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

David Scharfstein
dscharfstein@hbs.edu
Harvard University and NBER

Adi Sunderam
asunderam@hbs.edu
Harvard University

June 2013

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 strength of the housing channel of monetary policy transmission varies in both the time series and the cross section. In the cross section, increasing concentration by one standard deviation reduces the overall impact of a decline in MBS yields by approximately 50%. In the time series, a decrease in MBS yields today has a 40% smaller effect on the average county than it would have had in the 1990s because of higher concentration today.

---

* We are grateful to Zahi Ben-David, Scott Frame, Andreas Fuster, Ed Golding, David Lucca, Amit Seru, Jeremy Stein, Amir Sufi, and seminar participants at the Federal Reserve Bank of New York, Harvard University, the NBER Corporate Finance Spring Meetings, and the UCLA/FRB-San Francisco Conference on Housing and the Macroeconomy for helpful comments and suggestions. We thank Freddie Mac for data and Toomas Laarits for excellent research assistance. We also thank the Harvard Business School Division of Research for financial support.

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 affects 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 lenders, as would be the case if borrowers are more liquidity constrained, then refinancing should boost aggregate consumption in the presence of frictions. 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).

Using monetary policy to support housing credit has been an increasing focus of the Federal Reserve 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. One of the aims of quantitative easing was to lower mortgage rates by reducing financing costs for mortgage lenders (Bernanke 2009, 2012). However, it has been argued that the efficacy of this policy has been hampered by the high indebtedness of many households (Eggertson and Krugman, 2012; Mian, Rao, and Sufi, 2012). "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 conclude that the increase remains a puzzle.

In this paper, we explore in more detail whether market power in mortgage lending can explain a significant amount of the increase in the primary-secondary spread and thereby impede the transmission of monetary policy to the housing sector. We build on the literature in industrial organization that argues 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 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. As shown in Figure 1, concentration in the mortgage lending industry increased substantially between 1994 and 2011. Figure 2 shows the average primary-secondary spread calculated as the 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. [1] The yield on Freddie Mac MBS is the amount paid to investors in the securities, which are used to finance the mortgages. Thus, 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.

Recent trends are one reason that market power has not received much scrutiny as an explanation for rising primary-secondary spreads. Most recently, the spread spiked in 2011-2012 though concentration in mortgage lending has not increased since 2010 (Avery, et al., 2012 and Fuster, et al., 2012).[2] These recent trends are misleading for two reasons. First, they focus on the market share of the top ten lenders at the *national* level. However, evidence suggests that a significant part of competition in mortgage lending takes place at the *local* level, and at the local level concentration is rising due to increased geographic segmentation of mortgage lending.[3]

---

[1] 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.

[2] Fuster, et. al. (2012) also argue that the higher fees charged by the GSEs for their guarantees cannot account for the rise in spreads.

[3] To see this, 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%.

Second, as we discuss below, in the presence of capacity constraints, the effects of increased concentration would be most clearly revealed when MBS yields fall. Thus, the time series correlation between spreads and concentration may understate the true relationship. 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 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. 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. 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: monetary policy transmission through the mortgage market has approximately half the impact in the high-concentration county relative to the average county.

Our estimates also suggest that increases in the concentration of mortgage lending can explain a substantial fraction of the rise in the primary-secondary spread. Extrapolating from our results, the 250 bps decline in MBS yields since the onset of the financial crisis should translate into a 150 bps reduction in mortgage rates given the current level of concentration. This implies that the decline in MBS yields should be associated with an approximately 100 bps increase in the primary-secondary spread – roughly the magnitude of the increase observed by Fuster, et al. (2012). Our estimates suggest that if the concentration of mortgage lending were instead at the lower levels observed in the 1990s, the same decline in MBS yields would have resulted in a 40% smaller increase in the spread – an increase in the spread of 60 bps rather than 100 bps.[4]

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 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 are important, 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 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.

Finally, using data on bank profits and employment, we provide evidence consistent with the market power mechanism being 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

[4] Guarantee fees charged by the GSEs have also increased in recent years, but Fuster et al. (2012) argue that this accounts for a relatively small part of the increase in the primary-secondary spread.

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; as MBS yields fall originators hire more workers to process mortgage applications, or there is entry in mortgage origination. However, the sensitivity is less negative (i.e., lower in absolute terms) in high-concentration counties, meaning that in such counties originators expand hiring less aggressively in response to a decline in MBS yields, or there is less entry. Thus, while it is true that capacity constraints limit mortgage origination, these capacity constraints are endogenous to the degree of competition in the market. In all, the evidence is consistent with the idea that mortgage market concentration decreases the transmission of monetary policy to the housing sector.

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. 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. 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 (see Figure 4 for a graphical depiction).

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 Agency. 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.

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.[5] 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 characteristics.[6] 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.[7,8]

---

[5] However, there is some relative minor variation in fees charged across lenders.

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

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

[8] 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.

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, 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.[9] 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. Indeed, Gurun, Matvos, and Seru (2013) find evidence that local advertising affects consumer mortgage choices, suggesting that local competition is important.

III. Model

We now briefly present a simple model of mortgage market competition. The model is meant to motivate our empirical analysis, and to show that many of the results we find in the data can be obtained in a simple model where differences in market competition are the driving force. 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

[9] Aubusel (1990) documents the impact of this kind of consumer behavior on the effective level of competition in the credit card market.

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

$$p(Q) = a - bQ$$

where *p(Q)* is the mortgage rate corresponding to demand of *Q* in the local area given this rate. The linear demand assumption can be motivated by assuming that there are fixed costs to refinancing and pre-existing mortgage rates are uniformly distributed.[10] 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, *r*. Thus, we are effectively normalizing other production costs associated with mortgage origination to zero given that production is below pre-existing capacity. However, if a lender wishes to produce more than its pre-existing capacity, it has increasing, convex production costs, which capture the idea that it is costly to produce above some 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

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

We assume Cournot competition,[11] so firms solve the following maximization problem

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

[10] In particular, suppose that borrowers have existing mortgages and that the rates on their mortgages, p_0, are uniformly distributed on the interval [x-Δ/2,x+Δ/2]. Refinancing is desirable if the new rate, p, plus transaction costs, k, are less than the old rate, p_0. Thus, the quantity of refinancing, Q, is equal to M[1-(p+k)/ Δ], where M is a measure of the size of the market (e.g. population). We can therefore write the demand function, p(Q) = a – bQ, where a=Δ-k and b = Δ/M.

[11] 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.

