Mortgage Securitization and Shadow Bank Lending*

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Abstract

We show how securitization affects the size of the nonbank lending sector through a novel price-based channel. We identify the channel using a regulatory spillover shock to the cross-section of mortgage-backed security prices: the U.S. Liquidity Coverage Ratio. The shock increases secondary market prices for FHA-insured loans by granting them favorable regulatory status once securitized. Higher prices lower nonbanks' funding costs, prompting them to loosen lending standards and originate more of such loans. This channel accounts for 22% of nonbanks' growth in overall mortgage market share over 2013-15. While the shock creates financial stability risks, it also raises homeownership.

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1 Introduction

A critical function of securitization is to give borrowers access to capital markets by transforming illiquid loans into liquid asset-backed securities (e.g. Strahan 2012). This process of liquidity transformation generated intense policy debate in the wake of the 2008 Financial Crisis (e.g. Willen 2014), with allegations that it destabilized the financial system by channeling credit to risky *borrowers*. We provide evidence that securitization also affects financial stability by channeling market share to risky *lenders*. This lender-oriented view is particularly relevant given the recent expansion of the nonbank lending sector, often called the shadow banking system. In the mortgage space, nonbanks originate around 80% of loans insured by the Federal Housing Administration (FHA) and more than 50% of all mortgages. This trend concerns policymakers, who fear that nonbanks introduce excessive credit risk into the financial system, and a credit-induced bust could spark a financial crisis because of nonbanks' fragile funding model (e.g. Pinto and Oliner 2015; Wallace 2016; Di Maggio and Kermani 2017).

We document spillover effects from liquidity regulation, and, in so doing, we show how securitization increases the size of the shadow banking system through a novel price-based channel. The underlying theory that we test begins with variation in how lenders fund mortgage originations. Unlike banks, nonbanks lack access to stable deposit funding, and so they fund originations through short-term, warehouse debt that is collateralized by the originated mortgage and repaid once the mortgage has been securitized (e.g. Kim et al 2018). An increase in mortgage-backed security (MBS) prices raises nonbanks' revenue per mortgage originated, and it lowers their funding costs by improving the value of their collateral. Both forces incentivize nonbanks to extend more credit in the primary market, which they accomplish by relaxing lending standards. Consequently, higher MBS prices increase nonbanks' market share.

Testing this hypothesis with a naive regression of nonbanks' market share on MBS prices would suffer two econometric issues. The first issue is omitted variables bias: unobserved factors (e.g. expectations about the housing market) affect both primary market lending and secondary market prices. To overcome this challenge, we develop a novel empirical strategy based on the cross-section of MBS returns. Broadly-speaking, the U.S. MBS market is segmented into two categories: securities insured by Ginnie Mae (GNMA); and securities insured by the government-sponsored enterprises (GSEs), namely Fannie Mae (FNMA) or Freddie Mac (FHLMC).[1] This market segmentation allows us to difference out common shocks to MBS submarkets and study the relative supply of credit across their corresponding primary markets. In particular, only loans to borrowers satisfying specific requirements stipulated by the Federal Housing Administration (FHA) can be securitized into GNMA MBS. Thus, according to our theory, an increase in the price of GNMA MBS relative to, say, FNMA MBS should increase the relative supply of credit by nonbank lenders in the FHA market.

The second econometric issue is reverse causality: changes in the relative supply of FHA credit affect the relative price of GNMA MBS, whereas we are interested in the reverse effect. We address this challenge by appealing to a natural experiment: the introduction of the U.S. Liquidity Coverage Ratio (LCR). Proposed in October 2013, the LCR is intended to ensure that sufficiently large financial institutions have enough liquidity-weighted assets to survive a 30-day stress period. However, by assigning a preferential regulatory weight to GNMA MBS, this policy also stimulated GNMA demand and consequently increased the market price of GNMA MBS relative to other securities. Using an event study, we find that the introduction of the LCR indeed increased GNMA prices and lowered the required return on GNMA MBS by 22% (55 basis points). Since the LCR announcement was largely unexpected and unrelated to contemporaneous trends in the U.S. housing market, it provides exogenous variation in the cross-section of MBS prices. We use this variation to identify the effect of MBS prices on the relative supply of nonbank credit.

Our first exercise is a loan-level, triple difference-in-difference research design. We obtain identification from the triple difference between: banks vs. nonbanks (i.e. "treated lenders"); conventional vs. FHA loans (i.e. "treated loan types"); and the GNMA premium from before vs. after the LCR shock (i.e. the "treatment"). This strategy allows us to include lender-year, MSA-year, and MSA-lender fixed effects along with borrower controls that might otherwise affect origination decisions. Consequently, we rely on a very weak identification assumption. We find that nonbanks respond to the increase in GNMA prices by relaxing their lending standards and denying 15% (2.1 pps) fewer FHA loan applicants, relative to banks.

[1] A third category, the private label market, evaporated in the years following the 2008 Financial Crisis, and so we focus on GNMA and GSE-backed MBS.

We assess the implications of our loan-level results for nonbanks' overall mortgage market share using a zip code-level regression, where "treated zip codes" are those with greater reliance on both FHA credit and nonbanks in 2013. Per our loan-level results, such zip codes are more exposed to the LCR-induced increase in nonbanks' credit supply. We find that more-exposed zip codes experience higher growth in nonbanks' market share over 2013-15 as well as higher growth in overall mortgage volume, suggesting that nonbanks drive an increase in credit supply rather than merely substituting for banks. Using our zip code-level estimates, we perform an aggregation exercise in the spirit of Chodorow-Reich (2014). Accordingly, we find that the shock accounts for 22% (1.2 pps) of nonbanks' observed growth in market share over 2013-15. As expected, the effect is substantially stronger within the FHA market, where the shock accounts for 48% of nonbanks' growth.

The increase in nonbanks' market share affects financial stability through two channels: credit risk and funding fragility. First, nonbanks' relaxation of lending standards and willingness to approve larger loans imply an increase in credit risk, and especially so in our setting because FHA loans are intended for riskier borrowers (e.g. Urban Institute 2017). Indeed, we find that zip codes more exposed to the LCR-induced increase in nonbank lending see higher mortgage default rates. Second, a larger nonbank lending sector increases average funding fragility because nonbanks' short-term funding model makes them more prone to run-like withdrawals (e.g. Kim et al 2018).[2]

Yet, despite these negative implications for financial stability, the spillovers from LCR regulation have an ambiguous effect on overall welfare. For example, we also find that the increase in nonbanks' credit supply raises zip code-level homeownership, which may increase welfare by giving lower-income households access to mortgage credit.

We pursue several extensions to evaluate the theory by which higher secondary market prices increase nonbanks' share of the primary market. First, to confirm that the relevant mechanism is variation in funding models, we obtain similar results when defining "treated lenders" as those with less historical reliance on deposit funding or greater historical reliance on securitization. In fact, the results are almost the same when dropping nonbanks from the sample, consistent

[2]Quoting the financial press, "Many nonbanks remain highly reliant on short-term funding ..., so if wholesale markets froze again, many Americans would quickly lose access to mortgage finance" (The Economist 2020).

with heterogeneity in bank funding models (e.g. Loutskina 2011; Cornett et al 2011; Dagher and Kazimov 2015). Second, we find that nonbanks do not tighten their lending standards among non-FHA loans to compensate for their looser lending in the FHA market, and this lack of reallocation supports the validity of our large estimated effect on nonbanks' overall market share. However, consistent with a new literature pioneered by Chakraborty, Goldstein, and MacKinlay (2018, 2020), we find that capital-constrained banks who rely on securitization indeed reallocate loanable funds across mortgage types, as they loosen standards among FHA borrowers but tighten them among non-FHA borrowers.

Our findings are also robust to a variety of other tests meant to assess internal validity. For example, the results are similar when restricting the sample to small lenders, studying other measures of credit supply (e.g. loan volume, interest rates), and controlling for regulatory arbitrage incentives, as measured by capital ratios or stress testing requirements. To ensure the validity of our zip code-level results, we conduct a placebo test over the 2011-13 period and find no effect. Furthermore, our measure of a zip code's exposure is uncorrelated with other drivers of nonbanks' market share, such as household demographics or the strength of local banks' balance sheets, further supporting the results' validity. Indeed, based on a wide variety of robustness tests, we find no evidence that our findings are driven by: increased litigation risk associated with the False Claims Act; the Fed's Quantitative Easing program; a pre-trend in nonbank denial rates; or spurious correlation between the introduction of the LCR and the increase in the GNMA premium.

The remainder of the paper proceeds as follows. We conclude this section by situating our contribution within the related literature. Section 2 describes an organizing theory. Section 3 describes our identification strategy and the details of the Liquidity Coverage Ratio shock. Section 4 contains our loan-level analysis of the effect on nonbanks' lending standards. Section 5 assesses the effect on nonbanks' market share. Sections 6 and 7 study implications for financial stability and homeownership, respectively. Section 8 assesses the robustness of our main findings. Section 9 concludes. The online appendix contains additional material.

Related Literature

Our paper makes three contributions to the literature. First, a large number of papers have studied how securitization affects the quantity and quality of credit in primary lending markets (e.g. Loutskina and Strahan 2009; Keys, Mukherjee, Seru, and Vig 2010; Keys, Seru, and Vig 2012; Benmelech, Dlugosz, and Ivashina 2012; Nadauld and Sherlund 2013). These papers focus on how securitization affects the distribution across types of loans that are originated in the primary market. By contrast, we study how securitization affects the distribution across types of lenders who intermediate those loans, which has implications for financial stability.

Second, we contribute to a growing number of papers on the consequences and causes of recent growth in the nonbank lending sector. In terms of consequences, several papers highlight the systemic risks associated with greater reliance on nonbanks (e.g. Kim et al 2018; Drechsler, Savov, and Schnabl 2019; D'Avernas, Vandeweyer, and Pariès 2020; Hanson et al 2015). In terms of causes, the existing literature has found that nonbanks' market share depends on regulatory arbitrage (e.g. Buchak et al 2018), technological innovation (e.g. Fuster et al 2019), bank capitalization (e.g. Irani et al 2019; Chernenko, Erel, and Prilmeier 2019), and creditor protection in the warehouse lending market (e.g. Ganduri 2019). Our paper shows how secondary market prices are another force − among the aforementioned ones − that affects nonbanks' market share. In addition, we document potentially welfare-improving consequences of a larger nonbank lending sector, such as access to homeownership.

Third, there is growing interest in how financial regulations introduced in the wake of the Financial Crisis affect housing markets. To date, papers have documented important effects related to stress tests (e.g. Calem, Correa and Lee 2019; Gete and Reher 2018), qualified-mortgage requirements (e.g. De Fusco, Johnson, and Mondragon 2020), litigation risk (e.g. D'Acunto and Rossi 2019; Gissler, Oldfather, and Ruffino 2016), and capital requirements (e.g. Reher 2020). In Europe, Van Bekkum, Gabarro, and Irani (2017) show how MBS rating requirements affect credit supply. We show how liquidity regulation (i.e. the LCR) also affects the housing market in meaningful ways, such as raising nonbanks' share of mortgage lending, increasing credit risk, and bolstering homeownership. These effects are an unintended consequence of the LCR, and they must be weighed against the intended effect of increasing banks' liquid asset holdings (e.g. Roberts, Sarkar, and Shachar 2018).

2 Theory

Our empirical analysis is grounded in a theory of mortgage markets where lenders vary in how they fund mortgage originations. The theory has several steps, which we describe here and complement with a simple framework in Appendix B.

1. *Difference in Funding Model*: Nonbanks fund mortgage originations using short-term warehouse credit because they do not have access to deposits. Consequently, nonbanks have an originate-to-securitize funding model as shown in panel (a) of Figure 1: they fund a mortgage using short-term debt that is borrowed from a separate warehouse lender and collateralized by the mortgage; then, they securitize and sell the mortgage in the secondary market at a price P_S; lastly, using the proceeds from this sale, they repay the warehouse lender at the effective gross interest rate R_W (e.g. Kim et al 2018; Echeverry, Stanton, and Wallace 2016). Depository institutions (i.e. banks), on the other hand, can fund originations using deposits, as shown in panel (b).

   Summarizing the two funding models shown in Figure 1, the originate-to-securitize model is a loan-by-loan funding model because warehouse lenders have a claim on the loans originated. By contrast, depositors have a claim on the collective value of the lender's assets.

2. *Nonbanks' Funding Costs*: An increase in MBS prices improves the value of nonbanks' collateral and lowers their funding costs, since warehouse lenders can expect to break even at a lower promised interest rate.[3] In our empirical setting, MBS prices increase because a regulatory shock incentivizes large financial institutions to buy more MBS. Indeed, the shock we study comes with a reduction in nonbanks' cost of warehouse credit, as we will show in Figure 4.

[3]We implicitly assume that warehouse lenders are competitive and that the reduction in interest rates is for a given level of borrower credit risk.

3. *Credit Supply*: An increase in MBS prices not only lowers nonbanks' funding costs, as mentioned in Step 2, but it also raises their revenue per dollar of mortgage credit originated. Both channels incentivize nonbanks to originate more loans in the primary mortgage market. Nonbanks originate more loans by denying fewer borrowers, as we will show in Table 2. They also originate larger loans, as in Table 9.

4. *Market Share*: More relaxed lending standards increase the relative supply of credit by nonbanks because, as described in the next point, banks do not respond to higher MBS prices in the same way as nonbanks. Therefore, nonbanks' mortgage market share increases, as Tables 3 and 4 will show.[4] This effect stems from differences between banks and nonbanks' funding models, as distinct from other differences like risk aversion.[5]

5. *Choice of Funding Model*: Banks can adopt an originate-to-securitize model in principle, but in our data only 4% of banks choose to securitize at the same rate as the median nonbank. This observation is consistent with a literature on the advantages that deposit funding confers on banks. A partial list of such advantages includes: the ability to exert market power over depositors (e.g. Drechsler, Savov, and Schnabl 2017); extract a money premium from the fact that deposits are government-insured (e.g. Hanson et al 2015); and the option to cross-sell other products, such as insurance, to depositors.[6] Consistent with these advantages, Appendix Table A2 shows how banks with more market power over depositors choose to securitize fewer of their loans.[7]

[4]This step implicitly assumes there are no crowd-out effects across different types of mortgages. We do not find any evidence of crowding out by nonbanks, as discussed in Section 8.4.

[5]If nonbanks are less risk averse than banks, then their steady-state market share among riskier loan types will be higher, but their response to a change in MBS prices will be the same. We formalize this argument in Appendix B and substantiate it empirically in Table 8 and Appendix Table A7.

[6]Molyneux, Reghezza, and Xie (2019) show how banks complement higher deposit rates with higher fees.

[7]Market power is proxied by taking a bank's average deposit market share across U.S. counties in which the bank has a branch. We control for various bank risk factors studied in Cornett et al (2011) as well as the bank's average mortgage market share, which ensures that the negative relationship between securitization activity and deposit market share is not driven by the scale of the bank's mortgage lending. The only variable that is consistently significant across specifications is the bank's deposit market share.

3 Identification

The theory described in Section 2 predicts that higher MBS prices will lower nonbanks' lending standards and increase the overall share of mortgage credit that they intermediate. We test this hypothesis in the U.S. market using a novel methodology that has two key features: (a) we obtain identification through the cross-sectional distribution of MBS prices; and (b) we utilize an exogenous, regulatory shock to this cross-sectional distribution.

First, we address the challenge of omitted variables bias by turning to the cross-section of MBS prices, or, to be precise, MBS expected returns. Specifically, we focus on the price of Ginnie Mae (GNMA) MBS *relative* to either Fannie Mae (FNMA) or Freddie Mac (FHLMC) MBS. This technique differences out common shocks to the MBS market, such as expected housing demand or the Fed's Quantitative Easing program, which also affect outcomes in the primary mortgage market. Correspondingly, in our main analysis we study how increases in the relative price of GNMA MBS − or, equivalently, reductions in expected return − affect nonbanks' market share among borrowers whose loans are eligible for securitization as GNMA MBS, namely Federal Housing Administration (FHA) loans.

Second, we address the question of reverse causality by turning to a natural experiment: the introduction of the U.S. Liquidity Coverage Ratio (LCR). Exogenous changes in nonbanks' FHA lending standards can affect GNMA prices − the reverse of the causal relationship we are interested in estimating. Thus, we perform our analysis over a period during which there was an exogenous shift in the GNMA premium due to the introduction of the LCR, which we now describe.

3.1 The Liquidity Coverage Ratio

The U.S. Liquidity Coverage Ratio was introduced as part of the post-Crisis regulatory overhaul, and it was intended to ensure that sufficiently large financial institutions have enough liquid assets to survive a 30-day period of cash outflows. The policy assigned different liquidity weights to assets, where a higher weight implies more favorable regulatory treatment.[8] In particular, the rule favored GNMA MBS with a weight of one, as opposed to 0.85 for FNMA and FHLMC MBS. This distinction reflects the explicit government guarantee associated with GNMA MBS, versus the implicit guarantee associated with FNMA and FHLMC MBS because they are not officially government entities and, under normal circumstances, would be publicly-listed companies. The regulation was proposed on October 24, 2013 and finalized in September 2014, with few changes relative to the initial proposal. Before this proposal, there was uncertainty over the institutional details of the LCR, since Federal Reserve Governor Daniel Tarullo had raised the possibility that the U.S. LCR implementation might differ from international standards, but he did not indicate how it would differ.[9] We therefore refer to the introduction of the LCR on October 24, 2013 as the "LCR shock", and we define the "shock year" as 2014, the first full year after this introduction.

Given these details, one might expect the introduction of the LCR to affect MBS prices through: (a) an increase in affected institutions' demand for GNMA MBS; and (b) consequently, an endogenous increase in GNMA market liquidity, which would increase non-affected institutions' GNMA demand. Both channels imply that GNMA prices should rise − and expected returns should fall − because of an increase in demand. Importantly, banks affected by the LCR must purchase GNMA MBS on the secondary market to satisfy the regulatory requirement: they cannot satisfy the requirement by simply originating more FHA loans and holding them on their balance sheets.[10]

Beginning with quantities, in Figure 2 we examine the direct effect of the LCR shock (i.e. channel (a) from the previous paragraph) by plotting the GNMA portfolio holdings of banks subject to the LCR rule. The figure shows how affected banks substantially increase their holdings of GNMA MBS after the LCR shock. In particular, the increase equals 7 pps of

[8] Explicitly, a bank's liquidity coverage ratio is defined as the sum of liquidity-weighted assets divided by 30-day cash outflows. This ratio is required to exceed one for affected banks. See the report by the Basel Committee on Bank Supervision (2013) or Diamond and Kashyap (2016) for discussion of additional institutional details and the policy's motivation.

