Bank Balance Sheet Capacity and the Limits of Shadow Banks

Greg Buchak, Gregor Matvos, Tomasz Piskorski and Amit Seru*

This Version: OCTOBER 2018

Abstract

We study which types of activities migrate to the shadow banking sector, why migration occurs in some sectors, and not others, and the quantitative importance of this migration. We explore this question in the \$10 trillion US residential mortgage market, in which shadow banks account for more than half of new lending. Using micro data, we document a large degree of market segmentation in shadow bank penetration. They substitute for traditional —deposit taking—banks in easily securitized lending, but are limited from engaging in activities requiring on-balance sheet financing. Traditional banks adjust their financing and lending activities to balance sheet shocks, and behave more like shadow banks following negative shocks. Motivated by this evidence, we build a structural model. Banks and shadow banks compete for borrowers. Banks face regulatory constraints, but benefit from the ability to engage in balance sheet lending. Like shadow banks, banks can choose to access the securitization market. To evaluate distributional consequences, we model a rich demand system with income and house price differences across borrowers. The model is estimated using spatial pricing rules and bunching at the regulatory threshold for identification. We study the consequences of capital requirements, conforming credit limits, and unconventional monetary policy on lending volume and pricing, bank stability and the distribution of consumer surplus across rich and poor households. Our results suggest that a complete policy analysis of the credit market requires simultaneously analyzing the impact on banks and shadow banks, and accounting for their equilibrium interactions.

Keywords: Shadow Banks, Balance Sheet Capacity, Market Segmentation, Capital Requirements, Lending, Mortgages, GSEs, Unconventional Monetary Policy

---

* Buchak is with the University of Chicago (buchak@uchicago.edu), Matvos is with the McCombs School of Business, University of Texas at Austin and NBER (Gregor.Matvos@mccombs.utexas.com), Piskorski is with Columbia Graduate School of Business and NBER (tp2252@gsb.columbia.edu), and Seru is with Stanford GSB, the Hoover Institution, SIEPR and NBER (aseru@stanford.edu). We thank Darell Duffie, Neil Esho, Andreas Fuster, Arvind Krishnamurthy, Chris Mayer, Hyun Shin, Adi Sunderam and seminar participants at Bank for International Settlements, University of Texas at Austin and participants at NBER Summer Institute, Kellogg Housing and Macroeconomics conference and Stanford Institute of Theoretical Economics Financial Regulation conference for helpful comments. We also thank Susan Cherry, Monica Clodius, and Sam Liu for outstanding research assistance.

First Version: February 2018.

Section I: Introduction

Policy makers, as well as researchers, have commonly viewed deposit taking institutions—traditional banks—as the main supplier of loans to households and firms. As a result, when thinking about stability of credit provision, they have largely focused on regulation and supervision of activities on the asset and liability sides of banks' balance sheets. This has changed in recent years with an emerging concern that increased regulation of banks results in substantial migration of financial activity to the less regulated, shadow banking sector. [1,2] For instance, in the $10 trillion US residential mortgage market, 20 percentage points (pp) of the market migrated to shadow banks after the financial crisis, and shadow banks now account for the majority of new lending (Buchak et al. 2017). In this paper, we document that this migration was selective: shadow banks substitute for traditional banks in some markets, but not in others. Intermediation activities which require on-balance sheet financing do not migrate to the shadow bank sector, suggesting that deposit taking institutions retain an advantage in balance-sheet intensive activities. We illustrate that ignoring differences in endogenous substitutability between banks and shadow banks alters the qualitative and quantitative inferences on equilibrium quantity, price, and distribution of credit resulting from different policies, and misestimates the impact of policies on bank stability as well as on distributional consequences.

We start by documenting a series of new facts related to two main residential mortgage market segments in the US: the conforming market and the jumbo market. These two segments account for the vast majority of residential mortgages originated during our sample period (2007 to 2016). The conforming loan market is the largest residential market segment and consists of mortgages with balances below the conforming loan limit. Mortgages which exceed the conforming limit are termed "jumbo." Conforming loans are issued with the participation of government sponsored enterprises (GSEs), which facilitates their securitization. Because jumbo mortgages are ineligible for GSE financing, they are issued without government guarantees and are significantly more difficult to securitize. Indeed, unlike conforming loans, the vast majority of jumbo loans are retained on the lenders' balance sheets.

We first document large swings in the share of jumbo mortgage originations during this period. The share of jumbo originations declined precipitously—29% to 10%—from 2007 to 2009 relative to conforming mortgages, only to reverse back to 30% by 2016. Second, we document that these market swings coincided with a dramatic increase in the share of residential mortgages originated by shadow banks. Consistent with Buchak et al (2017), we find that the share of conforming mortgages originated by shadow banks grew from less than 20% in 2008 to almost 50% by 2015. The market for jumbo mortgages, on the other hand, saw little penetration of shadow banks, despite

[1] For instance, the banking regulation proposal of the Minneapolis Federal Reserve, "The Minneapolis Plan," discusses taxing activity which migrates to shadow banking following higher capital requirements, https://www.minneapolisfed.org/~/media/files/publications/studies/endingtbtf/the-minneapolis-plan/the-minneapolis-plan-to-end-too-big-to-fail-final.pdf

[2] See Gennaioli, Shleifer, and Vishny (2013), Ordonez (2018), and Moriera and Savov (2017) for models of shadow banking and Adrian and Ashcraft (2016) for a comprehensive review.

large declines in the quantity of lending by traditional banks, with the market share of traditional banks persisting well above 80%.

These results suggest that market segmentation occurs because traditional banks and shadow banks differ in their ability to extend jumbo and conforming mortgages. Shadow banks face a lower regulatory burden, which has allowed them to expand. We argue that the comparative advantage of traditional banks in the jumbo market arises from their ability to hold these loans on their balance sheets. To separate this explanation from alternatives, we examine the market share of shadow banks around the conforming loan size limit. Most alternative explanations for the comparative advantage of banks suggest that this advantage would increase continuously with mortgage size. For example, if richer borrowers prefer borrowing from banks, one would imagine that borrowers' demand for banking services would increase continuously with mortgage size, as mortgages transition from conforming to jumbo. The ability to securitize a mortgage, on the other hand, discontinuously drops at the conforming loan amount. We find a 10 percentage point (pp) sharp increase in banks' market share at the conforming limit. In other words, our results suggest that jumbo and conforming markets are segmented, with traditional banks holding an advantage in the jumbo sector relative to the conforming sector.

To show that balance sheet capacity is the cause of market segmentation as opposed to other regulatory differences between banks and shadow banks, we look within the banking sector itself. We show that better capitalized banks, those with larger balance sheet capacity, are more likely to hold loans on their balance sheet. As banks' capitalization increases, so does the share of originations they hold on the balance sheet. Moreover, well capitalized banks' market share jumps by over 10% at the conforming limit. These result points to market segmentation within traditional banking sector between well and poorly capitalized banks: well capitalized banks are more likely to retain larger fraction of their loans and specialize in the segment of loans that are harder to securitize. The results also suggest that banks business models are adaptable. Banks, which are flush with capital, behave as standard models of banking would suggest: they use deposits to extend loans which they hold on their balance sheets. However, as a bank's balance sheet capacity declines, it switches to originating mortgages, which it can sell, behaving more like a shadow bank.

In addition to the changes in the market share of mortgages, we document large changes in the relative pricing of jumbo mortgages relative to conforming mortgages. While jumbo loans are generally more expensive, the relative price differential experiences a significant variation during our sample period. Relative price of jumbo mortgages increased by almost 40 basis points on average from 2007 to 2009, at the same time as quantities of jumbo originations declined; the spread then declined by up to around 60 basis points from 2009 to 2014 as jumbo originations increased. If the quantity decline from 2007 - 2009 was due lower demand for jumbo loans, either because of declining house prices or temporary increases in conforming loan limits during this time, we would expect lower jumbo spreads. Instead contemporaneous decrease in quantity and increase in price suggests a negative supply shock to jumbo mortgages during the 2007 to 2009 period. Moreover, jumbo spread evolves with the aggregate relative capitalization of lenders in the jumbo and conforming sector. The balance sheet driven market segmentation appears to be also an important determinant of aggregate mortgage prices.

Together, these facts provide a consistent view of the role of banks and shadow banks in the mortgage market. Banks' advantage lies in originating mortgages on their balance sheet, and their balance sheet capacity is limited by their capitalization. This advantage implies that traditional banks dominate the jumbo mortgage segment where it is harder to securitize loans and compete with shadow banks in the conforming market. More capitalized banks endogenously shift their business model towards more balance sheet retention, and towards the jumbo market segment. Shadow banks, on the other hand, benefit from a lower regulatory burden and mainly focus on the originate-to-distribute (OTD) conforming market. Such specialization implies that shocks and interventions, which affect only one type of lender, spill over to other lenders. Moreover, because markets are segregated, interventions have redistributive consequences, and affect bank stability. For example, tightening capital requirements on banks may decrease the supply of jumbo mortgages, and could increase the supply of conforming mortgages. Moreover, mortgage risk could shift from bank balance sheets to GSEs. Because of the expansion of off-balance sheet lending, this increase in bank stability might have small effect on overall mortgage volume, which would primarily be borne for highest income borrowers. In other words, this policy would have strong redistributional consequences.

To quantitatively analyze these effects in equilibrium, we build and estimate a model of the US residential mortgage market. The goal of the model is to capture the interaction of traditional and shadow banks across mortgage markets, and to allow banks to choose which mortgages to originate and how much to originate on balance sheet versus selling. We capture the redistributive consequences and accommodate realistic consumer substitution patterns by allowing rich heterogeneity on the demand side within a discrete choice framework (Berry et al., 1995; Nevo, 2000). Consumers with heterogeneous preferences over price, quality, and mortgage size choose among a menu of mortgages offered by various types of originators. We depart from discrete choice models by also allowing consumers to *choose* their mortgage size, and consequently, decide whether they want a conforming or jumbo mortgage.

We separately estimate demand and supply parameters. We identify demand using two types of variation. First, we instrument for price endogeneity in demand estimation by exploiting an institutional feature of how GSEs set prices of conforming mortgages across regions. Second, we use micro moments from the conforming limit cutoff directly in the demand estimation; intuitively, we apply the logic of regression discontinuity design within standard demand estimation. Having estimated demand, we estimate supply side parameters using firm price setting and financing decisions. Our model captures the salient features of the data, such as the extent of bunching at the conforming discontinuity across markets, and matches estimates such as price elasticity from the literature. Moreover, we observe several market level conforming loan limit changes during our sample period, and find that our model can replicate the equilibrium response quite well.

We next use our estimated model to consider three policy relevant counterfactuals. First, we study the impact of stricter capital requirements and other regulatory constraints on the types and prices of mortgages originated. Second, we study the impact of unconventional monetary policy such as Quantitative Easing on the mortgage market equilibrium. Third, we study the impact of the GSE conforming loan limit to investigate how the presence of available but restricted GSE credit has affected shadow bank growth, loan pricing, and the types of mortgage products that banks offer. This counterfactual can also inform the ongoing policy debate regarding the progressive lowering of conforming loan limits as a way of downsizing the GSEs. These policies lead to significant changes in the quantity, pricing, and distribution of mortgage credit, as well as determining where the credit risk in the economy is held. Importantly, we demonstrate that the equilibrium response of the shadow bank sector plays an important role in the *nature* and *magnitude* of these effects, accounting for more than 70 percent of the aggregate response in some cases. In addition, endogenous changes in the business model of traditional banks in response to various shocks also plays a critical role in generating these effects.

We illustrate that ignoring the differences between banks and shadow banks, and solely focusing on bank data can both severely *underestimate* or *overestimate* the effects depending on specific policy. In particular, in the case of interventions that adversely affect traditional banks (e.g., tighter capital requirements), solely focusing on bank balance sheet overstates the adverse effect of such polices on overall lending volume. Part of the reason is that lending migrates from the traditional banks to shadow banks. Moreover, banks adjust on the retention margin, deciding to securitize instead of holding loans on the balance-sheet. For example, our model predicts that increasing bank capital requirements to 9% reduces bank *balance sheet* lending by 67%. However, it reduces *total bank* lending by only 9%, and reduces *overall* lending by only 2%, as banks adjust their business from retention to selling and shadow banks expand their lending.

On the other hand, in the case of interventions that adversely affect secondary mortgage market (e.g., altering GSE financing costs), solely focusing on bank data understates the adverse effect of such polices on the overall lending volume. These polices also concurrently contract shadow bank lending. For example, in the case of unconventional monetary policy that raises GSE financing costs by 100 basis points, bank lending actually *increases* by $55 billion, while shadow bank lending *decreases* by nearly $300 billion. Ignoring the role of shadow banks would yield not only the wrong magnitude of the aggregate effect, but also the wrong direction. Finally, we also find that these interventions have significant re-distributional consequences as certain type of households benefit at the expense of others.

More broadly, our paper speaks to the theories of banking in the presence of shadow banks. The traditional view of banks is that they use deposits to make loans, which they hold on their balance sheet. Our results suggest that banks' choice of business model depends on both their capitalization and their equilibrium interaction with shadow banks. We show that banks' choice of business model is fluid, and depends on their balance sheet capacity. On one end of the spectrum are well capitalized banks, which dominate the market for loans that are held on the balance sheet. At the other end of the spectrum are shadow banks, which originate to distribute. In the middle are poorly capitalized banks with limited balance sheet capacity, whose participation in the market for portfolio loans is limited.

II: Institutional Setting and Data

II.A US Residential Mortgage Market

The residential mortgage market is the largest consumer finance market in the US. There are currently more than 50 million residential properties that have a mortgage with a combined outstanding debt of about $10 trillion (Source: Corelogic Data). In the US, the process by which a mortgage is secured by a borrower is called origination. This involves the borrower submitting a loan application and documentation related to his or her financial history and/or credit history to the lender. We discuss the main segments of the US residential mortgage market and the associated lenders active in these markets below.

II.A.1 Banks, Shadow Banks, and Business Models

There are two main groups of mortgage originators in the US: banks and shadow banks (non-bank lenders). These originators differ on at least three dimensions. First, banks (traditional banks and credit unions) rely on their insured deposit base as part of their capital. Shadow banks do not take deposits. Second, they differ in terms of their business models. After originating a loan, the originator can keep the loan on their balance sheet as a portfolio loan. Alternatively, the originator can originate-to-distribute, i.e. sell the loan as well as servicing rights. Banks engage in the origination of portfolio loans, comprising about 40% of their originations, and originate-to-distribute about 60% of their originations during our sample period. Shadow banks, on the other hand, do not retain loans and engage almost exclusively in the originate-to-distribute model. Finally, banks are subject to substantially higher regulatory burdens than shadow banks, including capital requirements, enhanced supervision from a wide set of regulators, such as the FDIC, FED, OCC, and state regulators, as well as compliance with a more extensive set of rules.[3]

The nature of lenders in the mortgage market has changed substantially from 2008 to 2015. Buchak et al. (2017) document a decline in traditional bank originations and the growth of shadow banks, with the shadow bank market share growing from 30% to more than 50% by 2015. The rise in shadow banks has coincided with a shift away from "brick and mortar" originators to online intermediaries. Buchak et al. (2017) provide evidence that both the increasing regulatory burden faced by traditional banks and growth of technology can account for a substantial part of this trend.

II.A.2 Mortgage Products

We focus on two main residential mortgage market segments in the US: the conforming loan market and the jumbo loan market. Together these two segments account for more than 80% of all US residential mortgages originated during our sample period (based on HMDA). The largest residential market segment in the US consists of conforming loans. These are usually extended to

[3] See Stanton et al. (2014, 2017) for discussion of the industrial organization of the US residential mortgage market.

borrowers with relatively high credit scores, conservative loan-to-value (LTV) ratios (e.g., up to 80%), and fully documented incomes and assets. Conforming mortgages must be below the conforming loan limit, which grew from $417,000 in 2006 to $453,100 in 2018 for a one-unit, single-family dwelling in a low-cost area, and from $625,000 to $679,650 for the same unit type in a high cost area. In addition, the American Recovery and Reinvestment Act of 2009 temporarily increased these limits in certain high cost areas to up to 729,500. Mortgages that exceed the conforming limit are termed "jumbo."

Conforming loans are issued with the participation of government sponsored enterprises (GSEs), while jumbo loans are not. GSEs allow for a substantially easier securitization of conforming mortgages. For example, Fannie Mae and Freddie Mac, the two most prominent GSEs, purchase conforming mortgages and package them into mortgage-backed securities (MBS), insuring default risk. These MBS are particularly attractive to investors interested in relatively safe assets. In 2017, conforming loans packed in mortgage-backed securities guaranteed by Fannie Mae and Freddie Mac made up about 50% of the outstanding residential loans (Source: Securities Industry and Financial Markets Association Data). Because jumbo mortgages are ineligible for GSE financing, they are issued without government guarantees. Consequently, these mortgages are significantly more difficult to securitize and the vast majority are retained on the balance sheets.

II.B Description of Datasets

Our paper brings together a number of datasets which we describe below.

HMDA: Mortgage level application data is the main source for market shares across lender and product types. The Home Mortgage Disclosure Act (HMDA) collects the vast majority of mortgage applications in the United States, along with their approval status. In addition to the application outcome, the data includes loan type, purpose, amount, year of origination, and location information down to the applicant's census tract. It further contains demographic information on the applicant, including race and income. Important for this analysis, it includes the originator's identity, which we link manually across years. Finally, it documents whether the originator sells the loan to a third party, and if so, whether the loan purchaser is a GSE. An important caveat with the sales data is that if the originator retains the loan through the end of the calendar year and sells it in the subsequent year, it is recorded in HMDA as a non-sale. We use data beginning in 2010 and ending in 2016.

Fannie Mae and Freddie Mac Single-Family Loan Origination Data: These datasets, provided both by Fannie Mae and Freddie Mac, contain origination data from the GSEs' 30-year, fully amortizing, full documentation, single-family, conforming fixed-rate mortgage purchases.[4] The

[4] The dataset does not include ARM loans, balloon loans, interest-only mortgages, mortgages with prepayment penalties, government-insured mortgage loans such as FHA loans, Home Affordable Refinance Program mortgage loans, Refi Plus™ mortgage loans, and non-standard mortgage loans. The data also excludes loans that do not reflect current underwriting guidelines, such as loans with originating LTVs over 97%, and mortgage loans subject to long-term standby commitments, those sold with lender recourse or subject to other third-party risk-sharing arrangements, or were acquired by Fannie Mae on a negotiated bulk basis.

loan-level data contain information on the loan, property, and borrower, including loan size, interest rate, loan purpose, property location, borrower credit score, loan-to-value ratio, and importantly, the identity of the lender that sold the loan to the GSE. We use this data to calculate average interest rates by lender type and market.

Black Knight McDash Loan-Level Mortgage Performance Dataset: BlackKnight is a private company that provides a comprehensive, dynamic loan-level dataset on mortgages, including loans serviced by the ten largest US mortgage servicers, and accounts for approximately 75% of all mortgages in the US as of year-end 2010 (Black Knight McDash estimate). Importantly for our purpose, Black Knight includes information on both jumbo and GSE loans and includes loans retained on banks' balance sheets. Much like the Fannie Mae and Freddie Mac data, Black Knight McDash data contain interest rates and a large number of borrower and loan-specific characteristics, including FICO score at origination, loan-to-value ratio, five-digit zip code of origination, loan purpose, and whether the loan is fixed or adjustable-rate. The Black Knight McDash data also include dynamic data on monthly payments, mortgage balances, and delinquency status.

Blackbox: BlackBox is a private company that provides a comprehensive, dynamic loan-level dataset with information about more than twenty million privately securitized subprime, Alt-A, and prime loans originated after 1999. These loans account for about 90% of all privately securitized mortgages from that period. Much like the Fannie Mae and Freddie Mac data, the Blackbox data contain interest rates and a large number of borrower and loan-specific characteristics, including FICO score at origination, loan-to-value ratio, five-digit zip code of origination, loan purpose, and whether the loan is fixed or adjustable-rate. The BlackBox data also include dynamic data on monthly payments, mortgage balances, and delinquency status.

US Census Data: We use metropolitan statistical area-level data from the US Census and American Community Survey between 2010 and 2015. In particular, we use incomes, homeownership rates, and home values.

Federal Reserve Bank Data: We use banking regulatory call reports to measure bank capital ratios, assets, deposits, and other data from bank balance sheets.

II.C Lender Classification

We classify lenders as in Buchak et al. (2017). Briefly, a "bank" is a depository institution and "shadow bank" is not. This definition parallels that of the Financial Stability Board, which defines banks as "all deposit-taking corporations" and shadow banks as "credit intermediation involving entities and activities outside of the regular banking system." (see Buchak et al. (2017)).

Section III: Empirical Analysis

We begin by presenting a set of empirical facts regarding recent changes in the price, quantity, and distribution of mortgage credit, which motivate our analysis and model. In doing so, we also shed light on the drivers of the comparative advantage of banks and shadow banks.

We note that larger balance sheet capacity, potentially tied to the subsidized deposit financing, could provide traditional banks with an advantage in making loans that are harder to sell in the secondary loan market. Accordingly, the extent of this advantage could vary with access to the securitization market, with shadow banks having a relatively larger presence in the markets in which it is easier to securitize loans. On the other hand, the relatively lighter regulatory regime faced by shadow banks could provide some comparative advantage relative to traditional banks. In this case, we would expect that the stricter regulatory regime including bank capital requirements faced by traditional banks would facilitate expansion of shadow bank lending, especially in highly regulated market segments.

We focus our analysis on two main residential mortgage market segments in the US: the conforming loan market and the jumbo loan market. These two segments account for more than 80% of all US residential mortgages (based on HMDA) originated during our sample period (2007-2016). The data used in our analysis are similar to that used in the literature (e.g., Buchak et al. (2017)). Appendix shows summary statistics for the main datasets used in our analysis.

III.A Aggregate Facts

We start by documenting several aggregate facts, which motivate the analysis and model in the rest of the paper. We document large changes in the composition and pricing of mortgages originated by the traditional banking and shadow banking sector, and relate those changes to the balance sheet capacity of the banking sector.

III.A.1 Origination Trends: Conforming and Jumbo Market Segments

We first present two aggregate market trends in the quantity and pricing of jumbo and conforming mortgages. The conforming loan origination volume varied between about \$750 billion to more than \$1.25 trillion per year (Figure 1, Panel (a)). The jumbo origination volume was smaller, ranging from \$150 billion to around \$500 billion per year. The changes in volume were not uniform. The relative share of the jumbo market in the overall loan origination volume declined sharply from about 28% in 2007 to less than 10% in 2009 (Figure 1, Panel (b)). From 2009 onwards, the jumbo share experienced a substantial increase reaching more than 30% in the 2015 to 2016 period. The jumbo market collapsed relative to the conforming market and then recovered back to similar levels.

