Mortgage Securitization and Shadow Bank Lending*

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Abstract

We find that higher secondary market prices increase the relative supply of credit by nonbank lenders (i.e. shadow banks) in the primary mortgage market. We estimate the effect by exploiting a regulatory shock to the cross-section of mortgage-backed security prices, the introduction of the U.S. Liquidity Coverage Ratio. The shock increases secondary market prices for particular loan types (i.e. FHA loans) by granting them favorable regulatory status as a securitized product. Nonbanks respond by loosening standards for such loans, and consequently their market share grows by 23% over 2013-15. Moreover, zip codes more exposed to nonbanks experience growth in 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 has generated intense policy debate since the 2008 Financial Crisis, with allegations that it destabilized the financial system by channeling credit to risky *borrowers*.[1] However, securitization might also affect financial stability by channeling market share to more fragile *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 now originate around 80% of loans insured by the Federal Housing Administration (FHA) and more than 50% of all mortgages, shown in Figure 1. This trend concerns policymakers, because many of the nonbanks that were active before the Financial Crisis either failed or were restructured.[2]

We find that higher mortgage-backed security (MBS) prices lower nonbanks' lending standards in the primary mortgage market, thereby increasing their market share relative to banks. Our period of analysis is 2010-15, during which the introduction of the U.S. Liquidity Coverage Ratio increased secondary market prices for FHA-insured loans. Relative to banks, nonbanks respond to this increase in MBS prices by denying fewer FHA borrowers, especially low-income borrowers on the margin of homeownership. While we focus on the period after the Great Recession because of the aforementioned regulatory shock, we also provide evidence that fluctuations in MBS prices contributed nonbanks' growth in market share over 2000-06. Our results thus illustrate how recurring fluctuations in secondary markets can affect not only the supply of credit in the primary market, but also the types of lenders that intermediate that credit.

The theory we test begins with variation in how lenders fund mortgage originations, and specifically variation in lenders' funding liquidity (Brunnermeier and Pedersen 2008). Unlike banks, nonbanks lack access to stable deposit funding, and so they fund originations through securitization (e.g. Echeverry, Stanton, and Wallace 2016; Hanson et al 2015). This funding model makes nonbank lending more sensitive to secondary market prices, and thus the supply of nonbank-produced MBS is relatively-elastic. By contrast, banks fund lending through a mixture of deposit funding and securitization, and so the supply of bank-produced MBS is relatively-inelastic. Consequently, higher secondary market prices encourage nonbanks − or, more generally, lenders with limited funding liquidity − to extend more credit in the primary mortgage market. Thus, the relative size of the nonbank (i.e. "shadow bank") lending sector

[1] For example, Willen (2014) discusses how popular backlash against securitization contributed to the adoption of the Risk Retention Ratio.

[2] See Wallace (2016) or Pinto and Oliner (2015).

grows.

Two econometric hurdles make it challenging to test this hypothesis. The first is omitted variables bias: unobserved factors, such as 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).[3] 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 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 challenge is reverse causality: lending behavior affects the supply of collateral and thus MBS prices. 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 research design, 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 baseline exercise is a difference-in-difference research design, where "treated lenders" are nonbanks and the "treatment" is the LCR-induced increase in GNMA prices. We find that nonbanks respond to the increase in GNMA prices by denying 15% fewer FHA loan applicants. To confirm that funding liquidity is the key channel, we obtain similar results when defining "treated lenders" as those with less historical reliance on core deposit funding or greater historical reliance on securitization. In fact, the results are almost the same when dropping nonbanks from the sample, consistent with substantial heterogeneity in bank funding liquidity (e.g. Loutskina 2011; Cornett et al 2011; Dagher and Kazimov 2015). While our baseline outcome is a

[3] 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.

lender's denial rate, we also show that nonbanks disproportionately lower the interest rate on FHA loans in response to an increase in GNMA prices.

We assess the aggregate implications of our findings by conducting a similar difference-in-difference exercise at the census tract level. By aggregating to the census tract level, the point estimates reflect how nonbanks both deny fewer applicants and, through offering more favorable terms, attract more applications. We use our central point estimate to compute nonbanks' counterfactual market share in the absence of LCR regulation. This back-of-envelope calculation indicates that the LCR-induced increase in GNMA prices accounts for 23% (2.2 percentage points) of nonbanks' growth in FHA market share between 2013-15.

Turning to distributional implications, the baseline results are strongest for borrowers with high loan-to-income ratios, who are often on the margin of homeownership. Motivated by this finding, we ask whether nonbanks' expansion in credit supply may have attenuated the post-Crisis collapse in homeownership rates. Based on a cross-sectional regression across zip codes, we find that zip codes with greater reliance on nonbanks in 2011 see lower mortgage denial rates, and, consequently, a less severe decline in homeownership over 2011-15. Thus, while an increase in MBS prices raises the market share of fragile nonbank lenders, it also facilitates access to homeownership.

We focus on the 2010-15 period because of the exogenous variation in MBS prices generated by the introduction of the LCR. However, we document a similar relationship between MBS prices and nonbank lending over 2000-06. While we cannot rule out the possibility of reverse causality over that period, this finding suggests that fluctuations in nonbanks' market share can occur routinely as a byproduct of fluctuations in secondary markets. It also suggests that our baseline results are not due to spurious correlation between the introduction of the LCR and other time-varying factors. Indeed, based on a wide variety of robustness exercises, we find no evidence that our baseline result is driven by: increased litigation risk associated with the False Claims Act; the introduction of the Net Stable Funding Ratio; regulatory arbitrage; changing credit quality of nonbank and FHA loan applicants; the Fed's quantitative easing program; or a pre-trend in nonbank denial rates. For further robustness, we estimate a triple difference-in-difference equation that obtains identification from the triple product of treated lenders (i.e. nonbanks), treated loan types (i.e. FHA loans), and the treatment (i.e. GNMA prices). This strategy allows us to include lender-year, MSA-year, and MSA-lender fixed effects. We again find that nonbanks respond to higher GNMA prices by denying fewer FHA applicants.

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.

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, Kim et al (2018) highlight the systemic risks associated with greater reliance on nonbanks. In terms of causes, the existing literature has found that nonbanks' market share depends on regulatory arbitrage (Buchak et al 2018), technological innovation (Fuster et al 2018), bank capitalization (Irani et al 2018; Chernenko, Erel, and Prilmeier 2018), and creditor protection in the warehouse lending market (Ganduri 2018). Our paper shows how secondary market prices are also a force that significantly affects nonbanks' market share, in addition to the aforementioned forces.

Third, there is growing interest in how financial regulations introduced in the wake of the Financial Crisis affect U.S. housing markets. To date, papers have documented important effects related to stress tests (Calem, Correa and Lee 2016; Gete and Reher 2018), qualified-mortgage requirements (De Fusco, Johnson, and Mondragon 2019), litigation risk (D'Acunto and Rossi 2017; Gissler, Oldfather, and Ruffino 2016), and capital requirements (Reher 2019). We provide the first evidence that the Liquidity Coverage Ratio also affects the housing market in meaningful ways, such as increasing nonbanks' share of mortgage lending and bolstering homeownership.

The remainder of the paper proceeds as follows: Section 2 briefly describes our theory and presents stylized facts about our setting, the U.S. mortgage market; Section 3 describes our identification strategy and the details of the Liquidity Coverage Ratio shock; Section 4 contains our main analysis; Section 5 performs a variety of robustness exercises; Section 6 studies implications for homeownership; and Section 7 concludes. All figures and tables may be found at the end of the main text. The online appendix has additional material.

2 Framework and Setting

2.1 Framework

Our empirical analysis is grounded in a theory of mortgage markets with heterogeneous lenders. We illustrate this theory using the stylized diagram in Figure 1.

First, unlike banks, nonbanks do not have access to stable deposit funding, and thus they cannot hold loans on their balance sheet. Instead, they finance lending through short-term arrangements such as repurchase agreements or warehouse lines of credit, using the loans they have originated as collateral. Higher MBS prices increase the collateral value of these loans, enabling nonbanks to obtain more funding. In addition, to the extent that higher MBS prices reflect greater secondary market liquidity, this liquidity makes it easier for nonbanks to sell the loans they originate and thus unwind their funding arrangements. Consequently, nonbanks' supply of MBS is relatively-sensitive to MBS prices, leading to a relatively-elastic supply curve as shown in Figure 1a.

By contrast, banks can use deposits to finance primary market lending, and so they respond less to an increase in MBS prices. Consequently, banks' supply of MBS is relatively-inelastic, per Figure 1b. An increase in MBS prices from P_0 to P_1 therefore significantly increases nonbanks' supply of MBS from M_0^{NB} to M_1^{NB}, shown in Figure 1a, while banks' supply of MBS increases by a more modest amount from M_0^B to M_1^B, as in Figure 1b.

Turning to the primary market, an increase in the supply of nonbank and bank-produced MBS necessitates a corresponding increase in the supply of nonbank and bank-intermediated loans, as illustrated in panels (c) and (d) of Figure 1. Therefore, at any given mortgage interest rate R, the supply of nonbank-intermediated loans increases from L_0^{NB} to L_1^{NB}, while the supply of bank-intermediated loans only increases from L_0^B to L_1^B.[4] In summary, higher MBS prices disproportionately increase nonbanks' supply of credit in the primary market, and thus their market share rises.

2.2 Setting

We investigate this theory in the context of the U.S. mortgage market. Figure 2 shows that nonbanks' for-purchase mortgage origination share has increased dramatically since the Financial Crisis.[5] In the top panel, we see that nonbanks historically comprised around 50% of the FHA market. Their share grew during the Crisis, fell around 2010, and has seen sustained

[4]In reality, banks and nonbanks may face a downward-sloping demand curve so that, with the additional assumption of monopolistic competition (e.g. Scharfstein and Sunderam 2016), the interest rate on nonbank-intermediated loans falls relative to bank-intermediated loans.