[9] See the November 4, 2011 speech "The International Agenda for Financial Regulation" and Getter (2014).

[10] In principle, banks could originate more FHA loans, sell them as GNMA MBS, and immediately repurchase the securitized loan. However, based on conversations with industry practitioners, this would be an unprofitable strategy relative to simply buying GNMA MBS directly because originating new loans entails additional operating costs. We thank an anonymous referee for encouraging us to investigate this possibility.

the holdings by affected plus non-affected banks. Appendix Figure A1 suggests the supply of GNMA MBS increased to meet this demand, showing that the share of FHA loans sold on the secondary market increases relative to non-FHA loans after the introduction of the LCR. This supply response comes with a substantial reduction in the cost of warehouse credit used to produce GNMA MBS, as discussed in the context of Figure 4 below. These large direct effects of the LCR shock help reconcile the large spillover effects that we estimate in Sections 4 and 5.

Turning to prices, in Figure 3 we plot the 12-month-ahead GNMA total gross return (i.e. expected return) relative to FNMA MBS. The expected return on GNMA and FNMA MBS track each other closely in the months leading up to the LCR shock, after which the return on GNMA is lower because its price is higher (i.e. high expected returns correspond to low prices, and vice versa). Phrased differently, investors who purchase GNMA MBS on or after the announcement of LCR regulation would be willing to receive a lower return relative to holding FNMA MBS. By contrast, this differential was absent in the pre-announcement period. To get a sense of magnitude, the change in the expected return to GNMA MBS relative to FNMA MBS in the three months after the LCR shock is 37% larger than the analogous change after Fannie Mae was delisted in June 2010.

The previous results provide evidence that the introduction of the LCR increased the demand for and the price of GNMA MBS, in both absolute terms and relative to non-GNMA MBS. We provide more rigorous evidence by conducting an event study which estimates the GNMA premium generated by the introduction of the LCR. To keep the paper focused, we defer details on this exercise to the online appendix. Briefly, our central estimate in Appendix Table A15 suggests that the introduction of the LCR lowered the expected total return to GNMA MBS relative to FNMA MBS by 55 basis points, which we call the "LCR premium".[11] This premium is equal to 22% of the average real total return to GNMA MBS over 2000-15 and 0.9 standard deviations of the FNMA-GNMA spread. We obtain similar results when studying the

[11]The "control securities" in our setting are FNMA or FHLMC MBS, since, like GNMA MBS, these are also comprised of mortgages and carry a government guarantee against credit risk, as with GNMA MBS. This research design allows us to credibly identify the GNMA premium by differencing out common shocks to the mortgage market, but it makes our results conservative because FNMA and FHLMC MBS also received favorable regulatory status compared to, say, certain types of corporate bonds. Following Diep, Eisfeldt, and Richardson (2017), we focus on MBS total returns measured using the Bloomberg-Barclays Total Return Index, since total returns are less model-dependent than an option-adjusted spread (OAS).

option-adjusted spread (OAS) as opposed to total return, which implies that the results are not driven by changes in prepayment risk.

3.2 Graphical Evidence

Before conducting our main analysis, we begin with some preliminary evidence which situates the LCR shock within our theory. As described in Section 2, an exogenous increase in GNMA MBS prices should incentivize nonbanks to originate more FHA loans, in part because higher MBS prices lower their funding costs in the warehouse credit market. This is exactly what we find in Figure 4. Based on novel data on nonbanks' income statements from the Mortgage Bankers' Association (2014), the introduction of the LCR comes with a 0.9 pp decline in the average nonbank's cost of warehouse credit, measured by the ratio of its interest expense to the value of its credit lines.

By stimulating originations, higher MBS prices should also increase nonbanks' share of the mortgage market. Figure 5 provides evidence in favor of this hypothesis which strongly supports the parallel trends assumption made later in the paper. Using the already-established dataset from Buchak et al (2018), we plot the dynamics of nonbanks' FHA mortgage market share.[12] The figure reveals a secular trend in nonbanks' FHA market share leading up to the policy's introduction, which is also present in the non-FHA (i.e. conventional) market. This secular trend has been well-documented by the literature on nonbanks referenced in the introduction. However, the introduction of the LCR comes with a sharp break from trend, and nonbanks' FHA market share in 2015 is 17 pps higher than what one would have predicted based on its pre-LCR growth rate. By contrast, there is no break from trend within the non-FHA market. Appendix Figure A2 shows how the increase in nonbanks' FHA market share drives an increase in their overall market share, which in 2015 was 8 pps higher than the value implied by its pre-LCR trend.

Collectively, these preliminary results support the idea that the LCR-induced increase in MBS prices raises the supply of nonbank credit and contributes to nonbanks' growth in overall market share. The rest of the paper rigorously evaluates this hypothesis, studying credit supply

[12]We thank Greg Buchak for sharing the data.

(i.e. lending standards) in Section 4 and market share in Section 5. To be clear, our research hypothesis is not that the LCR-induced increase in MBS prices is the only driver of nonbanks' market share, but rather that it is a first-order contributor among the others which have been documented in the literature (e.g. regulatory arbitrage, technology, etc.).

4 Effect on Lending Standards

Our parameter of interest is the effect of an increase in the GNMA premium on the supply of nonbank credit for FHA-eligible borrowers, recalling that only FHA loans can be securitized as GNMA MBS. We measure credit supply using loan denial rates, which allows us to use microdata and include multiple fixed effects to absorb confounding factors. Moreover, studying denial rates allows us to focus on the extensive margin of credit, so that our estimates have the interpretation of an effect on lending standards. We study other outcomes in Section 8 (e.g. loan size, interest rates).

4.1 Data

Our core dataset is a merge of the Home Mortgage Disclosure Act (HMDA) mortgage application registry with bank FRY-9C Call Reports. In the interest of space, we defer a detailed description of all our datasets to Appendix A. Briefly, HMDA data contain information on the borrower and outcome of almost all mortgage applications in the U.S. We retain FHA and conventional loan applications for the purchase of owner-occupied, single-family dwellings. We use the term "conventional" to describe non-FHA loans whose value is below the associated conforming loan limit (i.e. non-jumbo loans). These restrictions give a sample of 396 lenders over the 2010-15 period, 123 of which are non-depository institutions, which we call "nonbanks". The upper panels of Table 1 summarize the resulting dataset. For computational convenience, we perform our loan-level analysis on a 25% random sample of the full data.

4.2 Loan-Level Specification

We perform a triple difference-in-difference analysis across lenders, years, and loan types, and our baseline regression equation is

$$\text{Denial}_{i,l,s,t} = \beta\left(\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s\right) + \gamma X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + ... \quad (1)$$

$$... + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,s,t},$$

where i, l, s, and t index borrower (i.e. loan applicant), lender, loan type, and year, respectively; $\text{Denial}_{i,l,s,t}$ indicates if the application was denied; Nonbank_l indicates if the lender is a nonbank; and the set of loan types are FHA or conventional. In words, "treated lenders" are nonbanks, "treated loan types" are FHA loans, and the "treatment", Premium_t, is a measure of the relative price of GNMA MBS and thus nonbanks' incentive to originate FHA loans.

Our first measure of Premium_t is an indicator for whether Liquidity Coverage Ratio (LCR) regulation is in place. Specifically, we use an indicator for whether $t \geq 2014$, the first full year after the LCR announcement in October 2013. More directly, we also measure Premium_t using the spread in the one-year-ahead total return between FNMA and GNMA MBS.[13] For purely interpretive purposes, we normalize the FNMA-GNMA spread by 55 basis points, which is the estimated effect of LCR regulation discussed in Section 2 and estimated in the online appendix.

From the standpoint of identification, the most powerful feature of our triple difference-in-difference research design is the lender-year fixed effect, $\alpha_{l,t}$, which absorbs shocks to a lender's overall level of credit supply. Thus, any confounding factor coinciding with Premium_t would not only need to disproportionately affect nonbanks, but it would also need to affect nonbanks' willingness to approve FHA over conventional loans. The type-year fixed effects $\alpha_{s,t}$ absorb time variation in lending standards for FHA loan applications due to, say, greater litigation risk. In addition, the type-lender fixed effect $\alpha_{s,l}$ accounts for the effect of lenders' sorting into FHA or conventional loan markets.

The remaining fixed effects ensure robustness to geographic variation. The MSA-year fixed

[13] We take the average 12-month-ahead total return among months in year t, where total returns are measured using the Bloomberg Barclays MBS Total Return indices. Based on the law of iterated expectations, the realized 12-month-ahead return in a given month equals the expected return in that month, on average.

effect $\alpha_{m(i),t}$ captures contemporaneous shocks to local demand in borrower i's MSA of residence, $m(i)$. These contemporaneous demand shocks might otherwise bias the estimate to the extent that they also affect a borrower's propensity of being denied (e.g. expected income growth). We also restrict variation to the same geographic lending relationship by including an MSA-lender fixed effect, $\alpha_{m(i),l}$. This fixed effect rules out the possibility that nonbanks sort into markets where their applicant pool is of better credit quality. Finally, the borrower controls $X_{i,t}$ account for time variation in the observable credit quality of bank versus nonbank applicants.[14]

The identification assumption implicit in equation (1) is

$$0 = \mathbb{E}\left[\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s \times u_{i,l,s,t} \middle| \, \alpha_{l,t}, \alpha_{m(i),t}, \alpha_{m(i),l}, \alpha_{s,t}, \alpha_{s,l}, X_{i,t}\right]. \tag{2}$$

In words, equation (2) states that the LCR-induced increase in the GNMA premium does not coincide with unobserved shocks that affect nonbanks' propensity to deny FHA borrowers over conventional borrowers, relative to banks' propensity. Under this assumption, the parameter β in equation (1) may be interpreted as the effect of the GNMA premium on nonbanks' relative FHA denial rate. Note that this effect is conditional on the various fixed effects and controls in equation (2), which together make the assumption rather weak.[15]

We devote Section 8 to investigating the validity of equation (2), but, as a first pass, Figure 6 inspects pre-trends by plotting the relative denial rate on FHA loans over conventional loans for banks and nonbanks over time. The relative denial rates for the two groups of lenders follow parallel trends leading up the introduction of the LCR, after which nonbank denial rates on FHA loans fall. This observation suggests that equation (2) is not invalid because of a pre-trend.

Table 2 contains the results from estimating equation (1) over the 2010-15 period.[16] In the first column, we find that nonbanks are 2 pps less likely to deny an FHA loan over a conventional loan in the post-LCR period, relative to banks. To make the channel more precise, the second column implies that the increase in the FNMA-GNMA spread due to the introduction

[14]Borrower controls are requested loan-to-income ratio, log income, and an indicator for whether the borrower is black or Hispanic.

[15]The fixed effects $\alpha_{l,t}$, $\alpha_{s,t}$, and $\alpha_{m(i),t}$ subsume the direct effect of Premium_t.

[16]We cluster standard errors by lender-year bins and report p-values in parentheses.

of the LCR lowers nonbanks' relative denial rate by 0.8 pps. We obtain a similar result when considering the FHLMC-GNMA spread in the third column. All results are significant at the 1% level, per the p-values that we report in parentheses.

Collectively, these results imply that higher GNMA prices due to the introduction of the LCR lower nonbanks' relative FHA denial rates by 1-2 pps, or roughly 40% of the difference between the unconditional FHA denial rate (i.e. 13.8%) and conventional denial rate (i.e. 10%). The next section traces this effect through to nonbanks' market share.

5 Effect on Market Share

We estimate the effect of the LCR-induced increase in GNMA prices on nonbanks' market share through a zip code-level regression. Then, we use our zip code-level estimates and methods from the applied macroeconomics literature (e.g. Chodorow-Reich 2014) to calculate nonbanks' counterfactual aggregate market share in the absence of the LCR shock.

5.1 Zip Code-Level Specification

We estimate the effect of the LCR shock on nonbanks' market share by aggregating to the zip code-level. Zip codes contain roughly 8,000 people, and so they are still granular enough to control for confounding geographic effects, yet large enough to capture alternative margins through which nonbanks increase credit supply, besides lowering denial rates (e.g. larger loans). We then estimate the following cross-sectional regression equation,

$$\Delta \text{Nonbank Market Share}_z = \beta \left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + \ldots \tag{3}$$
$$\ldots + \gamma X_z + \alpha_{c(z)} + u_z,$$

where ΔNonbank Market Share$_z$ is a measure of the 2013-15 change in the share of the mortgage volume that is originated by nonbanks, which can be defined either in terms of FHA market share or *overall* market share; FHA App Share$_z$ is the 2013 share of mortgage applications for FHA loans; Nonbank App Share$_z$ is the 2013 share of FHA applications to nonbanks; and $\alpha_{c(z)}$

is a county fixed effect, where the notation $c(z)$ denotes the county to which zip code z belongs. All specifications control for FHA App Share$_z$ and Nonbank App Share$_z$, as standard.[17]

Under an identification assumption discussed shortly, the parameter β in equation (3) represents the effect of the LCR shock on nonbanks' market share in zip codes marginally more exposed to this shock. Building on the core analysis from Section 4, more-exposed zip codes are those where borrowers historically sought a large share of their mortgage credit (a) in the form of FHA loans and (b) from nonbanks. As standard, we control for both the initial FHA application share (FHA App Share$_z$) and nonbank share (Nonbank App Share$_z$), which account for features of FHA-prevalent or nonbank-prevalent markets that correlate with changes in nonbanks' market share. Moreover, the county fixed effect $\alpha_{c(z)}$ limits variation to within the same county, which accounts for changes in nonbanks' market share due to county-level unobservables, such as ease of construction (e.g. Saiz 2010). We identify the effect of the LCR-induced increase in MBS prices on nonbanks' market share (i.e. β) using the previously-documented finding that nonbanks loosened standards among FHA loans.

In order for the parameter β in equation (3) to recover the effect of the LCR shock on nonbanks' market share, we make an identification assumption similar to equation (2),

$$0 = \mathbb{E}\left[\text{FHA App Share}_z \times \text{Nonbank App Share}_z \times u_z \middle| X_z, \alpha_{c(z)}\right]. \tag{4}$$

In words, we assume that the treatment exposure variable, given by the product of FHA and nonbank shares in 2013, is conditionally uncorrelated with unobserved drivers of nonbanks' market share over 2013-15, which are subsumed by the residual term u_z. Appendix Table A3 shows how the treatment exposure variable is indeed conditionally uncorrelated with various well-known drivers, such as changes in the capital adequacy of local banks, growth in mortgage applications from minorities, or changes in the average applicant's loan-to-income ratio, a proxy for credit risk. This lack of correlation supports the validity of the assumption in equation (4).

[17] Additional zip code-level controls are the 2013-15 changes in: the average requested loan-to-income ratio; share of applications from black or Hispanic borrowers; and the average applicant's log income. We weight zip codes in equation (3) by 2013 mortgage origination volume so that we can use the point estimates to calculate an aggregate market share, as described in Section 5.2, and we control for nonbanks' share of origination volume in 2013.

The results in columns 1 and 2 of Table 3 show how zip codes more exposed to nonbanks' expansion in the FHA market see a significant increase in nonbanks' *overall* mortgage market share. Quantitatively, the point estimate implies that a 1 standard deviation increase in the treatment exposure variable increases the growth rate in nonbanks' market share by 40% of its average value. We supplement this calculation with a more formal aggregation exercise in the next subsection, which accounts for the fact that we obtain identification from the cross-section and therefore need a more precise definition of treated and control zip codes. The results are similar after including additional controls in column 2, suggesting relatively-little scope for bias based on unobservables, which we verify through an Oster (2017) correction.[18] In columns 3 and 4, we study nonbanks' FHA market share and obtain substantially larger point estimates, as expected.

Finally, Appendix Table A4 complements Table 3 by showing how the sum of bank and nonbank-intermediated mortgage origination volume is significantly higher in zip codes more exposed to the LCR shock. Therefore, the increase in nonbanks' market share documented in Table 3 comes from an increase in overall credit supply, rather than a substitution between bank and nonbank lending.

Collectively, the results in Table 3 imply that the LCR shock increases nonbanks' market share, both overall and within the FHA market. In the next subsection, we use these results to calculate a counterfactual growth rate in nonbanks' market share absent the LCR shock.

5.2 Counterfactual Aggregate Market Share

Using the estimates from Table 3, we perform an aggregation exercise to calculate nonbanks' counterfactual market share in the absence of the LCR-induced increase in GNMA prices. In particular, we ask what share of nonbanks' observed growth in market share over 2013-15 can be attributed to the LCR shock, which we denote by η. To make progress on this question, we perform a similar exercise as Chodorow-Reich (2014), which, in our setting, requires two additional assumptions. Both assumptions reflect the fact that we obtain identification from

[18]Oster (2017) proposes an additive correction to the point estimate which depends on the difference in R^2 between specifications with and without control variables. The corrected point estimate in column 2 is 0.15, based on a maximum R^2 parameter of 0.60.

the cross-section.

Assumption 1 (Control Group) The LCR-induced increase in MBS prices does not affect the 2013-15 change in the share of mortgage volume that is originated by nonbanks in zip codes where nonbanks' FHA application share in 2013 was less than or equal to the B^{th} percentile across zip codes. Therefore, the effect of the LCR shock on zip code z is

$$\begin{aligned} \beta_z = \beta \times \text{FHA App Share}_z \times ... \\ ... \times \max\left\{\text{Nonbank App Share}_z - P_B\left(\text{Nonbank App Share}_z\right), 0\right\}, \end{aligned} \tag{5}$$

where P_B (Nonbank App Share$_z$) denotes the B^{th} percentile of Nonbank App Share$_z$ across zip codes.

We introduce Assumption 1 because we have a continuous measure of treatment exposure, and we therefore need to define some minimum threshold for this measure below which a zip code is considered unexposed to the shock (i.e. in the "control group"). Assumption 1 defines the control group as zip codes where nonbanks' share of FHA applications in 2013 was less than the B^{th} percentile across zip codes. This assumption is conservative, since nonbanks have an incentive to respond to LCR regulation by entering markets where they have historically received a small share of applications. For example, even zip codes in the bottom centile of Nonbank App Share$_z$ (i.e. $B = 0.01$) saw growth in nonbanks' overall market share of 4.6 pps over 2013-15. Nevertheless, we find similar results for various definitions of the control group, as parameterized by B, and we report results for B up to 0.10.

