy on housing may have fallen substantially on average. Figure 1 shows that average concentration rose approximately 11% between 1997 and 2011. Extrapolating from our estimates, this suggests that the impact of a 100 bps drop in MBS yields in 2011 was 30% smaller than it would have been in 1997.

Appendix

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

$$0 = a - bQ - bq - r.$$

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

$$q^*_{low} = \frac{a-r}{b(N+1)}.$$

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

$$0 = a - bQ - bq - r - cq.$$

In a symmetric equilibrium this implies that

$$q^*_{high} = \frac{a-r}{b(N+1)+c}.$$

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

$$\bar{q} = q^*_{low} = \frac{a-\bar{r}}{b(N+1)} \quad \text{and}$$

$$\bar{q} = q^*_{high} = \frac{a-\underline{r}}{b(N+1)+c} \quad .$$

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

$$\frac{\partial Q^*_{low}}{\partial r} = \frac{-N}{b(N+1)} < 0, \quad \frac{\partial Q^*_{high}}{\partial r} = \frac{-N}{b(N+1)+c} < 0\,.$$

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

$$\frac{\partial^2 Q^*_{low}}{\partial r \partial N} = \frac{-1}{b(N+1)^2} < 0, \quad \frac{\partial^2 Q^*_{high}}{\partial r \partial N} = \frac{-(b+c)}{(b(N+1)+c)^2} < 0$$

Proof of Proposition 3. $\frac{\partial Q^*_{low}}{\partial r}, \frac{\partial Q^*_{high}}{\partial r} \to -\frac{1}{b}$ as $N \to \infty$.

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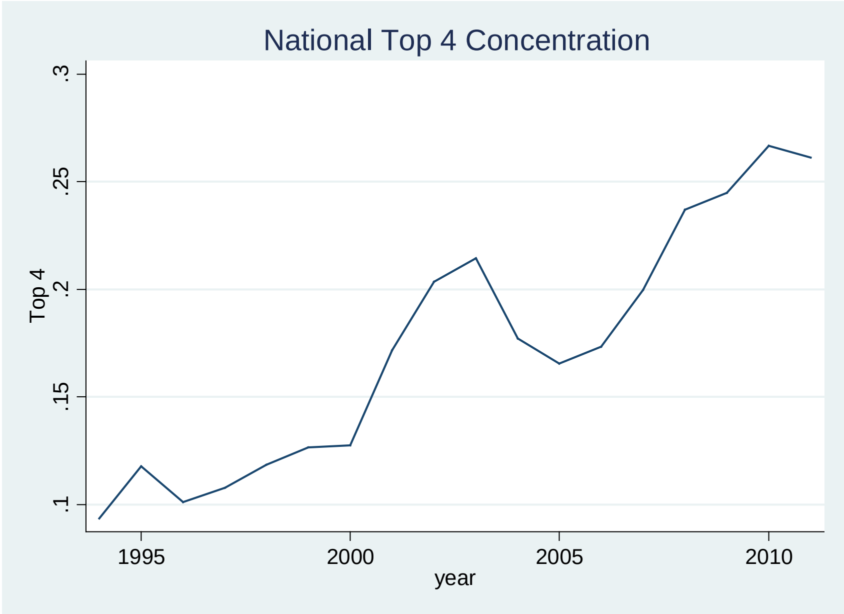


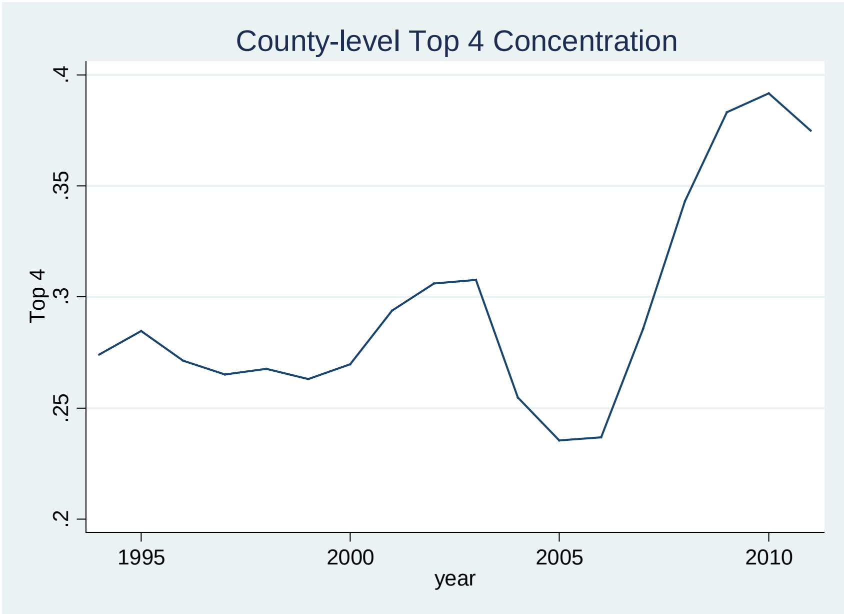


Figure 1
Mortgage Market Concentration in HMDA

This figure shows top 4 mortgage market share at the national level (top) and the value-weighted average of county-level top 4 share (bottom) in data from the Home Mortgage Disclosure Act.

