Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks

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Abstract

We study the rise of fintech and non-fintech shadow banks in the residential lending market. The market share of shadow banks in the mortgage market has nearly doubled from 2007-2015. Shadow banks gained a larger market share in the refinancing market and among less creditworthy borrowers accounting for three-quarters of loan originations to most indebted borrowers. Shadow banks were significantly more likely to expand their market share where traditional banks faced more capital and regulatory constraints. This suggests that traditional banks facing increased capital and regulatory burden retreated from residential mortgage lending, and that shadow banks stepped into this gap. Fintech firms accounted for almost a third of shadow bank loan originations by 2015. To investigate the role of technology in the decline of traditional banking, we focus on technology differences *between* shadow banks, holding the regulatory differences between different lenders fixed. Fintech lenders serve more creditworthy borrowers and are more active in the refinancing market. Analyzing fintech firms' pricing decisions, we find some evidence that fintech lenders use different methods in determining corresponding interest rates. Importantly, the online origination technology appears to allow fintech lenders to originate loans with greater convenience for their borrowers. Among the borrowers most likely to value convenience, fintech lenders command an interest rate premium for their services. We use a simple model to decompose the relative contribution of technology and regulation to the rise of shadow banks. This simple quantitative assessment indicates that increasing regulatory burden faced by traditional banks and financial technology can account, respectively, for about 55% and 35% of the recent shadow bank growth.

Keywords: Fintech, Shadow Banks, Regulatory Arbitrage, Lending, Mortgages, FHA

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I. Introduction

In the last decade, the market for financial consumer products has undergone a dramatic change. Intermediation has shifted away from traditional banks to less regulated shadow banks. This change has coincided with a shift away from "brick and mortar" originators to online intermediaries.[1] These developments have generated an intense debate, and have resulted in significant concerns among regulators and market participants. Despite this large structural shift in household lending, there is little systematic analysis of this change.

We study the rise of fintech and non-fintech shadow banks in the largest consumer loan market in the US, the residential lending market, which has been at the center of this drastic change. As we document,[2] the market share of shadow banks[3] in the mortgage market has nearly doubled from roughly 30% to 50% from 2007-2015. In the Federal Housing Administration (FHA) mortgage market, which serves less creditworthy borrowers, the market share of shadow banks increased from 45% to a staggering 75% over the same period. "Fintech" lenders have increased their market share from essentially 0% to roughly 16% in both the conforming and FHA mortgage markets in the same period.

Two leading classes of hypotheses have attempted to explain the decline in traditional banking: Increased regulatory burden on traditional banks, and disruptive technology. The idea behind the first explanation is that shadow banks exploit regulatory arbitrage. The narrative is that banks are subject to an ever-increasing regulatory burden, heightened legal scrutiny, and larger capital requirements, which have affected which products they can provide and have changed the cost of their funding. Therefore, banks, especially those facing tighter capital constraints, are withdrawing from markets with high regulatory costs. Shadow banks, which are largely free of regulatory costs and such concerns, then step into this gap.

The second hypothesis is that the shift from traditional banks is driven by changes in technology. Fintech shadow banks have disrupted the market, because they provide better products, or provide existing products more cheaply. Consider Quicken Loans, which has grown to the third largest mortgage lender in 2015. The Quicken "Rocket Mortgage" application is done mostly online, resulting in substantial labor and office space savings for Quicken Loans. The "Push Button. Get Mortgage" approach[4] is also more convenient and faster for internet savvy consumers. Last, fintech shadow banks might be better able to screen potential borrowers using

[1] Goldman Sachs Report, March 3, 2015: "The Future of Finance: The Rise of the new Shadow Bank."
[2] See Figures 1-3.
[3] We use the term "shadow bank" to refer to non-bank lenders. See Adrian and Ashcraft (2016), who define the "shadow banking system" more generally as a "web of specialized financial institutions that conduct credit, maturity, and liquidity transformation without direct, explicit access to public backstops."
[4] https://www.nerdwallet.com/blog/mortgages/quickenloansandrocketmortgagereview/ [Accessed on 11/8/2016]

big data approaches inherent in technology based lending, benefitting some segments of consumers, and possibly hurting others.

To examine whether it is plausible that the tighter capital constraints and increased regulatory burden was the driving force behind the decline of traditional mortgage banking, we examine the market share of all shadow banks, irrespective of their fintech affiliation. While the market share of shadow banks in the mortgage market has nearly doubled from 2007-2015, they now dominate among loans insured by Federal Housing Authority (FHA). The FHA loans allow lower income and less creditworthy households to borrow money for the purchase of a home while putting down as little as 3.5% of the property value as down payment. In 2015 shadow banks accounted for about 75% of all FHA originations. The dominance in this market is strong evidence that shadow banks' advantage over traditional banks is especially strong in a market dominated by riskier borrowers. This evidence is consistent with the narrative that this is the segment in which the regulatory burden in has risen substantially because of a "series of costly lawsuits brought by the federal government surrounding these loans" [5] and heighten regulatory scrutiny.

Shadow banks have also expanded in the conforming loan market. While they do not dominate the this market to the same extent as the riskier FHA market, their market share of conforming mortgages has risen from 25% in 2007 to roughly 50% in 2015. One might therefore infer that shadow banks generally focus on the less creditworthy, lower income parts of borrowers. To examine that intuition, we look within the conforming sector. We find some evidence that shadow banks grow more aggressively among less creditworthy borrowers within the conforming sector. They also seem to enter areas with larger shares of minorities. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of minority borrowers, it may not be surprising that banks are retreating from that sector somewhat. Overall, this evidence suggests that the regulatory distinction between FHA loans aimed at least creditworthy borrowers and conforming loans targeted at prime borrowers is importantly driving the difference in penetration rates of shadow banks.

The differences between shadow and traditional banks are not limited to customer characteristics. Shadow banks have gained much larger market share in the refinancing market relative to purchase loan market. One possible reason behind this is that traditional banks are also substantially more likely to hold loans on their own balance sheet than shadow banks. Approximately one fourth of traditional banks loans in HMDA are held on their own balance sheet. For shadow banks, the share is closer to 5%. Because refinancing loans held on the balance sheet cuts directly into a bank's profit, their incentives to refinance are smaller. Second,

[5] http://www.wsj.com/articles/banksnolongermakethebulkofusmortgages1478079004 [Accessed on 11/8/2016]

shadow banks' business models might be better suited at refinancing because they can avoid labor-intensive "purchase" activity.

To more directly link the rise of shadow banks to an increased capital constraints and regulatory burden of traditional banks, we focus on three potential sources for this increase: Capital requirements, changes in regulatory treatment of mortgage servicing rights, mortgage-related enforcement actions, and mortgage lawsuits. Unlike shadow banks, traditional banks are deposit taking institutions, and are thus subject to capital requirements, which do not bind shadow banks. As regulatory risk-based capital requirements increased, constrained banks may have been forced to build balance sheet buffers rather than originate new mortgages using their own capital. If this is the case, we should see larger penetration of shadow banks in places in which banks most increased their risk-based capital holdings. Indeed, we find a larger growth of shadow banks in counties in which a larger share of traditional banks built up capital reserves over the last decade. We also collect data on enforcement actions directed at depositary institutions (i.e. not shadow banks) as well as mortgage related lawsuits. We find that areas in which a larger share of lenders have been subject to enforcement and legal actions are also areas in which we see a larger market share of shadow banks. This evidence is consistent with the idea that traditional banks are retreating from markets with a larger regulatory burden, and that shadow banks fill this gap.

Our results suggest that the rise of shadow banks in the mortgage market is importantly driven by their lower regulatory burden. In other words, shadow banks find it cheaper to originate mortgages. We next examine if these cost advantages are passed through to consumers: i.e. is the change we observe in the market limited to quantities, or is it also reflected in prices of mortgages. We find that if differences in pricing do exist, they are *on average* negligible. However, we also note that controlling for other observables shadow banks loans are also more likely to prepay and default, which may suggests that on average shadow banks loans are slightly cheaper to borrowers. We later show that the average interest rate difference hide some interesting variation in the pricing of the loans originated by fintech lenders *relative* to non-fintech shadow banks.

Regulation is not the only possible reason why the market share of traditional banks may have declined over time. To examine the role that technology has played in the decline of traditional banking, we focus on technology differences *between* shadow banks. Examining the role of technology within shadow banks allows us to hold the regulatory differences between different lenders fixed. First, we collect the information on a shadow bank's online presence, to classify their lending operations as fintech or non-fintech. We then examine in which markets fintech firms have grown faster than non-fintech shadow banks.

Fintech firms accounted for about a third of shadow bank loan originations by 2015. These simple facts suggest that on-line origination technology was an important force in the decline of traditional banks during the last decade. There are several large and consistent factors associated with a greater penetration of fintech. First, counties where there are more residents with bachelor's degrees see significantly more penetration from fintech lenders. Given that fintech lenders operate online, it is not surprising that education plays an important role in fintech penetration. Second, while we find that shadow banks are on average more likely to be found in counties with greater minority populations, the opposite is true for fintech lenders among shadow banks: counties with greater minority populations see less penetration by shadow banks. Consistent with this observation we find that fintech lenders are much less likely to serve less creditworthy (FHA) borrowers

As we document above, shadow banks are more likely than traditional banks to refinance mortgages. Within shadow banks, refinances of all types are nine to thirteen percent more likely to be fintech-originated, and first-time buyers are significantly less likely to be fintech customers. One possible reason is that the tasks involved in mortgage refinancing are the best fit for fintech technology: In refinancing, the fintech lender benefits from many on-the-ground activities, such as a title check, structural examination, negotiations between buyer and seller, having already taken place at the time of purchase. It is these somewhat non-standardized activities that may be least-well suited to technological comparative advantages of a fintech lender.

Fintech shadow banks have disrupted the market, either because they provide better products, or because they provide existing products more cheaply. If fintech lenders offer a better experience for the customers, they should potentially be able to charge more for originating mortgages. Conversely, if the main consequence of fintech is to lower costs for the lender, then one would expect fintech lenders to potentially pass-through some of the cost savings to the borrowers. Recall that shadow banks on average charge similar interest rates as traditional banks.

Within shadow banks, on the other hand, we find that fintech firms charge on average higher interest rates, suggesting that fintech consumers are willing to pay for the convenience of transacting online. Notably, the fintech interest rate premium is lower for the least creditworthy (low FICO) borrowers and higher for the most creditworthy borrowers. These results suggest that fintech lenders are able to price discriminate between different groups of borrowers when competing with brick and mortar shadow banks.

Fintech shadow banks might also use different models and data inherent in technology based lending. We find some evidence that interest rates of fintech lenders are more predictive of subsequent prepayments outcomes relative to non-fintech lenders. More importantly, we find evidence that is consistent with fintech lenders using hard information differentially relative to non-fintech lenders. In particular, we find that a large amount of the variation (62%) in interest rates across borrowers of non-fintech shadow bank lenders can be accounted for by variation in observable borrower and loan characteristics. On the other hand, among fintech lenders less than 45% of variation in interest rates can be accounted for by variation in observable borrower characteristics. These results suggest that fintech lenders do use substantially different technology in setting mortgage interest rates.