Assumption 2 (Partial Equilibrium) The effect of the LCR-induced increase in MBS prices on the aggregate 2013-15 change in the share of mortgage volume that is originated by nonbanks is equal to the average of zip code-level effects, β_z, weighting by the size of each zip code's mortgage market in dollars in 2013, w_z. In particular, the share of nonbanks' observed growth in market share that is due to the LCR shock is

$$\eta = \frac{\sum_z \beta_z \times w_z}{\sum_z \Delta\text{Nonbank Market Share}_z \times w_z}. \tag{6}$$

Table 4 summarizes the results of this aggregation exercise. Each row considers a separate definition of control group (i.e. B), per Assumption 1. Focusing on the first row of the table, our baseline estimates and set of assumptions imply that 22% of nonbanks' observed growth in overall market share over 2013-15 is due to the LCR shock. To provide some context, nonbanks' market share grew by 5.4 pps over 2013-15, so that 1.2 pps is attributable to the shock (i.e. $1.2 = 5.4 \times 0.22$). The results are of a similar magnitude under alternative assumptions about the control group, shown in the second row. Turning to the rightmost column of the table, the LCR shock accounts for between 37% and 48% of nonbanks' observed growth in FHA market share. Per Assumption 2, all of the results in Table 4 should be interpreted as partial equilibrium effects.[19]

In summary, nonbanks' relaxation of lending standards in response to the LCR-induced increase in GNMA prices increases their share of the FHA market and, consequently, of the overall mortgage market. This increase in the size of the shadow banking system has implications for financial stability, to which we turn in the next section.

6 Implications for Financial Stability

The LCR-induced increase in nonbanks' market share affects financial stability through two channels: credit risk and funding fragility. First, nonbanks' relaxation of lending standards among FHA borrowers (i.e. lower denial rates) increases aggregate credit risk. This credit risk is borne by the U.S. government, which insures FHA loans. Second, the increase in nonbanks' overall mortgage market share increases average funding fragility, since, as mentioned in Section 2, nonbanks rely on short-term funding arrangements which are more prone to runs than

[19] We introduce Assumption 2 because the LCR shock affects nonbanks' market share through general equilibrium forces, but these forces are subsumed by the fixed effects in equation (3). It is theoretically unclear how accounting for general equilibrium forces would impact our results. In one direction, the increase in homeownership rates documented in Section 7 may raise starter house prices within a county. This force would discourage would-be FHA borrowers from applying for a loan, thus dampening nonbanks' growth in market share across zip codes within the county. We cannot identify this channel because it is captured by the county fixed effect, leading us to overstate the effect of the LCR shock on nonbanks' overall market share. In the opposite direction, the reduction in interest rates documented in Section 8.8 would encourage borrowers to seek FHA credit. By the same logic as in the previous example, this channel would lead us to understate the effect of the LCR shock. Since it is beyond the scope of this paper to quantify general equilibrium forces, we follow the custom in the applied macroeconomics literature and present our results as partial equilibrium effects.

traditional deposits. This section directly studies implications of the LCR regulatory spillover for credit risk and funding fragility.

6.1 Credit Risk

Based on the logic of standard credit rationing models, lower denial rates correspond to an increase in average credit risk because riskier borrowers enter the market. In our setting, higher credit risk *ex ante* can also lead to higher default costs *ex post* because securitization reduces the ability of distressed borrowers to renegotiate their loan terms (e.g. Piskorski, Seru, and Vig 2010).

We estimate the effect of the LCR-induced increase in nonbanks' credit supply on credit risk at the zip code-level. Mirroring equation (3), we estimate

$$\begin{aligned}\Delta Y_z = \beta\left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + ... \\ ... + \gamma X_z + \alpha_{c(z)} + u_z,\end{aligned} \tag{7}$$

where the outcome ΔY_z is a measure of the 2013-15 change in a measure of credit risk. The two outcomes we study are: the 2013-15 change in the FHA mortgage application denial rate; and the 2013-15 change in the 30+ day mortgage delinquency rate for the surrounding county, since default rates are only observed at the county level as described in Appendix A.

Table 5 reports the results from estimating equation (7), and it reveals an increase in credit risk in zip codes more exposed to the LCR shock. The estimates in columns 1 and 2 imply that more-exposed zip codes see a significant reduction in FHA mortgage denial rates over 2013-15. To assess the broader impact of this finding, we next replace the outcome variable with the 2013-15 change in the mortgage delinquency rate across all loan types. The corresponding results in columns 3 and 4 show how more-exposed zip codes also experience an overall increase in mortgage default.

Nonbanks' relaxed lending standards affect default rates through two channels: an increase in the size of the FHA market, and an increase in the riskiness of FHA borrowers. First, FHA loans are riskier by design, since they are targeted toward first-time homeowners. For example, in 2017 the delinquency rate on FHA loans was 3.8 times the conventional delinquency rate (Urban Institute 2017). Therefore, the increase in the relative supply of FHA credit increases overall credit risk, even if the riskiness of FHA borrowers does not change.

Second, a reduction in FHA denial rates ushers riskier borrowers into the FHA market, thereby raising credit risk among FHA loans. For example, Figure 7 shows how the median relative FICO score on nonbank-originated FHA loans tracks that of bank-originated loans until the introduction of the LCR, after which the FICO score on nonbank-originated loans falls substantially. By contrast, the median FICO scores on bank and nonbank-originated loans in the conventional market track each other closely throughout the observation window, as shown in Appendix Figure A3. To substantiate this point further, Appendix Table A5 shows that nonbanks lower denial rates by an additional 25% (0.3 pps) for FHA borrowers with a 1 standard deviation higher loan-to-income ratio, a proxy for credit risk.[20]

6.2 Funding Fragility

A number of papers have highlighted how nonbanks' reliance on short-term, uninsured warehouse credit makes them more prone to run-like withdrawals such as those seen during the 2008 Financial Crisis (e.g. Kim et al 2018; Drechsler, Savov, and Schnbal 2019; D'Avernas, Vandeweyer, and Pariès 2020; Hanson et al 2015). By contrast, banks can fund mortgage originations through deposits, which are more stable during periods of financial crisis. Building on this literature, we assess how the LCR shock affects funding fragility by reestimating the zip code-level regression equation (3) and replacing the outcome variable with the 2013-15 change in the average lender's non-core funding ratio. Explicitly, we estimate

$$\Delta\text{Non-Core Funding Ratio}_z = \beta\left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + ... \tag{8}$$
$$... + \gamma X_z + \alpha_{c(z)} + u_z.$$

[20]Explicitly, the table estimates a variant of the difference-in-difference equation introduced in Section 8.4 after interacting the treatment variable with the average requested loan-to-income ratio (LTI) in the applicant's MSA of residence. While FHA borrowers are subject to debt-to-income ceilings, lenders can increase this ceiling by invoking "compensating factors" such as cash reserves or residual income.

The results in Appendix Table A6 imply that zip codes more exposed to the LCR shock see an increase in funding fragility, as proxied by the average non-core funding ratio.

6.3 Discussion

The previous two sets of results suggest that the LCR-induced increase in nonbanks' market share reduces financial stability. However, we lack a sufficiently long time series to directly test this prediction, and nonbanks' growth might improve financial stability through margins that we cannot test empirically. For example, risk may be more dispersed in a financial system with both banks and nonbanks.[21] In addition, recent work by Jiang et al (2020) suggests that nonbank mortgage lenders are better-capitalized than their bank counterparts. Outside the mortgage market, Bernstein, Lerner, and Mezzanotti (2019) argue that private equity improves financial stability. Therefore, the overall welfare content of our results is unclear, as we discuss in our conclusion.

7 Implications for Homeownership

By the same token that the LCR shock increases credit risk, it may also enable borrowers constrained by credit frictions to become homeowners. Most of our analysis occurs in the context of the FHA market, which caters to households on the margin of homeownership. Thus, it is natural to ask whether the relaxation in nonbanks' lending standards affects homeownership rates.

We estimate a regression equation of the same form as equation (7), after replacing the outcome variable with the 2013-15 change in the zip code's homeownership rate. Explicitly, we estimate

$$\Delta\text{Homeownership Rate}_z = \beta\left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + ... \tag{9}$$
$$... + \gamma X_z + \alpha_{c(z)} + u_z.$$

[21] We thank an anonymous referee for raising this possibility.

The results in Table 6 imply that zip codes more exposed to nonbanks' increase in credit supply see significantly higher growth in homeownership. Quantitatively, the point estimate implies that a 1 standard deviation increase in the treatment exposure variable leads to a 4.2 pps higher homeownership rate in 2015. This effect is substantial given that national homeownership rates fell 5.3 pps between 2004 and 2015, according to the Census' HVS survey.

8 Robustness

In this section, we perform a variety of robustness tests to evaluate our primary identification assumptions, the exclusion restrictions in equations (2) and (4). The results of these tests support the validity of the assumptions.

To provide a brief outline, we: check that the key mechanism is reliance on an originate-to-securitize funding model (8.1); explicitly control for regulatory arbitrage incentives (8.2); study how the shock affects the size of nonbank-originated loans (8.3); test for crowd-out effects among non-FHA loans (8.4); perform a placebo test to evaluate the role of pre-trends in our zip code-level and loan-level analyses (8.5); perform a placebo test in the conventional loan market (8.6); reperform our analysis after excluding large lenders and nonbanks to check that litigation risk does not drive the results (8.7); study interest rates on FHA loans (8.8); demonstrate robustness to the effects of Quantitative Easing (8.9) or the Net Stable Funding Ratio (8.10); reperform the analysis using the option-adjusted spread to account for changes in prepayment risk (8.11); test the mechanism over the pre-Crisis period (8.12); and check that the results are robust to a monthly frequency (8.13).

8.1 Testing the Mechanism

The mechanism through which MBS prices increase nonbanks' lending is their originate-to-securitize funding model: nonbanks do not have access to stable deposit funding, and so their lending capacity is more dependent on demand from MBS investors. Consequently, nonbanks' lending behavior responds more elastically to MBS prices than banks'. This conjecture motivates us to estimate a more general variant of equation (1),

$$\text{Denial}_{i,l,s,t} = \beta\left(F_l \times \text{Premium}_t \times \text{FHA}_s\right) + \gamma X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + ... \qquad (10)$$
$$... + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,s,t},$$

where F_l is a measure of lender l's reliance on an originate-to-securitize funding model, in contrast to a deposit funding model. Our first measure is the lender's ratio of securitized loans to total originations in 2010, which we call the lender's "securitization rate". This variable is meant to proxy for technological specialization in an originate-to-distribute model, which might arise from a lack of access to stable deposit funding, as discussed in Section 2. Our second measure, called "non-core funding", is one minus the ratio of total deposits to total assets in 2010. By definition, nonbanks have non-core funding equal to one. Appendix Table A1 summarizes the distribution of these two measures and other lender-level variables. Note, in particular, that there is substantial variation in banks' securitization rates, so that equation (10) can be estimated among the subsample of bank lenders, as we do in subsequent tests.[22]

Table 7 contains the results of the more general equation in (10). The estimates in the first column suggest that lenders who rely entirely on securitization respond to the LCR-induced GNMA premium by denying 1.2 pps fewer FHA loan applicants than lenders who do not securitize. We obtain a similar result in terms of non-core funding in the rightmost two columns. Collectively, these findings support our theory by showing how the baseline effect works through variation in lenders' funding models.

8.2 Regulatory Arbitrage

As documented by Buchak et al (2018), regulatory arbitrage has been a key driver of nonbanks' increasing market share. Thus, our baseline analysis may capture differential costs of

[22]The securitization rate does not equal one for all nonbanks for two reasons. The principal reason is that our core HMDA data only record a loan as securitized if it was sold within the same calendar year, per Appendix A. Since it takes around 50 days to securitize a mortgage (Echeverry, Stanton, and Wallace 2016), the observed securitization rate understates the true securitization rate. However, because our identification comes from the cross-section, this measurement error does not produce biased estimates and, if anything, leads to attenuation bias toward zero. Second, a small minority (i.e. 5%) of nonbanks' originations are booked as held-for-investment mortgages, which are funded by long-term debt (Mortgage Bankers' Association 2014).

regulation across lenders rather than a response to LCR-induced changes in MBS prices. To evaluate this possibility, we reestimate our more-general triple difference-in-difference regression equation (10) on the set of bank lenders after including the triple interaction between Premium_t, FHA_s, and an indicator for whether the bank has a high regulatory arbitrage incentive. The additional triple interaction term captures changes in relative denial rates stemming from the possibility that FHA loans are more capital-intensive, subject to greater putback risk, or otherwise less attractive to originate for risk averse lenders seeking to minimize their regulatory exposure.

Our first measure of a high regulatory arbitrage incentive is an indicator for whether l's capital ratio in 2010 is below the median across banks. In principle, such banks should raise more equity capital to satisfy Basel III regulatory capital requirements. In practice, they often respond to these requirements by reducing their holdings of relatively-risky assets (e.g. Buchak et al 2018), which, in our setting, would correspond to an increase in the relative denial rate on FHA loans. We also use an indicator for whether the change in l's capital ratio is below the median, which captures the bank's deterioration in capital. Finally, we use an indicator for whether l's ratio of mortgage servicing rights (MSRs) to equity in 2010 is above the median across banks. Since regulators penalize MSRs with a high regulatory risk weight, such banks also have an incentive to reduce their holdings of relatively-risky assets, as pointed out by Buchak et al (2018) who use an analogous MSR-based measure. Appendix Table A1 summarizes the distribution of the capital and MSR ratios.

Table 8 contains the results of this test. Across all columns, the estimated coefficients of interest are similar to their analogues from Table 7. In columns 2-4, we assess whether our measures of a high regulatory arbitrage incentive simply proxy for bank size by including an additional triple interaction between Premium_t, FHA_s, and an indicator for whether the bank's assets are above the median. We continue to obtain similar estimates for the coefficient of interest.[23]

The regulatory arbitrage hypothesis begins with the idea of time variation in regulatory

[23] We measure the capital ratio using the ratio of total equity to total assets (i.e. economic capital ratio) because we observe this statistic for a larger share of the sample than the ratio of tier-1 equity to net risk-weighted assets (i.e. regulatory capital ratio). However, in untabulated results, we obtain a significant point estimate of -0.016 for the coefficient of interest when using the regulatory capital ratio.

burdens. If Premium_t covaries with such regulatory burdens in the time series, then the regulatory arbitrage hypothesis would predict a positive coefficient on the triple interaction term associated with regulatory arbitrage incentives. Consistent with this logic, we estimate a positive and significant coefficient on the measures of a high regulatory arbitrage incentive, even after accounting for the possibility that these measures proxy for bank size.

In Appendix Table A7, we perform a similar exercise at the zip code-level. Explicitly, we reestimate equation (3) after controlling for various measures of local banks' regulatory arbitrage incentives, which we aggregate to the zip code-level weighting by the bank's mortgage origination volume in the zip code. As in Section 5, zip codes more exposed to the LCR shock see significant growth in nonbanks' mortgage market share, and the magnitude of the effect is almost the same as in Table 3.

Collectively, the results of this robustness test provide strong evidence that variation in funding models, rather than other differences among lenders, is the key mechanism through which higher MBS prices lower nonbanks' lending standards and increase their market share. These findings also suggest that nonbanks' growth has multiple roots, including both a retreat of bank lending because of regulatory arbitrage and an expansion of nonbank lending because of the LCR-induced increase in MBS prices.

8.3 Loan Volume

We study denial rates as our primary loan-level outcome given our interest in lending standards. However, lower denial rates may not increase nonbanks' market share if nonbanks compensate by originating smaller loans. We study the effect of the LCR-induced increase in the GNMA premium on the size of originated loans in Table 9. The positive point estimates imply that nonbanks respond to the GNMA premium by increasing the relative size of FHA loans that they originate. This expansion in the intensive margin of credit amplifies our baseline findings on the extensive margin, and it helps explain the large effect on market share documented in Tables 3 and 4.

8.4 Crowd-Out Effects

Nonbanks may respond to higher GNMA prices by reallocating internal funds away from other forms of credit to FHA loans, leading to a crowd-out of non-FHA credit. Note that such a reallocation must occur within the mortgage market, since nonbanks are highly-specialized lenders, and, in contrast to banks, there are no relevant nonbanks in both the mortgage and corporate credit markets. That said, if nonbanks respond to an increase in the relative MBS price of FHA loans by originating fewer conventional loans, then it is unclear why their market share should increase.

We evaluate the scope for reallocation through the following difference-in-difference regression equation,

$$\text{Denial}_{i,l,t} = \beta\left(F_l \times \text{Premium}_t\right) + \gamma X_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{11}$$

which we estimate on the subsample of either FHA or conventional loans.[24] As in equation (10), F_l is a measure of lender l's reliance on an originate-to-securitize funding model, in contrast to a deposit funding model.

Columns 1 and 2 of Table 10 contain the results from estimating equation (11) on the subsample of FHA loans. Consistent with our baseline results in Tables 2 and 7, we find that nonbanks and, more generally, originate-to-securitize lenders deny fewer FHA borrowers in response to the LCR-induced increase in the GNMA premium. However, we find no effect when restricting the sample to conventional loans in columns 3 and 4. This lack of tightening in the conventional market suggests that nonbanks respond to higher MBS prices for FHA loans by obtaining warehouse credit to originate more of these loans, rather than by reallocating internal funds away from other forms of credit.

Collectively, the results in Table 10 imply that nonbanks do not reallocate internal funds away from conventional borrowers to FHA borrowers, and so the large estimated effect of the LCR shock on nonbanks' market share is plausible. However, this finding does not imply that

[24] Our baseline triple difference-in-difference analysis does not inform whether nonbanks reduce their supply of conventional loans, since, for the sake of internal validity, it obtains identification from the difference between FHA and conventional loans.

reallocation does not occur, but, rather, that nonbank lenders do not reallocate. In Appendix Table A8, we find that poorly-capitalized banks who rely on securitization do indeed tighten the supply of credit for conventional borrowers following the increase in the GNMA premium. This apparent reallocation within the set of bank lenders is consistent with Chakraborty, Goldstein, and MacKinlay (2018, 2020), and it may stem from the fact that banks face overall leverage constraints (e.g. capital requirements) whereas nonbanks face loan-by-loan leverage constraints (e.g. repo haircuts).