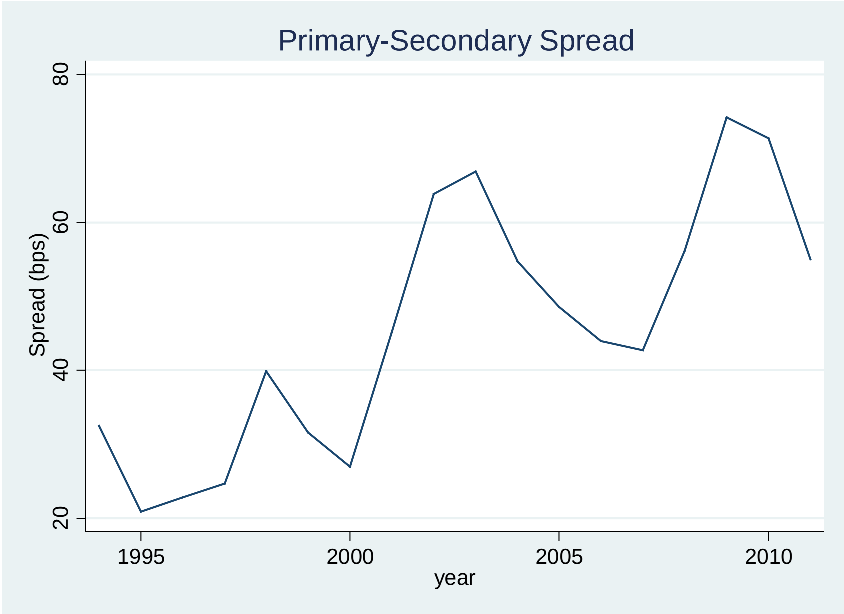
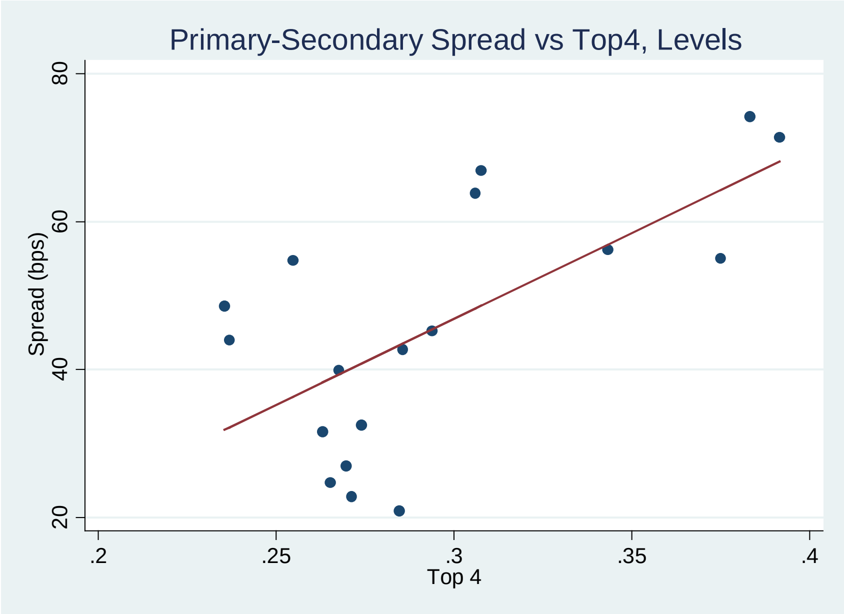


Figure 2
Primary-Secondary Spread

This figure shows the average rate charged to borrowers whose mortgages are guaranteed by Freddie Mac minus the yield on current coupon Freddie Mac MBS minus Freddie Mac's average fee for guaranteed mortgages.



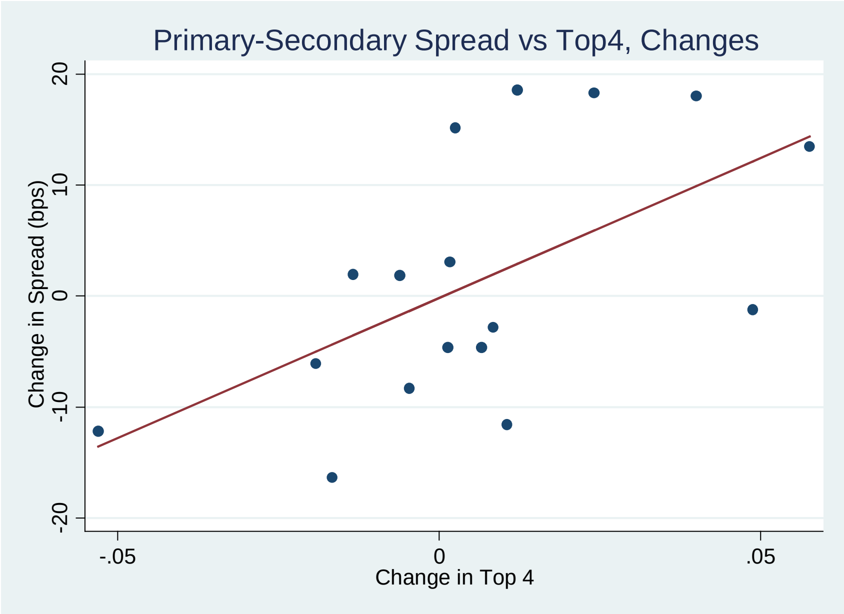


Figure 3

Primary-Secondary Spread vs. Market Concentration in Levels and Changes

This figure plots the relationship between primary-secondary spread and the value-weight average of county-level top 4 mortgage market share. The top figure shows the relationship in levels and the bottom shows it in changes.