III.A.2 Relative Product Pricing: Conforming and Jumbo Interest Rate Spread

The changes in the jumbo market share were accompanied by changes in the relative interest rates of jumbo mortgages to conforming mortgages (jumbo spread). Panel (c) of Figure 1 presents time series data relating interest rate spreads between conforming and jumbo loans. Before the crisis, the aggregate data shows virtually no aggregate jumbo spread. As quantity of jumbo mortgages contracted towards 2009, their relative price increased by almost 40 basis points on average and as much as 70 basis points in the early 2009. As the market share of jumbo mortgages recovered, the jumbo spread decreased by up to 60 basis points. The positive correlation between aggregate price and quantity suggests that supply shocks were at least partially responsible for driving the aggregate trends. If the contraction in jumbo quantity were solely driven by demand for jumbos (e.g., due to a decline in house prices), we should also observe a decrease in the pricing of jumbo mortgages.

III.A.3 Market Segmentation: Shadow Banks and Bank Business Model

We next investigate the penetration of shadow banks in the mortgage lending market during the same period. Consistent with Buchak et al (2017), we find a dramatic increase in the share of residential mortgages originated by the shadow banks during the 2011 to 2016 period. We further note that Buchak et al. (2017) find that the tightening of regulatory constraints faced by traditional banks was an important driver of this shadow bank expansion.

Interestingly, while the overall traditional bank market share has been declining significantly, we find that these effects occur entirely within the conforming mortgage market. Traditional bank market share in the conforming market has declined from slightly under 80% in 2007 to about 50% in 2016 (Figure 2 Panel (a)). This contrasts significantly with the jumbo market. Bank market share in the jumbo market has remained roughly constant, varying between 85% to 95%. In other words, the contraction and later expansion in the amount of jumbo lending is mainly driven by changes in originations by traditional banks. The changes in the conforming market, on the other hand, are driven by changes in both shadow bank and traditional bank originations.

One possible way to interpret the facts above is that traditional banks *uniformly* contracted their lending, but shadow banks chose to only enter the conforming market. Here we show that this is not the case and that traditional banks significantly changed their lending composition. In particular, as panel (b) of Figure 2 shows the share of traditional bank originations in the jumbo market doubled during the expansion of shadow bank lending in the conforming sector (from about 20% in 2011 to more than 40% by 2016). This suggests that that an expansion of shadow bank lending in the conforming market has resulted in traditional banks shifting their originations towards the jumbo market segment. We note, however, that before this shift, traditional banks first contracted jumbo lending significantly, from 30% in 2007 to 10% in 2009 and initially focused on the conforming loan market.

Overall, these results imply that traditional banks substantially changed their business model during the crisis. Jumbo mortgages are mainly held on the balance sheet of the originating bank, while conforming loans are mainly securitized and sold to GSEs. As banks first shifted their origination from jumbo mortgages towards conforming, and then back to jumbo mortgages during the shadow bank expansion, they also switch between the classic banking model (originating for portfolio loans) and the originate-to-distribute model (selling to GSEs).

III.A.4 Balance Sheet Capacity of the Banking Sector, Product Pricing and Quantity

We next show that the capitalization of the banking sector is correlated with trends in the mortgage market. Panel (a) of Figure 3 illustrates that the banking sector capitalization originally declined, bottoming out in 2009, and then began increasing. Moreover, panels (b) and (c) point to a strong positive association between bank capitalization and volume and share of jumbo originations.

Overall, these patterns along with our prior findings indicate that traditional bank capitalization closely follows the share of jumbo mortgage originations, their relative pricing, and banks' choice of whether to lend on their balance sheet or originate-to-distribute.

III.A.5 Summary of Aggregate Facts

The aggregate facts we document are consistent with the idea that banks and shadow banks differ in their ability to extend jumbo and conforming mortgages, resulting in market segmentation. We argue that this market segmentation arises because jumbo mortgages are mainly kept on the portfolio of lenders. Since shadow banks do not have much balance sheet capacity, they originate-to-distribute, which is limited to the conforming market.

Such market segmentation implies that a decline in the balance sheet capacity of the banking system leads to a relatively larger contraction in traditional jumbo mortgage supply through two channels. First, shadow banks, lacking balance sheet capacity, respond to the decline in the conforming market, but cannot do so in the jumbo market. Second, traditional banks, lacking balance sheet capacity, tilt their activity towards conforming originations and the originate-to-distribute model. The larger contraction in the supply of jumbo mortgages leads to an increase in their relative price, i.e. an increase in the jumbo-conforming spread.

III.B. Micro Evidence

In this section, we provide micro-level evidence on balance sheet capacity, market segmentation, and relative product pricing. Consistent with our aggregate facts, this evidence points to the balance sheet capacity induced market segmentation in the mortgage market.

III.B.1 Market Segmentation at the Conforming Loan Limit

We start our analysis by looking at the conforming loan size limit to take a first stab at establishing the importance of bank balance sheet capacity in driving the market segmentation. As we discussed in Section III, there is a sharp loan amount cutoff to qualify as a conforming loan. One would imagine that borrowers' demand for banking services would not increase discontinuously with mortgage size, as mortgages transition from conforming to jumbo. The ability to securitize a mortgage, on the other hand, discontinuously drops at the conforming loan amount. Thus, observing a discontinuous jump in the bank market share at the conforming limit would reject the demand alternative.

We first confirm that the probability of loan securitization indeed discretely jumps at the conforming loan limit. We form bins based on the relative percentage of the conforming loan limit and calculate the percentage of loans retained on the balance sheet in that bin. For example, a bin contains all loans of 95% - 100% of the conforming loan limit size. For each bin *b,* we compute the share of the loans held on the balance sheet:

$$ShareHeld_b = \frac{1}{T_b}\sum_{l \in b} Held_l$$

In which T_b is the number of loans in a bin and $Held_l$ is an indicator variable taking the value of 1 if the loan was not sold, i.e. if the loan is a portfolio loan. Panel (a) of Figure 4 confirms that the probability that a loan is held on the balance sheet discretely increases at the conforming limit: only 20% of loans just below the conforming loan limit are held on the balance sheet, whereas 60-70% of loans just above the conforming loan limit are held on the balance sheet.

We next examine whether banks' market share discretely increases at the conforming loan limit. In other words, we test whether banks specialize in large loans or in conforming loans. We examine the same bins as before, but we compute banks' market share within each bin:

$$ShareBank_b = \frac{1}{T_b}\sum_{l \in b} Bank_l$$

In which $Bank_l$ is an indicator variable taking the value of 1 if the mortgage was originated by a bank and 0 if it was a shadow bank. Panel (b) of Figure 4 shows that banks' market share of loans just below the cutoff is roughly 60%, whereas bank market share above the cutoff is roughly 75%. The results suggest that banks have a comparative advantage in originating jumbo loans because these loans are difficult to sell.

We more formally test whether there is a jump in loan retention and bank market shares at the discontinuity. We focus on mortgages within 1% of the conforming cutoff and estimate the following regression discontinuity specification around the conforming loan limit:

$$Held_{ilt} = \beta \times Jumbo_i + X_i'\Gamma + \gamma_{lt} + \epsilon_{ilt} \tag{1}$$

$$Bank_{ilt} = \beta \times Jumbo_i + X_i'\Gamma + \gamma_{lt} + \epsilon_{ilt} \tag{2}$$

Where $Held_{ilt}$ and $Bank_{ilt}$ are $\{0,1\}$ indicator variables for whether the loan *i* in census tract *l* originated in year *t* is financed on the balance sheet or originated at a bank, respectively. $Jumbo_i$ is an indicator for whether the loan size is above the conforming loan limit in the time-county of origination, and the corresponding coefficient β is the object of interest. X_i' is a vector of loan-level controls including log loan size, log applicant income, dummy variables for race, ethnicity, sex, loan type, loan purpose, occupancy, and property type. γ_{lt} is a census tract-origination year fixed effect, which absorbs any variation in local conditions over time, as well as regulatory differences. In other words, we examine the effect by comparing loans from the same census tract and year around the conforming limit, adjusting for observable borrower differences. For robustness, we also experiment with larger samples, those within 5%, 10%, and 25% of the conforming loan limit.

Table 1 Panel (a), which uses loan level data from HMDA for all mortgage originations, shows that loans immediately above the conforming loan limit are roughly 50% more likely to be held on the balance sheet of the lender—portfolio loans. Increasing the bandwidth above 1% produces similar results, as shown in columns (2)-(4). Moreover, focusing only on 2015 data paints an even more striking picture. Loans directly above the cutoff being 63% more likely to be held on balance sheet than loans directly below the cutoff in the same census tract and year.

The differences in financing sources carry through to stark differences in the type of loan originator. Panel (b) column (1) of Table 1 shows that loans directly above the conforming loan limit are nearly 25% more likely to have been originated by a traditional bank, as opposed to a shadow bank. As above, when considering only loans originated in 2015, this difference grows to 38%. It is worth emphasizing that this effect is driven entirely by the presence, or lack thereof, of the GSE financing option for conforming loans. While there exist private financing options for conforming and non-conforming loans alike, the presence of the GSEs in the conforming market appears to exert significant influence on whether a mortgage is financed on the balance sheet, and consequently whether the mortgage is originated by traditional banks.

III.B.2 Within Bank Analysis

Our findings above are consistent with the idea that banks' ability to finance loans with their balance sheets generates a strong comparative advantage in the segment for difficult to securitize loans—jumbo loans. However, balance sheet capacity is not the only differentiating factor between banks and shadow banks; for example, shadow banks are subject to a very differential regulatory burden than traditional banks (see Buchak et al. 2017). To isolate the effect of balance sheet capacity further, we look within traditional banks, keeping the regulatory regime fixed.

Specifically, we compare better capitalized banks, those with larger balance sheet capacity, to poorly capitalized banks, those with low balance sheet capacity. If low balance sheet capacity is the source of market segmentation between banks and shadow banks, then we should observe similar segmentation between well capitalized and poorly capitalized banks. Last, we look within banks' changes in balance sheet capacity and show that changes in balance sheet capacity are tightly linked to the business model of banks. As balance sheet capacity declines, banks move from portfolio lending towards the originate-to-distribute model.

We first examine whether a bank's capitalization is indeed related to its balance sheet capacity, i.e. its ability to originate loans and hold them on the balance sheet. In other words, we examine whether bank capitalization is related to a bank's choice of business model on the dimension of originating portfolio loans versus originating-to-distribute. We calculate the percentage of loans held on the balance sheet by bank b in year t, $Held_{bt}$, and regress this on the bank capital ratio CR_{bt} with observations at bank-year level:

$$Held_{bt} = \beta CR_{bt} + \gamma_t + \gamma_b + X'_{bt}\Gamma + \epsilon_{bt}$$

γ_b are bank fixed effects, controlling for differences in banks' propensity towards portfolio lending, as well other time invariant differences in business models. γ_t are time fixed effect, which absorb any aggregate changes that would affect the business model of banks, including aggregate demand or supply fluctuations that would affect the propensity to hold loans on the balance sheet. X_{bt} contains bank controls, including log number of originations, log bank assets, deposits to liabilities, log of the average loan size and applicant income of the bank's originations, and log of the number of unique census tracts in which the bank lends. These specifications are estimated for both levels and changes in these variables.

Table 2 shows that a 1% increase in a bank's capital ratio is associated with roughly a 4.5% increase in the share of originations which are held on the balance sheet (column 2). We find similar evidence when we estimate the above specification in changes (column 4). In particular, banks that experience a 1% increase in their capital ratio increase the share of originations held on their balance sheets by about 2.4% (column 4).

Figure 5 presents these results less parametrically, through binned scatterplots of $Held_{bt}$ and CR_{bt}, with respect to controls. Panel (a) shows a simple scatter plot of banks' shares of loans held on the balance sheet as a function of their capital ratios. The plot illustrates a strong positive relationship: better capitalized banks retain a higher portion of originated loans on the balance sheet. Panel (b) shows that this is the case within banks as well. Panel (c) and (d) of Figure 5 show that the same inference holds for changes in these variables. Banks that experience a decrease in balance sheet capacity are more likely to sell loans, rather than keep them on the balance sheet. In other words, banks' business models are linked to their balance sheet capacity. In the cross-section, banks with lower balance sheet capacity are more likely to engage in originate-to-distribute, rather than portfolio lending. In the time series, as banks' balance sheet capacity declines, they shift towards the originate-to-distribute model, and then move back towards portfolio lending as their balance sheet capacity improves. Both Figure 5 and Table 2 also suggest that banks shift their business model from originate-to-distribute to portfolio lending as their balance sheet capacity decreases.

Last, we confirm that the balance sheet effect also leads to the jumbo/conforming market segmentation among traditional banks. We begin with an approach similar to that used above, by looking at originations above and below the conforming loan limit. First, we look on the retention around the conforming loan limit among traditional banks only. Second, rather than looking at the traditional bank market above and below the limit, we look at the market share of well capitalized banks relative to other traditional banks. If balance sheet capacity leads to market segmentation, we should see well-capitalized banks' origination share relative to other banks' increase discontinuously through the conforming loan limit.

We define a bank to be well capitalized if its capital ratio is in the top 25% of bank capital ratios in the given year. Panel (a) of Figure 6 shows that within traditional banks, the balance sheet retention also dramatically increases among loans above the conforming loan limits. Panel (b) plots the well capitalized banks' share of overall bank lending by conforming loan limit percentile. The figure shows that below the cutoff, the top quarter of banks by capitalization originate slightly more than 40% of loans. Above the cutoff, however, well capitalized banks play an outsized role in originations, accounting for roughly 75% of originations even though they comprise only one quarter of lenders by definition.

As above, we more formally test for these effects in Table 3, which uses loan level origination data from HMDA that were made by traditional banks. We focus only on traditional bank originators and first test whether there are significant differences in financing between loans just above and below the threshold. Panel (a) of Table 3 indicates that, among traditional banks, jumbo loans are much more likely to be held on balance sheet relative to conforming loans confirming what we observed in Figure 6. Panel (b) of Table 3 confirms that the fraction of loans originated by the well capitalized banks substantially increases for loans just above the conforming loan limit. These results suggest that the balance sheet capacity of well-capitalized banks gives them a comparative advantage in the jumbo sector both relative to shadow banks and poorly capitalized traditional banks, leading to market segmentation.

Finally, Table 4 confirms this inference by studying the association between bank-level capital ratios and bank origination financing and product mix. Like Table 2, this regression is at the lender-year level among traditional banks. Column (1) shows that better capitalized banks are more likely to originate jumbo loans, but the inclusion of bank fixed effects in Column (2) eliminates this effect and shows that variation in jumbo loan origination comes from cross-bank variation in capitalization. Columns (3)-(4) and (5)-(6) compare how banks adjust financing for jumbo loans and conforming loans, respectively. These results reveal no significant effect for jumbo loans which is consistent with the fact that because no secondary market for jumbo loans exists, banks are unable to adjust whether they sell or retain loans. In contrast, with conforming loans we find a large effect of capitalization on financing. This is consistent with banks able to access external financing for conforming, but not jumbo loans. These effects hold both across and within banks, suggesting that banks vary their business model on conforming side in response to changes in their own capitalization.

III.B.3 Relative Product Pricing

The aggregate results indicate that balance sheet contraction of traditional banks leads them to contract supply of jumbo mortgages, increasing the jumbo spread. The aggregate jumbo spread may partially reflect the differences in the mortgage composition, since jumbos are larger and cater to a different population segment. To shed more light on conforming and jumbo loan pricing, we examine the mortgage interest rates around the conforming limit in Figure 7, and compare the period during which the spread was high (2008) with the period in which the spread was low (2014) in the aggregate data. Similar to aggregate data, there is a sharp discontinuity of about 30 to 40 basis points at the conforming loan cutoff in 2008 (panel (b) of Figure 7). By 2014, on the other hand we observe much more modest increase in mortgage rates on loans above the conforming loan limit.

As we discussed above, the positive correlation between aggregate price and quantity and bank capitalization suggests that supply shocks were at least partially responsible for driving the aggregate trends. If the contraction in jumbo lending in 2007-2009 period were solely driven by demand for jumbos (e.g., due to a decline in house prices), we should also observe a decrease in the pricing of jumbo mortgages. Instead we find the opposite effect: jumbos are relative more expensive in times of low jumbo market share.

III.B.4 Supply or Demand? Evidence from "Bunching" around Conforming Loan Cutoff

We start by examining the distribution of mortgages around the conforming loan limit cut-offs. There is a significant mass of borrowers right below the conforming loan cutoff including those with higher incomes (Figure 8). This fact has also been documented in prior work (e.g., DeFusco and Paciorek 2017) and suggests that the conforming loan limit is in fact a binding constraint for many borrowers and informs us about unmet demand for jumbo loans. As will become clear, our model exploits micro moments related to "bunching" around the conforming limit discontinuity for estimation. Therefore, we now test if exogenous changes to supply of bank credit changes this unmet demand.

In our test we exploit exogenous change in supply of bank credit and assess if unmet demand of jumbo loans changes, as captured through changes in mass of borrowers at the cutoff. The intuition underlying this test is that the borrowers who get loans exactly at the conforming loan limit choose precisely that size because they would otherwise prefer a larger jumbo loan, but due to relatively better supply on the conforming side these borrowers sacrifice the desired loan size and get the largest conforming loan possible. When the relative supply of jumbo loans changes, we expect some of these potentially constrained borrowers to be more likely to choose their desired (jumbo) loan size. We run this analysis at the county-year level.

In this test, we measure the mass of borrowers in county *c* and origination year *t* at the conforming loan limit as

$$\%AtCutoff_{ct} = \frac{1}{T_{ct}} \sum_{\boldsymbol{i}} \boldsymbol{I}\left(\frac{LoanSize_i}{LoanLimit_{ct}} \in (0.999{,}1.001)\right)$$

That is, $\%AtCutoff_{ct}$ represents the percentage of originations in county *c* originated in year *t* that are within 0.1% of the conforming loan limit in that market. T_{ct} is the total loans originated in county *c* in year *t*. We also run the tests for larger bandwidths between (0.995,1.001) and (0.990,1.001). Note that roughly 1% of loans are within the (0.999,1.001) band, 1.1% of loans are within the (0.995,1.001) band, and 1.2% are within the (0.990,1.001) band. The supply of bank credit in a region is measured by *%Bank* variable. Our regression specification is:

$$\%AtCutoff_{ct} = \beta(\%Bank_{ct}) + \gamma_c + \gamma_t + \epsilon_{ct}$$

where γ_c and γ_t are county and year fixed effects, respectively. The prediction is that $\beta < 0$.[5]

To obtain exogenous variation in %Bank, we utilize the differential geographic impact of the closure of the OTS. The OTS, which was a "lax" regulator, closed in 2011 and its duties were folded into stricter banking regulators (see Agarwal et al. 2014). Counties that ex-ante had a greater share of OTS-regulated lending were hit harder by this change (Buchak et al. 2017). Consequently, we use the OTS closure (in the time series) interacted with county-level OTS share in 2007 (in the cross section) to obtain time-county variation in market share of banks. The first stage regression at county *c* origination year *t* level is:

[5] There are several alternatives that might conflate the proposed relationship. For instance, counties with many borrowers exactly at the conforming loan cutoff may differ in terms of number of banks or shadow banks operating. Additionally, if the size of loans demanded is large for a given year, it could indicate a healthy local economy with relatively high house prices, and these good local economic conditions could attract more bank or shadow banks.

$$\%Bank_{ct} = \gamma Post_t \times \%OTS_{2007,c} + \gamma_c + \gamma_t + \epsilon_{ct}$$

$Post_t$ is an indicator taking the value 1 in 2012 and years after. The IV regression uses predicted $\%Bank_{ct}$ from this regression. From this we obtain variation in *%Bank* that is plausibly exogenous to local economic conditions driving loan demand that are not absorbed by time or county fixed effects. Table 5 shows the results of these series of regressions. Panel (a) shows the (0.990, 1.001) band, and Panel (b) shows the (0.995, 1.001) band.

Focusing on Panel A, column (1) is the first stage regression. It shows a negative relationship between bank market share and OTS closure times ex-ante OTS share. This is consistent with the prediction: Counties with higher OTS share in 2007 received a harsher shock to bank regulation following OTS closure. Column (2) is the reduced form of *%AtCutoff* regressed on $Post_t \times \%OTS_{2007,c}$. This column shows a positive and statistically significant relationship between OTS closure times ex-ante OTS, indicating that counties receiving this negative shock to bank credit supply see more borrowers getting conforming loans immediately below the line. A 1% greater OTS share corresponds to 0.027% increase in bunching of conforming loans immediately below the cutoff, representing an increase in the number of borrowers who appear to want larger loan sizes but instead get conforming loans.

Column (3) shows the OLS regression, finding a negative and significant relationship between bank share and percentage of bank borrowers immediately below the conforming loan cutoff. Recall for the reasons discussed above, this regression has several endogeneity concerns. The IV result in column (4) shows the results using bank share variation obtained from the OTS closure. This column shows a large negative and statistically significant relationship between bank market share and borrowers at the jumbo cutoff. In other words, decreases in the supply of bank credit appear to increase the number of borrowers exactly below the conforming loan cutoff, as borrowers increasingly take smaller-than-desired loans in exchange for more favorable conforming loan terms. In terms of quantities, this result finds that a 1% increase in bank market share is associated with a 0.14% decrease in conforming loans exactly at the loan limit. The results in Panel B, which widens the bandwidth, are essentially unchanged quantitatively, indicating that most of the variation in shares is indeed coming from borrowers who are pushed to the conforming loan limit.

III.C Summary

Before describing the model, we summarize our evidence established above. Shadow banks have gained significant market share, during the period of tightening regulatory constraints faced by traditional banks, but the majority of these gains have been in the OTD conforming sector. Traditional banks retained market share in the jumbo sector by shifting their origination activity towards this sector where their balance sheet capacity gives them an advantage. To confirm this, we note a striking discontinuity in market shares and balance sheet financing around the conforming loan limit. Similar results hold when comparing well capitalized to poorly capitalized banks. Within bank regressions confirm the capitalization channel, with greater capitalization being strongly associated with more balance sheet lending and more jumbo lending. As banks were shifting their origination activity towards jumbo sector we observe a progressive decline of jumbo interest rates relative to the conforming market rates.

Together, these facts provide a consistent view of the role of banks and shadow banks in the mortgage market. Banks' advantage lies in originating mortgages on their balance sheet, and their balance sheet capacity is limited by their capitalization. This advantage implies that traditional banks dominate the jumbo mortgage segment where it is harder to securitize loans and compete with shadow banks in the conforming market. More capitalized banks endogenously shift their business model towards more balance sheet retention and towards jumbo market segment. Shadow banks, on the other hand, benefit from a lower regulatory burden and mainly focus on the originate-to-distribute conforming market. Such market segmentation and potential endogenous substitutability between banks and shadow banks implies that assessing the impact of shocks and interventions on bank stability as well as on borrowers is non-trivial. We next turn to a structural model that allows us to make such assessments.