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 MBS yield r and is given by*

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

where

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

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 low, demand will be high, and lenders will add capacity to meet this demand. For intermediate values of MBS yields, the increase in marginal cost 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 $\bar{q} = \bar{Q}/N$ where $\bar{Q}$ is aggregate industry capacity. Thus, as we vary *N*, aggregate industry capacity is fixed but is distributed among a larger number of lenders. Note that this normalization implies that both $\underline{r}$ and $\bar{r}$ approach $a - b\bar{Q}$ 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. *Mortgage quantities rise when MBS yields fall:* $\partial Q^* / \partial r < 0$. *In addition, mortgage rates fall when MBS yields fall:* $\partial P\left(Q^*\right) / \partial r > 0$. *Finally, these sensitivities are larger in magnitude when there are more lenders:* $\partial^2 Q^* / \partial r \partial N < 0$, $\partial^2 P\left(Q^*\right) / \partial r \partial N > 0$.

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. [12]

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 do not fall as much as MBS yields fall. However, with more lenders, this asymmetry vanishes. Each lender makes a small capacity adjustment, leading to a large increase in aggregate capacity.

The model, while simple, serves to motivate our empirical analysis, 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

[12] 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.

competition. It shows that while capacity constraints may be related to high spreads, the full impact of the capacity constraints is related to the degree of 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, a lender identifier, as well as loan characteristics including year, county, dollar amount, and borrower income. We construct an annual, county-level sample using this data over 1994-2011.[13] 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 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 lenders in the county. 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. Our results are robust to using other measures of concentration such as the Herfindahl-Hirschman index (HHI). Appendix Table 1 shows our main results using HHI. While these measures of concentration are surely imperfect proxies for the level of local competition, the empirics require only that they capture some of the variation in local competition.

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

[13] The HMDA data are available back to 1990, but we focus on the 1994-2011 period for two reasons. First, because of changing reporting requirements, the number of counties with reporting institutions varies by more than 10% from year to year prior to 1994. Second, the FDIC deposits data we use later in the paper starts in 1994. We obtain similar results if we use the full 1990-2011 sample.

CoreLogic. All large servicers are included, 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, 30-year fixed-rate loans. The sample runs from 2000-2011, and 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 measure refinancing activity by the number of mortgages refinanced in a given year, normalized by the county's population in that year.[14] 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.[15] 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 refinancing 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 refinancing 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

[14] Similar results are obtained using dollar loan volume, rather than the number of refinancings.

[15] 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.

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. 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 refinancing 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 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; Hannan and Berger, 1992; 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, loan-to-income ratios,[16] and house price appreciation.[17] 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. Though we control for population in the regressions, the analysis still equal-weights counties, raising the possibility that our results are driven by small, low-population counties. Appendix Table 2 shows that this is not the case. Our main results are

[16] The loan-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).

[17] 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.

robust to weighting the sample by population and excluding counties with populations below the median or mean for a given year.

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 scope for variation in refinancings per person since renters do not refinance. To address this concern, Panel C displays the same specifications as Panel B but uses as the dependent variable the change in refinancing 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.[18] 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.

An additional concern with our results could be that our concentration measures are proxying 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). This could make their refinancing behavior less sensitive to MBS yields. Thus, if small, localized lenders do a larger share of the refinancing in more concentrated markets, it is possible that our measures of concentration are proxying for the behavior of these localized lenders. Panel A of Table 3 documents that small, localized lenders do, in fact, have a larger share of refinancing in more concentrated markets. In this table, we regress the share of refinancings originated by small lenders on our top 4 concentration measure. In the first column, for example, the refinancing share of small lenders is defined as the share of lenders operating in fewer than 10 counties, while in the second column it is the share of lenders that operate in fewer than 50 counties. The table shows that smaller lenders generally have a larger share in counties where concentration is high.

[18] 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 a county is a reasonable assumption.

Panel B of Table 3 shows, however, that lenders respond to local mortgage market conditions the same way, whether they are localized or not. Each column runs the baseline specification from Table 2 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 sample to loans made by lenders operating in fewer than 10 counties, and the second column restricts the samples to loans made by lenders that operate in 10 or more counties. We rescale the dependent variable by the national market share of the lenders in the sample to make the coefficients comparable to those in the Table 2. Thus, the coefficients can be interpreted as the sensitivity of refinancing to MBS yields, assuming all refinancings in the country were done by the lenders in our restricted sample. For instance, the first column of Table 3 shows the sensitivity of refinancing to MBS yields, assuming all refinancing was performed by lenders than operate in fewer than 10 counties. The results in Panel B of Table 2 are uniform across lender types. Refinancings originated by both small and large lenders are less sensitive to MBS yields in more concentrated markets. Panel C of Table 3 shows that these results are unaffected by year fixed effects. Thus, while smaller lenders do have a larger market share in more concentrated counties, the results cannot be explained by the lower sensitivity of their refinancing behavior to MBS yields.

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 30-year 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 4 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 sensitivity between high- and low-concentration counties, which is our main focus, is unaffected by such time aggregation. For robustness, Appendix Table 3 presents the same results as Table 4 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 mortgage rates by 27% (=.626 * 17.4%/40%). The second column in Table 4 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 market power.[19] 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 4 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 4 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.

[19] Kahn, Pennacchi, and Sopranzetti (2005) document asymmetric pass-through in rates on personal loans.

Unfortunately, our data does not contain information on up-front points, fees, and closing costs. Thus, our results essentially assume that these costs do not covary negatively with market concentration. 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 4 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.[20]

Table 5 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.[21] 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 loan-to-income (LTI) ratios. These LTIs are

[20] 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.

[21] Caplin and Tracy (1997) study the impact of refinancing constraints in earlier recessions.

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 LTI within a county had no effect on refinancing, while the interaction of LTI and MBS yields is negative. When MBS yields fall, borrowers are more likely to refinance in counties that have high LTIs. This is presumably because borrowers with high LTIs 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 LTI, which corresponds to slightly more than one standard deviation of LTI.

The second column of Table 5 restricts the sample to the financial crisis period, 2007-2011. Now we see that the level of LTI has a negative effect on refinancing, consistent with Mian, Rao, and Sufi (2012). However, the interaction of MBS yields and LTI is still negative, implying that borrowers in high LTI 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 LTI implies that a one standard deviation increase in LTI 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 LTI 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 5 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 (DTI) 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 LTIs from HMDA.

The final two columns of Table 5 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.[22] 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, rather than 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 4 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 5, 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

[22] 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.

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. Demographic characteristics are known to be correlated with household financial decisions (Campbell, 2006). 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. 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). If market structure is correlated with local characteristics that impact the curvature of the demand function, our results may reflect differences in characteristics rather than market power.[23] 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.F 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

[23] A growing literature, including Goldberg and Hellerstein (2008, 2013), Hellerstein (2006), Nakamura and Zerom (2010), has used structural models to study the pass-through of changes in exchange rates to local prices. These studies are interested in decomposing in full all sources of incomplete pass-through, and therefore require structural models. In contrast, we are interested in simply identifying that market power is an important source of incomplete pass-through, so a reduced form approach is adequate (Goldberg and Knetter 1997).

