Evidence and Explanations for the Reversal of the Conditional Jumbo-Conforming Mortgage Rate Spread

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Datasets and code used in the creation of this paper are available upon request.

Abstract

During the Global Financial Crisis, the private-label mortgage-backed securities market collapsed, and the conditional jumbo-conforming mortgage rate spread, or the difference between the average jumbo mortgage rate and the average GSE-eligible conforming mortgage rate, after controlling for differences in loan characteristics, increased dramatically. The widening was consistent with the pre-crisis view that a positive conditional jumbo-conforming spread resulted from liquidity differences between the private-label and agency securitization markets. Movements in the conditional jumbo-conforming spread since the crisis are not consistent with that view. The first part of this paper estimates the conditional jumbo-conforming spread from 2004-2006 using a single regression equation and a decomposition method. The resulting estimates imply the conditional spread was around 20-30 basis points pre-crisis, rose to over 80 basis points during the crisis, and decreased to -20 basis points post-crisis, suggesting mortgage rates are now lower for jumbo borrowers than conforming borrowers, all else equal. The second part of this paper proposes three possible explanations for the reversal of the spread. First, GSE guarantee fees have increased around 40 basis points since the crisis. I use a diff-in-diff-in-diff estimator to show these increases pass through almost one-for-one to conforming mortgage rates, likely explaining the majority of the declining trend in the conditional spread. Second, I estimate 2 to 6 basis points of the decline in the spread owes to the rising share of conforming origination by nonbank mortgage companies, which typically offer higher loan rates than banks. Finally, the decline in relative jumbo prices, along with an increase in relative jumbo quantities, is consistent with an increase in jumbo supply. I account for this supply increase by describing why holding jumbo loans on balance sheet became more attractive to banks post-crisis.

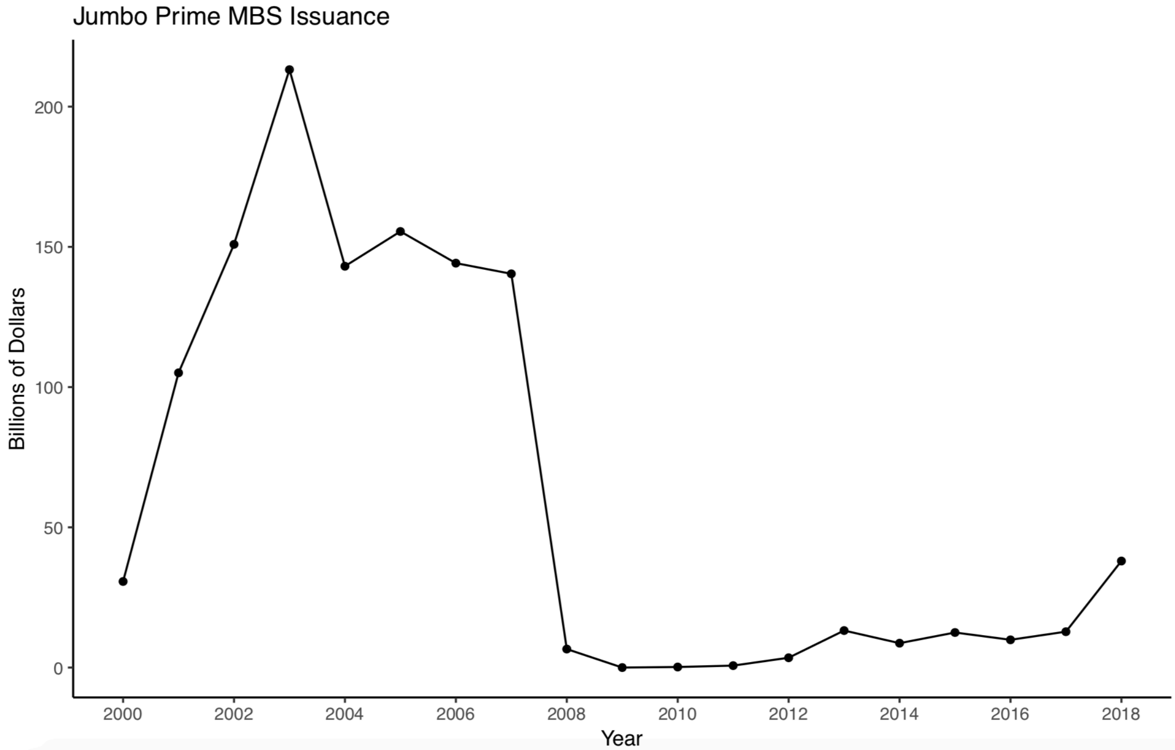
JEL codes: G12, G21

I. Introduction

At the onset of the Global Financial Crisis, significant losses on subprime mortgage-backed securities (MBS) crippled investor confidence in the private-label securitization market, and non-agency MBS issuance ground to a halt. This stall included jumbo MBS issuance, prompting a sharp decline in originations of high-balance loans that are ineligible for sale to the government-sponsored enterprises (GSEs). Moreover, the price of jumbo loans relative to the price of GSE-eligible conforming loans increased dramatically. Prior to the crisis, superior liquidity in the agency securitization market relative to the private-label securitization market was thought to explain why, for a given borrower, jumbo mortgage rates were higher than conforming mortgage rates. As the difference in liquidity between the agency and private-label securitization markets increased during the crisis, the difference between the average jumbo mortgage rate and the average conforming mortgage rate understandably increased as well.

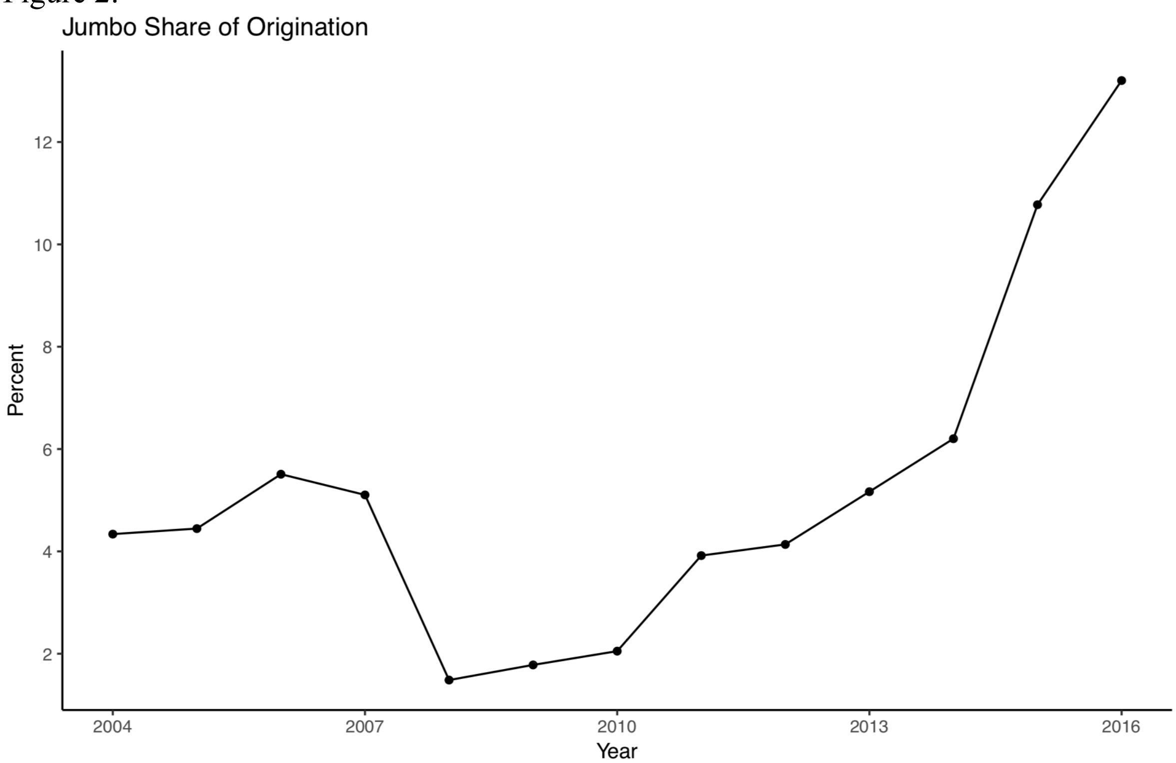
Though the jumbo MBS market has slowly restarted since its complete halt in 2009, issuance volumes leading up to the crisis dwarf issuance volumes since (Figure 1). Nevertheless, originations of jumbo loans picked up relatively quickly following the crisis and, in 2015, the proportion of jumbo origination relative to total mortgage origination exceeded pre-crisis levels (Figure 2). Jumbos now account for roughly 20 percent of total first-lien originations for major commercial banks (*Inside Mortgage Finance*). Furthermore, as the relative quantity of jumbo loans has increased, the relative price of jumbo loans has decreased since the crisis. The difference between the average jumbo mortgage rate and the average conforming rate, or the unconditional jumbo-conforming spread, decreased to zero basis points in 2012 before decreasing further to -40 basis points in 2016 (meaning jumbo loans are now cheaper for borrowers than conforming loans).

Figure 1:



Source: SIFMA

Figure 2:



Source: MIRS Data

The unconditional jumbo-conforming spread, however, does not control for differences in average loan characteristics between jumbo borrowers and conforming borrowers. For example, if jumbo borrowers have stronger credit characteristics than conforming borrowers, which is typical, then the unconditional jumbo-conforming spread is an underestimate of the spread that arises solely because jumbo loans are priced differently than conforming loans, or the conditional jumbo-conforming spread. Prior to the crisis, there was an extensive effort to estimate the conditional jumbo-conforming spread to quantify the impact of the relatively liquid agency securitization market on conforming mortgage rates. Overall this work suggests that, after controlling for various loan characteristics, conforming loans were roughly 20 basis points cheaper than jumbo loans through the 1990s to the mid-2000s. This estimate implies the GSE funding advantage is sizeable. Therefore, it is quite surprising that the unconditional jumbo-conforming spread is now negative, as the liquidity difference between the agency and private-label securitization markets is greater than the liquidity difference pre-crisis.

A natural question of interest is whether the unconditional jumbo-conforming spread reversal reflects increased credit standards for jumbo loans relative to conforming loans (changes in the difference in average loan characteristics), or rather whether jumbo loans are being priced more cheaply relative to conforming loans *for a given borrower* (changes in the conditional jumbo-conforming spread). In the first part of this paper, I estimate the conditional jumbo-conforming spread from 2004-2016 to answer this question using two methodologies. This paper concludes a decline in the conditional jumbo-conforming spread is the main driver of the downward trend in the unconditional jumbo-conforming spread. I estimate that the conditional jumbo-conforming spread is roughly -20 basis points at the end of my sample period in 2016.

The second part of this paper presents three possible explanations for the reversal of the conditional jumbo-conforming spread. First, the “guarantee fees” that originators pay when selling conforming loans to the GSEs, to compensate them for bearing the credit risk of the loans, have increased almost threefold over the past decade. These higher fees are passed through to conforming loan primary rates, boosting the average conforming mortgage rate relative to the average jumbo mortgage rate. Second, the share of conforming loan origination by nonbank mortgage companies has increased 30 percent since 2009, rising twice as fast as the share of jumbo loan origination by nonbank mortgage companies. Nonbank entities typically offer higher rates than banks because of their business model, and because they face higher funding costs, also boosting the average conforming mortgage rate relative to the average jumbo rate. Third, the increase in relative jumbo quantities, along with the decrease in relative jumbo prices, implies that the supply of jumbo loans has increased. A supply increase suggests that lenders have been relatively more willing to lend to jumbo borrowers despite the lack of a robust jumbo securitization market. Banks’ strong desire to hold jumbo loans on their balance sheets post-crisis, because of their strong credit quality and relatively favorable capital treatment, supports an increase in the relative supply of jumbo loans that lowered their relative price.

The remainder of the paper is organized as follows. Section II provides an overview of the mortgage market, and Section III reviews the literature on estimating the conditional jumbo-conforming spread. Sections IV and V describe the data and methodology I use for this exercise, respectively. Section VI presents the results, and Section VII discusses the three possible explanations for the reversal of the conditional jumbo-conforming spread in more detail. The final section concludes.

II. Overview of the Mortgage Market

The mortgage market plays an impactful role in ordinary Americans' lives, is sensitive to a variety of policy changes, and has a highly segmented and developed secondary market. At the end of 2016, mortgage debt outstanding for one-to-four family residences totaled over $10 trillion ("Mortgage Debt Outstanding", Federal Reserve Board). Annual first-lien originations exceeded $2 trillion in 2016 (Bai et al, 2018). Depository institutions and nonbank mortgage companies originate the vast majority of mortgages post-crisis, though thrifts and credit unions each comprise a small share of total mortgage origination (HMDA data). The price of mortgage loans is affected by the type of mortgage, the borrower's credit score, the loan-to-value (LTV) ratio, and the borrower's debt-to-income ratio, among other factors. For a given loan price, the borrower can elect to pay higher closing fees (often referred to as points) at origination to lower the mortgage rate on the loan. In other words, there are many possible rate/point combinations that yield identical effective mortgage rates. After origination, mortgage loans can be held in portfolio or sold into the secondary market and securitized into mortgage-backed securities. Loans that meet certain criteria (conforming loans) are eligible for sale to Fannie Mae and Freddie Mac (known collectively as the government-sponsored enterprises, or GSEs).[1]

Congress established the GSEs in 1932 to promote homeownership, in part by facilitating capital flows to mortgage lenders through the creation of a liquid secondary market for conforming loans. Conforming loans must be of sufficiently high credit quality and, crucially, cannot exceed the conforming loan limit established by the Federal Housing Finance Agency (FHFA). Such loans can be packaged and sold as mortgage-backed securities guaranteed by the GSEs (agency MBS), meaning investors take on only the interest rate risk from borrower

[1] Ginnie Mae and the Federal Home Loan Banks are also government agencies. Ginnie Mae is similar to Fannie Mae and Freddie Mac, with notable differences. Loans securitized through the Ginnie Mae platform are backed by government agencies like the Federal Housing Administration. A more detailed discussion of the differences can be found in Kim et al (2018). Going forward, I will refer to Fannie Mae and Freddie Mac as the GSEs for simplicity.

prepayment and not the credit risk from borrower default. Lenders compensate the GSEs for bearing the credit risk through a guarantee fee (g-fee) both at the time of transaction and during the life of the loan; this fee has varied over time. The demand for agency mortgage-backed securities makes it cheaper and thus more profitable for lenders to originate conforming loans. A commercial bank, for example, does not have to rely on short-term deposits on the liabilities side of its balance sheet to fund these long-term assets, when it can instead sell them after origination, essentially replacing deposits with bonds (or funds from capital markets) as a source of finance.

Jumbo loans, or loans with a loan amount exceeding the conforming loan limit, are not eligible for GSE securitization. Though they can still be securitized and sold in the private-label secondary market, there is less demand and therefore less liquidity for non-agency products, because the credit risk is not insured by the government. Furthermore, there is far greater liquidity risk, the notion of *changes* in liquidity, in the private-label market relative to the agency market. During the crisis, agency MBS issuance remained robust, while the private-label secondary market collapsed (SIFMA). As jumbo MBS issuance ground to a halt, lenders significantly pulled back from the jumbo business (Figures 1 and 2). Calem, Covus, and Wu (2013) document the collapse of the private-label market and underscore the significance of the secondary market on the primary market, showing that banks more dependent on the private-label MBS market pulled back relatively more from jumbo originations than well-capitalized banks. They conclude the “drop in jumbo lending subsequent to the shutdown of the private-label residential MBS market was in large measure a consequence of loss of access to secondary market funds, and not simply a reaction to worsening perceptions of mortgage credit risk” (p. 89). This analysis builds on work by Loutskina and Strahan (2009) that shows the volume of jumbo originations by commercial banks increases with liquid assets and decreases with bank deposit costs, while the volume of conforming loan originations does not.

Given the relevance of secondary market liquidity for the volume of mortgage originations, in the midst of the housing market deterioration during the crisis, conforming loan limits were raised substantially for certain “high-cost areas” (from $417,000 to a maximum of $729,750), with the passage of the Economic Stimulus Act (ESA) in February of 2008 (Vickery and Wright, 2013, p. 10). These increases were initially temporary, extending through the remainder of 2008, and designed to enable the GSEs to support the jumbo market by providing secondary market liquidity after the collapse of the private-label secondary market. Mortgages with loan amounts greater than the national conforming loan limit, but still eligible for sale to the GSEs under the high-cost limits, are referred to as “superconforming” loans.

Although the temporary high-cost area conforming loan limit increases were announced in February, the GSE funding advantage likely applied to superconforming loans only after May 2008 (Vickery and Wright, 2013, p. 10-12). There are many different agency securities backed by conforming loans, ranging from simple pass-through securities (known as “TBA”, or To Be Announced) to complex derivatives, like Collateralized Mortgage Obligations (CMOs), that strip off the interest and principal cash flows to cater to different investor risk profiles. The liquidity in the agency MBS market is in the TBA market. A TBA trade is a forward contract where the counterparties agree on various characteristics of the loans to be delivered to the pool (such as the issuer, maturity, coupon, price, par amount, and settlement date), but not the actual identity (or the specific CUSIPs) of the securities (Vickery and Wright, 2013, p. 5). “Specified pool” trading makes up a much smaller portion of the agency MBS trading volume than TBA trading. In the specified pool market, the identity of the specific securities is known at the time of transaction. Specified pools typically trade at a premium to TBAs because the loans backing them have more favorable prepayment characteristics from an investor's point of view (meaning they are less likely to prepay). However, such securities are much less liquid than TBAs.