[5]Since all depository institutions are subject to a federal supervisor, we use the associated Home Mortgage Disclosure Act (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 (2017) 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 institution and focus on the largest lenders. Appendix Table A1 provides a list of the top 50 nonbanks in our data based on their FHA originations in 2013 and 2014.

rapid growth since then. The bottom panel shows how nonbanks historically held a smaller share of the overall mortgage market, although their share grew markedly during the boom period. Their market share has grown since the Crisis, and now they comprise over half of all for-purchase mortgage originations.

3 Identification Strategy

The framework discussed in Section 2 predicts that higher MBS prices increase the relative supply of mortgage credit by nonbank lenders. We test this hypothesis using a novel methodology that has two key features: (a) we obtain identification through the cross-sectional distribution of MBS prices; (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 GNMA MBS *relative* to either FNMA or 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, called FHA loans.[6]

Second, we address the question of reverse causality by turning to a natural experiment: the introduction of the U.S. Liquidity Coverage Ratio (LCR). Since exogenous changes in nonbanks' FHA lending standards affect the supply of collateral for GNMA MBS, it is possible that fluctuations in GNMA prices reflect shocks to the primary market − 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.

[6]As mentioned in the introduction, these borrowers must satisfy specific requirements stipulated by the Federal Housing Administration (FHA), which are meant to facilitate access to homeownership for first-time homebuyers with stable incomes. Specifically, FHA borrowers must typically have a FICO credit score above 580 and a debt-to-income ratio under 43%, although there is discretion over the debt-to-income ceiling based on "compensating factors". FHA loans feature down payments as low as 3.5%, but they require a mortgage insurance premium. Thus, FHA loans require a lower up-front payment at the cost of higher payments over the life of the loan. They are therefore appealing to first-time homebuyers with stable incomes but limited resources to finance a down payment.

3.1 A Natural Experiment: 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.[7] In particular, the rule favored GNMA MBS with a weight of 1, 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 due to government conservatorship. 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.[8]

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 make GNMA MBS attractive for non-affected institutions. Both channels imply that GNMA prices should rise − and expected returns should fall − because of an increase in demand. In Figure 3, we examine the direct effect of the LCR shock by plotting the portfolio holdings of banks affected by the LCR rule. Affected banks substantially increase the amount of GNMA MBS on their balance sheets in the year after the LCR proposal. Importantly, both banks and other financial institutions subject to the LCR must purchase GNMA MBS on the secondary market to satisfy the regulatory requirement: they cannot satsify the requirement by simply originating more FHA loans and holding them on their balance sheets.

Turning to prices, we begin in Figure 4 by plotting MBS prices from the To-Be-Announced market for GNMA and FNMA MBS.[9] The price of both GNMA and FNMA MBS increase following the LCR proposal, consistent with both classes of MBS receiving positive regulatory

[7]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 1 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.

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

[9]Following Echeverry, Stanton, and Wallace (2016), we consider MBS prices in the To-Be-Announced (TBA) market for 30-year fixed-rate mortgages. For each trading day, we take the price of the most-commonly traded bond in terms of settlement date and coupon. Our data source is FINRA's TRACE database. Because securities change from day to day, we smooth the data by taking the monthly average MBS price in the TBA market. Vickery and Wright (2013) and Gao, Schultz and Song (2017) discuss the TBA market in more detail.

weights. As expected, the price of GNMA MBS increases by more. We see a similar effect when considering FHLMC MBS in the bottom panel of Figure 4. Appendix Figure A1 documents an increase in securitization activity for FHA loans relative to non-FHA loans coinciding with the introduction of the LCR.

The previous results provide qualitative 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 A9 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".[10] 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 option-adjusted spread (OAS) as opposed to total return, which implies that the results are not driven by changes in prepayment risk. Finally, Appendix Figure A5 shows how the total return profiles of GNMA and FNMA MBS track each other closely in the months leading up to the LCR announcement, after which they diverge markedly.

4 Main Analysis

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. This increase in credit supply can occur through two channels: (a) lower denial rates, taking the number of applications as given; and (b) more favorable loan terms, which increases the number of applicants. We focus on the former channel, denial rates, for two reasons. First, we do not observe interest rates in our core data (HMDA). In Section 5, we use an auxiliary dataset to study interest rates. Second, focusing on application-level denial rates as opposed to an aggregated measure of credit supply (e.g. number of loans) allows us to use microdata, and thus we can include multiple fixed effects to absorb confounding factors.

[10]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). Based on the law of iterated expectations, the realized total return from t to $t+k$ equals the expected total return over that period, on average.

4.1 Data

The core dataset is a merge of the Home Mortgage Disclosure Act (HMDA) mortgage application registry with bank FR Y-9C Call Reports. 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). We focus on lenders which received at least 10 applications each year, and which have a record in HMDA from 2011 through 2015.[11] This gives a sample of 396 lenders over the 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.[12] The upper two panels of Table 1 summarize the resulting two datasets. For computational convenience, we perform our application-level analysis on a 25% random sample of the full data.

4.2 Baseline Specification

Our baseline analysis consists of two exercises. In our primary exercise, we estimate a difference-in-difference equation across lenders and years. The difference-in-difference analysis allows us to study the effect of the GNMA premium on the level of nonbanks' FHA lending, relative to banks' lending. In our secondary exercise, we estimate a triple difference-in-difference equation across lenders, years, and loan types (i.e. FHA versus non-FHA loans). The triple difference-in-difference equation provides the most tightly-identified estimates, but its interpretation is limited because we cannot infer whether the point estimates reflect a change in the level of FHA lending, or simply a contraction of non-FHA lending.

4.2.1 Level Effect: Difference-in-Difference

We begin by estimating the following difference-in-difference equation on the subset of FHA loan applications,

$$\text{Denial}_{i,l,t} = \beta\left(\text{Nonbank}_l \times \text{GNMA-Premium}_t\right) + \gamma X_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{1}$$

[11] The latter condition gives a balanced sample around the introduction of the Liquidity Coverage Ratio.
[12] We intentionally omit the 2007-09 period because of the Great Recession.

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

Our first measure of GNMA-Premium_t is an indicator for whether Liquidity Coverage Ratio (LCR) regulations are 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 GNMA-Premium_t using the spread in the one-year-ahead total return between FNMA and GNMA MBS.[13] For 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.

The identification assumption implicit in (1) is

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

Under this assumption, the parameter β may be interpreted as the effect of the GNMA premium on nonbanks' denial rate relative to banks. Note that this effect is conditional on an MSA-year fixed effect $\alpha_{m(i),t}$, which subsumes the direct effect of GNMA-Premium_t and 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.

We devote Section 5 to investigating the validity of (1), but, as a first pass, Figure 5 plots FHA denial rates for banks and nonbanks over time. Denial rates for the two groups of lenders follow parallel trends leading up the introduction of the LCR, after which nonbank denial rates fall disproportionately. This observation suggests that (1) is not invalid because of a pre-trend.

The first three columns of Table 2 contain results from estimating (1) over the 2010-15 period.[14] In the first column, we find that nonbanks are 2.0 pps less likely to deny an FHA loan in the post-LCR period, relative to banks. To make the channel more precise, the second column

[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. As mentioned in Section 3.1, the one-year-ahead return is equal to the expected return on average, based on the law of iterated expectations.

[14] We cluster standard errors by lender-year bins, the level at which the "treatment" is administered.

suggests that the increase in the FNMA-GNMA spread due to the introduction of the LCR lowered nonbanks relative denial rate by 1.4 pps. We obtain a similar result when considering the FHLMC-GNMA spread in the third column. In Appendix Table A2, we instrument for the FNMA and FHLMC spreads using the post-LCR indicator, and we obtain a significant result of almost the same magnitude. This similarity implies that the results in columns 2-3 are not due to reverse causality, and it is consistent with LCR regulation as the dominant driver of the cross-section of MBS prices over our period of analysis. Lastly, Appendix Table A3 verifies that the results are robust to using the option-adjusted spread to measure GNMA-Premium$_t$, which 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. Collectively, these results imply that higher GNMA prices due to the introduction of the LCR lowered nonbanks' FHA denial rates by 1-2 pps, or roughly 15% of the unconditional denial rate of 11.2%.

Higher MBS prices should, in principle, affect the relative supply of credit by nonbanks in other periods as well. To test this hypothesis, we reestimate (1) over the 2000-06 period and present the results in the rightmost two columns of Table 2. For the sake of a consistent interpretation, we continue to normalize MBS spreads by 55 basis points. 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, the results are both qualitatively and quantitatively consistent with those obtained in the context of the LCR natural experiment. This similarity suggests that our baseline result is not biased because of spurious correlation between the introduction of the LCR and unobserved time-series dynamics.

Theoretically, the channel through which MBS prices increase nonbank lending is funding liquidity: nonbanks do not have access to stable deposit funding, and so their lending capacity is more dependent on demand from MBS investors, leading to a relatively-elastic supply of MBS as illustrated in Figure 1. This conjecture motivates us to estimate a more general variant of equation (1),

$$\text{Denial}_{i,l,t} = \beta \left(F_l \times \text{GNMA-Premium}_t\right) + \gamma X_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{3}$$

where F_l is a measure of lender l's funding illiquidity. 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 funding liquidity.[15] Our second measure, called "noncore funding", is 1 minus the ratio of core deposits total assets in 2010. By definition, nonbanks

[15] While there is little variation in nonbank securitization rates, bank securitization rates vary substantially, with a mean of 0.40 and standard deviation of 0.37.

have non-core funding equal to 1. We normalize a lender's securitization and non-core funding rates to have a mean of 0 and variance of 1.

Table 3 contains the results of the more general equation in (3). The estimates in the first column suggest that lenders with a 1 standard deviation higher securitization rate respond to the LCR-induced GNMA premium by denying 1.5 pps fewer loan applicants. We obtain a similar result in terms of non-core funding in the rightmost two columns. Together, the results from Table 3 support a theory where higher secondary market prices increase the relative supply of primary market credit by funding-illiquid lenders, of which nonbanks are a prime example.

