# Mortgage Securitization and Shadow Bank Lending*

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**Abstract**

We document a new channel through which securitization affects financial stability: higher prices in the secondary market increase the supply of credit in the primary market by lenders with little funding liquidity, especially nonbanks. 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, which raises their market share and also increases 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 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. This trend concerns policymakers, who fear that a credit-induced bust (e.g. Di Maggio and Kermani 2017) could more easily spark a financial crisis if the mortgage market is dominated by nonbanks.[1]

We show how securitization affects financial stability by increasing the size of the shadow banking system: higher mortgage-backed security (MBS) prices lower nonbanks' lending standards in the primary mortgage market, thereby increasing their market share relative to banks. The underlying theory that we test begins with variation in how lenders fund mortgage originations, and specifically variation in lenders' funding liquidity. Unlike banks, nonbanks lack access to stable deposit funding, and so they fund originations through securitization. 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 less funding liquidity − to extend more credit in the primary mortgage market. Thus, the relative size of the nonbank lending sector 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).[2] This market segmentation allows us to difference out

[1]Many of the nonbanks that were active before the Financial Crisis either failed or were restructured (e.g. Wallace 2016; Pinto and Oliner 2015).

[2]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.

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 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, 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). Using an auxiliary dataset, we show that nonbanks also disproportionately lower the interest rate on FHA loans in response to an increase in GNMA prices, which is consistent with the results from our baseline exercise.

We perform a variety of tests to evaluate the validity of our baseline exercise. For example, 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, which substantially reduces the likelihood that the identification assumption is violated. We again find that nonbanks respond to higher GNMA prices by denying fewer FHA applicants. Indeed, based on a wide variety of robustness tests, 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; a pre-trend in nonbank denial rates; or the choice of monthly versus yearly frequency.

To assess the aggregate implications of our findings, we conduct 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 both nonbanks and FHA credit 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 period after the Great Recession because of the exogenous variation generated by the LCR, but we also document a similar relationship between MBS prices and nonbank lending over 2000-06. This finding suggests that our baseline results are not due to spurious correlation between the introduction of the LCR and other time-varying factors. It also suggests that fluctuations in nonbanks' market share can occur routinely as a byproduct of recurring fluctuations in secondary markets.

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 theoretical framework. 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 tests. Section 6 studies implications for interest rates, nonbanks' market share, and homeownership. Section 7 concludes. All figures and tables may be found at the end of the main text. The online appendix has 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, 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 (e.g. Buchak et al 2018), technological innovation (e.g. Fuster et al 2019), bank capitalization (e.g. Irani et al 2018; Chernenko, Erel, and Prilmeier 2018), and creditor protection in the warehouse lending market (e.g. 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 (e.g. Calem, Correa and Lee 2019; Gete and Reher 2018), qualified-mortgage requirements (e.g. De Fusco, Johnson, and Mondragon 2019), litigation risk (e.g. D'Acunto and Rossi 2017; Gissler, Oldfather, and Ruffino 2016), and capital requirements (e.g. Reher 2019). We provide the first evidence that the Liquidity Coverage Ratio (LCR) also affects the housing market in meaningful ways, such as increasing nonbanks' share of mortgage lending and bolstering homeownership. This effect is an unintended consequence of the LCR, and it must be weighed against the intended effect of increasing banks' liquid asset holdings (e.g. Roberts, Sarkar, and Shachar 2018).

# 2 Framework

Our empirical analysis is grounded in a theory of mortgage markets where lenders vary in their funding liquidity (Brunnermeier and Pedersen 2008). We begin by describing this theory and provide a complementary diagram in Appendix Figure A1.

First, unlike banks, nonbanks do not have access to stable deposit funding, and thus they cannot hold loans on their balance sheets (Hanson et al 2015). 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 (Echeverry, Stanton, and Wallace 2016). 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 the upper panel of Appendix Figure A1. An increase in MBS prices therefore significantly increases the amount of nonbank-produced MBS. By contrast, banks can use deposits to finance primary market lending, and so they respond less to an increase in MBS prices. Thus, banks' supply of MBS is relatively-inelastic, and so an increase in prices has a more modest effect on the quantity bank-produced MBS.

Turning to the primary market, the supply of nonbank and bank-intermediated loans increases to enable the increase in the supply of nonbank and bank-produced MBS, as illustrated in the bottom panels of Appendix Figure A1. Therefore, at any given mortgage interest rate, the supply of nonbank-intermediated loans increases substantially, while the supply of bank-intermediated loans only increases modestly.[3] In summary, higher MBS prices disproportionately increase nonbanks' supply of credit in the primary market, and thus their market share rises.

We investigate this theory in the context of the U.S. mortgage market, where nonbanks' recent surge in market share has prompted concerns about financial stability. Based on data from the Home Mortgage Disclosure Act (HMDA), nonbanks originated 30%-45% of for-purchase mortgages over the 2000-11 period, but they account for 55% of originations in 2015.[4] Their growth has been even more dramatic in the FHA market, where they account for 80% of originations in 2015, compared to 50%-60% over 2000-11.

[3] In reality, banks and nonbanks may face a downward-sloping demand curve so that, with the additional assumption of monopolistic competition, the interest rate on nonbank-intermediated loans falls relative to bank-intermediated loans. We test this hypothesis in Section 5.

[4] 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 (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 institutions 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.

# 3 Identification Strategy

The framework discussed in Section 2 predicts that higher MBS prices increase the relative supply of mortgage credit intermediated 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; 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 FHA loans.[5]

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.

## 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

[5]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 but higher payments over the life of the loan.

weights to assets, where a higher weight implies more favorable regulatory treatment.[6] 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.[7] 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.

Beginning with quantities, in Figure 1 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 the amount of GNMA MBS on their balance sheets after the LCR shock. Appendix Figure A2 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.

Turning to prices, in Figure 2 we plot the 12-month-ahead GNMA total gross return relative to FNMA MBS (i.e. expected return). 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

[6]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.

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

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.