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 by employing 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 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 6 Panel A. The first two columns match on county population and average wages. The second two columns match on population, average wages, LTI, and loan size. The final two columns match on population, average wages, LTI, loan size, and house prices. Appendix Table 5 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 6 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 6 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 6 Panel B show that we obtain very similar results to the baseline in Table 4 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.[24] Specifically, we focus on 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.[25] Within the sample, we examine how the sensitivity of refinancings and mortgage rates to MBS yields changes after the merger takes place.

Table 7 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

[24] We must measure the impact of bank mergers using deposits, not mortgage loans, because we cannot link bank identifiers to HMDA identifiers before 2000.

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

deposits in the county, but the county itself makes up no more than 2% of the bank's total deposits.[26] 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

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

where the hats on $\widehat{Top\ 4_{i,t}}$ and $\widehat{\Delta MBS\ Yield_t \times Top\ 4_{i,t}}$ indicate that those variables are instrumented for using the post-merger indicator and the post-merger indicator interacted with the change in MBS yields. 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.

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

[26] 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%.

$\Delta MBS\ Yield_t \times Top\ 4_{i,t}$. 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 7 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 instrumented by the post-merger indicators, the results are not statistically significant.

Panel B of Table 7 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 7 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. Moreover, in Appendix Table 7 we show that observable characteristics do not change within a county after the merger. The table also shows characteristics of the counties in the merger samples relative to those excluded. Counties in the first sample are somewhat larger than average, but counties in the second sample are similar to the average county in our full sample.

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 8 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 8 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.

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 is 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 40% 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:

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

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

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

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

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

References

Amel, D., Kennickell, A., Moore, B., 2008. Banking market definition: evidence from the survey of consumer finances. Unpublished working paper. Finance & Economic Discussion Series, U.S. Federal Reserve Board.

Atkeson, A., Burstein, A., 2008. Pricing-to-market, trade costs, and international relative prices. American Economic Review 98, 1998-2031.

Ausubel, L., 1990. The failure of competition in the credit card market. The American Economic Review 81, 50–81.

Avery, R., Bhutta, N., Brevoort, K., Canner, G., 2012. The mortgage market in 2011: highlights from the data reported under the home mortgage disclosure act. Federal Reserve Bulletin.

Bergin, P., Feenstra, R., 2001. Pricing-to-market, staggered contracts and real exchange rate persistence. Journal of International Economics 54, 333-359.

Bernanke, B., 2009. Reflections on a year in crisis. Remarks at the Federal Reserve Bank of Kansas City's Annual Economic Symposium, Jackson Hole, Wyoming.

Bernanke, B., 2012. Challenges in housing and mortgage markets. Remarks at the Operation HOPE Global Financial Dignity Summit, Atlanta, Georgia.

Bernanke, B., Gertler, M., 1995. Inside the black box: the credit channel of monetary policy transmission. The Journal of Economic Perspectives 9, 27-48.

Blinder, A., 1994. On Sticky Prices: Academic Theories Meet the Real World. In: Mankiw, N. (Ed.), Monetary Policy. University of Chicago Press, Chicago, pp. 117-154.

Blinder, A., Canetti, E., Lebow, D., Rudd, J., 1998. Asking about Prices: A New Approach to Understanding Price Stickiness. Sage Foundation, New York.

Borenstein, S., Cameron, A., Gilbert, R., 1997. Do gasoline prices respond asymmetrically to crude oil price changes? The Quarterly Journal of Economics 112, 305-339.

Bulow, J., Pfleiderer, P., 1983. A note on the effect of cost changes on prices. Journal of Political Economy 91, 182-185.

Caplin, Freeman, and Tracy (1997), "Collateral Damage: How Refinancing Constraints Exacerbate Regional Recessions, Journal of Money, Credit and Banking, 496-516, 1997.

Campbell, J., . Household finance. Journal of Finance 61, 1553-1604.

Dafny, L., Duggan, M., Ramanarayanan, S., 2012. Paying a premium on your premium? Consolidation in the US health insurance industry. American Economic Review 102, 1161-85.

Dornbusch, R., 1987. Exchange rates and prices. American Economic Review, 77, 93-106.

Dudley, W., 2012. The recovery and monetary policy. Remarks at the National Association for Business Economics Annual Meeting, New York City.

Eggerttson, G., Krugman, P., 2012. Debt, deleveraging, and the liquidity trap: a Fisher-Minsky Koo approach. The Quarterly Journal of Economics 127, 1469-1513.

Fuster, A., Goodman, L., Lucca, D., Madar, L., Molloy, L., Willen, P., 2012. The rising gap between primary and secondary mortgage rates. Unpublished working paper. Federal Reserve Bank of New York.

Goldberg, P., Hellerstein, R., 2013. A structural approach to identifying the sources of local currency price stability. Review of Economic Studies 80, 175-210.

Goldberg, P., Hellerstein, R., 2008. A structural approach to explaining incomplete exchange rate pass-through and pricing-to-market. American Economic Review 98, 423-29.

Goldberg, P., Knetter, M., 1997. Goods prices and exchange rates: what have we learned? Journal of Economic Literature 35, 1243-73.

Gurun, U., Matvos, G., Seru, A., 2013. Advertising expensive mortgages. Unpublished working paper. University of Chicago.

Hannan and Berger (1991), “The Rigidity of Prices: Evidence from the Banking Industry” The American Economic Review , Vol. 81, No. 4 (Sep., 1991), pp. 938-945.

Hellerstein, R., 2006. A decomposition of the sources of incomplete cross-border transmission: the case of beer. Unpublished working Paper, Federal Reserve Bank of New York.

Hurst, E., Stafford, F., 2004. Home is where the equity is: liquidity constraints, refinancing and consumption. Journal of Money, Credit and Banking 36, 985-1014.

Imbens, G., 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. Review of Economics and Statistics 86, 4-29.

Jackson, W., 1997. Market structure and the speed of price adjustments: evidence of non-monotonicity. Review of Industrial Organization 12, 37-57.

Karrenbrock, J., 1991. The behavior of retail gasoline prices: symmetric or not? Federal Reserve Bank of St. Louis Review 73, 19-29.

Kahn, C., Pennacchi, G., Sopranzetti, B., 2005. Bank consolidation and the dynamics of consumer loan interest rates. Journal of Business 78, 99-133.

Knetter, M., 1989. Price discrimination by U.S. and German exporters. American Economic Review 79, 198-210.

Kreps, D., Scheinkman, J., 1983. Quantity precommitment and Bertrand competition yield cournot outcomes. The Bell Journal of Economics 14, 326-337.

Lacko, J., Pappalardo, J., 2007. Improving consumer mortgage disclosures. Bureau of Economics Staff Report, USA Federal Trade Commission.