The effect of an increase in the GNMA premium on the supply of nonbank credit for conventional loans is theoretically unclear. If nonbanks face funding constraints, then one would predict an increase in conventional denial rates as nonbanks transfer loanable funds to the FHA market. By contrast, if nonbanks are unconstrained, then the effect should depend on the change in non-GNMA prices. If non-GNMA prices fall, then one would again predict an increase in the denial rate among conventional loans, since their value as a securitized product is lower. Otherwise, one would predict either no effect or, in the case where non-GNMA prices actually increase, a decrease in conventional denial rates. We investigate these questions by reestimating (1) on the subsample of conventional loans. Consistent with the theoretical ambiguity, there is variation in the sign and significance of the resulting point estimates, shown in Appendix Table A4. In general, however, the results suggest a weakly positive effect on conventional denial rates, which may reflect a role for funding constraints.[16]

4.2.2 Reallocation Effect: Triple Difference-in-Difference

Complementing our primary difference-in-difference equation, we now estimate the following triple difference-in-difference equation,

$$\begin{aligned}\text{Denial}_{i,l,s,t} = \beta\,(\text{Nonbank}_l \times \text{GNMA-Premium}_t \times \text{FHA}_s) + \gamma X_{i,t} + \alpha_{l,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + ...\\ ... + \alpha_{s,t} + \alpha_{s,l} + u_{i,l,t}, \qquad (4)\end{aligned}$$

where s indexes loan type, which now can be either FHA or conventional. Thus, while our difference-in-difference equation (1) obtained identification from the double product of "treated lenders" (Nonbank_l) in "treated years" (GNMA-Premium_t), equation (4) obtains identification from the additional product with "treated loan types" (FHA_s).

[16]The null result when using the FNMA and FHLMC spreads over 2010-15 likely reflects an LCR-induced increase in the value of FNMA and FHLMC MBS, as suggested by Figure 4, albeit a smaller increase than that associated with GNMA MBS.

The advantage to estimating a triple difference-in-difference equation is that it allows us to include lender-year fixed effects, $\alpha_{l,t}$. Thus, any confounding shock coinciding with GNMA-Premium$_t$ would not only need to disproportionately affect nonbanks, but it would also have 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 loans. As in (1), we continue to limit variation to borrowers within the same MSA-year bin ($\alpha_{m(i),t}$), geographic lending relationship ($\alpha_{m(i),l}$), and with similar observable profiles ($X_{i,t}$).

The interpretation of β in (4) is the effect of the GNMA premium on nonbanks' allocation between FHA and conventional loans, relative to banks' allocation. To be clear, (4) does not allow us to infer whether nonbanks actually increase their supply of credit for FHA loans: this effect is subsumed by the lender-year fixed effect, $\alpha_{l,t}$. That said, equation (4) provides a useful complement to the difference-in-difference equation (1) because it involves a weaker identification assumption.

The results in Table 4 suggest that nonbanks respond to an increase in the GNMA premium by denying fewer FHA loans than conventional loans. Specifically, their relative denial rate on FHA loans falls by 0.7-2.1 pps. We obtain a similar result in Appendix Table A5 when replacing Nonbank$_l$ with the lender's securitization rate. As discussed above, a lender's securitization rate captures its funding illiquidity, and so Appendix Table A5 provides additional support for the more general mechanism through which MBS prices disproportionately affect nonbanks.

4.3 Heterogeneous Effects: Risky Borrowers

There are two reasons to suspect that the effect of the GNMA premium on nonbank denial rates might be greater for borrowers in riskier markets. First, viewed through the lens of a credit rationing model, these markets have a greater mass of borrowers on the extensive margin of credit. Second, while FHA borrowers are subject to debt-to-income ceilings, lenders can increase this ceiling by invoking "compensating factors".[17] Thus, lenders have more discretion over denial rates for risky borrowers with a high debt-to-income ratio.

We test this hypothesis by reestimating equation (1) and interacting the treatment effect, Nonbank$_l$ $\times$ GNMA-Premium$_t$, with the average requested loan-to-income ratio (LTI) in the applicant's MSA of residence.[18] The results in Table 5 indicate that nonbanks lower their denial

[17]Examples of compensating factors include cash reserves or residual income.

[18]The results are the same when including the interaction with the borrower's requested LTI. Taking the

rates by an additional 0.3 pps (25%) in MSAs with a 1 standard deviation higher LTI. This finding suggests that nonbanks respond to higher MBS prices by disproportionately lowering their standards for higher-risk borrowers.

4.4 Aggregate Effects

While attractive for the purposes of identification, an application-level analysis is unsuitable for making inferences about the aggregate effects of an increase in MBS prices. This limitation reflects how such an analysis takes the number of bank versus nonbank applications as given. In reality, nonbanks may attract a larger applicant pool by offering more favorable loan terms, or possibly through an increase in advertising. To capture this additional effect, we aggregate our microdata to the census tract level and reproduce the baseline analysis. One should think of each census tract as a representative household which has relationships with multiple lenders. Carrying the baseline intuition into this setting, our research hypothesis is that lending relationships involving a nonbank should see growth in FHA originations following an increase in the GNMA premium.

We estimate the following difference-in-difference equation across census tracts,

$$\log\left(\text{Loans Originated}_{c,l,t}\right) = \beta\left(\text{Nonbank}_l \times \text{GNMA-Premium}_t\right) + \alpha_{c,t} + \alpha_{c,l} + u_{c,l,t}, \quad (5)$$

where: c, l, and t index census tract, lender, and year; Loans Originated$_{c,l,t}$ is the number of FHA loans originated within each tract-lender-year triplet; and $\alpha_{c,l}$ is a tract-lender fixed effect, which has the interpretation of a lender's steady-state market share in tract c. We include a tract-year fixed effect $\alpha_{c,t}$ to absorb time-varying credit demand shocks, and this technique is conceptually similar to that used in the literature studying bank-firm lending relationships (e.g. Amiti and Weinstein 2018; Greenstone, Mas, and Nguyen 2017; Khwaja and Mian 2008).

The identification assumption implicit in equation (5) is that fluctuations in the GNMA premium do not coincide with shocks affecting the *distribution* of credit between banks and nonbanks in a given tract-year bin. We do not need to assume that these fluctuations are orthogonal to shocks to the *level* of credit demand: these shocks would be subsumed by $\alpha_{c,t}$. Put differently, we assume that FHA borrowers within a given census tract do not switch from applying to banks to applying to nonbanks when the GNMA premium is higher. This assumption is similar to that associated with equation (2), and it is plausible because census

MSA average reduces the effect of measurement error from potential misreporting (e.g. Mian and Sufi 2009). Note that the direct effect of an MSA's average LTI is subsumed by $\alpha_{m(i),t}$.

tracts are relatively granular geographic units comprising around 4,000 people.[19] Thus, there is limited scope for demographic variation within a census tract, which might bias the results if nonbanks cater to a certain demographic subpopulation and this subpopulation experiences a credit demand shock.

Table 6 contains the results of (5). Consistent with the application-level results, a higher GNMA premium due to the introduction of the LCR leads to a relative increase in nonbank loan originations, as reflected by the positive and significant point estimates. We next ask how much smaller nonbanks' FHA market share would have been in 2015 absent the LCR-induced increase in the GNMA premium. Explicitly, let η_{15} denote nonbanks' FHA market share in 2015, where

$$\eta_{15} = \frac{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \text{Nonbank}_l}{\sum_c \sum_l \text{Loans Originated}_{c,l,15}} \tag{6}$$

Empirically, $\eta_{15} = 0.80$. We are interested in computing the market share $\hat{\eta}_{15}$ that would have arisen had the GNMA premium not increased due to the introduction of the LCR. Using (5), this counterfactual share can be written

$$\hat{\eta}_{15} = \frac{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \text{Nonbank}_l \times e^{-\beta^{LCR}}}{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \left[(1 - \text{Nonbank}_l) + \text{Nonbank}_l \times e^{-\beta^{LCR}}\right]}, \tag{7}$$

where $\beta^{LCR} = 0.13$ is the average point estimate across columns in Table 5. The resulting counterfactual market share is $\hat{\eta}_{15} = 0.77$, which is 2.2 pps lower than the true market share.[20] To place these numbers in perspective, nonbanks' FHA market share grew by 9.5 pps from 2013 to 2015, so that the LCR-induced increase in the GNMA premium can account for around 23% of nonbanks' 2013-15 growth in market share.

5 Robustness

In this section, we investigate our primary identification assumption, the exclusion restriction in equation (2). While we conduct part of our baseline analysis over 2000-06, we focus our attention on the 2010-15 period and the introduction of the LCR, we which we argue is an exogenous source of variation in MBS prices.

[19] The difference relative to equation (2) is that we must assume the treatment effect, $\text{Nonbank}_l \times \text{GNMA-Premium}_t$, is orthogonal both to shocks affecting nonbanks' FHA denial rates and to shocks affecting the number of FHA applications to nonbanks, whereas in (2) only the former assumption is necessary.

[20] Note that because (5) is specified in logs and our focus is on nonbanks' counterfactual share of originations, the unestimated effect of the GNMA premium on all lenders cancels out when taking the ratio in (7).

5.1 Litigation Risk

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 that make litigation risk 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.[21] Thus, if litigation risk is a significant source of bias, one would expect to see similar results among conventional loans. However, as discussed above, the corresponding results in Appendix Table A4 are either null or of the opposite sign.

To more directly address bias from litigation risk, we reestimate our baseline specifications in (1) and (4) on the set of lenders with less than 2% of the total mortgage market in 2010, measured by origination share. The results in Appendix Table A6 are qualitatively similar to those in Tables 2 and 4.

5.2 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 aimed to ensure that banks "maintain sufficient levels of stable funding, thereby reducing liquidity risk in the banking system", per the Federal Reserve's press release on May 3, 2016. However, the NFSR was not proposed in the U.S. until May 2016, more than two years after the LCR proposal. It is thus unlikely that the NSFR is affecting the results. Nonetheless, it is possible that lenders updated their expectations about the NSFR following the LCR announcement, and that banks with less funding liquidity subsequently aimed to shrink their balance sheets.

The previous logic contradicts Appendix Table A7, where we reestimate (3) and (4) after excluding nonbanks from the sample. The results suggest that banks with greater historical reliance on securitization denied fewer FHA applicants after the increase in GNMA liquidity. While the standard errors increase due to the reduced sample size, the point estimates are quite

[21]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.

similar to their counterparts from Tables 3 and 4 and are all statistically significant at the 10% threshold.