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 A7 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".[8] 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.

# 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. We measure credit supply using loan denial rates, which allows us to use microdata and include multiple fixed effects to absorb confounding factors.

## 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. 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.[9] This gives a sample of 396 lenders over the 2010-15 period, 123 of which are non-depository

[8]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).

[9]The latter condition gives a balanced sample around the introduction of the Liquidity Coverage Ratio.

institutions, which we call "nonbanks". We then construct an analogous dataset over the 2000-06 period.[10] 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

We perform a difference-in-difference analysis across lenders and years, and we estimate the following equation on the subset of FHA loan applications,

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

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 $\text{Nonbank}_l$ indicates if the lender is a nonbank. In words, "treated lenders" are nonbanks, and the "treatment", $\text{Premium}_t$, is a measure of the relative price of GNMA MBS and thus nonbanks' incentive to originate FHA loans.

Our first measure of $\text{Premium}_t$ 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 $\text{Premium}_t$ using the spread in the one-year-ahead total return between FNMA and GNMA MBS.[11] 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.

The identification assumption implicit in (1) is

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

Under this assumption, the parameter $\beta$ 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 $\text{Premium}_t$ 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

[10] We intentionally omit the 2007-09 period because of the Great Recession.

[11] 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.

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 3 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.[12] 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 implies that the increase in the FNMA-GNMA spread due to the introduction of the LCR lowers 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 suggests that the OLS estimator used in columns 2-3 is not biased because of 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. Appendix Table A3 verifies that the results are robust to using the option-adjusted spread to measure $\text{Premium}_t$, 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.[13]

The effect of the GNMA premium on nonbank denial rates should theoretically be stronger for borrowers in riskier markets. Viewed through the lens of a credit rationing model, these markets have a greater mass of borrowers on the extensive margin of credit. In addition, while FHA borrowers are subject to debt-to-income ceilings, lenders can increase this ceiling by invoking "compensating factors".[14] Thus, lenders have more discretion over denial rates for risky borrowers with a high debt-to-income ratio. We test this hypothesis by interacting the treatment effect, $\text{Nonbank}_l \times \text{Premium}_t$, with the average requested loan-to-income ratio (LTI) in the applicant's MSA of residence, a proxy for the probability of default.[15] Columns 4-5 of

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

[13] 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.

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

[15] The results are the same when including the interaction with the borrower's requested LTI. Taking the 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 $\alpha_{m(i),t}$.

Table 2 imply that nonbanks lower their denial 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.

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%. The results are not driven by changes in prepayment risk, and they are stronger for borrowers in riskier markets.

### 4.3 Identifying the Channel

The theoretical 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. This conjecture motivates us to estimate a more general variant of equation (1),

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

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.[16] Our second measure, called "non-core funding", is 1 minus the ratio of core deposits to total assets in 2010. By definition, nonbanks 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.

Collectively, the results from this section 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. These lenders have a fragile funding model which makes them more prone to failure, as discussed in the introduction. Thus, our findings suggest that securitization affects financial stability through the distribution of market share across different types

[16] 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.

of lenders.

# 5 Robustness

In this section, we perform a variety of robustness tests to evaluate our primary identification assumption, the exclusion restriction in equation (2). The results of these tests support the validity of (2).

## 5.1 Reallocation Effect: Lender-Year Fixed Effects

First, we propose a methodology which shuts down any confounding shock to a lender's overall level of FHA lending and obtains identification from lenders' allocation between FHA and non-FHA, conventional loans. Specifically, we estimate a triple difference-in-difference equation which allows us to include lender-year fixed effects,

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

where $s$ indexes loan type, which now can be either FHA or conventional. Thus, while our difference-in-difference equation (1) obtains identification from the double product of "treated lenders" ($\text{Nonbank}_l$) in "treated years" ($\text{Premium}_t$), equation (4) obtains identification from the additional product with "treated loan types" ($\text{FHA}_s$).

The primary advantage to estimating a triple difference-in-difference equation is that the lender-year fixed effect, $\alpha_{l,t}$, absorbs shocks to a lender's overall level of credit supply. Thus, any confounding factor coinciding with $\text{Premium}_t$ 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 loan markets. 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 ($X_{i,t}$).

We interpret the parameter $\beta$ in (4) as 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, $\alpha_{l,t}$. For this reason, equation (4) is not a suitable baseline equation, but, rather, it provides an important robustness test due to its relatively-weak identification assumption.

The results in Table 4 imply 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 A4 when replacing $\text{Nonbank}_l$ with the lender's securitization rate. As discussed above, a lender's securitization rate captures its funding illiquidity, and so Appendix Table A4 provides additional support for the more general mechanism through which MBS prices disproportionately affect nonbanks.

### 5.2 Litigation Risk: Dropping Large Lenders

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.[17] 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 6.4 below, the corresponding results are either null or of the opposite sign.

To more directly address bias from large lenders' 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 Table 5 are similar to their analogues in Tables 2 and 4.

### 5.3 Net Stable Funding Ratio: Dropping Nonbanks

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

[17]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.

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. 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.

We consider this possibility by reestimating equations (3) and (4) after excluding nonbanks from the sample. The results in Table 6 suggest that banks with greater historical reliance on securitization deny fewer FHA applicants after an increase in the GNMA premium. While the standard errors increase due to the reduced sample size, the point estimates are quite similar to their counterparts from Tables 3 and 4 and are all statistically significant at the 10% threshold. It is therefore unlikely that expectations about the NSFR are affecting the results.

## 5.4 Regulatory Arbitrage: Testing the Mechanism Before the Crisis

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 5.3. Second, we obtain similar results after excluding relatively large lenders who have a greater incentive for regulatory arbitrage, as discussed in Section 5.2.

Third, Appendix Table A5 documents a strong link between the GNMA premium and the relative supply of FHA credit by nonbanks over the 2000-06 period, before the Financial Crisis and 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.