Therefore, from a funding standpoint, pricing for superconforming loans in the primary market is crucially dependent on their TBA eligibility. Directly following the announcement that the Economics Stimulus Act was expanding conforming loan limits for high-cost areas in mid-February of 2008, the Securities Industry and Financial Markets Association (SIFMA) announced these superconforming loans would not be eligible for TBA trading, and could only be traded as specified pools. To support the superconforming market, Fannie Mae announced in May that it would purchase pools of superconforming loans at a price on par with TBA-eligible pools through the remainder of 2008, which encouraged more superconforming specified pool issuance over the summer. The primary mortgage rates of the underlying superconforming loans backing these specified pools began to converge to primary mortgage rates for standard conforming loans as a result (Vickery and Wright, 2013, p. 14).

Elevated high-cost area conforming loan limits were renewed at the beginning of 2009 under the Housing and Economic Recovery Act (HERA), though lowered to a maximum of $625,000. Furthermore, SIFMA announced in the fall of 2008 that superconforming loans would be eligible to comprise up to 10 percent of a TBA pool, for superconforming loans originated on or after October 1, 2008, but only for TBAs settling from January 1, 2009, onward. Through various pieces of legislation since the HERA, superconforming limits continued to be extended, and high-cost limits are now annually reviewed and adjusted along with the national conforming loan limit. SIFMA's *de minimis* limit for superconforming loans continues to remain in effect.

Therefore, the GSE funding advantage for superconforming loans should be comparable to that of standard conforming loans from May 2008 on, so long as the 10 percent limit does not bind.

III. Literature Review

There is an extensive pre-crisis literature on estimating the conditional jumbo-conforming spread. Hendershott and Shilling (1989) provides an initial framework for this analysis, estimating the spread as a function of the loan-to-value ratio, the loan size, and whether the loan amount is far above, just above, or below the conforming loan limit. The inclusion of the latter predictor arises from endogeneity concerns: borrowers that take out more expensive mortgages right above the conforming limit might display negative credit characteristics, the implication being they are unable to modestly reduce their loan size to secure a lower mortgage rate.[2]

There are various competing methodologies refining this basic construction. Though the vast majority of these studies use the FHFA's Monthly Interest Rate Survey data, Ambrose, LaCour-Little, and Sanders (2004) uses an alternative dataset obtained from a large national lender because it includes the borrower's FICO score, as well as borrower age and income, allowing for better control of loan risk. They obtain an estimate of 27.7 basis points for the jumbo-conforming spread from 1995 to 1997, attributing 9 basis points to GSE conforming loan underwriting guidelines, 4 basis points to differences in property price volatility, and 15 basis points to the conforming loan limit. This results in a volatility-adjusted conditional spread of approximately 24 basis points. The authors conclude that the GSEs pass through between 50 and 95 percent of their debt funding advantage to borrowers in the conforming loan market in the form of lower interest rates. McKenzie (2002) estimates a comparable spread of 22 basis points over a longer time period, from 1986-2000, with regional controls. His results also suggest that

[2] This logic, of course, assumes that conforming loan rates are lower than jumbo loan rates. If the reverse were true, borrowers would be incentivized to take out larger loans to secure a lower mortgage rate.

loan-to-value (LTV) ratios affect jumbo loan rates more than non-jumbo loan rates. Blinder, Flannery, and Lockhart (2006) includes interaction terms as well as capital market controls in its regressions, obtaining an estimate of 25 basis points for the jumbo-conforming spread from April 1997 to May 2003, better capturing the latter observation from McKenzie. After estimating a number of model specifications with the single regression equation framework, they group the loans by loan size and employ a decomposition method to isolate the pricing difference between loans that are 80-100 percent of the conforming loan limit and loans that are right above-120 percent of the conforming loan limit. They pool all loans over time, however, thus obtaining only one estimate of the spread over their sample period. Consequently, no analysis of the changes in the conditional jumbo-conforming spread over time can be performed.

Passmore, Sherlund, and Burgess (2005) derives a theoretical model for the conditional jumbo-conforming spread, arguing the spread should widen when mortgage demand is high or when core deposits are not sufficient to fund mortgage demand, and tighten as the mortgage market becomes more liquid. They control for a variety of factors that theoretically influence the spread: cost of funding, credit risk, prepayment risk, and maturity mismatch, to isolate the effect of the GSEs, concluding the GSE funding advantage accounts for 7 basis points of the 15-18 basis point jumbo-conforming spread. It is worth noting that a variety of econometric concerns have been raised regarding their regressions to obtain this estimate, which rely on the estimated spread as the dependent variable. Sherlund (2008) constructs a rich dataset by appending indicators for various state-level foreclosure law regimes and ZIP-code-level demographic information to the MIRS dataset. The latter entails merging demographic information for each ZIP code with the ZIP code corresponding with each loan’s origination location. Using local linear regression and controlling for unobserved borrower and market characteristics through geographic location, he constructs a time series of spread estimates over his sample period from January 1993 to June 2007, which allows for analysis of movements in the spread over time. His estimates range from 13 to 24 basis points. This extensive literature on formally estimating the conditional jumbo-conforming spread is confined to pre-crisis sample periods.

During the crisis, Vickery and Wright (2013) and Fuster and Vickery (2015) underscore the increase in the unconditional spread after August 2007, the month that BNP Paribas suspended convertibility for two hedge funds, which is typically defined as the onset of the private-label MBS market freeze. The conditional spread is not estimated, however.

Since the crisis, two studies have implied that the conditional jumbo-conforming spread turned negative around 2013. Di Maggio, Kermani, and Palmer (2016) estimates the effect of large-scale asset purchases on both interest rates and refinancing volumes, using Equifax's Credit Risk Insight Servicing McDash dataset. To quantify the effect of quantitative easing on mortgage rates, they estimate conditional monthly mortgage rates for loans above and below the conforming loan limit separately, controlling for the borrower's FICO credit score and LTV ratio. The estimated conditional monthly mortgage rate for loans above the conforming loan limit is consistently higher than that for loans below the conforming loan limit from January 2008 to December 2012. At the beginning of 2013, however, the conditional rate for loans below the conforming loan limit coincides and then exceeds the conditional rate for loans above the conforming loan limit for the remainder of the year. The sample is restricted to refinance loans and the conditional jumbo-conforming spread is not carefully estimated. Furthermore, many relevant controls are omitted. Nonetheless, this work is supportive of the claim that the conditional jumbo-conforming spread approached zero before turning negative around early 2013, even after directly controlling for the borrower's FICO score and LTV ratio.

The second study is a CoreLogic Insights Blog post (Pradhan, 2018). The author first notes that the unconditional jumbo-conforming spread has turned negative over recent years. The conditional spread is then estimated from Q1 2001 to Q2 2018 using internal CoreLogic loan-level mortgage data. A single regression framework is employed and loan size, credit score, LTV ratio, DTI ratio, and geographic location are used as controls. The estimated conditional spread is negative from Q1 2013 to Q2 2018, ranging from -5 basis points to -15 basis points. There are serious concerns with this estimation, however. The most problematic is that the mortgage rate, as opposed to the effective mortgage rate, is used as the dependent variable, and points are not controlled for to compensate for this shortcoming. This is highly misleading. The contract mortgage rate and the effective mortgage rate can differ by more than 50 basis points. A jumbo-conforming spread could arise simply because certain types of borrowers are more likely to pay points up front, which is completely unrelated to the relative pricing between the two groups of loans. Furthermore, many observations from the pre-crisis literature are not accounted for, such as the observation that LTV ratios affect jumbo loan rates more than non-jumbo loan rates.

This paper is the first to formally estimate the conditional jumbo-conforming spread since the onset of the crisis using methodologies from the pre-crisis literature. It is also the first to emphasize the reversal of the conditional jumbo-conforming spread and provide possible explanations to account for the reversal.

IV. Data

a. Monthly Interest Rate Survey Data

This paper uses the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS) data from 2004 to 2016 to estimate the conditional jumbo-conforming spread annually.

The data include conventional,[3] fully amortizing, single-family, non-farm, purchase-money loans closed during the last five business days of the month. FHA-insured and VA-guaranteed loans, multifamily loans, mobile home loans, and loans created by refinancing another mortgage are excluded. The loan-level information collected includes the effective mortgage rate, loan amount, home sales price, mortgage term, mortgage type (adjustable or fixed), year of mortgage,[4] lender type (mortgage company, commercial bank, or thrift), and FIPS CBSA code.[5] It does not include, however, the borrower's FICO score, a standard indicator of credit quality. Therefore, the MIRS data cannot categorically identify a loan as conforming, as conforming criteria include high credit quality and underwriting standards, in addition to a minimum loan amount. Instead, the data allow differentiation between jumbo and non-jumbo loans. This paper, however, follows the literature in taking the liberty of referring to the controlled difference between the average jumbo loan rate and the average non-jumbo loan rate as the conditional jumbo-conforming spread. [6]

I append CBSA-code-level demographic information from the Census Bureau's 2012-2016 American Community Survey 5-year estimates for the entire sample period. Demographic information includes urban/suburban/rural indicators, race, age, education, median income, and median home value for each CBSA (Table 1). Average CBSA demographic information should be correlated with the credit characteristics of borrowers in the CBSA, and can thus serve as a

[3] Conventional loans exclude loans backed by government agencies.
[4] Of course, the Monthly Interest Rate Survey is collected monthly. However, the FHFA's user agreement only allows the year to be shared publicly given identification concerns.
[5] From the United States Census Bureau, Core Based Statistical Areas (CBSAs) consist of the county or counties or equivalent entities associated with at least one core (urbanized area or urban cluster). The general concept of a CBSA is that of a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core.
[6] This means that I may capture some non-conforming mortgages in my conforming mortgage group. As a result, my estimates of the conditional spread might be conservative, as the inclusion of non-conforming loans slightly blurs the distinction between the two loan groups. Furthermore, assuming the impact of non-jumbo non-conforming mortgages remains roughly constant over time, their inclusion should not affect the trend of the estimated spread.

credit control. Furthermore, state foreclosure laws affect severity rates in the event the borrower defaults, and thus affect the profitability of lending and the effective mortgage rate as well. Therefore, I also include two foreclosure law variables, which indicate whether a state requires the lender to proceed through the courts to foreclose on a property ("judicial flag") or allows creditors to collect a deficiency judgment equal to the lender's foreclosure losses against the borrower's other assets ("deficiency flag") (Pence, 2006 and U.S. Foreclosure Laws).

I follow widely used practices in the literature when filtering the data. This includes restricting attention to 30-year fixed-rate mortgages with LTV ratios between 20 and 100 percent, excluding mortgages smaller than one-eighth of the conforming loan limit, excluding mortgages with missing or invalid CBSA codes, and excluding mortgages originated in Alaska and Hawaii, as the Federal Housing Finance Agency (FHFA) applies special statutory provisions to loans in these states. To address the concern raised by Hendershott and Shilling (1989) and McKenzie (2002) regarding the unusual behavior of jumbo loans that exceed the conforming loan limit by a small amount, I follow the approach taken by Blinder, Flannery, and Lockhart (2006), and exclude jumbo loans whose principal amount lies below the following year's conforming loan limit. This ensures against two possible biases: originators could wait to sell such loans to the GSEs until the following year when they fall under the new conforming loan limit (which should reduce their rates if conforming status is valuable) or borrowers unable to modestly reduce their loan size to secure a lower mortgage rate may display negative credit characteristics (which should raise their rates if conforming status is valuable).[7] In totality, these data filters result in a sample size of 925,200 loans.

[7] Results are not sensitive to these specifications. Specifically, removing jumbo loans with loan amounts less than the following year's conforming loan limit only removes 0.35 percent of the sample. I take into account county specific conforming loan limits when employing this filter.

In regards to differentiating between jumbo and non-jumbo loans, the MIRS data include a jumbo indicator variable, denoting whether the loan amount is above the national conforming loan limit. This does not take into account high-cost area conforming loan limits, however. To create an accurate jumbo loan indicator that reflects the geographic heterogeneity in conforming loan limits from 2008 onward, I obtain conforming loan limits for each CBSA region annually from 2008-2016 from the FHFA's historical records. I then merge with the MIRS data on both year and CBSA code. A loan is classified as jumbo if the loan amount exceeds the conforming loan limit in its region the year it was originated, and superconforming if the loan amount is below the conforming loan limit in its region, but greater than the national conforming loan limit the year it was originated.

This is straightforward for 2009-2016. 2008 poses more of a challenge as the MIRS data include only the year of origination and not the month, and the GSE funding advantage from TBA eligibility applied to superconforming loans only after May 2008. Therefore, I define the conforming loan limits for 2008 as an average of the national conforming loan limit and the regional conforming loan limit, reflecting the funding status change roughly halfway through the year. I recognize this is imperfect, but should reasonably categorize the loans correctly on average, given the large sample size. Regardless, this paper is focused on explaining the trend of the spread after the crisis, so any bias in the 2008 spread estimate does not significantly affect the paper's analysis. I decide to group the sample into three different categories (conforming, superconforming, and jumbo), as opposed to classifying the superconforming and conforming loans together as one agency-eligible group, given SIFMA's sustained *de minimis* limit.

Finally, the lender type variable in the MIRS data becomes misleading beginning in 2010. Commercial banks began routing their mortgage originations through nonbank mortgage company subsidiaries with the passage of the Dodd-Frank Act, and thus their loans are reported under the mortgage company lender type after this time. This conflates the two lender types. To underscore the difficulty this imposes, there is no commercial bank jumbo origination from 2014-2016 according to the lender type variable in the MIRS data, despite commercial banking organizations originating the vast majority of jumbo loans. The Home Mortgage Disclosure Act data, described below, is used to circumvent this reporting issue.

Table 2 shows summary statistics for the relevant variables in the MIRS dataset. In addition to the effective mortgage rate and jumbo flag, the following variables are included in the table. **X** specifies a vector of controls.

LTV is a categorical variable with four levels: (0, 75], (75, 80], (80, 90], (90, 100].

X includes the following features:

- Lender type (factor)
    - Mortgage company, commercial bank, thrift
- Fees percentage
    - Controls for any biases in the effective mortgage rate from amortization of fees
- Log loan size
    - Captures economies of scale in loan origination or servicing
- State-level foreclosure law indicators
    - Judicial flag
    - Deficiency flag
- CBSA-level demographic variables
    - Urban percentage
    - Rural percentage
    - Black percentage
    - Asian percentage
    - Log median age
    - Old age dependency ratio
    - Child dependency ratio

  - High school or more percentage
  - Bachelors degree or more percentage
  - Log median earnings
  - Log median home value
  - Marriage percentage
- State for geographic control

b. Home Mortgage Disclosure Act Data

This paper uses loan-level information from the Home Mortgage Disclosure Act (HMDA) dataset from 2009-2017 to analyze shares of mortgage origination by lender type. The Home Mortgage Disclosure Act requires financial institutions to maintain, report, and publicly disclose loan-level information about mortgages. While the MIRS data include the effective mortgage rate of the loan while the HMDA data do not, the HMDA data are far broader, covering 92-95 percent of the mortgage market. All regulated financial institutions with assets above $30 million are required to report every purchased mortgage loan, loan application, and loan origination in a given year, not just a sample. Furthermore, the HMDA data include a 10-digit respondent ID identifying the lender for each loan.

To mimic the types of loans included in the MIRS data, I restrict the sample to conventional, single-family, purchase loans that are owner-occupied. I then merge with the annual geographic conforming loan limits set by the FHFA by both county code and state code to account for high-cost area conforming loan limits. A loan is flagged as “jumbo” if the loan amount exceeds the conforming loan limit in its geographic region. I then sum the total number of jumbo and conforming originations for each unique respondent in the data each year. With the help of the FHFA’s mapping file,[8] the respondent IDs in the HMDA data can be matched to an

[8] Special thanks to Robert Avery, Project Director of National Mortgage Database at the FHFA, for compiling this file and allowing it to be used publicly.

accurate characterization of the type of institution, based on the nature of the filer and from a match to the NIC structure database.

Table 3 shows summary statistics for the relevant variables in the HMDA dataset.

V. Methodology

a. Single Regression Equation

I first estimate the conditional jumbo-conforming spread with a single regression equation using the MIRS data, drawing on the framework of Hendershott and Shilling (1989). I include an interaction term between the jumbo flag and LTV indicator variables, as McKenzie (2002) and Blinder, Flannery, and Lockhart (2006) suggest jumbo loans rates are more sensitive to LTV than conforming loan rates (this is confirmed in the results). I include the CBSA-level demographic variables to control for credit characteristics and include state dummies to control for unobserved borrower and market characteristics that may vary geographically (Sherlund 2008). I run the following regression for the effective mortgage rate for each year in my sample period from 2004-2016. A weighted OLS regression model is used – each observation is weighted by its sample weight provided in the MIRS data. The parameter of interest is α_1.

(1)

$$ER_i = \alpha_0 + \alpha_1 J_i + \boldsymbol{\alpha_2 LTV_i} + \boldsymbol{\alpha_3} J_i \times \boldsymbol{LTV_i} + \boldsymbol{\alpha_4 X_i} + \epsilon_i$$

b. Decomposition Method

Second, I employ a decomposition method by running annual weighted linear regressions for jumbo mortgages and conforming mortgages separately, using the same controls previously specified, **X**. This method is a more flexible variation of the single regression equation method; by running the regressions for jumbo mortgages and conforming mortgages separately, I am allowing the coefficients on all predictors to differ between the two groups of loans, not just the intercept and LTV coefficients. It is comparable to running the single regression equation with interaction terms between the jumbo flag and all of the predictors. This is an extension of the final methodology used in Blinder, Flannery, and Lockhart (2006).

(2)

$$ER_i^c = \alpha_0 + \boldsymbol{\alpha_1} \boldsymbol{LTV_i^c} + \boldsymbol{\alpha_2} \boldsymbol{X_i^c} + \epsilon_i^c$$

$$ER_i^j = \beta_0 + \boldsymbol{\beta_1} \boldsymbol{LTV_i^j} + \boldsymbol{\beta_2} \boldsymbol{X_i^j} + \epsilon_i^j$$

This can be rewritten as the following, where **W** is [1, **LTV**, **X**]', **A** is $[\alpha_0, \boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}]$, and **B** is $[\beta_0, \boldsymbol{\beta_1}, \boldsymbol{\beta_2}]$.