5.3 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 regulation across lenders rather than a response to LCR-induced changes in MBS prices. Such bias is unlikely for three reasons. First, we obtain similar results on the subsample of banks, as just discussed in Section 5.2. Second, we obtain similar results after excluding relatively large lenders, as previously discussed in the Section 5.1. Finally, Table 2 documents a strong link between the GNMA premium and the relative supply of FHA credit by nonbanks over the 2000-06 period, before the post-Crisis regulatory overhaul.

5.4 Changing Applicant Pool

Since our core analysis is at the application level, it takes as given the distribution of borrower quality across different loan types. If FHA loan applicants are becoming less risky, this alone would not generate the results in Section 4. One would further need that lenders who are less sensitive to the GNMA premium have some cost of adjusting to the new quality of FHA borrowers. However, Appendix Figure A2 shows that the requested loan-to-income ratios (LTI) for FHA and non-FHA applicants have grown at approximately the same rate. If anything, Figure A2 suggests that FHA applicants have become slightly riskier, in terms of LTI, relative to non-FHA applicants. The dynamics shown in Figure A2 therefore make it unlikely that the results are biased due to exogenous improvements in the credit quality of FHA borrowers.

Similarly, the results may spuriously capture improvements in the credit quality of applicants to nonbanks. However, Appendix Figure A3 provides evidence to the contrary. The top panel of Appendix Figure A3 shows how the gap in the requested loan-to-income ratio of applicants to banks versus nonbanks has been remarkably stable over time.

5.5 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 towards GSE MBS per the report by the Board of Governors (2016). Appendix Figure A4 shows that the ratio of Fed's purchases was weighted against GNMA MBS, and so these purchases are unlikely to account for the increase in GNMA MBS prices relative to GSE MBS.

5.6 Monthly Frequency and Interest Rates

One drawback to the baseline analysis is that HMDA data are only available at the yearly frequency, which increases the possibility of spurious time-series correlation. We address this issue by using data from the HUD FHA Single Family Portfolio Snap Shot to perform a similar analysis at the monthly frequency. Relative to our core HMDA dataset, we only observe originated FHA loans in the HUD data, as opposed to applications. Thus, we turn our attention away from denial rates ("quantity of credit") to the interest rates charged by nonbanks ("price of credit").

We estimate a similar equation as (1) over the 2012-15 period,

$$\text{Rate}_{i,l,t} = \beta \left(\text{Nonbank}_l \times \text{GNMA-Premium}_t \right) + \gamma Z_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{8}$$

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 GNMA-Premium_t by the implied effect of LCR, 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.[22]

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 MBS prices to lower mortgage rates, relative to banks. The first two columns of Appendix Table A8 show that nonbanks' rate of pass-through is 5 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 GNMA-Premium_t.

Collectively, these results suggest that our baseline results are not biased because of a yearly frequency. The results also suggest that nonbanks disproportionately lower the price of credit,

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

in addition to approving more loans, following an increase in MBS prices.

6 Implications for Homeownership

To this point, we have focused on how higher MBS prices affect the distribution of market share across lenders in the primary mortgage market. However, securitization may also enable borrowers constrained by credit frictions to obtain a mortgage. Most of our analysis occurs in the context of the FHA market, which caters to households on the margin of homeownership. Thus, a natural question is whether the increase in nonbank-intermediated credit influences homeownership rates.

We study how nonbanks' expansion has affected homeownership using zip code level data from the American Housing Survey's 5-year estimates, in which we observe a zip code's homeownership rate in 2011 and 2015.[23] Because the 5-year estimates are designed to study medium-to-long run changes in homeownership, we depart from a panel approach and run a cross-sectional regression. We estimate the following equation,

$$\begin{aligned}\Delta\ \text{Homeownership}_{z,\text{11-15}} = {} & \beta\,(\text{Nonbank-Share}_{z,11} \times \text{FHA-Share}_{z,11}) + \ldots \\ & \ldots + \gamma_0 \text{Nonbank-Share}_{z,11} + \gamma_1 \text{FHA-Share}_{z,11} + \ldots \\ & \ldots + \gamma_2 X_z + \alpha_{c(z)} + u_z, \end{aligned} \tag{9}$$

where: z indexes zip code; $\Delta\text{Homeownership}_{z,\text{11-15}}$ denotes the change in the homeownership rate between 2011 and 2015; $\text{Nonbank-Share}_{z,11}$ and $\text{FHA-Share}_{z,11}$ are the 2011 share of mortgage applications which are to nonbanks and which are for FHA loans, respectively; and $\alpha_{c(z)}$ is a county fixed effect. The controls in X_z are the 2011 homeownership rate and the 2011-15 changes in: the average requested loan-to-income ratio; share of applications from black or Hispanic borrowers; and the average applicant's log income.[24]

The treatment group in (9) consists of zip codes with (a) a high initial nonbank share and (b) a high share of FHA applicants. Building on the core analysis in Section 4, these are the groups most likely to experience a loosening of standards due to the effect of a higher GNMA premium on nonbank lending. As standard, we control for both the initial nonbank share ($\text{Nonbank-Share}_{z,11}$) and FHA application share ($\text{FHA-Share}_{z,11}$), which account for features of

[23] Zip codes are typically larger than census tracts. We merge each zip code to a census tract in our core HMDA data using the HUD-produced crosswalk file, and then we aggregate to the zip code level.

[24] We weight zip codes by 2011 renter population so that the results are not driven by sparsely-populated areas.

nonbank-prevalent or FHA-prevalent markets that correlate with changes in homeownership. Moreover, the county fixed effect $\alpha_{c(z)}$ limits variation to within the same county, which accounts for changes in homeownership due to county-level unobservables, such as ease of construction (e.g. Saiz 2010). We identify the effect of MBS prices, β, using the previously-documented fact that nonbanks loosened standards specifically among FHA loans.

The result in Table 7 shows how zip codes more exposed to nonbanks' expansion in the FHA market see a less-severe decline in homeownership. Taking the average zip code's FHA share of 0.43, the point estimate in column 2 implies that homeownership rates fall 1.2 pps less (i.e. 0.03×0.43) in zip codes with full exposure to nonbanks in 2011 relative to zip codes with no nonbank exposure. Given that the average zip code saw a 2.8 pp decline in homeownership over 2011-15, the effect is quantitatively significant. The point estimate is similar after including additional controls in column 2, suggesting relatively-little scope for bias based on unobservables, and we obtain a quantitatively similar result after applying an Oster (2017) correction.[25]

In the third column, we use the treatment variable, Nonbank-Share$_{z,11}$ $\times$ FHA-Share$_{z,11}$, as an instrument for the change in the FHA loan application denial rate from 2011 to 2015. The result implies that a 1 pp reduction in denial rates leads to a 0.2 pp higher homeownership rate, which is within a range of the estimates found in the literature (e.g. Gete and Reher 2018). Collectively, the results from this section suggest that the increase in the relative supply of nonbank credit has facilitated access to homeownership during a period when the U.S. homeownership rate was collapsing toward a historic low.

7 Conclusion

In this paper we found that changes in MBS prices can significantly affect the size of the shadow banking sector and the amount of credit risk in the primary mortgage market. Specifically, we used 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 show that LCR regulation, designed to prevent runs in secondary mortgage markets, have attracted nonbanks to the FHA market and lowered their lending standards. Thus, as an unintended consequence, LCR regulation may have increased the credit risk borne by U.S. taxpayers by making the FHA more exposed to nonbanks.

[25]The Oster (2017) correction yields a point estimate of 0.023, based on a default selection parameter of $\delta = 0.30$.

It is unclear how the LCR-induced increase in nonbanks' market share affects welfare. On one hand, the financial system may have become more fragile. On the other hand, the expansion in nonbank credit appears to have bolstered homeownership during a period when the U.S. homeownership rate approached a historic low. Moreover, while the LCR shock is a focal point of our paper, we also find that MBS prices affect nonbanks' market share in periods without major a regulatory overhaul. This last finding shows how fluctuations in the size of the shadow banking sector are not necessarily inefficient, and they can also be a natural and routine byproduct of fluctuations in secondary markets.