## 5.5 Changing Applicant Pool

If applicants to nonbanks − or, more generally, funding-illiquid lenders − are becoming less risky, the results may spuriously capture improvements in applicant credit quality. However, Figure 4 shows how the requested loan-to-income ratio (LTI), a proxy for an applicant's default probability, has evolved quite similarly for bank and nonbank applicants over time.

Similarly, if FHA loan applicants are becoming less risky and banks have some cost of adjusting to the new quality of FHA borrowers, then our results could reflect changes in the credit quality of FHA loan applicants. However, Appendix Figure A3 shows that the LTI for FHA and non-FHA applicants have grown at approximately the same rate. If anything, Figure A3 suggests that FHA applicants have become slightly riskier, in terms of LTI, relative to non-FHA applicants. The dynamics shown in Figure A3 therefore make it unlikely that the results are driven by exogenous improvements in the credit quality of FHA borrowers.

## 5.6 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). In particular, Appendix Figure A4 shows that the ratio of the Fed's purchases was weighted against GNMA MBS, and so these purchases are unlikely to account for nonbanks' substitution toward FHA lending.

## 5.7 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 difference-in-difference exercise at the monthly frequency. The results, discussed in Section 6.1, are similar to those from our baseline analysis.

# 6 Implications of the Baseline Results

The main implication of our baseline results is that higher MBS prices increase the relative supply of credit by funding-illiquid lenders (e.g. nonbanks), which may pose risks for financial stability. In this section, we explore four additional implications of our findings: (1) if mortgage markets are imperfectly competitive (e.g. Scharfstein and Sunderam 2016), then an increase in the GNMA premium may lower the interest rate charged by nonbanks on FHA loans; (2) lower interest rates – or, more generally, more favorable loan terms – may attract more nonbank applicants, amplifying the application-level increase in credit supply documented in our baseline analysis; (3) because FHA borrowers tend to be on the extensive margin of mortgage markets, this increase in credit supply may influence homeownership rates; and (4) the supply of non-FHA credit may fall if nonbanks reallocate their portfolio toward FHA loans.

## 6.1 Interest Rates

First, we use data from HUD's FHA Single Family Portfolio Snap Shot to study how higher MBS prices affect the relative interest rate charged by nonbanks on FHA loans. This exercise also allows us to test the sensitivity of our baseline results to the yearly frequency of our HMDA dataset, since the HUD data are available monthly.[18]

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

$$\text{Rate}_{i,l,t} = \beta\left(\text{Nonbank}_l \times \text{Premium}_t\right) + \gamma Z_{i,t} + \alpha_{m(i),t} + \alpha_{m(i),l} + u_{i,l,t}, \tag{5}$$

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 $\text{Premium}_t$ 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.[19]

Mortgage interest rates typically fall when the GNMA premium rises, measured using either total return or option-adjusted spreads. Thus, the parameter $\beta$ 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 Table 7 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 $\text{Premium}_t$.

[18] However, we cannot use the HUD data for our baseline analysis, since it only contains information on originated loans.

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

The results of this exercise imply that nonbanks disproportionately lower the price of credit, in addition to approving more loans, following an increase in MBS prices. The results also suggest that our baseline results are not biased because of the HMDA dataset's yearly frequency.

## 6.2 Nonbank Market Share

Next, we perform an aggregated version of our baseline exercise. This exercise allows us to make inferences about the effects of an increase in MBS prices on nonbanks' aggregate market share, since it captures how nonbanks both deny fewer applicants and can attract a larger applicant pool by offering more favorable loan terms. 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,

$$\log\left(\text{Loans Originated}_{c,l,t}\right) = \beta\left(\text{Nonbank}_l \times \text{Premium}_t\right) + \alpha_{c,t} + \alpha_{c,l} + u_{c,l,t}, \tag{6}$$

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 (6) 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 tracts are relatively granular geographic units comprising around 4,000 people.[20] Thus, there

[20]The difference relative to equation (2) is that we must assume the treatment effect, $\text{Nonbank}_l \times \text{Premium}_t$, 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.

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 that affects the GNMA premium.

Table 8 contains the results of (6). 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 $\eta_{15}$ denote nonbanks' FHA market share in 2015, where

$$\eta_{15} = \frac{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \text{Nonbank}_l}{\sum_c \sum_l \text{Loans Originated}_{c,l,15}} \tag{7}$$

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 (6), this counterfactual share can be written

$$\hat{\eta}_{15} = \frac{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \text{Nonbank}_l \times e^{-\beta^{LCR}}}{\sum_c \sum_l \text{Loans Originated}_{c,l,15} \times \left[(1 - \text{Nonbank}_l) + \text{Nonbank}_l \times e^{-\beta^{LCR}}\right]}, \tag{8}$$

where $\beta^{LCR} = 0.13$ is the average point estimate across columns in Table 6. The resulting counterfactual market share is $\hat{\eta}_{15} = 0.77$, which is 2.2 pps lower than the true market share.[21] 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.

### 6.3 Homeownership

Third, we study whether securitization enables 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 nonbank-driven increase in credit supply 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 home-

[21] Note that because (6) 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 (8).

ownership rate in 2011 and 2015.[22] 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,

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

where: $z$ indexes zip code; $\Delta\text{Homeownership}_{z,11\text{-}15}$ denotes the change in the homeownership rate between 2011 and 2015; Nonbank $\text{Share}_{z,11}$ and FHA $\text{Share}_{z,11}$ 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.[23]

The treatment group in (9) consists of zip codes with (a) a high initial nonbank share and (b) a high initial 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 (Nonbank $\text{Share}_{z,11}$) and FHA application share (FHA $\text{Share}_{z,11}$), which account for features of 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, $\beta$, using the previously-documented finding that nonbanks loosened standards specifically among FHA loans.

The result in Table 9 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. $0.03 \times 0.43$) 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

[22]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.

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

(2017) correction.[24]

In the third column, we use the treatment variable, Nonbank $\text{Share}_{z,11} \times$ FHA $\text{Share}_{z,11}$, 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 0.15 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 has collapsed toward a historic low.