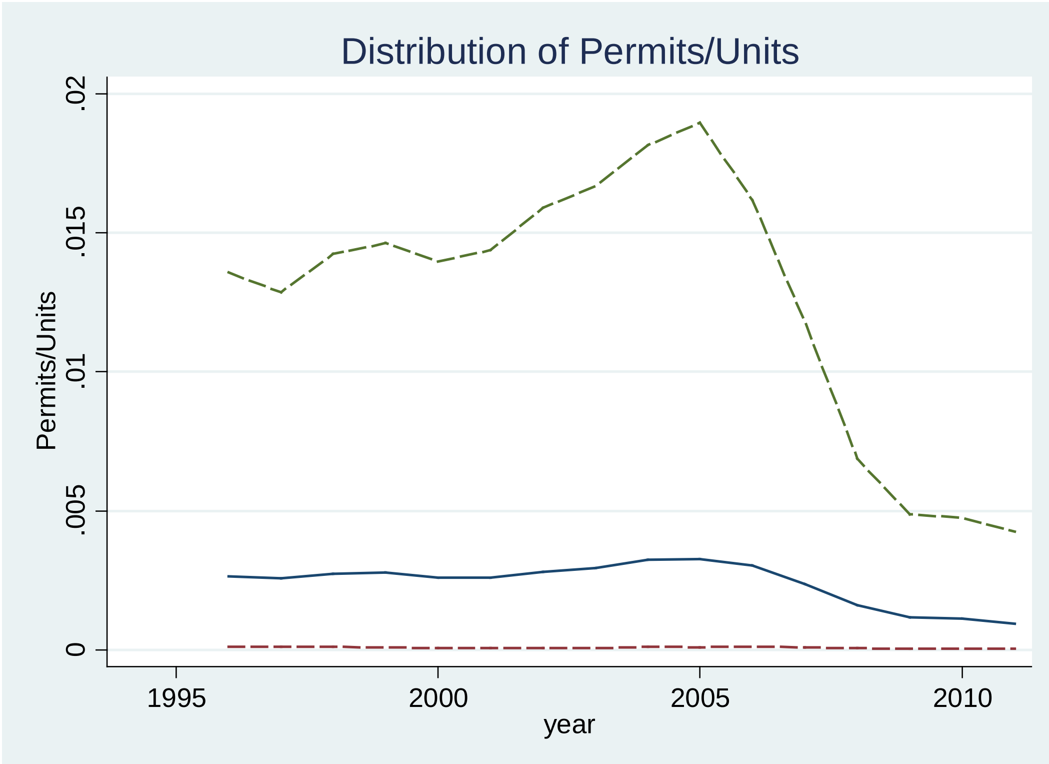


Figure 4
Distribution of Permits/Units

This figure plots for each year the 10th percentile (bottom dashed line), median (solid line), and 90th (top dashed line) percentile across counties of single-family residence building permits granted per total housing units.

Table 1
Summary Statistics

This table presents summary statistics for the two samples used in the paper. Panel A presents summary statistics for the HMDA data, which runs annually from 1994-2011. The unit of observation is county-year. 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 county from year t to year t+1. ln(Wage) is the log average weekly wage in the county-year from the BLS's Quarterly Census of Employment and Wages. ln(Population) is the log population from the Census. ln(LoanSize) is the log loan size in HMDA in thousands. ln(Price) is the log average price in the county from Zillow. DTI is the debt-to-income ratio calculated for borrowers in HMDA. Top 4 is the share of the top 4 mortgage originators in each county in HMDA. ΔMBS Yield is the change in the current-coupon Fannie Mae 30-year FRM MBS yield from year t to year t+1 from Bloomberg. Panel B presents summary statistics for the CoreLogic data, which runs monthly from 2000-2011.The unit of observation is county-month, and averages across all prime, conforming, fixed rate, full documentation loan in CoreLogic with FICO > 620 and LTV between 50 and 101. The sample is restricted to county-months with at least 5 such loans. Rate is the average mortgage rate reported, FICO is the credit score, and LTV is the loan-to-value ratio. ln(Price) is the log average price in the county from Zillow. Top 4 is the share of the top 4 mortgage originators in each county in HMDA. ΔMBS Yield is the change in the current-coupon Fannie Mae 30-year FRM MBS yield from month t to month t+1 from Bloomberg. ΔRate is the change in average mortgage rate from month t to month t+1.

	Panel A: HMDA Sample				
	N	Mean	Std Dev	Min	Max
Refi/Population	52384	0.014	0.012	0.000	0.178
ln(Wage)	52377	6.310	0.256	5.231	8.370
ln(Population)	52384	10.280	1.397	6.043	16.107
ln(LoanSize)	52384	4.505	0.477	1.099	7.285
ln(Price)	8070	11.914	0.508	9.425	13.721
DTI	52365	1.678	0.450	0.650	3.374
Top 4	52384	0.465	0.176	0.118	1.000
ΔMBS Yield	52384	-0.234	0.594	-1.301	0.856
ΔRefi/Pop	52384	0.000	0.009	-0.111	0.082

	Panel B: CoreLogic Sample				
	N	Mean	Std Dev	Min	Max
Rate	38068	6.117	0.918	3.834	10.263
FICO	38068	702.89	22.91	620.14	805.00
LTV	38068	85.82	7.01	50.43	100.74
ln(Price)	30566	12.098	0.472	9.405	13.525
Top 4	38068	0.284	0.072	0.135	0.565
ΔMBS Yield	38068	-0.027	0.244	-1.206	0.649
ΔRate	38068	-0.026	0.217	-1.920	1.707