8.5 Placebo Test over the Pre-LCR Period

The treatment exposure measure in our zip code-level analysis is based on the product of initial exposure to the FHA market and to nonbanks. We evaluate the measure's validity by performing a placebo test over the 2011-13 period, which precedes the LCR shock but follows the post-Crisis regulatory overhaul. If the measure is valid, it should not explain growth in nonbanks' market share over this period. We test this hypothesis by reestimating equation (3) over 2011-13. The results in columns 1 and 2 of Table 11 show that the measure of exposure cannot explain nonbanks' growth in market share over 2011-13. However, consistent with the validity of assumption (4), it explains a large share of nonbanks' growth in market share over 2013-15, as we showed in Table 3.

Likewise, we evaluate our loan-level results by reestimating equation (1) and its more-general variant, equation (10), over the 2011-13 period. If the main results indeed stem from the LCR-induced increase in GNMA prices, the results should be insignificant when replacing Premium_t with a linear time trend.[25] Consistent with this this prediction, the point estimates in columns 3 and 4 of Table 11 are insignificant. Together, the results in Table 11 suggest that the baseline zip code and loan-level estimates are not biased because of a pre-trend in nonbanks' market share.

[25]We remove any effect of MBS prices by residualizing the trend against the FNMA spread.

8.6 Placebo Test on Conventional Loans

Similar in spirit to the previous test, we assess the robustness of the zip code-level results through a placebo test on conventional loans over the post-LCR period. Since conventional loans represent our control loan type, as substantiated by columns 3 and 4 of Table 10, we should not expect to see an effect on nonbanks' market share or default rates among such loans. We test this prediction by reestimating equation (7) after replacing the outcome with zip code-level variables that describe the conventional loan market. The results in columns 1 and 2 of Appendix Table A9 show how more-exposed zip codes do not experience an increase in nonbanks' conventional market share. Neither do such zip codes experience an increase in default rates on conventional loans, as shown in columns 3 and 4. This finding suggests that the LCR-induced increase in GNMA prices is the relevant mechanism behind the main results in Tables 3 and 5, rather than increased risk-taking by nonbanks across the board.

8.7 Litigation Risk by Lender Size

Beginning with a 2011 suit against Deutsche Bank, the U.S. Department of Justice sued a number of large banks over 2011-15, alleging that their FHA lending behavior violated the False Claims Act. To the extent that an increase in expected litigation activity coincided with the introduction of the LCR, the baseline results may reflect heightened legal risk rather than a higher GNMA premium. However, there are two reasons why litigation risk is an unlikely source of bias. First, large nonbank lenders, such as Quicken Loans, were also subject to lawsuits related to their lending in FHA markets. Second, the Department of Justice also sued large lenders over their behavior in conventional mortgage markets.[26] Thus, if litigation risk is a significant source of bias, one would expect to see similar results among conventional loans. However, as discussed in Section 8.4, we find no evidence of relaxed standards in the conventional market.

To more directly address bias from large lenders' litigation risk, we reestimate our baseline

[26]For example, in 2012 the Department of Justice alleged that Bank of America violated the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 by selling low-quality loans to Fannie Mae and Freddie Mac.

specification on the set of lenders with less than 2% of the total mortgage market in 2010, measured by origination share. The results in columns 1 and 2 of Appendix Table A10 imply that, within this restricted subsample, nonbanks respond to the increase in the GNMA premium by lowering their relative denial rate on FHA loans. This finding suggests that our baseline result is not driven by differences in litigation risk between large and small lenders.

In columns 3 and 4 of Appendix Table A10, we perform a similar exercise after dropping nonbanks from the sample, and, consistent with our results in Table 7, we find that banks with an originate-to-securitize funding model respond to a higher GNMA premium by lowering their relative denial rate on FHA loans. This finding confirms the key mechanism: MBS prices disproportionately increase nonbanks' credit supply because nonbanks rely on an originate-to-securitize funding model, rather than a deposit funding model.

8.8 Interest Rates

We now study how higher GNMA prices affect the relative interest rate charged by nonbanks on FHA loans, using data from HUD's FHA Single Family Portfolio Snap Shot. To do so, we estimate a similar equation as equation (11) over the 2012-15 period,

$$\text{Rate}_{i,l,t} = \beta \left(\text{Nonbank}_l \times \text{Premium}_t\right) + \gamma Z_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{12}$$

where i, l, and t index borrowers, lenders, and months; each observation is an originated loan; and $\text{Rate}_{i,l,t}$ is the interest rate on the loan. Unlike in our baseline analysis, we do not normalize Premium_t by the implied effect of the LCR shock, since our outcome variable is now an interest rate. The controls in $Z_{i,t}$ are log loan size and an indicator for whether the loan is a fixed-rate mortgage. The remaining notation is the same as in prior equations.[27]

Mortgage interest rates typically fall when the GNMA premium rises, measured using either total return or option-adjusted spreads. Thus, the parameter β captures nonbanks' rate of pass-through from higher MBS prices to lower mortgage rates, relative to banks' rate of pass-through. The first two columns of Appendix Table A11 show that nonbanks' rate of pass-through is 5

[27] We classify lenders as nonbanks if their parent company's name does not contain "Bank", "Credit Union", or variant spellings of these terms.

percentage points greater than banks'. To place this number in perspective, the unconditional pass-through of the FNMA-GNMA spread to mortgage interest rates is 30%, so that nonbanks have a 17% (i.e. 0.05/0.30) higher pass-through rate. The rightmost columns obtain a similar result when using the option-adjusted spread to measure Premium_t.

The results from this exercise imply that nonbanks disproportionately lower interest rates following an increase in MBS prices. In fact, this finding understates the true reduction in the price of credit, since we have already seen that nonbanks also originate riskier loans, which would tend to increase interest rates.

8.9 Quantitative Easing

The third round of MBS purchases by the Fed overlapped with the introduction of the LCR, as it lasted from 2012 to 2014. The Fed bought MBS sponsored by the GSEs (i.e. FNMA and FHLMC) and by GNMA, with a tilt toward GSE MBS per the report by the Board of Governors (2016). In particular, Appendix Figure A4 shows that the ratio of the Fed's purchases was weighted against GNMA MBS. Therefore, assuming the price elasticity of demand is the same for both GNMA MBS and GSE-backed MBS, these purchases are unlikely to account for the increase in the GNMA premium and nonbanks' substitution toward FHA lending.[28]

8.10 Net Stable Funding Ratio

The Basel III accords involved not only a Liquidity Coverage Ratio, but also a complementary Net Stable Funding Ratio (NSFR). The NSFR aims to ensure that banks "maintain sufficient levels of stable funding, thereby reducing liquidity risk in the banking system". However, the NSFR was not proposed in the U.S. until May 2016, more than two years after the LCR shock. Therefore, our results do not confound spillovers related to the NSFR.

[28]We thank an anonymous referee for pointing out that this argument requires the price elasticity of demand to be the same.

8.11 Prepayment Risk

In Appendix Table A12, we reestimate equation (11) using the option-adjusted spread (OAS) to measure Premium_t and find similar results. Since the OAS strips out changes in the prepayment risk premium, this finding suggests that the baseline results are not driven by either spurious correlation or changes in the relative prepayment risk of GNMA versus non-GNMA MBS.[29]

8.12 Testing the Mechanism Before the Crisis

In Appendix Table A13, we reestimate equation (11) and document a strong link between the GNMA premium and the supply of FHA credit by nonbanks over the 2000-06 period, before the post-Crisis regulatory overhaul. On one hand, the point estimates from the 2000-06 period are less informative because this period lacks an exogenous source of variation in the cross-section of MBS prices. On the other hand, higher MBS prices should, in principle, affect the relative supply of credit by nonbanks in periods outside the 2010-15 window. Indeed, the results obtained over 2000-06 are both qualitatively and quantitatively consistent with those obtained in our baseline analysis. This similarity suggests that the baseline estimates are not biased because of spurious correlation between the LCR shock and unobserved time-series dynamics, such as an increase in incentives for regulatory arbitrage.

8.13 Monthly Frequency

Our core dataset, HMDA, is only available at a yearly frequency. We evaluate how this data restriction affects our results by performing a similar exercise at the monthly frequency using data from HUD's FHA Single Family Portfolio Snap Shot. The results, discussed in Section 8.8, are similar to those from our baseline analysis.

[29]Option-adjusted spreads are computed by Bloomberg. For purely interpretive purposes, we normalize the FNMA and FHLMC OAS spreads by 13 basis points, which is the estimated effect of LCR regulation as discussed in Section 3.1.

9 Conclusion

We document spillover effects from liquidity regulation, and, in so doing, we identify a novel, price-based channel through which securitization affects financial stability. In particular, we find that changes in MBS prices can significantly affect the size of the shadow banking system and the amount of credit risk in the primary mortgage market. Our empirical strategy used exogenous variation in the cross-section of MBS prices induced by the introduction of the U.S. Liquidity Coverage Ratio (LCR) to identify the effect of MBS prices on the supply of nonbank credit. We showed that LCR regulation, designed to prevent runs in secondary mortgage markets, has inadvertently attracted nonbanks to the FHA market and lowered their lending standards. Thus, as an unintended consequence, LCR regulation has increased the market share of lenders with a fragile funding model, and it has increased the credit risk borne by U.S. taxpayers who insure FHA loans.

However, it is unclear how this unintended, LCR-induced increase in nonbanks' market share affects welfare. On one hand, the financial system may have become more unstable. On the other hand, the expansion in nonbank credit appears to have bolstered homeownership during a period when the U.S. homeownership rate has approached a historic low.

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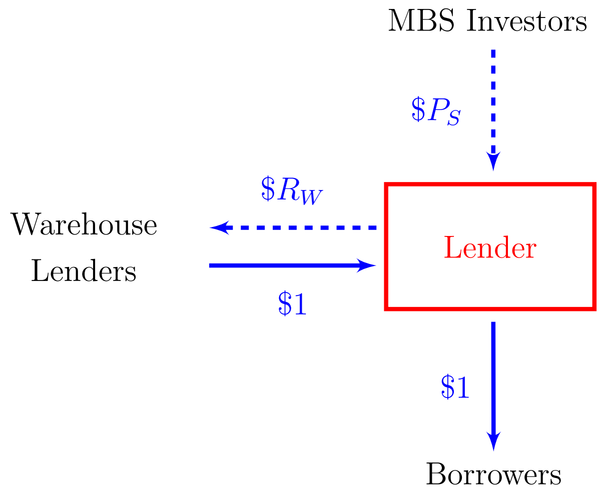
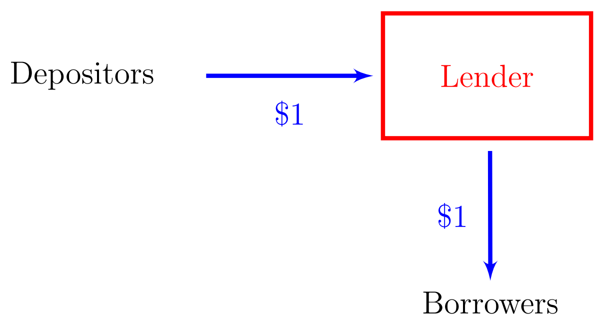
Figures and Tables



(a) Funding through Securitization



(b) Funding with Deposits

Figure 1. Financing a $1 Loan by Lender's Funding Model. This figure presents a simple diagram which contrasts lenders' funding models. In panel (a), the lender borrows $1 in warehouse credit to originate a $1 loan, sells the loan to MBS investors at price P_S, and repays the warehouse lender at the gross interest rate R_W. In panel (b), the lender raises $1 in deposits to originate a $1 loan.

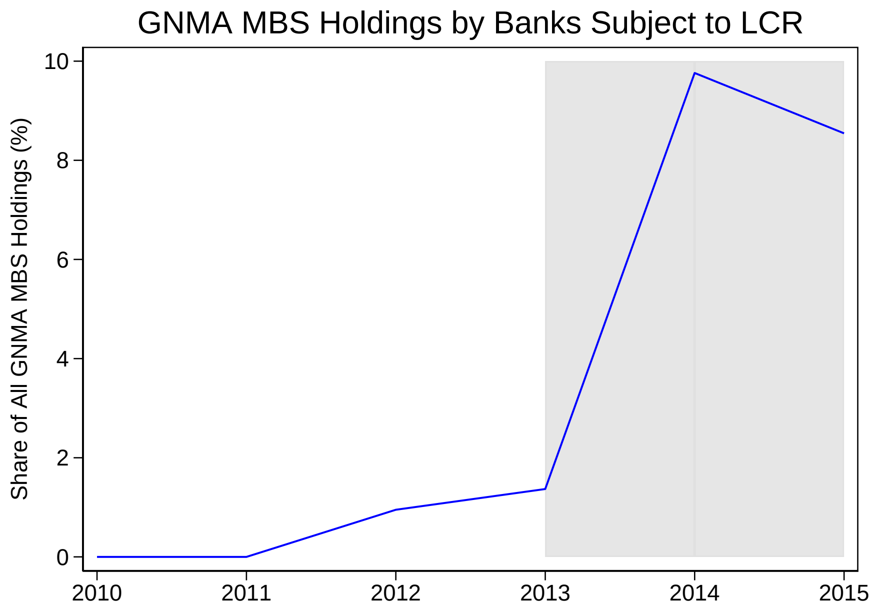


Figure 2. GNMA MBS Holdings by Banks Subject to Liquidity Regulation. This figure plots average Ginnie Mae (GNMA) MBS held by banks subject to the LCR policy divided by the sum of average GNMA MBS held by such banks plus average GNMA MBS held by banks not subject to the LCR. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Data are from the Call Reports (FRY-9C).

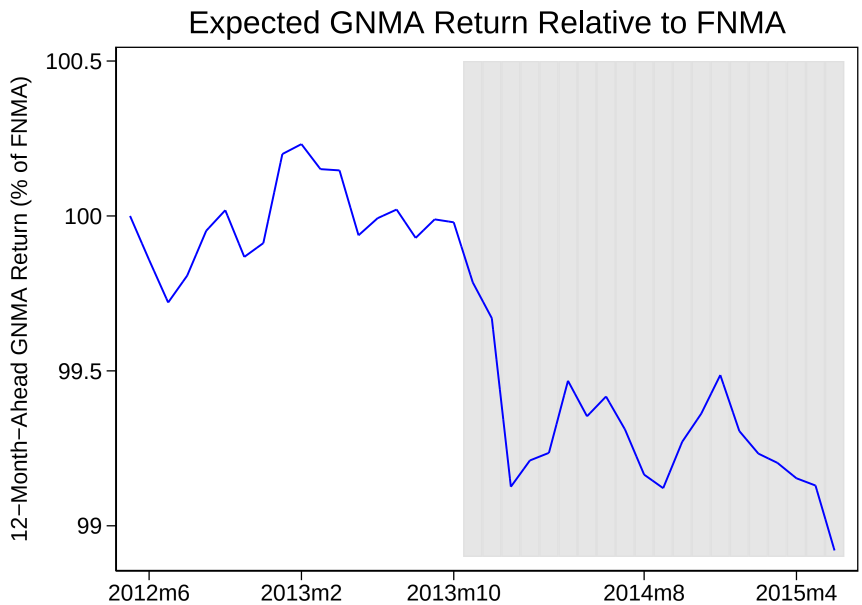


Figure 3. Expected MBS Return. This figure plots the ratio of the 12-month-ahead total gross return for GNMA relative to FNMA MBS, measured using the Bloomberg-Barclays Total Return Index. A drop in the relative return means that GNMA prices have increased more than FNMA prices. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Data are from Bloomberg.

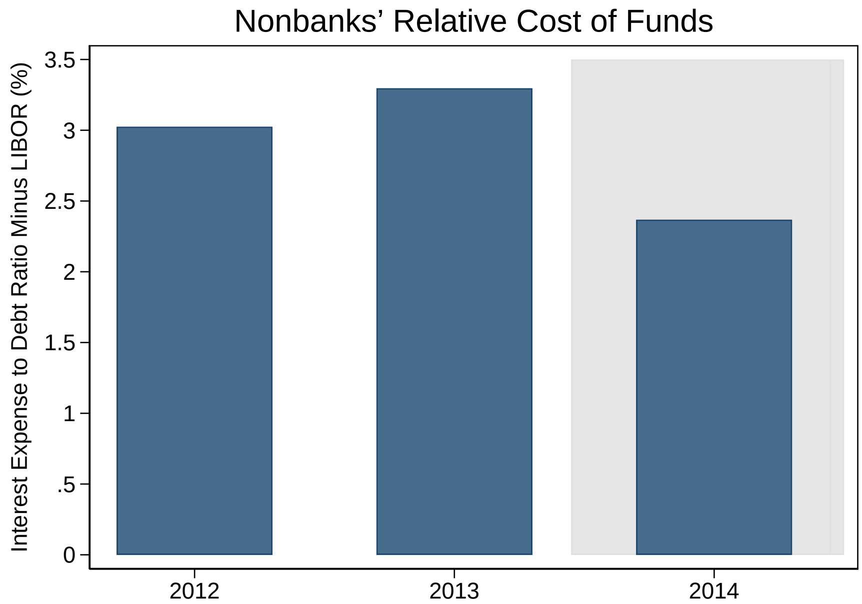


Figure 4. Nonbanks' Cost of Warehouse Funding. This figure plots the difference between the ratio of the average nonbank's warehouse interest expense to the value of its credit lines and the 3-month LIBOR rate. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Data are from the Mortgage Bankers' Association (2014) and are available for the 2012-14 period.

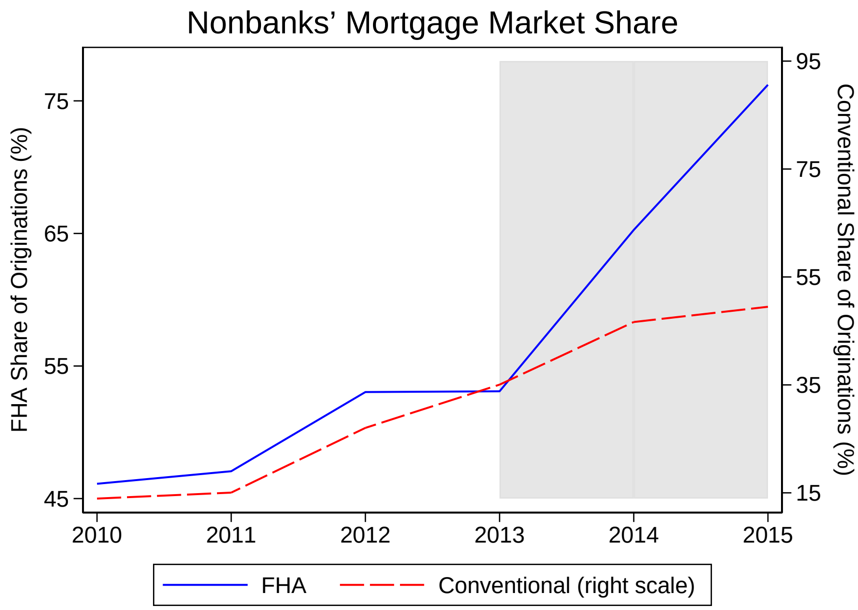


Figure 5. Nonbank Market Share. This figure plots the share of loans originated by nonbank lenders. The blue and red curves plot this ratio for the FHA and conventional mortgage markets, respectively. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Data are from Buchak et al (2018).