Traditional banks' market share has declined precipitously over the last decade. Taken together, our results suggest that the additional regulatory burden faced by banks opened a gap that was filled by shadow banks. In addition, our evidence suggest that financial technology related to on-line lending platforms has partially disrupted the mortgage market by offering increased convenience to borrowers.

We use a simple model to decompose the relative contribution of technology and regulation to the rise of shadow banks. We calibrate the model every year from 2008 onwards to see how the funding costs, quality, and regulatory constraints faced by traditional banks have changed over the period. We combine the detailed mortgage interest rate data and movements in market shares of lenders to identify the relative importance of these factors over time. Our quantitative model implies that traditional banks have slightly lower shadow cost of funding and provide higher quality products than shadow banks. Despite this, they lose market share during this period because of an implied large increase in the intensity of regulatory burden after 2010. We note that this period coincides, among others, with passage of the Dodd-Frank Act, a formation of Consumer Financial Protection Bureau, and the new Basel III capital rules imposing more onerous limits on the amount of mortgage servicing payments that can count towards the bank regulatory capital. Our model also predicts a substantial increase in perceived quality and convenience of on-line origination platforms by borrowers that occurred during 2009-2012 period. Overall, using this simple quantitative model, we find that increasing regulatory burden can account for about 55% of shadow bank growth during 2008-2015 period with advancement in on-line lending technology accounting for another 35%.

II. Related Literature

Our paper ties together separate strands of the literature relating to residential mortgage lending, banking regulation, and the growing role of financial technology.

The Structure of the Residential Mortgage Market

Many papers have studied the changing structure of the mortgage origination chain, with particular attention paid to the originate-to-distribute model and the costs and benefits thereof (e.g., Berndt and Gupta 2009, Piskorski et al. 2010, Keys et al. 2010 and 2013, Purnanandam 2011). The focus has primarily been on the run-up to the financial crisis, rather than on the immediate aftermath and recovery following the crisis.

Bank-like activities taking place outside of traditional deposit-taking institutions has attracted considerable attention in the literature and at Federal banking regulators (see Adrian and Ashcraft (2016) for an exhaustive summary). The literature (e.g., Bord and Santos 2012) has primarily focused on the maturity transformation role of banks taking place elsewhere. Our paper instead focuses on mortgage origination taking place outside the traditional banking system and its accompanying regulatory structure.

Banking Regulation and GSEs

Our paper relates to a large literature has examined the role of government programs undertaken during the financial crisis. (e.g., Mayer et. al. 2014, Haughwout et. al. 2016, Agarwal et al. 2012 and 2015). Like Agarwal et. al. (2014), Lucca et. al. (2014), Granja et al. (2014), Piskorski et al (2015), Fligstein and Roehrkasse (2016), we study lawsuits, regulatory enforcement actions arising out of the financial crisis, and capital constraints. We make use of geographical heterogeneity in regulatory burdens to show that shadow banks, facing relatively lower regulatory pressure in heavily regulated markets, gain market share.

Because shadow banks are so dependent on GSEs and FHA guarantees, our paper relates to literature studying GSEs and their role in mortgage lending. GSEs were established to promote housing ownership, particularly in underserved areas, and a number of papers (Hurst et al 2015, Bhutta 2014, Acharya et. al. 2011) have studied their role in income redistribution and house ownership, finding mixed results. Our paper suggests that government policies of increased regulatory burden of traditional banks combined with GSEs and FHA guarantees have contributed greatly to the rise of the shadow banking sector.

Financial Technology

Our paper connects to the growing literature on financial technology, e.g., Philippon (2015, 2016) and Greenwood and Scharfstein (2013). To our knowledge, ours is the first paper that performs a detailed analysis on fintech and non-fintech firms operating within the residential mortgage industry in an effort to explore what technological advantages fintech lenders have over non-fintech ones. Using a methodology similar to Rajan et al. (2015), we document that fintech lenders appear to use substantially different methods to set interest rates. Philippon (2015) documents that advances in financial technology have failed to reduce intermediation costs. In that spirit, our paper shows fintech lenders in fact offer higher interest rates than non-fintech lenders. However, consumers' willingness to use more expensive fintech lenders may also reflect more convenient services offered by these lenders.

Finally, while Philippon (2016) proposes that fintech can offer a way towards structural change in the financial industry, because political economy considerations can stifle change in the traditional part of the sector. Our paper advises caution: while fintech lenders do enter to help fill the gap left by the banks, they have done so by having relied almost exclusively on explicit and implicit government guarantees as customers.

III. Data and Lender Classification

III.A Description of Datasets

We use and combine the following datasets in our paper.

HMDA: We use mortgage application data collected under the Home Mortgage Disclosure Act (HMDA) to examine loan-level and area-level lending patterns. HMDA records the vast majority home mortgage applications and approved loans in the United States. The data provides, among other things, the application outcome, the loan type and purpose, the borrower's race, income, loan amount, year, census tract, and importantly for our purpose, the originator's identity. Due to mergers and name changes, the identification of HMDA lenders changes over time, and to overcome this limitation, we manually linked lenders across years. HMDA further records whether the originator retains the loan on balance sheet or sells the loan within one year to a third party, including to a GSE. If the originator retains a loan for more than a year before selling it, we would observe this as a non-sale.

Fannie Mae Single-Family Loan Performance Data: This dataset provides origination and performance data on a subset of Fannie Mae's 30-year, fully amortizing, full documentation, single-family, conforming fixed-rate mortgages that are the predominant conforming contract type in the US.[6] This loan-level monthly panel data has detailed information on a rich array of loan, property, and borrower characteristics (e.g., interest rates, location of the property, borrower credit scores, LTV ratios) and monthly payment history (e.g., delinquent or not, prepaid). The loans in our data were acquired between January 1, 2000 and October 2015. The monthly performance data runs through June 2016.

[6] The dataset does not include adjustable-rate mortgage loans, balloon mortgage loans, interest-only mortgage loans, mortgage loans with prepayment penalties, government-insured mortgage loans, Home Affordable Refinance Program (HARP) mortgage loans, Refi Plus™ mortgage loans, and non-standard mortgage loans. Also excluded are loans that do not reflect current underwriting guidelines, such as loans with originating LTV's of 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.

The Freddie Mac Single Family Loan-Level Dataset: Similar to the Fannie Mae data, this dataset contains a subset of loan-level origination, monthly loan performance, and actual loss data of fully amortizing, full documentation, single family mortgages. Included in the dataset are 30-year fixed-rate mortgages originating between January 1999 and September 2015 and purchased by Freddie Mac. Also included are 15- and 20-year fixed-rate mortgages originating between January 2005 and September 2015. The monthly loan performance data runs until March 2016 for all the loans provided.[7] Combining the Fannie Mae and Freddie Mac datasets gives us coverage of the majority of conforming loans issued in the United Sates during the period of our study.

The Federal Housing Administration Dataset: This data provided by the U.S. Department of Housing and Urban Development (HUD) contains single-family portfolio snapshots of loans insured by the Federal Housing Administration (FHA). The FHA program is intended to aid borrowers with particularly low credit scores who may otherwise be unable to borrow from conventional lenders. The data begins in February, 2010 and is updated monthly through December 2016. The FHA data records product type (adjustable or fixed-rate), loan purpose (purchase or refinance), interest rate, state, county, MSA, and importantly for our purposes, the originating mortgagee. Notably absent from the FHA data are borrower FICO scores, so while by the nature of the program, FHA borrowers have low credit scores, we cannot directly control for borrower credit score within the FHA data. For this reason, when studying loan interest rates and outcomes, we focus our analysis primarily on the loans from Fannie Mae and Freddie Mac databases.

US Census Data: We use county-level demographic data from the US Census and American Community Survey between 2006 and 2015. We collect population, population density, racial and ethnic characteristics, education, income and poverty, and homeownership statistics.

Regulatory Burden of Depository Institution Data: In studying the market share of shadow banks we investigate whether shadow banks are likely to enter areas where the traditional banking system faces heightened regulatory scrutiny. We draw on a number of data sources to measure these regulatory burdens between 2006 and 2015. We use the Summary of Deposits (SOD) data from the FDIC, to calculate bank presence in a county. The SOD tracks bank deposits at the branch level. We supplement the SOD data with bank balance sheet data from the bank call reports, from which we calculate bank capitalization. We use two other measures in addition to bank capital to measure bank regulatory burdens. As in Lucca et. al. (2014), we obtain a regional

[7] Not included are ARMs, balloon loans, mortgages with step rates, relief reliance mortgages, government-insured mortgages, affordable loan mortgages such as Home Possible® Mortgages, mortgages delivered to Freddie Mac under alternate agreements, mortgages associated with Mortgage Revenue Bonds, and mortgages with credit enhancements other than primary mortgage insurance.

measure of bank regulator activity by examining enforcement actions brought by the primary banking regulators: The Federal Reserve, the FDIC, the OCC, and the (no-longer active) OTS. Regulators use enforcement actions to discipline banks that receive poor examination reports, and the formal enforcement actions are disclosed to the public.[8][9][10] Like Lucca et. al., we focus on the harshest enforcement actions: Cease and Desist orders, Prompt Corrective Action Directives, and Termination and Suspension of Deposit Insurance. We extend the period covered by the data through 2015.

Lawsuit Settlements Data: Finally, following Piskorski et al. (2015) and Fligstein and Roehrkasse (2016), we collect lawsuit settlements arising out of the financial crisis brought against banks, lenders, and mortgage servicers. We construct a timeline of settlements and settlement amounts by year and bank by aggregating data from a number of sources. From Law360[11], a news service that covers all aspects of litigation, we collect data on lawsuit settlements associated with RMBS, mortgage foreclosures, fraud, deceptive lending, securitization, refinancing, and robo-signing. The Law360 data spans 2008 through 2016. From the SEC[12], we collected all legal actions taken by the SEC regarding misconduct that led to, or arose from the financial crisis. The SEC data spans 2009 through 2016. From SNL Financial[13], now a part of S&P Global Intelligence, we collect a timeline of major bank settlements arising out of the financial crisis between 2011 and 2015.

III.B Lender Classification

Central to this paper is the classification of mortgage lenders as Banks or Shadow Banks, and within shadow banks, as fintech or non-fintech. We perform this classification manually. The Fannie Mae, Freddie Mac, and FHA data identify each loan's originator if the originator was among the top-50 originators in the reporting period. HMDA identifies all originators. We classify the identified lenders in the Fannie Mae, Freddie Mac, and FHA data. Additionally, we classify the largest lenders in HMDA that are not identified in the Fannie, Freddie, or FHA data, so that our classified sample covers 80% of total originations by value in 2010. The classification of Bank versus Shadow bank is straightforward: A lender is a Bank if it is a depository institution; a lender is a Shadow Bank if it is not.