Loutskina, E. Strahan, P., 2011. Informed and uninformed investment in housing: The downside of diversification. Review of Financial Studies 24, 1447-1480.

Mian, A., Rao, K., Sufi, A., 2012. Household balance sheets, consumption, and the economic slump. Unpublished working paper. University of Chicago.

Nakamura, E., Zerom, D., 2010. Accounting for incomplete pass-through. Review of Economic Studies 77, 1192-1230.

Neumark, D., Sharpe, S., 1992. Market structure and the nature of price rigidity: evidence from the market for consumer deposits. The Quarterly Journal of Economics 107, 657-80.

Peltzman, S., 2000. Prices rise faster than they fall. Journal of Political Economy 108, 466-502.

Rajan, U., Seru, A., Vig, V., 2012. The failure of models that predict failure: distance, incentives and defaults. Journal of Financial Economics, forthcoming.

Rubin, D., Thomas, N., 1992. Affinely invariant matching methods with ellipsoidal distributions. Annals of Statistics 20, 1079-1093.

Rotemberg, J., Saloner, G., 1987. The relative rigidity of monopoly pricing. The American Economic Review 77, 917-926.

Staiger, D., Stock, J., 1997. Instrumental variables regression with weak instruments. Econometrica 65, 557-586.

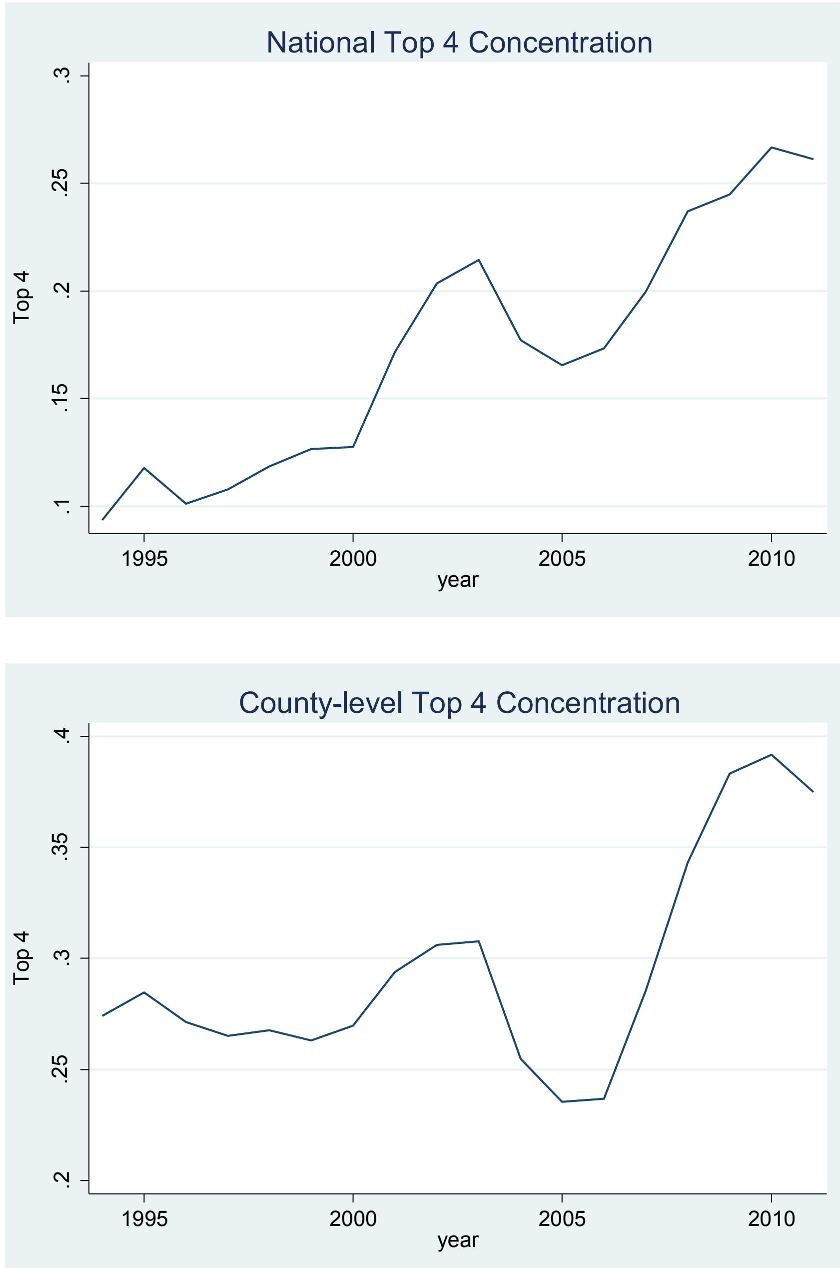


Figure 1
Mortgage Market Concentration in HMDA

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.

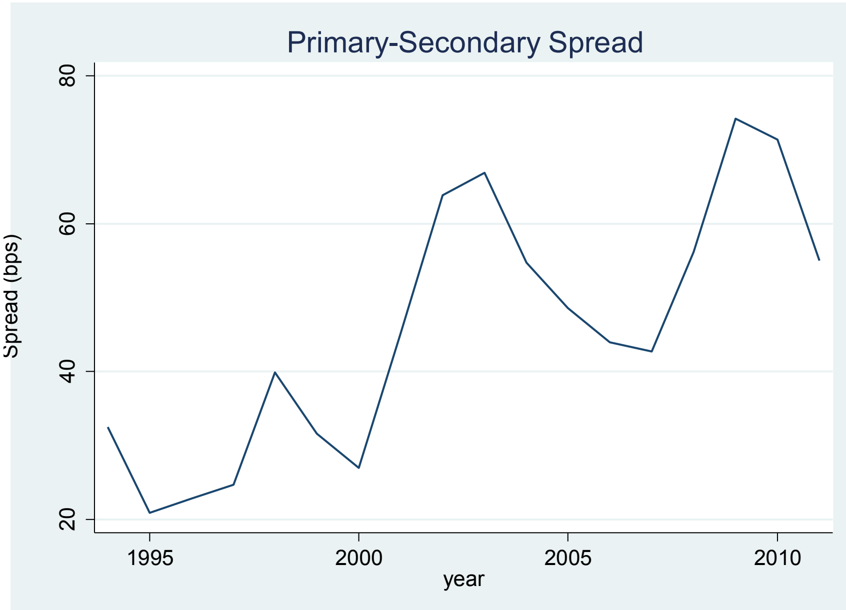
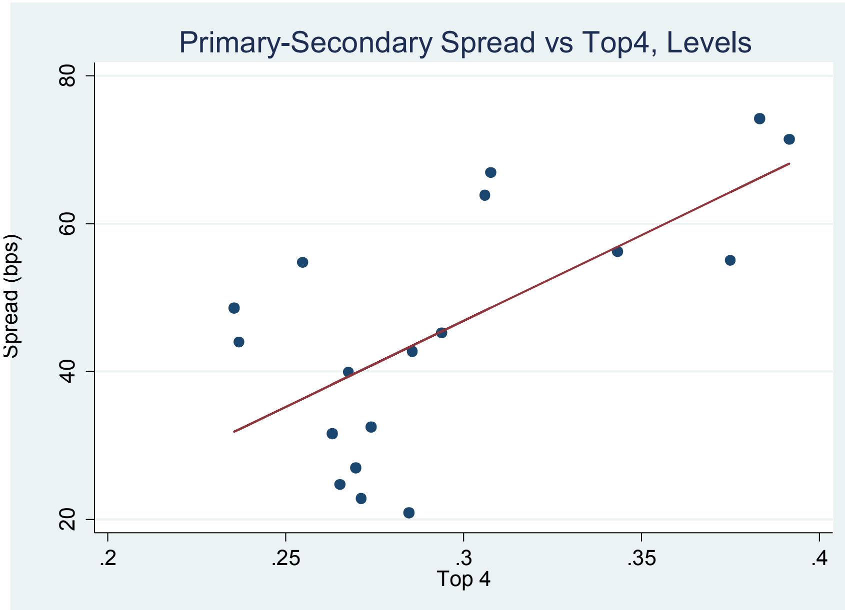