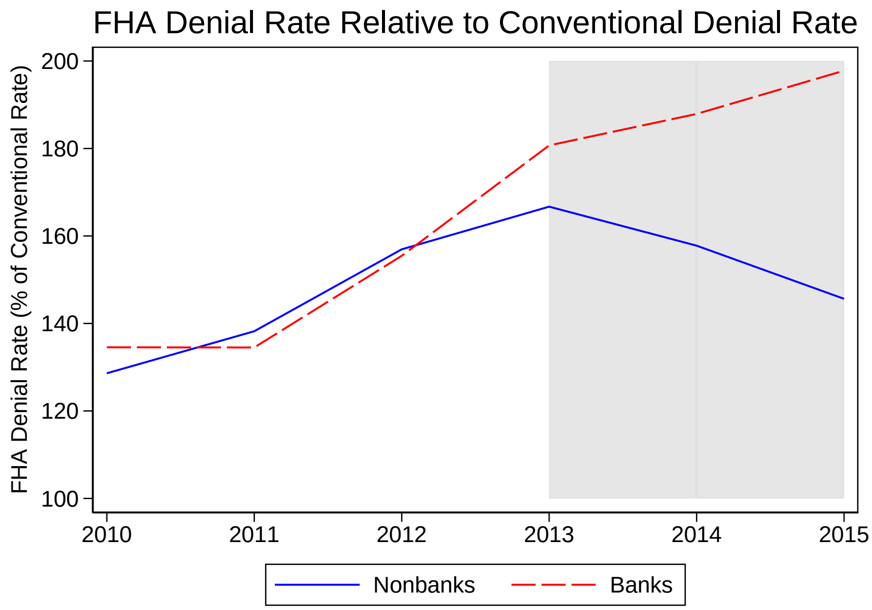


Figure 6. Relative Denial Rate on FHA Loans for Banks and Nonbanks. This figure plots the ratio of the average lender's denial rate on FHA loan applications to the average lender's denial rate on conventional loan applications, which assesses the scope for pre-trends in our baseline regression equation (1). The blue and red curves plot this ratio for nonbank and bank lenders, respectively. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Data are from HMDA.

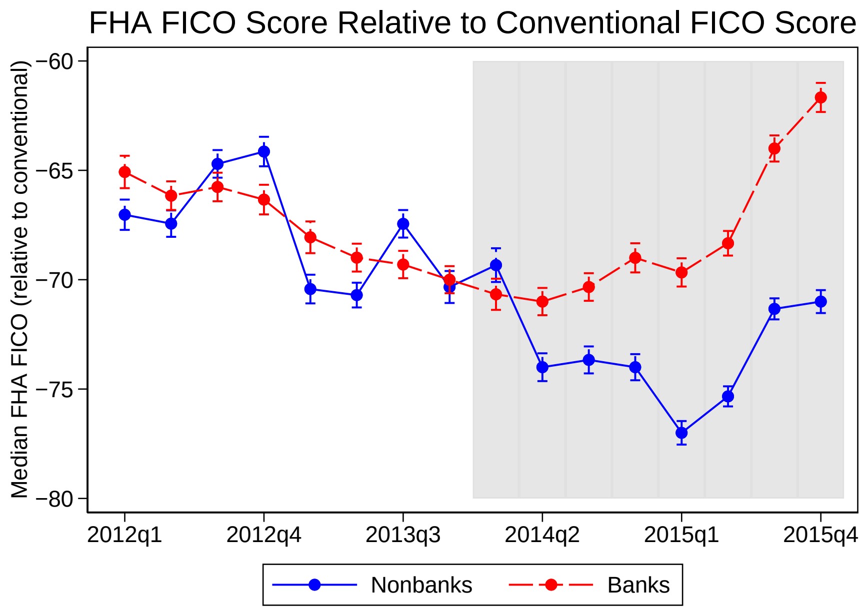


Figure 7. Relative FICO Score on FHA Loans for Banks and Nonbanks. This figure plots the difference in the median lender's FICO score between FHA and conventional loan originations. The blue and red curves plot this difference for nonbank and bank lenders, respectively. Brackets correspond to a 95% confidence interval. Data are from Recursion.

Table 1: Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation
Loan-Level Variables:			
All Loans:			
Denial Indicator	13,114,592	0.112	0.316
Nonbank Indicator	13,114,592	0.495	0.500
FHA Indicator	13,114,592	0.320	0.467
Securitization Rate	10,409,953	0.828	0.263
Non-Core Funding Ratio	10,646,461	0.723	0.351
Loan-to-Income Ratio	13,114,592	2.786	2.361
Minority Indicator	13,114,592	0.176	0.381
FHA Loans:			
Denial Indicator	4,199,495	0.138	0.345
Nonbank Indicator	4,199,495	0.621	0.485
Loan-to-Income Ratio	4,199,495	3.011	1.870
Minority Indicator	4,199,495	0.303	0.460
Conventional Loans:			
Denial Indicator	8,915,097	0.100	0.300
Nonbank Indicator	8,915,097	0.435	0.496
Loan-to-Income Ratio	8,915,097	2.680	2.553
Minority Indicator	8,915,097	0.116	0.619
Zip Code-Level Variables:			
ΔNonbank Market Share, 2013-15	4,506	0.054	0.125
Nonbank App Share, 2013	4,545	0.695	0.186
FHA App Share, 2013	4,545	0.241	0.145
Time-Series Variables:			
GNMA Total Return (pps)	16	5.012	2.739
FNMA Spread (pps)	16	0.075	0.559
FHLMC Spread (pps)	16	0.035	0.624

Note: In the Loan-Level panels, each observation is a loan application for the purchase of an owner-occupied single-family dwelling over 2010-15, and the variables are defined as follows: Denial indicates if the application was denied; Nonbank indicates if the lender is a non-depository institution; FHA indicates if the application is for an FHA loan; Securitization Rate is the lender's ratio of securitized mortgages to total originations in 2010; Non-Core Funding Ratio is one minus the ratio of total deposits to total assets in 2010, which equals one for nonbanks by definition; Loan-to-Income is the ratio of the applicant's requested loan to her reported annual income; and Minority indicates if the applicant is black or Hispanic. In the Zip Code-Level panel, each observation is a zip code weighted by 2013 origination volume, and the variables are defined as follows: ΔNonbank Market Share is the change in the share of mortgage volume originated by nonbanks; FHA App Share$_z$ is the share of mortgage applications for FHA loans; and Nonbank App Share$_z$ is the share of FHA applications to nonbanks. In the Time-Series panel, each observation is a year over the 2000-2015 window, and the variables are defined as follows: GNMA Total Return is the average 12-month-ahead total return to Ginnie Mae (GNMA) MBS, where total returns are measured using the Bloomberg Barclays MBS Total Return indices; FNMA Spread is the difference between Fannie Mae (FNMA) Total Return and GNMA Total Return; and FHLMC Spread is analogously defined in terms of Freddie Mac (FHLMC) Total Return.

Table 2: LCR and Nonbanks' Lending Standards

Outcome:	$\text{Denial}_{i,l,s,t}$		
$\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s$	-0.021	-0.008	-0.007
	(0.000)	(0.000)	(0.000)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes
Loan Type-Lender FE	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes
R-squared	0.116	0.116	0.116
Number of Observations	3,267,670	3,267,670	3,267,670

Note: P-values are in parentheses. This table estimates equation (1), which is our baseline triple difference-in-difference equation. Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Each observation is a loan application. The regression equation is of the form

$$\text{Denial}_{i,l,s,t} = \beta\left(\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s\right) + \gamma X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + ...$$
$$... + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,s,t},$$

where $\text{Denial}_{i,l,s,t}$ indicates if the loan application is denied; Nonbank_l indicates if the lender is a nonbank; Premium_t is a measure of the GNMA premium; FHA_s indicates whether the loan's type is FHA, where the possible types are FHA and Conforming Non-FHA, which we call "conventional" in the text; and $\alpha_{l,t}$, $\alpha_{s,t}$, $\alpha_{s,l}$, $\alpha_{m(i),t}$, and $\alpha_{m(i),l}$ are lender-year, type-year, type-lender, MSA-year, and MSA-lender fixed effects. Each column interacts Nonbank with a different measure of the Ginnie Mae (GNMA) premium: Post-LCR indicates whether $t \geq 2014$, the first full year after LCR regulation was announced; FNMA Spread is the difference in expected total return between Fannie Mae (FNMA) and GNMA MBS; and FHLMC Spread is the analogous difference between Freddie Mac (FHLMC) and GNMA MBS. Expected total return is measured using the average 12-month-ahead total return in year t, where total returns are measured using the Bloomberg Barclays MBS Total Return indices. Borrower controls are requested loan-to-income ratio, log income, and an indicator for whether the borrower is black or Hispanic. The sample consists of applications for FHA or conventional loans for the purchase of an owner-occupied single-family dwelling. The sample period is 2010-15. Standard errors are clustered by lender-year bins.

Table 3: Effect on Nonbanks' Share of Origination Volume

Outcome:	ΔNonbank Market Share$_z$			
FHA App Share$_z$ $\times$ Nonbank App Share$_z$	0.207	0.202	0.688	0.690
	(0.001)	(0.002)	(0.000)	(0.000)
Market	All Mortgages		FHA Mortgages	
County FE	Yes	Yes	Yes	Yes
Zip Code Controls	No	Yes	No	Yes
R-squared	0.541	0.545	0.369	0.370
Number of Observations	4,069	4,025	4,069	4,025

Note: P-values are in parentheses. This table estimates equation (3), which assesses how the LCR shock affects nonbanks' market share at the zip code-level. Subscript z indexes zip code. The regression equation is of the form

$$\Delta \text{Nonbank Market Share}_z = \beta \left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + ...$$
$$... + \gamma X_z + \alpha_{c(z)} + u_z,$$

where ΔNonbank Market Share$_z$ is a measure of the 2013-15 change in the share of mortgage volume that is originated by nonbanks; FHA App Share$_z$ is the 2013 share of mortgage applications for FHA loans; Nonbank App Share$_z$ is the 2013 share of FHA applications to nonbanks; and $\alpha_{c(z)}$ is a county fixed effect. The outcome in columns 1-2 is the change in nonbanks' share of all mortgage volume, and the outcome in columns 3-4 is the change in their share of FHA mortgage volume. All specifications control for FHA App Share$_z$, Nonbank App Share$_z$, and nonbanks' share of origination volume in 2013. Zip code controls are the 2013-15 changes in: the average requested loan-to-income ratio; share of applications from black or Hispanic borrowers; and the average applicant's log income. Observations are zip codes weighted by 2013 mortgage origination volume.

Table 4: Share of Nonbanks' Growth due to the LCR Shock

Market:	All Mortgages	FHA Mortgages
Share of Growth due to Shock, $B = 0.01$	22%	48%
Share of Growth due to Shock, $B = 0.10$	17%	37%
Source of Point Estimate (β):	Table 3, Column 1	Table 3, Column 3

Note: This table shows the implied contribution of LCR regulation to the aggregate 2013-15 change in the share of the mortgage volume that is originated by nonbanks, denoted η in the text and defined in equation (6). The implied contribution is based on Assumption 1 (Control Group) and Assumption 2 (Partial Equilibrium). Each row makes a different assumption about which zip codes are not affected by LCR regulation, denoted B. The first and second rows respectively assume LCR regulation has no effect on zip codes where nonbanks' share of FHA applications in 2013 (i.e. Nonbank App Share_z) is below the first or tenth percentile across zip codes, respectively. The first column summarizes this calculation for the overall mortgage market, and the second column summarizes this calculation for the FHA market.

Table 5: Implications for Credit Risk

Outcome:	ΔDenial Rate$_z$		ΔDefault Rate$_{c(z)}$	
FHA App Share$_z$ $\times$ Nonbank App Share$_z$	-0.288	-0.277	0.006	0.006
	(0.011)	(0.014)	(0.028)	(0.042)
County FE	Yes	Yes	No	No
Zip Code Controls	No	Yes	No	Yes
R-squared	0.154	0.166	0.057	0.058
Number of Observations	2,707	2,659	3,963	3,925

Note: P-values are in parentheses. This table estimates equation (7), which assesses how nonbanks' expansion in the FHA market affects various measures of credit risk. Subscripts z and $c(z)$ index zip code and county. The regression equation is of the form

$$\Delta Y_z = \beta \left(\text{FHA App Share}_z \times \text{Nonbank App Share}_z\right) + ...$$
$$... + \gamma X_z + \alpha_{c(z)} + u_z,$$

where the outcome ΔY_z is a measure of the 2013-15 change in a measure of credit risk. The outcomes in columns 1-2 and 3-4 are, respectively: the 2013-15 change in the FHA mortgage application denial rate; and the 2013-15 change in the 30+ day mortgage delinquency rate for the surrounding county, which includes all loan types. Default (i.e. delinquency) rates are only observed at the county level as described in Appendix A. All specifications control for FHA App Share$_z$ and Nonbank App Share$_z$. Zip code controls are those from Table 3. Observations are zip codes.

Table 6: Implications for Homeownership

Outcome:	ΔHomeownership Rate$_z$	
Nonbank App Share$_z$ $\times$ FHA App Share$_z$	0.314	0.319
	(0.014)	(0.013)
County FE	Yes	Yes
Zip Code Controls	No	Yes
R-squared	0.352	0.357
Number of Observations	4,536	4,460

Note: P-values are in parentheses. This table estimates a variant of equation (7), which assesses how nonbanks' expansion in the FHA market affects homeownership. Subscript z indexes zip code. The regression equation is the same as in Table 5, replacing the outcome with the 2013-15 change in the homeownership rate. The remaining notation, notes on specification, and sample are the same as in Table 5.

Table 7: Variation in Funding Models as the Mechanism

Outcome:	Denial$_{i,l,s,t}$			
Securitization Rate$_l$ × Premium$_t$ × FHA$_s$	-0.012	-0.011		
	(0.000)	(0.000)		
Non-Core Funding$_l$ × Premium$_t$ × FHA$_s$			-0.013	-0.012
			(0.000)	(0.000)
Premium Measure	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes	Yes
Loan Type-Lender FE	Yes	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.115	0.115	0.113	0.113
Number of Observations	2,594,800	2,594,800	2,652,502	2,652,502

Note: P-values are in parentheses. This table estimates equation (10), which allows us to test whether the baseline effect works through variation in lenders' funding models. Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Each observation is a loan application. The regression equation is of the form

$$\text{Denial}_{i,l,s,t} = \beta \left(F_l \times \text{Premium}_t \times \text{FHA}_s\right) + \gamma X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + ...$$
$$... + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,s,t},$$

where F_l is a measure of lender l's reliance on an originate-to-securitize funding model: Securitization Rate is the lender's ratio of securitized mortgages to total originations in 2010; and Non-Core Funding is one minus the ratio of total deposits to total assets in 2010, which equals one for nonbanks by definition. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table 8: Robustness to Regulatory Arbitrage Incentives

Outcome:	$\text{Denial}_{i,l,s,t}$			
Securitization $\text{Rate}_l \times \text{Premium}_t \times \text{FHA}_s$	-0.012	-0.013	-0.017	-0.015
	(0.034)	(0.024)	(0.004)	(0.012)
High $\text{Incentive}_l \times \text{Premium}_t \times \text{FHA}_s$	0.007	0.007	0.008	0.010
	(0.007)	(0.014)	(0.003)	(0.000)
$\text{Large}_l \times \text{Premium}_t \times \text{FHA}_s$		0.001	0.004	0.002
		(0.763)	(0.139)	(0.471)
Incentive Measure	Low Initial Capital	Low Initial Capital	Low Change in Capital	High Initial MSR
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes	Yes
Loan Type-Lender FE	Yes	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.110	0.110	0.110	0.110
Number of Observations	1,331,695	1,331,695	1,331,695	1,331,695

Note: P-values are in parentheses. This table estimates a variant of equation (10), which allows us to assess whether the results are robust to correlation between reliance on an originate-to-securitize funding model and measures of regulatory arbitrage incentives. Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Each observation is a loan application to a bank lender. The regression equation is of the form

$$\begin{aligned}\text{Denial}_{i,l,s,t} &= \beta\,(\text{Securitization Rate}_l \times \text{Premium}_t \times \text{FHA}_s) + ...\\ &... + \gamma_0\,(\text{High Incentive}_l \times \text{Premium}_t \times \text{FHA}_s) + ...\\ &... + \gamma_1\,(\text{Large}_l \times \text{Premium}_t \times \text{FHA}_s) + ...\\ &... + \gamma_2 X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,s,t},\end{aligned}$$

where Securitization Rate_l is the lender's ratio of securitized loans to total originations in 2010; and High Incentive_l is an indicator for whether l has a strong regulatory arbitrage incentive based on some measure: columns 1-2 use an indicator for whether l's ratio of total equity to total assets is below the asset-weighted median across bank lenders in 2010; column 3 uses an indicator for whether the 2010-15 change in this ratio is below the asset-weighted median across bank lenders; column 4 uses an indicator for whether l's ratio of mortgage servicing rights to total equity is above the asset-weighted median across bank lenders in 2010. Columns 2-4 include the interaction between Securitization Rate_l, Premium_t, and an indicator for whether l's average assets over 2010-15 exceed the asset-weighted median across banks, denoted Large_l. All columns measure Premium_t using the FNMA spread, defined in Table 2. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table 9: Robustness to the Effect on Nonbanks' Loan Volume

Outcome:	$\log\left(\text{Loan Size}_{i,l,s,t}\right)$		
$\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s$	0.027	0.010	0.009
	(0.000)	(0.000)	(0.000)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes
Loan Type-Lender FE	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes
R-squared	0.600	0.600	0.600
Number of Observations	2,385,666	2,385,666	2,385,666

Note: P-values are in parentheses. This table estimates a variant of equation (1), which allows us to assess implications for financial stability by testing whether nonbanks respond to higher secondary market prices by approving larger loans. Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Loan Size is the size of the loan, in dollars. The sample consists of originated FHA or conventional loans for the purchase of an owner-occupied single-family dwelling. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table 10: Effect on Nonbanks' Lending Standards by Loan Type