The classification of fintech and non-fintech is less straightforward: A lender is a fintech lender if it has a strong online presence and if nearly all of the mortgage application process takes place

[8] https://www.federalreserve.gov/newsevents/press/enforcement/2014enforcement.htm
[9] https://www5.fdic.gov/EDO/DataPresentation.html
[10] https://www.occ.gov/topics/laws-regulations/enforcement-actions/index-enforcement-actions.html
[11] https://www.law360.com/faq
[12] https://www.sec.gov/spotlight/enf-actions-fc.shtml
[13] https://www.snl.com/InteractiveX/Article.aspx?id=33431645

online with no human involvement from the lender. For example, an applicant to Quicken Loans, the prototypical fintech lender, can be approved for a loan with a locked-in interest rate with no human interaction; the borrower meets a Quicken Loans loan officer for the first time only at closing (see Appendix A5). An applicant at a non-fintech firm, on the other hand, interacts with a human loan officer much earlier in the process, even if the process begins online. For instance, a borrower may input her name and location online, and then be directed to phone a local loan officer to continue. A lender using this process is classified as a non-fintech lender. Appendix A1 shows the list of main lenders in each of these three categories.

IV. Institutional Background

A. Banks, Shadow Banks and Fintech

This section provides an overview of the institutional details and history of shadow banking before and after the financial crisis. We use the term shadow banking broadly to refer to non-bank financial intermediaries that engage in activities which have traditionally been the business of banks.[14] The key difference between shadow and traditional banks is that shadow banks do not take deposits, which frees them from a large amount of regulatory oversight to which traditional banks are not subject. Not being subject to the regulations affecting depository institutions, shadow bank lenders are free to engage in regulatory arbitrage, giving them a number of advantages over traditional banks.

B. History of Shadow Banking in the Retail Mortgage Market

Although this paper focuses on the rise of shadow banking in mortgage origination after the crisis and the factors that contribute to the rise, it is important to note that in the run-up to the financial crisis, shadow banks' share of mortgage origination was quite high. Goldman Sachs estimates that shadow banks originated roughly 30% of all mortgages for the years 2004—2006 and mostly specialized in loans issued without government guarantees (e.g., non-agency subprime loans). The market share of shadow bank lenders was heavily concentrated. Countrywide Financial accounted for more than half of the shadow banks' share of originations.[15]

As shadow bank originators do not take deposits, they rely almost exclusively on making loans that are originated for sale, and earn revenue through the sale of mortgage servicing rights (MSRs)---the capitalized value of future cash flows from the mortgages, a small amount of interest income between origination and sale, and servicing income.[16] Because shadow banks

[14] GS Report, Pg. 5
[15] GS Report, Pg. 51
[16] GS Report, Pg 51.

rely so heavily on sale of MSRs to third parties, they are particularly sensitive to the financial health of these third parties. The potential buyer depends on the originated product: Conventional, conforming loans are typically sold to Fannie Mae and Freddie Mac. Government-insured loans, such as FHA or VA mortgages, are typically sold to Ginnie Mae. Non-conforming loans, such as jumbo or subprime mortgages, were typically securitized into non-agency MBS.

As the secondary market for non-conforming subprime and jumbo loans dried up in 2007, shadow bank lenders like Countrywide and New Century found themselves unable to secure additional financing. As a result, many shadow bank lenders either went bankrupt or had to be sold to traditional banks (e.g., purchase of Countrywide Financial by Bank of America).[17] Consequently, during the financial crisis, shadow bank mortgage origination fell significantly, and in 2008 accounted for roughly 10% of total originations. This paper studies shadow banks' subsequent rise in the years following their fall.

C. Regulatory Changes

In the years following the financial crisis, there have been a number of regulatory changes that directly impact shadow banks' mortgage origination activity. Weakened bank balance sheets in the wake of the financial crisis, combined with new capital rules being implemented under Basel III disproportionately impact banks. In particular, new Basel III capital rules place limits on banks counting MSRs towards regulatory capital requirements.[18] This rule change was proposed, finalized, and implemented between 2010 and 2015.[19] Additionally, Basel III capital requirements and changes to risk weighting---not only in mortgage origination directly, but in other lines of business such as commercial real estate---place new constraints on bank capital that shadow banks do not face. More broadly, the passage of Dodd Frank Act in 2010 and formation of the Consumer Finance Protection Bureau in 2011 may have contributed to the increase in regulatory costs of residential mortgage lending faced by traditional banks.

IV. The Decline of Traditional Banks: Basic Facts

We begin our analysis by documenting the rapid decline of traditional banks in residential mortgage lending in the US during the 2007-2015 period following the start of the Great Recession.

A. Residential Lending Volume

[17] http://www.charlotteobserver.com/news/business/banking/article9151889.html, Accessed April 15, 2017
[18] GS Report, Pg 54.
[19] See https://deepblue.lib.umich.edu/bitstream/handle/2027.42/110908/1213_Shakespeare_March2016.pdf

There are substantial aggregate fluctuations in the amount of residential mortgages originated during that we examine. We begin our analysis by focusing on all residential loans in the broadest dataset, the HMDA data. Figure 1, Panel A, shows the value of new residential mortgages in the US by year of their origination: in 2007 the originations reached over $2 trillion, in 2008 it declined to less than 1.4 trillion, only to peak at almost 2.2 trillion in 2011 before declining again. This simple aggregate fact illustrates that the steady decline in traditional banking that we illustrate later is therefore not mechanically tied to loan volumes in this market.

Aggregate fluctuations in lending volume were not uniform across different sectors of the residential mortgage market, possibly because of differential government intervention.[20] Figure 1, Panel B shows the lending volume in the most popular residential loans in the US[21], conforming mortgages. These loans conform to the Fannie Mae or Freddie Mac (Government Sponsored Enterprises, GSE). In our sample almost half of loans were loans sold to GSEs within the year (Table 1, Panel B).[22] Because of its size, the conforming residential market volumes largely mirror those of the market as a whole. The marked difference arises at the beginning of the crisis; the conforming market suffered only a small decline in loan issuance in 2008.

Figure 1, Panel C presents loan volumes insured by the Federal Housing Authority (FHA loans). The FHA loans allow lower income and less creditworthy households to borrow money at often below private market rates for the purchase of a home that they would not otherwise be able to afford. Usually borrowers with FHA loans finance only about 3.5% of the property value through a down payment with the rest being financed with an FHA loan. These loans account for approximately 10% of our sample (Table 1, Column 1), and are the second most popular loan segment in the United States. The trend in FHA loan volumes differs substantially from the conforming mortgages. This segment grew increase in the issuance of FHA loans from $70 billion in 2007, and peaked in 2009 at over $340 billion. This dramatic growth reflects among other things the disappearance of the private subprime lending market to which FHA loans are the closest substitute.

B. The Rise of Shadow Banks, and the Role of Fintech

Despite these large fluctuations in the aggregate amount of residential mortgage originations, the *share* of shadow banks has been steadily increasing over time. Figure 2 shows that the share of

[20] For example, Home Affordable Refinancing Program (HARP), a large-scale federal program aimed at stimulating refinancing of conforming loans with high loan to value ratios.

[21] Prior to the Great Recession private non-conforming (non-agency) loans had an important market share, but virtually disappeared after 2007. The exception is the jumbo loan segment catering to high creditworthy borrowers buying expensive homes (see Keys et al. 2013).

[22] The HMDA data only allows a loan to be classified as conforming if it was sold to the GSEs in the same year as the year of loan origination. As a result the estimate of conforming loans based on HMDA understates the overall market share of conforming loans in the United States.

mortgages originated by shadow banks across different markets. Panel A shows that in the overall market reported in the HMDA data, the share of shadow banks has increased substantially, growing from roughly 30% in 2007 to 50% in 2015. While there were some signs of a shift to shadow banks early in the sample, the majority of the growth in the total market takes place after 2011.

This growth in shadow banks was not confined to a specific segment of the residential market. We observe a large growth of shadow banks among conforming loans: shadow bank share in this sector more than doubled, reaching roughly 50 percent in 2015, with the largest growth occurring after 2011. Figure 2, Panel C, shows that the growth of shadow banks in the FHA loan market has been dramatic: the shadow bank origination share grew from about 45% in 2007 to about 75% in 2015. Note that the share of shadow banks grew both in the period of rising volumes from 2007 to 2009, as well as declining volumes from 2010 to 2014. These aggregate data suggest a structural shift has taken place in who lends in this market.

The rise in shadow banks has coincided with a shift away from "brick and mortar" originators to online intermediaries. Here, we document the extent of this shift in the residential mortgage market. In 2007 fintech lenders originated less than 5% of residential loans. By 2015 fintech shadow bank lenders accounted for more than 12% of loan issuance. Figure 3 shows that fintech shadow bank lenders account for a substantial part of the expansion of shadow bank lending. Moreover, the fintech share of shadow bank lending has slowly increased over time, especially in 2009-2013 period.

More interesting is the shift in the composition of fintech lending. Fintech share of shadow bank lending in the conforming loans directly sold to GSEs was practically nonexistent in 2007. By 2015 fintech firms comprise almost 30% of shadow bank conforming originations directly sold to GSEs (Figure 3, Panel B). Similarly, among shadow banks in the FHA loan market, the share of fintech grows from a roughly 5% in 2007 to 20% in 2015 (Figure 3, Panel C).

C. Financing of Shadow Banks

We conclude this section by presenting a few basic facts on the financing side of shadow bank residential mortgage lending. Panel B of Table 1 shows that traditional banks tend to hold almost a quarter of their originated loans on balance sheet, shadow bank lenders do so rarely, at approximately 7.5%.[23] This fact suggests that the lack of a depository base, and the associated

[23] The actual number retained on balance sheets is likely even smaller. In particular, HMDA loans that are not sold within the *calendar year* of origination are recorded as not sold. It is likely that these loans recorded as not sold are in fact sold in the next calendar year. To confirm this, we verify that among the Fannie Mae and Freddie Mac dataset (which records both date of origination and date of sale), roughly 9% of shadow bank loans are sold in a year that is

government guarantees on deposits, may be responsible for the use of the originate-to-distribute model. Shadow banks sell their originated loans to government or government sponsored enterprises: Fannie Mae, Ginnie Mae, Freddie Mac, or Farmer Mac. Fannie Mae and Freddie Mac are the purchasers of conforming loans, while Ginnie Mae is the primary purchaser of FHA loans. Moreover, whereas banks hardly ever sell their loans to other banks, this is a reasonably common practice for shadow banks, which do so with more than 15% of the loans they originate.

Figure 4 confirms this inference by showing the time trends of loan disposition among traditional banks, shadow banks, and fintech lenders, respectively. Panel A shows that bank loans are overwhelmingly either held on balance sheet by the originator or affiliate of the originator, or sold to GSEs. Banks have been shifting towards holding fewer loans on balance sheet, moving from holding roughly 60% of originations in 2007 to 30% in 2012, though in recent years this number has increased again to 40%. Contrast this with Panel B, which shows that shadow banks almost never retain originations on balance sheet, and are increasingly reliant on GSEs. The composition of shadow bank funding has shifted dramatically: In 2007, the majority of shadow bank funding came was bank, insurance company, and other capital, with only roughly 30% of funding coming from GSEs. By 2015, roughly 60% of shadow bank loans were sold to GSEs after origination.