Section IV: Model of Mortgage Demand and Supply

We build a structural model of the U.S. mortgage market, which features banks competing with shadow banks for consumers. Our model builds on Buchak et al. (2017), but is substantially richer on several dimensions on both demand and supply side. Most importantly, our model accounts for the market segmentation between conforming and jumbo mortgages both on the demand and supply side. We briefly discuss some salient features of supply and demand side before describing the model in detail.

On the supply side we explicitly model different financing choices across intermediaries. The supply side of the market consists of three types of lenders, banks, and two distinct types of shadow banks: non-fintech shadow bank, and fintech shadow bank. These financial intermediaries engage in two activities, loan origination and financing. Intermediaries can finance mortgages two different ways: portfolio (balance-sheet) lending or originate-to-distribute. In portfolio lending the intermediary finances the mortgage from its own funds. Therefore, differences in lenders' internal funds—balance sheet capacity—will change their willingness to engage in this activity. Furthermore, capital requirements put regulatory restrictions on the amount of portfolio lending a bank can engage in. Alternatively, intermediaries can originate-to-distribute: they finance the mortgage by selling it to a third-party financier through GSEs. Of course, an intermediary can engage in both types of financing simultaneously. We also allow banks to face regulatory pressures beyond capital requirements. These can arise from legal or regulatory enforcement actions, or the anticipation of future actions on the part of the regulators or prosecutors. These regulatory pressures constrain banks' lending activity even if banks are well capitalized.

Following the institutional setup of the US mortgage market, a central distinction between jumbo and conforming mortgages is that only conforming mortgages can be financed by originating-to-distribute; jumbo loans are portfolio loans. Moreover, only banks can access deposits, which give them the ability to finance portfolio loans.[6] Shadow banks can only originate-to-distribute. With this set-up, our model generates endogenous market segmentation between traditional and shadow banks and within the traditional banking sector between well and poorly capitalized banks.

On the demand side, we build a rich discrete choice framework, with an application to the mortgage market. Importantly, we allow preferences of borrowers to be correlated with their income. These differences in preferences, especially for larger mortgages, play a critical role in studying the distributional aspects of policies.

IV.A Mortgage Demand

A market c in year t is defined at the MSA-loan purpose level. For example, a market may be borrowers in New York City attempting to refinance their mortgages. Each market has $i = 1, \ldots, I_{ct}$ consumers, with an ideal mortgage size, F_i, and $j = 1, \ldots, J$ lenders.[7] Lenders can offer up to two types of products, conforming and jumbo mortgages. Conforming mortgage amounts that are available to an individual borrower, $\overline{F_{ict}}$, have to satisfy two constraints. First, the amount has to be below the market-specific conforming loan limit $\overline{F_{ct}}$, which is \$417,000 in most markets. Second, the loan has to satisfy the individual-specific LTV constraint, where $\overline{LTV} \times P_i$ is the LTV constraint times the borrower's house price. Any mortgage that does not satisfy these two conditions is a jumbo mortgage. Then the individual's maximum conforming loan size $\overline{F_{ict}}$ is the smaller of the market level conforming level, and the LTV constraint:

$$\overline{F_{ict}} = \min\{\overline{F_{ct}}, \overline{LTV} \times P_i\} \tag{D.1}$$

Let $g \in \{C, NC\}$ denote whether the mortgage is conforming (*C*) or jumbo (*NC*). Conditional on an offered rate, consumers can choose any loan size subject to the limits described above.

Consumers' utility from a mortgage depends on the mortgage interest rate r_{jctg}, the chosen mortgage size F_i^*, which can differ from idea mortgage size, and the convenience or quality of the service provided by the lender:

$$u_{ijctg} = \underbrace{-\alpha_i r_{jctg}}_{rate} - \underbrace{\beta_i I(F_i^* < \overline{F_{ict}}) I(F_i > \overline{F_{ict}}) + \gamma_i I(F_i^* < \overline{F_{ict}})}_{size} + \underbrace{q_{jt} + \xi_{jct} + \epsilon_{ijctg}}_{service} \tag{D.2}$$

A consumer's utility declines in the mortgage rate $\alpha_i r_{jctg}$, with α_i measuring the consumer specific sensitivity to interest rates. Without loss of generality, we normalize the utility from a jumbo mortgage to 0. Borrowers that choose a conforming mortgage, regardless of their preferences, obtain consumer specific utility γ_i, which captures the non-rate attributes of a conforming

[6] Because banks have access to a subsidized funding of their balance sheet through insured deposits, one can model the shadow bank decision not to engage in balance sheet lending as a competitive outcome with a corner solution.

[7] We define market size for new originations as 10% of households in a given market in a year under the assumption that households remain in place for roughly 10 years. The market size for refinances is the total number of households with mortgages.

mortgage versus a jumbo mortgage such as points or fees. Additionally, a borrower choosing a conforming mortgage when her ideal mortgage size exceeds the conforming loan limit suffers a disutility from choosing a smaller mortgage $\beta_i \boldsymbol{I}(F_i^* < \overline{F_{ict}}) I(F_i > \overline{F_{ict}})$,[8] with β_i measuring the consumer specific disutility. Consumers differ in their preference over mortgages $\mathrm{B}_i \equiv (\alpha_i, \beta_i, \gamma_i, F_i)'$. In other words, the optimal mortgage size, interest rate sensitivity, the relative preference for conforming loan, as well as the cost of departing from the optimal mortgage size are consumer specific.

In addition, consumers' preferences over lender differ based on the lender's convenience and/or service quality. $q_{jt} + \xi_{jct}$ measures convenience differences between lender, where q_{jt} is observed by the researcher, and ξ_{jct} is not. q_{jt} is the year-lender type invariant quality difference.[9] Intuitively, consumers like to borrow from fintech shadow banks such as Quicken, because they offer a convenient way to interact online. Last, borrowers preferences over lenders differ idiosyncratically, which is captured in the i.i.d. T1EV borrower specific utility shock ϵ_{ijctg}. For example, some lenders prefer to borrow from JPMorgan Chase over Quicken, because they have a bank account with the former, making it easier to transact.

Consumers' preferences are drawn from a distribution, where the distribution is a function of income and house prices in a market. In particular,

$$\mathrm{B}_i = \overline{\mathrm{B}} + \Pi(D_{ict} - \overline{D}) + \Sigma \nu_i \tag{D.3}$$

$\overline{\mathrm{B}}$ is the vector of mean consumer preferences, Π maps demeaned consumer demographic characteristics such as income and house prices $(D_{ict} - \overline{D})$ to individual consumer preferences. For example, higher income borrowers can have different price sensitivity than lower income borrowers, and their preferences over mortgage size can differ. Σ scales normal i.i.d. shocks $\nu_i \sim N(0, I)$. In other words, even borrowers with the same observable characteristics, such as income, can differ in their price elasticity or optimal mortgage size. The demand parameters to be estimated are then $\theta_d = (\overline{\mathrm{B}}, \Pi, \Sigma)$.

Consumers choose the mortgage that maximizes their utility by choosing between offered mortgages. If they do not choose a mortgage they choose and outside good with a fixed utility, u_{i0}. In other words, given product characteristics for each mortgage offered in the market $jctg$ (including interest rate, mortgage type, lender type, statutory size limits, and service quality), and demand parameters θ_d, the set of borrower characteristics (including product-borrower match utilities ϵ_{ijc}), such that borrowers with these characteristics in market ct choose a mortgage of type g from lender j is:

$$A_{jctg}(r_{\cdot ct\cdot}, g_{\cdot ct\cdot}, \overline{F}_{ct}, q_{\cdot t}, \xi_{\cdot ct}; \theta_d) = \{(D_i, \epsilon_{i0ctg}, \dots, \epsilon_{iJctg}) \mid u_{ijctg} \geq u_{ikctl}, \forall k, l\} \tag{D.4}$$

[8] A consumer will never choose a mortgage which is too large.

[9] Because of large changes in the quality of fintech providers over time, we allow the quality of fintech shadow banks to evolve over time as well.

$A_{jctg}(\cdot)$ denotes the set of demographic characteristics, D_i, and idiosyncratic shocks $\epsilon_{i\cdot ctg}$ such that given loan characteristics $(r_{\cdot ct.}, g_{\cdot ct.}, \bar{F}_{ct}, q_{\cdot t}, \xi_{\cdot ct})$ and parameters θ_d, consumers with those demographics and preference shocks obtain more utility from choosing the loan from lender j of type g, u_{ijctg}, than from all other lenders and loan types, u_{ikctl}. Integrating over demographics and shocks yields the market share of mortgage lender j offering product g in market ct:

$$s_{jctg}(r_{\cdot ct.}, g_{\cdot ct.}, \bar{F}_{ct}, q_{\cdot t}, \xi_{\cdot ct}; \theta_d) = \int_{A_{jctg}} \frac{\exp\left(u_{ijctg}(\mathrm{B}_i)\right)}{\sum_{k,l} \exp\left(u_{ikctl}(\mathrm{B}_i)\right)} dB(B_i) \tag{D.5}$$

Note that the size of mortgages a consumer chooses is implicitly captured in expression D.4. If a consumer prefers a jumbo-sized mortgage, and chooses a jumbo mortgage, she does so at the optimal size. If, instead, this consumer chooses a conforming mortgage, she will choose the largest conforming mortgage possible, which implies bunching at the conforming loan limit.

IV.B Mortgage Supply

There are N_{bct} banks, N_{nct} non-fintech shadow banks, and N_{fct} fintech shadow banks in market *ct*. Lenders choose simultaneously which mortgages to originate across all markets, and how to finance them. A lender j who originates m_{jctg} dollars of mortgage type *g* in market *ct* has to decide how many to retain as portfolio loans on the balance sheet, m^b_{jctg}, and finances the remainder through GSE securitization $m_{jctg} - m^b_{jctg}$. Jumbo mortgages cannot be securitized, and are held on the balance sheet, $m_{jctNC} = m^b_{jctNC}$. Each bank has only one balance sheet across markets in which it participates. Denote by $m^b_{jg} = \sum_{ct} m^b_{jctg}$ the amount of type *g* mortgages that lender *j* chooses to retain on the balance sheet. In other words, suppose the bank originates conforming mortgages in the New York City and Houston MSA, and it chooses to finance \$100 million on its balance sheet. From a financing perspective, it does not matter which market these mortgages were originated from. We first describe the cost of mortgage origination, and then turn to financing costs.

IV.B.1 Origination

Mortgage origination is costly, beyond the mere financing cost of a mortgage. Lenders' incur non-financing costs, such as costs of an appraisal and title check, document processing, and loan closure, which involve labor and equipment. We designate the per dollar origination cost of lender j of mortgage type *g as* w_{jg}, and the total origination cost in market *ct* is

$$\sum_g m_{jctg} w_{jg} \tag{S.1}$$

This specification allows for different origination costs across banks, non-fintech shadow bank, and fintech shadow banks. For example, this heterogeneity allows us to capture potential cost savings from technology employed by fintech shadow banks who use less labor in lending.

IV.B.2 Financing and Regulatory Burden

Recall that mortgages can be financed two ways. Conforming mortgages can be sold to through GSEs, i.e. originate-to-distribute. Alternatively, conforming and jumbo mortgages can be financed by using the bank's internal funds as portfolio loans. These two types of financing can have different costs.

Originate-to-Distribute Financing

Lenders can securitize conforming mortgages though GSEs. Since GSEs purchase mortgages at pre-determined prices, all lenders face the same originate-to-distribute financing cost in a given market, which we model as an ability to obtain funding for a conforming mortgage at a rate $\sigma_t^{GSE} = r_{d,t} + \sigma^{GSE}$. $r_{d,t}$ represents the underlying financing costs of the loan absent any costs arising from intermediation and captures the current interest rate environment in the macroeconomy. σ^{GSE} captures additional costs coming from the lender using GSE financing. In other words, when the firm originates-to-distribute a mortgage, it earns the spread on the mortgage rate, minus the financing and non-financing origination costs, $r_{jctg} - \sigma_t^{GSE} - w_{jg}$ for every dollar of the mortgage. Reflecting the post-crisis period, which we study, we assume that securitization is only available for conforming loans; jumbo loans must be retained on balance sheet. One could easily account for a jumbo securitization in the same way.

Costs of Portfolio Lending

The cost of portfolio lending depends on the composition of the lenders balance sheet, and the amount of equity capital e_{jt}. A lender sources financing at the firm level, and has one balance sheet comprising mortgage assets across markets. There are two types of assets held on a lender's balance sheet, mortgages, the amount of which is chosen by the lender in each market, and other assets in the amount m_{jto}^b. The choice of the latter is determined outside the model, and represent other assets that the bank chooses to hold on the balance sheet, such as government bonds, or commercial loans, which it did not securities. Lenders also differ in the amount of equity capital e_{jt}. The amount of equity and the asset composition of the balance sheet jointly determine the cost of portfolio lending for an intermediary.

A lender's risk-adjusted capital ratio, ρ_{jt}, depends on the banks equity capital e_{jt}, and banks' risk weighted assets $\xi_o m_{jto}^b + \sum_{ctg} \xi_g m_{jctg}^b$:

$$\rho_{jt} = \frac{e_{jt}}{\xi_o m_{jto}^b + \sum_{ctg} \xi_g m_{jctg}^b} \tag{S.2}$$

Where ξ_g represents the risk weight of mortgage of type g, and ξ_o the risk weight of other assets the bank holds. Since jumbo mortgages' have higher risk weights, they use up more statutory capital per dollar of actual lending. A banks capital needs to be below its statutory capital requirement $\bar{\rho}$ if it wants to lend on its balance sheet.

The per dollar cost of financing a portfolio loan of lender j depends on its capitalization:

$$\sigma_{jt}^{p} = r_{d,t} + \sigma^{b1}\left(\rho_{jt} - \bar{\rho}\right)^{-\phi} \tag{S.3}$$

The closer a banks risk-adjusted capital ratio is to the statutory requirement, i.e. the smaller is $\left(\rho_{jt} - \bar{\rho}\right)$, the larger is the cost of portfolio loan financing, with $\phi > 0$ and σ^{b1} measuring the extent of the cost. This formulation captures in reduced form the fact that lenders face capital constraints, and that banks choose a capital buffer above the hard capital requirement. The micro-foundations of such a buffer can be generated in a dynamic setting, but are not the central interest in this paper.[10] We assume that shadow banks' capitalization ρ_{jt} is so low that portfolio lending is prohibitively expensive $\rho_{jt} = \bar{\rho}$. This assumption captures in reduced form the notion that shadow banks do not have access to a subsidized deposit funding and must use external financing instead.

Regulatory Burden

Banks face regulatory pressures beyond capital requirements. These regulatory pressures constrain banks' lending activity even if banks are well capitalized. Rather than changing costs of lending, which we model directly, regulatory burdens may also reduce traditional banks' activity on the extensive margin. For example, binding capital requirements, risk constrains, or lawsuits may sometimes prevent a traditional bank from lending to a given borrower altogether. We capture this type of regulatory burden through parameter $1/\zeta_{tg}$.

For banks the probability of lending to a specific borrower of mortgage *g* in market *ct* is scaled by a factor ζ_{tg}. A higher $1/\zeta_{tg}$ (lower ζ_{tg}) captures a relatively constrained bank; a lower $1/\zeta_{tg}$ (higher ζ_{tg}) captures a relatively unconstrained bank. These shocks are i.i.d. across lender-borrower pairs, which accounts for the uncertainty that a bank faces with respect to which loans may ex post be subject these issues.

IV.B.2 Choosing Mortgage Rates and Financing

Taking other lenders' actions as given, an individual lender sets interest rates across all markets, as well as the choice of securitization, in order to maximize its profits. Denote by $\boldsymbol{r_{jt}}$ the set of prices of all products, conforming and jumbo, across all markets, $\boldsymbol{r_{jt}} = \{r_{jctg}: \forall c, g\}$. Since all jumbo mortgages are securitized, the only decision in addition to setting interest rates is how many, if any, conforming mortgages to hold on the balance sheet m_{jctC}^{b}, and how many to securitize, $m_{jt}^{GSE} = \sum_{c}\left(m_{jctC} - m_{jctC}^{b}\right)$. Then the lenders chooses interest rates, and the amount of conforming mortgages to hold on the balance sheet by maximizing the following profits:

$$max_{r_{jt}, m_{jctC}^{b}} \underbrace{\sum_{ctg} r_{jctg} m_{jctg}}_{rate\ income} - \underbrace{\sum_{ctg} m_{jctg} w_{jg}}_{origination\ cost} - \underbrace{\left(m_{jt}^{GSE}\sigma_{t}^{GSE} + \sum_{ctg}\left(m_{jctg}^{b}\right)\sigma_{jt}^{p}\right)}_{financing\ cost} \tag{S.4}$$

[10] See, for example, Corbae and D'Erasmo (2018).

The first term labeled *rate income* is the yearly income that the lender earns from the loans that it has made, equal to the sum of interest rates times mortgage volumes across all loan types and markets. The second term labeled *origination cost* is the costs the lender occurs in originating the loans, such as the wages of mortgage brokers, advertising, and administrative expense. The third term labeled *financing cost* is the financing cost of the mortgage, reflecting the costs of either GSE or balance sheet financing, depending on the lender's optimal financing cost.

Intermediaries' profits comprise interest rate income (either collected by themselves, or through servicing rights), origination costs, and financing costs. Note that interest rates enter profits both directly and indirectly through market shares. Market shares are also affected by regulatory constraints. In other words, the amount of mortgages originated, m_{jctg}, is implicitly a function of both the interest rates of the lender $\boldsymbol{r}_{jt}$, other lenders $\boldsymbol{r}_{-jt}$, and the regulatory burden parameter ζ_{tg}, which we omit for ease of notation.

IV.B.3. Equilibrium

We study symmetric equilibria. Demand is characterized by consumers' choice of mortgages and market share equations. Consumers maximize utility taking prices and lender characteristics as given. Supply is characterized by intermediaries' maximization in S.4. Banks, non-fintech shadow banks, and fintech shadow banks set mortgage rates across all markets in which they participate. Moreover, banks decide how many of the mortgages to hold on the balance sheet.

IV.C Estimation

We estimate the demand and supply parameters separately. To estimate the model, we aggregate the loan level data to market-lender-type observations. A market is defined as an MSA-year-loan purpose, e.g., refinances in New York City in 2013. In each MSA-year, we measure demographic data including means and standard deviations of log incomes and log house prices from the ACS. Within MSA-years, we separate markets into mortgages originated for new purchases and mortgages originated for refinances, the idea being that a borrower looking for one type of loan is not in the market for another type. Among each offering, we adjust conforming and jumbo interest rates by regressing interest rates on FICO and LTV, and then adjusting each individual loan to the overall average FICO and LTV values on the basis of the regression before averaging interest rates within product offering. LTV constraint is based on GSE guidelines.[11]

In addition to market shares from HMDA and prices from Fannie Mae, Freddie Mac, and Blackbox, we obtain the number of unique lenders (N_{bct}, N_{fct}, and N_{nct}) by taking the median number of lenders per census tract within the MSA. This captures the typical number of loan offerings from each type of lender that a borrower faces. Market size is defined as one tenth of the total number of households in the case of new originations, under the assumption that one tenth of

[11] See for instance, https://www.fanniemae.com/content/eligibility_information/eligibility-matrix.pdf

households are potentially in the market for a new home per year, and as the total number of outstanding mortgages in the case of refinances.

IV.C.1 Demand Estimation

Our estimation roughly follows Berry et al (1995), and Nevo (2000) with several differences. The most important difference is the use of the discontinuity at the conforming loan limit. As is standard, we calculate the model-implied market shares of each offer in each market. We apply the contraction mapping given in Nevo (2000) to obtain a vector $\xi_{\cdot ct}$ such that model-implied market shares are equal to observed market shares. We exploit an institutional feature of how GSEs set interest rates of conforming mortgages to instrument for prices. Hurst et al. (2016) show that, for political economy reasons, mortgage pricing for GSE loans does not adjust for spatial risk. Accordingly, we use the variation in mortgage pricing across regions to obtain relative variation in conforming and jumbo interest rates that is driven by GSE constraints and not by borrower demand.

In addition to aggregate data, we also exploit several micro-level data moments, specifically, the mean and standard deviation of realized loan sizes for jumbo and conforming loans within a market. These moments help identify the latent distribution of optimal mortgage size.

The most significant departure from the standard Berry et al (1995) and Nevo (2000) style estimation is the use of the discontinuity at the conforming loan limit. We discuss the nature of the discontinuity extensively in Sections IV. This type of discontinuity has been used in reduced form work to identify the price elasticity of demand. We use two moments around the conforming limit discontinuity. First, we use the market share of borrowers who obtain conforming loans exactly at the conforming loan limit (see Figure 8 panel a). Intuitively, as the model suggests, these are the borrowers who would have preferred a jumbo mortgage, but chose a conforming mortgage instead because of the lower price. The second moment we match is the income difference between borrowers exactly at the conforming loan limit and those nearby (see Figure 8 panel b). This moment aids in identifying the correlation between income and preferences for a jumbo mortgage, i.e., the structure of the correlation in the random coefficients.

Demand Estimates

We estimate the model over the period 2010-2015. The results are shown in Table 6. Recall that borrowers broadly differ on their price sensitivity, and their preference over mortgage size, both in how large their optimal mortgage is, and how costly departures from the optimal size are.

One way to evaluate the model fit is to see whether our model can match the size distribution from the data. Figure 9 shows the bunching at the conforming loan limit generated by our model, versus the actual amount of bunching observed in the data. The model fits the data quite closely, both in qualitatively replicating the bunching patters, as well as quantitatively matching the extent of bunching in the data.

Price sensitivity

Our estimates of mean price sensitivity suggest that borrowers are quite price elastic, and the differences in price elasticity are small. The mean parameter $\bar{\alpha} = 0.80$ implies a price elasticity of roughly 3.2. This estimate is close to DeFusco and Paciorek (2017), who estimate the elasticity from the conforming loan discontinuity using reduced form methods. The estimate of $\sigma_{\alpha}^{2} = .10$ suggests moderate borrower differences in price elasticity, ranging from 2.4 to 4 for borrowers two standard deviations below the mean, and borrowers with two standard deviations above the mean in price sensitivity. Second, borrowers in higher house price areas are less price elastic. Since jumbo mortgages cater to wealthier borrowers in high house price areas, this implies that they cater to a less price elastic part of the borrower population, allowing, all else equal, higher mark-ups earned on these mortgages.