Figure 2
Primary-Secondary Spread

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.



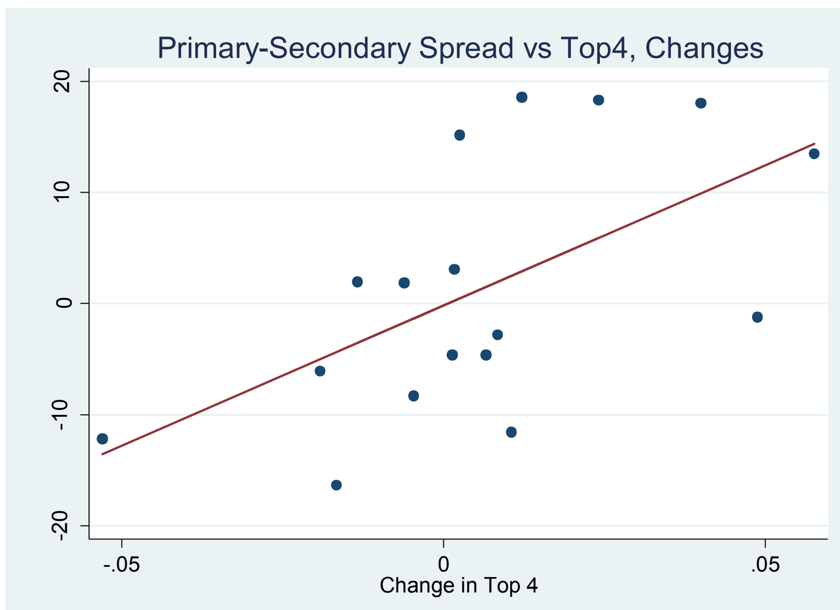


Figure 3
Primary-Secondary Spread vs. Market Concentration in Levels and Changes

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.

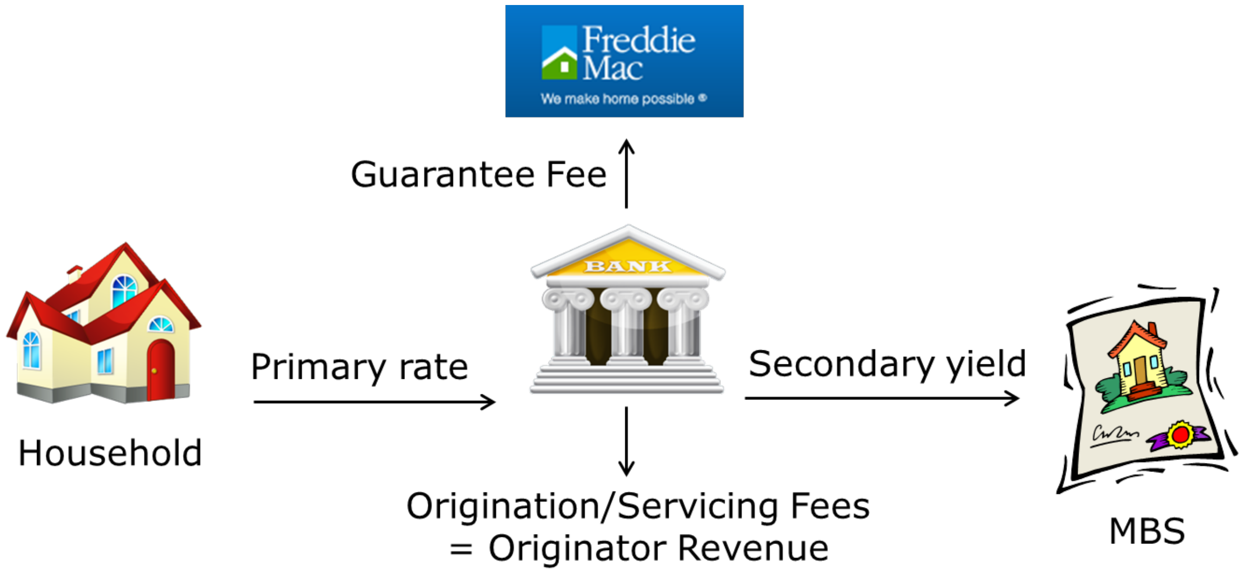


Figure 4
Description of Mortgage Market

This figure shows a simplified schematic of the conforming mortgage market. Households pay the primary mortgage rate, while investors in mortgage-backed securities (MBS) receive the secondary yield. The government sponsored entities, Fannie Mae and Freddie Mac, charge a guarantee fee in return for insuring MBS investors from default risk. The mortgage originator and servicer charge fees for originating and servicing the loan.