Similarly, within shadow banks, Panel C illustrates a significant shift in the composition of fintech lending. In 2007 and 2008 fintech lenders sold most of their mortgages to insurance companies. From 2008 onward, fintech lenders started shifting their sales towards broadly defined GSEs (including FHA insured loans). By 2015, more than 80% of loans originated by fintech lenders were loans with some form of government guarantee. Overall, these results suggest that shadow banks, and fintech shadow banks in particular, are much more reliant on government guarantees in the form of GSEs and FHA insurance relative to traditional banks that can also rely on government guaranteed deposits for funding.

While shadow banks ultimately sell vast majority of their originated loans, there is a time period between origination and sale. Among the Fannie Mae and Freddie Mac origination data, we observe both origination date and sale date, and we investigate how this differs among traditional banks, shadow banks, and within shadow banks, fintech and non-fintech shadow banks. In particular, we define Time_to_Sale as follows:

$$Time\_to\_Sal_{\ i} = Quarters\_Between(Sale, Origination)$$

different from their origination year. To the extent that this pattern is repeated across loan types, this fully explains the 7.5% of not-sold shadow bank originations.

The mean Time_to_Sale is roughly 40 days. To investigate how this varies across lender types, we run the following regression:

$$Time\_to\_Sal_{\ i} = \beta\, Type_i + X_i'\Gamma + \delta_{zt} + \epsilon_{izt}$$

Where $Type_i$ is bank, shadow bank, fintech, or non-fintech, X_i is a vector of loan controls, and δ_{zt} are zip-time fixed effects. The results are shown in Table 4. The results show that the time to sale for shadow banks is shorter by roughly 0.10 quarters as compared to traditional banks, or roughly 9 days. Breaking differences out by fintech and non-fintech lenders, non-fintech shadow banks' time-to-sale is roughly 0.08 quarters, or roughly 7 days faster than traditional banks, and fintech shadow banks' time-to-sale is roughly 0.15 quarters, or roughly 14 days, faster than traditional banks. These results are consistent with traditional banks having greater ability to hold loans on their balance sheet, even when those loans are ultimately sold.

V. Comparative Advantage of Shadow Banks and Fintech

In this section we document the rise of shadow banks and fintech in more detail. We first examine the characteristics of loans and borrowers, who obtain mortgages from shadow banks and fintech firms, both within and across geographic markets. In the second part of this section we investigate the differences in the pricing and performance of loans originated by different institutions. These facts provide suggestive evidence on the role of regulation and technology in the decline of traditional banks. In the following sections we investigate this idea more directly by measuring potential sources of the increased regulatory burden and technological benefits.

A. Who Borrows from Shadow Banks and Fintech?

Our first cuts of the data are based on the idea that we should observe the largest decline of traditional banks in areas in which their relative disadvantage to shadow banks is highest. Since regulation is the main differentiating factor between shadow bank and traditional banks, such results suggest that these are the sectors in which the additional regulatory burden of banks is highest.

The rise in shadow banks has coincided with a shift away from "brick and mortar" originators to online intermediaries. The quintessential example is Quicken Loans, which grew to be the second largest retail mortgage lender in the U.S, and the largest lender in (VA) and FHA loans.[24] From a regulatory perspective, fintech banks are just another example of shadow banks. The difference between fintech lenders and other shadow banks is in their use of financial technology and on-line access in their lending process. To shed light on the role that technology may have played in the rise of shadow banks, we focus on technology differences *between* shadow banks,

[24] http://www.quickenloans.com/press-room/fast-facts/#lWzJ9PCOX7ArMDFl.99 [Accessed on 3/15/2017]

holding regulatory differences between different lenders fixed. To do so, we examine in which markets fintech firms have grown faster than non-fintech shadow banks.

A.1 Descriptive Statistics

We begin our descriptive analysis by examining differences between traditional bank borrowers and shadow bank borrowers in the HMDA data. We display these differences during the expansion period, 2007-2015 as well as the final year in our data, 2015, at which point the shadow bank lending had already substantially expanded (Table 2, Panel A).

Compared with traditional banks, shadow bank borrowers have approximately \$4,000 lower annual incomes on average. This difference became more pronounced in the recent period growing to \$9,000 by 2015. Among shadow bank borrowers, those using fintech firms report slightly higher incomes.

We do not observe dramatic differences in race across borrowers. Non-fintech shadow banks have a roughly equal proportion of borrowers reporting as white and a slightly larger proportion of borrowers reporting to be African-American (in 2015). Racial differences are more striking between fintech and other lender types: Fintech borrowers are much more likely to report "other" or "unknown" race. In 2015, approximately one quarter of fintech borrowers did not report their race. Presumably, some borrowers may choose not to report their race when lenders cannot easily observe it, especially in the context of online lending. This result also suggests that any results on the racial composition of the borrower pool have to be interpreted with care.

A.1.1 Borrower and Loan Characteristics within Geographic Markets

We examine which markets shadow banks enter in the next section. In this section we examine which types of borrowers were more likely to borrow from shadow banks and fintech firms within a given geographic market.

We analyze which types of borrowers obtain mortgages from traditional versus shadow banks in a given market, by estimating the following linear probability specification for *all residential loans*:

$$Shadow\_Lender_{ict} = X_i'\Gamma + \delta_{ct} + \epsilon_{ict} \quad (1)$$

We estimate the corresponding specification to understand which customers choose fintech versus non-fintech lenders *conditional on choosing to borrow from a shadow bank*:

$$Fintech\_Lender_{ict} = X_i'\Gamma + \delta_{ct} + \epsilon_{ict} \quad (2)$$

In both regressions, an observation is a residential mortgage i in county c originated in year t. However, in the second specification we limit the sample to loans originated by shadow banks.

$Shadow\_Lender_{ict}$ is an indicator variable that take takes a value 1 if the residential mortgage was originated by a shadow bank and 0 otherwise. The dependent variable $FintechLende_{ict}$ measures whether the originator was a fintech lender. Both specifications have the same controls: we include county x time fixed effect δ_{ct} so that we compare borrowers in the same market, at the same point in time. X_i is a vector of borrower and loan characteristics, such as borrower income and race, the purpose of the loan (omitted category is home purchase) or loan type loan type (omitted category is conventional).

We estimate these specifications using two different datasets. We present results using HMDA data in Table 2. We re-estimate the specifications focusing using from Fannie Mae and Freddie Mac data. HMDA data are broader, so they allow us more insight on the overall residential mortgage market. They also contain information on borrower race and financing of loans: are these loans sold to GSEs or held for portfolio purposes. Fannie Mae and Freddie Mac data are limited to conforming FRMs loans, but contain more detailed credit information than HMDA data we examined above. We present these results in Table 3.

A.1.2 Race and Income

In simple mean difference earlier, we find that shadow banks' borrowers are more likely to be low income, black, and "unreported race" borrowers. Consistent with simple mean differences, borrowers with lower incomes are more likely to be shadow bank borrowers. These results suggest that shadow banks are replacing traditional banks the consumer segment in which traditional banks have experienced larger regulatory pressures through lawsuits and enforcement actions.

Within shadow banks, higher income borrowers are more likely to borrow through fintech lenders, but the magnitudes are small. Conditioning on borrower characteristics such as income, however, shows that black borrowers are less likely to be shadow bank borrowers before controlling for loan type. These results do not necessarily imply that shadow banks' borrowers are more likely lower income whites. As in descriptive statistics "unknown" race, and "NA" sex are much more likely to be shadow bank borrowers. This is especially the case for fintech shadow banks. Because a large share of borrowers do not disclose race, so these differences have to be interpreted with caution.

A.1.3 Home Purchase, Refinancing and Home Improvement

The most significant differences between lenders arise in the purpose of mortgage originations. Shadow banks are slightly less active in the market for refinancing mortgages: a refinance is roughly 2 percentage points less likely to be a shadow bank loan than a home purchase. (Table 2). When restricting to conforming mortgage data in Table 3, we find that the difference is small and in the opposite direction. A similar pattern is repeated when considering cash-out refinances.[25]

Striking differences emerge within shadow bank loans, suggesting that technology plays a large role in the types of mortgages that lenders specialize in. Among all shadow bank loans, refinance is roughly 20% more likely to be a fintech loan (Table 2). This is the case for conforming mortgages as well: fintech lenders are especially likely to tilt their portfolio towards refinancing, being 9-13% more likely to originate a cash-out and non-cash-out refinance mortgage (Table 3). Interestingly, shadow bank as a whole, and fintech lenders more specifically, focus on lending towards primary residences rather than secondary or investment properties. Finally, first-time buyers are significantly less likely to be shadow bank or fintech customers.

One reason for these data patters is that refinancing an existing mortgage is more mechanical than originating a mortgage for a new purchase. In refinancing, the fintech lender benefits from many on-the-ground activities, such as a title check, structural examination, negotiations between buyer and seller, having already taken place at the time of purchase. It is these somewhat non-standardized activities that may be less-well suited to technological comparative advantages of a fintech lender.

A.1.4 Financing: Portfolio Loans, GSEs, or Government Programs

Shadow banks are also substantially more likely to originate loans across segments, in which government intervention is meant to increase mortgage access. Aggregate data, presented in Figure 2 indicate that the FHA market, which serves less creditworthy borrowers, experienced large growth of shadow banks. Even conditional on borrower characteristics such as income and race, shadow banks are substantially more active in the FHA market: a FHA loan is 9 percentage points more likely to be originated by a shadow bank. Shadow banks loans are also more likely among US Veterans (VA) loans, and US Department of Agriculture and Rural Housing Service (RHA) loans.

There are several reasons why shadow bank participation may be more likely in such programs. One reason may be measurement: HMDA data does not include detailed borrower attributes such

[25] While "unspecified refinance" has a large coefficient, it represents only about 0.04% of Fannie Mae loans and does not exist in Freddie Mac data.

as their consumer credit scores or debt-to-income ratios. So FHA, VA, and RHA loans are simply a proxy for creditworthiness of borrowers. Fannie Mae and Freddie Mac data contain more detailed credit information than HMDA and can shed light on this potential explanation. While there are differences in the creditworthiness of shadow bank borrowers relative to traditional banks in the conforming sector, these are very small (Table 3). Borrowers with lower FICO scores, and greater debt-to-income ratios tend to be shadow bank loans, though interestingly, loans with lower loan-to-value ratios also tend to be shadow bank loans. These differences are quantitatively very small: a borrower with a 100 point lower FICO score is 0.6 percentage points less likely a shadow bank borrower. Similarly, larger mortgages tend to be shadow bank originations, but the effect is quantitatively small.

The second reason why shadow bank participation may be more likely in government related programs is that these types of loans are tied to the originate-to-distribute model, which is more prevalent among shadow banks. The results in Table 2 show that even conditioning on borrower and loan characteristics, loans which are sold are more likely to have been originated by shadow banks. This is the case for mortgages sold to GSEs, as well as to other banks and financial institutions, or mortgages, which were privately securitized. While shadow banks tend to originate to distribute, it is unclear why the comparative advantage of this model should have been growing. A possible reason for this change is regulatory. Shadow banks that cannot rely on government guaranteed deposits for funding appear to be very reliant on government guarantees in the form of GSEs and FHA insurance. As capital constraints on mortgages tightened, for example, with the advent of Basel III, it depressed relative subsidies of traditional banks in favor of shadow banks. We examine this channel in more detail in Section VI.