Table 2
Refinancing and Concentration

This table presents regressions of the form:

$$\Delta\left(\frac{Refi}{Pop}\right)_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{i,t-1} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{i,t-1} + \varepsilon_{i,t}.$$

The county-level sample runs annually 1994-2011. 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(LoanSize) is the log loan size in thousands; ln(Price) is the log average price; DTI is the debt-to-income ratio in HMDA. In Panel A the second column reports the specification for the full sample, while the third column restricts the sample to the years before the financial crisis, 1994-2006. Panel B reports specifications with a variety of additional controls. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

	Panel A: Basic Results						
Δ MBS Yield$_t$	-0.015						
	[-4.21]						
Δ MBS Yield$_t$ x Top4$_{i,t-1}$	**0.016**	**0.019**	**0.022**				
	[3.70]	**[4.70]**	**[4.70]**				
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				0.004	0.004	0.004	0.008
				[0.87]	[0.93]	[0.91]	[0.87]
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**0.026**	**0.026**	**0.026**	**0.027**
				[4.59]	**[4.63]**	**[4.61]**	**[2.87]**
Top 4$_{i,t-1}$	0.004	0.001	0.001	0.004	0.004	0.004	0.006
	[1.26]	[0.23]	[0.07]	[1.00]	[0.98]	[1.00]	[1.12]
Δ ln(Wage$_{i,t}$)					0	0	-0.007
					[0.23]	[0.25]	[-1.36]
Δ ln(Population$_{i,t}$)					0.018	0.018	0.103
					[2.00]	[2.01]	[2.24]
Δ ln(LoanSize$_{i,t}$)						-0.001	-0.005
						[-0.97]	[-1.10]
Δ DTI$_{i,t}$						0	0.002
						[0.61]	[1.15]
Δ ln(Price$_{i,t}$)							0.013
							[3.06]
R^2	0.33	0.534	0.544	0.54	0.541	0.541	0.779
N	52384	52384	36774	52384	52384	52384	7542
County FE	N	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y	Y

	Panel B: Additional Controls				
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**0.019**	**0.019**	**0.021**	**0.015**	**0.015**
	[4.70]	**[4.76]**	**[3.78]**	**[3.87]**	**[3.84]**
Top 4$_{i,t-1}$	0.001	0.001	0.002	-0.005	-0.003
	[0.23]	[0.22]	[0.38]	[-0.92]	[-0.59]
Δ ln(Wage$_{i,t}$)		0.001	-0.007		-0.001
		[0.41]	[-1.35]		[-0.35]
Δ ln(Population$_{i,t}$)		0.021	0.104		0.065
		[2.10]	[2.24]		[2.62]
Δ ln(LoanSize$_{i,t}$)		-0.001	-0.005		0.007
		[-0.93]	[-1.10]		[2.55]
Δ DTI$_{i,t}$		0	0.002		-0.002
		[0.02]	[1.13]		[-0.89]
Δ ln(Price$_{i,t}$)			0.013		0.013
			[3.09]		[3.48]
Δ MBS Yield $_t$				0.002	0.002
x ln(Population$_{i,t-1}$)				[5.70]	[5.92]
Δ MBS Yield $_t$				-0.002	-0.001
x ln(Wage$_{i,t-1}$)				[-1.53]	[-0.92]
Δ MBS Yield $_t$				0.004	0.004
x DTI$_{i,t-1}$				[2.82]	[2.61]
Δ MBS Yield $_t$				-0.003	-0.004
x ln(LoanSize$_{i,t-1}$)				[-1.67]	[-2.04]
Δ MBS Yield $_t$				-0.01	-0.01
x ln(Price$_{i,t-1}$)				[-3.54]	[-3.54]
ln(Wage$_{i,t-1}$)				0.001	-0.003
				[0.29]	[-0.96]
ln(Population$_{i,t-1}$)				-0.005	-0.001
				[-1.18]	[-0.18]
ln(LoanSize$_{i,t-1}$)				0	0.005
				[-0.06]	[1.19]
DTI $_{i,t-1}$				-0.003	-0.003
				[-1.57]	[-1.51]
ln(Price$_{i,t-1}$)				-0.003	-0.003
				[-0.94]	[-1.04]
R^2	0.534	0.536	0.779	0.813	0.821
N	52384	52384	7542	7542	7542
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