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 the 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. LTI is the loan-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
LTI	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; LTI is the loan-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						
	[-4.20]						
Δ MBS Yield$_t$ x Top4$_{i,t-1}$	**0.016**	**0.019**	**0.022**				
	[3.67]	**[4.65]**	**[5.33]**				
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				0.004	0.004	0.004	0.008
				[0.87]	[0.93]	[0.91]	[0.88]
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**0.026**	**0.026**	**0.026**	**0.027**
				[4.56]	**[4.59]**	**[4.58]**	**[2.63]**
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]	[1.10]
Δ ln(Wage$_{i,t}$)					0	0	-0.007
					[0.23]	[0.25]	[-1.27]
Δ ln(Population$_{i,t}$)					0.018	0.018	0.103
					[2.00]	[2.00]	[2.25]
Δ ln(LoanSize$_{i,t}$)						-0.001	-0.005
						[-0.97]	[-1.08]
Δ LTI$_{i,t}$						0	0.002
						[0.61]	[1.12]
Δ ln(Price$_{i,t}$)							0.013
							[2.82]
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**
	[4.65]	**[4.71]**	**[3.28]**	**[2.94]**	**[2.98]**
Top 4$_{i,t-1}$	0.001	0.001	0.002	-0.005	-0.003
	[0.23]	[0.22]	[0.38]	[-0.89]	[-0.58]
Δ ln(Wage$_{i,t}$)		0.001	-0.007		-0.001
		[0.40]	[-1.26]		[-0.35]
Δ ln(Population$_{i,t}$)		0.021	0.104		0.065
		[2.09]	[2.26]		[2.65]
Δ ln(LoanSize$_{i,t}$)		-0.001	-0.005		0.007
		[-0.92]	[-1.08]		[2.41]
Δ LTI$_{i,t}$		0	0.002		-0.002
		[0.02]	[1.10]		[-0.90]
Δ ln(Price$_{i,t}$)			0.013		0.013
			[2.84]		[3.11]
Δ MBS Yield $_t$				0.002	0.002
x ln(Population$_{i,t-1}$)				[3.86]	[3.92]
Δ MBS Yield $_t$				-0.002	-0.001
x ln(Wage$_{i,t-1}$)				[-0.85]	[-0.39]
Δ MBS Yield $_t$				0.004	0.004
x LTI$_{i,t-1}$				[2.20]	[2.05]
Δ MBS Yield $_t$				-0.003	-0.004
x ln(LoanSize$_{i,t-1}$)				[-1.23]	[-1.49]
Δ MBS Yield $_t$				-0.01	-0.01
x ln(Price$_{i,t-1}$)				[-3.26]	[-3.29]
ln(Wage$_{i,t-1}$)				0.001	-0.003
				[0.31]	[-1.14]
ln(Population$_{i,t-1}$)				-0.005	-0.001
				[-1.20]	[-0.19]
ln(LoanSize$_{i,t-1}$)				0	0.005
				[-0.06]	[1.15]
LTI $_{i,t-1}$				-0.003	-0.003
				[-1.54]	[-1.48]
ln(Price$_{i,t-1}$)				-0.003	-0.003
				[-0.95]	[-1.05]
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**
	[3.15]	**[3.24]**	**[2.71]**	**[3.09]**	**[3.11]**
Top 4$_{i,t-1}$	0.009	0.01	0.011	-0.027	-0.02
	[0.49]	[0.52]	[0.55]	[-1.31]	[-1.07]
Δ ln(Wage$_{i,t}$)		-0.014	-0.035		-0.007
		[-0.70]	[-1.44]		[-0.55]
Δ ln(Population$_{i,t}$)		0.116	0.441		0.256
		[1.46]	[2.37]		[3.18]
Δ ln(LoanSize$_{i,t}$)		-0.016	-0.022		0.023
		[-0.97]	[-1.16]		[2.05]
Δ LTI$_{i,t}$		0.01	0.012		-0.004
		[1.27]	[1.19]		[-0.48]
Δ ln(Price$_{i,t}$)			0.054		0.05
			[2.53]		[2.69]
Δ MBS Yield $_t$				0.003	0.003
x ln(Population$_{i,t-1}$)				[1.81]	[1.76]
Δ MBS Yield $_t$				-0.007	-0.003
x ln(Wage$_{i,t-1}$)				[-0.83]	[-0.35]
Δ MBS Yield $_t$				0.008	0.007
x LTI$_{i,t-1}$				[0.94]	[0.83]
Δ MBS Yield $_t$				-0.014	-0.016
x ln(LoanSize$_{i,t-1}$)				[-1.02]	[-1.28]
Δ MBS Yield $_t$				-0.035	-0.035
x ln(Price$_{i,t-1}$)				[-2.94]	[-2.96]
ln(Wage$_{i,t-1}$)				0.007	-0.009
				[0.52]	[-0.76]
ln(Population$_{i,t-1}$)				-0.019	-0.002
				[-1.07]	[-0.15]
ln(LoanSize$_{i,t-1}$)				-0.001	0.018
				[-0.07]	[0.88]
LTI $_{i,t-1}$				-0.018	-0.018
				[-1.87]	[-1.61]
ln(Price$_{i,t-1}$)				-0.013	-0.011
				[-0.90]	[-1.06]
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
Lender Breakdown

This table examines the behavior of different types of lenders. Panel A shows the relationship between top 4 concentration and the market share of lenders that operate in the number of counties shown in the column heading. Panels B and C present regressions of the form:

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

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 less than 10 counties. 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 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. Standard errors are clustered by county and year, and t-statistics are reported in the brackets.

	Panel A: Lender Types and Top 4			
	< 10	< 50	< 250	< 500
$Top4_{i,t-1}$	-0.081	0.197	0.299	0.226
	[-8.63]	[11.98]	[20.46]	[15.72]
R^2	0.021	0.051	0.122	0.076
N	3141	3141	3141	3141

	Panel B: Without Year FE							
	< 10	≥ 10	< 50	≥ 50	< 250	≥ 250	< 500	≥ 500
Δ MBS Yield $_t$	-0.017	-0.015	-0.015	-0.015	-0.015	-0.015	-0.015	-0.015
	[-4.60]	[-4.07]	[-3.87]	[-4.12]	[-3.99]	[-4.17]	[-3.94]	[-4.21]
Δ MBS Yield $_t$ x $Top4_{i,t-1}$	**0.018**	**0.016**	**0.011**	**0.017**	**0.011**	**0.018**	**0.012**	**0.018**
	[3.66]	**[3.58]**	**[2.54]**	**[3.75]**	**[2.93]**	**[3.91]**	**[3.02]**	**[3.96]**
$Top4_{i,t-1}$	0.001	0.004	0	0.005	0.002	0.005	0.002	0.005
	[0.31]	[1.17]	[0.10]	[1.38]	[0.38]	[1.51]	[0.47]	[1.53]
R^2	-0.016	0.282	0.081	0.275	0.164	0.263	0.185	0.254
N	52384	52384	52384	52384	52384	52384	52384	52384
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N