Optimal mortgage size

The preference over mortgage size is a central driver of consumers choosing jumbo versus conforming mortgages. The optimal mortgage size is larger for wealthier individuals, with an elasticity of 0.22. In other words, as income rises by 1%, the desired mortgage size increases by 0.22%. This estimate is close to the heuristic that household debt should not exceed 30% of household income. Desired loan size also increases with house prices, with an elasticity of approximately 0.5. When borrowers depart from their optimal mortgage size, they find this departure costly. For borrowers who would otherwise prefer a jumbo mortgage, we estimate a mean disutility of taking a smaller loan to be $\bar{\beta} = 3.85$, which is equivalent to roughly a 4.8% higher interest rate. This parameter is identified primarily off of the amount of bunching at the conforming loan limit: Greater disutility from taking a smaller loan means that more borrowers will choose jumbo loans rather than bunch at the conforming limit.

Next, we find that borrowers with high income are less sensitive to taking smaller loans, while borrowers with high house prices are more sensitive to taking smaller loans. This is an intuitive finding: High-income borrowers are likely to be able to adjust to smaller loan sizes by putting up more of their own money. Borrowers buying high-price homes, on the other hand, are more dependent on larger loan sizes and consequently are less willing to substitute a small conforming loan for a large jumbo loan. Finally, we find a positive and substantial preference for conforming loans overall as opposed to jumbo loans, possibly reflecting the unmodelled costs of qualifying for and obtaining a jumbo loan (e.g., increased screening and loan documentation requirements and additional time and effort needed to obtain a jumbo loan relative to conforming loan). In addition, lenders may steer borrowers towards more standardized conforming loans.

IV.C.2 Supply Estimation and Results

To estimate the supply-side parameters, which govern intermediaries' behavior, we use the revealed preferences of intermediaries in setting interest rates and choosing how many loans to retain on the balance sheet. We estimate parameters governing the costs of origination for the three types of intermediaries we observe, the financing cost of balance sheet lending, and the costs of originate-to-distribute. Intuitively, using demand estimates, we can compute the mark-ups that intermediaries earn. We use the lenders' pricing decisions, combined with these mark-ups to infer the costs of lending. For example, if an intermediary is charging higher prices for a given mark-up, this implies that the intermediary is facing higher lending costs, which the lender passes on to consumers. Recall that for a bank, the cost of portfolio lending depends on its current capital ratio ρ_j, the statutory capital requirement $\bar{\rho}$, other parameters such as the risk weights, ξ_g and ξ_j, and the type of mortgage. To the extent that low capitalization indeed causes a higher cost of portfolio lending, the model implies how these higher costs should be passed through to different types of mortgages given estimated demand. Table 7 shows the estimated parameters.

Because we estimate costs using intermediaries' pricing decisions, we cannot separate the baseline origination and financing costs. Intuitively, if a bank's baseline financing costs increase by 0.5% (50 basis points), but origination costs decline by 0.5%, the costs of making a loan do not change. With that in mind, the baseline costs of originating and financing a mortgage varies from 2.3% – 2.8%. This number represents the cost of financing and originating a new purchase mortgage for a bank that is flush with capital.

To better understand the different costs of mortgages, Figure 10 plots total marginal costs for different levels of excess bank capitalization, defined as the difference between the bank's capital ratio and the statutory requirement, $\rho - \hat{\rho}$. Several things stand out. First, well capitalized banks have a cost advantage over poorly capitalized banks, because they can lend with lower-cost balance sheet financing. Second, even poorly capitalized banks have a cost advantage over shadow banks, because while both can finance mortgages through GSEs, the model estimates that banks' origination costs are lower.

Second, financing jumbo mortgages is more expensive than financing conforming mortgages, even when the latter are held on the balance sheet. Jumbo mortgages' risk weight is 2.5 that of conforming mortgages, i.e. a dollar in a jumbo mortgage tightens the capital constraint more than a dollar of conforming mortgages, resulting in higher financing costs. This difference declines with bank capitalization. In other words, if the capital constraint is loose, then a higher risk weight has a small cost. For a bank, whose capital exceeds the statutory capital by 3%, the additional financing cost is 30bp; at 10% of capital above the statutory limit, the cost difference declines to approximately 5bp.

Quantitatively, these numbers are reasonable. In 2009, a time period outside of the estimation window, the typical bank originator of a jumbo loan had an excess capital ratio of roughly 7%. According to our model, this corresponds to a roughly 3.1% marginal cost. At the same time, the typical bank origination of a conforming loan had an excess capital ratio of roughly 6.7%, which corresponds to roughly a 2.5% marginal cost. This implies a conforming-jumbo marginal cost, which is roughly in line with the observed rate spread in Figure 1.

Finally, the model suggests that originating refinancing mortgages is less costly than originating mortgages for purchase by approximately 15-20 basis points. In refinancing, lenders benefit from many on-the-ground activities having already taken place at the time of purchase, such as a title check, structural examination, negotiations between buyer and seller, which reduces costs.

IV.C.3 Bank Regulatory Burden and Fintech Quality

Finally, Table 8 shows the estimated bank regulatory burden and fintech quality parameters implied by our structural estimation procedure. A higher regulatory burden parameter captures a relatively constrained traditional bank; a lower burden captures a relatively constrained bank. An increase in the fintech quality parameter indicates an increase in the perceived quality of services offered by shadow bank fintech lenders relative to other lenders.

Consistent with Buchak et al. (2017), Table 8 indicates that traditional banks experienced a relative tightening of non-capital requirement related regulatory constraints, especially after 2012. This tightening of regulatory constraints faced by traditional banks helps explain a significant increase in the shadow bank market share during this period. Moreover, and consistent with Buchak et al. (2017), there is a steady improvement in the quality of services provided by fintech lenders in both new originations and refinancing relative to non-fintech shadow bank originations of the same loan purpose. Additionally, the model estimates that fintech quality in new originations is slightly below non-fintech quality during the entire sample, while fintech quality is significantly higher than non-fintech quality in refinancing. This is consistent with the idea that the online origination is particularly well-suited to refinancing.

Section V: Counterfactual Policy Analysis

In this section, we use the estimated model to study the consequences of several policy changes. Our baseline scenario is based on 2015 lending volumes, as reported in HMDA, together with 2015 regulatory policies. We evaluate the effects of policies on the amount, distribution, and pricing of loans, as well as the resulting market structure. Because policies impact bank profits and balance sheet loan retention, they have implications for bank stability. Moreover, the policies have a differential impact across borrowers of different incomes, changing the level of inequality.

V.A Changes to Bank Capital Requirements

We first study the consequences of changing capital requirements. The level of the capital requirement is one of the main tools used by policy makers to regulate banks. Assessing how much activity might migrate to shadow banks in response to changes in bank capital requirements is at the center of many policy proposals.[12] Our model allows us to do a more complete analysis of this policy since it simultaneously analyzes the impact on banks and shadow banks accounting for their equilibrium interactions. The capital requirement was 4% in 2010 and increased in several increments to 6% in 2015. Taking the 2015 market as given, we counterfactually study the impact

[12] For instance *The Minneapolis Plan* of the Minneapolis Federal Reserve proposes substantially increased capital ratios, above 20%. One of the critical inputs involves projections on the amount of activity that could migrate to the shadow banking sector (https://www.minneapolisfed.org/~/media/files/publications/studies/endingtbtf/the-minneapolis-plan/the-minneapolis-plan-to-end-too-big-to-fail-final.pdf).

of the capital requirement being set at 3%, 4.5%, 7.5%, 9%, and 12%. Table 9 and Figure 11 shows the results.

Increasing capital requirements tightens the capital constraint, increasing banks' cost of lending on the balance sheet. As we show below, lowering capital requirements would primarily affect the share of mortgages held on bank balance sheets, but would otherwise have little effect on mortgage origination. Raising capital requirements, on the other hand, would decrease the share of mortgages on bank balance sheets, but also lead to substantial changes in mortgage origination. This additional stability in the banking sector would come at a cost of substantially fewer jumbo mortgages, which would partially be offset by more conforming originations. The decline of the jumbo market would be mostly felt by higher income individuals. In other words, tightening capital requirements trades-off bank stability with welfare of high-income consumers and bank profits.

Mortgage Origination and Redistribution

The effect of changing capital requirements has an asymmetric impact on mortgage origination. Even reducing capital requirements to 3% would result in very modest changes in the origination of mortgages. The total volume would increase by $13 billion to $1,776 billion, driven primarily by increases in jumbo lending. The market structure of lending would not change much either, except about 15 basis point decline in jumbo interest rates. Both high income borrowers and banks benefit from loosening capital requirements, but the benefits are small, with consumer surplus increasing by less than $3 billion,[13] and lender profits increasing by $4 billion if capital requirements fall to 3%. These gains in consumer surplus fall primarily to high income individuals, with individuals in the top quartile of income gaining roughly $122 in consumer welfare, compared to $71 for individuals in the bottom quartile of income.

Increasing capital requirements, on the other hand, does change mortgage originations. The largest impact is on the jumbo market, which services high income and high house price markets. As capital requirements increase, banks start retreating from jumbo mortgages. Consider the capital requirement of 9%. Jumbo lending decreases by $150 billion, or 40%, relative to the market with capital requirement of 6%. The large decrease in the supply of jumbo mortgages results in a 89 basis point increase in jumbo rates, while the conforming rate remains virtually unchanged, resulting in a large increase in the jumbo spread. A substantial number of borrowers who would have borrowed jumbo loans still obtain mortgages: $120 billion worth of mortgages shift to the conforming market. The rest of the borrowers exit the mortgage market completely, resulting in an $31 billion decrease in mortgage lending. Banks and shadow banks each capture approximately $60 billion of these. While banks and shadow banks share equally in originating these new conforming loans, the new bank originations are primarily financed by GSEs.

Higher capital requirements primarily hurt banks and high-income borrowers. Given the capital requirement of 9%, bank profits decrease by roughly $28 billion, while shadow bank profits are

[13] We compute consumer surplus as a lifetime present-value dollar equivalent measure of *expected utility* (integrated over consumer specific shocks ϵ_{ijctg}), assuming a subjective discount rate of 4.00% over a period of 10 years.

essentially unchanged. This is because as capital requirements increase, banks lose their comparative advantage of financing loans on balance sheet. Consumer surplus declines by roughly $8 billion, with the majority of these declines occurring for borrowers in the top income quartile. A typical borrower sees her consumer surplus decline by roughly $800 under the 9% capital requirement scenario versus the baseline. Welfare effects differ significantly within the income distribution, with a borrower in the top income quartile seeing consumer surplus decline by more than $1,000, while a borrower in the bottom quartile sees a decline by roughly $600. These changes are driven by decreasing jumbo originations, which are overwhelmingly made to higher income borrowers. Finally, it is important to note that these losses have to be weighed against possible welfare gains of moving risk from bank balance sheets (e.g., Egan et al (2017)).

Bank Stability

There are two dimensions through which capital requirements affect bank stability: holding mortgage risk on bank balance sheets and bank profits. Even a small reduction in capital requirements results in a large increase in the share of loans held on the bank balance sheets. Reducing capital requirements to 4.5% expands the balance sheet holdings of mortgages by 48% ($349 billion annually). Conversely, the primary consequence of increasing capital requirements is a large decline in on-balance sheet lending. As capital requirements increase to 9% and balance sheet financing becomes significantly more expensive, the share of balance-sheet financed lending drops from 41% to 14%, and banks' balance sheet holdings of mortgages drop by 71%. Offsetting somewhat the decrease in risk is also a decrease in expected bank profits, which decline with tighter capital requirements.

As capital requirements tighten, banks switch their business model substantially, from portfolio lending to originate-to-distribute. Thus, even a moderate increase in capital requirements substantially decreases mortgage risk on bank balance sheets, decreasing the risk born by banks. This risk is instead shifted to GSEs and indirectly taxpayers, who insure securitized mortgages.

V.B Quantitative Easing and GSE Market Intervention

One of the major policies during the last financial crisis was the sequence of policies referred to as quantitative easing (QE), during which the Federal Reserve purchased large amount of GSE guaranteed mortgages, hoping to decrease the rates at which borrows were able to access mortgages. Estimates of the impact vary across different QE operations, decreasing mortgage rates between 20-100bp. We model QE as a change in the GSE financing costs, which was the intent of the policy. We also experiment with increasing GSE rates to better understand the implications of the policy. Taking the 2015 costs as the baseline, we counterfactually study the impact of decreasing and decreasing GSE financing costs by 10, 25, and 100 basis points. These results are shown in Table 10 and Figure 12.

One can compare the QE intervention with that of relaxing capital requirements, since QE was used in part to encourage lending by banks, which had experienced a contraction in capital. Both policy interventions result in more mortgages, but impact different parts of the mortgage market.

In particular, they have dramatically different distributional consequences across the income spectrum and result in markedly different allocations of mortgage risk in the economy.

Mortgage Origination and Redistribution

The main effect of QE is to decrease conforming loan rates and increase conforming mortgage lending volumes significantly: a 25bp decrease in GSE rates leads to an essentially one-to-one decrease in conforming loan rates and roughly $165 billion of new conforming mortgage origination. Jumbo interest rates are unaffected, and in consequence, jumbo volumes decrease slightly as consumers shift towards cheaper conforming loans. The net effect is a $159 billion increase in total origination volume. Aggregate consumer surplus increases by roughly $43 billion, driven by both increased lending and lower interest rates. The impact is slightly larger for borrowers in the bottom quartile of the income distribution, who see their welfare increase by roughly $1,450 on average. Borrowers in the top quartile see their welfare increase by roughly $1,400 on average. This difference is due to low-income borrowers being more likely to obtain conforming loans, which is where the interest rate decreases occur.

An *increase* in GSE financing costs has a relatively smaller impact on interest rates and on lending volumes. A 25bp increase in rates only leads to a 14bp increase in conforming loan rates. This muted effect is due to the fact that as GSE financing costs increase, banks substitute towards cheaper balance sheet financing. In this scenario, conforming mortgage origination declines by only $70 billion, in comparison to the $159 billion increase caused by an equivalent GSE rate decrease. Jumbo origination volumes are largely unaffected. Aggregate consumer surplus declines by roughly $20 billion, with individual surplus declining slightly more for borrowers in the bottom income quartile, who see their welfare decline by roughly $950, versus welfare losses of roughly $850 for high income borrowers.

This asymmetry in response to rate increases and decreases becomes more apparent in more extreme scenarios. A 100bp decline in GSE financing costs leads to roughly a 97bp decline in average interest rates. In contrast, a 100bp increase in GSE financing costs leads to only a 31bp increase in average interest rates. This asymmetric response of interest rate reflects the use of bank balance sheet financing as a substitute for GSE financing when GSE financing becomes more expensive. The implications for lending volumes and consumer welfare are similarly asymmetric, with a 100bp decrease leading to origination volume increases of $729 billion and consumer surplus gains of $196 billion, compared to origination volume decreases of $235 and welfare losses of $66 for a 100bp increase.

Bank Stability

This asymmetry occurs because of significant changes to banks' business models. In the baseline scenario, conforming loans comprise roughly half ($375 billion) of balance sheet lending, but even a slight decline in GSE funding costs creates large enough incentives to move these loans from the balance sheet to be securitized. In other words, QE shifts conforming loans off the balance sheet even on the intensive margin. This endogenous shift towards GSE financing explains why conforming interest rates are so sensitive in particular to *decreases* in GSE financing costs: when GSE financing is cheaper, all conforming originations are GSE financed, and so further changes to GSE rates are passed through roughly one-to-one to conforming loan rates. QE also expands traditional bank profits, increasing them by $3 billion, or roughly 2% for a 25 basis points decrease in GSE rates.

In contrast, banks are able to respond to increases in GSE financing costs by shifting originations onto their balance sheets. In response to GSE cost increases, the balance sheet financing share increases substantially, from 42% to 74%, which mutes the effect on rates and aggregate lending volumes. In other words, once GSE financing costs increase, the cheap on-balance sheet funding of banks gives them a large comparative advantage. Shadow bank lending volume shrinks substantially by around 42%. Bank profits are initially unaffected as GSE costs increase because lending volumes decrease overall, which is offset by increases in more profitable balance sheet lending. However, for larger increases in GSE costs, the latter effects dominate as borrowers' substitute more and more towards jumbo loans, and bank profits increase by a small amount.

This counterfactual illustrates how the effects of QE differ substantially from capital requirements. Both increases to capital requirements and decreases to GSE financing costs have the effect of shifting origination off balance sheet and into GSE subsidized financing. Increased capital requirements, however, do so by contracting lending volume and bank profits. Decreases to GSE financing costs, on the other hand, lead to increases in lending volume, consumer welfare, and bank profits.

V.C Changes to Conforming Loan Limits

We next consider changing the conforming loan limits. This current policy sets the reach of GSE financing in the mortgage market and does so differentially across markets. This policy has been actively changed since the beginning of the crisis, with the explicit purpose of intervening in the mortgage market. Prior to 2008, GSE mortgages were limited to a $417,000 cap. As we illustrate in Figure 1, at the beginning of the crisis the jumbo market experienced a contraction, which was particularly relevant for high housing cost markets. In order to increase lending in these areas, their GSE loan limit was increased to $729,750. Since 2015, the conforming loan limits is $417,000 in most counties. The policy of higher limits has persisted since then, although the limit for high cost areas was reduced most recently in 2015 to $625,000.

Changing the limit allows us to understand the impact of GSEs on the overall lending volumes considering shifts between balance sheets and conforming loans and the response of shadow bank sector. Such understanding is also important for the ongoing policy debate regarding the potential downsizing of the GSE role by progressively lowering the conforming loan limits.[14] Moreover, because the policy caps loan amounts, its consequences potentially differ substantially across markets with different house prices and households with different mortgage demand. We consider

[14] See, for example: https://www.housingwire.com/articles/27344-affordability-concerns-surface-in-conforming-loan-limit-debate [accessed on October 2, 2018.]

expanding the role of GSEs to the whole market by removing the limit. We also change the limit amounts by +/- 25%. We also explore the effect of changing the policy to its pre-crisis version with a nationwide limit of $417,000 and also setting the limit nationwide to the $625,000 limit. These results are shown in Table 11 and Figure 13.

Mortgage Origination and Redistribution

We first consider the stark change of expanding GSE coverage to the whole mortgage market by removing the conforming loan limit requirement. This (extreme) counterfactual highlights the redistributive impact of expanding GSE coverage because of the changed market structure. Total origination volumes increase by more than $300 billion, with conforming origination volumes increasing by $365 billion, while jumbo origination volumes decrease by $53 billion as some loans that were previously jumbo mechanically become conforming loans. Note that even under this extreme scenario, not all loans are conforming, because there are still loans that fail to meet the GSE loan-to-value requirement. This policy has a significant effect on mortgage interest rates, with conforming rates decreasing by 11 basis points and jumbo rates decreasing by 57 basis points. Intuitively, as conforming loan limits increase, borrowers who desired a large loan, previously restricted to the jumbo market, now have the option of obtaining a conforming loan, leading to reduced market power and smaller markups in the jumbo loan market.

Consumer surplus increases by $305 billion, with high-income borrowers being the largest beneficiaries. Borrowers in the top income quartile see welfare increase by nearly $30,000, while borrowers in the bottom income quartile see welfare increase by just $14,000. This uneven distribution of welfare gains is driven by the fact that high-income borrowers desire larger loan sizes and in consequence benefit from both increased conforming loan limits and decreased jumbo interest rates. These distributional consequences are even larger when comparing across markets, with total welfare in the top quartile of markets by average income increasing by $161 billion, compared to $17 billion in the bottom quartile of markets. We note, however, that this very substantial increase in consumer surplus following the elimination of the conforming loan limit requirement should be interpreted with caution since it partly reflects a sizeable estimated preference for conforming loans among borrowers desiring large loan sizes.

The broad consequences of increasing and decreasing conforming loan limits are confirmed in more moderate counterfactuals. Increasing conforming loan limits leads to increases in overall and conforming volume, decreases in jumbo volume, and increases in consumer welfare. High-income borrowers are more sensitive to increases in the conforming loan limit because they tend to prefer larger loans. Extending conforming loans above the current levels offer welfare benefits primarily accruing to higher income borrowers and higher income markets.

Finally, it is interesting to consider the two scenarios of unifying conforming loan limits across counties. Column (5) of Table 12 considers setting all limits to the $417,000 lower limit; Column (6) considers setting all limits to the $625,000 higher limit. While lowering the limit decreases lending volumes overall and raising the limit increases lending volumes overall, these gains are not evenly distributed. Decreasing limits in all markets to $417,000 has essentially no impact on low-income area consumer surplus, while it significantly reduces high-income area consumer surplus, relative to the baseline scenario. On the other hand, increasing limits across all markets to $625,000 significantly increases high-income consumer surplus among both low- and high-income areas, with the majority of the welfare gains accruing to high income areas and high-income borrowers.

Bank Stability

While changes to the conforming loan limit mechanically have large impact on conforming loan volumes, interestingly, the impact on loan financing is more muted. Decreasing the conforming loan limit by 25% raises the share of loans financed on balance sheet by 3 percentage points driven largely by increased jumbo lending as a share of overall lending, which increases by 7 percentage points as a fraction of overall lending. Increasing or removing the conforming loan limit has similarly small effects on the share of balance sheet financing, which declines from 41% to 38%. While a substantially greater share of mortgage originations is conforming, banks continue to hold a significant share of these originations on balance sheet rather than selling them to GSEs. Increasing conforming loan limits does impact the distribution of profits between banks and shadow banks. Removing conforming loan caps entirely sees bank profits decline by $18 billion while shadow bank profits increase by $17 billion, as shadow bank lending volumes increase and bank make comparatively fewer high-margin jumbo loans.

Finally, we note an interesting difference between the effects of lowering conforming loan limit (Table 11 and Figure 13) versus increasing capital requirements (Table 9 and Figure 11) on the aggregate lending volume. Both polices decrease the aggregate lending volume. However, in the case of increased capital requirements the shadow banking sector *alleviates* the adverse effect of policy on the aggregate lending volume. In other words, in the case of tighter capital requirements, solely focusing on bank data would overstate the adverse effect of such policy on overall lending volume due to the migration of some of the traditional bank lending activity to shadow banks. On the other hand, in the case of lowering the conforming loan limit, the shadow banking sector *amplifies* the adverse impact on aggregate lending volume as this policy also causes a contraction of shadow bank lending.[15] These counterfactuals also suggest that focusing only on bank data would significantly understate the adverse effect of reducing GSE reach.

To summarize, the conforming loan limit has significant effects not only on overall lending volumes and lender market shares, but on the distribution of welfare and profits in the mortgage market. Extending conforming loan limit beyond their current level further increases consumer surplus, but these gains are primarily felt in the highest-income areas, as is the impact of the current policy of having higher limits in high-cost MSAs. The consequences of this policy for the

[15] This observation may help explain why lowering the conforming loan limit has much bigger adverse aggregate effect on lending volume compared to raising capital requirements: almost $300 billion reduction due to decline of conforming loan limit by 25% compared to about $13 billion reduction in aggregate lending volume due to increasing capital ratios by 25% (from 6% to 7.5%).

distribution of mortgage risk in the economy are relatively limited, with banks retaining substantial amounts of mortgages on their balance sheets.