(3)

$$ER_i^c = \boldsymbol{AW_i^c} + \epsilon_i^c$$

$$ER_i^j = \boldsymbol{BW_i^j} + \epsilon_i^j$$

Using lower case letters to represent means and estimated coefficients, the expected value of the former equation can be subtracted from the latter.

(4)

$$er_i^j - er_i^c = \boldsymbol{bw_i^j} - \boldsymbol{aw_i^c} = \boldsymbol{a}\left(\boldsymbol{w_i^j} - \boldsymbol{w_i^c}\right) + (\boldsymbol{b} - \boldsymbol{a})\boldsymbol{w_i^j}$$

The first term captures the impact of differences in typical loan characteristics between jumbo and conforming loans, evaluated using the conforming loan regression coefficients. The second term measures the spread that arises solely because jumbo loans are priced differently – that is, the difference in the regression coefficients evaluated using the average characteristics of jumbo loans. The second term is the estimate of interest.[9]

[9] Means are weighted by the sample weights just as the regressions are weighted.

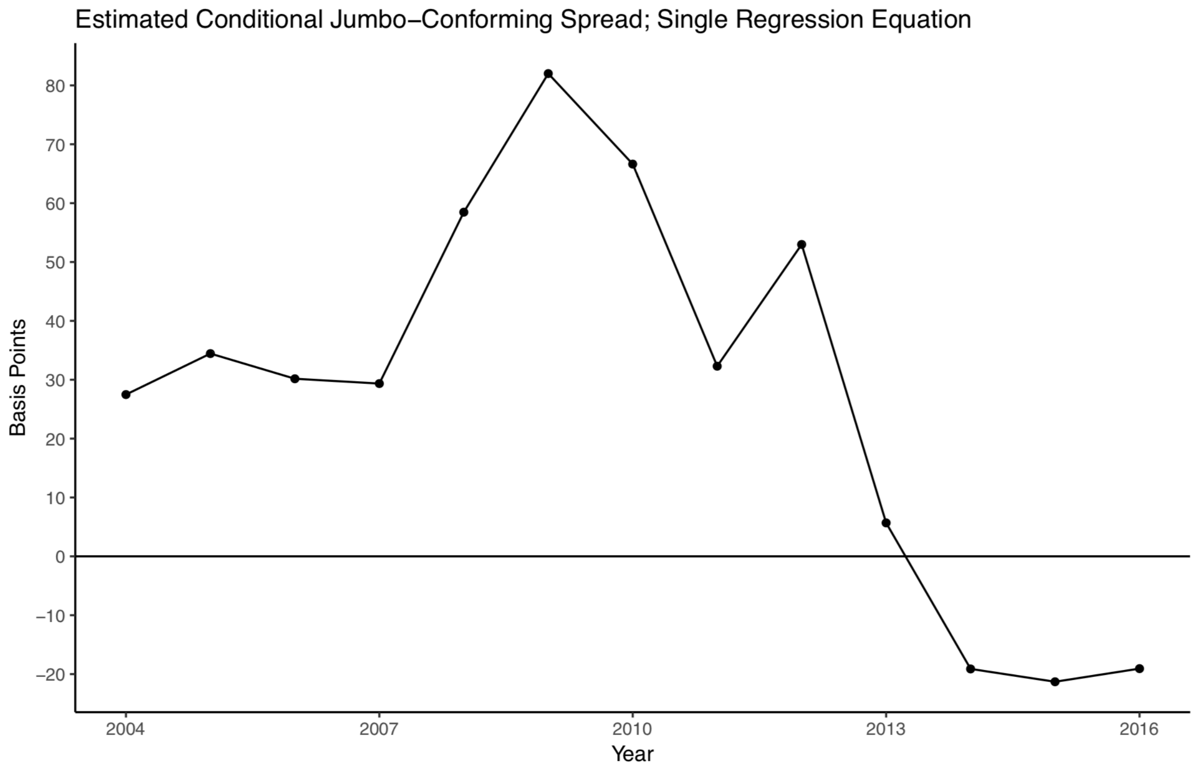
VI. Results

a. Single Regression Equation

The annual regression results from equation (1) are shown in Table 4. The highlighted coefficients on the jumbo flag are the estimates of interest and are plotted in Figure 3. The estimated coefficients on the jumbo flag match the estimated coefficients in the literature very closely pre-crisis. During the crisis, the jumbo-conforming spread estimate increases significantly with the collapse of the private-label MBS market in 2008, and then declines to nearly zero in 2013. The estimated spread turns negative in 2014, and remains around -20 basis points for the remainder of the sample period. Thus after controlling for a host of loan characteristics, jumbo effective mortgage rates are lower than conforming effective mortgage rates over the last three years of the sample period. The same trend is depicted much more subtly with the superconforming-conforming spread, which also converges towards zero until 2013, before turning slightly negative. This likely reflects the increased tendency of originators to sell superconforming loans into the private-label secondary market as opposed to the GSEs, as discussed in Section VII (a). Nonetheless, the pricing of superconforming loans closely matches the pricing of conforming loans from 2009-2016, as the FHFA desired when setting different limits for high-cost areas. All estimated spread coefficients are significant at the 1 percent level.

Turning briefly to the coefficients on the control variables, though the coefficients on the LTV variables do not always increase monotonically, as they do for example in 2015, there is a general tendency of higher rates for higher LTVs. Blinder, Flannery, and Lockhart (2006), Sherlund (2007), and others also find that the increase is not perfectly monotonic. There are a couple of possible explanations – first, with private mortgage insurance required on conforming loans with LTVs greater than 80, the loss given default (or the severity rate) tends to be lower for

Figure 3:



high LTV conforming loans. Second, the GSEs have eligibility matrices to value a borrower's creditworthiness when determining conforming eligibility; borrowers can have higher LTVs if they also have higher credit scores, a variable I cannot directly employ as a control. As far as the jumbo/LTV interaction terms, the results are consistent with the observation in the literature that the rate of increase in the mortgage rate with increases in LTV is greater for jumbo loans, presumably reflecting the greater risk borne by the lender on such loans.

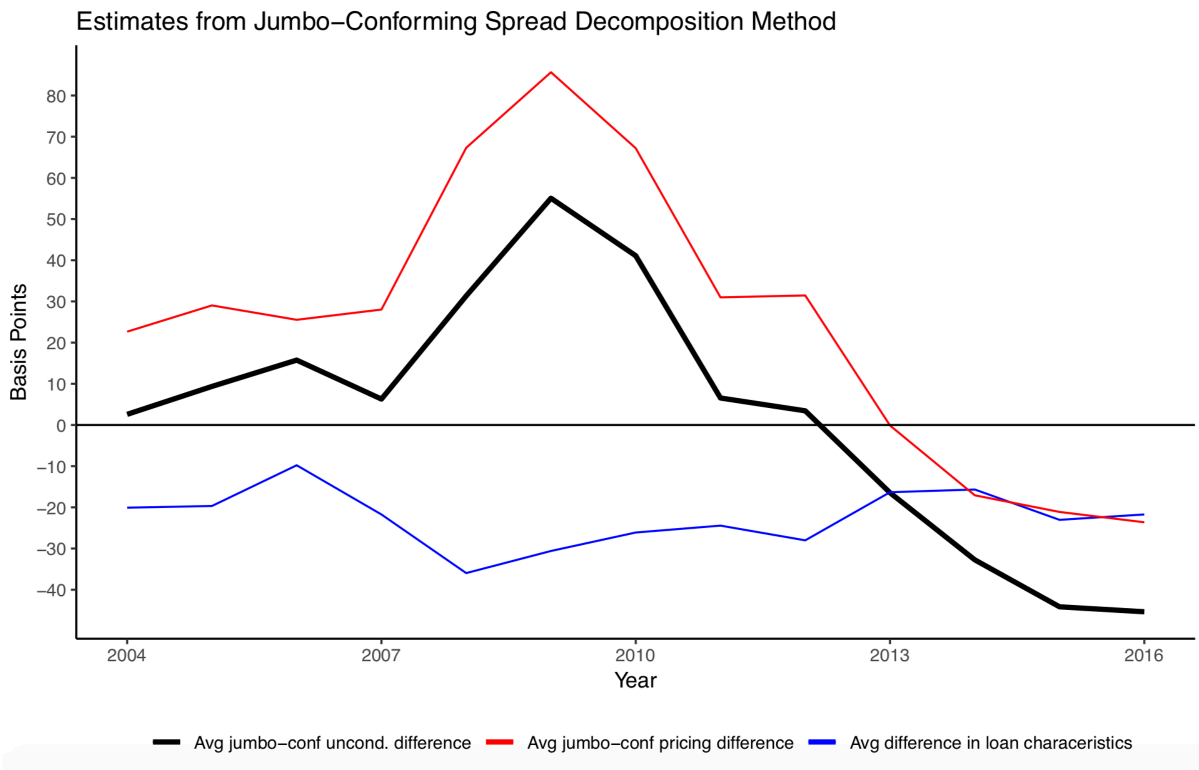
The coefficients on the fees variable are uniformly positive and significant, as expected, just as the coefficients on the loan amount variable are uniformly negative and significant. For the lender type indicators, from 2004-2009, the coefficients on the commercial bank dummy are uniformly negative and significant, suggesting that bank loan rates were lower on average than mortgage company loan rates all else equal. This observation is widely acknowledged and will be used in Section VII (b). Conversely, the coefficients on the thrift dummy are overwhelmingly positive and significant from 2004-2009, suggesting that thrift loan rates were higher on average than mortgage company loan rates all else equal. From 2010 on, the coefficients on the lender type indicators become deceptive, due to mortgages originated by commercial banking institutions being reported under the mortgage company lender type. This explains why the bank indicator coefficients are not uniformly negative throughout the rest of the sample period.

The R-squared values range from 12 percent to 39 percent, meaning the model explains less than half of the variation in effective mortgage rates for a given year. This is unsurprising and not too concerning, however, as naturally the key explanatory variable of heterogeneity in annual mortgage rates is interest rates (mortgage rates most closely track the 7-year Treasury yield). Given that the data are annual, controlling for monthly changes in interest rates is not feasible, and thus the model is going to have limited overall explanatory power for a given year. Studies that employ similar methodologies and estimate the spread for a given time period obtain similar R-squared values around 12 percent; those that estimate a single spread across time and thus include interest rate and other market controls obtain R-squared values far higher, around 80 percent. Given the interest in the pricing difference between jumbo and conforming loans, and the reasonable assumption that the monthly distribution of origination dates between the two groups is roughly comparable, these values are not particularly relevant to the analysis.

b. Decomposition Method

The results of the decomposition method, in which the regressions on the effective mortgage rate are run separately for jumbo and conforming loans, are shown in Figure 4. The black line represents the unconditional difference between the weighted average jumbo effective mortgage rate and the weighted average conforming effective mortgage rate for each year. This

Figure 4:



difference is decomposed into the conditional jumbo-conforming spread, the red line, and the impact of differences in typical loan characteristics between jumbo and conforming loans, the blue line. At the beginning of the sample period, the unconditional difference is around zero. On average, however, jumbo borrowers had superior loan characteristics that would result in a 20 basis point lower rate if jumbo and conforming loans were priced identically. Therefore, the estimate for the difference in loan characteristics is -20 basis points. The estimation thus concludes that, for a given borrower, the conditional spread between average jumbo and conforming mortgage rates, or the spread that arises because jumbos are priced differently, was around 20 basis points in 2004, offsetting the impact of superior jumbo loan characteristics.

The estimates for the conditional jumbo-conforming spread match closely with the estimates obtained from the single regression method. After dramatically increasing to over 80 basis points during the crisis, the spread declines to around zero in 2013, and then declines further, turning negative for the last three years of the sample period. Focusing on the beginning and end of the sample period, the estimated conditional jumbo-conforming spread decreases from 23 basis points in 2004 to -24 basis points in 2016. Turning to the impact of differences in typical loan characteristics, the estimate increases towards zero prior to the crisis, meaning the average loan characteristics between jumbo and conforming loans became more comparable, before decreasing quite sharply during the crisis, from -10 basis points in 2006 to -36 basis points in 2008. Attributing these fluctuations to supply-side factors, the decrease in the average difference in loan characteristics estimate is consistent with the prevailing notion that underwriting standards tightened significantly during the crisis, especially for non-conforming loans, as banks would only lend to the most pristine borrowers. In other words, it became much more difficult to obtain a jumbo loan.

Nonetheless, tightening underwriting standards do not explain the movements in the conditional jumbo-conforming spread, which are overwhelmingly driving the movements in the unconditional jumbo-conforming spread. Given the pre-crisis view that conforming loan rates are lower than jumbo loan rates because of superior liquidity in the secondary market, the recent negative spread, along with its sizeable magnitude of roughly 20 basis points, is rather remarkable, all the more so when taking into account that the difference between liquidity in the agency and private-label securitization markets is far greater post-crisis than it was pre-crisis. The secondary market liquidity difference clearly matters – the spread blew up when liquidity in the private-label market first dried up. Naturally, one wonders what could explain the recent preferential pricing of jumbo loans for a given borrower. The remainder of this paper explores this question and proposes three possible explanations.

VII. Possible Explanations

The three possible explanations include the increase in GSE guarantee fees, the increase in the nonbank mortgage company share of conforming origination, and the increase in banks' demand for jumbo mortgages.

a. The increase in GSE guarantee fees

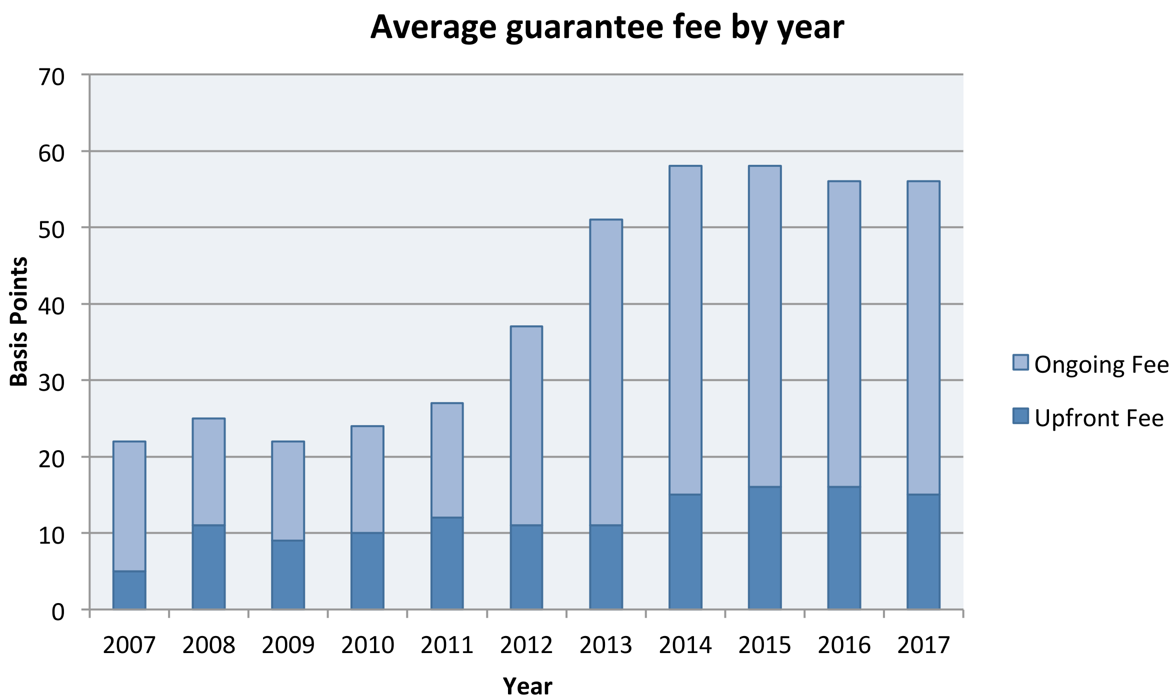
The first explanation for the reversal of the conditional jumbo-conforming spread, which suggests conforming loans are relatively expensive for borrowers as opposed to jumbo loans being relatively cheap, is the rise of government-sponsored enterprise guarantee fees (g-fees). The GSEs incur costs when they acquire single-family loans from lenders, whether delivering cash payment in return for a pool of loans, as is typical for small lenders, or an agency mortgage-backed security, as is typical for large lenders. These costs include overhead expenses and residual risks (the non-credit costs), as well as covering the credit risk of the borrowers (the credit costs). The lenders must compensate the GSEs for assuming the credit risk through an insurance premium. According to the FHFA, the g-fee "covers administrative costs, projected credit losses from borrower defaults over the life of the loans, and the cost of holding capital to protect against projected losses that could occur during stressful macroeconomic conditions, if the enterprises held capital" (Single-Family Guarantee Fee Annual Reports, FHFA, p. 2).

The guarantee fee comprises both upfront and ongoing components. The ongoing portion is a monthly flow payment, which is a fixed fraction of the original loan balance, and based primarily on the product type (such as a 30-year or 15-year fixed-rate loan). Lenders that exchange loans for MBS can choose to pay the given ongoing fee monthly, convert all or part of the fee into an up-front premium by "buying down" the g-fee, or conversely receive an up-front transfer from the GSE by "buying up" the g-fee (Fuster et al, 2013, p. 20). For lenders that exchange loans for cash, the discounted present value of the ongoing fees over the expected duration of the loans is subtracted from the price at the time of sale. The upfront portion, on the other hand, is a one-time payment made by the lender upon loan delivery, and dependent on the specific risk attributes of the borrower. These “loan level pricing adjustments,” as Fannie Mae refers to them, vary with the borrower’s LTV ratio and credit score. Riskier borrowers with higher probabilities of default warrant a higher insurance premium and incur higher upfront fees.