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Figures and Tables

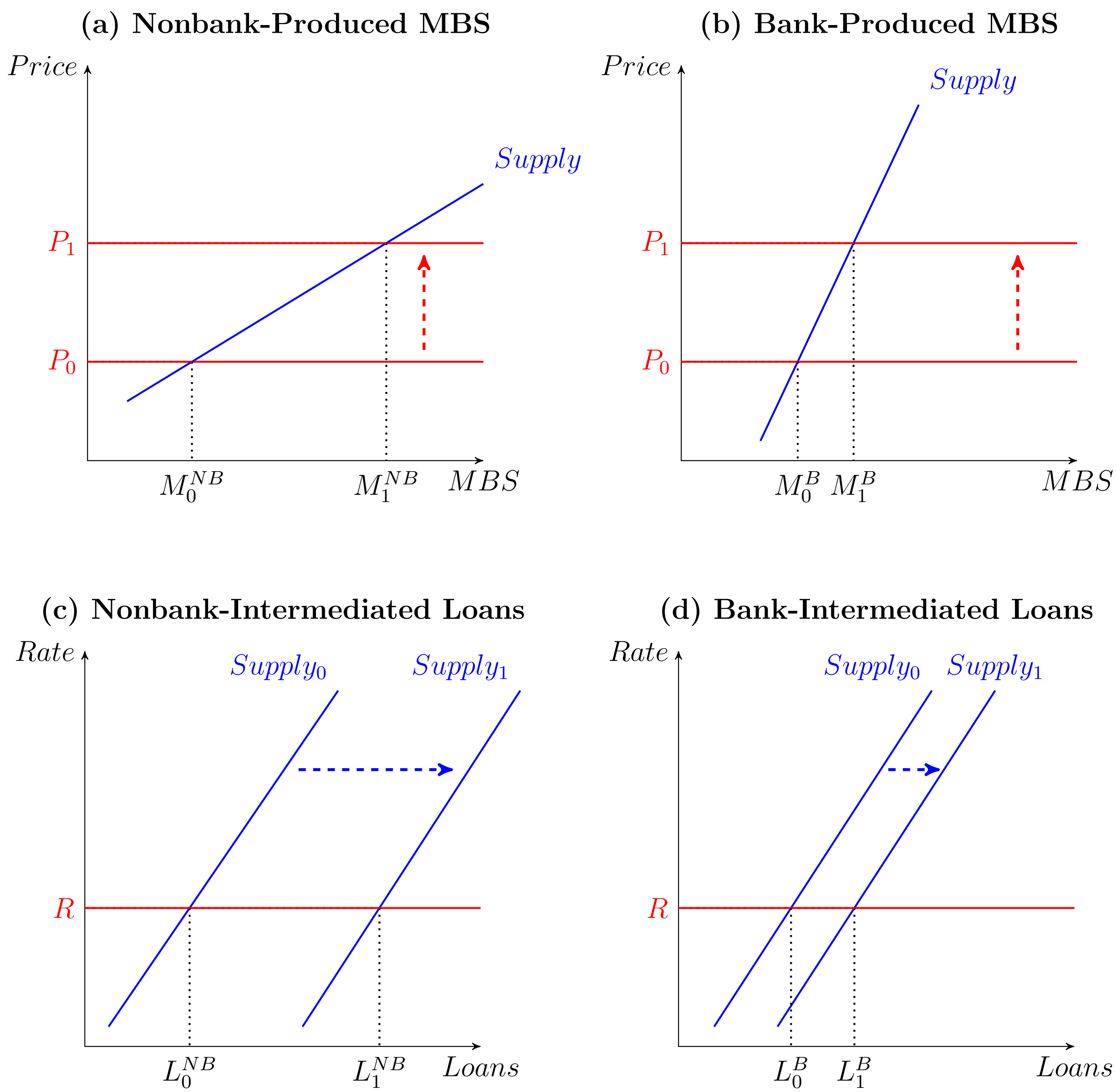


Figure 1. Theoretical Effect of Higher MBS Prices on Credit Supply. This figure plots the theoretical effect of an increase in MBS prices on the supply of mortgage credit in the primary market. The upper panel plots the supply of nonbank and bank-produced MBS, and the lower panel plots the supply of nonbank and bank-intermediated loans in the primary market. When MBS prices increase from P_0 to P_1, the supply of nonbank-produced MBS rises from M_0^{NB} to M_1^{NB}, and the supply of bank-produced MBS rises from M_0^B to M_1^B. Correspondingly, the supply of nonbank-intermediated loans rises from L_0^{NB} to L_1^{NB}, and the supply of bank-intermediated loans rises from L_0^B to L_1^B.

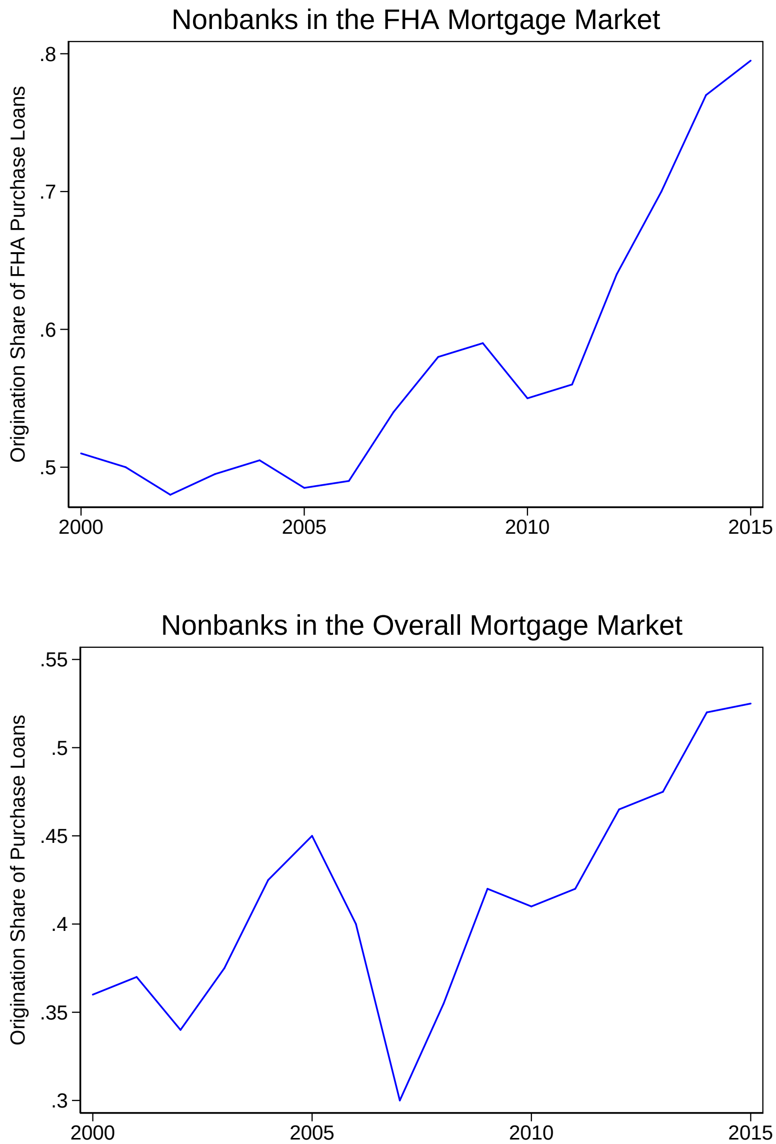


Figure 2. Market Share of Non-depositary Institutions Among FHA and All Loans for Home Purchases. This figure shows the share of FHA mortgage dollar volume (top) and of total mortgage dollar volume (bottom) originated by nonbanks for home purchases. Source: HMDA.

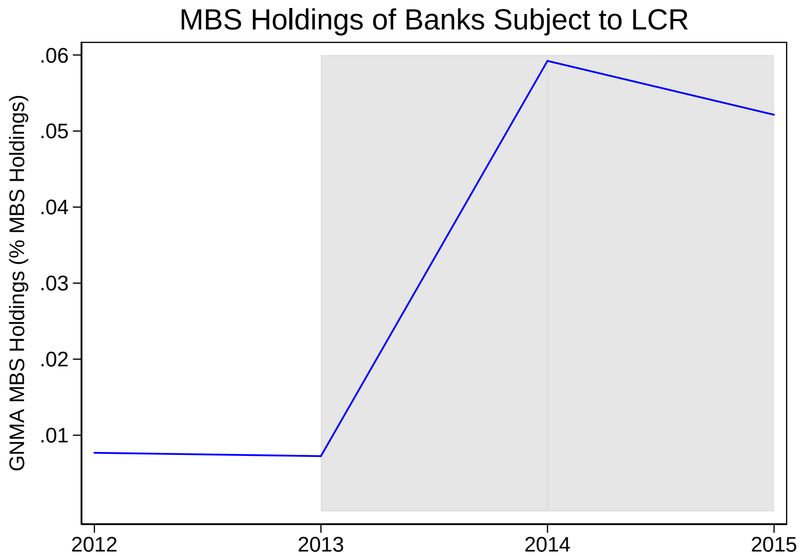


Figure 3. MBS Holdings of Institutions Affected by Liquidity Regulation. This figure plots the holdings of GNMA-backed MBS as a percent of all securities held by banks subject to the LCR policy. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Source: Call Reports (FRY-9C)

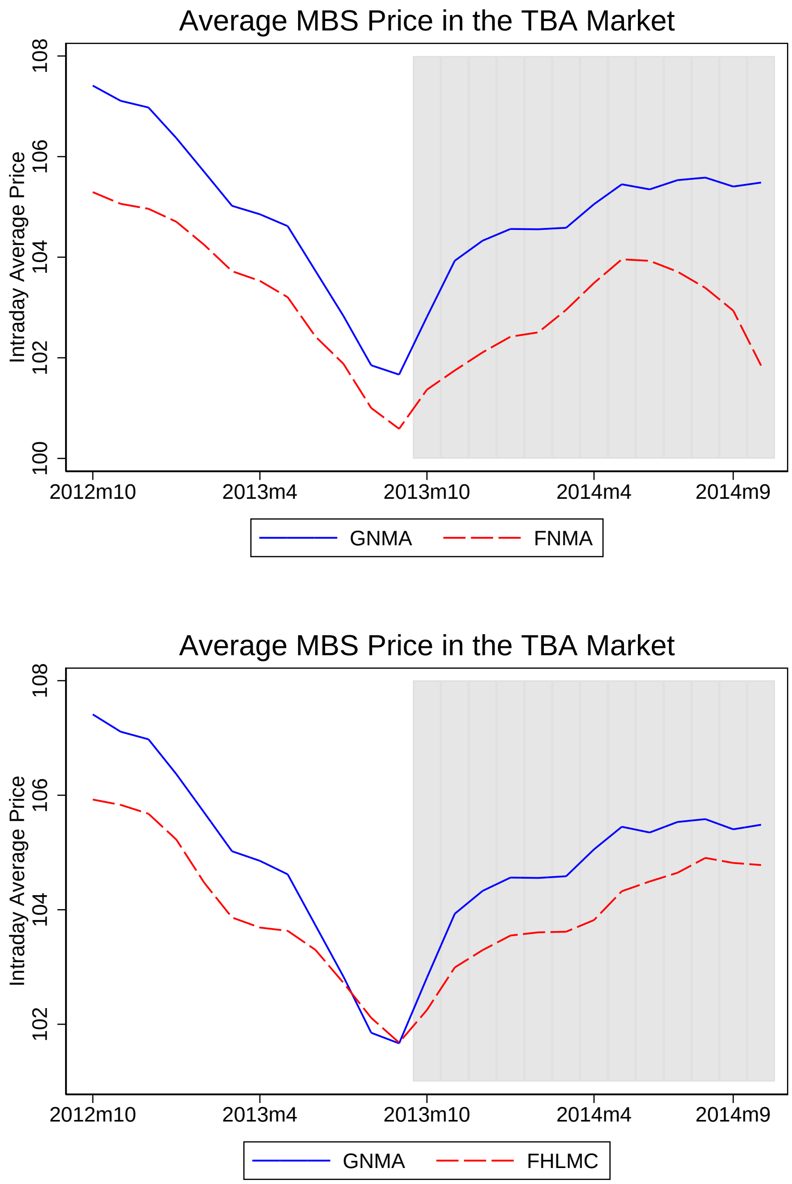


Figure 4. GNMA, FNMA and FHLMC MBS Prices in the TBA Market. The price corresponds to the monthly average of the most-commonly traded bond on a given day. We smooth prices using a 3-month moving average. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Source: Trade Reporting and Compliance Engine (TRACE).