	Panel C: Refinancings/Owner-Occupied Housing Units				
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**0.078**	**0.077**	**0.064**	**0.036**	**0.035**
	[3.31]	**[3.41]**	**[3.35]**	**[3.07]**	**[3.07]**
Top 4$_{i,t-1}$	0.009	0.01	0.011	-0.027	-0.02
	[0.49]	[0.53]	[0.55]	[-1.35]	[-1.09]
Δ ln(Wage$_{i,t}$)		-0.014	-0.035		-0.007
		[-0.71]	[-1.57]		[-0.55]
Δ ln(Population$_{i,t}$)		0.116	0.441		0.256
		[1.54]	[2.35]		[3.09]
Δ ln(LoanSize$_{i,t}$)		-0.016	-0.022		0.023
		[-0.98]	[-1.19]		[2.10]
Δ DTI$_{i,t}$		0.01	0.012		-0.004
		[1.30]	[1.22]		[-0.47]
Δ ln(Price$_{i,t}$)			0.054		0.05
			[2.80]		[3.07]
Δ MBS Yield $_t$				0.003	0.003
x ln(Population$_{i,t-1}$)				[3.18]	[3.18]
Δ MBS Yield $_t$				-0.007	-0.003
x ln(Wage$_{i,t-1}$)				[-1.13]	[-0.57]
Δ MBS Yield $_t$				0.008	0.007
x DTI$_{i,t-1}$				[1.13]	[1.00]
Δ MBS Yield $_t$				-0.014	-0.016
x ln(LoanSize$_{i,t-1}$)				[-1.25]	[-1.56]
Δ MBS Yield $_t$				-0.035	-0.035
x ln(Price$_{i,t-1}$)				[-3.22]	[-3.19]
ln(Wage$_{i,t-1}$)				0.007	-0.009
				[0.49]	[-0.67]
ln(Population$_{i,t-1}$)				-0.019	-0.002
				[-1.05]	[-0.15]
ln(LoanSize$_{i,t-1}$)				-0.001	0.018
				[-0.07]	[0.91]
DTI $_{i,t-1}$				-0.018	-0.018
				[-1.92]	[-1.63]
ln(Price$_{i,t-1}$)				-0.013	-0.011
				[-0.90]	[-1.04]
R^2	0.74	0.743	0.796	0.833	0.841
N	12444	12444	6603	6603	6603
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table 3
Mortgage Rates and Concentration

This table presents regressions of the form:

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

The county-level sample runs monthly 2000-2011. ; 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; Rate is the average mortgage rate reported in CoreLogic, FICO is the credit score, and LTV is the loan-to-value ratio; ln(Price) is the log average price. Standard errors are clustered by county and month, and t-statistics are reported in the brackets. In Panel A the second column reports the specification for the full sample, while the third column restricts the sample to the years before the financial crisis, 2000-2006. Panel B reports specifications with a variety of additional controls.

	Panel A: Baseline Results					
Δ MBS Yield $_t$	0.679	0.655	0.696		0.641	0.647
	[7.90]	[7.28]	[5.39]		[7.32]	[7.37]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-0.626**	**-0.564**	**-0.584**		**-0.549**	**-0.577**
	[-2.77]	**[-2.39]**	**[-1.69]**		**[-2.38]**	**[-2.48]**
(Δ MBS Yield)$^+$				0.601		
				[3.90]		
(Δ MBS Yield)$^-$				0.75		
				[3.84]		
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				-0.312		
				[-0.74]		
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**-0.916**		
				[-1.78]		
Top 4$_{i,t-1}$	-0.057	-0.001	-0.011	-0.142	-0.002	-0.01
	[-0.94]	[-0.04]	[-0.18]	[-1.05]	[-0.05]	[-0.23]
Δ LTV$_{i,t}$					0.004	0.004
					[3.52]	[3.35]
Δ FICO$_{i,t}$					-0.002	-0.002
					[-9.70]	[-9.21]
Δ ln(Price$_{i,t}$)						0.409
						[1.54]
R^2	0.318	0.317	0.242	0.314	0.345	0.36
N	38068	38068	22575	38068	38068	30560
County FE	N	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y

	Panel B: Additional Controls			
Δ MBS Yield $_t$	1.126	1.729	1.978	1.843
	[1.98]	[1.63]	[1.69]	[1.64]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-0.563**	**-0.469**	**-0.512**	**-0.53**
	[-2.45]	**[-2.57]**	**[-2.62]**	**[-2.72]**
Δ MBS Yield $_t$	-0.008	-0.017	-0.01	-0.011
x ln(Population$_{i,t-1}$)	[-0.50]	[-1.37]	[-0.79]	[-0.94]
Δ MBS Yield $_t$	-0.056	-0.04	-0.039	-0.042
x ln(Wage$_{i,t-1}$)	[-0.53]	[-0.48]	[-0.61]	[-0.68]
Δ MBS Yield $_t$		-0.004	-0.005	-0.004
x LTV$_{i,t-1}$		[-1.58]	[-1.41]	[-1.30]
Δ MBS Yield $_t$		0	0	0
x FICO$_{i,t-1}$		[-0.45]	[-0.10]	[-0.03]
Δ MBS Yield $_t$			-0.041	-0.033
x ln(Price$_{i,t-1}$)			[-1.17]	[-0.95]
Top 4$_{i,t-1}$	-0.001	0.018	-0.004	-0.003
	[-0.03]	[0.53]	[-0.09]	[-0.08]
ln(Population$_{i,t-1}$)	-0.011	0.007	0.027	0.008
	[-0.26]	[0.15]	[0.65]	[0.22]
ln(Wage$_{i,t-1}$)	0.013	0.01	0.041	0
	[0.24]	[0.17]	[0.71]	[0.01]
LTV$_{i,t}$		-0.002	-0.002	0
		[-1.70]	[-1.69]	[0.01]
FICO$_{i,t}$		0.001	0.001	0
		[5.81]	[5.38]	[0.63]
ln(Price$_{i,t}$)			-0.015	0.005
			[-0.75]	[0.25]
Δ ln(Wage$_{i,t}$)				0.916
				[0.73]
Δ ln(Population$_{i,t}$)				0.444
				[1.70]
Δ LTV$_{i,t}$				-0.411
				[-1.62]
Δ FICO$_{i,t}$				0.004
				[2.87]
Δ ln(Price$_{i,t}$)				-0.002
				[-7.38]
R^2	0.317	0.328	0.342	0.361
N	38068	38068	30560	30560
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 4
Assessing Magnitudes