V.C.1 Validation of Counterfactual Results using Actual Conforming Limit Changes

We exploit actual changes to conforming loan limits over time in the US mortgage market to validate the counterfactual results generated by our model. The data are at the county-year level between 2007 and 2016. The main variables of interest at the level of county and origination year are jumbo origination share (*%Jumbo*), bank origination share (*%Bank*), and the mass of borrowers at conforming limit cutoff (*%AtCutoff*). The main explanatory variable captures the change in conforming limit in a given county in a given year. It is measures as the percentage difference between the conforming loan limit in year *t* in county *c*, and the conforming loan limit in 2007 for the same county *c*:

$$LimitIncrease_{ct} = \frac{Limit_{ct}}{Limit_{c2007}} - 1$$

The origination amount weighted mean of $LimitIncrease_{ct}$ is 0.102 and the median is 0. The specifications to test the impact of these limit increases on jumbo and bank share are as follows:

$$\%Jumbo_{ct} = \beta LimitIncrease_{ct} + \gamma_c + \gamma_t + \epsilon_{ct} \quad (3)$$

$$\%AtCutoff_{ct} = \beta LimitIncrease_{ct} + \gamma_c + \gamma_t + \epsilon_{ct} \quad (4)$$

$$\%Bank_{ct} = \beta LimitIncrease_{ct} + \gamma_c + \gamma_t + \epsilon_{ct} \quad (5)$$

Where γ_c and γ_t are county and year fixed effects, respectively. Specification (3) investigates whether jumbo share of originations decline along with conforming loan limit increases. Specification (4) tests whether the number of *conforming* originations within 0.1% of the conforming loan limit declines. Specification (5) tests whether bank market share declines.

The results of these regressions are given in Table 12 columns (1)-(3). Column (1) shows that increasing the conforming loan limit by 1% leads to approximately a 0.35% reduction in the jumbo share in the county, indicating that as the conforming loan limit increases, there is a significant shift into selecting conforming loans. This is roughly in line with what the model suggests in Table 11, which shows that a 1% increase in the conforming loan limit decreases jumbo market share by roughly 0.2%. Column (2) shows that when the conforming loan limit increases, the mass of borrowers exactly at the conforming loan cutoff decreases, suggesting that many of these borrowers would have selected larger loans had the conforming loan limits not been in place, and now that the limit has been relaxed, they are able to select larger, now-conforming loans. Column (3) shows that a 1% increase in the conforming loan limit decreases bank market share by roughly 0.03% percentage points. This is broadly consistent with what the model suggests in Table 11, which finds that a 1% increase in the jumbo loan limit leads to roughly a 0.08% decrease in bank market share around the current limit.[16]

V.D Summary: Importance of Shadow Banks and Endogenous Bank Business Model

Our results suggest that one can make incorrect inferences from policies targeted at regulating banks if one ignores how such policies impact shadow banks as well as endogenous change in bank business model between selling and retaining. We summarize these points with some examples.

Consider the effect of tightening capital requirements, a policy that is directly targeted at banks. As our analysis above reveals, focusing on banks leads to significantly overstating the consequences for mortgage lending. Consider increasing capital requirements to 9% relative to the baseline of 6% (Table 9 and Figure 11). Our model suggests that focusing on bank balance sheet lending only would suggest a decline of lending volume by 67%. However, *overall* bank lending – including loans now securitized by banks -- would suggest a decline of only 9%. Moreover, the *overall* volume of mortgage lending, which also includes shadow bank lending, would decline by only 2% because shadow banks increase their lending by about $61 billion.

One might conclude that omitting shadow banks is problematic, because it *overestimates* the impact of that a given policy can have on the mortgage market. However, as noted in Section VI.C in the case of tightening the conforming loan limits, ignoring the differences between banks and shadow banks, and solely focusing on bank data can also severely *underestimate* the effect of policies. This is particular the case for polices that adversely affect the secondary mortgage market where shadow banks operate (e.g., securitization through GSEs). For example, consider increasing the cost of GSE funding by 100 basis points. This seemingly large policy change has the impact of increasing overall bank lending by only $55 billion because instead of securitizing, banks can also finance jumbo and conforming originations on balance sheet. In contrast, shadow bank lending contracts by $290 billion (Table 10 and Figure 12) since shadow banks rely solely on GSEs. The net result of such a policy is to reduce overall lending by roughly $235 billion, but focusing only on banks would lead one to the opposite conclusion.

Overall, this analysis suggests that a complete policy analysis of the mortgage sector critically requires analyzing simultaneously the impact of the policy on banks and shadow banks, and accounting for their equilibrium interaction. The equilibrium response of the shadow bank sector

[16] We also assess if there is a change in bank market share as more jumbo loans are originated by using the following specification $BankShare_{ct} = \beta JumboShare_{ct} + \gamma_c + \gamma_t + \epsilon_{ct}$. The results in column (4) find a positive and significant association between bank share and jumbo share. This coefficient, here estimated as roughly 0.25, is roughly in line with the relationship suggested in the model from Tables 9, 10, and 11, which finds that bank share increase by roughly 0.50 percentage points per percent increase in jumbo market share. Note that variation in jumbo share from regression (6) obtains from all sources, such as variation in demand, supply and policy variation, whereas the cross-validating variation in the model comes entirely from policy variation where one would expect a stronger relationship between jumbo share and bank share.

plays an important role in the *nature* and *magnitude* of such effects, accounting for more than 70 percent of the aggregate response in some cases.

Section VI: Discussion and Conclusion

Using micro data, we document a large degree of market segmentation in shadow bank penetration. They substitute for traditional —deposit taking—banks in easily securitized lending, but are limited from engaging in activities requiring on-balance sheet financing. Traditional banks adjust their financing and lending activities to balance sheet shocks, and behave more like shadow banks following negative shocks. Motivated by this evidence, we build a structural model. Banks and shadow banks compete for borrowers. Banks face regulatory constraints, but benefit from the ability to engage in balance sheet lending. Like shadow banks, banks can choose to access the securitization market. To evaluate distributional consequences, we model a rich demand system with income and house price differences across borrowers. The model is estimated using spatial pricing and bunching at the regulatory threshold for identification. We study the consequences of capital requirements, conforming credit limits, and unconventional monetary policy on lending volume and pricing, bank stability and the distribution of consumer surplus across rich and poor households. Our results suggest that a complete policy analysis of the credit market requires simultaneously analyzing the impact on banks and shadow banks, and accounting for their equilibrium interactions.

VI.A Related Literature

Our paper is most closely related to other studies that have examined the changing nature of mortgage origination in the United States. The wake of the financial crisis saw increased interest in the functioning t of the originate-to-distribute model and its impact on recent housing crisis. In particular, papers have focused on the originate-to-distribute model and its costs and benefits. See, for example, Berndt and Gupta (2009), Mian and Sufi (2009), Piskorski et al. (2010), Keys et al. (2010) and (2013), Purnanandam (2011), Bord and Santos (2012), Piskorski et al. (2015).

In addition to the originate-to-distribute model specifically, the increased amount of bank-like activity taking place outside the traditional banking system has attracted increased attention. Buchak et al. (2017) analyze the recent dramatic growth of shadow banks and fintech lenders in the residential mortgage market and find that the regulatory burden faced by traditional banks and growth of financial technology can account, respectively, for about two third and one third of the recent shadow bank growth. Fuster et al. (2018) provide complementary evidence that suggests that fintech lenders adjust supply more elastically than other lenders in response to exogenous mortgage demand shocks, thereby alleviating capacity constraints associated with traditional mortgage lending. Kim et al. (2018) discusses potential liquidity risks faced by shadow bank lenders. Irani et al. (2018) focus on corporate loans and study the role of bank capital regulation in growth of shadow banks. In contrast, this paper focuses particularly on what has driven the originate-to-distribute model following the crisis, and how it has impacted the structure of the mortgage market both in segments where originate-to-distribute is common and in segments where it is less common. In addition, our structural model allows us to assess the role of capital requirements, government credit subsidies, and unconventional monetary policy on the overall distribution of mortgage credit across borrowers as well as on bank stability.

Our paper is also related to the literature on the GSEs.[17] We focus particularly on the role of GSE financing and its interaction with recent regulatory and bank capital changes in explaining growth of shadow banks. We study how market segmentation arises out of GSE financed market interacting with bank balance sheet capacity and bank capital regulation, and how it affects overall origination volume, distribution of credit across borrowers, and relative pricing of products.

Our paper also connects to a large literature that examines the impact of government regulations and various policy interventions adopted during and after the financial crisis on banking. See, for example, Mayer et al. 2014, Haughwout et. al. 2016, Agarwal et al. 2015 and 2017). Like Agarwal et. al. (2014), Lucca et. al. (2014), Granja et al. (2014), Piskorski et al (2015), Fligstein and Roehrkasse (2016), Di Maggio et al. (2016, 2017), Gete and Reher (2017). Our paper focuses, instead, on the growth of shadow banks and their interplay with traditional banks in the aftermath of the crisis.

Our paper is also related to a growing literature using tools for consumer demand estimation in the context of consumer finance. Our model follows the form of consumer demand models like Berry et al. (1995) and described in detail in Nevo (2000), and applies these modeling techniques for the purpose of answering regulatory and policy questions in finance. Egan, Hortacsu, and Matvos (2017), for example, study banking competition and financial fragility through the context of a structural model of demand for bank deposits, and Egan, Lewellen, and Sunderam (2017) structurally decompose the sources of bank value.[18] Buchak et al. (2017) use a structural framework to analyze the drivers of the recent growth of shadow bank and fintech lenders in the US residential mortgage market. Benetton (2018) uses a structural framework to analyze the impact of bank capital regulation on the UK residential mortgage market. We use similar tools to answer fundamentally different questions.

Our paper is also connected to recent quantitative equilibrium models of mortgage and housing markets with heterogonous agents (e.g., Favilukis, Ludvingson, Van Nieuwerburgh 2016; Kaplan, Mitman, and Violante 2016; Greenwald, Landvoigt, and Van Nieuwerburgh 2017; Guren, Krishnamurty, and McQuade 2017). Such models can provide many valuable insights, including the quantitative assessment of various effects. Unlike these papers that use computational tools developed in the quantitative macroeconomics literature, we follow the structural industrial

[17] Following the financial crisis and the collapse of the private securitization market, GSE securitizations and their accompanying guarantees have dominated mortgage securitization and consequently the organization of the overall residential mortgage market. GSEs were originally established to affect the political goal of promoting housing ownership, particularly in underserved and underbanked areas. Many papers, e.g., Acharya et al. (2011), Bhutta (2012), Hurst et al (2016), Elenev et al. (2016), have studied how successful GSEs have been in affecting these goals and have found mixed results.

[18] See also Cox (2017) who develops a structural model of the borrowers' repayment preferences in the student loan market and uses it to measure the overall gains in consumer surplus from risk-based pricing.

organization literature and build a credit market framework with supply and demand functions that can be directly estimated using micro data. Moreover, we focus mainly on implications for credit market outcomes taking into account shadow banks and their interplay with traditional banks.

Finally, our paper is related to the recent work focusing on various forms of bank-like activities taking place outside the traditional banking system and studding the implications of such shifts (see Gennaioli, Shleifer, and Vishny 2013, Ordonez 2018, and Moriera and Savov 2017 and Adrian and Ashcraft 2016). Among this recent work, Koijen and Yogo (2016) analyze the implications of reinsurance market that allows regulated life insurance companies to move some of their liabilities to shadow reinsurers. Dreschler et al. (2017) and Xiao (2017) show that when the Fed funds rate rises, banks widen the spreads they charge on deposits, and deposits flow out of the banking system towards the uninsured shadow banking sector, thereby affecting the transmission of monetary policy. Unlike these papers that focus on the consequences of deposits flows between traditional and shadow bank sector, we study the consequences of capital requirements, conforming credit limits, and unconventional monetary policy that operate independently from the deposit channel. In doing so, we study the impact of equilibrium interaction of shadow banks with traditional banks on quantity, price, allocation of mortgage credit as well as on bank stability.

VI.B Discussion

Our findings have a number of implications. First, they suggest that a complete policy analysis of the lending market critically requires simultaneously analyzing the impact of the policy on banks and shadow banks, and accounting for their equilibrium interaction. Any regulation that affects a part of the intermediation market spills over to other markets through competition, and affects which products are offered by which firms, which part of the household income distribution is impacted, as well as equilibrium prices. Therefore, policy and regulatory changes cannot be considered without a full view of the market equilibrium. This observation does not only apply to the residential mortgage market, the focus our study, but to any credit market with a large presence or possible entry of shadow banks.

Second, our paper highlights that the line between traditional and shadow banks from a functional perspective is not clearly determined, but is driven by the capitalization of banks and the banking sector. Well capitalized banks indeed behave as traditional models of banking suggest: they take deposits and use them to make loans, which they hold to maturity. Poorly capitalized banks, on the other hand, do not have balance sheet capacity and behave like shadow banks, originating loans and selling them off. The ability to do so allows these banks to originate loans despite depressed capital, offsetting some of the effect of capital tightening. Thus, without thinking about responses on shadow banking side, traditional policy tools, including capital ratios and other bank capital regulatory requirements, may have limited effectiveness.

More broadly, our paper suggests that one has to take a broad view of government insurance subsidies and regulation if one is to understand their impact on the financial intermediation system. On the one hand, traditional banks exploit cheap insured deposit financing. On the other, shadow banks and poorly capitalized banks predominantly use GSE insured mortgages. Our results suggest that as subsidies for banks in one sector decline, for example, because of restrictive capital requirements, they tilt their activity toward other sources of tax payer financed subsidies. Understanding the web of subsidies and regulations that pervade the financial system, their equilibrium interactions, and their impact on systematic risk and welfare remains a fruitful area for future research.

References

Acharya, Viral V., Matthew Richardson, Stijn Van Nieuwerburgh, and Lawrence J. White. 2011, Guaranteed to fail: Fannie Mae, Freddie Mac, and the debacle of mortgage finance. *Princeton University Press*.

Adrian, Tobias, and Adam B. Ashcraft, 2016, "Shadow banking: A review of the literature." In Banking Crises, pp. 282-315. *Palgrave Macmillan UK*.

Agarwal, Sumit, David Lucca, Amit Seru, and Francesco Trebbi, 2014, Inconsistent regulators: Evidence from banking, *Quarterly Journal of Economics* 129, 889-938.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, Amit Seru, 2017, Policy Intervention in Debt Renegotiation: Evidence from Home Affordable Modification Program, *Journal of Political Economy* 125, 654-712.

Agarwal, Sumit, Gene Amromin, Souphala Chomsisengphet, Tomasz Piskorski, Amit Seru, and Vincent Yao, 2015, Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinancing program, NBER working paper 21512.

Benetton, Matteo, 2018, Leverage regulation and market structure: An empirical model of the UK mortgage market, working paper.

Berndt, Antje, and Anurag Gupta, 2009, Moral hazard and adverse selection in the originate-to-distribute model of bank credit, *Journal of Monetary Economics* 56, 725-743.

Bhutta, Neil, 2012, GSE activity and mortgage supply in lower-income and minority neighborhoods: The effect of the affordable housing goals, *Journal of Real Estate Finance and Economics* 45, 238-261.

Bord, Vitaly M., and João AC Santos, 2012, The Rise of the Originate-to-Distribute Model and the Role of Banks in Financial Intermediation, *Economic Policy Review* 21.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2017, Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks, forthcoming in the *Journal of Financial Economics*.

Cox, Natalie, 2017, Pricing, Selection, and Welfare in the Student Loan Market: Evidence from Borrower Repayment Decisions, working paper.

DeFusco, Anthony A., and Andrew Paciorek. The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit, *American Economic Journal: Economic Policy* 9.1 (2017): 210-40.

Di Maggio, M., A. Kermani, C. Palmer, 2016, How Quantitative Easing Works: Evidence on the Refinancing Channel, working paper.

Di Maggio, M., A. Kermani, B. Keys, T. Piskorski, R. Ramcharan, A. Seru, V. Yao, 2017, Interest Rate Pass-Through: Mortgage Rates, Household Consumption and Voluntary Deleveraging, *American Economic Review* 107, 3550-88.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The Deposits Channel of Monetary Policy, *Quarterly Journal of Economics* 132, 1819-1876.

Elenev Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh, 2016, Phasing Out the GSEs, *Journal of Monetary Economics* 81, 111-132.

Erickson, T., Whited, T.M., 2002. Two-step GMM estimation of the errors-in-variables model using high-order moments. *Econometric Theory* 18, 776–799.

Fligstein, Neil, and Alexander F. Roehrkasse, 2016, The Causes of Fraud in the Financial Crisis of 2007 to 2009: Evidence from the Mortgage-Backed Securities Industry, *American Sociological Review* 81, 617-643.

Fuster, Andreas, Lo, Stephanie and Willen, Paul, 2017, The Time-Varying Price of Financial Intermediation in the Mortgage Market, Federal Reserve Bank of New York, Staff Report No. 805.

Fuster, Andreas, Matthew C. Plosser, Philip Schnabl, James I. Vickery, 2018, The Role of Technology in Mortgage Lending, working paper.

Gete, Pedro, and Michael Rehrer, 2017, Nonbanks and Lending Standards in Mortgage Markets. The Spillovers from Liquidity Regulation, working paper.

Gennaioli, Nicola, Andrei Shleifer, and Robert W. Vishny, 2013, A Model of Shadow Banking, *Journal of Finance* 68, 1331–1363.

Granja, João, and Christian Leuz. The Death of a Regulator: Strict Supervision, Bank Lending and Business Activity. No. w24168. National Bureau of Economic Research, 2017.

Granja, João, Gregor Matvos, and Amit Seru, 2014, Selling failed banks, forthcoming in the *Journal of Finance.*

Greenwood, Robin, and David Scharfstein, 2013, The growth of finance, *Journal of Economic Perspectives* 27, 3-28.

Haughwout, Andrew, Ebiere Okah, and Joseph Tracy, 2016, Second chances: Subprime mortgage modification and redefault, *Journal of Money, Credit and Banking* 48, 771-793.

Hurst, Erik, Benjamin J. Keys, Amit Seru, and Joseph Vavra, 2016, Regional redistribution through the US mortgage market, *American Economic Review* 106, 2982-3028.

Irani, Rustom, Raj Iyer, Ralf Meisenzahl and Jose-Luis Peydro, 2018, The Rise of Shadow Banking: Evidence from Capital Regulation, working paper.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig, 2010, Did securitization lead to lax screening? Evidence from subprime loans, *Quarterly Journal of Economics* 125, 307-362.

Keys, Benjamin J., Tomasz Piskorski, Amit Seru, and Vikrant Vig, 2013, Mortgage financing in the housing boom and bust. In *Housing and Financial Crisis*, edited by Edward L. Glaeser and Todd Sinai, 143-204, University of Chicago Press

Kim, You Suk, Steven M. Laufer, Karen Pence, Richard Stanton, 2018, Liquidity crisis in the mortgage market, working paper.

Koijen, Ralph S.J. and Motohiro Yogo, 2016, Shadow Insurance, *Econometrica* 84, 1265-1287.

Lucca, David, Amit Seru, and Francesco Trebbi, 2014, The revolving door and worker flows in banking regulation, *Journal of Monetary Economics* 65, 17-32.

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta, 2014, Mortgage modification and strategic behavior: Evidence from a legal settlement with Countrywide, *American Economic Review* 104, 2830-2857.

Mian, Atif, and Amir Sufi, 2009, The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis, *Quarterly Journal of Economics* 124, 1449-96.

Moriera, Alan and Savov, Alexi, 2017, The Macroeconomics of Shadow Banking. *The Journal of Finance* 72, 2381-2432.

Ordonez Guillermo, 2018, Sustainable Shadow Banking, American Economic Journal: Macroeconomics, 10(1), 1-25.

Piskorski, Tomasz, Amit Seru, and Vikrant Vig, 2010, Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis, *Journal of Financial Economics* 97, 369-397.

Piskorski, Tomasz, Amit Seru, James Witkin, 2015, Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market, *Journal of Finance* 70, 2635-2678.

Purnanandam, Amiyatosh, 2011, Originate-to-distribute model and the subprime mortgage crisis." *Review of Financial Studies* 24, 1881-1915.

Rajan, Uday, Amit Seru, and Vikrant Vig, 2015, The failure of models that predict failure: Distance, incentives, and defaults, *Journal of Financial Economics* 115, 237-260.

Stanton, Richard, Nancy Wallace, and Jonathan Walden, 2014, The industrial organization of the U.S. residential mortgage market, *Annual Review of Financial Economics* 6, 259-288.

Stanton, Richard, Nancy Wallace, and Jonathan Walden, 2017, Mortgage loan-flow networks and financial norms, forthcoming in the *Review of Financial Studies*.

Table 1: Financing on Balance Sheet and Originator Type (Banks vs. Shadow Bank) around Conforming Loan Limit

This table assesses the discontinuity of financing on balance sheet and originator type around the conforming loan limit. Panel A considers balance sheet lending versus outside financing. The left-hand side variable is an indicator for whether the loan is financed on the balance sheet or sold. Panel B considers bank originators versus shadow bank originators. The left-hand side variable is an indicator for whether the originator is a traditional bank. In both panels, Jumbo is an indicator for whether the loan size is above the conforming loan limit in the time-county of origination rendering it ineligible for securitization through GSEs. In both panels, columns (1)-(4) use the all sample, while (5)-(8) use 2015 originations only. Columns (1)-(4) and (5)-(8) consider discontinuity bandwidths from +/-1%, 5%, 10%, and 25% around the conforming loan limit. Controls include log loan amount, log applicant income, dummy variables for applicant race, ethnicity, sex, loan type, loan purpose, occupancy, and property type, and census tract-year fixed effects. Standard errors are in parentheses and clustered at the lender-year level.

Panel A: Loan Financed on Balance Sheet or Sold?

	All Sample				2015 Originations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth +/-	1%	5%	10%	25%	1%	5%	10%	25%
Jumbo	0.503	0.452	0.440	0.424	0.628	0.542	0.507	0.469
	(0.026)	(0.020)	(0.019)	(0.017)	(0.046)	(0.039)	(0.033)	(0.030)
Loan-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,152,391	2,136,598	3,249,506	7,679,499	104,713	216,897	348,413	850,795
R^2	0.271	0.259	0.254	0.228	0.359	0.335	0.322	0.287

Panel B: Loan with Bank as Originator?