### 6.4 Supply of Non-FHA Credit

Finally, we study the implications of our baseline results for non-FHA, conventional loans. The effect of an increase in the GNMA premium on nonbanks' supply of credit for such 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 A6. In general, however, the results suggest a weak increase in conventional denial rates, which may reflect a role for funding constraints.[25]

## 7 Conclusion

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. In this way, we documented a new channel through which securitization affects financial stability: the share of

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

[25]The null result when using the FNMA and FHLMC spreads over 2010-15 likely reflects an LCR-induced increase in the price of FNMA and FHLMC MBS because they received positive liquidity weights, although the weights were less favorable relative to GNMA MBS.

credit intermediated by bank versus nonbank lenders. 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 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.

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 has 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

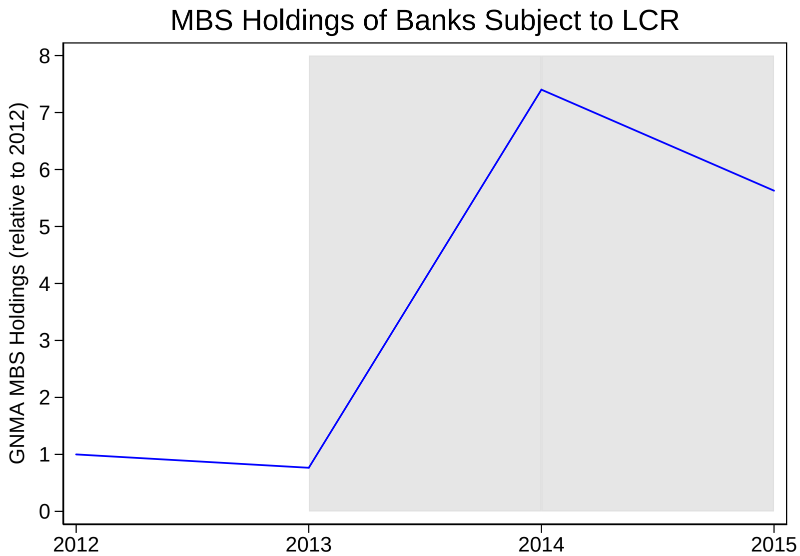


**Figure 1. MBS Holdings of Institutions Affected by Liquidity Regulation.** This figure plots the average holdings of Ginnie Mae (GNMA) MBS by banks subject to the LCR policy, relative to 2012. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013. Source: Call Reports (FRY-9C)

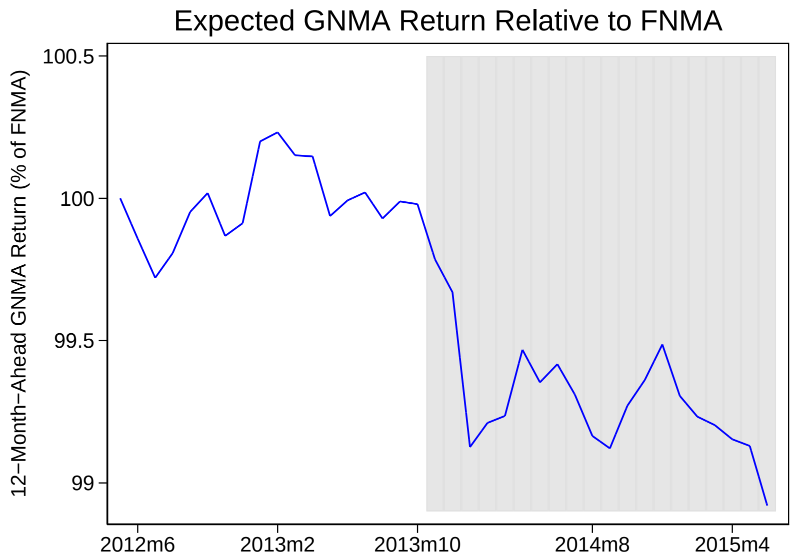


**Figure 2. Expected MBS Return.** This figure plots the ratio of the 12-month-ahead total gross return for GNMA relative to FNMA MBS, measured using the Bloomberg-Barclays Total Return Index. A drop in the relative return means that GNMA prices have increased more than FNMA prices. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

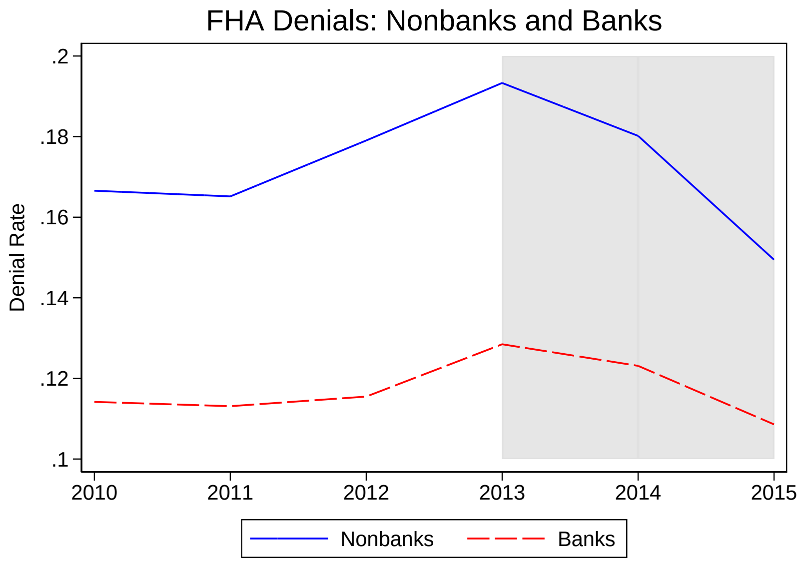


**Figure 3. Denial Rates for Banks and Nonbanks.** This figure plots banks' and nonbanks' denial rate among FHA loans. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