	Panel C: With Year FE							
	< 10	≥ 10	< 50	≥ 50	< 250	≥ 250	< 500	≥ 500
Δ MBS Yield $_t$ x	**0.021**	**0.019**	**0.014**	**0.02**	**0.014**	**0.021**	**0.015**	**0.021**
Top4$_{i,t-1}$	**[4.24]**	**[4.62]**	**[3.77]**	**[4.70]**	**[4.58]**	**[4.76]**	**[4.82]**	**[4.76]**
Top4$_{i,t-1}$	-0.005	0.001	-0.007	0.003	-0.004	0.004	-0.003	0.003
	[-0.59]	[0.31]	[-0.93]	[0.62]	[-0.70]	[0.89]	[-0.49]	[0.88]
R^2	0.005	0.528	0.178	0.514	0.328	0.491	0.374	0.473
N	52384	52384	52384	52384	52384	52384	52384	52384
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 4
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
	[7.87]	[7.26]	[5.38]		[7.30]	[7.36]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-0.626**	**-0.564**	**-0.584**		**-0.549**	**-0.577**
	[-2.75]	**[-2.37]**	**[-1.68]**		**[-2.37]**	**[-2.46]**
(Δ MBS Yield)$^+$				0.612		
				[3.96]		
(Δ MBS Yield)$^-$				0.693		
				[3.71]		
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				-0.352		
				[-0.84]		
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**-0.762**		
				[-1.55]		
Top 4$_{i,t-1}$	-0.057	-0.001	-0.011	-0.04	-0.002	-0.01
	[-0.96]	[-0.09]	[-0.74]	[-0.52]	[-0.10]	[-0.37]
Δ LTV$_{i,t}$					0.004	0.004
					[3.34]	[3.14]
Δ FICO$_{i,t}$					-0.002	-0.002
					[-9.09]	[-8.51]
Δ ln(Price$_{i,t}$)						0.409
						[1.47]
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
	[1.96]	[1.62]	[1.70]	[1.64]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-0.563**	**-0.469**	**-0.512**	**-0.53**
	[-2.44]	**[-2.54]**	**[-2.60]**	**[-2.70]**
Δ MBS Yield $_t$	-0.008	-0.017	-0.01	-0.011
x ln(Population$_{i,t-1}$)	[-0.49]	[-1.35]	[-0.79]	[-0.93]
Δ MBS Yield $_t$	-0.056	-0.04	-0.039	-0.042
x ln(Wage$_{i,t-1}$)	[-0.53]	[-0.48]	[-0.61]	[-0.67]
Δ MBS Yield $_t$		-0.004	-0.005	-0.004
x LTV$_{i,t-1}$		[-1.57]	[-1.41]	[-1.29]
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
	[-0.06]	[0.89]	[-0.12]	[-0.11]
ln(Population$_{i,t-1}$)	-0.011	0.007	0.027	0.008
	[-0.30]	[0.17]	[0.77]	[0.30]
ln(Wage$_{i,t-1}$)	0.013	0.01	0.041	0
	[0.28]	[0.19]	[0.84]	[0.01]
LTV$_{i,t}$		-0.002	-0.002	0
		[-1.68]	[-1.66]	[0.01]
FICO$_{i,t}$		0.001	0.001	0
		[5.83]	[5.35]	[0.67]
ln(Price$_{i,t}$)			-0.015	0.005
			[-0.80]	[0.28]
Δ ln(Wage$_{i,t}$)				0.916
				[0.73]
Δ ln(Population$_{i,t}$)				-0.411
				[-1.61]
Δ LTV$_{i,t}$				0.004
				[2.76]
Δ FICO$_{i,t}$				-0.002
				[-7.07]
Δ ln(Price$_{i,t}$)				0.444
				[1.61]
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 5
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; LTI is the mortgage loan-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 LTI$_{i,t-1}$	[-3.34]	[-5.93]				
LTI $_{i,t-1}$	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 6
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 and 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, LTI, Loan Size		Wage, Pop, LTI, 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 7
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 county and 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**				
	[2.98]				
Δ MBS Yield $_t$		-0.118		0.704	0.677
		[-2.12]		[1.60]	[1.60]
$\widehat{Top\ 4}_{i,t}$		0.025	0.013	0.142	0.146
		[0.64]	[0.69]	[0.61]	[0.17]
Δ MBS Yield $_t$ x $\widehat{Top\ 4}_{i,t}$		**0.251**	**0.135**	-0.649	-0.589
		[1.94]	**[4.05]**	[-0.46]	[-0.44]
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**				
	[2.71]				
Δ MBS Yield $_t$		-0.105		1.01	1.01
		[-2.66]		[2.67]	[2.69]
$\widehat{Top\ 4}_{i,t}$		-0.115	0.03	0.185	-0.001
		[-2.15]	[0.71]	[0.26]	[-0.00]
Δ MBS Yield $_t$ x $\widehat{Top\ 4}_{i,t}$		**0.211**	**0.263**	**-1.702**	**-1.713**
		[2.41]	**[1.04]**	**[-1.76]**	**[-1.68]**
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 8
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	
	[1.21]		[-6.40]	
Δ MBS Yield $_t$ x Top4 $_{i,t-1}$	-0.043	**-0.053**	**0.313**	**0.327**
	[-0.83]	**[-2.04]**	**[3.91]**	**[3.88]**
Δ ln(Employment$_{i,t}$)			1.255	0.496
			[3.03]	[2.32]
Top 4$_{i,t-1}$	0.091	0.186	-0.097	-0.17
	[1.48]	[6.11]	[-0.83]	[-2.44]
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

Appendix Table 1
Using HHI to Measure Concentration

This table presents regressions of the form:

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

and

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

The column headings show the dependent variable. 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. The columns with refinancings as the dependent variable are run yearly 1994-2011, and standard errors are clustered by county and 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.

	Δ Refi/Pop$_{i,t}$			Δ Rate$_{i,t}$		
Δ MBS Yield $_t$	-0.01			0.592	0.577	
	[-4.51]			[10.00]	[9.34]	
Δ MBS Yield $_t$ x HHI$_{i,t-1}$	**0.025**	**0.031**		**-2.632**	**-2.367**	
	[4.10]	**[5.27]**		**[-2.49]**	**[-2.18]**	
(Δ MBS Yield)$^+$						0.564
						[5.50]
(Δ MBS Yield)$^-$						0.59
						[4.64]
(Δ MBS Yield)$^+$ x HHI$_{i,t-1}$			0.009			-1.464
			[1.36]			[-0.79]
(Δ MBS Yield)$^-$ x HHI$_{i,t-1}$			**0.039**			**-3.278**
			[5.05]			**[-1.45]**
HHI$_{i,t-1}$	0.006	0.003	0.005	-0.274	0.027	-0.14
	[1.47]	[0.61]	[1.27]	[-0.98]	[0.37]	[-0.41]
R^2	0.318	0.517	0.52	0.318	0.317	0.317
N	52384	52384	52384	38068	38068	38068
County FE	N	Y	Y	N	Y	Y
Year FE	N	Y	Y	N	Y	Y

Appendix Table 2
Weighting the Sample by Population

This table presents regressions of the form:

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

and

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

The column headings show the dependent variable. The subheadings indicate whether (i) each county is weighted by its population; (ii) the sample is restricted to counties with population above the median in a given year; or (iii) the sample is restricted to counties with population above the mean in a given year. 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 county and 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.