	All Sample				2015 Originations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth +/-	1%	5%	10%	25%	1%	5%	10%	25%
Jumbo	0.245	0.217	0.203	0.183	0.384	0.328	0.301	0.266
	(0.020)	(0.015)	(0.014)	(0.012)	(0.030)	(0.029)	(0.027)	(0.026)
Loan-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,152,391	2,136,598	3,249,506	7,679,499	104,713	216,897	348,413	850,795
R^2	0.308	0.259	0.231	0.200	0.314	0.259	0.230	0.196

Table 2: Balance Sheet Retention and Bank Capitalization

This table assesses the relationship of bank capitalization and balance sheet retention for traditional banks. Observations are at the bank-year level. The left-hand side variable is the percentage of originated loans retained on the balance sheet within the calendar year for the given lender. Capital ratio is the bank's statutory capital ratio (in percentage). Log(Originations) is the (log) total number of originations for the lender in the given year. Log(Unique CTs) is the (log) number of unique census tracts in which the bank originates mortgages, a measure of geographical spread. Log(Average Loan Income) and Log(Average Loan Size) are the average borrower income and loan size for the loans the banks originates in the year. Log(Bank Assets) is the (log) total bank assets. Deposits / Total Liabilities is the percentage of the bank's liabilities that are deposits. In columns (1) and (2), all left- and right-hand side variables are in levels, while columns (3) and (4), left- and right-hand side variables are in differences. All columns have year fixed effects and columns (2) and (4) additionally include lender fixed effects. Standard errors in parentheses. Data are from HMDA and the Federal Reserve call reports.

	% Held (Levels)		% Held (Changes)	
	(1)	(2)	(3)	(4)
Capital Ratio	3.166	4.467	1.949	2.407
	(0.349)	(0.521)	(0.466)	(0.537)
Log(Originations)	-0.155	-0.232	-0.112	-0.139
	(0.015)	(0.027)	(0.025)	(0.027)
Log(Unique CTs)	0.046	0.154	0.083	0.081
	(0.016)	(0.040)	(0.040)	(0.043)
Log(Average Loan Income)	0.481	0.627	0.651	0.619
	(0.050)	(0.072)	(0.057)	(0.059)
Log(Average Loan Size)	-0.335	-0.258	-0.047	-0.035
	(0.028)	(0.041)	(0.040)	(0.043)
Log(Bank Assets)	0.037	0.004	0.016	0.014
	(0.005)	(0.008)	(0.008)	(0.009)
Deposits/Total Liabilities	-0.446	-0.241	-0.297	-0.259
	(0.064)	(0.124)	(0.117)	(0.128)
Year FE	Yes	Yes	Yes	Yes
Lender FE	No	Yes	No	Yes
Observations	1,224	1,224	1,223	1,223
R^2	0.422	0.702	0.269	0.284

Table 3: Financing on Balance Sheet and Capitalization of Traditional Banks around Conforming Loan Limit

This table assesses the discontinuity of financing on balance sheet and capitalization of traditional banks around the conforming loan limit. Panel A considers balance sheet lending versus outside financing. The left-hand side variable is an indicator for whether the loan is financed on balance sheet or sold. Panel B considers well versus poorly capitalized banks. The left-hand side variable is an indicator for whether the originator is well-capitalized. Banks are defined as well capitalized based if they are in the top quartile of capitalization for the given year. In both panels, Jumbo is an indicator for whether the loan size is above the conforming loan limit in the time-county of origination rending it ineligible for securitization through GSEs. In both panels, columns (1)-(4) use the 2007-2015 sample; (5)-(8) use 2015 originations only. Columns (1)-(4) and (5)-(8) consider discontinuity widths from +/-1%, 5%, 10%, and 25% around the conforming loan limit. Controls include log loan amount, log applicant income, dummy variables for applicant race, ethnicity, sex, loan type, loan purpose, occupancy, and property type, and census tract-year fixed effects. Standard errors in parentheses are clustered at the lender-year level.

Panel A: Loan Financed on Balance Sheet or Sold?

	All Sample				2015 Originations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth +/-	1%	5%	10%	25%	1%	5%	10%	25%
Jumbo	0.566	0.515	0.508	0.499	0.666	0.587	0.532	0.477
	(0.037)	(0.026)	(0.025)	(0.024)	(0.068)	(0.045)	(0.033)	(0.024)
Loan-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	313,788	580,777	883,273	2,047,329	24,923	57,114	97,493	237,146
R^2	0.442	0.409	0.396	0.352	0.627	0.561	0.522	0.469

Panel B: Loan with Well Capitalized Bank as Originator?

	All Sample				2015 Originations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth +/-	1%	5%	10%	25%	1%	5%	10%	25%
Jumbo	0.087	0.102	0.106	0.099	0.138	0.151	0.165	0.169
	(0.044)	(0.033)	(0.031)	(0.025)	(0.110)	(0.082)	(0.073)	(0.059)
Loan-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	313,788	580,777	883,273	2,047,329	24,923	57,114	97,493	237,146
R^2	0.521	0.445	0.393	0.322	0.541	0.379	0.302	0.219

Table 4: Product Mix, Retention and Bank Capitalization

This table assesses the relationship of bank capitalization and financing of loans on the balance sheet and how it varies with product mix. The regression is at the lender-year level among traditional banks. For columns (1) and (2) the left-hand side variable is percent of originated loans that are jumbo (non-conforming). For columns (3) and (4) the left-hand side variable is % jumbo originations not sold within the calendar year. For (5) and (6) the left-hand side variable is % conforming originations not sold within the calendar year. See the Table 2 notes for right-hand side variable definitions. All columns have year fixed effects. Columns (2), (4), and (6), additionally have lender fixed effects. Standard errors are in parentheses.

	% Jumbo		% Held (Jumbo)		% Held (Conforming)	
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Ratio	0.192	-0.178	0.319	-0.454	3.783	5.176
	(0.083)	(0.092)	(0.214)	(0.302)	(0.377)	(0.564)
Log(Originations)	-0.023	-0.033	-0.074	-0.079	-0.144	-0.232
	(0.004)	(0.005)	(0.010)	(0.015)	(0.017)	(0.029)
Log(Unique CTs)	0.010	0.005	-0.050	0.015	0.007	0.168
	(0.004)	(0.007)	(0.012)	(0.022)	(0.017)	(0.043)
Log(Bank Assets)	0.007	0.001	0.050	0.001	0.041	0.004
	(0.001)	(0.001)	(0.003)	(0.005)	(0.005)	(0.009)
Log(Deposits/Liabilities)	-0.011	0.156	-0.228	-0.271	-0.368	-0.254
	(0.015)	(0.022)	(0.035)	(0.086)	(0.069)	(0.134)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	No	Yes	No	Yes	No	Yes
Observations	1,226	1,226	1,206	1,206	1,226	1,226
R^2	0.299	0.836	0.196	0.770	0.361	0.719

Table 5: Contraction of Bank Credit and Bunching at Conforming Loan Cutoff

This table assesses the impact of contraction of bank credit on bunching of borrowers at the conforming loan limit. Column (1) of both panels shows the first stage regression of bank market share on post times OTS share. Post is defined as after 2011, the year that the Office of Thrift Supervision (OTS) was shut down. %OTS is the share of 2007 mortgage originations by banks overseen by the OTS in the county. Prior work shows that post OTS shutdown, the transfer to relatively stricter regulator led to contraction of bank mortgage credit. The left-hand side variable in the first stage following this idea is the local traditional bank market share of originations. Columns (2) to (4) use bunched share of borrowers (%At Cutoff) around the cutoff as left-hand side variable. It is defined as market share of borrowers near the conforming loan cutoff according to the bandwidth defined above each panel. Panel A uses a wider bandwidth comprising loans falling between 0.990 to 1.001 times the conforming loan limit to define bunched loan sizes, while Panel B uses a narrower bandwidth comprising loans falling between 0.995 to 1.001 times the conforming loan limit. Column (2) shows the reduced form regression of bunched share on post times OTS share. Column (3) is the OLS regression of bunched share on bank market share. Column (4) is the IV regression of bunched share on bank market share instrumented with post times %OTS. All columns have year and county fixed effects. Standard errors are in parentheses.

Panel A: Wide Bandwidth +/- (0.990, 1.001) to Construct Bunched Share at Cutoff

	% Bank	% At Cutoff		
	(1)	(2)	(3)	(4)
	First Stage OLS	Reduced Form OLS	OLS	IV
Post x %OTS	-0.200	0.027	-	-
	(0.009)	(0.002)	-	-
% Bank	-	-	-0.006	-0.137
	-	-	(0.001)	(0.013)
Year & County FE	Yes	Yes	Yes	Yes
Observations	32,110	32,110	32,110	32,110
R^2	0.902	0.628	0.626	0.516

Panel B: Narrow Bandwidth +/- (0.995, 1.001) to Construct Bunched Share at Cutoff

	% Bank	% At Cutoff		
	(1)	(2)	(3)	(4)
	First Stage OLS	Reduced Form OLS	OLS	IV
Post x %OTS	-0.200	0.022	-	-
	(0.009)	(0.002)	-	-
% Bank	-	-	-0.005	-0.111
	-	-	(0.002)	(0.013)
Year & County FE	Y	Y	Y	Y
Observations	32,110	32,110	32,110	32,110
R^2	0.902	0.649	0.648	0.588

Table 6: Structural Estimation – Key Demand Parameters

This table shows the estimated demand parameters. Consumer preferences are given by the equation $\mathrm{B}_i = \overline{\mathrm{B}} + \Pi(D_{ic} - \overline{D}) + \Sigma\nu_i$, where $\overline{\mathrm{B}}$ is the vector of parameter means, Π is the mapping between demographic characteristics, and Σ scales random shocks. Panels (a), (b), and (c) show the results for $\overline{\mathrm{B}}$, Π, and Σ, respectively.

Panel A: Mean Preference Parameters

	$\overline{\mathrm{B}}$	
Parameter	Description	Estimate
$\bar{\alpha}$	Price	0.80
$\bar{\beta}$	Disutility from smaller loan	3.85
$\bar{\gamma}$	Conforming preference	6.78
$\log \bar{F}$	Log loan size	12.31

Panel B: Demographic-Preference Relationships

		Π	
Parameter	Description	Estimate (log Income)	Estimate (log Price)
α_i	Price Elasticity	0.01	-0.40
β_i	Disutility from smaller loan	-0.23	0.08
γ_i	Conforming preference	-0.11	2.03
$\log F_i$	Log loan size	0.22	0.46

Panel C: Shocks

	Σ	
Parameter	Description	Estimate
σ_α^2	Price Elasticity	0.10
σ_β^2	Disutility from smaller loan	0.25
σ_γ^2	Conforming preference	0.23
$\sigma_{\log F}^2$	Log loan size	0.41

Table 7: Structural Estimation – Key Supply Parameters

This table shows the estimated supply parameters. Panels (a) and (b) show the linear parameters for capital and labor costs, respectively, that enter the initial origination costs. Panel (c) shows the non-linear parameters that determine the financing cost.

Panel A: Capital Costs

Parameter	Description	Estimate
$r_{d,2010}$	Capital cost in 2010	2.82
$r_{d,2011}$	Capital cost in 2011	2.87
$r_{d,2012}$	Capital cost in 2012	2.39
$r_{d,2013}$	Capital cost in 2013	2.51
$r_{d,2014}$	Capital cost in 2014	2.86
$r_{d,2015}$	Capital cost in 2015	2.54

Panel B: Labor Costs

Parameter	Description	Estimate
w_{bn}	Bank, purchase (baseline)	0.00
w_{br}	Bank, refinance	-0.32
w_{nn}	Shadow Bank, Non-fintech, purchase	0.02
w_{nr}	Shadow Bank, Non-fintech, refinance	-0.37
w_{fn}	Shadow Bank, Fintech, purchase	0.09
w_{fr}	Shadow Bank, Fintech, refinance	-0.21

Panel C: Financing Costs

Parameter	Description	Estimate
σ^{GSE}	External financing cost	0.04
σ^{b1}	Internal coefficient on capital adequacy	0.01
ϕ	Shape parameter for capital adequacy	1.46

Table 8: Structural Estimation – Regulatory Burden and Fintech Quality

This table shows the estimated bank regulatory burden and fintech quality parameters. The regulatory burden reported here is defined as 1/ζ, where ζ is the scaling factor on the probability of lending to a specific borrower as discussed in Section V.B.2. A higher bank regulatory burden parameter captures relatively constrained traditional banks; a lower burden captures relatively constrained traditional banks. An increase in the fintech quality parameter indicates an increase in the perceived quality of services offered by shadow bank fintech lenders relative to other lenders. Fintech quality is relative to non-fintech shadow bank originations of the same type (new origination or refinance).

		Fintech Quality	
Year	Bank Regulatory Burden	New Originations	Refinance
2010	0.63	-1.22	0.56
2011	0.69	-0.89	0.74
2012	0.48	-0.85	0.96
2013	0.83	-0.64	1.23
2014	1.37	-0.36	1.27
2015	1.21	-0.23	1.25

Table 9: Counterfactual Analysis – Capital Requirements

This table shows the impact of various capital requirements. Column (1) shows the case a 3% capital requirement. Column (2) for a 4.5% capital requirement. Column (3) for a 6% capital requirement (baseline). Column (4) for a 7.5% capital requirement. Column (5) for a 9% capital requirement. Column (6) for a 12% capital requirement. Rows show the predicted impact of the counterfactual change on various outcomes.

	Capital Requirement					
	(1)	(2)	(3)	(4)	(5)	(6)
	3%	4.5%	6% (Baseline)	7.5%	9%	12%
Lending Volumes						
Overall Lending Volume ($b)	1,776	1,772	1,763	1,750	1,732	1,698
Conforming Volume ($b)	1,373	1,375	1,385	1,411	1,503	1,668
Jumbo Volume ($b)	403	397	378	340	229	30
Bank Volume ($b)	1,102	1,095	1,079	1,051	986	871
Loan Financing						
Balance Sheet Lending ($b)	1,102	1,078	730	487	243	32
Share of Loans Financed on Balance Sheet (%)	62%	61%	41%	28%	14%	2%
Share of Conforming Loans Financed on Balance Sheet (%)	51%	50%	25%	10%	1%	0%
Shadow Bank Share of Conforming Loans (%)	49%	49%	49%	50%	50%	50%
Interest Rates (deviation from baseline)						
Conforming Interest Rate (%)	-0.04	-0.02	-	0.04	0.05	-0.06
Jumbo Interest Rate (%)	-0.17	-0.12	-	0.30	0.89	6.51
Jumbo - Conforming Spread (%)	-0.13	-0.10	-	0.25	0.84	6.56
Profits and Consumer Surplus (deviation from baseline)						
Overall Lender Profits ($b)	4	3	-	-5	-28	-64
Bank Profits ($b)	4	3	-	-5	-28	-64
Shadow Bank Profits ($b)	0	0	-	0	0	0
Overall Consumer Surplus ($b)	3	2	-	-3	-8	-17
Individual Consumer Surplus ($)	95	56	-	-217	-830	-1,616
Overall Consumer Surplus for Top Income Market ($b)	1	1		-1	-5	-10
Overall Consumer Surplus for Bottom Income Market ($b)	0	0		0	0	-1
Individual Consumer Surplus for Top Income Quartile ($)	122	77	-	-280	-1,058	-2,061
Individual Consumer Surplus for Bottom Income Quartile ($)	71	36	-	-157	-604	-1,168

Table 10: Counterfactual Analysis – GSE Financing Costs

This table shows the impact of raising capital requirements. Columns (1)-(3) show the impact of lowering GSE financing costs by 100, 25, and 10 basis points, respectively. Column (4) shows the 2015 baseline scenario. Columns (5)-(7) show the impact of increasing GSE financing costs by 10, 25, and 100 basis points, respectively. Rows show the predicted impact of the counterfactual change on various outcomes.

	Changes to GSE Financing Costs						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	-100bps	-25bps	-10bps	Baseline	+10bps	+25bps	+100bps
Lending Volumes							
Overall Lending Volume ($b)	2,492	1,922	1,824	1,763	1,728	1,688	1,528
Conforming Volume ($b)	2,122	1,550	1,450	1,385	1,354	1,315	1,156
Jumbo Volume ($b)	371	373	374	378	374	374	372
Bank Volume ($b)	1,450	1,157	1,106	1,078	1,079	1,089	1,133
Loan Financing							
Balance Sheet Lending ($b)	371	373	374	735	1,062	1,088	1,133
Share of Loans Financed on Balance Sheet (%)	15%	19%	21%	42%	61%	64%	74%
Share of Conforming Loans Financed on Balance Sheet (%)	0%	0%	0%	26%	51%	54%	66%
Shadow Bank Share of Conforming Loans (%)	49%	49%	50%	49%	48%	46%	34%
Interest Rates (deviation from baseline)							
Conforming Interest Rate (%)	-1.15	-0.29	-0.11	-	0.06	0.14	0.42
Jumbo Interest Rate (%)	0.06	0.02	0.00	-	-0.01	-0.01	-0.02
Jumbo - Conforming Spread (%)	1.20	0.31	0.11	-	-0.07	-0.15	-0.44
Profits and Consumer Surplus (deviation from baseline)							
Overall Lender Profits ($b)	35	7	2	-	-2	-5	-13
Bank Profits ($b)	17	3	1	-	0	1	8
Shadow Bank Profits ($b)	19	4	2	-	-2	-6	-21
Overall Consumer Surplus ($b)	196	43	16	-	-9	-20	-66
Individual Consumer Surplus ($)	5,984	1,412	557	-	-343	-885	-3,297
Overall Consumer Surplus for Top Income Market ($b)	90	20	7	-	-5	-10	-33
Overall Consumer Surplus for Bottom Income Market ($b)	17	4	1	-	-1	-2	-5
Individual Consumer Surplus for Top Income Quartile ($)	6,013	1,398	558	-	-323	-856	-3,179
Individual Consumer Surplus for Bottom Income Quartile ($)	6,124	1,468	571	-	-377	-945	-3,521

Table 11: Counterfactual Analysis – Conforming Loan Limit

This table shows the impact of altering the conforming loan limit. Column (1) shows the impact of reducing the limit by 25%; Column (2) shows the 2015 baseline scenario; Column (3) shows the impact of increasing the limit by 25%; Column (4) shows the impact of removing the limit altogether, so that all loans are eligible for GSE financing. Column (5) shows the impact of setting all limits to the lower national limit of $417,000. Column (6) shows the impact of setting all limits to the higher national limit of $625,000. Rows show the predicted impact of the counterfactual change on various outcomes.

	Changes to Conforming Loan Limit					
	(1)	(2)	(3)	(4)	(5)	(6)
	-25%	Baseline	25%	No Limit	$417k	$625k
Lending Volumes						
Overall Lending Volume ($b)	1,477	1,763	1,921	2,074	1,721	1,986
Conforming Volume ($b)	1,081	1,385	1,559	1,750	1,335	1,633
Jumbo Volume ($b)	396	378	362	325	386	353
Bank Volume ($b)	947	1,078	1,147	1,201	1,064	1,174
Loan Financing						
Balance Sheet Lending ($b)	656	718	736	780	715	752
Share of Loans Financed on Balance Sheet (%)	44%	41%	38%	38%	42%	38%
Share of Conforming Loans Financed on Balance Sheet (%)	24%	25%	24%	26%	25%	24%
Shadow Bank Share of Conforming Loans (%)	49%	49%	50%	50%	49%	50%
Interest Rates (deviation from baseline)						
Conforming Interest Rate (%)	0.05	-	-0.04	-0.11	0.00	-0.05
Jumbo Interest Rate (%)	0.25	-	-0.25	-0.57	0.03	-0.36
Jumbo - Conforming Spread (%)	0.20	-	-0.21	-0.46	0.03	-0.31
Profits and Consumer Surplus (deviation from baseline)						
Overall Lender Profits ($b)	-13	-	2	-1	-2	3
Bank Profits ($b)	3	-	-7	-18	2	-9
Shadow Bank Profits ($b)	-16	-	9	17	-4	12
Overall Consumer Surplus ($b)	-229	-	142	305	-43	203
Overall Consumer Surplus for Top Income Market ($b)	-124	-	77	161	-43	99
Overall Consumer Surplus for Bottom Income Market ($b)	-14	-	8	17	0	13
Individual Consumer Surplus ($)	-14,317	-	9,719	21,730	-3,396	13,719
Individual Consumer Surplus for Top Income Quartile ($)	-14,428	-	11,243	29,717	-4,065	16,850
Individual Consumer Surplus for Bottom Income Quartile ($)	-13,311	-	7,374	13,906	-2,555	10,119

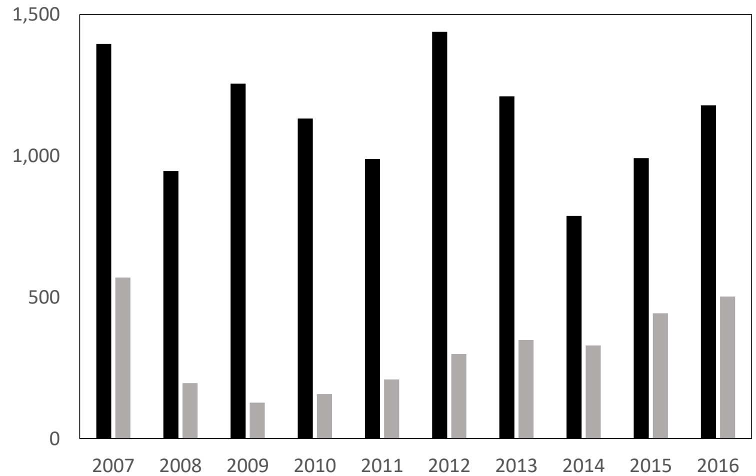
Table 12: Validation of Counterfactual Results using Conforming Loan Limit Changes

This table studies the response of jumbo market share, conforming loan bunching, and bank market share to changes in conforming loan limits at the year-county level. *Limit Increase* is the percentage increase in the conforming loan limit in a county between 2007 and year *t*. Column (1) regresses jumbo share on this increase. The left-hand side is the county-year level jumbo loan market share in percentage terms. Column (2) regresses the bunched market share of borrowers around the conforming loan cutoff on this increase (bandwidth??). The left-hand side variable is the county-year level market share of loans falling within 0.10% of the conforming loan limit in percentage terms. Column (3) is the reduced form of bank market share on the limit increase. Column (4) is the OLS of bank share on jumbo origination share. The left-hand side variable in columns (3) and (4) is the county-year level bank market share in percentage terms. All columns include year and county fixed effects. Standard errors are in parentheses.