The level of guarantee fees has risen substantially over the past decade (Figure 5). The GSEs introduced two new upfront fees in March 2008. In addition to the previously discussed loan-specific fee, this included a 25 basis point adverse market charge (as the probability of borrower default was clearly heightened during the housing market collapse). The FHFA announced this adverse market charge would be rolled off for all but four states (New Jersey, New York, Pennsylvania, and Connecticut) in December 2013, before deciding in January 2014 to delay implementation of the changes pending review. Following that review, the adverse market charge was uniformly eliminated in early 2015. The average upfront fee related to the borrower’s credit characteristics has increased gradually since its inception, from around 11 basis points in 2008 to 16 basis points in 2016.

The increases in ongoing fees have been far more dramatic. The FHFA directed the GSEs to raise ongoing fees by 10 basis points pursuant to Section 401 of the Temporary Payroll Tax Cut Continuation Act of 2011, effective mid-2012 and extending through 2022. This fee is paid to the U.S. Department of the Treasury to offset temporary reductions in federal payroll taxes, and is added on top of the level obtained from evaluating overhead expenses, residual risks, capital costs, and projected credit losses. The average ongoing fee increased from 15 basis points to 26 basis points from 2011 to 2012 in response. Ongoing fees rose another 14 basis

Figure 5:



Source: Federal Housing Finance Agency

points from 2012 to 2013 to 40 basis points, at the direction of the FHFA to "more fully compensate taxpayers for bearing credit risk" (Single-Family Guarantee Fee Annual Reports, FHFA, p. 6). Taking these increases in their entirety, the average overall g-fee nearly tripled from 22 basis points in 2007 to 57 basis points in 2016.

There is compelling evidence that the level of g-fees is now higher than the actuarially fair value plus general and administrative expenses. This is rather obvious for the non-credit costs. The 10 basis point increase to help pay for the payroll tax cut was a purely political decision and entirely supplemental to the FHFA's evaluations; it is an implicit tax on conforming borrowers. Politicians continue to view g-fee increases as a means to increase government revenue, particularly as g-fees have become a huge profit generator since the crisis, helping the

GSEs repay the taxpayer bailout from 2008. President Trump's administration, for example, has proposed raising g-fees another 20 basis points through 2023 to contribute to deficit reduction (Ramírez, 2018). Leaving aside the morality or potential distributional consequences of taxing conforming borrowers, including many first-time homeowners, and not other types of borrowers, like jumbo borrowers, raising g-fees is an effective way to generate government revenue with less public scrutiny than traditional tax increases.

In addition to the inflated non-credit costs, however, I argue the current level of credit costs overcharges originators for the true cost of default risk borne by the GSEs. The theoretical actuarially fair level is admittedly complex to calculate, as a myriad of assumptions must be made to do so. Goodman et al (2014) detail credit costs as the sum of expected losses and the required return on capital, which depends on the after-tax return required as well as the amount the firm could earn from reinvesting the capital. To calculate expected losses, they estimate default and severity rates in both a stress scenario (the 2007 vintage of loans) and a normal scenario (the 2001 vintage of loans) for various LTV/FICO buckets. Expected losses are defined as 95 percent of the normal scenario and 5 percent of the stress scenario. When calculating required capital, the requirement is based on a worst-case stress scenario, while allowing expected future income to reduce the amount of capital required. There is uncertainty around the required rate of return, as the FHFA's mandate that GSE capital should have the same "cost of capital allocated to similar assets held by other fully private regulated financial institutions" leaves room for interpretation (Temporary Payroll Tax Cut Continuation Act of 2011, Section 401.b.1.B). As a result, the authors run scenarios assuming a 10 percent required return on equity and a 5 percent required return on equity separately, with a 2 percent reinvestment rate on that capital. G-fees are calculated across LTV/FICO buckets under these assumptions.

Assuming a 10 percent after-tax return on equity, the calculated g-fees are lower than those of the FHFA for the majority of the buckets, and considerably lower for borrowers with high credit scores and low LTV ratios (Goodman et al, 2014, p. 7). Lowering the assumed rate of return from 10 percent to 5 percent causes calculated g-fees to fall in all buckets, and most significantly for high LTV/low FICO loans. In this scenario, calculated g-fees are higher than actual g-fees across all buckets. For average borrowers with LTV ratios between 60 and 80 and credit scores between 700 and 740, the actual g-fee is 13 basis points higher than the calculated g-fee (p. 7). The final conclusion of this analysis, conducted in 2014, after the major g-fee increases had been implemented; is that the credit component of current g-fees is too high (p. 8).

Another way to value the level of credit costs is by comparing the market's pricing of the credit risk of conforming loan pools with the FHFA's pricing. This comparison is achieved through backing out the market-implied g-fee from the pricing of Credit Risk Transfer (CRT) deals. The FHFA established CRT programs for Fannie Mae and Freddie Mac to transfer some of the credit risk borne by the GSEs to private investors, reducing the risk they pose to taxpayers while they are in conservatorship, and provide some liquidity in the non-agency MBS market. Investors are more comfortable with the integrity of these CAS and STACR securities issued by Fannie Mae and Freddie Mac, respectively, and the products are quite standardized. Though the program has evolved since its inception in 2013, broadly speaking, the GSEs issue unsecured, unguaranteed notes, whose payments are determined by the delinquency rate of a reference pool with private-label MBS structure. There are typically four tranches whose cash flows are determined by no more than the bottom 5 percent of the reference pool in totality (the thickness of each tranche can be ascertained from the attachment and detachment points shown in Appendix Figure 1). There are different variations of the deals, such as actual loss versus fixed severity payment structures and low LTV versus high LTV loans as collateral (Freddie Mac STACR 101, p. 30). Money managers are the dominant investors in the more prepayment-sensitive upper tranches, while hedge funds are most active in the more credit-sensitive, and much riskier, lower tranches (Freddie Mac STACR 101, p. 42). By the end of 2017, Fannie Mae and Freddie Mac had transferred a portion of credit risk on $2.1 trillion of unpaid principal balance (UPB), with a combined Risk in Force of ~$69 billion, or 3.2 percent of UPB (CRT Progress Report, FHFA, p. 2).

The CRT market provides a nice venue to examine the compensation private investors require to hold the same credit risk as the GSEs.[10] The FHFA performs the exercise of estimating the market-implied g-fee, adding the estimated credit cost, which includes the expected losses from borrower default and the cost of holding the modeled capital amount necessary to protect against much larger unexpected losses in a severe stress environment, to the non-credit costs of 25 basis points for low LTV pools and 35 basis points for high LTV pools[11] (CRT Progress Report, FHFA, p. 11-14). The market implied credit cost for a given CRT tranche is modeled as a function of the tranche size, the credit spread paid to investors, and the weighted average life (WAL) of each tranche and the overall collateral pool. To calculate the weighted average life, a simplified scenario of 10 percent constant prepayment rate, 0.2 percent constant default rate, and 25 percent loss given default (loss severity) is assumed. The results of this exercise are shown in Table 6 for both Fannie Mae and Freddie Mac from various CAS and STACR deals. The average market implied g-fee is 48 basis points, relative to the average actual g-fee of 57 basis points; only one of the sixteen deals exceeds this level at 57.7 basis points. The lowest is over 17 basis

[10] Models to value these securities are calibrated on the Single Family Loan-Level Datasets Fannie Mae and Freddie Mac provide, which include monthly performance data for conforming loans that served as collateral for agency MBS from 1999-2017. Thus the credit risk CRT investors are pricing is directly comparable to the credit risk the g-fee is pricing.

[11] This factors in both the loan level price adjustments and the 10 basis points from the payroll tax.

points below. In summation, this work implies g-fees are around 20 basis points higher than the administrative costs and projected credit losses – 10 basis points higher for the non-credit costs from the Payroll Tax Cut Act and 10 basis points higher for the credit costs relative to the market's pricing of the credit risk.

The FHFA's contemporaneous announcements of these increases suggest this "fat" in g-fees is somewhat intentional – in December 2012, the Acting Director of the FHFA announced the additional 10 basis point increase in ongoing fees was intended to "move Fannie Mae and Freddie Mac pricing closer to the level one might expect to see if mortgage credit risk was borne solely by private capital" ("FHFA Announces Increase in Guarantee Fees", FHFA, 2012). In other words, the increase reflected a desire to encourage private investors to participate in the non-agency market, serving a long-term goal of reducing the housing market's dependency on the GSEs, and not a response to changes in the estimated valuations of the specified components that comprise the g-fee. By and large, raising g-fees has not incentivized private actors to do their own securitizations, except more recently with the highest credit-quality loans, as will be further discussed shortly. The higher g-fee is still not high enough to overcome the superior execution Fannie Mae and Freddie Mac can achieve on the senior tranches relative to private actors, given the liquidity and size of the TBA market.

Maintaining the current level of g-fees above the market's value of the credit risk, however, has prompted unusual developments in the secondary market, with potentially unfavorable effects for the GSEs. It also has significant consequences for the housing market in general. One possible threat to the current equilibrium where g-fees attract private capital in the CRT market, profit the GSEs, yet do not incentivize private securitizations, is an adverse selection problem. The GSE risk-based pricing structure intentionally overprices the credit risk of high-quality loans to subsidize the pricing of loans for first-time homebuyers who have higher LTVs, lower credit scores, and higher DTIs (Goodman et al, 2014, p. 6). Originators are beginning to find that there exists better execution than selling to the GSEs for certain types of loans, such as superconforming loans or loans with strong borrower credit characteristics. Initially, this primarily involved banks holding an increasing share on balance sheet; more recently in 2018, high fees have induced private actors to undercut the GSEs for these specific groups of conforming loans (Finkelstein, 2018). These TBA-eligible loans are starting to find their way into private-label MBS, since the heightened loan-level price adjustments on top of the heightened ongoing fees are more punitive than what private actors demand. In sustaining the current g-fee level above the market's pricing of the credit risk, the FHFA risks originators selling the GSEs an increasing share of low-credit quality loans.

Furthermore, some lenders negotiate lower g-fees through private mortgage insurance or retaining the first-loss position. The former option is more prevalent, with the private mortgage insurance (PMI) market attracting over $9 billion in new capital since the crisis; loans with LTVs greater than 80 require PMI to absorb even more of the losses, making the risk to Fannie and Freddie equivalent to that on a mortgage with a 50 LTV (*Inside Mortgage Finance*). While PMI reduces the GSEs' exposure to credit risk, it increases their counterparty risk; if private insurers go out of business, the GSEs are ultimately responsible for the losses though they did not receive compensation for bearing the risk. Moreover, a small number of lenders have sold loans to Fannie Mae while retaining the first-loss position to negotiate lower g-fees. Two real estate investment trusts (REITs), Redwood and Penny Mac, entered into such a transaction in 2014, retaining the first 1 percent and 3 percent of losses, respectively (Goodman, Parrott, and Zandi, 2015, p. 2-4). These REITs hold the risk as an investment, meaning shareholders absorb any losses; other lenders have sold the exposure to third parties. Wells Fargo and J. P. Morgan have also engaged in similar deals – the level of g-fee discounts is not disclosed in these negotiations.

Lastly, and most relevant for the discussion of the conditional jumbo-conforming spread reversal, the FHFA's Office of Inspector General has raised the concern that the g-fee increases "could result in higher mortgage borrowing costs and dampen both consumer demand for housing and private sector interest in mortgage credit risk" as it is "likely that lenders will pass on to borrowers most or all of the costs associated with additional guarantee fee increases" (OIG Report, 2013, p. 3, 30). To appreciate why increases in g-fees affect conforming loan primary rates, it is necessary to understand how originators derive their profit when selling pools of loans into the TBA market. Following the work of Fuster et al (2013), originator net profit can be decomposed into the origination cash flow plus the present value of the servicing cash flows, defined by equations (1) and (2), respectively, minus unmeasured costs.

(1)

$$\Omega = Origination\ cash\ flow = TBA\left(r_{coupon}\right) + points - loan\ amount - UIP$$

(2)

$$\sigma_t = Servicing\ cash\ flow_t = r_{note} - gfee - r_{coupon}$$

(3)

$$originator\ profits = \ \Omega + \mathrm{PV}(\sigma_1, \sigma_2, \dots) - unmeasured\ costs$$

The origination cash flow depends on the price received from selling the TBA security in the secondary market, which is a function of the forward contracts' coupon rate, points if the borrower elects to pay higher closing fees to lower the mortgage rate, the loan amount that is transferred to the borrower, and the upfront insurance premium (UIP), which is comprised of the upfront portion of the g-fee plus or minus potential ongoing g-fee buy-ups or buy-downs. The monthly servicing cash flow depends on the difference between the primary rate paid in by the borrower and the secondary rate paid out to the investor holding the corresponding security, minus the ongoing portion of the g-fee. Thus the total profit is the origination cash flow plus the present value of the monthly servicing cash flows minus unmeasured costs (equation (3)).

Fuster et al (2013) constructs a times series of originator profits and unmeasured costs (OPUCs), or $\Omega + \text{PV}(\sigma_1, \sigma_2, \ldots)$, and shows that this measure increased significantly from 2008-2012, and most dramatically in 2012, despite the first big jump in g-fees from the Payroll Tax Cut Act that same year. Calculating the origination cash flow is straightforward; they estimate the present value of the servicing cash flows using a variety of methods, including referencing pricing of interest-only securities, which mimic the cash flows of the servicing income, and constant servicing multiples, which entails using fixed accounting multiples that reflect historical valuations of servicing. Rising g-fees do not appear to have eaten into originator profits, which strongly suggests that originators pass through most, if not all, of the g-fee on to the borrower, as profits would evidently fall if the note rate did not increase to offset the increase in the g-fee. The authors also assume that “increasing [g-]fees means that less money goes to borrowers (or equivalently, that they need to pay a higher rate),” and search for factors that potentially contribute to increasing originator profits and unmeasured costs (p. 28). They examine a number of possible unmeasured costs, such as pipeline hedging costs, a decline in mortgage servicing right valuations, and other loan production expenses, but conclude these explanations are insufficient to explain the increase in OPUCs. Therefore, they conclude that capacity constraints and market concentration are responsible for increasing originator profitability. These factors are less relevant for the conditional jumbo-conforming spread reversal, as they would likely contribute to higher originator profits for both jumbo and conforming loans.

While the increase in originator profits supports the view that g-fee increases are passed through to conforming borrowers, affecting the conditional jumbo-conforming spread, empirically quantifying this impact is challenging as there is no geographic heterogeneity in these fees.[12] An exercise that provides some insight into the g-fee pass-through effect takes advantage of the announcement at the end of 2013 that the 25 basis point adverse market charge would be rolled off for all but four states (New Jersey, New York, Pennsylvania, and Connecticut). Though the implementation of this policy was later delayed in January 2014, and the adverse market charge eventually uniformly eliminated in early 2015, a reasonable argument can be made that the expectation of future g-fees differed between those four states and the rest of the country in 2014. As the announcement stated the policy would be delayed, not rescinded, through 2014, market participants should have expected future g-fees to be higher for those four states. Furthermore, since originators often hold loans for a period of time before selling them to the GSEs, the difference in future g-fee expectations would immediately impact primary rates even if the policy had not yet actually gone into effect. In fact, because the expectation was for the adverse market charge to roll off for the majority of the country, originators would have been incentivized to lengthen the period of time from origination to the time of sale into the TBA market. It would be cheaper to sell loans to the GSEs after the charge rolled off.

I employ a differences-in-differences-in-differences approach along the New Jersey/Pennsylvania border to isolate the impact of differing future g-fee expectations between New Jersey, one of the four specified states, and Pennsylvania, on the conditional jumbo-conforming spread (Card and Krueger, 1994 and Duflo, 2001). I filter the MIRS data to include six CBSA regions, including counties Pike, Monroe, and Northampton in Pennsylvania, and

[12] Though the FHFA proposed imposing an additional upfront fee for loans in specific states where foreclosure laws lead to higher loss severities in September 2012, there was severe political pushback (out of concern it would weaken the housing markets in those states) and the plan was ultimately abandoned.

Sussex, Warren, Hunterdon, and Mercer in New Jersey.[13] The "treatment" period is 2014, as the expectation of future g-fees differed for New Jersey and Pennsylvania throughout that year. I compare the difference in the conditional jumbo-conforming spreads between the two states in 2014, with the differences in the year prior and the year after. Thus, the sample period is restricted to 2013-2015. Given that the expectation of future g-fees should haven been higher for New Jersey than Pennsylvania during the treatment period, I hypothesize that the conditional jumbo-conforming spread should be smaller, or more negative, for New Jersey, where conforming loans should have been relatively more expensive in 2014.

I run a weighted linear regression according to the model specified in equation (4). Fees, LTV indicators, and the log of the loan amount (denoted as $\mathbf{Z}$) are used as controls.