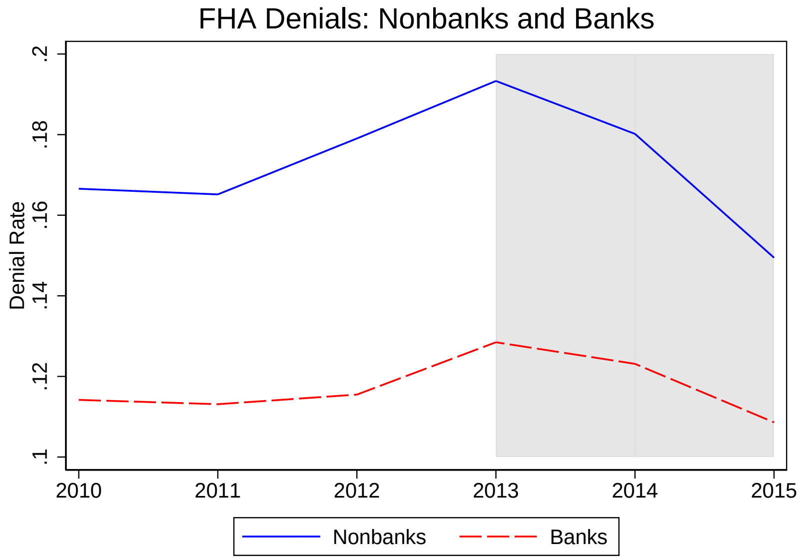


Figure 5. Denial Rate among FHA Loans. This figure plots banks' and nonbanks' denial rate among FHA loans. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

Table 1: Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation
Application-Level Variables, 2010-15:			
Denial	13,114,592	0.112	0.316
Nonbank	13,114,592	0.495	0.5
FHA	13,114,592	0.32	0.467
Securitization Rate	10,409,953	0.828	0.263
Non-Core Funding	10,646,461	0.723	0.351
Loan-to-Income	13,114,592	2.786	2.361
Application-Level Variables, 2000-06:			
Denial	53,476,760	0.157	0.364
Nonbank	53,476,760	0.419	0.493
FHA	53,476,760	0.091	0.288
Zip Code-Level Variables:			
ΔHomeownership	3,521	-0.028	0.034
Homeownership	3,521	0.616	0.171
Nonbank Share	3,521	0.457	0.173
FHA Share	3,521	0.432	0.222
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 Application-Level panels, each observation is a loan application for the purchase of an owner-occupied single-family dwelling over the indicated time period, 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 loans to total originations in 2010; Non-Core Funding is 1 minus the ratio of core deposits total assets in 2010, which equals 1 for nonbanks by definition; Loan-to-Income is the ratio of the applicant's requested loan to her reported annual income. In the Zip Code-Level panel, each observation is a zip code weighted by 2011 renter population, and the variables are defined as follows: ΔHomeownership is the change in homeownership rate between 2011 and 2015; Homeownership is the 2011 homeownership rate; Nonbank Share and FHA Share are the 2011 share of mortgage applications which are to nonbanks and which were for FHA loans, respectively. 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 among months in a given year, where total returns are measured using the Bloomberg Barclays MBS Total Return indices; FNMA Spread is the difference between FNMA Total Return and GNMA Total Return; and FHLMC Spread is analogously defined in terms of FHLMC Total Return. The time-series variables have units of percentage points (pps).

Table 2: GNMA Premium and Nonbank Lending in the FHA Market

Outcome:	Denial$_{i,l,t}$ Period: 2010-15			Denial$_{i,l,t}$ Period: 2000-06	
Nonbank$_l$ × GNMA-Premium$_t$	-0.020	-0.014	-0.012	-0.017	-0.011
	(0.051)	(0.000)	(0.000)	(0.029)	(0.036)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.117	0.117	0.117	0.132	0.132
Number of Observations	1,040,927	1,040,927	1,040,927	1,056,661	1,056,661

Note: P-values are in parentheses. This table estimates equation (1). Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. Denial indicates whether the application was denied. Nonbank indicates whether the lender is a nonbank. Each column interacts Nonbank with a different measure of the GNMA premium: Post-LCR indicates whether $t \geq 2014$, the first full year after LCR regulation was announced; FNMA Spread is the spread in expected total return between FNMA and GNMA MBS; and FHLMC Spread is the analogous spread between FHLMC and GNMA MBS. Expected total return is measured using 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. We normalize the FNMA and FHLMC spreads by 55 basis points, which is the estimated effect of LCR regulation as discussed in Section 3.1. Borrower controls are requested loan-to-income ratio, log income, and an indicator of whether the borrower is black or Hispanic. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling. The sample period is 2010-15 in columns 1-3 and 2000-06 in columns 4-5. Standard errors are clustered by lender-year bins.

Table 3: GNMA Premium and FHA Lending by Lender Funding Liquidity

Outcome:	Denial$_{i,l,t}$			
Securitization Rate$_l$ × GNMA-Premium$_t$	-0.015	-0.014		
	(0.008)	(0.005)		
Non-Core Funding$_l$ × GNMA-Premium$_t$			-0.020	-0.018
			(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
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.117	0.117	0.118	0.118
Number of Observations	841,475	841,475	919,025	919,025

Note: P-values are in parentheses. This table estimates equation (3). Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. Securitization Rate is the lender's ratio of securitized loans to total originations in 2010. Non-Core Funding is 1 minus the ratio of core deposits total assets in 2010, which equals 1 for nonbanks by definition. The remaining notation is the same as in Table 2. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table 4: GNMA Premium and Nonbank Portfolio Reallocation

Outcome:	Denial$_{i,l,s,t}$		
Nonbank$_l$ $\times$ GNMA-Premium$_t$ $\times$ FHA$_s$	-0.021	-0.008	-0.007
	(0.000)	(0.000)	(0.000)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Loan Type-Lender FE	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes
Lender-MSA FE	Yes	Yes	Yes
MSA-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 (4). Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Each observation is a loan application. FHA 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. The remaining notation is the same as in Table 2. The sample consists of FHA and conventional loan applications for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table 5: GNMA Premium and Nonbank Loan-to-Income Standards in the FHA Market

Outcome:		$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	-0.020	-0.014	-0.012
	(0.046)	(0.000)	(0.000)
$\text{Nonbank}_l \times \text{GNMA-Premium}_t \times \text{LTI}_{m(i),t}$	-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 (1). Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. LTI denotes the average loan-to-income ratio among borrowers in the applicant's MSA of residence, $m(i)$; it is normalized to have a variance of 1 and a mean of 0. The remaining notation is the same as in Table 2. The sample consists of applications for FHA 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 6: GNMA Premium and Nonbank Lending at the Census Tract Level

Outcome:	$\log\left(\text{Loans Originated}_{c,l,t}\right)$		
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	0.244	0.081	0.070
	(0.000)	(0.000)	(0.000)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Lender-Tract FE	Yes	Yes	Yes
Tract-Year FE	Yes	Yes	Yes
R-squared	0.625	0.623	0.623
Number of Observations	1,377,027	1,377,027	1,377,027

Note: P-values are in parentheses. This table estimates equation (5). Subscripts c, l, and t index census tract, lender, and year, respectively. Each observation is a tract-lender-year triplet. Loans Originated is the number FHA loans originated within each triplet. The remaining notation is the same as in Table 2. The sample consists of all triplets that featured at least 1 FHA loan application for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table 7: Nonbanks and Homeownership at the Zip Code Level

	ΔHomeownership$_{z,11\text{-}15}$		
Nonbank-Share$_{z,11}$ $\times$ FHA-Share$_{z,11}$	0.028	0.030	
	(0.022)	(0.017)	
ΔDenial Rate$_{z,11\text{-}15}$			-0.154
			(0.036)
Estimator	OLS	OLS	IV
County FE	Yes	Yes	Yes
2011 Nonbank-Share	Yes	Yes	Yes
2011 FHA-Share	Yes	Yes	Yes
Zip code controls	No	Yes	Yes
R-squared	0.217	0.237	
F-Statistic			9.661
Number of Observations	3,384	3,045	1,902

Note: P-values are in parentheses. This table estimates equation (9). Subscript z indexes zip code. ΔHomeownership$_{z,11\text{-}15}$ denotes the change of homeownership rate between 2011 and 2015 in zip code z. Nonbank-Share$_{z,11}$ and FHA-Share$_{z,11}$ are the 2011 share of mortgage applications which are to nonbanks and which were for FHA loans, respectively. ΔDenial Rate$_{z,11\text{-}15}$ is the change in the FHA loan application denial rate from 2011 to 2015. The estimator in columns 1-2 is OLS. The estimator in column 3 is 2SLS, and the instrument for ΔDenial Rate$_{z,11\text{-}15}$ is Nonbank-Share$_{z,11}$ $\times$ FHA-Share$_{z,11}$. All specifications control for Nonbank-Share$_{z,11}$ and FHA-Share$_{z,11}$. Additional zip code controls are the 2011 homeownership rate and the 2011-15 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 2011 renter population.