This table reports specifications to help assess the economic magnitudes of our results. The column headings show the dependent variable. The first four columns present results for the quantity of refinancings in the HMDA sample, county-level annual data. The first and third columns use the full sample 1994-2011, while the second and fourth columns restrict attention to the crisis period 2007-2011. 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; DTI is the mortgage debt-to-income ratio in HMDA; DTI-MS is the total debt-to-income ratio in 2006 used by Mian, Rao, and Sufi (2012). The last two columns present results for mortgage rates in the CoreLogic sample, county-level monthly data 2000-2011. FICO is the credit score, and LTV is the loan-to-value ratio

	Δ Refi/Pop$_{i,t}$				Δ Rate$_{i,t}$	
Δ MBS Yield $_t$					0.654	0.636
					[7.35]	[7.27]
Δ MBS Yield $_t$	**0.014**	**0.007**	**0.011**	**0.007**	**-0.572**	**-0.538**
x Top4$_{i,t-1}$	**[4.22]**	**[5.74]**	**[4.92]**	**[4.24]**	**[-2.45]**	**[-2.34]**
Δ MBS Yield $_t$	-0.005	-0.005				
x DTI$_{i,t-1}$	[-3.34]	[-5.93]				
DTI $_{i,t-1}$	0	**-0.002**				
	[-0.54]	**[-2.37]**				
Δ MBS Yield $_t$			-0.006	-0.004		
x DTI-MS$_i$			[-3.99]	[-5.29]		
DTI-MS $_i$			-0.001	**-0.003**		
			[-1.30]	**[-3.43]**		
ΔLTV$_{i,t-1}$					**0.007**	
					[5.74]	
ΔFICO$_{i,t-1}$						**-0.002**
						[-12.11]
Top 4$_{i,t-1}$	0	0.002	0.001	0.003	-0.002	-0.005
	[0.06]	[1.35]	[0.71]	[1.61]	[-0.07]	[-0.14]
R^2	0.553	0.393	0.672	0.525	0.331	0.34
N	52335	15586	35431	11095	38068	38068
County FE	Y	Y	N	N	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 5
Matched Samples

This table presents results for matched samples. The column headings report the variables that we match on to construct the matched samples. In Panel A, we present results for the quantity of refinancings in the HMDA sample, county-level annual data 1994-2011. The dependent variable is ΔRefi/Pop is the change in the number of refinancings divided by the population. Standard errors are clustered by county and year, and t-statistics are reported in the brackets. In Panel B, we present results for mortgage rates in the CoreLogic sample, monthly data 2000-2011. The dependent variable is ΔRate. 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 month, and t-statistics are reported in the brackets.

	Panel A: HMDA Sample					
	Wage, Pop		Wage, Pop, DTI, Loan Size		Wage, Pop, DTI, Size, Price	
Δ MBS Yield $_t$ x Top4 $_{i,t-1}$	**0.012**		**0.006**		**0.010**	
	[4.73]		**[4.78]**		**[1.93]**	
(Δ MBS Yield)$^+$ xTop4 $_{i,t-1}$		0.002		0.002		-0.004
		[0.91]		[1.01]		[-0.57]
(Δ MBS Yield)$^-$ x Top4 $_{i,t-1}$		**0.016**		**0.008**		**0.016**
		[4.35]		**[3.92]**		**[2.05]**
Top 4$_{i,t-1}$	0.002	0.004	0	0.001	0.002	0.007
	[0.98]	[2.04]	[0.19]	[1.27]	[0.75]	[1.37]
R^2	0.493	0.495	0.536	0.537	0.803	0.803
N	36443	36443	28431	28431	2067	2067
Year FE	Y	Y	Y	Y	Y	Y

	Panel B: CoreLogic Sample					
	Wage, Pop		Wage, Pop, FICO, LTV		Wage, Pop, FICO, LTV, Price	
Δ MBS Yield $_t$	0.626		0.631		0.687	
	[8.30]		[8.96]		[9.91]	
Top 4 $_{i,t-1}$	-0.005	-0.018	0.041	0.007	0.021	-0.009
	[-0.20]	[-0.29]	[1.53]	[0.09]	[0.47]	[-0.13]
Δ MBS Yield $_t$ x Top4 $_{i,t-1}$	**-0.418**		**-0.45**		**-0.659**	
	[-2.28]		**[-2.41]**		**[-3.21]**	
(Δ MBS Yield)$^+$		0.624		0.582		0.664
		[4.03]		[4.19]		[4.84]
(Δ MBS Yield)$^-$		0.62		0.677		0.717
		[4.16]		[4.35]		[5.26]
(Δ MBS Yield)$^+$ xTop4 $_{i,t-1}$		-0.322		-0.244		-0.484
		[-0.82]		[-0.64]		[-1.21]
(Δ MBS Yield)$^-$ x Top4 $_{i,t-1}$		-0.49		-0.64		**-0.854**
		[-1.35]		[-1.52]		**[-2.18]**
R^2	0.312	0.312	0.363	0.363	0.382	0.382
N	26263	26263	11313	11313	3418	3418
Year FE	Y	Y	Y	Y	Y	Y