	Δ Refi/Pop$_{i,t}$			Δ Rate$_{i,t}$		
	Pop Weight	Pop > Median	Pop > Mean	Pop Weight	Pop > Median	Pop > Mean
Δ MBS Yield$_t$ x Top4$_{i,t-1}$	**0.023**	**0.021**	**0.017**	**-0.67**	**-0.662**	**-0.68**
	[4.13]	**[4.26]**	**[2.90]**	**[-2.46]**	**[-2.44]**	**[-2.44]**
Δ MBS Yield$_t$				0.674	0.67	0.669
				[6.68]	[6.77]	[6.46]
Top4$_{i,t-1}$	0.005	0.003	0.005	-0.003	-0.008	0
	[0.99]	[0.63]	[0.98]	[-0.13]	[-0.32]	[0.00]
R^2	0.722	0.661	0.758	0.336	0.349	0.34
N	52384	26609	9875	38068	19022	11748
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Appendix Table 3
Mortgage Rates and Concentration, Lags

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 $_t$	0.68	0.663	0.679	0.651	0.661
	[8.46]	[7.69]	[5.64]	[7.63]	[7.70]
Δ MBS Yield $_{t-1}$	0.082	0.065	0.138	0.055	0.055
	[1.13]	[0.82]	[1.37]	[0.71]	[0.69]
Δ MBS Yield $_{t-2}$	0.112	0.096	0.068	0.093	0.093
	[1.32]	[1.18]	[0.86]	[1.12]	[1.08]
Δ MBS Yield $_{t-3}$	0.013	-0.002	0.011	-0.003	0
	[0.20]	[-0.03]	[0.11]	[-0.04]	[0.00]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-0.647**	**-0.588**	**-0.563**	**-0.58**	**-0.622**
	[-3.13]	**[-2.64]**	**[-1.69]**	**[-2.63]**	**[-2.79]**
Δ MBS Yield $_{t-1}$ x Top4$_{i,t-1}$	-0.028	0.037	-0.074	0.06	0.088
	[-0.13]	[0.17]	[-0.25]	[0.27]	[0.39]
Δ MBS Yield $_{t-2}$ x Top4$_{i,t-1}$	-0.151	-0.099	-0.058	-0.095	-0.097
	[-0.73]	[-0.49]	[-0.25]	[-0.46]	[-0.46]
Δ MBS Yield $_{t-3}$ x Top4$_{i,t-1}$	0.043	0.108	-0.054	0.102	0.097
	[0.25]	[0.56]	[-0.18]	[0.53]	[0.49]
Top 4$_{i,t-1}$	-0.051	0.001	-0.014	0.003	-0.006
	[-0.91]	[0.03]	[-0.42]	[0.12]	[-0.21]
Δ LTV$_{i,t}$				0.004	0.004
				[2.95]	[2.76]
Δ FICO$_{i,t}$				-0.002	-0.002
				[-8.73]	[-8.08]
Δ ln(Price$_{i,t}$)					0.229
					[0.95]
R^2	0.341	0.339	0.26	0.366	0.381
N	36902	36902	21431	36902	29648
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Appendix Table 4
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
	[10.15]	[11.36]	[9.19]		[9.44]	[8.49]
Δ MBS Yield $_t$ x Top4$_{i,t-1}$	**-1.365**	**-1.089**	-0.018		**-1.008**	**-1.193**
	[-4.15]	**[-4.39]**	[-0.05]		**[-4.25]**	**[-3.96]**
(Δ MBS Yield)$^+$				0.875		
				[4.39]		
(Δ MBS Yield)$^-$				1.238		
				[6.03]		
(Δ MBS Yield)$^+$ x Top4$_{i,t-1}$				-0.771		
				[-1.38]		
(Δ MBS Yield)$^-$ x Top4$_{i,t-1}$				**-1.262**		
				[-2.56]		
Top 4$_{i,t-1}$	-0.254	-0.141	-0.034	-0.214	-0.147	-0.188
	[-2.21]	[-1.74]	[-0.41]	[-1.38]	[-1.88]	[-1.93]
Δ LTV$_{i,t}$					0.005	0.005
					[2.28]	[2.37]
Δ FICO$_{i,t}$					-0.004	-0.004
					[-4.32]	[-3.93]
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 5
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 6
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]
LTI	**-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]

Appendix Table 7
Merger Sample Characteristics

This table reports characteristics of the counties used in the merger sample results reported in Table 7 of the main text. Panels A and C report the coefficient from running a regression of the specified variable on an indicator for whether the county is in the first merger sample and whether the county is in the second (more restrictive) merger sample, respectively. Panels B and D report the coefficient from running a regression of the specified variable on a post-merger indicator for counties in the first merger sample and the second (more restrictive) merger sample, respectively. t-statistics clustered by county are reported in the brackets.

	Panel A: Characteristics of Counties in First Merger Sample						
	ln(Pop)	ln(Price)	ln(Wage)	ln(Loan Size)	LTI	LTV	FICO
Merger Sample$_i$	0.599	-0.103	0.049	0.124	0.107	-0.964	-0.801
	[11.29]	[-2.12]	[6.79]	[10.22]	[7.36]	[-6.44]	[-1.41]
R^2	0.043	0.008	0.015	0.032	0.018	0.013	0
N	3120	530	3120	3120	3120	3120	3120

	Panel B: Post-Merger Characteristics of Counties in First Merger Sample						
	Δln(Pop)	Δln(Wage)	Δln(Price)	Δln(Loan Size)	LTI	LTV	FICO
Post Merger$_{i,t}$	0.001	-0.001	-0.016	0.006	-0.002	0.23	4.587
	[1.25]	[-0.71]	[-2.48]	[1.96]	[-0.18]	[1.25]	[6.71]
R^2	0.349	0.074	0.448	0.06	0.23	0.338	0.158
N	32063	32063	5540	32063	32063	24419	24419
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

	Panel C: Characteristics of Counties in Second Merger Sample						
	ln(Pop)	ln(Price)	ln(Wage)	ln(Loan Size)	LTI	LTV	FICO
Merger Sample$_i$	0.027	-0.04	0.006	0.122	0.157	0.149	1.886
	[0.41]	[-0.86]	[0.61]	[6.74]	[8.19]	[0.50]	[1.87]
R^2	0	-0.001	0	0.013	0.016	0	0
N	3120	530	3120	3120	3120	3120	3120

	Panel D: Post-Merger Characteristics of Counties in Second Merger Sample						
	Δln(Pop)	Δln(Wage)	Δln(Price)	Δln(Loan Size)	LTI	LTV	FICO
Post Merger$_{i,t}$	0.001	0	-0.018	-0.005	-0.077	-0.377	0.6
	[0.53]	[-0.42]	[-1.28]	[-0.95]	[-1.86]	[-0.76]	[0.28]
R^2	0.151	0.041	0.569	0.091	0.444	0.649	0.526
N	5566	5566	992	5566	5566	3555	3555
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y