Online Appendix

Estimating the LCR Premium

In this appendix, we estimate the effect of Liquidity Coverage Ratio (LCR) regulations on the expected return of GNMA MBS, which we call the "LCR premium". 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 $s \in \{\text{GNMA}, \text{FNMA}\}$. We suppose the total return between periods t and $t{+}1$ depends on a vector of factors, $f_{t\to t+1}$, which captures credit, prepayment, and other risk factors in period t. In addition, we suppose each type of MBS delivers a convenience yield, $\bar{R}_t^s$, which captures regulatory incentives for holding MBS of type s or the overall ease of trading them, which we call "liquidity". Thus, the expected total return to MBS s from t to $t{+}1$ can be written

$$\mathbb{E}_t\left[R^s_{t\to t+1}\right] = \bar{R}^s_t + \phi^s \bar{f}_t, \tag{A1}$$

where $\bar{f}_t \equiv \mathbb{E}_t\left[f_{t\to t+1}\right]$ denotes the marketwide 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 (A1) between GNMA and FNMA MBS yields

$$\mathbb{E}_t\left[R^{FNMA}_{t\to t+1} - R^{GNMA}_{t\to t+1}\right] = \bar{R}^{FNMA}_t - \bar{R}^{GNMA}_t + \left(\phi^{FNMA} - \phi^{GNMA}\right)\bar{f}_t. \tag{A2}$$

We model the announcement of LCR regulation as disproportionately increasing the convenience yield for holding GNMA MBS, $\bar{R}^{GNMA}_t$, 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 LCR may have also raised the convenience yield for FNMA MBS, thus lowering $\bar{R}^{FNMA}_t$, the more favorable regulatory weights granted to GNMA MBS should theoretically lower $\bar{R}^{GNMA}_t$ by more. In particular, we suppose the difference $\bar{R}^{FNMA}_t - \bar{R}^{GNMA}_t$

increases by some amount $\bar{R}^{LCR}$ because of the regulation.

Moving to a regression equation, (A2) becomes

$$R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12} = \beta_0 + \beta_1 \text{Post-LCR}_t + u_t, \tag{A3}$$

where t indexes months. Under the assumption that the introduction of LCR regulation does not coincide with exogenous changes in the credit, prepayment, or other risk of GNMA relative to FNMA MBS (i.e. $\phi^{FNMA} - \phi^{GNMA}$), then β_1 recovers the LCR premium, $\bar{R}^{LCR}$. This assumption seems plausible, since GSE conservatorship implies approximately equal levels of credit risk over our sample period. Moreover, because we obtain identification from the cross-section of MBS returns, any baseline difference in FNMA versus GNMA prepayment risk is differenced out in (A3). Thus, any confounding shock related to the relative quantity of prepayment risk would need to coincide exactly with the introduction of LCR regulation. To further rule out this possibility, we obtain similar results using Bloomberg's Option-Adjusted Spread (OAS), which, in principle, strips out the effect of embedded options and thus the quantity of prepayment risk.

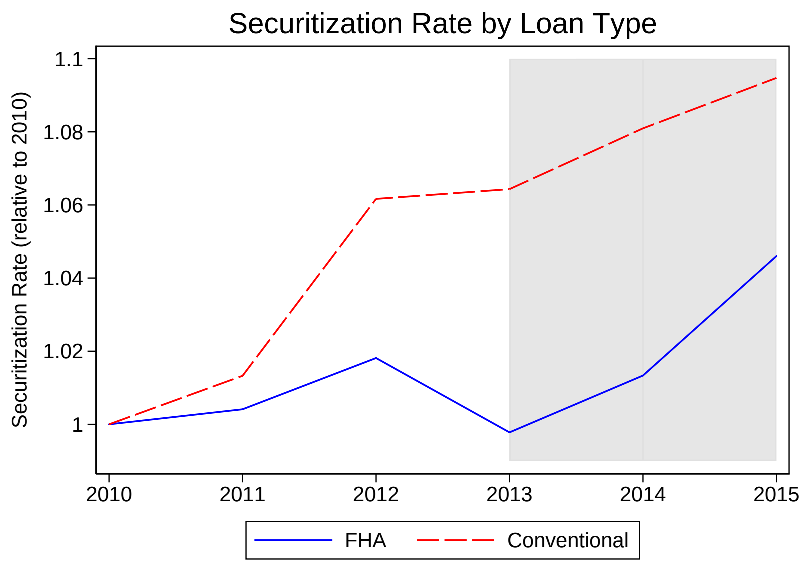
The results of (A3) are in Table A9. We measure GNMA and FNMA returns using the Bloomberg Barclays GNMA and FNMA Total Return indices, respectively. The baseline point estimate in column 1 suggests that LCR increases the expected return to FNMA MBS by 42 bps relative to GNMA MBS. This effect is equal 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 the Post-LCR$_t$ indicator captures spurious time 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 Bloomberg's Option-Adjusted Spread (OAS) which, as mentioned above, is model-dependent and aims to strip out prepayment risk.[26] We find that the FNMA-GNMA OAS was 13 bps higher in the post-LCR period, equal to 0.8 standard deviations. This effect is equal to 29% of the average GNMA OAS over the period.

Figure A5 visualizes the results in Table A9. We plot the 12-month-ahead cumulative total return for GNMA and FNMA MBS, where cumulative total return is measured using the Bloomberg-Barclays Total Return Index. Up to a normalization, this variable is the one-year holding period return as of the indicated month. Notice that investors who purchase FNMA MBS on or after the announcement of LCR regulation would need to be compensated with

[26] Boyarchenko, Fuster, and Lucca (2015), Gabaix, Krishnamurthy and Vigneron (2007) and Diep, Eisfeldt and Richardson (2017) show that the risk of homeowner prepayment is priced in the MBS market.

a positive premium relative to GNMA MBS. By contrast, this differential was absent in the pre-announcement period.

Additional Figures and Tables



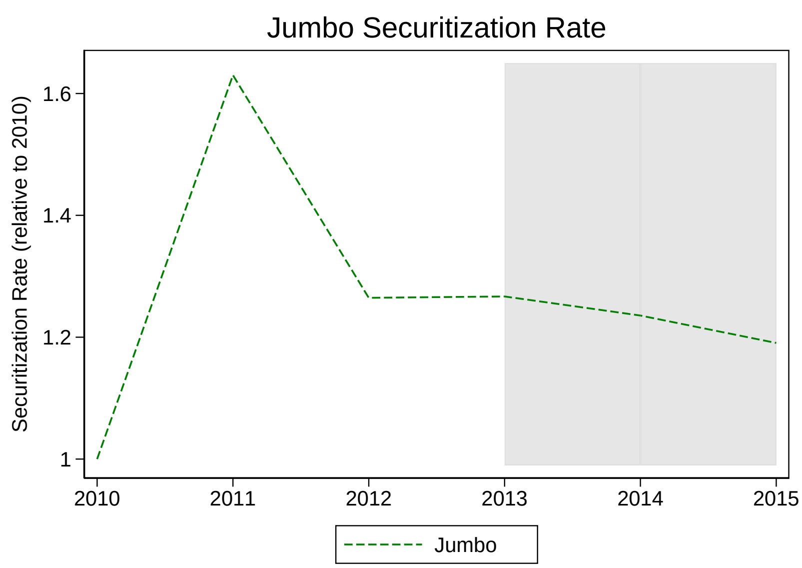


Figure A1. Securitization by Loan Type. This figure shows the fraction of FHA (top), conventional (top), and jumbo (bottom) loans that are securitized, normalized by the 2010 value. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Source: HMDA.

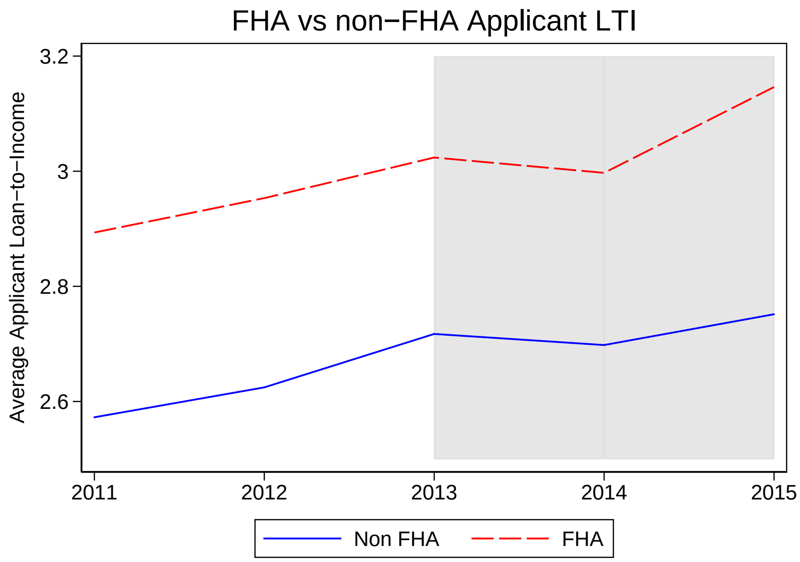


Figure A2. Credit Quality of FHA Applicants. This figure plots the average loan-to-income ratio for FHA versus non-FHA loans over our main sample period. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

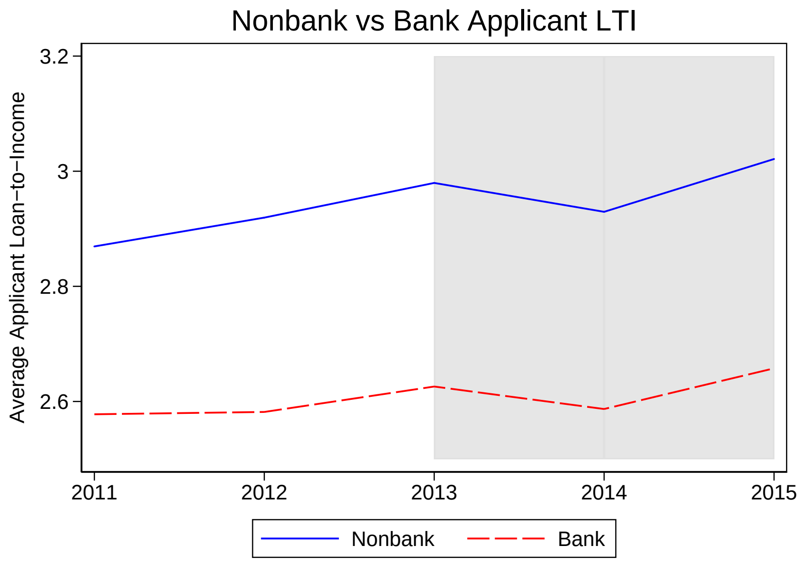


Figure A3. Credit Quality of Applicants to Banks and Nonbanks. This figure plots the average loan-to-income ratio among applicants to banks versus nonbanks over our main sample period. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