Table 6
Merger Sample

This table reports results where we use bank mergers as an instrument for concentration. We examine bank mergers where the bank makes up a large fraction (>15% in Panel A, >30% in Panel B) of deposits in a county but the county is only a small fraction (<2% in Panel A, <1% in Panel B) of the bank's deposit base. We examine the effect of the merger on the county's mortgage market concentration in the first column:

$$Top\ 4_{i,t} = \alpha_t + \beta \cdot Post\ Merger_{i,t} + \varepsilon_{i,t}.$$

We then use the fitted value from first column in the remaining columns to examine the effect of concentration on refinancings and rates:

$$\Delta\left(\frac{Refi}{Pop}\right)_{i,t} = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot \widehat{Top\ 4_{i,t}} + \beta_3 \cdot \Delta MBS\ Yield_t \times \widehat{Top\ 4_{i,t}} + \varepsilon_{i,t}.$$

The column headings show the dependent variable. 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. The columns with refinancings as the dependent variable are run yearly 1994-2011, and standard errors are clustered by year with t-statistics reported in brackets. The columns with rates as the dependent variable are run monthly 2000-2011, and standard errors are clustered by county and month with t-statistics reported in brackets.

	Panel A: Baseline Merger Sample				
	Top 4 $_{i,t}$	Δ Refi/Pop$_{i,t}$		Δ Rate$_{i,t}$	
Post Merger$_{i,t}$	**0.031**				
	[4.95]				
Δ MBS Yield $_t$		-0.074		1.349	
		[-3.09]		[0.85]	
$\widehat{Top\ 4_{i,t}}$		-0.075	0.013	0.531	-0.033
		[-1.98]	[0.69]	[0.35]	[-0.08]
Δ MBS Yield $_t$ x $\widehat{Top\ 4_{i,t}}$		**0.139**	**0.093**	-2.956	-2.567
		[2.68]	**[3.02]**	[-0.54]	[-0.46]
R^2	0.239	0.318	0.557	0.311	0.315
N	32063	32063	32063	24419	24419
County FE	N	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y

	Panel B: Restrictive Merger Sample				
	Top 4 $_{i,t}$	Δ Refi/Pop$_{i,t}$		Δ Rate$_{i,t}$	
Post Merger$_{i,t}$	**0.021**				
	[4.16]				
Δ MBS Yield $_t$		-0.105		1.805	1.793
		[-2.82]		[2.45]	[2.34]
$\widehat{Top\ 4_{i,t}}$		-0.115	0.03	0.185	-0.001
		[-2.15]	[0.73]	[0.24]	[-0.00]
Δ MBS Yield $_t$ x $\widehat{Top\ 4_{i,t}}$		**0.211**	**0.11**	**-4.685**	**-4.661**
		[2.55]	**[2.12]**	**[-1.77]**	**[-1.69]**
R^2	0.318	0.349	0.6	0.297	0.299
N	5566	5566	5566	3555	3555
County FE	N	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y

Table 7
Bank Profits and Real Estate Credit Employment

This table reports results on bank profits and employment. The column headings show the dependent variable. The first two columns of this table examine the relationship between concentration and loan and fee income on real estate loans for banks exclusively located in a single county. The second two columns examine the relationship between concentration and real estate credit employment. Δ ln(LoanIncome) is the change in interest and fee income from real estate loans averaged across single-county banks in each county from the Call Reports; 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; Δ ln(RE Employment) is the change in employment in real estate credit, and Δ ln(Employment) is the change in total employment. The county-level sample runs annually 1994-2011 and standard errors are clustered by county and year with t-statistics in brackets.

	Δ ln(LoanIncome$_{i,t}$)		Δ ln(RE Employment$_{i,t}$)	
Δ MBS Yield$_t$	0.059		-0.223	
	[1.22]		[-6.48]	
Δ MBS Yield$_t$ x Top4$_{i,t-1}$	-0.043	**-0.053**	**0.313**	**0.327**
	[-0.85]	**[-2.19]**	**[3.93]**	**[3.89]**
Δ ln(Employment$_{i,t}$)			1.255	0.496
			[3.08]	[2.45]
Top 4$_{i,t-1}$	0.091	0.186	-0.097	-0.17
	[1.48]	[6.07]	[-0.82]	[-2.37]
R^2	0.006	0.031	0.003	0.054
N	27824	27824	11002	11002
County FE	Y	Y	Y	Y
Year FE	N	Y	N	Y

Table 8
Building Permits

This table presents regressions of the form:

$$\Delta \ln(Permits_{i,t}) = \alpha + \beta_1 \cdot \Delta MBS\ Yield_t + \beta_2 \cdot Top\ 4_{i,t} + \beta_3 \cdot \Delta MBS\ Yield_t \times Top\ 4_{i,t} + \varepsilon_{i,t}.$$

The county-level sample runs annually 1996-2011. The column headings show the dependent variable. The dependent variable in the first four columns is Δ ln(Permits), the change in log permits for single-family residence construction, and the dependent variable in the second four columns is Permits/Units, the change in permits per housing unit. We report results for both the full sample and excluding the financial crisis period (pre-2008). Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