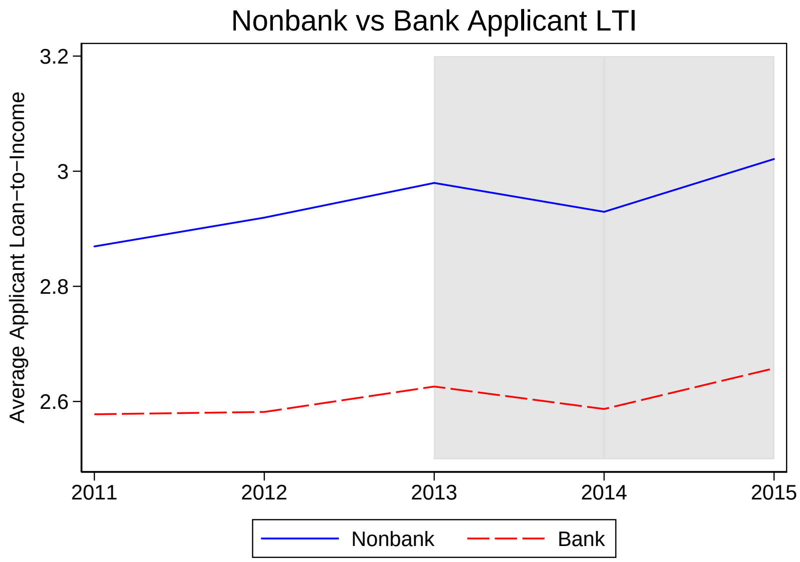


**Figure 4. Credit Quality of Applicants to Banks and Nonbanks.** This figure plots the average loan-to-income ratio (LTI) among applicants to banks versus nonbanks over our main sample period. The LTI is a proxy for the probability of default. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

Table 1: Summary Statistics

| Variable | Number of Observations | Mean | Standard Deviation |
|---|---|---|---|
| Application-Level Variables, 2010-15: | | | |
| Denial 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 |
| Log Income | 13,114,592 | 4.257 | 0.612 |
| Application-Level Variables, 2000-06: | | | |
| Denial Indicator | 53,476,760 | 0.157 | 0.364 |
| Nonbank Indicator | 53,476,760 | 0.419 | 0.493 |
| FHA Indicator | 53,476,760 | 0.091 | 0.288 |
| Zip Code-Level Variables: | | | |
| $\Delta$Homeownership Rate, 2011-15 | 3,521 | -0.028 | 0.034 |
| Homeownership Rate, 2011 | 3,521 | 0.616 | 0.171 |
| Nonbank Share, 2011 | 3,521 | 0.457 | 0.173 |
| FHA Share, 2011 | 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 Ratio is 1 minus the ratio of core deposits to 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; Minority indicates if the applicant is black or Hispanic. In the Zip Code-Level panel, each observation is a zip code weighted by 2011 renter population. 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. The time-series variables have units of percentage points (pps).

Table 2: Secondary Market Prices and Nonbank Lending

| Outcome: | $\text{Denial}_{i,l,t}$ | | | | | |
|---|---|---|---|---|---|---|
| $\text{Nonbank}_l \times \text{Premium}_t$ | -0.020 | -0.014 | -0.012 | -0.020 | -0.014 | -0.012 |
| | (0.051) | (0.000) | (0.000) | (0.046) | (0.000) | (0.000) |
| $\text{Nonbank}_l \times \text{Premium}_t$... | | | | -0.006 | -0.003 | -0.003 |
| ... $\times \text{LTI}_{m(i),t}$ | | | | (0.117) | (0.009) | (0.002) |
| Premium Measure | Post-LCR | FNMA Spread | FHLMC Spread | Post-LCR | FNMA Spread | FHLMC Spread |
| Lender-MSA FE | Yes | Yes | Yes | Yes | Yes | Yes |
| MSA-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.117 | 0.117 | 0.117 | 0.117 | 0.117 | 0.117 |
| Number of Observations | 1,040,927 | 1,040,927 | 1,040,927 | 1,040,927 | 1,040,927 | 1,040,927 |

Note: P-values are in parentheses. This table estimates equation (1), which is our baseline difference-in-difference equation. 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 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. Columns 4-6 include the interaction with the average loan-to-income ratio (LTI) among borrowers in the applicant's MSA of residence, $m(i)$, which is a proxy for default probability. LTI is normalized to have a variance of 1 and a mean of 0. 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. Standard errors are clustered by lender-year bins.

Table 3: Funding Liquidity as the Transmission Channel

| Outcome: | Denial$_{i,l,t}$ | | | |
|---|---|---|---|---|
| Securitization Rate$_l$ $\times$ Premium$_t$ | -0.015 | -0.014 | | |
| | (0.008) | (0.005) | | |
| Non-Core Funding$_l$ $\times$ 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), which allows us to test whether the baseline effect works through lenders' funding illiquidity. 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 to total assets in 2010, which equals 1 for nonbanks by definition. Both Securitization Rate and Non-Core Funding are normalized to have a mean of 0 and variance of 1. The remaining notation, sample period, and standard errors are the same as in Table 2.

Table 4: Robustness to Including Lender-Year Fixed Effects

| 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 |
| 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), which allows us to include lender-year fixed effects and thus assess the effect on lenders' portfolio allocation. 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 sample consists of FHA and conventional loan applications 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 5: Robustness to Excluding Lenders with Over 2% of the Market

| Outcome: | $\text{Denial}_{i,l,t}$ Diff-in-Diff | | $\text{Denial}_{i,l,s,t}$ Triple Diff-in-Diff | |
|---|---|---|---|---|
| $\text{Nonbank}_l \times \text{Premium}_t$ | -0.007 | -0.007 | | |
| | (0.000) | (0.000) | | |
| $\text{Nonbank}_l \times \text{Premium}_t \times \text{FHA}_s$ | | | -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). We 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. Subscripts $i$, $l$, $s$, and $t$ index borrower, lender, loan type, and year, respectively. The remaining notation, remarks on sample, and standard errors for columns 1-2 and columns 3-4 are the same as in Tables 2 and 4, respectively.