(4)

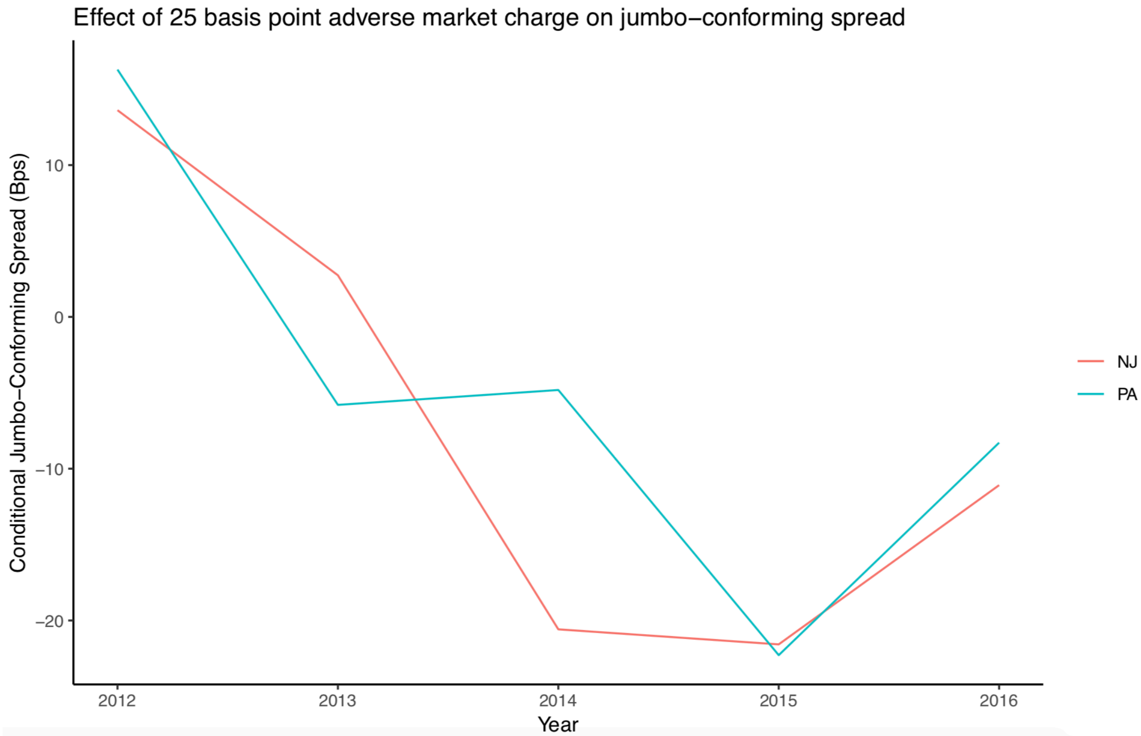
$$ER_i = \alpha_0 + \boldsymbol{\alpha_1 year_i} + \alpha_2 PA_i + \alpha_3 J_i + \boldsymbol{\alpha_4 Z_i} + \alpha_5 PA_i \times J_i + \alpha_6 PA_i \times J_i \times 2014_i$$

$$+ \boldsymbol{\alpha_7 year_i} \times PA_i + \boldsymbol{\alpha_8 year_i} \times J_i + \boldsymbol{\alpha_9 year_i} \times \boldsymbol{Z_i} + \epsilon_i$$

The year indicator variables capture changes in the overall level of mortgage rates over time, and the state indicator variable and its interaction with the year indicators are used as geographic controls over time. The jumbo flag, as well as its interaction with the year indicators, captures the estimated conditional jumbo-conforming spread for New Jersey in each year over the sample period. The coefficient α_5 estimates the difference in the conditional jumbo-conforming spread for Pennsylvania relative to the annual New Jersey conditional jumbo-conforming spread estimates for the whole sample period. The estimate of interest is α_6; this coefficient represents the difference of the difference between New Jersey and Pennsylvania's estimated conditional jumbo-conforming spreads between 2014 and the rest of the sample

[13] CBSA regions are quite large and can include areas of multiple states. I subset by the following CBSA codes that include the counties mentioned and then further limit the sample to only loans originated in PA or NJ: 35620, 20700, 10900, 37980, 47620, and 45940.

Figure 6:



period. Thus, this coefficient should capture the effects of a difference in future g-fee expectations between Pennsylvania and New Jersey during that year.

The regression results are shown in Table 5. The coefficient on the PAxjumbox2014 indicator is 0.194, implying that the conditional jumbo-conforming spread in Pennsylvania was nearly 20 basis points higher than the conditional jumbo-conforming spread in New Jersey in 2014, relative to the difference in the conditional spreads for the rest of the sample period. This estimate is statistically significant at a significance level of 5 percent, with a p-value of 4.5 percent.[14] Figure 6 shows estimates for the conditional jumbo-conforming spreads for Pennsylvania and New Jersey from 2012-2016 for a visual depiction of this result. The difference in the conditional spread estimates between Pennsylvania and New Jersey widens

[14] As a robustness check, I run the same weighted regression over a longer sample period, from 2012-2016. The results are comparable: the estimate of the coefficient is 0.16, with a p-value of 5.5 percent.

sharply in 2014, before the two spreads essentially converge in 2015. This analysis strongly supports the claim that increasing g-fees lower the conditional jumbo-conforming spread. The estimated pass-through effect is 77 percent (a difference of 19.4 basis points relative to the 25 basis point adverse market charge), and this is likely an underestimate of the actual pass-through effect given that it was only the expectation of future g-fees that differed between the two states in 2014, and not the actual g-fees. This implies that the increases in g-fees since the crisis have been passed through to conforming loan primary rates, boosting conforming mortgage rates relative to jumbo mortgage rates, and reducing the conditional jumbo-conforming spread.

In summation, this section aims to detail two aspects of the effect of g-fees on the conditional jumbo-conforming spread – one relevant for the level of the spread, and the other relevant for the trend. In regards to the level of the spread, there is another effect besides the funding difference between jumbo and conforming loans that causes a conditional jumbo-conforming spread. While private capital is holding the credit risk for jumbo loans and thus offering jumbo loan primary rates with respect to the market's value of the risk, the valuation of credit risk that is relevant for the determination of conforming loan primary rates is the g-fee. When obtaining estimates for the conditional jumbo-conforming spread, the credit risk is being priced uniformly across the two groups of loans and intended to mimic the market's pricing of the risk. G-fees that are above the market's pricing of the credit risk, however, pass through additional costs in excess of the credit risk being controlled for in the regressions, contributing negatively to the conditional jumbo-conforming spread. It was previously concluded that g-fees are now 20 basis points higher than administrative costs plus credit costs – 10 basis points higher for the non-credit costs from the Payroll Tax Cut Act and 10 basis points higher for the credit costs relative to the market's pricing of the credit risk. Taking this literally, and assuming administrative costs are roughly comparable for the GSEs and private actors, this suggests the major contributor to the most recent jumbo-conforming spread estimate of -20 basis points is the current level of g-fees. It also suggests that the negative contribution to the conditional spread from relatively high g-fees is significantly overpowering the positive contribution from the liquidity difference between the private-label and agency secondary markets. Conversely, though we do not have contemporaneous CRT pricing as a confirmation, g-fees were likely below the market's pricing of the credit risk pre-crisis.[15] This likely resulted in a positive conditional jumbo-conforming spread greater in magnitude than what would have resulted if the spread were solely due to the funding advantage of conforming loans, or the liquidity of the TBA market.

The other result relevant for the trend of the conditional jumbo-conforming spread estimate is that increases in g-fees are passed through to conforming loan primary rates, and thus through to the conditional spread. This is demonstrated by both the absence of erosion in originator profits following g-fee increases and the exercise performed along the New Jersey/Pennsylvania border. Focusing on just the beginning and end of the sample period, and thus momentarily ignoring the unusual liquidity and credit environment through the crisis,[16] the estimated conditional jumbo-conforming spread decreased roughly 40 basis points from 20 basis points in 2004 to -20 basis points in 2016, closely reflecting the 40 basis point increase in g-fees over the same time period. It is beyond the scope of this paper to draw a normative conclusion on the current level of g-fees, but my results strongly suggest that bringing fees in line with their actuarially fair value would result in a small positive jumbo-conforming spread, reflecting only the funding advantage, and continue to promote demand for CRTs, enabling the GSEs to pass

[15] The losses sustained by the GSEs during the crisis support this claim. "The GSEs experienced large losses in the wake of the collapse of the housing market…their losses on loans that they had guaranteed ended up…reaching $235 billion by 2012" (Elul, 2015, p. 17).
[16] It also allows the 25 basis point adverse market charge to be ignored.

through credit risk from taxpayers to private investors. Any further increases would be passed through to conforming loan primary rates, borne by conforming borrowers, and result in a more negative jumbo-conforming spread. Further increases may also exacerbate an adverse selection problem where originators increasingly sell the GSEs the lowest credit-quality loans.

b. Nonbank mortgage companies take over

The second explanation for the reversal of the conditional jumbo-conforming spread explained here also implies that conforming loans are relatively expensive. The share of conforming mortgage origination by nonbank mortgage companies has significantly increased relative to pre-crisis levels. This is in part because, for a variety of reasons, direct mortgage lending became less attractive for large depository institutions following the crisis, particularly for conforming loans. First, in an effort to recover a portion of the significant credit losses they took in their capacity as credit guarantors of conforming loans, in the aftermath of the crisis, the GSEs, along with the U.S. government, eagerly worked to show that one or more of the "representations and warranties" that were made upon delivery of some of these defaulted loans were inaccurate. In such cases, the originator is forced to repurchase the defaulted loan and bear the credit loss itself (Kim et al, 2018, p. 355-56). According to McCoy and Wachter (2017), the GSEs recouped $76.1 billion in losses from such originator repurchases by the end of 2015. These "legacy issues" led to significant unexpected losses for mortgage lenders, leading many to become wary of assuming the legal responsibilities of direct lending, and incentivizing them to lend to nonbank mortgage companies through lines of credit to attain mortgage exposure instead.

Second, Basel III increased overall bank capital requirements, and more specifically, increased the risk weights on mortgage servicing rights (MSRs) quite dramatically, from 100 percent to 250 percent, making it one of the most costly asset classes in the entire Basel III framework (GAO, 2016, p.7). Initially, when these capital rules were announced in 2013, the standards were to apply to the banking sector at large, including small and mid-sized banks, for which MSRs are a significant part of their asset holdings. Naturally many such banks reduced their exposures to MSRs in anticipation of the expected implementation of these rules at the beginning of 2018. Though a revised proposal in late 2017 increased the likelihood that the standards will now only be applied to large internationally active banks, the anticipation of higher risk weights alone for the years following the initial 2013 announcement drove a significant portion of the mortgage servicing business to shift from the banking system to the shadow banking system.

Furthermore, a host of other factors increased the attractiveness of mortgage lending for nonbank mortgage companies. First, the IRS ruled in 2012 that certain assets associated with mortgage servicing count as qualified assets for real estate investment trusts (REITs), which encouraged REITs to hold such assets from a tax perspective (Kim et al, 2018, p. 357). Second, the FHFA's 10 basis point g-fee increase at the end of 2012 was "allocated in a way that…reduced differences in the ongoing fees of small volume lenders and large volume lenders" (Single-Family Guarantee Fee Annual Reports, FHFA, p. 6). As a result, the share of loans purchased by the GSEs from small lenders (those outside the top 100 in volume sold to the GSEs) increased from 8 percent in 2010 to 28 percent in 2014, while the share from the five largest lenders fell from 60 percent to 39 percent (Collins, 2015). Third, and most significantly, nonbanks were generally much faster to adopt fintech than banks – in fact, much of the growth in mortgage lending by nonbanks stems from the growth in fintech lenders that primarily originate mortgages online. Buchak et al (2018) estimates a quantitative model of mortgage lending to quantify the contributions of tougher regulation and the rise of fintech to the shift of mortgage origination from banks to nonbanks, concluding that regulation accounts for roughly 60 percent of shadow bank growth, while technology accounts for roughly 30 percent.

The success of nonbank mortgage companies also depends critically on the liquidity of the agency secondary market and the high volume of agency MBS issuance. Unlike banks that fund long-term assets on their balance sheets with deposits on the liabilities side, nonbanks do not have balance sheets as they do not accept deposits – they rely on short-term funding from warehouse lines of credit to originate mortgages. Nonbanks draw on lines of credit to fund mortgages at the time of closing, typically borrowing 95 percent of the value of the loan; the mortgage is then transferred to the warehouse lender as collateral, while the nonbank finds a purchaser for the loan (Kim et al, 2018, p. 361). When the mortgage is transferred to the buyer, the proceeds from the sale are used to pay back the warehouse lender. Buyers for these loans are typically issuers of MBS. Before the crisis, buyers included private-label issuers as well as the GSEs. With the continued absence of significant private-label MBS issuance since the market's collapse during the crisis, however, buyers post-crisis are almost exclusively Fannie Mae, Freddie Mac, and Ginnie Mae investors.[17] To underscore this point, Buchak et al (2018) shows that nonbanks have grown increasingly reliant on the GSEs. The share of nonbank loans funded by the GSEs increased nearly 70 percent from 2007 to 2015, and 80 percent of loans originated by fintech lenders in 2015 were loans financed by some underlying government guarantee (p. 12). The GSEs provide nonbanks with reliable and consistent buyers for loans they need to sell quickly – finding a buyer to pay back the warehouse lender in a timely manner is crucial, as exceeding a specified time limit leads to penalties and harsher future lending standards. As the

[17] Unlike Fannie Mae and Freddie Mac, Ginnie Mae does not directly issue MBS, but rather has financial institutions do so on its behalf through the Ginnie Mae platform (Kim et al, 2018, p. 353).

ease of finding buyers for conforming loans far exceeds that of finding buyers for jumbo loans,[18] nonbanks naturally focus primarily on originating conforming loans.

The HMDA data demonstrate that the nonbank mortgage company business model, as well as the factors that both discouraged banks and encouraged nonbanks to originate mortgages, prompted a significant rise in the share of mortgage origination by nonbank mortgage companies, particularly for conforming loans. The share of conforming origination by nonbank mortgage companies rose from roughly 20 percent in 2009 to roughly 50 percent in 2017, while the share of jumbo origination by nonbank mortgage companies rose from roughly 5 percent in 2009 to roughly 20 percent in 2017 (Figure 7). Thus the rate of increase in the share of nonbank origination has been twice as fast for conforming loans relative to jumbo loans. Meanwhile, the conforming origination share by commercial banks, including commercial bank subsidiaries, dropped from roughly 60 percent in 2009 to roughly 35 percent in 2017. By contrast, banks' jumbo origination share fluctuates moderately over time, but has remained around 70 percent, underscoring that commercial banks are the primary jumbo lenders over the sample period (Figure 8). Figure 9 shows that mortgage companies surpassed commercial banks in their share of conforming loan originations around 2014.[19] This narrative is highlighted through an examination of the largest lenders for each lender type as well. At the end of 2017, Quicken Loans, a large nonbank lender, overtook Wells Fargo as the largest home lender, with a roughly 6 percent market share. Wells Fargo's 12 percent market share in the jumbo lending market, however, far outpaces Quicken Loans' 1 percent share in this market (HMDA data).

[18] Jumbo loans can be sold back to banks, given their increased propensity to hold jumbo loans on balance sheet (Section VII (c)), or to jumbo prime MBS issuers.
[19] It is worth noting that this excludes refinance mortgages, which are considered to be the specialty of nonbank mortgage companies.

Figure 7:

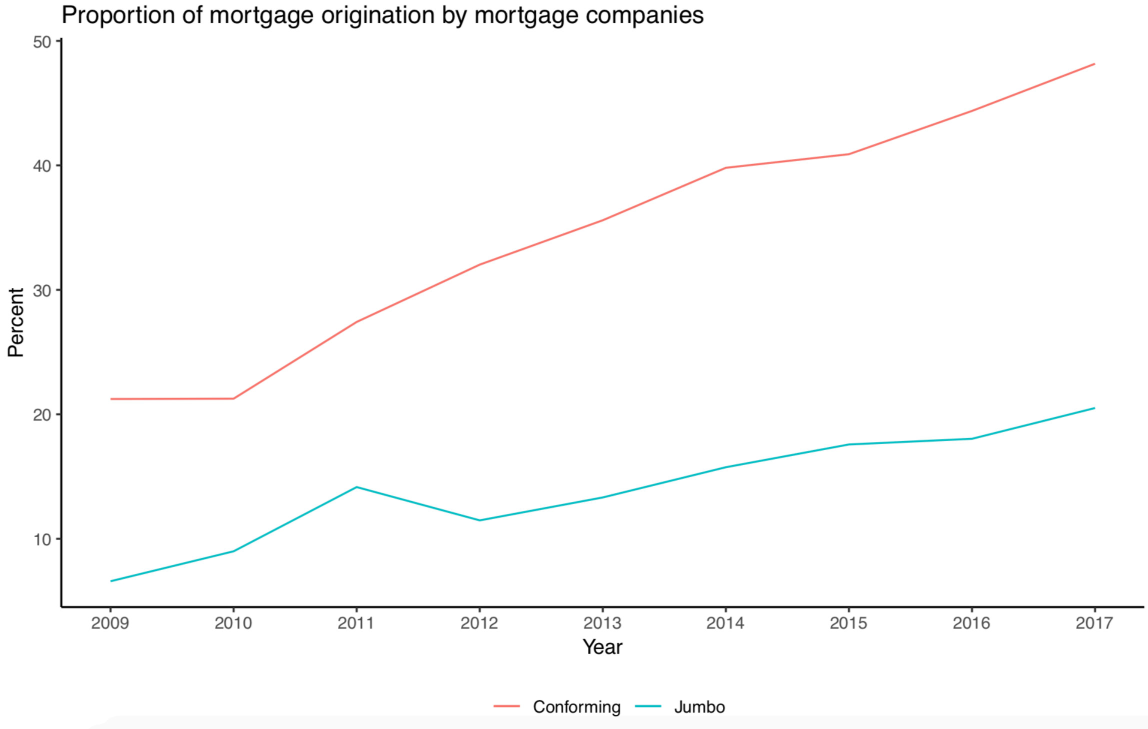


Figure 8:

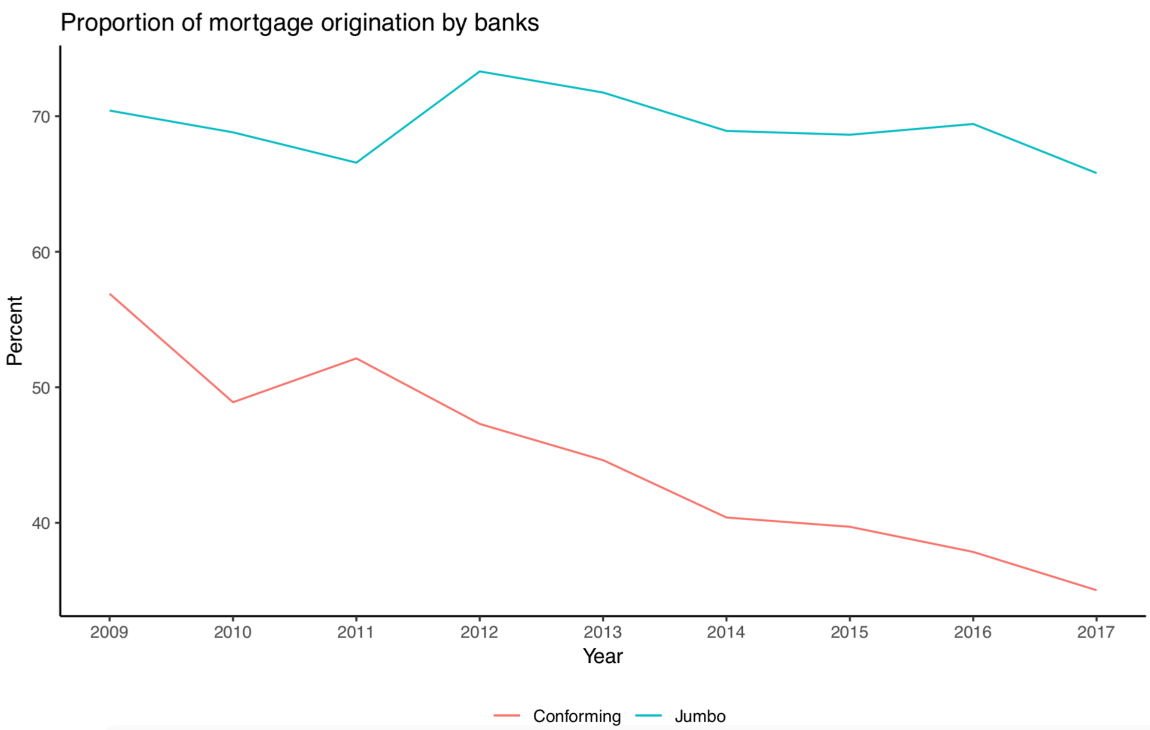
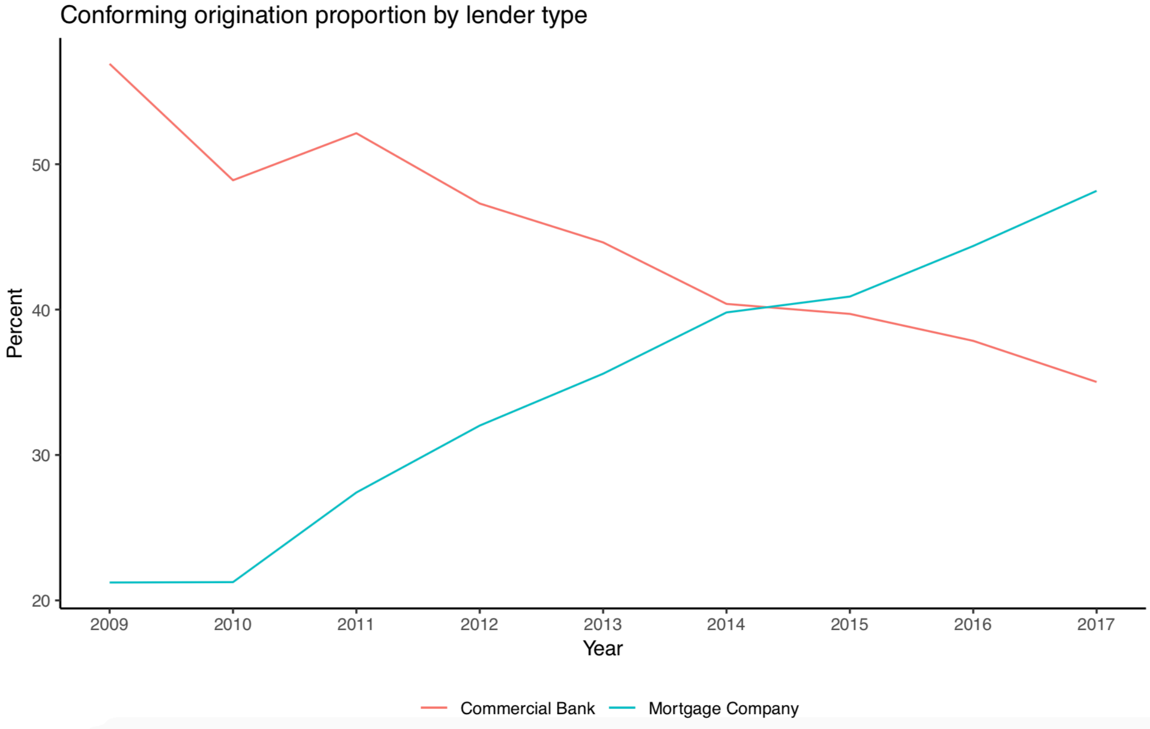


Figure 9:



Moreover, it is widely accepted in the mortgage industry that, for a given borrower, rates offered by nonbank mortgage companies are higher than rates offered by commercial banks. The standard explanation is higher funding costs – nonbanks pay more to their warehouse lenders than banks pay to their depositors. In support of this claim, Buchak et al (2018) demonstrates that traditional banks have lower costs of funding and provide higher quality products than nonbanks, and estimates that fintech lenders charge a premium of 14-16 basis points over bank lenders (p. 34). Furthermore, personal finance websites acknowledge that while Quicken Loans has great customer service and flexibility, "where [it] falls short is with rates…for the most part, rates are higher than those at competitors" (Smart Asset). When documenting the rise of Quicken Loans and other nonbank mortgage companies, *The Economist* explains that "because [Quicken] relies on relatively expensive wholesale funding, it struggles to compete with other providers on price. Its interest rates are typically 0.25-0.4 percentage points higher than the cheapest alternatives."

According to Bankrate's recent survey of the nation's largest mortgage lenders on February 23, 2019, the benchmark 30-year fixed-rate mortgage rate was 4.25 percent for Wells Fargo, Bank of America, and J.P. Morgan Chase, and 4.375 percent for Quicken Loans, a difference of 12.5 basis points.[20]

In conclusion, the share of nonbank mortgage origination is now greater for conforming loans than jumbo loans, and has grown twice as fast for conforming loans since the crisis. Moreover, nonbank rates are on average higher than commercial bank rates, all else equal. Based on a range of nonbank premium estimates from 12.5 to 40 basis points, the decline in the conditional jumbo-conforming spread attributable to the rising nonbank conforming origination share is estimated to be around 2 to 6 basis points. The reasoning is as follows: the share of conforming origination on which the premium applies has risen from 20 percent to 50 percent since the crisis, while the share of jumbo origination on which the premium applies has risen from 5 percent to 20 percent. Differencing the changes in the nonbank shares between conforming and jumbo loans and multiplying by the estimated premium yields these results.[21] Though this impact is rather modest relative to the estimated decline from the rise in g-fees, it is still meaningful, particularly in terms of partially counteracting the GSE funding advantage.

c. Increased bank demand for jumbo mortgages

The final more qualitative explanation, that likely accounts for some of the decline in the conditional jumbo-conforming spread, is that the supply of jumbo mortgages increased post-

[20] Given the interest in isolating the rate spread for various lender types after controlling for borrower credit characteristics, it would be ideal to analyze the regression coefficients on the lender type indicators from the annual regressions reported in Table 4. The lender type reporting issue complicates this analysis. That being said, the MIRS data do allow for analysis of the controlled mortgage company/bank rate spread before the crisis, and the difference in funding costs should be comparable pre- and post-crisis. From 2004-2009, the average of the coefficients on the mortgage company indicator relative to the commercial bank baseline, after controlling for specified loan characteristics, is 17 basis points. This is consistent with the specified range of estimates.

[21] For example, assuming a premium of 40 basis points, the contribution to the decline in the jumbo-conforming spread is 0.4*((0.5-0.2)-(0.2-0.05)) = 6 basis points.

crisis. This claim is supported by an increase in the relative quantity of jumbo mortgages, while the relative price of these mortgages declined. A straightforward explanation for the supply increase is that holding jumbos on balance sheet became more attractive to banks after the crisis. Jumbo loans are overwhelmingly held on bank balance sheets as investments, particularly given the lack of resurgence in the jumbo MBS market. In the aftermath of the crisis, banks were drawn to the strong credit characteristics of jumbo borrowers and their relatively attractive yield in a low interest rate environment. The probability of default for these high-FICO, high-income borrowers is low, and once long-term interest rates reached historic lows at the end of 2012, the interest rate risk from borrower prepayment negligible.[22] J.P. Morgan's CEO, Jamie Dimon, noted in an earnings call in 2016 that jumbo loans were helping to increase the bank's lending at a pace faster than growth in the overall economy, while the CFO, Marianne Lake, noted, "these are the customers that we like" (Ensign, 2016).

As a consequence of this increased desire to hold jumbo mortgages on balance sheet, banks significantly ramped up their supply of jumbo mortgages post-crisis. Figure 2 shows that in the MIRS sample, the weighted proportion of jumbo origination relative to total mortgage origination decreased from a high of roughly 6 percent in 2006 to a low of less than 2 percent in 2008. The share then steadily rose to pre-crisis levels in 2014 before jumping significantly higher in 2015 – the estimated share is greater than 13 percent at the end of the sample period in 2016. Moreover, there was a significant jump in jumbo production specifically in 2015 for the largest depository institutions. The total dollar volume of jumbo originations for the three largest jumbo lenders, Wells Fargo, J.P. Morgan Chase, and Bank of America, is shown from 2008 to 2017 in

[22] Prepayment will be structural (relocation, for example), which is straightforward to account for and hedge, and not cyclical, which is much more challenging to hedge – prepayment due to refinancing into a lower rate becomes much less likely when mortgages are taken out at very low rates.

Appendix Figure 2.[23] Together these three banks consistently comprise over 30 percent of jumbo originations. In 2015, J.P. Morgan Chase's jumbo originations increased 88 percent, from $20 billion to $37 billion, and Bank of America's increased 68 percent, from $14 billion to $23 billion. Jumbo mortgages accounted for 52 percent of Citigroups's total mortgage dollars originated in 2015, with a 53 percent increase in jumbo mortgage originations.

For the largest lenders, the substantial increase in jumbo originations in 2015 is likely the result of the Basel III final rule coming into effect in January of that year – jumbo loans received relatively favorable capital treatment, and as banks restructured their balance sheets to minimize their capital requirements under these new rules, they likely prioritized this business as a result. Though Basel III meaningfully increased the risk weights on mortgage servicing rights, penalizing banks subject to these rules to hold this asset class, the risk weights for single-family residential conventional mortgages remained relatively consistent (GAO, 2016). Under the new rules, for banks not categorized as large internationally active banks, the risk weights on single-family residential loans are 50 percent if the loan meets certain underwriting standards and 100 percent if not. The risk weights on the same category of residential loans for large internationally active banks are "determined by a formula defined by regulators for retail exposures using, among other considerations, estimates of the probability of default and loss given default derived from banks' internal systems" (p. 7). Thus the risk weights under the advanced internal ratings-based approach depend on the probability of default, which is highly correlated with the borrower's credit score, and the loss given default, which is highly correlated with the loan-to-value ratio. Finally, the risk weights on mortgage securitization exposures increased significantly, from 7 percent to 650 percent based on long-term credit ratings under Basel II, to 20 percent to 1,250 percent under Basel III.

[23] Jumbo dollar volumes for the top 50 jumbo lenders were provided to me by the Mortgage Bankers Association.

As a result of these changes, banks were evidently incentivized to hold whole loans as opposed to securities – a theme that extended beyond mortgages to all asset classes. Moreover, though the capital treatment of residential loans did not explicitly change, with overall capital requirements and risk weights on other asset classes increasing substantially, there was arguably a motive for large banks to shift more of their mortgage lending to high FICO/low LTV mortgage borrowers to benefit from the lower risk weights on low-probability-of-default loans. The variance of risk weights on these residential loans is substantial – for example, Table 7 shows the breakdown for Citigroup as part of their Pillar 3 disclosures for the quarterly period ending December 31, 2015. Citigroup shifted almost 70 percent of its residential mortgage portfolio into the probability of default band ranging from 0-0.05 percent, which receives a risk weight of just 4.03 percent. The 0.75-1.35 percent probability of default band receives a 75 percent risk weight, and the 2.5-5.5 percent probability of default band receives a 175 percent risk weight. The substantial risk weight variance across bands is comparable to other large banks.

While banks do not break down their jumbo and conforming holdings separately, jumbo loans consistently have lower LTVs and higher FICO scores than conforming loans to compensate for the higher loan amount (which, crucially, is not a contributor to the calculation of the risk weight). Appendix Figure 3 shows the weighted average LTV for conforming and jumbo loans over time for the MIRS data; in general, the average LTV for conforming loans is a couple of percentage points higher than the weighted average LTV for jumbo loans. Though the MIRS data do not include FICO scores, CoreLogic shows the average credit score for homebuyers with 30-year fixed-rate conventional mortgages over time using internal data. Jumbo FICO scores are consistently higher (Appendix Figure 4). It is therefore reasonable to conclude that, on average, jumbo loans have lower probabilities of default and lower severity rates than conforming loans based on the formula derived from internal systems. Thus on average, jumbo loans should have lower risk weights than conforming loans for large banks. More favorable capital treatment further explains why large banks' desire to originate and hold jumbo mortgages increased post-crisis, and in particular, increased substantially in 2015. The risk weight explanation also implies that large internationally active banks should be driving the increase in jumbo production, as lower probability of default mortgages receive lower risk weights only for these institutions. Using the HMDA data, the share of jumbo origination by the four largest lenders, namely Wells Fargo, J.P. Morgan Chase, Bank of America, and Citigroup, increased 47 percent from 2011 to 2015, consistent with this story.[24]

In conclusion, various factors increased banks' desire to hold jumbo mortgages on their balance sheets following the crisis, including relatively low risk weights for large banks. The increase in banks' demand for jumbo mortgages likely increased banks' willingness to compete for jumbo borrowers, driving down jumbo mortgage rates, and contributing to a decline in the conditional jumbo-conforming spread. While the regressions on the effective mortgage rate to estimate the conditional jumbo-conforming spread include LTV and other credit controls, these characteristics are used to price the risk of the loan. The regressions do not take into account the further impact these loan attributes have on the loan's attractiveness, and thus the loan's price, beyond reflecting its probability of default (like impacting the loan's capital treatment).

VIII. Conclusion

My regression estimates imply that the conditional jumbo-conforming spread was around 20-30 basis points pre-crisis, rose to over 80 basis points during the crisis, and decreased substantially to roughly -20 basis points post-crisis. As the pre-crisis explanation for the positive

[24] Though the increase in the share of jumbo origination by the largest lenders could be affected by consolidation, this effect is likely modest from 2011-2015, as the banks were building capital over this time horizon.

conditional jumbo-conforming spread rests on the difference in secondary market liquidity for jumbo and conforming loans, it makes sense that when the secondary market liquidity difference increased dramatically with the collapse of the private-label MBS market during the crisis, the conditional jumbo-conforming spread increased dramatically as well. The GSE funding advantage story, however, falls short in explaining the estimated conditional jumbo-conforming spread trend since the crisis. The estimated spread is negative over the last three years of the sample period despite persistence in the secondary market liquidity differential. In fact, the difference in agency and private-label liquidity is far greater post-crisis than it was pre-crisis.

I propose three possible explanations for the reversal of the conditional jumbo-conforming spread. First, GSE guarantee fees increased from around 20 basis points in 2004 to nearly 60 basis points in 2016. These increases appear to be passed through to conforming loan primary rates, likely explaining the majority of the declining trend in the conditional jumbo-conforming spread. The roughly 40 basis point g-fee increase over the sample period nicely matches the roughly 40 basis point decrease in the spread. Moreover, I present evidence that g-fees are now 20 basis points higher than GSE administrative costs plus the market's value of conforming credit risk, likely explaining the majority of the level of the current -20 basis point estimate of the spread as well. Another consequence of the higher level of g-fees that deserves further attention is that banks should be incentivized to hold large, low-risk conforming loans on their balance sheets to earn the high g-fee. The evidence presented that superconforming loans and loans with strong borrower credit characteristics are increasingly being held on bank balance sheets or securitized in the private-label market supports this hypothesis, but further research to understand how g-fee increases influence bank behavior would be worthwhile.

Second, a few basis points in the decline of the conditional jumbo-conforming spread is likely attributable to the rise in nonbank conforming originations. Nonbank mortgage company loans tend to be more expensive than commercial bank counterparts because of their business model, and because they face higher funding costs. The share of conforming loans associated with the nonbank premium has increased twice as fast as the share of jumbo loans. Based on a range of nonbank premium estimates from 12.5 to 40 basis points, this effect on the conditional jumbo-conforming spread decline is estimated to be between 2 to 6 basis points.

Third, an increase in the relative supply of jumbo loans that drove down their relative price is consistent with banks' increased preference for holding jumbo loans on balance sheet post-crisis. Risk-averse and flush with reserves, banks were attracted to the strong credit quality of jumbo borrowers. Furthermore, for large internationally active banks, the average risk weight on jumbo loans is arguably lower than the average risk weight on conforming loans. With the Basel III final rule coming into effect in January 2015, raising capital requirements, large depository institutions would have been incentivized to shift more of their mortgage portfolios into low probability of default loans. Consistent with the risk weight explanation, large banks overwhelming drove the increase in jumbo production following the crisis.

In more recent developments in the jumbo market, jumbo MBS issuance finally picked up meaningfully in 2018, encouraging more nonbank jumbo originations, as the greater number of buyers for these high-balance loans increases the ease of paying back warehouse lenders in a timely manner. Commercial banks also increasingly provide liquidity for jumbo loans in the secondary market (Appendix Figure 5). As bank lending to nonbanks has also been increasing, this suggests banks are increasingly lending to nonbanks to originate jumbo loans, and then buying the loans, increasing the interconnectedness between the banking and shadow banking systems. Given nonbank reliance on short-term funding, increasing nonbank jumbo originations raises the concern that if investor demand for jumbo loans softens and it becomes more difficult to find buyers in the secondary market, nonbank entities will face severe liquidity pressures, potentially severely restricting lending. Furthermore, nonbank jumbo loans tend to have relatively weak credit standards,[25] and, in an effort to compete, banks are beginning to loosen their jumbo underwriting standards (Federal Reserve SLOOS, October 2018). The financial stability consequences of these developments in the jumbo market warrant further research.