Last, the GSEs mortgage segment, especially FHA, were subject to several enforcement actions and lawsuits that had specifically targeted traditional banks' so, it may not be surprising that banks are retreating from that sector somewhat. We examine this channel in more detail in Section VI.

A.2 Differences across Geographic Markets

In the previous subsections, a substantial part of the analysis is focused within a specific geographic market (by controlling for county FE). In this section, we analyze differences in the shadow bank and fintech penetration across geographic markets. This allows us to explore differences in household attributes such as education and unemployment rates, which are not available at the borrower level. Figure 5 shows significant heterogeneity in the county-level shadow bank penetration, ranging from less than 10% to more than 80%, suggesting that the decline of traditional banks across markets is not uniform.

Simple descriptive statistics in Panel A of Table 5 suggests that consumer characteristic that tilt towards shadow banks and fintech in a given market also predict across market variation in shadow bank and fintech penetration. Counties with a large shadow bank presence have more minorities and worse socioeconomic conditions: there are more African American and Hispanic residents, and a greater percentage of residents earning below \$35 thousand per year. Interestingly, shadow banks are also more predominant in areas with significantly lower lending concentration as measured by a Herfindahl Index, and with more unique lenders on average. Perhaps most surprising, fintech firms are most present in counties with less educated populations. This is surprising since access to fintech lending requires a certain degree of technological sophistication on the part of borrowers.

We next investigate how different geographical characteristics are associated with the market share of shadow banks and fintech lenders in a county more formally, by estimating the following regressions:

$$\%Shadow\_Bank\_Loans_c = X_c'\Gamma + \epsilon_c \tag{3}$$

$$\%Fintech\_Loans_c = X_c'\Gamma + \epsilon_c \tag{4}$$

In which an observation is a county in 2015; X_c is a vector of county level characteristics, and

$$\%Shadow\_Bank\_Loans_c = \frac{\sum_{i \in nshshadow} Dollars\ Originate\ \ _{ic}}{\sum_{i \in all} Dollars\ Originate\ \ _{ic}}$$

is the county-level regional penetration by shadow banks in 2015. And

$$\%Fintech\_Loans_c = \frac{\sum_{i \in nfintech} Dollars\ Originated_{ic}}{\sum_{i \in shado}\ \ Dollars\ Originate\ \ _{ic}}$$

is the county-level regional penetration by fintech firms as a share of shadow bank loans in 2015. Panel B of Table 5 shows these results. Across specifications, we confirm the insight from the simple descriptive statistics above. Counties with more African American, and in particular, more Hispanic residents have more shadow banks. Recall that we do not find large differences in the share of African American and Hispanic borrowers when looking at individual borrower data, but we found that borrowers who do not declare race more likely borrowed from a shadow banks. The county level results suggest that shadow banks are tilted towards minority borrowers, but that these borrowers may frequently choose not to disclose their race in their mortgage application.

Counties with worse socioeconomic conditions also have greater penetration of shadow banks. They have a larger share of in counties with fewer high-school graduates. Moreover, there is a strong positive association between the unemployment rate and shadow bank penetration: In the baseline specification, a 1% greater unemployment rate is associated with a 0.6% greater penetration of shadow banks. Further, we see that shadow banks tilt their lending to serve both FHA borrowers within a market and counties with a greater share of FHA borrowers. These results again point to the idea that shadow banks are replacing traditional banks in the consumer segment in which traditional banks have experienced larger regulatory pressures.

There are several large and consistent factors associated with a greater penetration of fintech. First, counties with lower unemployment rates see larger market share of fintech lenders, though this effect varies significantly depending on competition controls. Second, we also see greater fintech penetration among counties where a greater fraction of the population that has lived in the same home for over a year. This is consistent with findings we report below, that fintech lenders specialize in refinancing. Third, counties with greater lending concentration and fewer unique lenders see more fintech penetration.

B. Pricing and Costs of Shadow Banks and Fintech

B.1 Loan Pricing: Are Traditional Banks More Expensive?

As we document, the market share of shadow banks in US residential mortgages has grown explosively in the last decade, both in the overall market, and in the conforming mortgage market. At least two questions arise. How did shadow banks increase their market share: is it because they offer cheaper mortgages? If traditional banks are indeed suffering from an increased regulatory burden, is the cost of this burden passed through to consumers by charging more?

Moreover, differences in pricing can be informative on the role that technology has played in this market? One view is that technology allows fintech shadow banks to extend cheaper loans, because lending online results in less labor, and other costs, associated with making loans. If this is the case, one would expect fintech firms to pass some of the savings to their consumers. Such differential pricing might explain the large rise of fintech market share in the conforming and FHA market. Lending online could also lead to product differentiation: because online loans do not require a visit with a physical mortgage officer they may save time and be more convenient also from consumers' perspective.

Ideally, we want to examine the differences in mortgage rates charged to identical borrowers by traditional banks, non-fintech shadow banks and fintech shadow banks. We approximate this through experiment by estimating the following regression in the conforming loan sample, for which interest rate data is available:

$$rate_{izt} = \beta_1 Non\, fintech\, SB_{izt} + \beta_2 Fintech\, SB_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \quad (5)$$

in which an observation is a mortgage i, originated in zipcode z in quarter t. The dependent variable $rate_{izt}$ is the mortgage rate. $Non\, fintech\, SB_{izt}$ is a dummy variable for whether the originator was a non-fintech shadow bank. $Fintech\, SB_{izt}$ is a dummy variable for whether the originator was a fintech shadow bank. We control for borrower characteristics such as FICO, loan-to-value, and ex-post prepayment and default in X_i. Last, to compare pricing of mortgages in the same market, at the same point in time, we include zipcode x quarter fixed effect δ_{zt}. This fixed effect controls for differences in supply and demand conditions across markets, as well as any regulatory differences across markets that may explain the market penetration by shadow banks and fintech lenders. The results are presented in Table 6.

We measure the differences in rates that shadow banks and fintech lenders charge relative to traditional banks. Brick and mortar shadow banks charge rates that are slightly, around 3bp, lower than those of traditional banks. In other words, shadow banks gained a substantial market share by charging slightly lower average prices than traditional banks. This finding suggests that consumers perceive some product differentiation, which allows for differences in average rates. However, there appears to be enough competition among shadow banks and among traditional banks that prices are pushed very close, even if consumers perceive these as differentiated, lenders do not have substantial market power to extract surplus, at least across these groups. We quantify the differences between these two forces more formally using a model in Section VIII.

The results show sizeable differences in interest rates offered on conforming loans comparing fintech and non-fintech firms. Fintech firms charge 10 basis points greater interest rates than traditional banks to observably similar borrowers in the same zip code in the same quarter. This is equivalent to roughly a 2.5% premium over the mean non-fintech interest rate, or, alternatively, would reflect a 60 point difference in FICO score. The difference between fintech and non-fintech shadow banks is even larger at 11-15bp. We further note that this interest premium is unlikely to be explained by differences in origination fees between fintech and non-fintech lenders (see Appendix A4). Overall, this pricing evidence suggests that more creditworthy and arguably wealthier fintech borrowers pay a premium for fintech loans. One possible reason is that this represents a premium for convenience. Alternatively, higher income borrowers who are attracted to fintech are less price elastic.

Finally, for robustness, we also investigate the interest pricing of FHA loans, a market segment with a very substantial presence of shadow banks. Controlling for borrower and loan attributes we also do not find economically large differences in interest rates charged by shadow banks relative to traditional banks: shadow bank loans carry interest rates that appear to be on average about 3.7 basis points higher compared to similar loans issued by traditional bank lenders (see

Appendix A1). These small differences, however, should be interpreted with caution because FHA data provides less comprehensive borrower controls than the conforming loan database. [26]

B.2 Loan Performance

Shadow banks could also "price" loans differently by giving loans at similar interest rates to worse performing borrowers. To better understand loan performance, it is worth discussing a few institutional details regarding the conforming loan market. First, essentially all conforming loans are securitized in our data. Second, a default in a pool of conforming loans is insured by the GSEs, hence investors may not require interest rate premia for bearing default risk beyond insurance fees charged by the GSEs. Since these insurance fees depend on a few key loan and borrower characteristics (e.g., FICO. LTV) our specifications with a full set of controls should already account for variation in interest rates induced by these fees. On the other hand, originators may want to charge higher interest rates for loans with higher default risk to compensate for possibly higher subsequent legal liability risk (e.g., being sued by GSEs for violations of representation of warranties). Finally, since prepayment risk is not insured by the GSEs, investors may want to require a higher interest rates on loans with higher prepayment risk. We examine both dimensions of loan performance.

We estimate the differences in loan bank borrowers are more likely to exhibit worse performance holding their characteristics, and importantly, interest rate fixed, using the following specifications:

$$\begin{aligned} Default_{izt} &= \beta_1 Non\,fintech\,SB_{izt} + \beta_2 Fintech\,SB_{izt} + +\beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \\ Prepayment_{izt} &= \beta_1 Non\,fintech\,SB_{izt} + \beta_2 Fintech\,SB_{izt} + +\beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \end{aligned} \tag{6}$$

$Defau_{izt}$ measures whether a mortgage i, originated in zipcode z, in quarter t, is delinquent within two years of its origination.[27] $Prepaymen_{izt}$ is defined analogously. We control for the mortgage interest rate $rate_{izt}$, borrower and mortgage characteristics, X_i. We compare mortgage performance within a market at the same point in time, using zipcode x quarter fixed effects δ_{zt}.

Shadow banks conforming loans are more likely to default than traditional bank loans (Table 7, Panel A). The magnitudes are small: shadow bank borrowers' default rates at about 0.3% higher rate compared traditional bank borrowers, the effect equivalent to about a 4 point lower in FICO

[26] We repeat a similar exercise among FHA mortgages. We present the results in Appendix A3. Because we do not observe a number of variables that are important in determining interest rates, FICO, loan-to-value, and debt-to-income these results should be interpreted with severe caution. We find fintech rates are consistently lower among FHA loans.

[27] We therefore restrict loans to have two years of performance. This reduces our sample to loans originated between 2010 and 2013.

score. As we observe this effect is mostly driven by non-fintech shadow bank lenders whose borrowers default at about 0.040% higher rate over the two-year period. The base rate of default within two years of origination over this time period is 0.23%, meaning that this difference, while small in absolute terms, means that non-fintech shadow bank borrowers are about 16.5% more likely to default on their loans compared to traditional bank borrowers. At the same time, Column (4) of Table 7A shows that controlling for other observables fintech conforming borrowers have very similar default rates as traditional bank borrowers.