Table 6: Robustness to Excluding Nonbanks

| Outcome: | $\text{Denial}_{i,l,t}$ Diff-in-Diff | | $\text{Denial}_{i,l,s,t}$ Triple Diff-in-Diff | |
|---|---|---|---|---|
| Securitization $\text{Rate}_l \times \text{Premium}_t$ | -0.019 | -0.018 | | |
| | (0.083) | (0.050) | | |
| Securitization $\text{Rate}_l \times \text{Premium}_t \times \text{FHA}_s$ | | | -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). We exclude nonbanks from the sample 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 loans to total originations in 2010, normalized to have a mean of 0 and variance of 1. The remaining notation, sample period, and standard errors for columns 1-2 and columns 3-4 are the same as in Tables 2 and 4, respectively.

Table 7: 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<br>(0.000) | -0.053<br>(0.000) | -0.124<br>(0.000) | -0.125<br>(0.000) |
| Premium Measure | FNMA<br>Spread | FHLMC<br>Spread | FNMA<br>OAS Spread | FHLMC<br>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 (5), which assesses the effect 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 2. 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 8: GNMA Premium and Nonbank Lending at the Census Tract Level

| Outcome: | $\log\left(\text{Loans Originated}_{c,l,t}\right)$ | | |
|---|---|---|---|
| $\text{Nonbank}_l \times \text{Premium}_t$ | 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 (6), which is an aggregated version of our baseline equation. 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 of FHA loans originated within each triplet. The sample consists of all triplets that featured at least 1 FHA loan application 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 9: Nonbanks and Homeownership at the Zip Code Level

| | $\Delta$Homeownership$_{z,11\text{-}15}$ | | |
|---|---|---|---|
| Nonbank Share$_{z,11}$ $\times$ FHA Share$_{z,11}$ | 0.028 | 0.030 | |
| | (0.022) | (0.017) | |
| $\Delta$Denial 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), which assesses how nonbanks' expansion in credit has affected homeownership. Subscript $z$ indexes zip code. $\Delta$Homeownership$_{z,11\text{-}15}$ denotes the change in 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 are for FHA loans, respectively. $\Delta$Denial 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 $\Delta$Denial 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*

## 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 funding-illiquid 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

$$R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12} = \beta_0 + \beta_1 \text{Post-LCR}_t + u_t, \tag{A1}$$

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 (A1) 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 $\delta^s_t$, 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

$$\mathbb{E}_t\left[R^s_{t\to t+12}\right] = -\delta^s_t + \phi^s \bar{f}_t, \tag{A2}$$

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, $\phi^s$, captures the quantity of risk for MBS of type $s$.

Taking the cross-sectional difference in (A2) between GNMA and FNMA MBS yields

$$\mathbb{E}_t\left[R^{FNMA}_{t\to t+12} - R^{GNMA}_{t\to t+12}\right] = \delta^{GNMA}_t - \delta^{FNMA}_t + \left(\phi^{FNMA} - \phi^{GNMA}\right)\bar{f}_t. \tag{A3}$$

We model the announcement of LCR regulation as disproportionately increasing the convenience yield for holding GNMA MBS, $\delta_t^{GNMA}$, 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 $\delta_t^{FNMA}$, the more favorable regulatory weights granted to GNMA MBS should theoretically raise $\delta_t^{GNMA}$ by more. In particular, we suppose the difference $\delta_t^{GNMA} - \delta_t^{FNMA}$ increases by some amount $\delta^{LCR}$ 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 $\beta_1$ in (A1) recovers the LCR premium, $\delta^{LCR}$. 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 $\beta_0$ in (A1) 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 (A1) are in Table A7. 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.[26] 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.

[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.