All in all, this paper underscores how various policies since the crisis have prompted jumbo loan rates to become lower than conforming loan rates, all else equal. These policies include the significant increase in GSE guarantee fees, harsher measures on banks that encouraged conforming mortgage origination to move to the shadow banking system, and the risk weight formula for large bank residential mortgage exposures under Basel III. Traditionally, the government aims to implement policies that subsidize the housing market for conforming borrowers, or make conforming loan rates lower than jumbo loan rates, all else equal. The GSEs were established for this very purpose. The analysis in this paper to explain the reversal of the conditional jumbo-conforming spread highlights that there are a variety of factors, beyond the existence of the GSEs, that impact the government's success in promoting homeownership.

[25] Nonbank lenders increasingly offer mortgages with $10-20 million loans amounts and home equity lines of credit up to $3 million (Finkelstein, 2018). LTVs on these high-balance loans go up to 95%, with no mortgage insurance and credit scores below 700. Verus Mortgage Capital even offers jumbos up to $5 million to credit-impaired borrowers with credit scores as low as 500. In some cases, lenders are willing to forego employment and income verifications (a risk highlighted in the Office of the Comptroller of the Currency December 2018 report).

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Table 1:

	Dataset	Notes
House Value	• 2012-2016 ACS 5-year estimates • 945 CBSA codes • B25077	• Median home value (dollars)
Age and Sex	• 2012-2016 ACS 5-year estimates • 945 CBSA codes • S0101	• Median age (years) • Old age dependency ratio • Child dependency ratio
Race	• 2012-2016 ACS 5-year estimates • 945 CBSA codes • B02001	• Total population • Black only • Asian alone ** Divide by total population to get shares within the region
Education Shares/Median Income	• 2012-2016 ACS 5-year estimates • 945 CBSA codes • S1501	• Percentage shares of high school or more and bachelors • Median income in the past 12 months (in 2016 inflation-adjusted dollars) for population 25 years and over with earnings: less than high school graduate, high school graduate (includes equivalency), some college, bachelor's degree, graduate or professional degree
Urban/Rural	• 2010 Census SF1 • 955 CBSA codes • P2	• Total urban o Inside urbanized areas o Inside urban clusters • Total rural ** Divide by total to get shares
Marital Status	• 2012-2016 ACS 5-year estimates • 945 CBSA codes • S1201	• Population 15 years and over (percent married)

Table 2:

MIRS Summary Statistics
(Weighted Means and Weighted Standard Deviations)

	All		Non-Jumbo		Jumbo		Superconforming	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Effective mortgage rate (%)	5.544	1.112	5.589	1.085	5.246	1.404	4.456	0.764
LTV: (0,75]	0.251	0.433	0.246	0.431	0.298	0.457	0.320	0.466
LTV: (75,80]	0.394	0.489	0.382	0.486	0.568	0.495	0.485	0.500
LTV: (80,90]	0.127	0.333	0.129	0.335	0.080	0.272	0.165	0.371
LTV: (90,100]	0.228	0.420	0.243	0.429	0.054	0.226	0.030	0.172
Fees percentage	0.575	0.812	0.579	0.822	0.522	0.684	0.543	0.641
Mortgage company flag	0.636	0.481	0.626	0.484	0.700	0.458	0.879	0.326
Commercial bank flag	0.217	0.412	0.222	0.416	0.185	0.389	0.105	0.307
Thrift flag	0.147	0.354	0.152	0.359	0.115	0.319	0.016	0.124
Log(loan amount)	12.162	0.582	12.075	0.509	13.304	0.247	13.170	0.136
Judicial flag	0.501	0.494	0.512	0.494	0.374	0.479	0.355	0.477
Deficiency flag	0.869	0.288	0.875	0.288	0.806	0.298	0.807	0.253
Rural percentage	0.141	0.125	0.147	0.126	0.081	0.084	0.050	0.045
Urban percentage	0.787	0.232	0.778	0.236	0.880	0.146	0.927	0.086
Black percentage	0.136	0.095	0.136	0.095	0.133	0.093	0.158	0.097
Asian percentage	0.052	0.050	0.047	0.042	0.096	0.081	0.143	0.088
Log(median age)	3.626	0.087	3.627	0.089	3.624	0.071	3.621	0.034
Old age dependency ratio	22.768	6.040	22.907	6.115	21.518	5.371	20.066	2.589
Child dependency ratio	37.039	4.451	37.164	4.494	35.938	3.968	34.592	2.149
High school or more %	88.900	4.697	88.925	4.754	88.389	4.334	88.962	2.822
Bachelors or more %	36.188	9.538	35.568	9.274	41.653	9.734	48.405	6.673
Log(median earnings)	10.556	0.159	10.544	0.153	10.661	0.169	10.795	0.113
Log(median home value)	12.220	0.434	12.177	0.401	12.634	0.480	13.003	0.305
Married percentage	48.058	2.965	48.049	3.003	48.171	2.544	48.185	2.178
Number of loans	925,200							
Weighted proportion			0.926		0.048		0.025	

Table 3:

HMDA Summary Statistics

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Number of unique respondent IDs	7,578	7,273	6,993	6,850	6,667	6,466	6,376	6,262	5,577
Total number of non-jumbo originations	1,110,181	1,168,787	983,051	1,227,896	1,577,238	1,663,376	1,804,075	2,012,564	2,182,581
Total number of jumbo originations	36,892	43,512	62,627	74,444	112,107	138,538	166,915	191,374	199,629
Share of lenders that originate jumbos	0.363	0.344	0.367	0.386	0.444	0.482	0.516	0.534	0.570
Share of mortgage companies	0.115	0.109	0.111	0.113	0.117	0.118	0.126	0.132	0.152
Share of commercial banks	0.527	0.518	0.512	0.507	0.495	0.495	0.484	0.480	0.457
Share of credit unions	0.240	0.253	0.260	0.266	0.279	0.282	0.289	0.293	0.293
Share of thrifts	0.118	0.120	0.116	0.113	0.109	0.105	0.101	0.096	0.097

Table 4:

Single Regression Equation Results (2004-2010)

	Effective Mortgage Rate						
	(2004)	(2005)	(2006)	(2007)	(2008)	(2009)	(2010)
Superconforming flag					0.388***	0.191***	0.108***
					(0.032)	(0.013)	(0.014)
Jumbo flag	0.275***	0.344***	0.302***	0.294***	0.585***	0.820***	0.666***
	(0.013)	(0.014)	(0.015)	(0.017)	(0.023)	(0.022)	(0.025)
LTV: (75,80]	0.061***	0.099***	0.127***	0.047***	0.089***	0.047***	0.050***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
LTV: (80,90]	0.243***	0.317***	0.265***	0.241***	0.186***	0.009*	0.030***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)
LTV: (90,100]	0.163***	0.135***	0.103***	0.184***	0.216***	0.113***	0.092***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Fees percentage	0.151***	0.133***	0.090***	0.095***	0.091***	0.123***	0.140***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Commercial bank flag	-0.164***	-0.233***	-0.357***	-0.177***	-0.037***	-0.062***	0.120***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Thrift flag	0.048***	0.131***	0.290***	0.194***	-0.149***	0.100***	0.010
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)
Log(loan amount)	-0.161***	-0.165***	-0.170***	-0.185***	-0.241***	-0.193***	-0.154***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Judicial flag	-0.048**	-0.157***	-0.142***	-0.033	-0.004	0.038	-0.073**
	(0.023)	(0.024)	(0.029)	(0.028)	(0.029)	(0.028)	(0.034)
Deficiency flag	-0.140***	-0.104**	0.056	-0.088**	-0.117**	-0.129***	-0.120**
	(0.040)	(0.041)	(0.046)	(0.043)	(0.049)	(0.047)	(0.055)
Rural percentage	0.084**	-0.064*	-0.016	0.222***	-0.064	-0.082**	0.192***
	(0.035)	(0.036)	(0.040)	(0.041)	(0.044)	(0.038)	(0.043)
Urban percentage	-0.056***	-0.132***	-0.097***	0.011	-0.065***	-0.077***	0.012
	(0.016)	(0.016)	(0.018)	(0.018)	(0.019)	(0.017)	(0.019)
Black percentage	0.161***	-0.144***	0.118**	0.183***	-0.055	-0.064	0.018
	(0.042)	(0.045)	(0.049)	(0.047)	(0.051)	(0.046)	(0.057)
Asian percentage	-0.329***	-0.283***	0.636***	0.164*	0.418***	0.200***	0.142*
	(0.089)	(0.097)	(0.102)	(0.094)	(0.081)	(0.065)	(0.077)
Log(median age)	-0.380***	-0.280***	-0.165***	-0.138**	-0.003	0.005	0.091
	(0.049)	(0.049)	(0.054)	(0.054)	(0.053)	(0.046)	(0.058)
Old age dependency ratio	0.004***	0.005***	0.0002	0.001	0.001	0.0001	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Child dependency ratio	0.006***	0.014***	0.012***	0.008***	0.007***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High school or more percent	0.004***	0.003***	0.009***	0.006***	0.002***	0.0004	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Bachelors or more percent	-0.002***	-0.001*	-0.003***	-0.003***	-0.005***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(median earnings)	-0.196***	0.201***	-0.326***	-0.090**	-0.105**	0.062	0.093**
	(0.040)	(0.040)	(0.043)	(0.041)	(0.043)	(0.039)	(0.042)
Log(median home value)	0.145***	0.023*	0.175***	0.177***	0.240***	0.158***	0.190***
	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)	(0.012)	(0.015)
Married percentage	-0.004***	-0.010***	-0.005***	-0.002	-0.005***	-0.006***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Superconforming:LTV(75,80]					-0.074*	-0.003	-0.027
					(0.041)	(0.016)	(0.017)
Jumbo:LTV(75,80]	-0.033**	-0.047***	-0.055***	-0.045**	0.058*	0.003	-0.093***
	(0.016)	(0.016)	(0.017)	(0.019)	(0.034)	(0.027)	(0.030)
Superconforming:LTV(80,90]					-0.090*	0.126***	-0.024
					(0.051)	(0.030)	(0.033)
Jumbo:LTV(80,90]	-0.035	-0.019	0.085**	0.125***	0.115**	0.237***	0.101
	(0.030)	(0.038)	(0.035)	(0.035)	(0.051)	(0.053)	(0.071)
Superconforming:LTV(90,100]					0.462***	0.767***	0.629***
					(0.099)	(0.120)	(0.182)
Jumbo:LTV(90,100]	-0.096***	0.126**	0.192***	0.200***	0.362***	0.302***	0.111**
	(0.036)	(0.050)	(0.056)	(0.030)	(0.040)	(0.038)	(0.045)
Constant	9.239***	6.388***	9.748***	7.296***	7.239***	5.116***	3.621***
	(0.388)	(0.395)	(0.414)	(0.398)	(0.412)	(0.379)	(0.403)
N	113,162	121,761	129,119	118,357	81,066	60,813	42,796
R^2	0.139	0.144	0.163	0.115	0.124	0.191	0.167
Adjusted R^2	0.138	0.143	0.163	0.115	0.123	0.190	0.166
Residual Std. Error	1.635 (df = 113090)	2.036 (df = 121689)	2.281 (df = 129047)	2.718 (df = 118285)	2.479 (df = 80990)	1.801 (df = 60737)	1.651 (df = 42720)
F Statistic	256.442*** (df = 71; 113090)	287.870*** (df = 71; 121689)	353.910*** (df = 71; 129047)	216.755*** (df = 71; 118285)	153.046*** (df = 75; 80990)	190.599*** (df = 75; 60737)	114.399*** (df = 75; 42720)
Notes:	***Significant at the 1 percent level.						
	**Significant at the 5 percent level.						
	*Significant at the 10 percent level.						

Coefficients on state geographic control omitted for convenience. Available upon request.

Single Regression Equation Results (2011-2016)

	Effective Mortgage Rate					
	(2011)	(2012)	(2013)	(2014)	(2015)	(2016)
Superconforming flag	0.047**	0.200***	0.055***	-0.038***	-0.137***	-0.071***
	(0.022)	(0.016)	(0.018)	(0.014)	(0.013)	(0.013)
Jumbo flag	0.323***	0.530***	0.057***	-0.191***	-0.213***	-0.191***
	(0.019)	(0.019)	(0.018)	(0.014)	(0.011)	(0.011)
LTV: (75,80]	0.068***	0.085***	0.106***	0.091***	0.108***	0.119***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
LTV: (80,90]	0.038***	0.082***	0.100***	0.097***	0.140***	0.104***
	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)
LTV: (90,100]	0.093***	0.142***	0.177***	0.182***	0.237***	0.212***
	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Fees percentage	0.163***	0.158***	0.140***	0.204***	0.195***	0.201***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Commercial bank flag	0.112***	-0.124***	-0.078***	0.217***	0.079***	-0.096***
	(0.011)	(0.011)	(0.012)	(0.010)	(0.012)	(0.015)
Thrift flag	-0.065***	-0.010	-0.032***	0.032***	-0.046***	-0.075***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Log(loan amount)	-0.158***	-0.221***	-0.120***	-0.112***	-0.171***	-0.201***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Judicial flag	-0.063*	-0.176***	-0.068	-0.088**	-0.067	-0.120***
	(0.038)	(0.039)	(0.044)	(0.035)	(0.043)	(0.038)
Deficiency flag	-0.216***	-0.340***	0.077	-0.020	0.080	-0.052
	(0.062)	(0.061)	(0.060)	(0.043)	(0.051)	(0.043)
Rural percentage	-0.256***	0.197***	-0.332***	0.045	0.043	-0.120***
	(0.046)	(0.044)	(0.049)	(0.040)	(0.043)	(0.042)
Urban percentage	-0.144***	0.060***	-0.185***	0.040**	0.022	0.004
	(0.019)	(0.017)	(0.021)	(0.017)	(0.019)	(0.017)
Black percentage	0.006	0.311***	-0.041	-0.110**	-0.181***	-0.052
	(0.064)	(0.062)	(0.068)	(0.054)	(0.057)	(0.057)
Asian percentage	0.250***	0.102	0.014	-0.372***	-0.220***	-0.573***
	(0.091)	(0.081)	(0.093)	(0.072)	(0.072)	(0.069)
Log(median age)	-0.181***	-0.076	0.146**	-0.095*	-0.068	-0.118**
	(0.062)	(0.060)	(0.068)	(0.051)	(0.054)	(0.058)
Old age dependency ratio	0.001	-0.001	-0.001	0.0002	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Child dependency ratio	0.001	-0.002	0.006***	0.002	0.003***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High school or more percent	-0.001	-0.001	0.002**	-0.0002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bachelors of more percent	-0.005***	-0.005***	-0.006***	-0.004***	-0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(median earnings)	0.040	0.027	0.324***	0.299***	0.334***	0.010

	(0.044)	(0.043)	(0.050)	(0.036)	(0.040)	(0.037)
Log(median home value)	0.151***	0.118***	0.031*	0.068***	-0.054***	0.009
	(0.017)	(0.016)	(0.017)	(0.013)	(0.014)	(0.014)
Married percentage	-0.002	0.0004	-0.004**	-0.001	-0.008***	0.003**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Superconforming:LTV(75,80]	0.024	-0.067***	0.026	-0.023	0.058***	-0.044***
	(0.027)	(0.020)	(0.022)	(0.016)	(0.016)	(0.015)
Jumbo:LTV(75,80]	-0.049**	-0.200***	-0.078***	-0.027*	-0.006	-0.078***
	(0.024)	(0.023)	(0.022)	(0.016)	(0.013)	(0.012)
Superconforming:LTV(80,90]	0.048	-0.018	0.174***	0.133***	0.327***	0.213***
	(0.040)	(0.025)	(0.027)	(0.019)	(0.019)	(0.019)
Jumbo:LTV(80,90]	-0.030	-0.172***	0.019	0.187***	0.294***	0.232***
	(0.044)	(0.039)	(0.038)	(0.023)	(0.019)	(0.017)
Superconforming:LTV(90,100]	0.141	0.067	-0.172*	0.376***	0.573***	0.195***
	(0.156)	(0.107)	(0.103)	(0.053)	(0.058)	(0.020)
Jumbo:LTV(90,100]	0.174***	-0.547***	-0.085**	0.465***	0.237***	0.210***
	(0.048)	(0.031)	(0.040)	(0.033)	(0.050)	(0.045)
Constant	5.684***	5.498***	1.274**	2.121***	3.708***	6.421***
	(0.456)	(0.440)	(0.508)	(0.369)	(0.393)	(0.380)
N	33,923	38,030	56,709	41,391	41,150	46,923
R^2	0.227	0.256	0.123	0.337	0.389	0.376
Adjusted R^2	0.225	0.254	0.122	0.335	0.388	0.375
Residual Std. Error	1.545 (df = 33847)	1.551 (df = 37954)	2.111 (df = 56633)	1.409 (df = 41315)	1.528 (df = 41074)	1.502 (df = 46847)
F Statistic	132.618*** (df = 75; 33847)	173.966*** (df = 75; 37954)	106.370*** (df = 75; 56633)	279.524*** (df = 75; 41315)	348.775*** (df = 75; 41074)	377.091*** (df = 75; 46847)
Notes:	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.					

Coefficients on state geographic control omitted for convenience. Available upon request.