We find larger absolute differences in loan prepayment (Table 7, Panel B). Shadow bank loans are more likely to be prepaid, with coefficients ranging roughly between 2.4% and 3.6% depending on the specification. The base rate of prepayment within two years of origination over the time period is approximately 11%. Therefore a shadow bank loan is between 22-32% more likely to be prepaid than a comparable traditional bank loan in the same market, with the same borrower characteristics, and with the same interest rate. In other words, shadow banks expansion was partially achieved by charging similar interest rates, to borrowers with similar absolute ex-post default rates, but drawing a pool of borrowers which is more likely to prepay mortgages. The differences are larger between fintech, traditional banks, and non-fintech shadow banks. Relative to traditional bank loans, fintech shadow bank loans are between 6.75% and 7% more likely to be prepaid, and relative to non-fintech shadow banks are between roughly 3.75% and 4.5% more likely to be prepaid.

V. Rise of Shadow Banks: Capital Requirements and Regulation

As we document, the shadow bank market share has roughly doubled over the 2007 – 2015 period, and has grown even more explosively among FHA mortgages. What is the change in the comparative advantage of shadow banks relative to traditional banks, which has allowed them to expand to such a large degree in a relatively short period of time? Regulation and tightening capital constraints is one of the main differentiating factors between shadow bank and traditional banks. This rise of shadow banks at the expense of traditional banking is consistent with the idea that traditional banks retreated from markets with a larger regulatory burden, especially those more capital constrained, and that shadow banks stepped into this gap. This phenomenon should occur most in sectors in which the additional regulatory burden of banks is highest. In this section, we investigate this idea more directly by measuring three potential sources of the increased regulatory burden faced by traditional banks: Capital requirements, mortgage-related enforcement actions, and mortgage lawsuits.

A.1 Capital Requirements

Shadow banks predominantly sell their originated loans to government or government sponsored agencies, and unlike traditional banks, almost never hold them for portfolio reasons. This fact suggests that unlike traditional banks that can also rely on government guaranteed deposits for funding, shadow banks are very reliant on government guarantees in the form of GSEs and FHA insurance. One possibility is that increased capital requirements indirectly lowered the relative subsidies available through government guaranteed deposits, partially contributing to the rise in shadow banks.

The Dodd-Frank act imposed minimum risk-based capital requirements on depository institutions. As a result, the average Tier 1 Risk-Based Capital ratio of US banks rose by roughly 5% from 22% in 2008 to 27% in 2015. The asset-weighted rise over this time period was roughly 4%. Therefore, we first investigate whether banks, in securing adequate capital buffers over this time period, withdrew from the mortgage market and the extent to which shadow banks entered as traditional banks withdrew.

We study which counties have had the largest changes in the capitalization of banks. To do so, we first calculate the change in individual bank b's risk-based capital ratio:

$$\Delta CR_b = T1RBC\%_{b2015} - T1RBC\%_{b200}$$

We aggregate these to the county level by weighing banks by their 2006 deposits:

$$\Delta Local\ Capital\ Ratio_c = 100 \times \sum_{b \in c} \Delta CR_b \frac{Originations_{bc2008}}{\sum_{d \in c} Originatio\quad_{dc2008}}$$

We estimate whether areas that saw banks responding to capital constraints by increasing their capital buffers led to a larger growth of shadow bank lending share and lending overall using the cross-sectional specification:

$$\Delta Shadow\ Bank\ Lending\ Share_c = \beta_0 + \beta_1 \Delta Local\ Capital\ Ratio_c + X_c' \Gamma + \epsilon_c, \qquad (7)$$

in which $\Delta Shadow\ Bank\ Lending\ Share_c$ represents the change in the share of shadow bank market shares from 2008 to 2015. We control for other county characteristics in X_c'.[28]

To test whether changes in shadow bank market share are the result of banks exiting or shadow banks entering, we further decompose the effect as

$$\Delta \text{All}\ Lending_c = 100 \times \frac{All\ Originations_{c2015} - All\ Originations_{c2008}}{All\ Originations_{c200}}$$

[28] Ideally we would control for changes in county characteristics during the period. County characteristics are measured by the census infrequently, so we instead control for characteristics in the year closest to 2006.

$$\Delta Bank\ Lendi \quad _c = 100 \times \frac{Bank\ Origination\ \ _{c2015} - Bank\ Originations_{c200}}{All\ Originations_{c20}}$$

$$\Delta Shadow\ Bank\ Lending$$
$$= 100 \times \frac{Shadow\ Originations_{c2015} - Shadow\ Originations_{c20}}{All\ Originations_{c2008}}$$

and run the same specification as Regression (7) with the left-hand side variables as defined above.

The estimates in Table 8 Panel A suggest that counties where traditional banks increased their risk-based capital buffers by 1% a 0.51% increase in shadow bank penetration. Given the average increase in Tier-1 Risk-Based Capital ratio of 5%, this corresponds to a 2.5% increase in shadow bank penetration. Columns (3)-(8) of Table 8 show that this result was driven both by banks exiting these markets and by shadow banks entering, with the exit of traditional banks being greater than the entry of shadow banks. These results are consistent with the prediction that traditional banks decreased lending in order to comply with new capital requirements, leading to both an absolute increase in shadow bank lending and a gain in shadow bank market share.

In addition to heightened capital requirements, new Basel III guidelines implemented by the Federal Reserve Board[29] regarding Mortgage Servicing Rights (MSRs). In particular, regulatory changes regarding the treatment of MSRs in regulatory capital made it costlier from a regulatory perspective for banks to hold these assets on balance sheet. Similar to heightened capital requirements, we test whether counties whose banks had a greater share of MSR assets comprising their Tier 1 capital saw a reduction in traditional bank lending and an increase in shadow bank lending. To test this, we calculate the origination-weighted MSR percent of Tier 1 capital at a county level:

$$\text{MSR\%}_\text{c} = 100 \times \sum_{b \in c} \text{MSR\%}_{\text{b2008}} \frac{Originations_{bc2008}}{\sum_{d \in c} Origination\ \ _{dc2008}}$$

And run specification (7) replacing local capital ratio change with local MSR%. The estimates in Table 8 Panel B suggest that counties where MSR assets were a large part of traditional banks' tier 1 capital saw greater entry by shadow banks. In particular, a county with a 1% greater MSR share of tier 1 capital saw 0.215% greater shadow bank entry. In scaled terms, counties with a 1 standard deviation (2.24%) greater MSR percentage of tier 1 capital saw roughly a 0.5% greater

[29] The Basel Committee released these proposed guidelines in 2009, and agreed upon the standards in 2010. The FRB issued the final rule implementing these guidelines in 2013 with the required compliance date being January 2015. Hendricks et. al. (2016) show that affected banks began changing their lending practices and reducing their MSR exposures early in this process.

increase in shadow bank share. MSR share appears to be highly correlated with the share of big banks lending in the county, however, and once controlling for this the effect nearly disappears.

Decomposing the effect between the entry of shadow banks and the exit of banks, it appears that both occur. Before controlling for big bank presence, counties with higher MSR shares saw negative and significant exit of traditional banks and positive and significant entry of shadow banks. Controlling for big bank presence removes the shadow bank entry effect but still shows the exit of traditional banks.

Finally, to study how MSR composition of Tier-1 capital impacts bank market shares over time, we rerun regression (7) as a repeated cross-section over time, keeping MSR fixed at the 2008 level, and plot the coefficients on MSR. Figure 6 shows the results. These results show that high MSR balance sheet composition initially leads to a higher bank market share, until after 2010, at which point counties with higher MSR compositions see banks losing market share to shadow banks. Return to this timeline in the model section.

A.2 Regulatory Oversight

The descriptive statistics suggest that shadow banks tilt their lending to markets with more minorities and worse socioeconomic conditions. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of minority borrowers, it may not be surprising that traditional banks retreated from that sector somewhat. Because shadow bank activities are more concentrated on new originations, they escape much of the scrutiny that full-service banks' receive from regulators and class action lawsuits with respect to their legacy loans.[30]

We next investigate the association between the intensity of lawsuits aimed at traditional banks on the market share of shadow banks. The idea behind this test is to investigate whether shadow banks expanded more in areas that were dominated by traditional banks that became significantly exposed to the crisis area mortgage liability and lawsuit risk. Such exposure may have limited the traditional banks' ability and willingness to serve riskier borrowers and could also result in substantial losses tightening the capital constraints of these banks

We collect data on large mortgage lawsuit settlements against large lenders, both traditional and shadow bank. 98% of observed lawsuits target traditional banks, as the subject matter of the lawsuits often concerns activities that pure originators do not engage in, such as securitization. Denote a bank b's accumulated lawsuit settlements between 2008 and 2015, in billions as L_b. We

[30] All major shadow banks that were exposed to the crisis area loans went bankrupt at the beginning of the crisis and are not part of our analysis (e.g., Countrywide, IndyMac, New Century).

calculate exposure to mortgage settlements of county c as a weighted average of 2008 lending activity of banks in that county as follows:[31]

$$\Delta Lawsuit\ Exposure_c = 100 \times \sum_{b \in c} L_b \frac{Originatio\quad_{bc2008}}{\sum_{d \in c} Originations_{dc2008}}$$

We estimate whether a higher exposure to lawsuits in a county lead to a larger withdrawal of traditional banks by using the cross-sectional specification:

$$\Delta Shadow\ Bank\ Lending\ Share_c = \beta_0 + \beta_1 \Delta Local\ Lawsuit\ Exposure_c + X_c' \Gamma + \epsilon_c \qquad (8)$$

in which $\Delta Shadow\ Bank\ Lending\ Share_c$ represents the change in the share of shadow bank market shares from 2008 to 2015. As in the case with capital ratio changes and MSR assets, we also test for entry and exit of traditional and shadow banks versus 2008 lending levels. We control for other county characteristics in X_c'. Table 8 Panel C the results.

We find that counties with greater exposure to lawsuit settlements saw an increase in the shadow banks' market share, suggesting that traditional banks retreated from counties that faced a larger regulatory burden. The magnitudes are substantial: consider a county where banks have mean additional lawsuit exposure of \$18.61 billion (at the national level) relative to a county with no lawsuit exposure. The former saw an additional 6.5 percentage points (0.351×18.61) increase in shadow banks' market share before controlling for big bank market share, and a 2.3% increase after controlling for big bank market share. Decomposing the change into traditional bank exit and shadow bank entry shows that both occurred, although after controlling for big bank share the effect of shadow bank entry nearly vanishes.

The findings of this section suggest that a tightening of capital constraints and increased regulatory scrutiny faced by the traditional banks may have meaningfully facilitated expansion of shadow bank lending in the residential mortgage market during the recent period. More broadly, the findings are consistent with the idea that traditional banks retreated from markets with a larger regulatory burden, and that shadow banks filled this gap.

VI. The Rise of Fintech Lenders: The Role of Technology:

The descriptive results point to significant differences between fintech and non-fintech lenders This section attempts to shed light on economic forces behind these differences. Because our comparison is across shadow bank lenders, the differences are unlikely driven by regulation. We therefore consider two explanations for the role of technology in the rise of fintech lenders. One explanation is that fintech lenders make use of more data and different models to price their

[31] We weigh lawsuits by lending activity, not deposits, because shadow bank lenders do not have deposits.

loans. A second explanation is that fintech, by requiring less effort from the borrower in the origination process, deliver a more convenient mortgage origination experience.