# Additional Figures and Tables

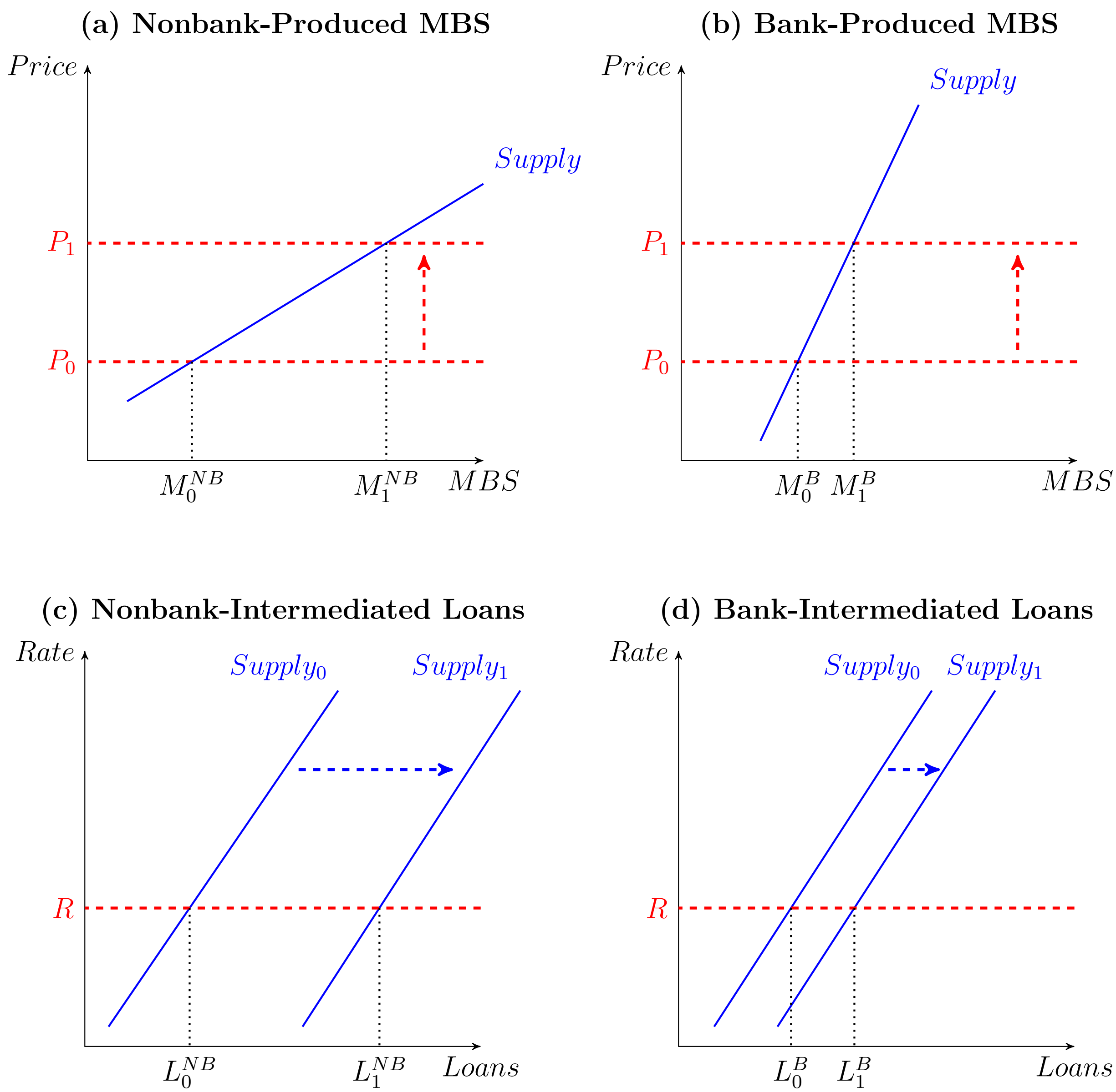


**Figure A1. Theoretical Effect of Higher MBS Prices on Credit Supply.** The upper panel plots the supply of nonbank and bank-produced MBS, and the lower panel plots the supply of nonbank and bank-intermediated loans in the primary mortgage market. The supply of nonbank-produced MBS is relatively-elastic because nonbanks are more sensitive to secondary market prices. 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 $L_1^B$.

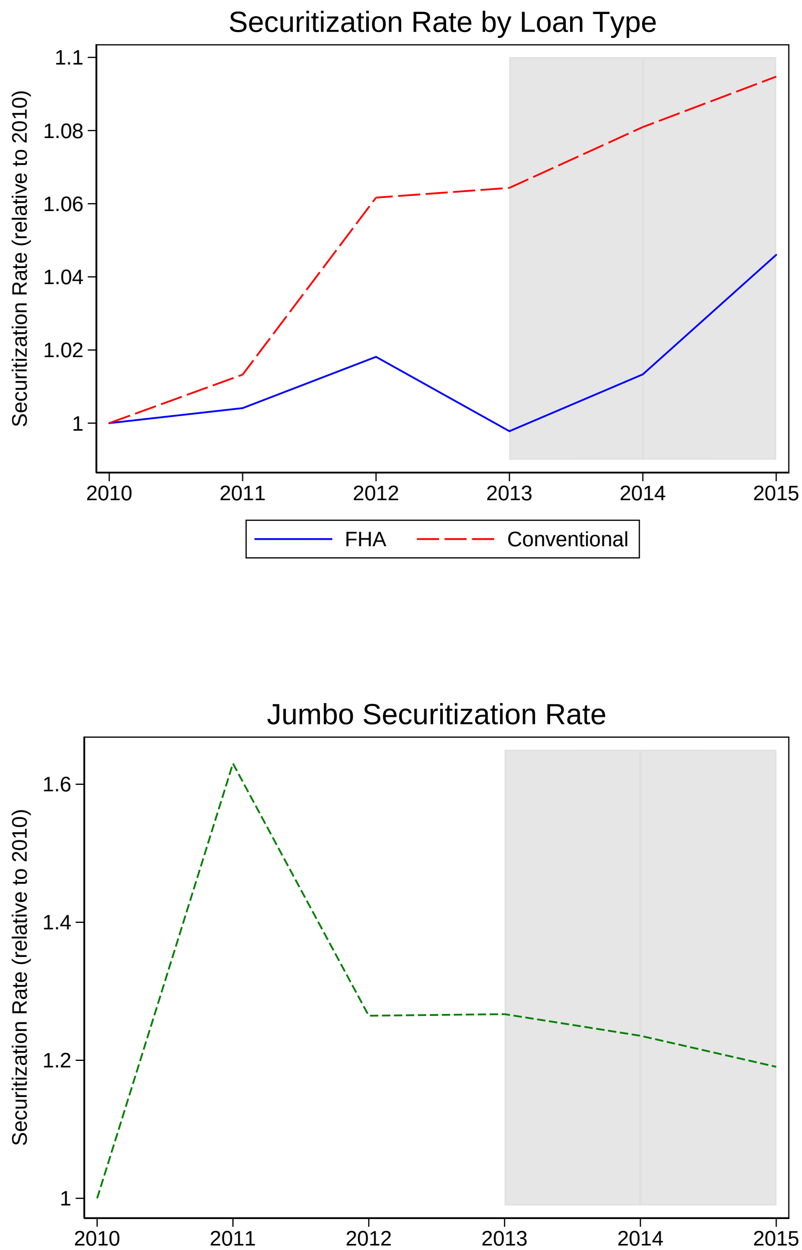


**Figure A2. Securitization by Loan Type.** This figure shows the fraction of FHA (top), conventional (top), and jumbo (bottom) loans that are securitized, normalized by the 2010 value. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