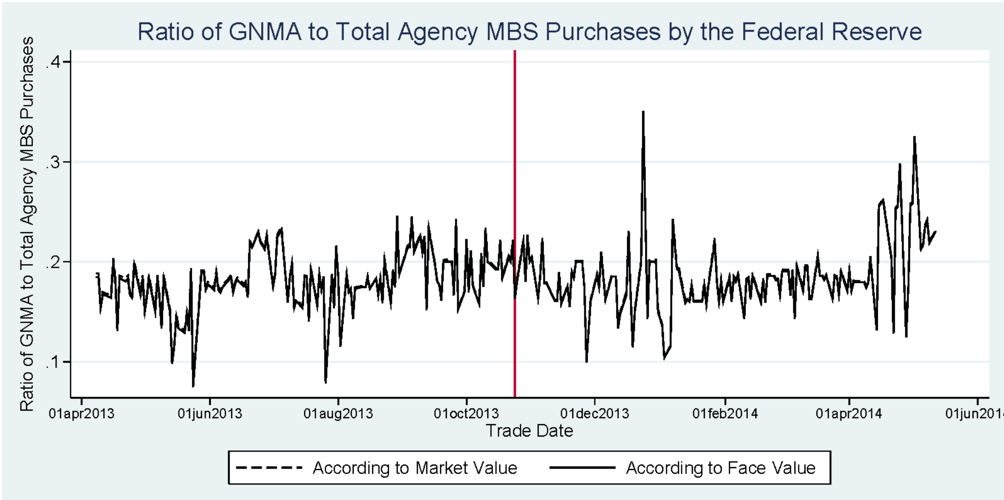


Figure A4. Ratio of GNMA to Total Agency MBS. This figure plots the GNMA share of the Fed's MBS purchases. The vertical line corresponds to October 24th, 2013, when the LCR rules were proposed. Source: federalreserve.gov.

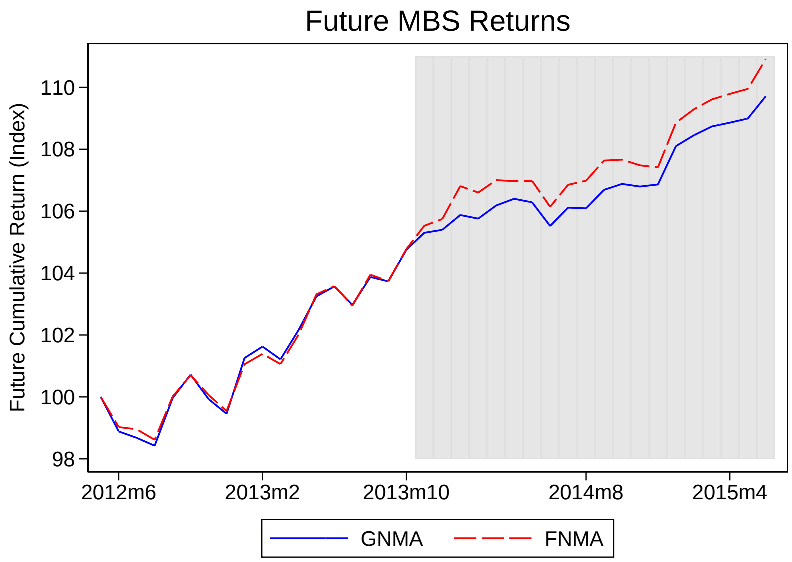


Figure A5. Future MBS Returns. This figure plots the 12-month-ahead cumulative total return for different types of MBS. Cumulative total return is measured using the Bloomberg-Barclays Total Return Index. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

Table A1: 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 A2: Instrumental Variable Specification for Nonbank FHA Lending

Outcome:	$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	-0.017	-0.018
	(0.040)	(0.036)
Premium Measure	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes
MSA-Year FE	Yes	Yes
Borrower Controls	Yes	Yes
F-Statistic	88.900	67.351
Number of Observations	1,040,927	1,040,927

Note: P-values are in parentheses. This table estimates equation (1). Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. The estimator is 2SLS, and the instrument for GNMA-Premium_t is an indicator for whether $t \geq 2014$, the first full year after LCR regulation was announced. The remaining notation is the same as in Table 2. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table A3: Robustness to using the OAS GNMA Premium

Outcome:	$\text{Denial}_{i,l,t}$	
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	-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 (1). Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. FNMA OAS Spread is the difference in option-adjusted spread between FNMA and GNMA MBS, and FHLMC OAS Spread is the analogous difference between FHLMC and GNMA MBS. Option-adjusted spreads are computed by Bloomberg. 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. The remaining notation is the same as in Table 2. The sample consists of applications for FHA loans for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table A4: GNMA Premium and Nonbank Lending in the Conventional Market

Outcome:	Denial$_{i,l,t}$ Period: 2010-15			Denial$_{i,l,t}$ Period: 2000-06	
Nonbank$_l$ × GNMA-Premium$_t$	0.013	-0.001	-0.001	0.034	0.022
	(0.012)	(0.760)	(0.707)	(0.096)	(0.148)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Lender-MSA FE	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.117	0.117	0.117	0.197	0.197
Number of Observations	2,219,363	2,219,363	2,219,363	10,085,110	10,085,110

Note: P-values are in parentheses. This table estimates equation (1) in the conventional mortgage market. Subscripts i, l, and t index borrower, lender, and year, respectively. Each observation is a loan application. The remaining notation is the same as in Table 2. The sample consists of applications for conforming non-FHA loans for the purchase of an owner-occupied single-family dwelling. The sample period is 2010-15 in columns 1-3 and 2000-06 in columns 4-5. Standard errors are clustered by lender-year bins.

Table A5: GNMA Premium and Portfolio Reallocation by Lender Funding Liquidity

Outcome:		$\text{Denial}_{i,l,s,t}$	
Securitization $\text{Rate}_l \times \text{GNMA-Premium}_t \times \text{FHA}_s$	-0.019 (0.008)	-0.012 (0.000)	-0.011 (0.000)
Premium Measure	Post-LCR	FNMA Spread	FHLMC Spread
Loan Type-Lender FE	Yes	Yes	Yes
Loan Type-Year FE	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes
Lender-MSA FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes
R-squared	0.115	0.115	0.115
Number of Observations	2,594,800	2,594,800	2,594,800

Note: P-values are in parentheses. This table estimates a variant of equation (4). Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Each observation is a loan application. Securitization Rate is the lender's ratio of securitized loans to total originations in 2010, normalized to have a mean of 0 and variance of 1. The remaining notation is the same as in Table 4. The sample consists of FHA and conforming non-FHA loan applications for the purchase of an owner-occupied single-family dwelling from 2010-15. Standard errors are clustered by lender-year bins.

Table A6: Robustness to Excluding Lenders with Over 2% of the Market

Outcome:	$\text{Denial}_{i,l,t}$			
	Diff-in-Diff		Triple Diff-in-Diff	
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	-0.007	-0.007		
	(0.000)	(0.000)		
$\text{Nonbank}_l \times \text{GNMA-Premium}_t \times \text{FHA}_s$			-0.004	-0.004
			(0.001)	(0.000)
Premium Measure	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Loan Type-Lender FE	No	No	Yes	Yes
Loan Type-Year FE	No	No	Yes	Yes
Lender-Year FE	No	No	Yes	Yes
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.119	0.119	0.122	0.122
Number of Observations	866,326	866,326	2,734,287	2,734,287

Note: P-values are in parentheses. Columns 1-2 of this table estimate equation (1), and columns 3-4 estimate equation (4). Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. The sample excludes lenders with over 2% of the total mortgage market in 2010, measured by origination share. The remaining notation and remarks on sample for columns 1-2 and columns 3-4 are the same as in Tables 2 and 4, respectively. Standard errors are clustered by lender-year bins.

Table A7: Robustness to Excluding Nonbanks

Outcome:	Denial$_{i,l,t}$			
	Diff-in-Diff		Triple Diff-in-Diff	
Securitization Rate$_l$ × GNMA-Premium$_t$	-0.019	-0.018		
	(0.083)	(0.050)		
Securitization Rate$_l$ × GNMA-Premium$_t$ × FHA$_s$			-0.015	-0.014
			(0.015)	(0.007)
Premium Measure	FNMA Spread	FHLMC Spread	FNMA Spread	FHLMC Spread
Loan Type-Lender FE	No	No	Yes	Yes
Loan Type-Year FE	No	No	Yes	Yes
Lender-Year FE	No	No	Yes	Yes
Lender-MSA FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
R-squared	0.106	0.106	0.110	0.110
Number of Observations	324,350	324,350	1,331,695	1,331,695

Note: P-values are in parentheses. Columns 1-2 of this table estimate equation (3), and columns 3-4 estimate a variant of equation (4). Subscripts i, l, s, and t index borrower, lender, loan type, and year, respectively. Securitization Rate is the lender's ratio of securitized loans to total originations in 2010, normalized to have a mean of 0 and variance of 1. The sample excludes nonbanks. The remaining notation and remarks on sample for columns 1-2 and columns 3-4 are the same as in Tables 2 and 4, respectively. Standard errors are clustered by lender-year bins.

Table A8: Interest Rate Pass-Through by Nonbanks at a Monthly Frequency

Outcome:	$\text{Rate}_{i,l,t}$			
$\text{Nonbank}_l \times \text{GNMA-Premium}_t$	-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 (8). 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. All measures of GNMA-Premium have units of percentage points and are not normalized. OAS spreads are based on Bloomberg's option-adjusted spread, as described in Table A3. 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 2. The sample consists of originated FHA loans for the purchase of a single-family dwelling from 2012-15. Standard errors are clustered by lender-month bins.

Table A9: Liquidity Coverage Ratio and the GNMA Liquidity 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 (A3). Subscript t indexes month. $R^{GNMA}_{t\to t+12}$ is the change in log Bloomberg-Barclays 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 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. Each observation is a month. Standard errors are Newey-West with a lag of 4 months.