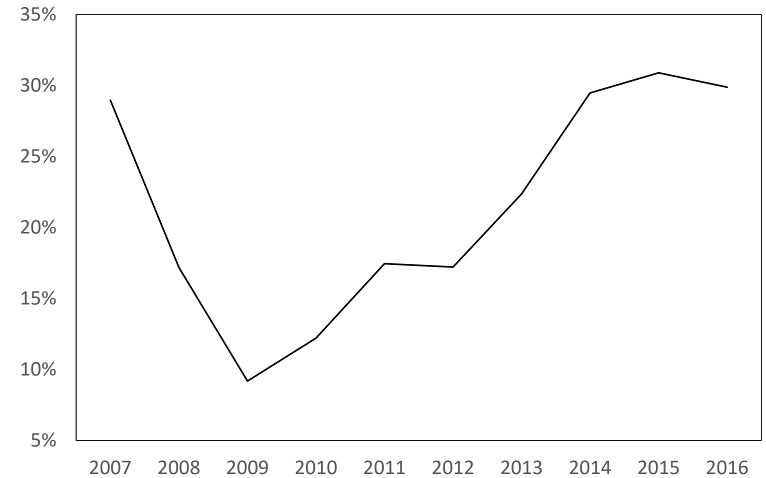
	Jumbo Share	Cutoff Share	Bank Share	
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Limit Increase	-0.356	-0.051	-0.029	-
	-0.003	-0.001	-0.003	-
Jumbo Share	-	-	-	0.223
	-	-	-	-0.005
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	32,147	32,147	32,147	32,147
R^2	0.874	0.696	0.901	0.908

Figure 1: Conforming and Jumbo Markets Origination Volumes and Relative Product Pricing

Panel (a) shows aggregate mortgage origination volumes in billions of dollars by conforming and jumbo mortgages. Panel (b) shows jumbo origination share (in %) of all conventional (non-FHA/VA/RHS) mortgages by dollars originated. Conforming loans are defined as “conventional” (non-FHA) in HMDA with loan amounts below the conforming loan limit. Panel (c) shows the conforming-jumbo interest rate spread (based on BlackKnight data). A negative spread means jumbo loans have higher rates.



(a) Conforming (black) and jumbo (grey) originations ($ billions)

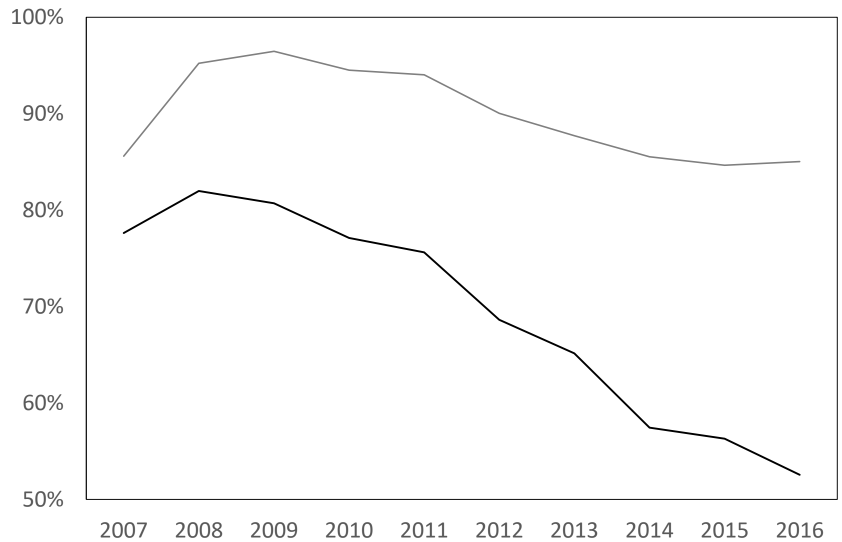


(b) Jumbo market share in total originations

(c) Conforming-jumbo interest rate spread

Figure 2: Traditional and Shadow Bank Market Shares in the Conforming and Jumbo Markets

Panel (a) shows bank market share (by dollars originated) in the confirming (black) and jumbo (grey) markets. Panel (b) shows jumbo lending share (by dollars originated) among banks (solid) and shadow banks (dotted). That is, panel (b) shows what percentage of lender originations are jumbo (non-conforming) among banks and shadow banks. Conforming loans are defined as "conventional" (non-FHA) in HMDA with loan amounts below the conforming loan limit.

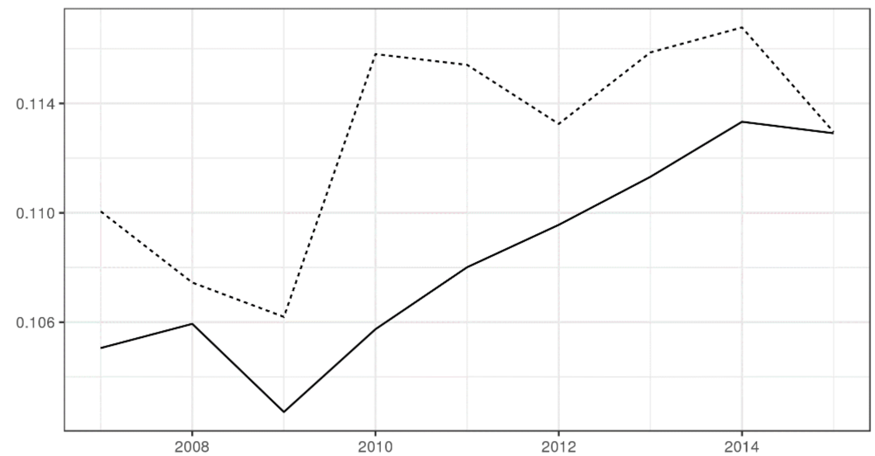


(a) Bank market share among conforming (black) and jumbo (grey) loans

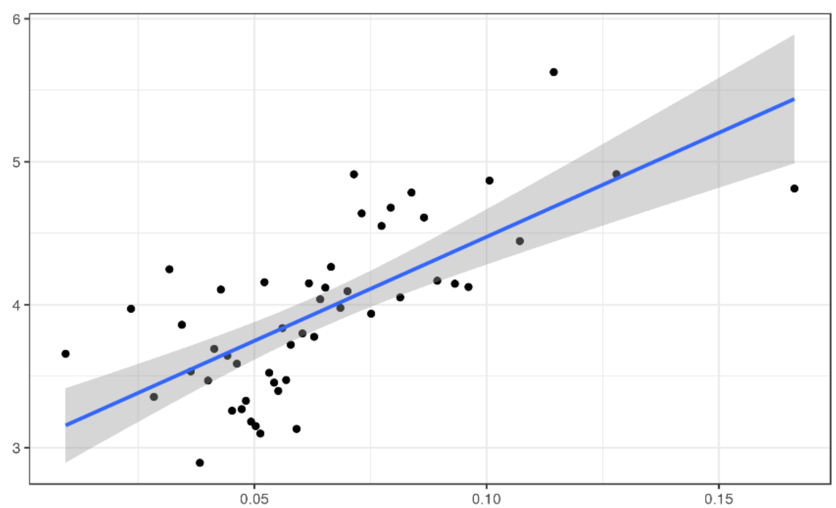
(b) Jumbo share of originations among banks (solid) and shadow banks (dotted)

Figure 3: Bank Capital and Jumbo Originations

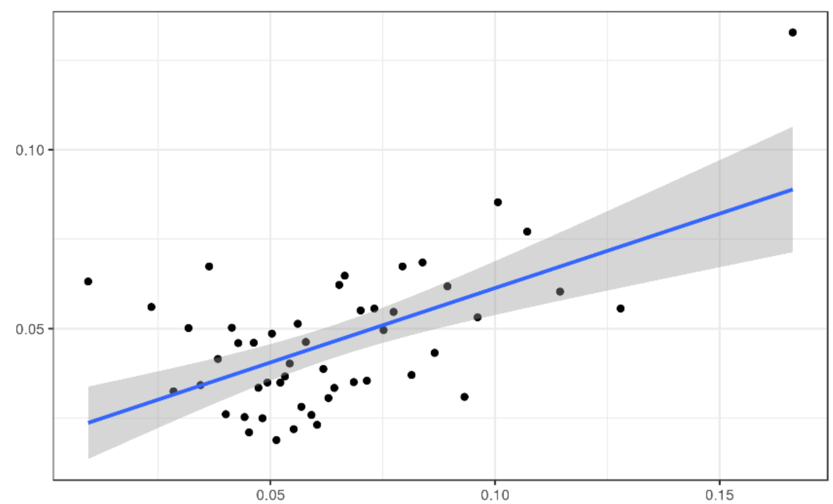
Panel (a) shows bank capital ratios over time. The solid line is the (simple) average across all banks; the dashed line is weighted by mortgage originations. Panel (b) shows a binned scatterplot of log numbers of jumbo originations versus bank capitalization above the statutory limit. Panel (c) shows a binned scatterplot of jumbo share of own bank originations versus bank capitalization above the statutory limit.



(a) Equal (black) and origination (grey) weighted capital ratios over time



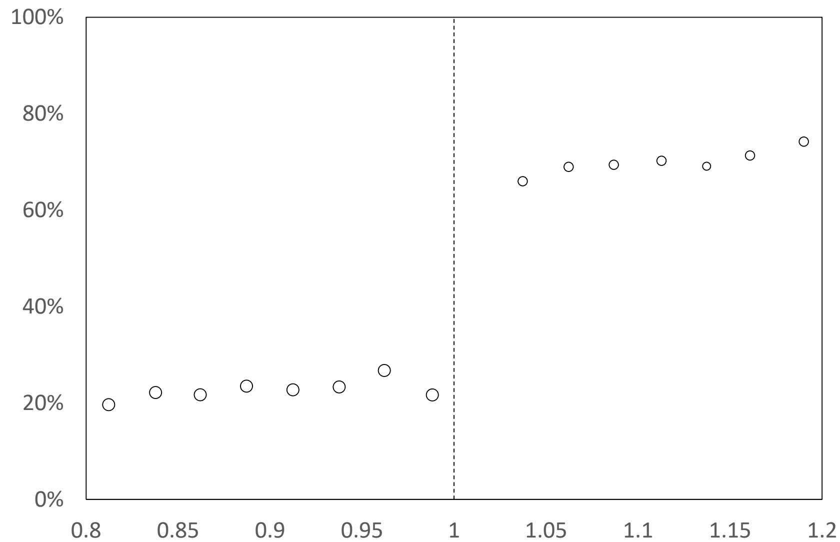
(b) Log(Jumbo Originations) versus excess capitalization



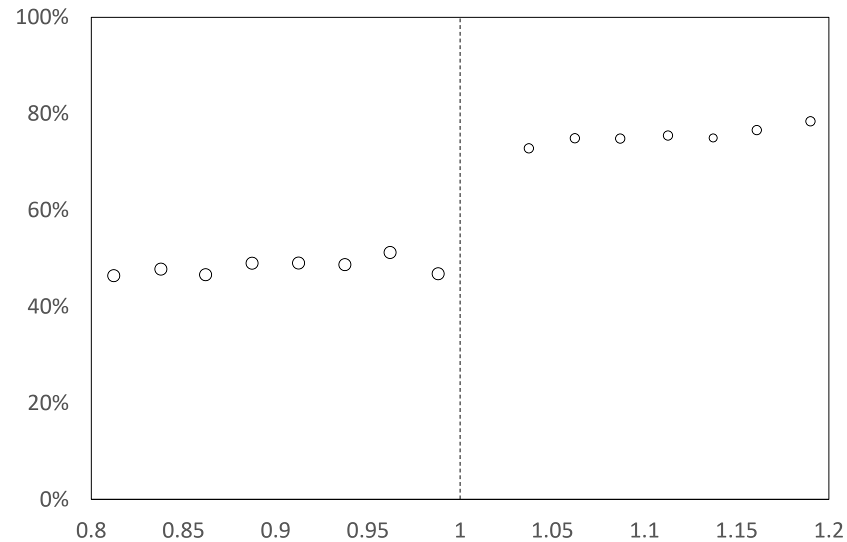
(c) Jumbo origination share versus excess capitalization

Figure 4: Balance Sheet Financing and Bank Lending around the Conforming Loan Limit Cutoffs

Panel (a) shows the percentage of mortgage originations retained on balance sheet by the loan amount divided by the conforming loan limit in the county-year of origination. The cutoff is at 1, shown by a dotted vertical lone. Panel (b) shows the percentage of originations that are done by banks around the conforming loan limit. Loan sizes are binned as a proportion of the conforming loan limit in 0.05 buckets, i.e., 0.91-0.95, 0.96-1.00, 1.01-1.05, and so on. Data are from HMDA.



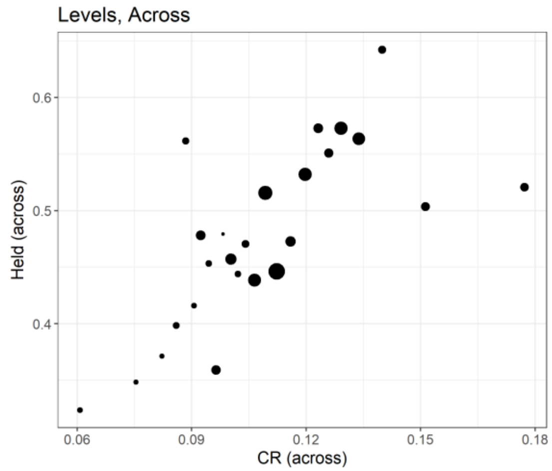
(a) Share of loans retained on balance sheet around the conforming loan limit



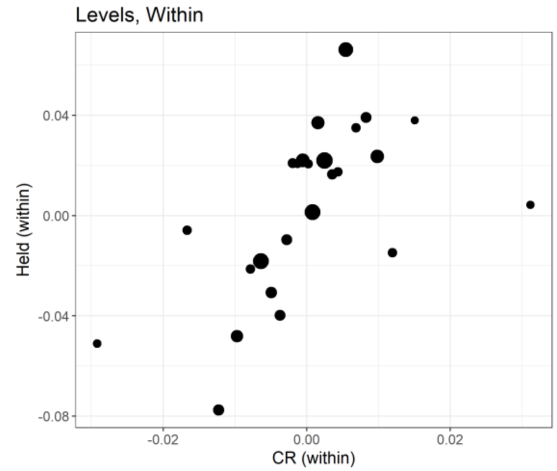
(b) Bank market share around the conforming loan limit

Figure 5: Balance Sheet Financing versus Bank Capital Ratios

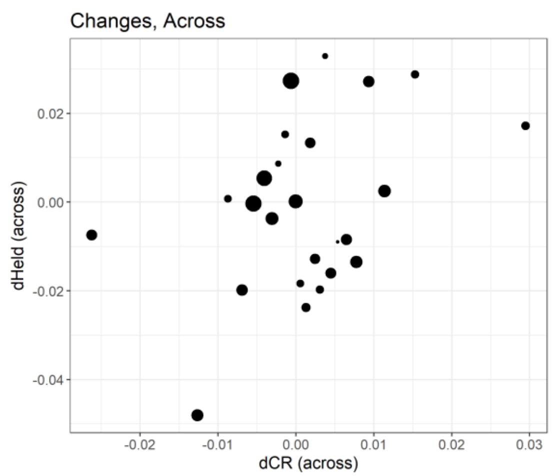
Figure 6 shows binned scatterplots (25 equal-sized bins) of bank percent of loans held on balance sheet versus bank capital ratios. All bins are residualized using controls as in Table 3. "Within" panels remove bank fixed effects. Panels (a) and (b) show the results in levels and correspond to Columns (1) and (2) of Table 3, respectively; (c) and (d) show the results in changes and correspond to Columns (3) and (4) of Table 3, respectively. Panels (a) and (c) are across banks; (b) and (d) are within banks.



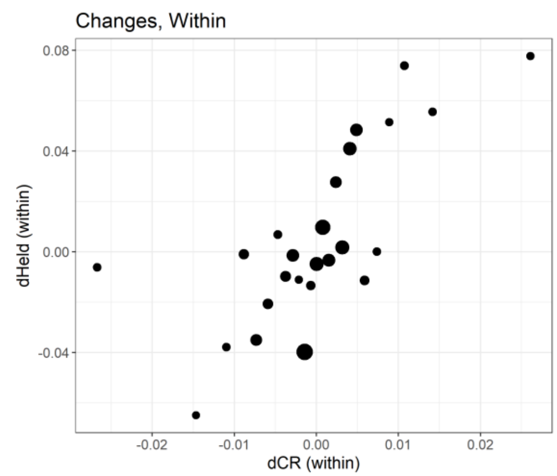
(a) Across banks, levels



(b) Within banks, levels



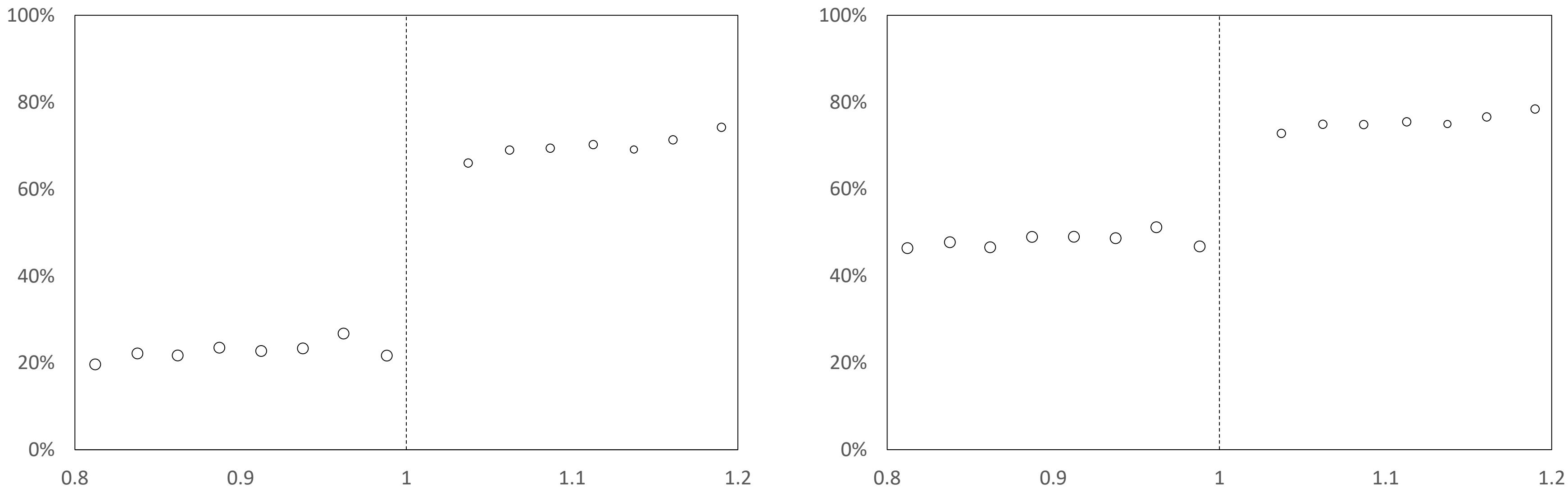
(c) Across banks, changes



(d) Within banks, changes

Figure 6: Traditional Bank Lending around the Conforming Loan Limit Cutoff

Panel (a) shows the percentage of originations of traditional banks retained on balance sheet by the loan amount divided by the conforming loan limit in the county-year of origination. The cutoff is at 1, shown by a dotted vertical line. Panel (b) shows the percentage of originations that are done by well-capitalized banks around the conforming loan limit. A well-capitalized bank is defined as a bank whose capital ratio is in the top quartile for the given year. Loan sizes are binned as a proportion of the conforming loan limit in 0.05 buckets, i.e., 0.91-0.95, 0.96-1.00, 1.01-1.05, and so on. Data are from HMDA.

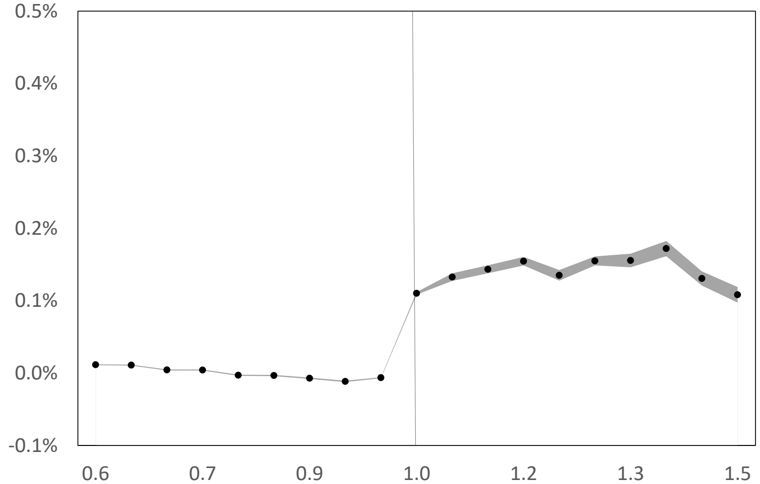


(a) Originations retained on balance sheet

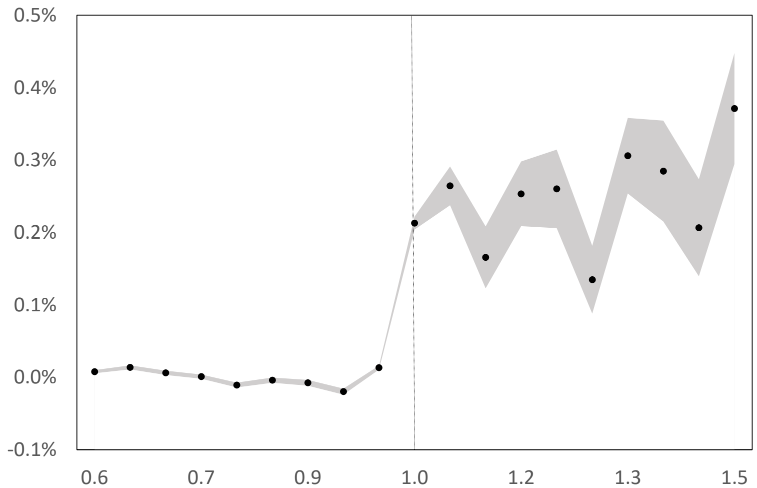
(b) Well-capitalized bank share of all bank originations

Figure 7: Interest Rates around the Conforming Limit

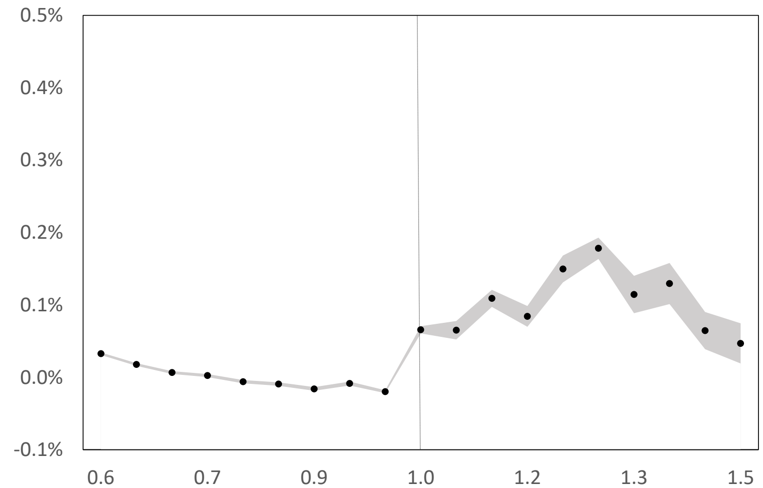
Panel (a), (b), and (c) show the interest rates of FRMs for the full sample (2007-2016), 2008, and 2014 respectively by the loan principal amount divided by the conforming loan limit in the county-year of origination. The cutoff is at 1, shown by a dotted vertical line. Interest rates are residualized against loan characteristics including purpose, credit score, LTV, and term. Shaded regions represent 95% confidence intervals. Data are from BlackKnight.