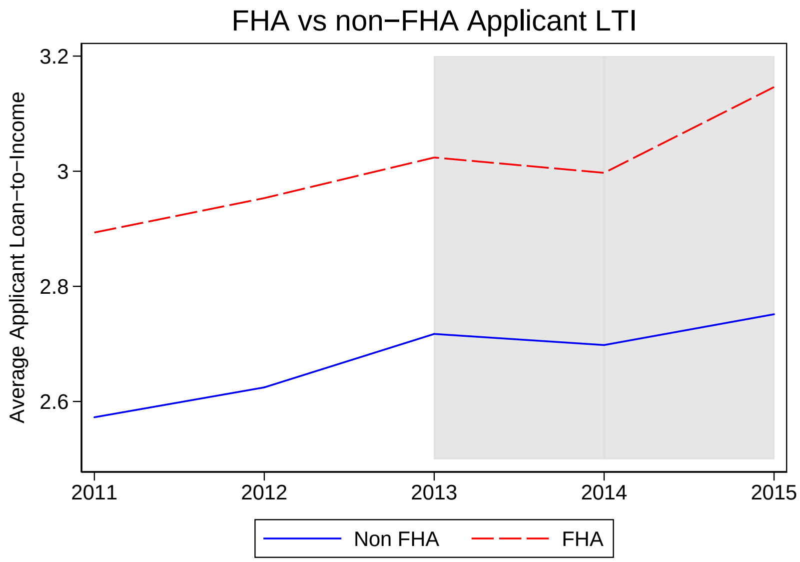


**Figure A3. Credit Quality of FHA Applicants.** This figure plots the average requested loan-to-income ratio (LTI) for FHA versus non-FHA loans over our main sample period. The LTI is a proxy for the probability of default. The shaded region corresponds to the period after LCR rules were proposed on October 24th, 2013.

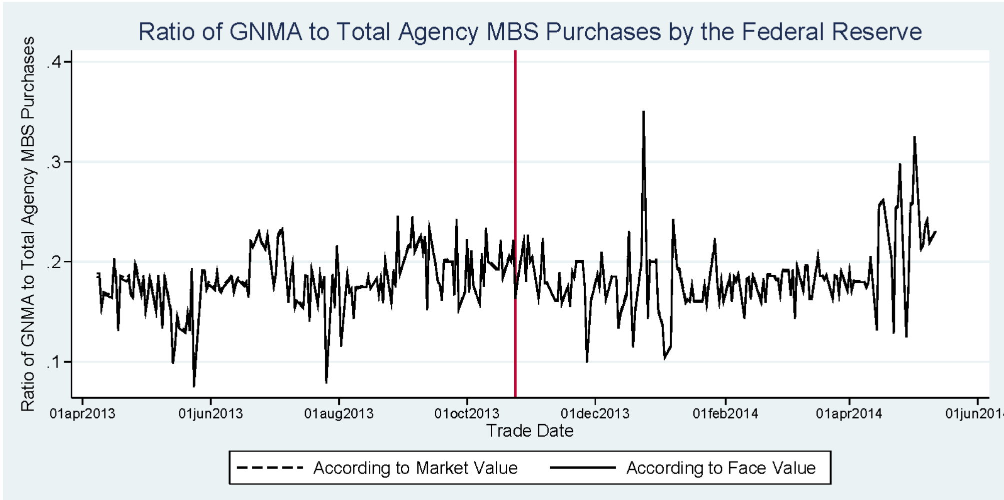


**Figure A4. Ginnie Mae Share of the Fed's MBS Purchases.** This figure plots the Ginnie Mae (GNMA) share of the Fed's MBS purchases. The vertical line corresponds to October 24th, 2013, when the LCR rules were proposed. Source: federalreserve.gov.

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: | $\text{Denial}_{i,l,t}$ | |
|---|---|---|
| $\text{Nonbank}_l \times \text{Premium}_t$ | -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) using Post-LCR as an instrument for the FNMA and FHLMC Spreads, which allows us to assess the scope for bias in our baseline analysis. Subscripts $i$, $l$, and $t$ index borrower, lender, and year, respectively. Each observation is a loan application. 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 2.

Table A3: 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 (1) 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. Each observation is a loan application. 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 remaining notation, sample period, and standard errors are the same as in Table 2.

Table A4: Robustness to Including Lender-Year Fixed Effects by Lender Funding Liquidity

| Outcome: | $\text{Denial}_{i,l,s,t}$ | | |
|---|---|---|---|
| $\text{Securitization Rate}_l \times \text{Premium}_t \times \text{FHA}_s$ | -0.019 | -0.012 | -0.011 |
| | (0.008) | (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 | 0.115 | 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), which allows us to test whether the baseline effect works through lenders' funding illiquidity and to include lender-year fixed effects. 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 sample consists of FHA and conforming non-FHA loan applications for the purchase of an owner-occupied single-family dwelling. The remaining notation, sample period, and standard errors are the same as in Table 4.

Table A5: Testing the Mechanism Over Another Non-Crisis Period, 2000-06

| Outcome: | Denial$_{i,l,t}$ | |
|---|---|---|
| Nonbank$_l$ × 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 (1) over the 2000-06 period, which assesses the baseline mechanism over another non-Crisis period. Subscripts $i$, $l$, and $t$ index borrower, lender, and year, respectively. Each observation is a loan application. The remaining notation and standard errors are the same as in Table 2.

Table A6: GNMA Premium and Nonbank Lending in the Conventional Market

| Outcome: | $\text{Denial}_{i,l,t}$ Period: 2010-15 | | | $\text{Denial}_{i,l,t}$ Period: 2000-06 | |
|---|---|---|---|---|---|
| $\text{Nonbank}_l \times \text{Premium}_t$ | 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 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. The remaining notation and standard errors are the same as in Table 2.

Table A7: Liquidity Coverage Ratio and the GNMA Premium

| Outcome: | $R_{t\to t+12}^{FNMA} - R_{t\to t+12}^{GNMA}$ | | | $\text{OAS}_t^{FNMA} - \text{OAS}_t^{GNMA}$ |
|---|---|---|---|---|
| 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 (A1). Subscript $t$ indexes month. $R_{t\to t+12}^{GNMA}$ is the change in log Bloomberg-Barclays Ginnie Mae (GNMA) Total Return Index from $t$ to $t$+12, multiplied by 100. $R_{t\to t+12}^{FNMA}$ 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. Each observation is a month. Standard errors are Newey-West with a lag of 4 months.