A.1 Different Credit Models

We want to understand two features of the differences in models used by fintech and non-fintech lenders. First, we want to see if the loan pricing better reflects observable and unobservable loan characteristics. If the model prices risk better, then the interest rate should reflect the probability of default or prepayment better, Following Rajan, Seru, and Vig (2015) we model the probability that a loan defaults as follows:

$$P(default_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \tag{9}$$

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \tag{10}$$

where r_i is the interest rate on the loan. Panel A of Table 11 presents the results for default. While the coefficients on interest rate are all positive, fintech interest rates appear slightly less related to default. The coefficient for non-fintech shadow banks without other controls is 0.479 versus 0.446 for fintech. Including controls, the coefficients become 0.190 and 0.085, respectively. As we discuss above, however, the base rate of default is very low, and fintech loans are significantly less likely to default than non-fintech loans, suggesting that fintech lenders are able to screen bad risks on the extensive margin.

As we discuss above, these loans have substantially higher differences in prepayment risk. Prepayment is bad for the investor but those borrowers who are able to repay are less likely to default. Consequently, the direction of the relationship between interest rates and prepayment is not obvious ex-ante. Panel B of Table 11 shows the results. The results are consistent both with and without controls: Both fintech and non-fintech lenders' rates are positively associated with repayment, but the association between fintech interest rates and prepayment is much stronger.

To formally test whether fintech shadow banks models in fact incorporate prepayment risk better than non-fintech shadow banks by estimating the following specification:

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + \beta_2 r_i \times Fintech_b + X_i'\Gamma + \delta_t) \tag{11}$$

The results are presented in Table 12. The results in column (4) show that there are important differences in how the interest rates fintech lenders charge on loans relates to the subsequent prepayment of borrowers relative other shadow banks. This evidence is consistent with fintech lenders using better pricing models that are more reflective of prepayment risk. Two important caveats need to be considered, however. First, for fintech lenders to care about better pricing, investors who buy these loans need to be aware that such lenders are able to better price prepayment risk and be willing pay a premium for these loans. Second, a stronger association between interest rates and subsequent prepayment on fintech loans may also reflect selection of borrowers who select into fintech lenders.

To shed more light on whether fintech lenders differentially use information in the interest rate setting process, we examine how much variation in interest rates is explained by borrower characteristics (hard information) across types of lenders. Following Rajan, Seru, and Vig (2015), we regress:

$$rate_{izt} = \beta_1 FICO_i + \beta_2 LTV_i + X_i' \Gamma + \delta_{zt} + \epsilon_{izt} \quad (12)$$

We run the regressions both over a pooled 2010-2013 period and by year. We are interested in the R^2 coming from these regressions. Because a large portion of variation in interest rates arises from nationwide macroeconomic effects and do not want to consider these time effects as arising from lenders' models, we difference out all fixed effects and calculate R^2 not including these fixed effects as part of the total variation in interest rates that can potentially be explained by lenders' models. In other words, the reported R^2s reflect only explained variation in interest rates once removing time or time-zip average differences.

We present the results in Table 13. Fintech shadow banks use substantially less hard information than non-fintech shadow banks: The R^2s are smaller across all specifications. In particular, we find that while FICO and LTV alone can explain more than 30% of the variation in non-fintech interest rates, these observables capture less than 14% of the variation in fintech interest rates. This pattern continues when including more controls, with more than 60% of variation in non-fintech interest rates explainable by these controls, which explain less than 45% of the variation in fintech interest rates. These patterns are robust to including non-linear controls and firm fixed effects.

These results suggest that fintech lenders do use substantially different methodologies in setting mortgage interest rates than non-fintech lenders, either by combining existing data, or by using other dimensions of data, not available to other lenders.[32]

A.2 Convenience and Cost Savings

Next, we consider the possibility that fintech's origination model also allows for lower cost and more convenient originations. Fintech has potentially lower cost originations because much of the process is automated. Such originations are also convenient for the borrower, because most

[32] We find similar evidence when we compare the determinants of interest rates of fintech lenders to traditional banks: the observable characteristics account for less variation in interest rates of fintech lenders relative to traditional banks.

of the process can be done quickly at the borrower's home computer, with only minimal outside activity necessary. Moreover, if borrowers' preferences for convenience are correlated with borrower characteristics, for example, because higher income borrowers value convenience more, then fintech lenders may be able to price discriminate.

In earlier results (Section VII.A.3), we found that fintech interest rates were roughly 11 basis points higher than non-fintech interest rates. At same time we found some evidence that among the lowest segment, FHA borrowers, fintech interest rates were roughly seven basis points lower than non-fintech interest rates for otherwise similar borrowers. These differences are consistent with low-quality, lower income FHA borrowers being price sensitive and with a low value of convenience, and high-quality conventional borrowers being less price sensitive and willing to pay for convenience. Bolstering this interpretation is the fact that in terms of default, among conforming borrowers with the same interest rate, fintech borrowers are less likely to default. This suggests that conforming borrowers of equal quality pay a premium for fintech loans. We note, however, that at least part of this premium may also reflect relatively higher prepayment risk of these borrowers.[33]

To examine this mechanism in more detail, we focus on conforming mortgages. We divide borrowers into those with FICO below 800, and a top segment, (High FICO) conventional borrowers with FICO above 800. We estimate the following regression:

$$rate_{izt} = \beta_s Fintech_{bzt} + \beta_{h\times s} Fintech_{bzt} \times HighFico_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \qquad (13)$$

We are interested in the coefficient on fintech, which captures the difference in interest rates for comparable ordinary borrowers, and the coefficient on the interaction term, which captures the additional difference in interest rates between fintech and non-fintech when the borrower's credit score is above 800.

The results presented in Table 14 show that fintech borrowers with the highest credit ratings pay an even greater premium for fintech loans, relative to other borrowers with the same characteristics. The highest Fico score fintech borrowers pay approximately 1.2 basis points more than borrowers in the ordinary Fico range do for fintech loans. This difference is roughly equivalent to the interest rate difference associated with a 7.5 point FICO differential. Relative to the baseline difference of 13.5 basis points, this estimate corresponds to a 9% increase in the premium of fintech over non-fintech rates. Including zip times quarter fixed effects reduces the effect to roughly 0.5 basis points, which is still significant and corresponds to a 4% increase in

[33] It seems unlikely that the prepayment risk is the sole driver of the premium since these borrowers could have obtained lower rates from non-fintech lenders.

premium. The results suggest that indeed, those borrowers most likely to value convenience are willing to pay for the convenience offered by fintech lenders.

To summarize, we find some evidence that fintech lenders use different technology in determining corresponding interest rates. In addition, fintech originations may provide a larger convenience, which their borrowers value. Among the most price sensitive borrowers, fintech loans have lower interest rates, among the borrowers most likely to value convenience, fintech lenders are able to command a premium for their services. Alternatively, it is also possible that different technology of setting interest rate may allow fintech lenders to better price discriminate borrowers.

VIII. Decomposing Effects of Regulation and Technology: A Simple Quantitative Framework

The shadow bank market share in conforming loan market grew by more than 33 percentage points in 2007 to 2015 period.[34] Of this increase, about 11.7 percentage points are attributable to the growth in fintech firms. The evidence presented above suggests that the rise of shadow banks and fintech firms at the expense of traditional banks was driven by the larger regulatory burden of traditional banks, as well as differences in the perceived convenience, quality, and other services offered by different types of lenders. In this section, we present a simple quantitative model, which we use to decompose the relative contribution of regulation and technology to the rise of shadow banks and fintech.

A. Model Framework

Three types of lenders compete for mortgage borrowers: banks, non-fintech shadow banks ("non-fintech") and fintech shadow banks ("fintech"). To capture the stylized facts from above, these lenders differ on three dimensions: regulatory burden, convenience, which we model as a difference in quality, and potential differences in costs of making loans. Pricing, firm entry and markups are determined endogenously for each type of lender.

A mass of borrowers, indexed by b faces the mortgage market, which comprises N_b bank lenders, N_n non-fintech lenders, and N_f fintech lenders. While the number of lenders is determined endogenously, the individual borrowers take pricing decisions and market structure as given. Lenders, indexed by i, offer mortgages at interest rate r_i.

A.1 Demand:

Borrower b's utility from choosing mortgage i is:

[34] We focus on the conforming loan market as we have reliable interest rate data for this segment.

$$u_{ib} = -\alpha r_i + q_i + \epsilon_{ib} \tag{14}$$

Borrowers' utility declines in the mortgage rate; $\alpha > 0$ measures the borrowers' mortgage rate sensitivity. Borrower also derive utility from non-price attributes of lenders: $q_i + \epsilon_{ib}$. Non-price attributes represent convenience, quality, and other services offered by the lender. In the case of a bank, this may include checking accounts or other financial services. In the case of a fintech lender, we interpret these attributes as capturing convenience. q_i represents average quality differences among lenders: all else equal, some lenders offer better services, or more convenience than others. Borrowers' preferences across lenders can also differ. Some borrowers prefer Quicken, and others Bank of America. These differences are captured in the utility shock ϵ_{ib}. To aggregate preferences across borrowers, we employ a standard assumption in discrete choice demand models (Berry, Levinsohn and Pakes 1995) that ϵ_{ib} is distributed i.i.d. Type 1 Extreme Value.

A2. Supply:

Lenders differ in quality of service q_i and in the marginal costs of providing a mortgage, ρ_i, which can reflect their shadow cost of financing. Operating within a market entails a fixed cost c_i, such as the cost of basic regulatory registrations, offices, support staff, and offices.

Lenders are identical within type, so that the lender side of the economy is parameterized by each type's quality $q_i \in \{q_b, q_n, q_f\}$, funding cost $\rho_i \in \{\rho_b, \rho_n, \rho_f\}$, entry costs $c_i \in \{c_b, c_n, c_f\}$

In addition to impacting a bank's marginal cost, regulatory impediments may also reduce traditional banks' activity on the extensive margin. That is, binding capital requirements, risk constrains, enforcement actions, or lawsuits may sometimes prevent a traditional bank from lending to a given borrower altogether. We capture this type of regulatory burden by γ_b, by assuming that if lender i is a bank, it will have greater or lower ability to lend to a specific borrower with probability by a factor γ_b. A higher γ_b captures a relatively unconstrained bank; a lower γ_b captures a relatively constrained bank. These shocks are i.i.d. across borrowers. These constraints do not affect shadow banks, i.e. non-fintech and fintech lenders, $\gamma_n = \gamma_f = 1$. Denote a lender's market share she would have obtained without regulatory impediments as s_i; the actual market share is then $\gamma_i s_i$.