Outcome:	Denial$_{i,l,t}$			
Nonbank$_l$ × Premium$_t$	-0.014		-0.001	
	(0.000)		(0.760)	
Securitization Rate$_l$ × Premium$_t$		-0.014		0.000
		(0.008)		(0.878)
Sample	FHA Loans		Conventional Loans	
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.118	0.118	0.101	0.099
Number of Observations	1,046,532	845,352	2,219,363	1,747,923

Note: P-values are in parentheses. This table estimates equation (11) in the FHA and conventional loan markets, which allows us to assess whether lenders who increase credit among FHA loans also tighten credit among conventional loans. Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. The regression equation is of the form

$$\text{Denial}_{i,l,t} = \beta\left(F_l \times \text{Premium}_t\right) + \gamma X_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t},$$

where F_l is a measure of lender l's reliance on an originate-to-securitize funding model: Nonbank indicates if the lender is a nonbank; and Securitization Rate is the lender's ratio of securitized mortgages to total originations in 2010. All columns measure Premium$_t$ using the FNMA spread, defined in Table 2. The sample in columns 1-2 consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling, and the sample in columns 3-4 consists of similar applications for conventional loans. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table 11: Robustness to Placebo Test over the Pre-LCR Period

Specification:	Zip Code-Level		Loan-Level	
Outcome:	ΔNonbank Market Share$_z$		Denial$_{i,l,s,t}$	
FHA App Share$_z$ × Nonbank App Share$_z$	0.045 (0.494)	0.077 (0.266)		
Nonbank$_l$ × Trend$_t$ × FHA$_s$			-0.003 (0.429)	
Securitization Rate$_l$ × Trend$_t$ × FHA$_s$				0.001 (0.858)
County FE	Yes	Yes		
Zip Code Controls	No	Yes		
Lender-MSA FE			Yes	Yes
MSA-Year FE			Yes	Yes
Lender-Year FE			Yes	Yes
Loan Type-Lender FE			Yes	Yes
Loan Type-Year FE			Yes	Yes
Borrower Controls			Yes	Yes
R-squared	0.554	0.551	0.126	0.124
Number of Observations	3,145	2,873	1,557,821	1,204,518

Note: P-values are in parentheses. This table estimates equations (3) and (7) over the 2011-13 period, which serves as a placebo test for our zip code-level and loan-level results. Columns 1-2 contain the results of regressions similar to those in the first two columns of Table 3, except that 2013 is replaced with 2011 and 2013-15 is replaced with 2011-13 in all variable definitions. Columns 3-4 contain the results of regressions similar to those in Tables 2 and 7, except that the sample period is 2011-13 and Premium$_t$ is measured by a linear time trend, denoted Trend$_t$ and residualized against the FNMA spread. The remaining notation and notes on specification in columns 1-2, 3, and 4 are the same as in Tables 3, 2, and 7, respectively.

Online Appendix

This document contains additional material referenced in the text. Appendix A describes our data. Appendix B presents a simple model to complement the theory described in the text. Appendix C estimates the effect of the LCR shock on the GNMA premium.

A Data Description

We first describe our core dataset, and then we describe auxiliary datasets.

Core Dataset

Our core dataset is a merge of the Home Mortgage Disclosure Act (HMDA) mortgage application registry with bank FRY-9C Call Reports. We merge the two datasets together using the fact that the lender's identifier in HMDA (i.e. Respondent ID) equals one of the following: OCC charter number, FDIC certificate number, NCUA charter number, National Information Center (NIC) RSSD, or federal tax ID.

First, HMDA data contain information on the borrower and outcome of almost all mortgage applications in the U.S. We retain FHA and conventional loan applications for the purchase of owner-occupied, single-family dwellings, where we use the term "conventional" to describe non-FHA loans whose value is below the associated conforming loan limit (i.e. non-jumbo loans). In terms of HMDA variables, we retain applications satisfying the following conditions: Occupancy = 1 (i.e. owner-occupied), Property Type = 1 (i.e. 1-to-4 family), Loan Purpose = 1 (i.e. for-purchase), and Action Taken $\neq 6$ (i.e. loan not purchased by institution). To maximize data quality, we additionally require that applications were not flagged for data quality concerns (i.e. Edit Status = "NA") and have a non-empty MSA code. We identify denied and originated loans as those with Action Taken = 3 and Action Taken = 1, respectively. FHA loans are those with Loan Type = 2.

Since all depository institutions are subject to a federal supervisor, we use the associated HMDA codes and identify nonbanks as lenders without a federal supervisor, that is, lenders not under the regulatory oversight of OCC, FRS, FDIC, NCUA, or OTS. Demyanyk and Loutskina (2016) and Huszar and Yu (2019) follow the same criteria. We cross-checked that our sample, which comes from HMDA and covers the vast majority of originators in the U.S. mortgage market, is consistent with Buchak et al (2018), who manually define nonbanks as non-depository institutions and focus on the largest lenders. Appendix Table A14 provides a list of the top 50 nonbanks in our data based on their FHA originations in 2013 and 2014.[30] We retain applications to lenders which received at least 10 applications each year and which have a record in HMDA from 2011 through 2015. The latter condition gives a balanced sample around the introduction of the Liquidity Coverage Ratio. This gives a sample of 396 lenders over the

[30] The largest 5 banks in the FHA market are Wells Fargo, PlainsCapital, JP Morgan Chase, Bank of America, and Fifth Third.

2010-15 period, 123 of which are non-depository institutions, which we call "nonbanks". We then construct an analogous dataset over the 2000-06 period. We intentionally omit the 2007-09 period because of the Great Recession. The upper panels of Table 1 summarize the resulting dataset. For computational convenience, we perform our loan-level analysis on a 25% random sample of the full data.

Second, FRY-9C Call Reports contain information about the balance sheet and income statements for U.S. depository institutions. We use variables associated with consolidated bank data (i.e. RCON), which we replace with the analogous variables from the domestic bank data (i.e. RCFD) when missing. We measure total equity, total assets, and total deposits using the Call Report variables RCON3210, RCON2170, and RCON2200, respectively. We measure banks' GSE and GNMA MBS holdings using BHCK1705 and BHCK1699, respectively. Banks with at least $50 billion in assets are subject to LCR regulation.

Auxiliary Datasets

- *MBS Returns*: Data on total GNMA, FNMA, and FHLMC MBS returns come from the Bloomberg-Barclays total return indices. Data on the GNMA, FNMA, and FHLMC MBS option-adjusted spread (OAS) come from Bloomberg.

- *Nonbank Financial Statements*: Data on average nonbank income statements come from the Mortgage Bankers' Association (2014). We rely on the 2014 Revenue, Cost, and Volume Statistics for Non-Depository Institutions Report, which comes from a survey of major nonbank mortgage lenders. This report contains information on the average nonbank mortgage lender's income statement in 2012, 2013, and 2014, which we use to construct Figure 4. Short-term liabilities are the sum of lines of credit, repurchase reserves, accrued expenses, and other short-term debt.

- *Homeownership*: Zip code-level homeownership rates come from the American Community Survey's 5-year estimates. The 5-year estimates are designed to study medium-to-long run changes in homeownership. Zip codes are typically larger than census tracts. We do not observe zip codes in HMDA, and so we merge each zip code to a census tract in our core HMDA data using the HUD-produced crosswalk file. Then, we aggregate to the zip code-level.

- *Mortgage Delinquency*: County-level mortgage delinquency rates used in Table 5 come from the Consumer Financial Protection Bureau's (CFPB) Mortgage Performance Trends data. The CFPB's data come from data maintained by one of the top three nationwide credit repositories, which contains a nationally representative, 5 percent sample of all outstanding, closed-end, first-lien, 1-4 family residential mortgages, which includes both FHA and non-FHA mortgages. The CFPB's data are available at the county level and monthly frequency dating back to January 2008. We use the December 2019 update. In Appendix Table A9, we restrict our analysis to conventional mortgages using the Fannie Mae Single-Family Loan Performance Dataset. These data contain a subset of Fannie Mae's 30-year and less, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages. To protect borrower privacy, we only observe zip codes at the 3-digit level. In both datasets, the default rate is defined as the sum of 30-89 and 90+ day delinquency rates.

- *Deposits*: Data on county-level deposits used to calculate average deposit market share in Appendix Table A2 come from the FDIC's 2010 Summary of Deposits.

- *Interest Rates*: We obtain data on the interest rate on FHA loans from HUD's FHA Single Family Portfolio Snap Shot. These data contain information on originated FHA loans at a monthly frequency. The variables we observe are the name of the lender, the loan size, the interest rate, and whether the loan is fixed-rate. We classify lenders as nonbanks if their parent company's name does not contain "Bank", "Credit Union", or variant spellings of these terms.

- *FICO Score*: We obtain data on the median FICO score for FHA and conventional loans originated by bank and nonbank lenders from Recursion. The data are available at a monthly frequency and are observed at the lender type (i.e. bank vs. nonbank) by loan type (i.e. FHA vs. conventional) level. Recursion manually defines a lender as a bank for the largest 100 lenders. The remaining lenders are defined as a bank if their name contains "bank", "banc", "bancshares" or "bank and trust". The Recursion data are available beginning in August 2013, which is when Ginnie Mae began to release loan-level data (e.g. Ginnie Mae 2013). We impute data prior to August 2013 through a time-series regression of the median FICO score within each lender-type-by-loan-type on the following variables observed in our core HMDA data: average loan-to-income ratio, average log income, share of minority applicants, and the interactions between these variables and quarter-of-year indicator variables. We also observe the standard deviation of FICO score, which is used to calculate the confidence intervals shown in Figure 7.

B Framework

We propose a simple framework to formalize the intuition described in Section 2 of the text. The framework is intended to complement the discussion in the text, and therefore we omit several realistic features of mortgage markets to focus on the theory's core intuition.

B.1 Setup

Environment

Consider a static economy with two types of mortgage lenders: nonbanks and banks. There are also MBS investors, warehouse lenders, mortgage borrowers, and retail depositors. Borrowers obtain M units of mortgage credit from mortgage lenders − whom we will simply refer to as "lenders" − at the gross interest rate R_M. To obtain closed-form results that highlight the intuition, we hold R_M fixed, although the logic would be the same with a downward-sloping mortgage demand curve.

Lenders fund mortgage originations M using W units of warehouse credit and D units of deposits, which carry gross interest rates of R_W and R_D, respectively. In terms of accounting,

$$M = W + D. \tag{B1}$$

An amount S of these mortgages are sold to MBS investors on the secondary market at price P_S, while the remaining L remain on the lender's balance sheet. The corresponding accounting identity is

$$M = S + L. \tag{B2}$$

In Section B.2, we calculate comparative statics of nonbanks' market share with respect to P_S, treating it as a parameter. However, in reality P_S is an equilibrium object, and, unless prices are perfectly elastic, it should depend on securitization volume.

Following Gete and Reher (2016), lenders internalize that borrowing more increases the interest rate on their cost of funds. The corresponding interest rate schedules are given by the increasing and convex functions $R_W\left(W; P_S\right)$ and $R_D\left(D; \delta\right)$, where δ is a parameter that governs the advantages associated with deposit funding described in Section 2. For example, the ability to exert market power, to extract a money premium, or to cross-sell other products to depositors would be captured by a high value of δ.

Explicitly, we assume

$$R'_W\left(W\right) > 0, \quad R''_W\left(W\right) > 0, \quad R'_D\left(D\right) > 0, \quad R''_D\left(D\right) > 0, \tag{B3}$$

$$\frac{\partial}{\partial P_S} R'_W\left(W\right) < 0, \quad \frac{\partial}{\partial \delta} R'_D\left(D\right) < 0, \tag{B4}$$

where it is understood that R_W and R_D depend on P_S and δ, respectively, as parameters. The first condition in line (B4) reflects how higher MBS prices improve the value of the mortgage lender's collateral, which allows the warehouse lender to break even at a lower interest rate.

Nonbanks

Nonbanks do not have access to deposit funding, reflecting their choice not to comply with the requirements needed to become an FDIC-insured bank. Therefore, using the subscript N to denote "nonbanks",

$$D_N = 0. \tag{B5}$$

Moreover, because warehouse credit arrangements are short-term and typically unwound within 30 days, nonbanks do not have a balance sheet on which they can hold originated mortgages. Therefore, $L_N = 0$ and $W_N = S_N$, so that

$$M_N = S_N = W_N. \tag{B6}$$

Consequently, nonbanks originate S_N units of mortgage credit using W_N in warehouse credit. They solve

$$\max_{W,S} \{P_S S - R_W(W)\} \quad s.t. \quad S = W. \tag{B7}$$

The solution W_N is characterized by the first-order condition

$$0 = P_S - R'_W(W_N). \tag{B8}$$

Equation (B8) defines W_N as an implicit function of P_S, which we express as $W_N = \bar{W}(P_S)$.

In particular, applying the implicit function theorem to equation (B8) gives

$$\bar{W}'(P_S) \propto \underbrace{1}_{\text{Higher Revenue}} - \underbrace{\frac{\partial}{\partial P_S} R'_W(W_N)}_{\text{Lower Cost of Funds}} > 0, \tag{B9}$$

where $\propto$ denotes proportionality. Equation (B9) reflects the two channels discussed in Section 2 through which higher MBS prices increase the supply of nonbank credit: lower funding costs in the warehouse market and higher revenue per unit of MBS sold. Empirically, Figure 4 shows how nonbanks' cost of warehouse credit falls after the LCR-induced increase in MBS prices.

Banks

Banks have access to both deposit funding and warehouse credit. As with the case of nonbanks, warehouse credit arrangements are short-term, so that mortgages funded with warehouse credit must be sold as MBS. Therefore, using the subscript B to denote "banks",

$$W_B = S_B. \tag{B10}$$

By contrast, deposit funding is stable, so that mortgages funded with deposits can either remain on the bank's balance sheet or be sold as MBS. In the former case, the deposits are backed by mortgages, and in the latter case they are backed by cash from the proceeds of an MBS sale. To keep the analysis tractable, we introduce a balanced-book assumption by which mortgages funded by deposits remain on the bank's balance sheet:

$$D_B = L_B. \tag{B11}$$

For example, Hanson et al (2015) show how deposits confer banks with a comparative advantage in holding long-dated assets to maturity. Finally, we prioritize our core intuition by abstracting from shareholders' equity, reserve requirements, and balance sheet constraints, but we later discuss in Section B.4 how these features would modify our conclusions.

Collectively, banks solve

$$\max_{D,W,S,L} \left\{ R_M L + P_S S - R_D\left(D\right) - R_W\left(W\right) \right\}, \quad s.t. \quad L = D, \quad S = W. \tag{B12}$$

The solutions D_B and W_B are characterized by the first-order conditions

$$0 = R_M - R_D'\left(D_B\right), \tag{B13}$$

$$0 = P_S - R_W'\left(W_B\right). \tag{B14}$$

Together, equations (B13) and (B14) define the implicit functions $D_B = \bar{D}\left(\delta\right)$ and $W_B = \bar{W}\left(P_S\right)$. Using the assumptions in condition (B4) and again applying the implicit function theorem gives the result

$$\bar{D}'\left(\delta\right) > 0. \tag{B15}$$

The share of mortgages funded through securitization (i.e. "securitization rate") is

$$\rho \equiv \frac{S}{S+L} = \underbrace{\frac{\bar{W}\left(P_S\right)}{\bar{D}\left(\delta\right) + \bar{W}\left(P_S\right)}}_{\text{Securitization Rate}}. \tag{B16}$$

From equation (B16), it is straightforward to show that

$$\frac{\partial \rho}{\partial \delta} < 0. \tag{B17}$$

Inequality (B17) is consistent with Appendix Table A2 and its discussion in Section 2, which shows how banks with more stable deposits (i.e. high δ) fund fewer of their mortgages through securitization. Moreover, if we think of nonbanks as having a δ that approaches its lower bound, then the inequality (B17) also explains why only 4% of banks in our core data securitize at the same rate as the median nonbank.

B.2 Market Share

Combining the solutions to problems (B7) and (B12), the share of mortgage credit originated by nonbanks is

$$\omega_N = \frac{M_N}{M_N + M_B} = \left[\frac{\bar{D}(\delta)}{\bar{W}(P_S)} + 2\right]^{-1}. \tag{B18}$$

From equation (B18), an increase in MBS prices raises nonbanks' market share,

$$\frac{\partial \omega_N}{\partial P_S} = \bar{W}'(P_S)\, D_B \left[\frac{\omega_N}{W_N}\right]^2 > 0. \tag{B19}$$

The core intuition behind inequality (B19) is that banks have access to stable deposit funding (i.e. $D_B > 0$), and so they rely less on securitization than nonbanks. Therefore, an increase in MBS prices increases the relative supply of credit by nonbanks. Empirically, credit supply expands because nonbanks lower their lending standards, as in Table 2, and originate larger loans, as in Table 9. Consequently, nonbanks' overall market share increases, per Table 3.

B.3 Multiple Loan Types

Mapping to our empirical setting, suppose there are two loan types, denoted F (i.e. FHA) and C (i.e. conventional). It is straightforward to modify the problems in (B7) and (B12) to incorporate this modification.[31] In particular, the loan-by-loan feature of warehouse credit leads to separate warehouse demand curves for the two loan types: $W_{N,F} = \bar{W}(P_{S,F})$ and $W_{N,C} = \bar{W}(P_{S,C})$. Note that $W_{N,F}$ does not depend on $P_{S,C}$ and likewise for $W_{N,C}$ and $P_{S,F}$. Consequently, the solution does not feature crowd-out effects, and we discuss how to generate such effects in Section B.4.

Nonbanks' market share in this setting is

$$\omega_N = \left[\frac{\bar{D}(\delta)}{\bar{W}(P_{S,F}) + \bar{W}(P_{S,C})} + 2\right]^{-1}, \tag{B20}$$

[31] Explicitly, nonbanks' problem becomes

$$\max_{W_C, W_F, S_C, S_F} \left\{P_{S,C} S_C + P_{S,F} S_F - R_W(W_C) - R_W(W_F)\right\}$$
$$s.t. \quad S_C = W_C, \quad S_F = W_F,$$

while banks' problem becomes

$$\max_{D, W_C, W_F, S_C, S_F, L} \left\{R_{M,C} L_C + R_{M,F} L_F + P_{S,C} S_C + P_{S,F} S_F - R_D(D) - R_W(W_C) - R_W(W_F)\right\}$$
$$s.t. \quad L_C + L_F = D, \quad S_C = W_C, \quad S_F = W_F.$$

so that

$$\frac{\partial \omega_N}{\partial P_{S,F}} = \bar{W}'\left(P_{S,F}\right) D_B \left[\frac{\omega_N}{W_{N,F} + W_{N,C}}\right]^2 > 0. \tag{B21}$$

From equation (B21), higher MBS prices for loans of type F increase nonbanks' overall market share. The denominator features an additional term relative to its counterpart in equation (B19), so that, all else equal, the magnitude of the effect is smaller than with a single loan type. These predictions are consistent with the results in Tables 3 and 4.