(a) Full sample



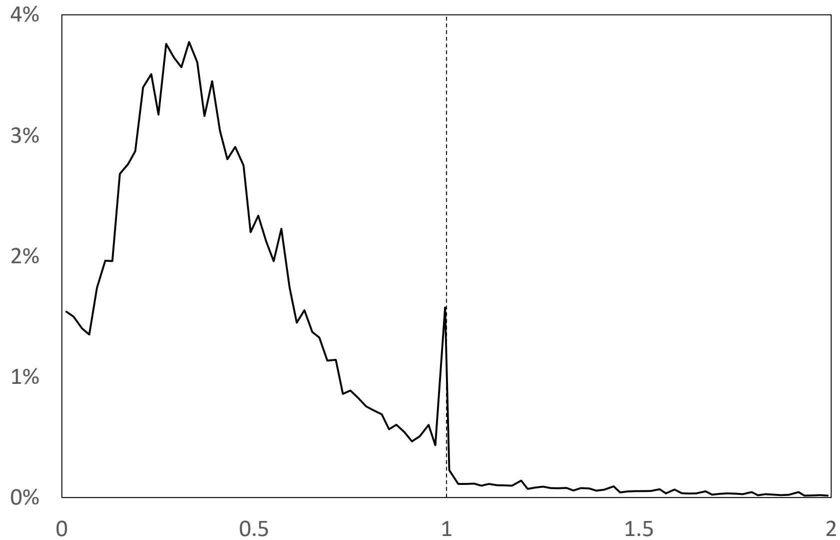
(b) 2008



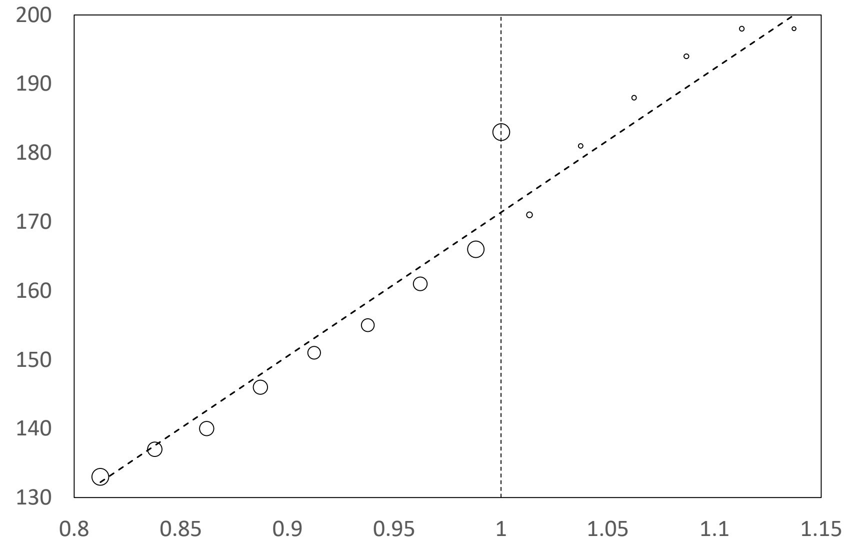
(c) 2014

Figure 8: Loan Distribution and Borrower Income around the Conforming Loan Limit

Panel (a) shows the distribution of loan principal amounts by the loan principal amount divided by the conforming loan limit in the county-year of origination. The cutoff is at 1, shown by a dotted vertical line. Panel (b) shows borrower binned average income around the conforming loan cutoff. Data are from HMDA.



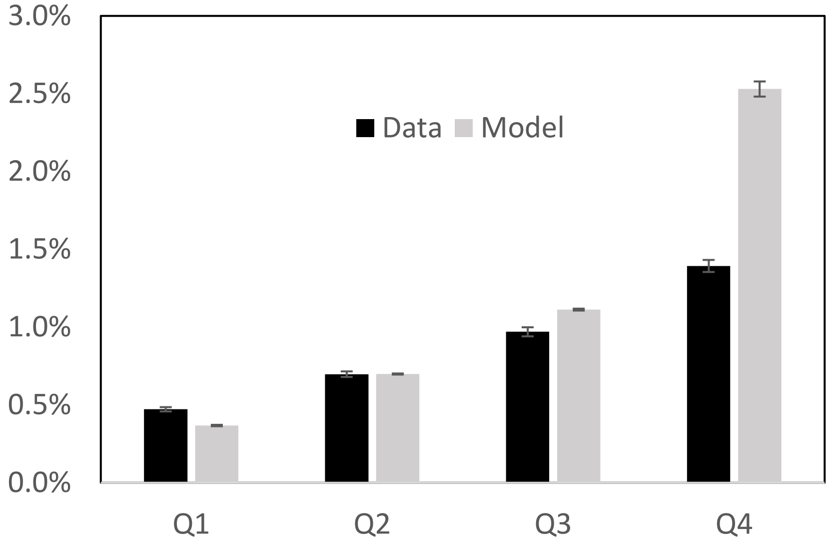
(a) Distribution of loan sizes



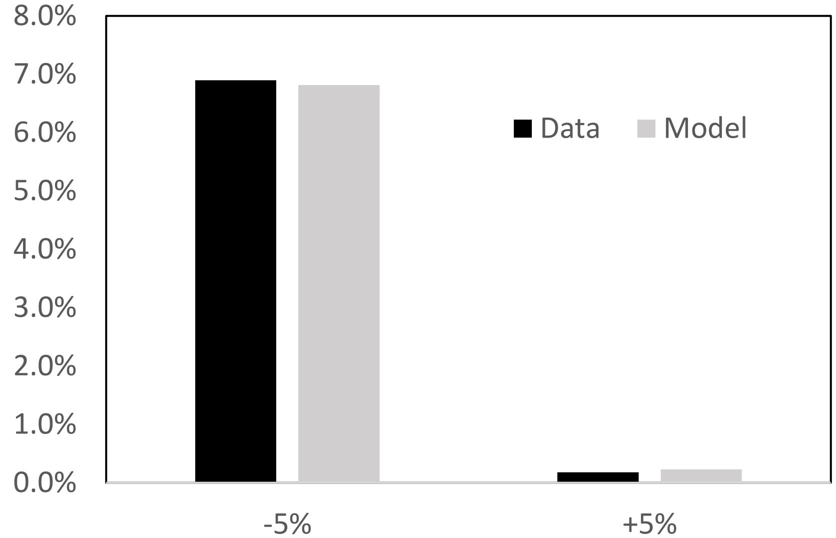
(b) Borrower average income

Figure 9: Empirical versus Model Conforming Loan Bunching

This figure shows actual and predicted market shares around the conforming loan limit. Panel (a) bins markets by predicted bunching quantile and plots the average market share of originations within +/-1pp of the conforming loan limit, with standard errors shown. The black bars are actual bunching market share; the gray bars are the bunching share predicted by the model. Panel (b) shows the average market share across all markets for +/-5pp of the conforming loan limit. Data are from HMDA and the estimated model.



(a) Actual and predicted bunching share by predicted quartile



(b) Actual and predicted market share around conforming loan limit

Figure 10: Marginal Loan Origination Costs for Traditional and Shadow Banks

Figure 10 shows model-implied marginal costs as a function of excess bank capitalization, the difference between the bank's capital ratio and the statutory requirement. The solid line shows the marginal cost for banks originating jumbo loans. The dashed black line shows marginal cost for banks originating conforming loans. The dashed grey line shows the marginal cost for shadow banks originating conforming loans.

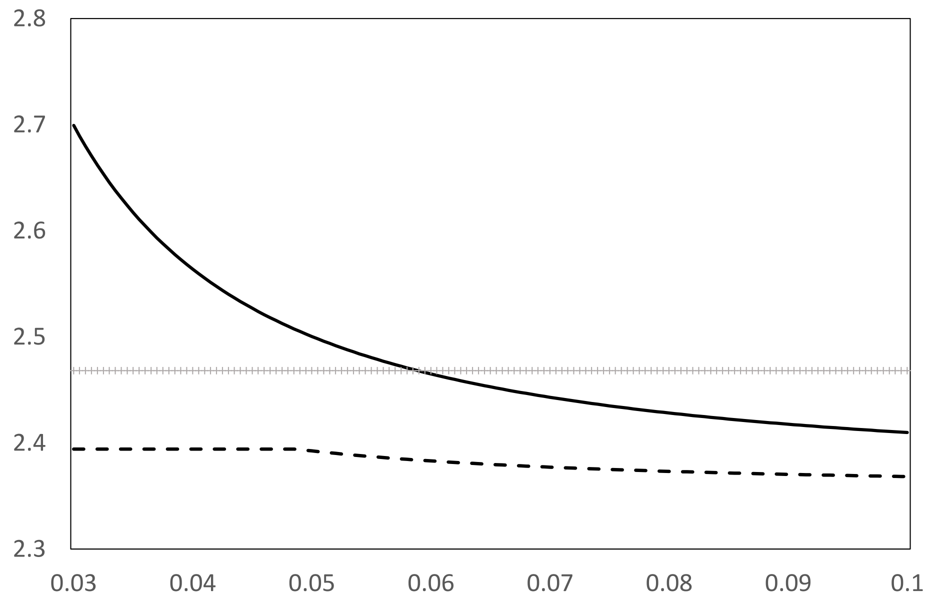
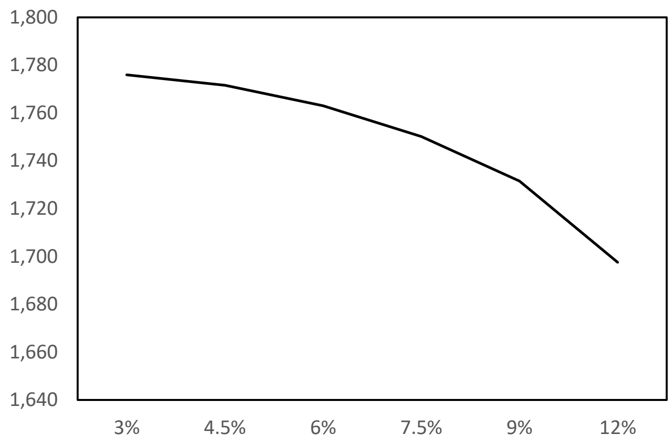
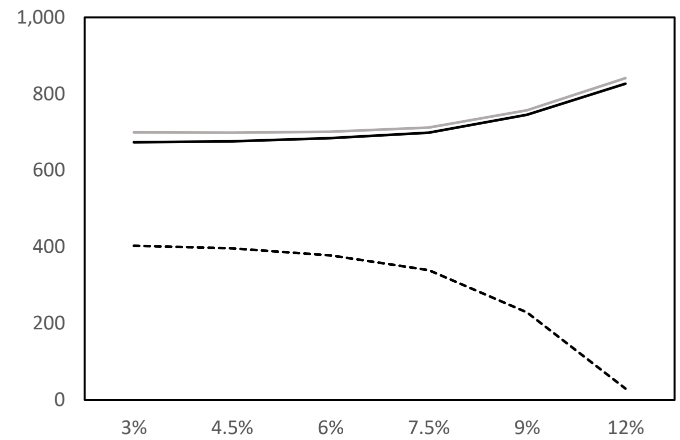


Figure 11: Counterfactual Analysis – Capital Requirements

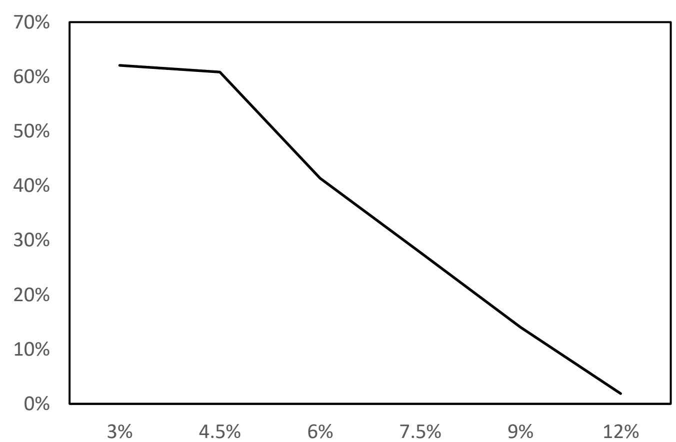
Panel (a) shows aggregate mortgage origination volume (in $ billions) across various bank capital ratio requirements (in %). Panel (b) shows the composition of aggregate lending (in $ billions) split by the shadow bank conforming lending volume (black line), bank conforming lending volume (grey line), and bank jumbo lending volume (dashed line) across various bank capital ratio requirements. Panel (c) shows the percentage of loans that are retained on banks' balance sheets across various capital requirements.



(a) Overall lending volume ($ billions)



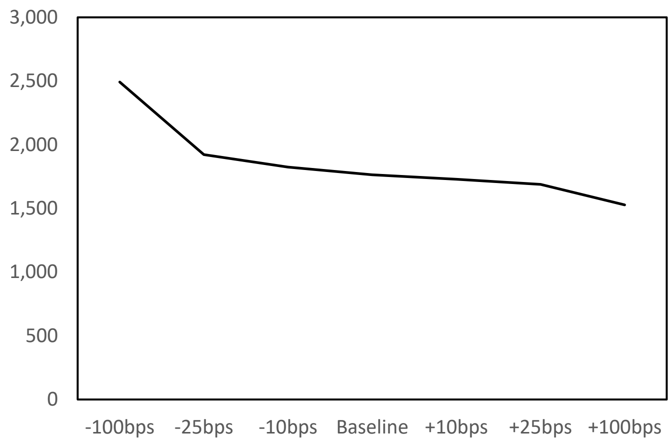
(b) Shadow bank conforming (black), bank conforming (grey) & jumbo (dashed)



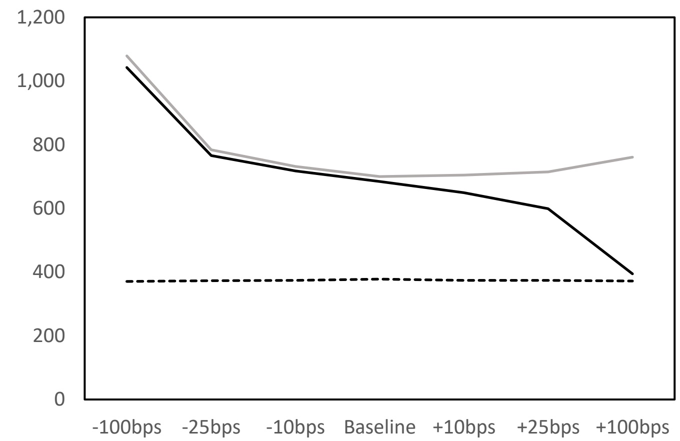
(c) Balance sheet financing share (in %)

Figure 12: Counterfactual Analysis – GSE Financing Costs

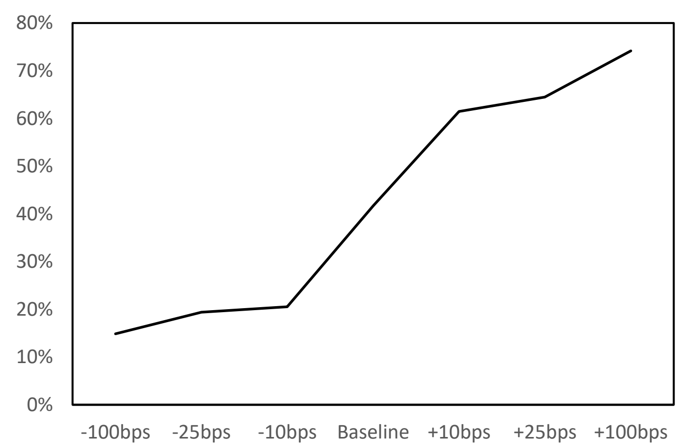
Panel (a) shows aggregate mortgage origination volume (in $ billions) across various changes to the GSE financing costs relative to the baseline (in basis points). Panel (b) shows the composition of aggregate lending (in $ billions) split by the shadow bank conforming lending volume (black line), bank conforming lending volume (grey line), and bank jumbo lending volume (dashed line) across various changes to the GSE financing costs. Panel (c) shows the percentage of loans that are retained on banks' balance sheets across various changes to the GSE financing costs.



(a) Overall lending volume ($ billions)



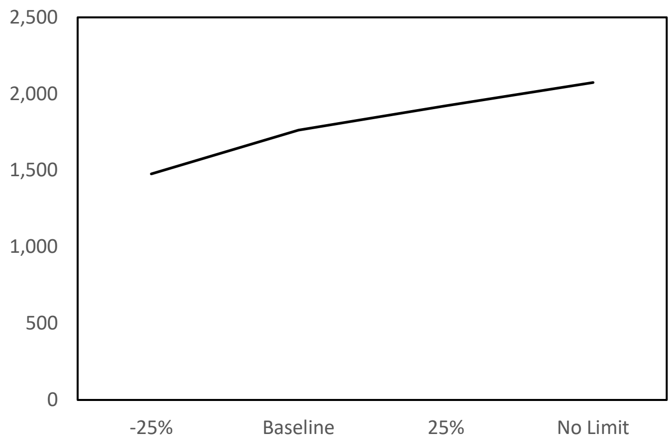
(b) Shadow bank conforming (black), bank conforming (grey) & jumbo (dashed)



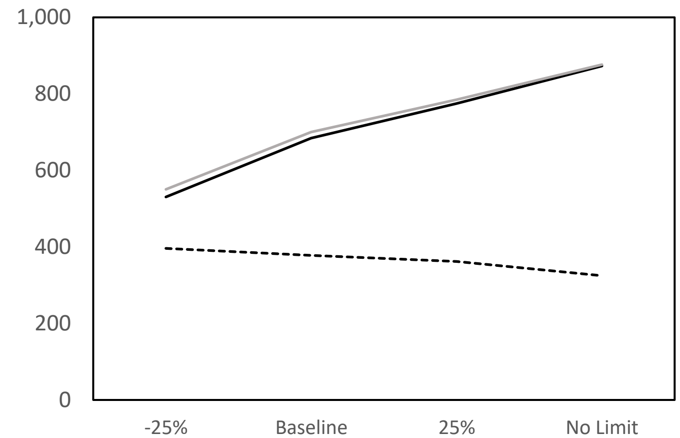
(c) Balance sheet financing share (in %)

Figure 13: Counterfactual Analysis – Conforming Loan Limit

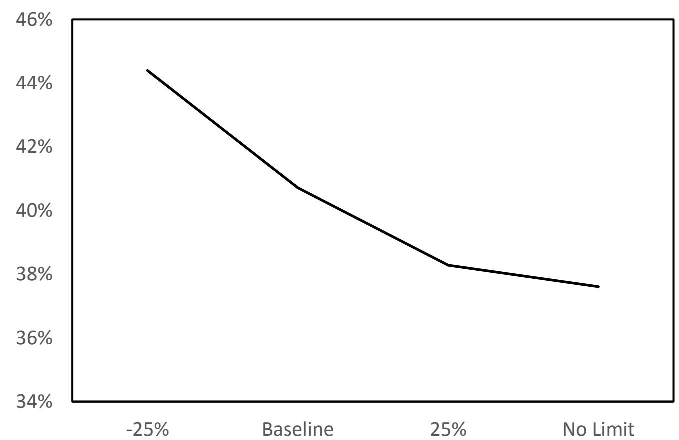
Panel (a) shows aggregate mortgage origination volume (in $ billions) across various changes in the conforming loan limit relative to the baseline (in %). Panel (b) shows the composition of aggregate lending (in $ billions) split by the shadow bank conforming lending volume (black line), bank conforming lending volume (grey line), and bank jumbo lending volume (dashed line) across various changes in the conforming loan limit relative to the baseline. Panel (c) shows the percentage of loans that are retained on banks' balance sheets across various changes in the conforming loan limit.



(a) Overall lending volume ($ billions)



(b) Shadow bank conforming (black), bank conforming (grey) & jumbo (dashed)



(c) Balance sheet financing share (in %)

Appendix

Table A1: Summary Statistics

Table A1 shows summary statistics for the datasets used in the reduced-form section of the paper. Panel A shows summary stats from the HMDA loan-level dataset, used in the regressions for Tables 1 and 3. Panel B shows summary stats from the bank-year level dataset, which is constructed from HMDA and call report data, which is used in the regressions for Tables 2 and 4. Panel C shows summary statistics from the county-year level dataset, which is constructed from HDMA and call report data, which is used in the regressions for Tables 5 and 6.

Panel A: HMDA Loan-Level Summary Dataset

	All Lenders	Traditional Banks	Shadow Banks
Total Originations	46,431,132	30,943,694	15,487,438
% Retained on Balance Sheet or Affiliate	28%	38%	8%
% Sold to Commercial Bank	10%	5%	18%
% Sold to GSE	49%	50%	45%
% Sold to Other	14%	6%	29%

Panel B: Bank-Year Dataset

	2008	2009	2010	2011	2012	2013	2014	2015
Unique Banks	138	120	149	156	173	168	165	157
Capital Ratio	11%	11%	12%	12%	12%	12%	11%	11%
% Loans Retained on Balance Sheet	59%	54%	46%	35%	29%	29%	41%	42%
% Jumbo Loans	3%	2%	3%	3%	4%	6%	10%	12%
% Jumbo Loans Retained on Balance Sheet	94%	92%	84%	86%	89%	86%	88%	90%
% Conforming Loans Retained on Balance Sheet	58%	53%	46%	34%	26%	26%	36%	35%

Panel C: County-Year Dataset

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Unique Counties	3213	3213	3214	3213	3210	3210	3211	3209	3207	3210
Bunching at 1% Cutoff	2.24%	2.32%	2.66%	2.21%	1.69%	1.99%	1.95%	1.82%	1.80%	1.92%
Bunching at 5% Cutoff	2.57%	2.65%	3.06%	2.61%	2.00%	2.26%	2.18%	2.08%	2.07%	2.21%
Bank Share	79%	79%	77%	75%	74%	69%	66%	60%	57%	55%
OTS Share	14%	-	-	-	-	-	-	-	-	-