Table 5:

Effect of 25 basis point adverse market charge on jumbo-conforming spread (2013-2015)	
	Effective Mortgage Rate
Year: 2014	-0.602*
	(0.316)
Year: 2015	0.427
	(0.298)
State: PA	0.025
	(0.017)
Jumbo flag	0.018
	(0.039)
Fees percentage	0.178***
	(0.008)
LTV: (75,80]	0.109***
	(0.017)
LTV: (80,90]	0.209***
	(0.022)
LTV: (90,100]	0.241***
	(0.022)
Log(loan amount)	-0.199***
	(0.016)
PAxjumbo	-0.036
	(0.053)
PAxjumbox2014	**0.194****
	(0.096)
2014xPA	-0.016
	(0.026)
2015xPA	0.075***
	(0.025)
2014xjumbo	-0.224***
	(0.058)
2015xjumbo	-0.229***
	(0.047)
	(0.024)
Constant	6.407***
	(0.204)
N	10,495
R^2	0.275
Adjusted R^2	0.273
Residual Std. Error	1.515 (df = 10469)
F Statistic	158.464*** (df = 25; 10469)
Notes:	***Significant at the 1 percent level.
	**Significant at the 5 percent level.
	*Significant at the 10 percent level.

Coefficients on interactions between year indicator variables and controls (α_9) are omitted for convenience. Available upon request.

Table 6:

Estimated Market Implied versus Average Guarantee Fees for Fannie Mae and Freddie Mac

The implied guarantee fee from market prices in 2017 ranged between 40 to 58 bps for CAS and STACR transactions, compared to the Enterprises' average guarantee fee of 57 bps in 2016.

Fannie Mae
Guarantee Fees Implied by CAS Bond Pricing
(in bps)

	2017 C01[1]	2017 C02[1]	2017 C03	2017 C04	2017 C05	2017 C06 (1)	2017 C06 (2)	2017 C07 (1)	2017 C07 (2)
Non-credit Costs	25.0	35.0	25.0	35.0	25.0	25.0	35.0	25.0	35.0
Market implied credit cost	20.6	21.6	18.4	19.4	14.8	16.1	18.6	16.7	17.7
Market Implied Guarantee Fee	**45.6**	**56.6**	**43.4**	**54.4**	**39.8**	**41.1**	**53.6**	**41.7**	**52.7**

Freddie Mac
Guarantee Fees Implied by STACR Bond Pricing
(in bps)

	2017 DNA-1[1]	2017 HQA-1[1]	2017 DNA-2	2017 HQA-2	2017 DNA-3	2017 HQA-3	2017 HRP-1
Non-credit Costs	25.0	35.0	25.0	35.0	25.0	35.0	26.4[2]
Market implied credit cost	18.1	22.7	17.3	18.1	16.2	19.3	26.4
Market Implied Guarantee Fee	**43.1**	**57.7**	**42.3**	**53.1**	**41.2**	**54.3**	**52.8**

Average Guarantee Fee for Fannie Mae and Freddie Mac in 2016: 57 bps

[1] Reflects current non-credit costs for comparability purposes.
[2] The 2017 HRP-1 transaction included high LTV and low LTV loans. The non-credit costs reflect a weighted average of the DNA and HQA non-credit costs.

Table 7: Citigroup Residential Mortgage Exposures by Probability of Default (Pillar 3 Disclosures)

In millions of dollars, except percentages — **December 31, 2015**

PD Range Bands	**Undrawn Exposures**[(1)]	**Total EAD**[(2)]	**CCF**[(3)]	**PD**[(3)]	**LGD**[(3)]	**Risk Weight**[(3)]
0.00% to < 0.05%	$ 11,839	$ 55,987	54.52 %	0.04 %	30.45 %	4.03 %
0.05% to < 0.10%	1,467	24,642	38.00	0.08	38.16	10.87
0.10% to < 0.15%	929	12,160	70.15	0.12	32.59	11.60
0.15% to < 0.20%	306	2,562	27.54	0.19	49.56	22.93
0.20% to < 0.25%	675	4,220	57.83	0.23	47.55	23.90
0.25% to < 0.35%	1,152	7,701	56.39	0.29	45.76	28.97
0.35% to < 0.50%	71	5,248	59.21	0.40	44.18	38.67
0.50% to < 0.75%	252	5,093	63.82	0.61	50.48	50.93
0.75% to < 1.35%	90	11,240	50.25	1.03	52.56	74.54
1.35% to < 2.50%	44	6,989	65.96	1.93	55.81	116.63
2.50% to < 5.50%	14	6,810	49.86	3.57	58.90	175.06
5.50% to < 10.00%	9	5,171	40.65	6.98	48.05	212.33
10.00% to < 20.00%	2	2,188	36.53	13.76	55.76	295.55
20.00% to < 100%	794	2,856	99.90	58.62	40.55	180.15
100% (Default)[(4)]	2	7,195	100.00	100.00	38.94	74.84
Total	**$ 17,646**	**$ 160,062**	**57.80%**	**6.35%**	**39.73%**	**44.49%**

(1) Amounts represent the face value of undrawn commitments.
(2) Represents total EAD for on-balance sheet and undrawn exposures.
(3) Exposure-weighted average by PD range bands and in total.
(4) The portion of EAD for defaulted residential mortgage exposures covered by an eligible guarantee from the U.S. government or its agencies, is assigned a 20% risk weight in accordance with the U.S. Basel III rules.

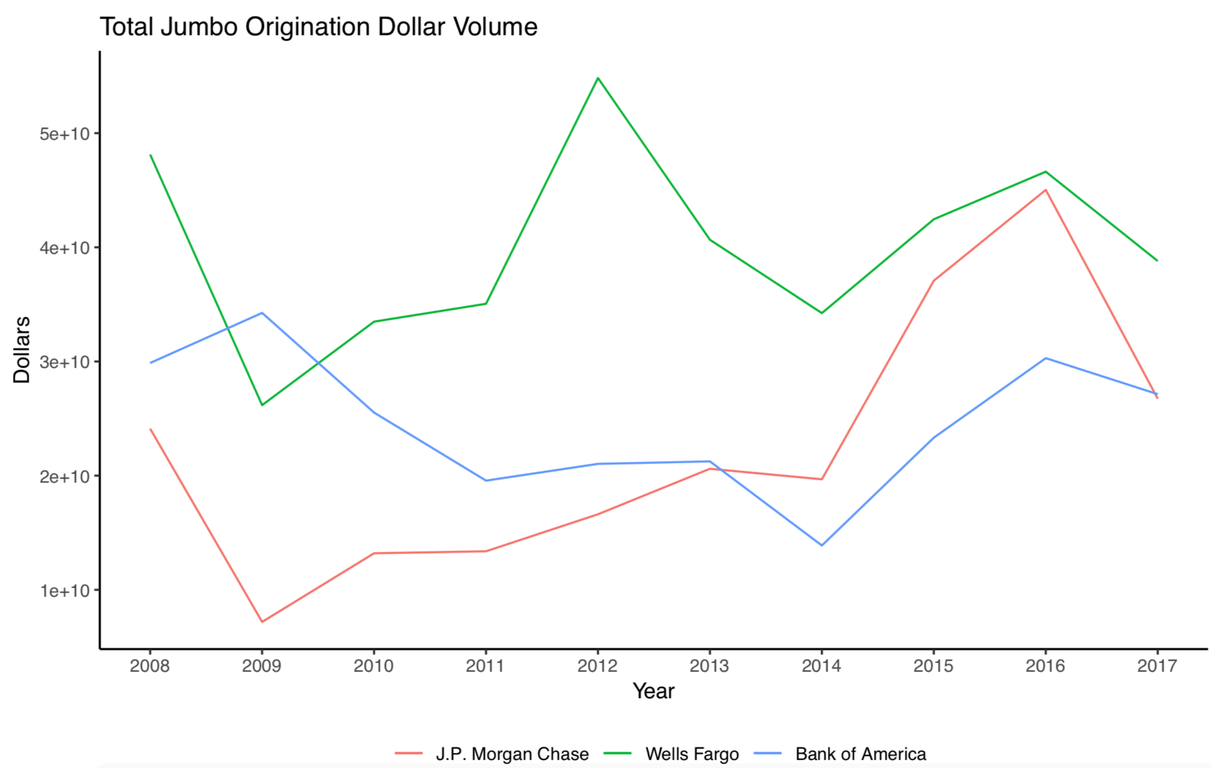
Appendix

Figure 1:

STACR 2019-DNA1													
						Early Redemption*				Maturity*			
Tranche	Loss Coverage		Expected Ratings		Balance ($)	WAL		Principal Window		WAL		Principal Window	
	Attach	Detach	S&P	DBRS		10%	5%	10%	5%	10%	5%	10%	5%
M-1	3.00%	4.25%	BBB+ (sf)	BBB (sf)	$215,000,000	1.78	3.21	6-39	11-69	1.78	3.21	6-39	11-69
M-2	1.10%	3.00%	B+ (sf)	B (high) (sf)	$327,000,000	6.50	9.02	39-120	69-120	6.54	10.87	39-131	69-205
B-1	0.60%	1.10%	B- (sf)	B (low) (sf)	$86,000,000	9.99	9.99	120-120	120-120	12.83	19.31	131-181	205-261
B-2	0.10%	0.60%	NR	NR	$86,000,000	9.99	9.99	120-120	120-120	18.77	24.62	181-291	261-335
Total					**$714,000,000**								

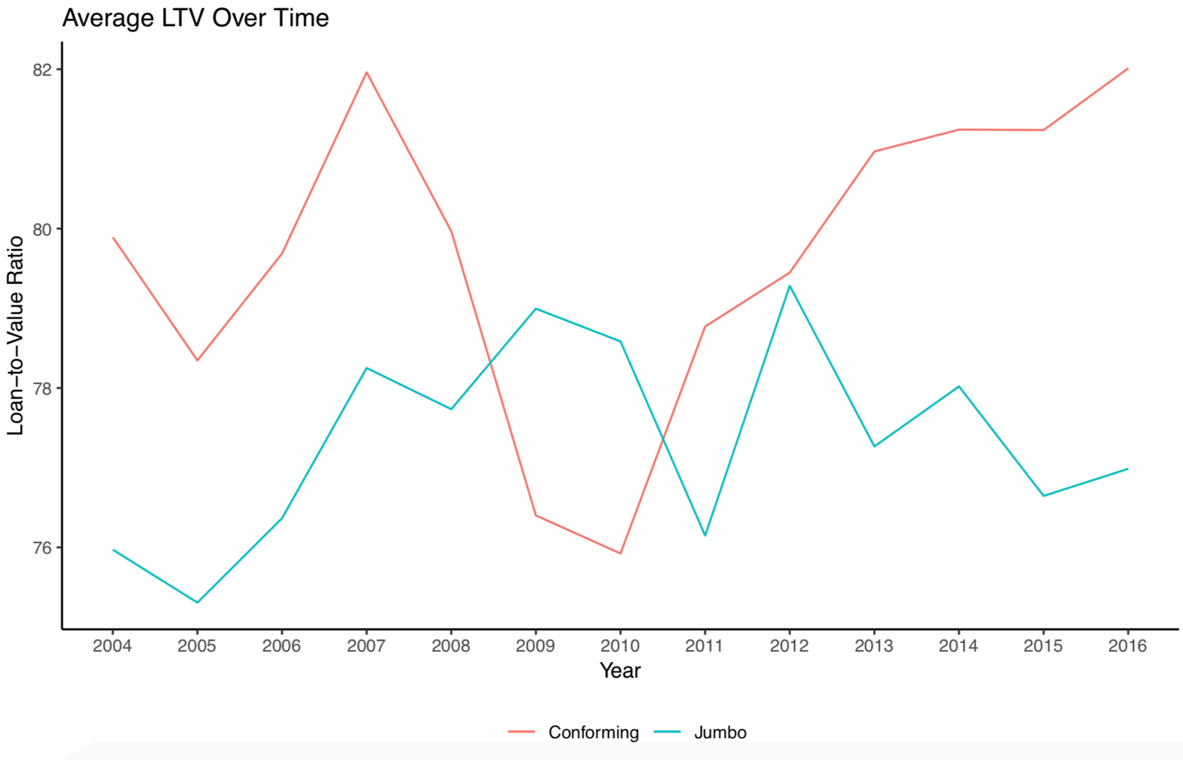
Source: Freddie Mac

Figure 2:



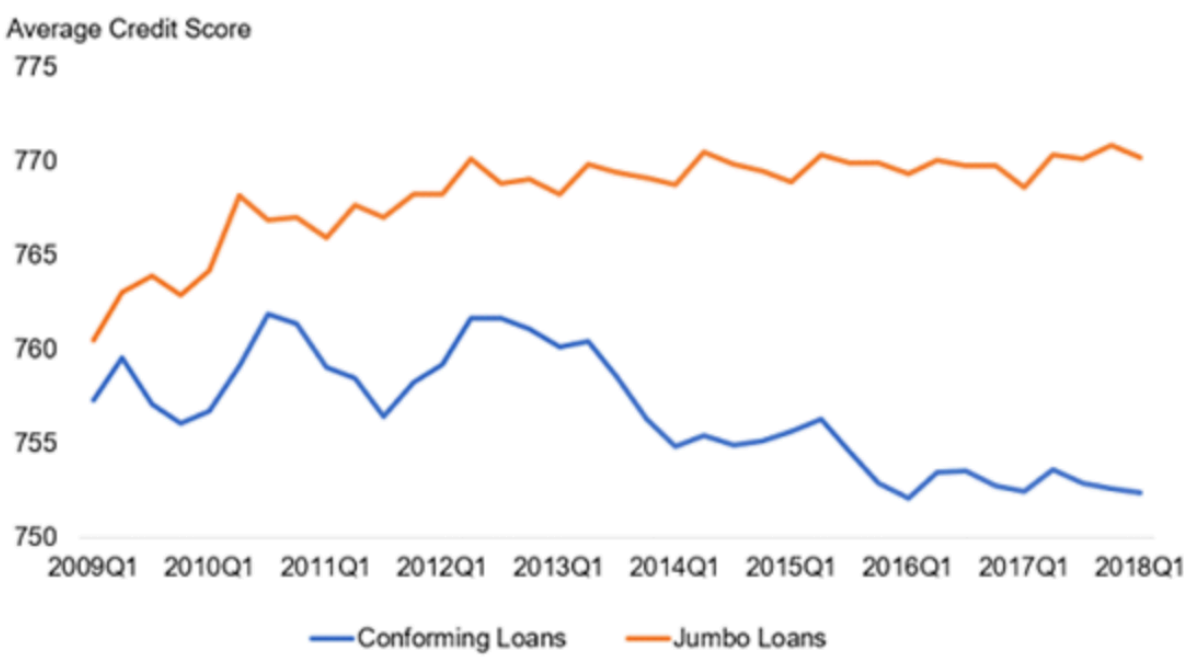
Source: Mortgage Bankers Association

Figure 3:



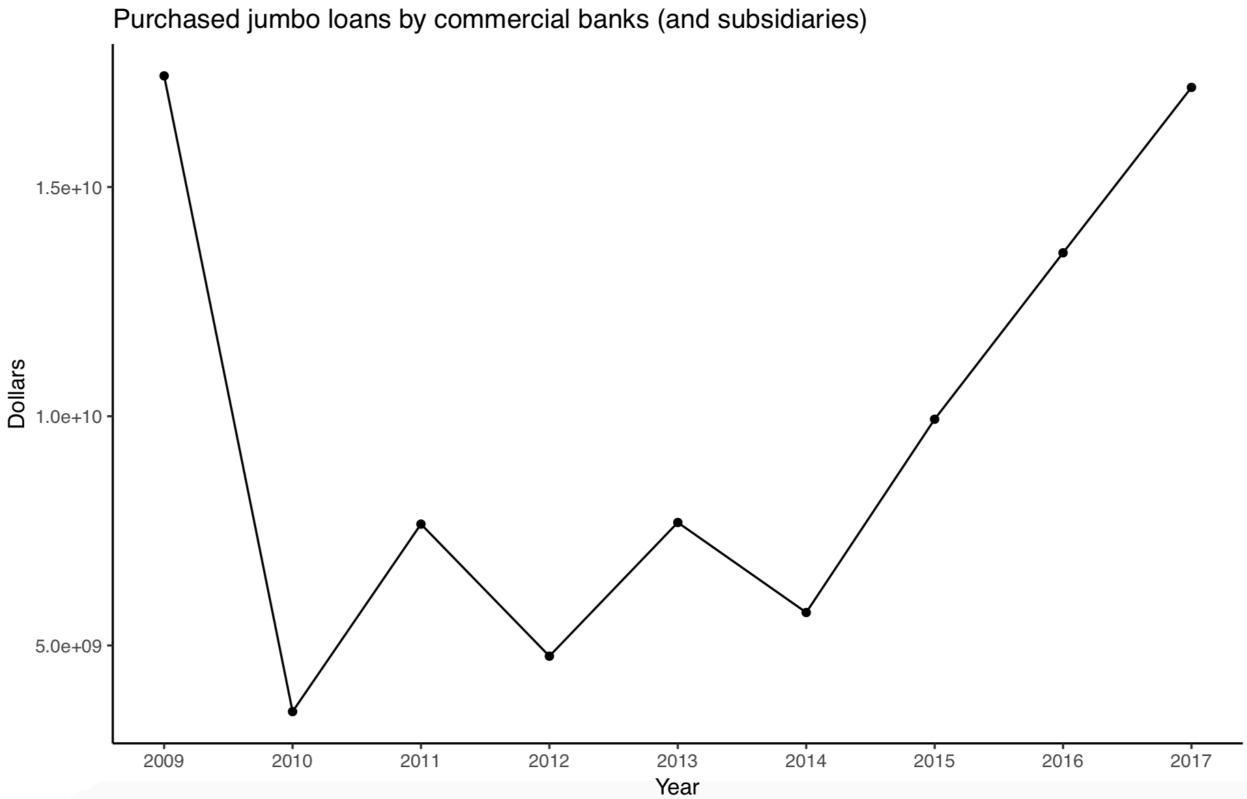
Source: MIRS Data

Figure 4:



Source: CoreLogic

Figure 5:



Source: HMDA Data