B.4 Discussion of Crowd-Out Effects

In the interest of tractability, we have abstracted from shareholders' equity and binding balance sheet constraints. If we were to incorporate these ingredients, the framework would capture credit reallocation in response to a change in relative MBS prices for different loan types. For example, banks would like to borrow more in the warehouse credit market to originate more loans of type F when their MBS price increases. However, if there are binding capital requirements, then banks would need to raise costly equity capital in order to originate more type-F loans. Instead, they transfer internal funds away from loans of type C to originate more loans of type F.

Empirically, Appendix Table A8 shows how banks who rely on securitization (i.e. low δ) and face balance sheet constraints increase their supply of the loan type whose MBS price increased (i.e. FHA loans) while reducing their supply of other loan types (i.e. conventional loans). This result is consistent with the findings of Chakraborty, Goldstein, and MacKinlay (2018, 2020).

B.5 Discussion of Risk Aversion

We have made no assumption about the riskiness of the two loan types because we have not incorporated risk aversion into our framework, again in the interest of tractability. The most basic way to understand the effects of risk aversion would be to reinterpret the interest rate on the two loan types, $R_{M,F}$ and $R_{M,C}$, as the expected gross return under a risk-neutral measure. If loans of type F are riskier than those of type C and banks are more risk averse than nonbanks, then banks are less willing to originate loans of type F. Consequently, nonbanks' market share among such loans is higher than among loans of type C,

$$\omega_{N,F} > \omega_{N,C}. \tag{B22}$$

Condition (B22) is consistent with the fact that nonbanks have historically originated a larger share of FHA loans relative to conventional loans, as shown in Figure 5. However, the expression for nonbanks' overall market share, ω_N, is the same as in equation (B20), and the effect of an increase in MBS prices is still characterized by equation (B21). Table 8 and Appendix Table A7 support this prediction, as they replicate the main results in Table 2 and Table 3 after controlling for measures of bank risk aversion due to regulatory burdens.

C Effect of the LCR on the GNMA Premium

In this appendix, we estimate the effect of Liquidity Coverage Ratio (LCR) regulation on the expected return of GNMA MBS. Summarizing the details from Section 3.1, the U.S. version of LCR regulation was proposed on October 24, 2013 and finalized in September 2014. The purpose of this extension is to substantiate the claim that LCR regulation increases nonbanks' and other originate-to-securitize lenders' incentives to originate FHA loans, which are eligible for securitization as GNMA MBS.

Following Diep, Eisfeldt, and Richardson (2017), we focus on MBS total returns measured using the Bloomberg-Barclays Total Return Index, since total returns are less model-dependent than an option-adjusted spread (OAS). Our interest is in the expected total return to MBS of type s, where s indexes Ginnie Mae (GNMA) versus Fannie Mae (FNMA) MBS. In particular, we estimate the following equation

$$R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12} = \beta_0 + \beta_1 \text{Post-LCR}_t + u_t, \tag{C1}$$

where t indexes month; $R^{GNMA}_{t\to t+12}$ is the change in the log Bloomberg-Barclays GNMA Total Return Index from t to t+12; and $R^{FNMA}_{t\to t+12}$ is analogously defined in terms of FNMA MBS.

We motivate equation (C1) as follows. First, suppose the total return between months t and t+12 depends on a vector of factors, $f_{t\to t+12}$, which captures credit, prepayment, and other traditional priced risk factors in period t. In addition, suppose the return to each type of MBS is discounted by a convenience yield λ^s_t, which captures both regulatory incentives for holding MBS of type s and the overall ease of trading it (i.e. market liquidity). The expected total return to MBS s from t to t+12 can then be written

$$\mathbb{E}_t\left[R^s_{t\to t+12}\right] = -\lambda^s_t + \phi^s \bar{f}_t, \tag{C2}$$

where $\bar{f}_t \equiv \mathbb{E}_t\left[f_{t\to t+12}\right]$ denotes the market wide price of risk in period t. The loading, ϕ^s, captures the quantity of risk for MBS of type s.

Taking the cross-sectional difference in equation (C2) between GNMA and FNMA MBS yields

$$\mathbb{E}_t\left[R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12}\right] = \lambda^{GNMA}_t - \lambda^{FNMA}_t + \left(\phi^{FNMA} - \phi^{GNMA}\right)\bar{f}_t. \tag{C3}$$

We model the announcement of LCR regulation as disproportionately increasing the convenience yield for holding GNMA MBS, λ^{GNMA}_t, which we justify for two reasons. First, institutions affected by this regulation can relax their regulatory constraint by purchasing more GNMA MBS, as described in Section 3. Second, the resulting increase in GNMA demand may endogenously generate market liquidity, which incentivizes non-affected institutions to purchase GNMA MBS. While the LCR may also increase the value of holding FNMA MBS, thereby raising λ^{FNMA}_t, the more favorable regulatory weights granted to GNMA MBS should theoretically raise λ^{GNMA}_t by more. In particular, we suppose the difference $\lambda^{GNMA}_t - \lambda^{FNMA}_t$ increases by some amount λ^{LCR} because of the regulation.

Under the assumption that the introduction of LCR regulation does not coincide with exogenous changes in the credit or prepayment risk of GNMA relative to FNMA MBS (i.e. changes in the difference $\phi^{FNMA} - \phi^{GNMA}$), then the coefficient β_1 in equation (C1) recovers the LCR premium, λ^{LCR}. In terms of credit risk, this assumption is plausible because GSE conservatorship implies approximately equal levels of default probability over our sample period. In terms of prepayment risk, any baseline difference in FNMA versus GNMA prepayment probability is subsumed by β_0 in equation (C1) because we obtain identification from the cross-section of MBS returns. Thus, bias can only arise because of changes in relative prepayment risk that coincide with the introduction of LCR regulation. To rule out this possibility, we perform a similar exercise using Bloomberg's Option-Adjusted Spread (OAS), which strips out the effect of embedded options and thus the quantity of prepayment risk.

The estimates of equation (C1) are in Table A15. We measure GNMA and FNMA returns using the Bloomberg Barclays GNMA and FNMA Total Return indices, respectively. The baseline point estimate in column 1 suggests that LCR increases the expected return to FNMA MBS by 42 bps relative to GNMA MBS. This effect is equal to 0.7 standard deviations of the FNMA-GNMA spread, or around 17% of the average real return to GNMA MBS over 2000-2015 (2.5%). To account for the possibility that Post-LCR$_t$ captures spurious time-series variation, we include a linear time trend in column 2, which yields a larger point estimate. Column 3 restricts the sample period to 2011-2015, which also gives a slightly higher point estimate of 55 bps. Finally, the outcome in column 4 is the difference in Bloomberg's Option-Adjusted Spread (OAS) between FNMA and GNMA MBS. As mentioned above, the OAS is model-dependent and aims to strip out prepayment risk.[32] We find that the OAS-based FNMA-GNMA spread was 13 bps higher in the post-LCR period, equal to 0.8 standard deviations and 29% of the average GNMA OAS over the period.

[32]Boyarchenko, Fuster, and Lucca (2019), Gabaix, Krishnamurthy and Vigneron (2007), and Diep, Eisfeldt and Richardson (2017) show that the risk of homeowner prepayment is priced in the MBS market.

Additional Figures and Tables

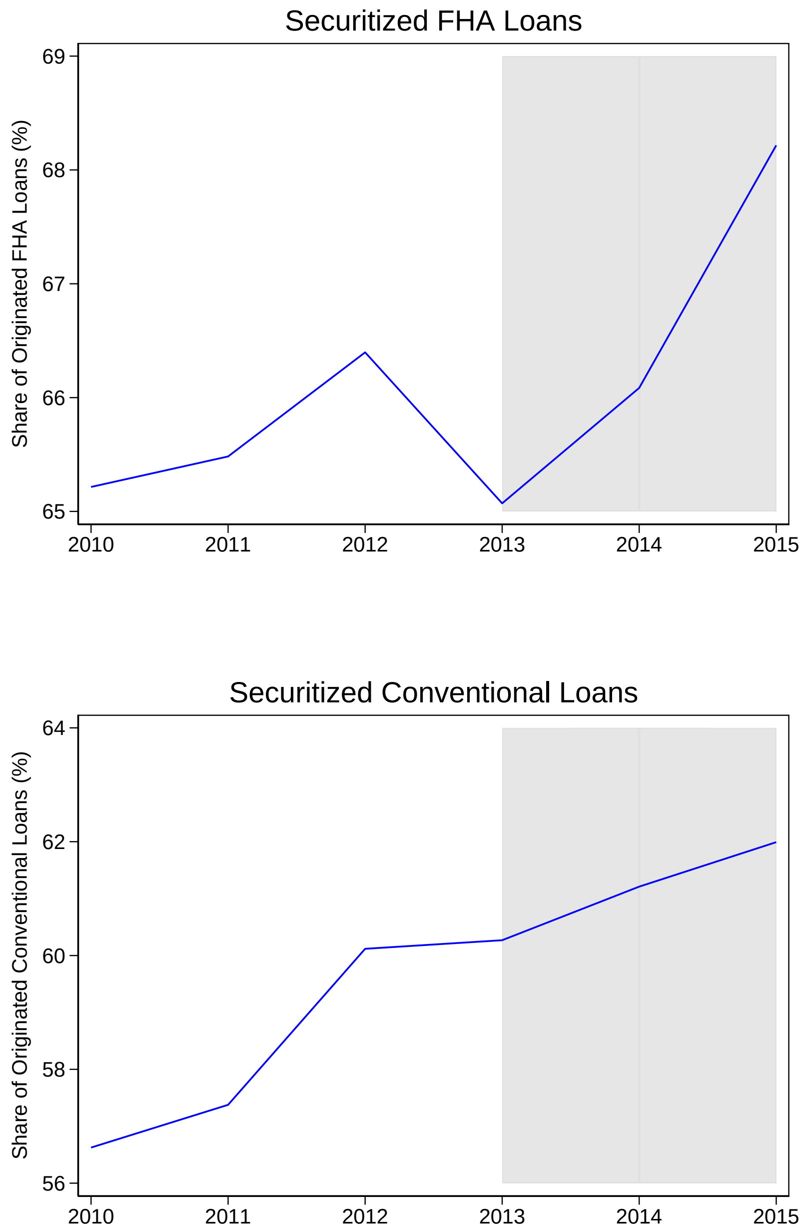


Figure A1. Securitization by Loan Type. This figure shows the fraction of FHA (top) and conventional (bottom) loans originated each year that are securitized. Data are from HMDA.

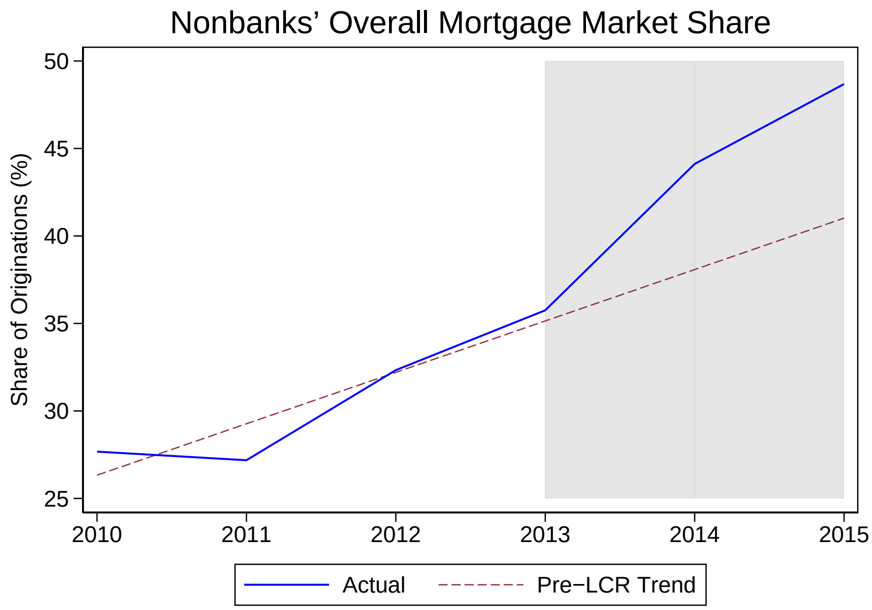


Figure A2. Nonbank Overall Market Share. This figure plots the share of loans originated by nonbank lenders in the overall mortgage market. Data are from Buchak et al (2018).

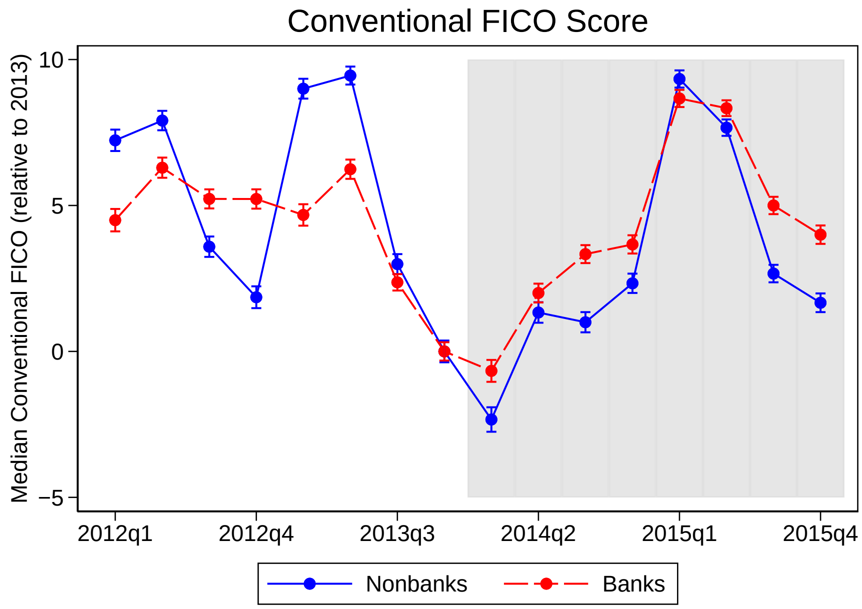


Figure A3. FICO Score on Conventional Loans for Banks and Nonbanks. This figure plots the median lender's FICO score on conventional loan originations, relative to its value in 2013Q4. The blue and red curves plot this statistic for nonbank and bank lenders, respectively. Brackets correspond to a 95% confidence interval. Data are from Recursion.

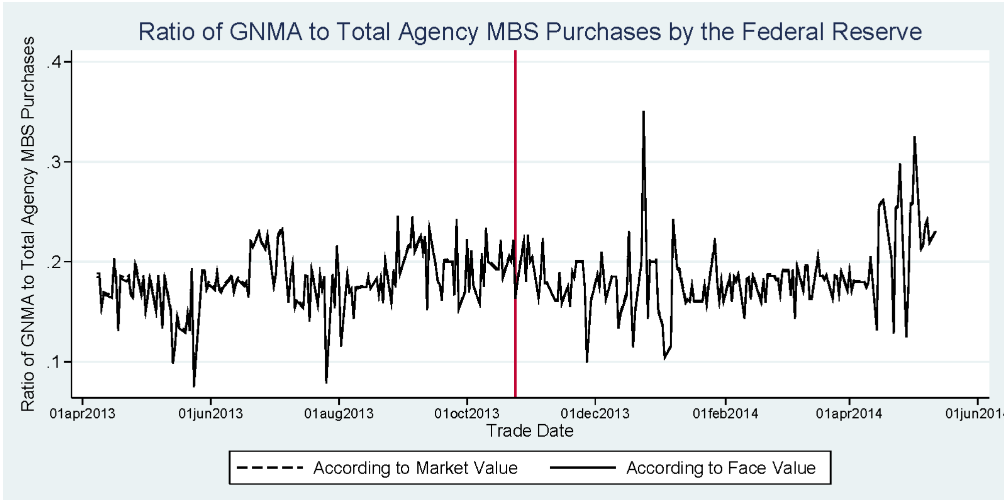


Figure A4. Ginnie Mae Share of the Fed's MBS Purchases. This figure plots the Ginnie Mae (GNMA) share of the Fed's MBS purchases. Data are from federalreserve.gov.

Table A1: Lender-Level Summary Statistics

Variable	Number of Observations	Percentile				
		5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
All Lenders:						
Securitization Rate	2,628	0.161	0.844	0.941	0.999	1
FHA Securitization Rate	936	0.745	0.865	0.987	1	1
Conventional Securitization Rate	2,617	0.085	0.787	0.941	0.999	1
Non-Core Funding Ratio	1,822	0.16	0.311	1	1	1
Capital Ratio	1,391	0.077	0.106	0.117	0.121	0.154
MSR Ratio	177	0	0	0	0.012	0.062
Nonbanks:						
Securitization Rate	425	0.337	0.951	0.998	1	1
FHA Securitization Rate	392	0.469	0.957	0.998	1	1
Conventional Securitization Rate	415	0.853	0.958	0.998	1	1
Non-Core Funding Ratio	431	1	1	1	1	1
Banks:						
Securitization Rate	2,203	0.029	0.718	0.852	0.86	0.997
FHA Securitization Rate	544	0.745	0.865	0.865	0.987	1
Conventional Securitization Rate	2,202	0.021	0.642	0.839	0.842	0.998
Non-Core Funding Ratio	1,391	0.134	0.221	0.311	0.358	0.415
Capital Ratio	1,391	0.077	0.106	0.117	0.121	0.154
MSR Ratio	177	0	0	0	0.012	0.062

Note: Each observation is a lender, and the variables are defined as follows: Securitization Rate is the lender's ratio of securitized mortgages to total originations in 2010; FHA Securitization Rate and Conventional Securitization Rate are the lender's securitization rate among FHA and conventional loans, respectively, in 2010; Non-Core Funding Ratio is one minus the ratio of total deposits to total assets in 2010, which equals one for nonbanks by definition; Capital Ratio is the ratio of total equity to total assets in 2010; and MSR Ratio is the ratio of mortgage servicing rights to total equity in 2010. Observations are weighted by mortgage origination volume over 2010-15.