	$\Delta \ln(Permits_{i,t})$				$\Delta Permits_{i,t}/Units_{i,t}$			
	Pre-2008		Full Sample		Pre-2008		Full Sample	
Δ MBS Yield $_t$	-0.103		-0.003		-0.001		-0.001	-0.001
	[-2.33]		[-0.04]		[-2.17]		[-1.15]	[-2.55]
Δ MBS Yield $_t$ x Top4 $_{i,t-1}$	**0.139**	**0.119**	0.060	0.039	**0.002**	**0.002**	0.001	0.001
	[1.69]	**[1.68]**	[0.60]	[0.44]	**[2.06]**	**[2.06]**	[1.31]	[1.17]
Top 4 $_{i,t-1}$	0.216	-0.008	0.285	0.007	0.002	-0.001	0.002	-0.001
	[0.99]	[-0.11]	[1.38]	[0.11]	[1.28]	[-0.15]	[1.76]	[-0.20]
R^2	0.045	0.078	0.028	0.111	0.056	0.116	0.043	0.128
N	30302	30302	41079	41079	30302	30302	41079	41079
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y

Appendix Table 1
Mortgage Rates and Concentration, Quarterly

This table presents regressions of the form:

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

The county-level sample runs quarterly 2000-2011. 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; Rate is the average mortgage rate reported in CoreLogic, FICO is the credit score, and LTV is the loan-to-value ratio; ln(Price) is the log average price. Standard errors are clustered by county and quarter, and t-statistics are reported in the brackets. The second column reports the specification for the full sample, while the third column restricts the sample to the years before the financial crisis, 2000-2006.

Δ MBS Yield $_t$	1.189	1.106	1		0.984	1.025
	[10.29]	[11.56]	[9.02]		[9.56]	[8.62]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-1.365**	**-1.089**	-0.018		**-1.008**	**-1.193**
	[-4.26]	**[-4.56]**	[-0.05]		**[-4.42]**	**[-4.10]**
(Δ MBS Yield)$^+$				0.875		
				[4.38]		
(Δ MBS Yield)$^-$				1.238		
				[6.04]		
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				-0.771		
				[-1.38]		
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**-1.262**		
				[-2.58]		
Top 4$_{i,t-1}$	-0.254	-0.141	-0.034	-0.214	-0.147	-0.188
	[-2.20]	[-1.50]	[-0.41]	[-1.31]	[-1.64]	[-1.74]
Δ LTV$_{i,t}$					0.005	0.005
					[2.33]	[2.44]
Δ FICO$_{i,t}$					-0.004	-0.004
					[-4.36]	[-3.98]
Δ ln(Price$_{i,t}$)						-0.052
						[-0.27]
R^2	0.775	0.784	0.769	0.788	0.814	0.829
N	10703	10703	6201	10703	10703	8228
County FE	N	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y

Appendix Table 2
Loan Quality and Concentration

This table reports the raw correlations between measures of loan quality and concentration in the data. The column headings show the dependent variable. The dependent variables across columns are (i) DTI, the ratio of mortgage debt to income for borrowers in HMDA, (ii) DTI-MS, the total debt to income for each county as calculated by Mian, Rao, and Sufi (2012), (iii) FICO scores from CoreLogic, and (iv) LTVs from CoreLogic. The samples in the first two columns run annually 1994-2011, while the samples in the second two columns run monthly 2000-2011. Standard errors are clustered by county, and t-statistics are reported in the brackets.

	$DTI_{i,t}$	$DTI\text{-}MS_{i,t}$	$FICO_{i,t}$	$LTV_{i,t}$
Top $4_{i,t}$	-1.033	-1.609	25.712	-0.765
	[-35.23]	[-26.14]	[1.82]	[-0.15]
R^2	0.273	0.138	0.239	0.267
N	52384	37657	38068	38068
Year FE	Y	Y	Y	Y

Appendix Table 3
Match Quality for Matched Samples

This table reports the quality of the matches for the matched samples used in Table 5 in the main text. Each entry in the table reports the coefficient from running a regression of the specified variable on an indicator for whether the observation in the matched sample is from a high-concentration county. t-statistics clustered by county are reported in the brackets.

	Panel A: HMDA Matched Samples					
	Wage, Pop		Wage, Pop, Size, DTI		Wage, Pop, Size, DTI, Price	
Top 4	**0.178**	**[44.32]**	**0.151**	**[37.37]**	**0.087**	**[15.16]**
Refi/Pop	**-0.003**	**[-6.56]**	0	[1.03]	-0.001	[-1.26]
ln(Population)	-0.011	[-0.34]	-0.029	[-1.36]	-0.005	[-0.09]
ln(Wage)	-0.001	[-0.19]	-0.004	[-0.88]	-0.003	[-0.32]
ln(Price)	-0.132	[-1.63]	-0.002	[-0.03]	-0.009	[-0.38]
ln(LoanSize)	**-0.192**	**[-14.60]**	-0.01	[-1.48]	-0.008	[-0.46]
DTI	**-0.221**	**[-11.52]**	-0.009	[-1.28]	-0.008	[-0.44]

	Panel B: CoreLogic Matched Samples					
	Wage, Pop		Wage, Pop, FICO, LTV		Wage, Pop, FICO, LTV, Price	
Top 4	**0.08**	**[15.78]**	**0.081**	**[15.16]**	**0.076**	**[10.35]**
Rate	0.003	[0.07]	0.014	[0.34]	0.014	[0.22]
ln(Population)	0.002	[0.03]	-0.006	[-0.11]	-0.011	[-0.14]
ln(Wage)	0	[0.01]	-0.002	[-0.17]	-0.004	[-0.28]
ln(Price)	0.043	[0.85]	-0.009	[-0.21]	0.005	[0.14]
FICO	**3.664**	**[2.44]**	0.138	[0.13]	0.284	[0.18]
LTV	-0.676	[-1.45]	0.003	[0.01]	-0.08	[-0.16]