Table A2: Securitization Rate and Lender Characteristics

Outcome:	Securitization Rate$_l$		
Deposit Market Share$_l$	-2.334	-2.255	-1.448
	(0.019)	(0.032)	(0.047)
Capital Ratio$_l$	4.843	1.330	-4.044
	(0.348)	(0.677)	(0.117)
Liquid Asset Ratio$_l$	3.929	4.290	-0.022
	(0.190)	(0.185)	(0.988)
Deposit Ratio$_l$	-0.022	-0.247	1.008
	(0.975)	(0.816)	(0.069)
Commitment Ratio$_l$	-2.965	-2.346	0.339
	(0.078)	(0.205)	(0.826)
Credit Ratio$_l$	5.628	6.601	-0.009
	(0.161)	(0.097)	(0.995)
log (Assets$_l$)	0.017	0.059	0.010
	(0.709)	(0.187)	(0.764)
Mortgage Market Share$_l$	2.447	2.469	-0.018
	(0.005)	(0.010)	(0.959)
Capital Ratio	Economic	Regulatory	Regulatory
Sample	All	All	Positive Securitization Rate
R-squared	0.438	0.410	0.667
Number of Observations	124	124	92

Note: P-values are in parentheses. This table estimates a regression of a bank's securitization rate on observed bank characteristics. Subscript l denotes bank. The regression equation is of the form

$$\text{Securitization Rate}_l = \alpha + \beta X_l + u_l,$$

where the controls in X_l are: the share of county-level deposits held by the bank, averaged across counties where the bank has a branch and denoted Deposit Market Share; the ratio of a measure of equity capital to a measure assets, denoted Capital Ratio; the ratio of the sum of cash, commitments-to-sell, available-for-sale securities and held-to-maturity securities to total assets, denoted Liquid Asset Ratio; the ratio of total deposits to total assets, denoted Deposit Ratio; the ratio of unused commitments to the sum of total assets and unused commitments, denoted Commitment Ratio; the ratio of the sum of unused commitments and loans and leases net of unearned income to the sum of total assets and unused commitments, denoted Credit Ratio; the log of total assets; and the share of county-level mortgage volume originated by the bank, averaged across counties where the bank receives a loan application and denoted Mortgage Market Share. Securitization Rate is the bank's ratio of securitized mortgages to total originations. Column 1 defines the capital ratio as the ratio of total equity to total assets (i.e. economic capital), and column 2 defines it as the ratio of tier-1 equity to net risk-weighted assets (i.e. regulatory capital). Column 3 restricts the sample to banks with a positive securitization rate. All variables are 2010 values. Observations are weighted by total assets. Standard errors are heteroskedasticity robust.

Table A3: Relationship Between LCR Exposure and Other Zip Code Dynamics

Outcome:	Nonbank App Share$_z$ $\times$ FHA App Share$_z$		
ΔLTI$_z$	-0.000		
	(0.742)		
ΔMinority$_z$		-0.008	
		(0.282)	
ΔCapital Ratio$_z$			-0.014
			(0.722)
County FE	Yes	Yes	Yes
R-squared	0.961	0.961	0.961
Number of Observations	4,473	4,473	4,305

Note: P-values are in parentheses. This table assesses the relationship between a zip code's exposure to the LCR-induced increase in nonbanks' credit supply and other zip code dynamics. Subscript z indexes zip code. The regression equation is of the form

$$\text{Nonbank App Share}_z \times \text{FHA App Share}_z = \gamma X_z + \alpha_{c(z)} + u_z.$$

As in Table 3, all specifications control for FHA App Share$_z$, Nonbank App Share$_z$, and nonbanks' share of origination volume in 2013. The other control variables in columns 1-3 are, respectively, the 2013-15 change in: the average requested loan-to-income ratio; share of applications from black or Hispanic borrowers; and the average ratio of total equity to assets among bank lenders, weighting lenders by origination volume. The remaining notation, notes on specification, and sample are the same as in Table 3.

Table A4: Effect on Origination Volume

Outcome:	$\Delta \log(\text{Volume}_z)$			
FHA App Share$_z$ × Nonbank App Share$_z$	0.449	0.456	0.913	0.808
	(0.035)	(0.033)	(0.031)	(0.057)
Market	All Mortgages		FHA Mortgages	
County FE	Yes	Yes	Yes	Yes
Zip Code Controls	No	Yes	No	Yes
R-squared	0.338	0.341	0.226	0.234
Number of Observations	4,506	4,458	4,069	4,025

Note: P-values are in parentheses. This table estimates a variant of equation (3), which assesses how the LCR shock affects mortgage origination volume. Subscript z indexes zip code. The regression equation is the same as in Table 3, replacing the outcome variable with a measure of the change in mortgage origination volume by both bank and nonbank lenders. The outcome in columns 1-2 is the 2013-15 change in log volume of all mortgages originated, and the outcome in columns 3-4 is the analogous change in log volume of FHA mortgages originated. The remaining notation, notes on specification, and sample are the same as in Table 3.

Table A5: Heterogeneous Effects on FHA Denial Rates by Borrower Riskiness

Outcome:		$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{Premium}_t$	-0.020	-0.014	-0.012
	(0.046)	(0.000)	(0.000)
$\text{Nonbank}_l \times \text{Premium}_t \times \text{LTI}_{m(i),t}$	-0.006	-0.003	-0.003
	(0.117)	(0.009)	(0.002)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes
R-squared	0.117	0.117	0.117
Number of Observations	1,040,927	1,040,927	1,040,927

Note: P-values are in parentheses. This table estimates a variant of equation (11) on the sample of FHA loan applications, which allows us to assess whether nonbanks lower their standards by a larger amount for borrowers in riskier markets. Subscripts i, l, m, and t index borrower, lender, MSA, and year, respectively. $\text{LTI}_{m(i),t}$ denotes the average loan-to-income ratio (LTI) among borrowers in the applicant's MSA of residence, $m(i)$, which is a proxy for credit risk and is standardized to have zero mean and unit variance. The remaining notation, sample period, and standard errors are the same as in Table 10.

Table A6: Implications for Funding Fragility

Outcome:	ΔNon-Core Funding Ratio$_z$	
Nonbank App Share$_z$ $\times$ FHA App Share$_z$	0.179	0.179
	(0.000)	(0.000)
County FE	Yes	Yes
Zip Code Controls	No	Yes
R-squared	0.471	0.473
Number of Observations	4,488	4,440

Note: P-values are in parentheses. This table estimates a variant of equation (3), which assesses how the LCR shock affects funding fragility. Subscript z indexes zip code. The regression equation is the same as in Table 3, replacing the outcome with the 2013-15 change in the average lender's non-core funding ratio, weighting lenders by origination volume. The non-core funding ratio is one minus the ratio of total deposits to total assets in 2010, which equals one for nonbanks by definition. The remaining notation, notes on specification, and sample are the same as in Table 3.

Table A7: Robustness of Effect on Nonbanks' Market Share to Regulatory Arbitrage Incentives

Outcome:	ΔNonbank Market Share$_z$		
FHA App Share$_z$ $\times$ Nonbank App Share$_z$	0.209	0.215	0.220
	(0.001)	(0.001)	(0.041)
Initial Capital Ratio$_z$	-0.061	-0.447	0.145
	(0.765)	(0.092)	(0.761)
Change in Capital Ratio$_z$		-0.434	0.241
		(0.023)	(0.477)
Initial MSR Ratio$_z$			-0.078
			(0.455)
County FE	Yes	Yes	Yes
R-squared	0.541	0.544	0.577
Number of Observations	3,995	3,924	1,733

Note: P-values are in parentheses. This table estimates a variant of equation (3), which allows us to assess whether the estimated effect on nonbanks' market share is robust to correlation between exposure to the LCR shock and measures of local banks' regulatory arbitrage incentives. Subscript z indexes zip code. The regression equation is the same as in column 1 of Table 3 after including additional control variables: Initial Capital Ratio$_z$ is the ratio of total equity to total assets in 2013; Change in Capital Ratio$_z$ is the 2013-15 change in this ratio; and Initial MSR Ratio$_z$ is the ratio of mortgage servicing rights to total equity in 2013. All variables are averages across banks, weighting by mortgage origination volume in the zip code. The remaining notation, notes on specification, and sample are the same as in Table 3.

Table A8: Reallocation by Capital-Constrained Banks who Rely on Securitization

Outcome:	$\text{Denial}_{i,l,t}$	
$\text{Securitization Rate}_l \times \text{Premium}_t$	-0.005	-0.004
	(0.425)	(0.487)
$\text{Securitization Rate}_l \times \text{Premium}_t \times \text{Low Capital}_l$	0.015	0.012
	(0.048)	(0.051)
Sample	Conventional Loans	
Premium Measure	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes
MSA-Year FE	Yes	Yes
Borrower Controls	Yes	Yes
R-squared	0.092	0.092
Number of Observations	1,006,948	1,006,948

Note: P-values are in parentheses. This table estimates a variant of equation (11) among bank lenders in the conventional loan market, which allows us to assess whether capital-constrained banks who rely on securitization tighten credit among conventional loans. Low Capital_l indicates whether l's ratio of total equity (i.e. economic capital) to total assets in 2010 is below the asset-weighted median across banks. The regression equation is the same as in Table 10 with the addition of two additional variables: $\text{Securitization Rate}_l \times \text{Premium}_t \times \text{Low Capital}_l$; and $\text{Premium}_t \times \text{Low Capital}_l$, whose estimated coefficient is not shown in the table. The sample consists of applications to bank lenders for conventional loans for the purchase of an owner-occupied single-family dwelling. The remaining notation, sample period, and standard errors are the same as in Table 10.

Table A9: Robustness of Zip-Code Level Results to Placebo Test on Conventional Loans

Outcome:	ΔNonbank Market Share$_z$		ΔDefault Rate$_z$	
FHA App Share$_z$ $\times$ Nonbank App Share$_z$	-0.020	-0.016	0.009	0.002
	(0.834)	(0.868)	(0.812)	(0.972)
County FE	Yes	Yes	Yes	Yes
Zip Code Controls	No	Yes	No	Yes
R-squared	0.174	0.174	0.373	0.385
Number of Observations	4,414	4,367	279	269

Note: P-values are in parentheses. This table estimates a variant of equation (7), which assesses the effect on nonbanks' market share and default rates in the conventional market as a placebo test. Subscript z indexes zip code. The regression equation is the same as in Table 5. The outcome in columns 1-2 is the 2013-15 change in the share of mortgage volume that is originated by nonbanks in the conventional loan market. The outcome in columns 3-4 is the 2013-15 change in the 30+ day mortgage delinquency rate for FNMA-insured loans, which are only observed at the 3-digit zip code level, as described in Appendix A. The remaining notation and notes on specification are the same as in Table 5.

Table A10: Robustness to Excluding Lenders with Over 2% of the Market and Nonbanks

Outcome:	Denial$_{i,l,s,t}$			
Nonbank$_l$ × Premium$_t$ × FHA$_s$	-0.004	-0.004		
	(0.001)	(0.000)		
Securitization Rate$_l$ × Premium$_t$ × FHA$_s$			-0.015	-0.014
			(0.015)	(0.007)
Excluded Group	Large Lenders		Nonbanks	
Premium Measure	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Loan Type-Lender FE	Yes	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes	Yes
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.122	0.122	0.110	0.110
Number of Observations	2,734,287	2,734,287	1,331,695	1,331,695

Note: P-values are in parentheses. This table estimates equation (1) after excluding certain lenders from the sample. Columns 1-2 exclude lenders with over 2% of the total mortgage market in 2010 to assess whether litigation risk or other size effects bias the baseline estimates. Columns 3-4 exclude nonbanks to assess whether regulatory arbitrage or other nonbank-specific effects bias the baseline estimates. Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Securitization Rate is the lender's ratio of securitized mortgages to total originations in 2010. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table A11: Interest Rate Pass-Through by Nonbanks at a Monthly Frequency

Outcome:	$\text{Rate}_{i,l,t}$			
$\text{Nonbank}_l \times \text{Premium}_t$	-0.052	-0.053	-0.124	-0.125
	(0.000)	(0.000)	(0.000)	(0.000)
Premium Measure	FNMA Spread	FHLMC Spread	FNMA OAS Spread	FHLMC OAS Spread
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.616	0.616	0.616	0.616
Number of Observations	2,130,962	2,130,962	2,130,962	2,130,962

Note: P-values are in parentheses. This table estimates equation (12), which assesses the effect of the LCR shock on interest rates using data from HUD's FHA Single Family Portfolio Snap Shot. Subscripts i, l, and t index borrower, lender, and month, respectively. Each observation is a new loan. Rate is the loan's interest rate, in percentage points. The OAS is computed by Bloomberg. Borrower controls are log loan amount and an indicator for whether the loan is a fixed-rate mortgage. The remaining notation is the same as in Table 10. The sample consists of originated FHA loans for the purchase of a single-family dwelling. The sample period is 2012-15. Standard errors are clustered by lender-month bins.

Table A12: Robustness to Changes in Prepayment Risk

Outcome:	$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{Premium}_t$	-0.018	-0.016
	(0.009)	(0.007)
Premium Measure	FNMA OAS Spread	FHLMC OAS Spread
Lender-MSA FE	Yes	Yes
MSA-Year FE	Yes	Yes
Borrower Controls	Yes	Yes
R-squared	0.117	0.117
Number of Observations	1,040,927	1,040,927

Note: P-values are in parentheses. This table estimates equation (11) using the option-adjusted spread (OAS), which strips out the effect of changes in prepayment risk across different types of MBS. Subscripts i, l, and t index borrower, lender, and year, respectively. FNMA OAS Spread is the difference in option-adjusted spread between Fannie Mae (FNMA) and Ginnie Mae (GNMA) MBS, and FHLMC OAS Spread is the analogous difference between Freddie Mac (FHLMC) and GNMA MBS. The OAS is computed by Bloomberg. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling. The remaining notation, sample period, and standard errors are the same as in Table 10.

Table A13: Testing the Mechanism Over Another Non-Crisis Period, 2000-06

Outcome:	$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{Premium}_t$	-0.017	-0.011
	(0.029)	(0.036)
Premium Measure	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes
MSA-Year FE	Yes	Yes
Borrower Controls	Yes	Yes
R-squared	0.132	0.132
Number of Observations	1,056,661	1,056,661

Note: P-values are in parentheses. This table estimates equation (11) over the 2000-06 period, which assesses the mechanism over another non-Crisis period. Subscripts i, l, and t index borrower, lender, and year, respectively. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling. The remaining notation and standard errors are the same as in Table 10.

Table A14: Nonbanks in the FHA Market

Name	*Number of Originations in 2013 and 2014*
QUICKEN LOANS	20,905
GUILD MORTGAGE COMPANY	15,692
PRIMARY RESIDENTIAL MORTGAGE	13,321
STEARNS LENDING	12,185
HOMEBRIDGE FINANCIAL SERVICES,	12,029
PROSPECT MORTGAGE LLC	11,477
FAIRWAY INDEPENDENT MORT CORP	10,399
STONEGATE MORTGAGE CORPORATION	9,352
PACIFIC UNION FINANCIAL, LLC	9,327
MOVEMENT MORTGAGE, LLC	9,113
CORNERSTONE HOME LENDING, INC.	8,946
PLAZA HOME MORTGAGE, INC.	8,936
EVERETT FINANCIAL INC	8,547
FRANLKIN AMERICAN MORTGAGE CO	8,518
ACADEMY MORTGAGE CORPORATION	8,187
DHI MORTGAGE COMPANY LIMITED	7,984
GUARANTEED RATE INC	7726
UNIVERSAL AMERICAN MTG. CO.LLC	7,602
PINNACLE CAPITAL MORTGAGE	7,397
CALIBER HOME LOANS	7,342
SECURITYNATIONAL MORTGAGE COMP	7,113
UNITED SHORE FINANCIAL SERVICE	7,111
PARAMOUNT RESIDENTIAL MORTGAGE	7,087
LOANDEPOT.COM, LLC	6,927
CARRINGTON MORTGAGE SERVICES	6,457
PHH HOME LOANS	6,057
NOVA HOME LOANS	5,930
FREEDOM MORTGAGE CORPORATION	5,888
NTFN, INC.	5,346
AMERICAN PACIFIC MORTGAGE CORP	5,294
SIERRA PACIFIC MORTGAGE	5,196
SUN WEST MORTGAGE COMPANY, INC	4,968
AMCAP MORTGAGE LTD	4,706
CMG FINANCIAL, INC	4,671
SWBC MORTGAGE CORPORATION	4,658
W. J. BRADLEY MORTGAGE CAPITAL	4,487
IMORTGAGE.COM, INC.	4,395
FIRST MORTGAGE CORP	4,118
MICHIGAN MUTUAL, INC.	4,053
WR STARKEY MORTGAGE, LLP	3,992
MORTGAGE 1 INCORPORATED	3,820
RESIDENTIAL MORTGAGE SERVICES	3,654
NATIONSTAR MORTGAGE LLC	3,641
COBALT MORTGAGE INC	3,623
NETWORK FUNDING LP	3,573
BROKER SOLUTIONS, INC.	3,550
CITYWIDE HOME LOANS, A UTAH CO	3,507
DAS ACQUISITION COMPANY, LLC	3,360
ENVOY MORTGAGE, LTD.	3,357
CALIBER FUNDING LLC	3,354

Table A15: Liquidity Coverage Ratio and the GNMA Premium

Outcome:	$R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12}$			$\text{OAS}^{FNMA}_t - \text{OAS}^{GNMA}_t$
Post-LCR$_t$	0.422	0.757	0.546	0.133
	(0.009)	(0.025)	(0.034)	(0.001)
Sample	2000-15	2000-15	2011-15	2011-15
Time Trend	No	Yes	Yes	Yes
Number of Observations	181	181	49	49

Note: P-values are in parentheses. This table estimates equation (C1). Subscript t indexes month. $R^{GNMA}_{t\to t+12}$ is the change in log Bloomberg-Barclays Ginnie Mae (GNMA) Total Return Index from t to t+12, multiplied by 100. $R^{FNMA}_{t\to t+12}$ is defined analogously in terms of the Bloomberg-Barclays Fannie Mae (FNMA) index. Post-LCR$_t$ indicates if the month is greater than or equal to October 2013. The sample period in columns 1 and 2 is October 2000 through October 2015, and the sample period is October 2011 through October 2015 in columns 3 and 4. Columns 2 through 4 include a linear time trend. Standard errors are Newey-West with a lag of 4 months.