Conditional on being present in a market, a lender sets its interest rate r_i to maximize its expected profit, which is a function of the spread it charges over its financing cost and the probability that its offer is accepted:

$$(r_i - \rho_i)\gamma_i s_i \tag{15}$$

Letting F represent the total face value of loans in the market (size of the market), total lender profit, net of entry cost c_i is:

$$\pi_i = (r_i - \rho_i)\gamma_i s_i F - c_i \tag{16}$$

A lender only operates in a market as long as: $\pi_i \geq 0$

A3. Equilibrium

We focus on equilibria in which all lenders within a type are symmetric. An equilibrium is a market structure comprising the number of lenders of each type N_b, N_n, N_f, the pricing decisions of lenders, r_b, r_n, r_f, and the market shares of lender types S_b, S_n, S_f,such that:

1) Borrowers maximize utility, taking market structure and pricing as given ((14) holds for all borrowers b)
2) Lenders set interest rates, to maximize profits, taking market structure and the pricing decisions of other lenders as given ((15) holds for all lenders i)
3) There is free entry: the number of firms of each type N_b, N_n, N_f is set such that profits of all firms are zero. ((16) equals zero for all lenders i)

Given the distribution of idiosyncratic taste shocks, consumers' optimal choices result in standard logistic market shares:

$$s_i\left(r_i, q_i; \{r_j, q_j\}\right) = \frac{\exp(-\alpha r_i + q_i)}{\sum_{j=1}^{N} \exp(-\alpha r_j + q_j)} \tag{17}$$

Recall that the actual market shares of firms depend on their regulatory impairment. Given lender attributes and the number of each type of lender operating in a market, N_b, N_n, N_f, aggregate market shares for each type are as follows:

$$S_b = \frac{\gamma_b N_b \exp(-\alpha r_b + q_b)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{18}$$

$$S_n = \frac{N_n \exp(-\alpha r_n + q_n)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{19}$$

$$S_f = \frac{N_f \exp(-\alpha r_f + q_f)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{20}$$

The solution to the lender's maximization problem gives the standard expression for markup over funding cost as a function of market share:

$$r_i^* - \rho_i = \frac{1}{\alpha}\frac{1}{1 - s_i}$$

Last, the free entry condition can be written as:

$$(r_i^* - \rho_i)\gamma_i s_i\left(r_i^*, q_i; \{r_j, q_j\}\right)F - c_i = 0$$

B. Calibration

To quantitatively decompose the contribution of different factors to the growth of shadow banks and fintech firms, we first calibrate the model to the conforming loan market data. We calibrate the model every year from 2008 onwards to provide a simple assessment of how the funding costs, quality, and regulatory different types of lenders banks have changed over the period.

We aggregate data to the zip-year level, and calibrate to observed data in the mean zip for each year. In other words, each year we observe the number of firms of each type (N_b, N_n, N_f) the market share of each lender type (S_n, S_f, N_b) the pricing of each lender type (r_b, r_n, r_f) and the market size F. We measure costs relative to the 10-year government yield, y_t. That is, we measure $\widetilde{\rho_i} = \rho_i - y_t$. We calibrate the model to obtain model primitives, each type's quality $q_i \in \{q_b, q_n, q_f\}$, funding cost $\rho_i \in \{\rho_b, \rho_n, \rho_f\}$, entry costs $c_i \in \{c_b, c_n, c_f\}$, and consumer price sensitivity α, which determine the model.

Additionally, we make the following normalizations: First, we measure quality and funding costs relative to banks, $\widetilde{\rho_b} = q_b = 0$. Setting $q_b = 0$ plays a similar role to setting the share of outside good in demand in Berry (1994) and Berry, Levinsohn, and Pakes (1995). We further assume that bank differ from non-fintech lenders in the quality of their service, but that the relative difference in service provision *between* brick and mortar lenders did not change during the period. Further, we measure the change in regulatory impairment relative to 2008, so we set $\gamma_b = 1$ in 2008 and allow it to change thereafter.

We obtain consumer's price sensitivity for every year α_t from the optimal pricing choices of traditional banks. We observe the markup over treasuries charged by traditional banks, $r_{bt} - y_t$, and the market shore of individual traditional banks market share s_{bt}. We calibrate α_t, by inverting the bank's first-order condition for each year:

$$\alpha_t = \frac{1}{r_{bt} - y_t} \frac{1}{1 - s_{it}}$$

Intuitively, smaller margins $r_{bt} - y_t$ imply that consumers are more price-sensitive.

Next, given α_t, we calibrate the marginal costs of lending for fintech and non-fintech shadow banks using the optimal pricing decisions of these lenders. Formally, we invert their first order pricing conditions:

$$\widetilde{\rho_{nt}} = (r_{nt} - y_t) - \frac{1}{\alpha_t} \frac{1}{1 - s_{nt}}$$

$$\widetilde{\rho_{ft}} = (r_{ft} - y_t) - \frac{1}{\alpha_t} \frac{1}{1 - s_{ft}}$$

Intuitively, given demand elasticity, i.e. given markup, a lender charges higher interest rates if it has higher marginal costs, accounting.

We next turn to calibrating the differences in quality of services between these lenders using optimal consumer choice (aggregate market share) equations (18)-(20). Recall that we set $q_b = 0$, so the service quality is relative to banks. We first calibrate the service quality of non-fintech shadow banks, q_n. The regulatory burden is normalized relative to 2008, i.e. $\gamma_{b,08} = 1$, so we can derive an expression for q_n as a function of observed interest rates, market shares, and price sensitivity, α, in 2008, which we calibrated above:

$$q_n = \alpha_{08}(r_{n,08} - r_{b,08}) + \log\left(\frac{s_{n,08}}{s_{b,08}}\right)$$

Intuitively, both higher quality and higher interest rates lead to larger market shares. The price sensitivity α measures the relative weight that consumers place on these characteristics. So holding market shares fixed, the higher interest rates that non-fintech shadow banks charge, the higher their implied quality. Holding fixed interest rates, a larger market share also implies higher quality.

Following similar logic, given quality of non-fintech shadow banks q_n and price sensitivity, α, we can calibrate the quality of fintech services for every year q_{ft} :

$$q_{ft} = \alpha_t(r_{ft} - r_{nt}) + \log\left(\frac{s_{ft}}{s_{nt}}\right) + q_n$$

The intuition for this expression is the following: because there are no regulatory differences between different types of shadow banks, the regulatory burden γ_{bt} does not affect the relative market shares of these lenders. So if fintech shadow banks charge higher rates than non-fintech shadow banks ($r_{ft} - r_{nt}$), holding market shares fixed, this implies they have higher quality. Similarly, if they obtain a larger market share for given rates, consumers must be choosing them because of higher quality.

Given α_t and q_n, we calibrate the regulatory burden for every year, by inverting the relative market shares of banks and non-fintech shadow banks:

$$\log \gamma_{bt} = \alpha_t(r_{bt} - r_{nt}) + \log\left(\frac{s_{bt}}{s_{nt}}\right) + q_n$$

Intuitively, given differences in quality and rates offered by traditional and non-fintech shadow banks, a smaller market share of traditional banks implies that there is a larger regulatory burden, $1 - \gamma_{bt}$, which prevents them from lending more.

Finally, the zero-profit condition implies that the fixed costs lenders face have to equal their profits, i.e. the margin on individual loans ($r_{it} - \widetilde{\rho_{it}} - y_t$) times the quantity of loans $\gamma_{it} s_{it} F_t$:

$$c_{it} = (r_{it} - \widetilde{\rho_{it}} - y_t)\gamma_{it} s_{it} F_t$$

C. Results

The results of the calibration are shown in Figure 7. Our estimates imply that non-fintech shadow banks offer lower quality services than traditional banks. Obtaining a mortgage from her primary bank is more convenient for the borrower; it does not involve search, the borrower can make automatic payments from linked accounts, and the bank offers other convenient banking services such of checking accounts. The simultaneous rise of fintech market share and higher prices of fintech mortgages imply that fintech is gaining market share through increased quality and convenience of providing mortgages online. Our estimates suggest fintech quality increases dramatically, reaching parity with traditional banks by 2012, and surpassing it thereafter.

Our estimates imply that the expansion of fintech would have been even larger if it were not for its rising marginal (funding) costs. Fintech funding costs rise initially to roughly 20 basis points above bank and non-fintech funding costs, and stay at this increased level after 2011 suggesting that the funding for these new entrants became scarcer as they grew. While fintech funding costs exceed that of other shadow banks, shadow bank marginal costs of funding still slightly exceeded those of traditional banks, which have access to a large (and subsidized) deposit base. These results are not surprising given that banks and shadow banks charge similar interest rates.

Rates are a markup over funding costs that depends on market shares. Neither the rate differential nor relative market shares of individual lenders underwent significant changes during this period, implying that relative funding costs could not have changed dramatically.

If traditional banks have slightly lower shadow cost of funding and higher quality than shadow banks, how is it possible that they have been losing market share during this period? One possibility would be fixed costs, for example, associated with a larger fixed cost of regulatory compliance. We do find that bank entry costs are consistently higher than non-fintech shadow bank entry costs, but these costs do not increase much during the period, so they cannot explain the rise of shadow banking.

Our estimates suggest that regulatory burden rose substantially during this period. Looking more closely, between 2008 and 2010, in the aftermath of the crisis, banks' ability to lend appears to increase. It is not until after 2010 and the passage of the Dodd-Frank Act that banks' regulatory position starts deteriorating substantially. These results suggests that rather than operating on the intensive margin of increasing the funding costs of traditional banks, new regulations reduce banks' abilities to lend function primarily through an extensive margin channel. These findings are consistent with evidence in Fuster, Lo and Willen (2017), who find evidence of an increased legal and regulatory burden over 2008-2014. They argue that an important part of this trend may reflect increased loan servicing costs and the changed treatment of servicing rights under revised capital regulations, which is also consistent with our findings regarding mortgage servicing rights.

We compare these model-based results, shown in Figure 7 Panel B, to the empirical results exploring the effect of county-level bank MSR exposure shown in Figure 6. Notice that these different approaches yield parallel stories: Banks' initially benefit from their regulatory position, and it is only after 2010 that their exposure to this regulatory shock begins to take hold.

The last interesting result to note is that, in addition to shadow funding costs, the fixed costs of fintech lending have increased over time, suggesting increasing barriers to entry in this sector. High entry costs in this sector are consistent with a rise in intellectual property and software development costs that the entry of new competitors requires, as well as potential un-modeled economies of scale in this sector.

D. Regulatory Burden and Technology: A Simple Decomposition

We recall that the shadow bank market share in mortgage market grew by more than 20 percentage points in 2008 to 2015 period. Of this increase, about 9 percentage points are attributable to the growth in fintech firms. We use our simple calibrated model to infer how much of this growth is attributable to an incased regulatory burden and how much to technology improvements.

First, we ask how the conforming mortgage sector would have developed if the regulatory burden of traditional banks were frozen at the level of 2008, and the technological progress would not have taken place. We do so by setting both bank regulatory status γ_b and fintech quality q_f to their 2008 levels. We allow other fitted parameters to evolve as calibrated, and report the growth of non-fintech and fintech shadow banks. Our estimates presented in Figure 8 suggest that fintech shadow banks would have gained approximately 1 percentage point market share between 2008 and 2015, with essentially no growth in non-fintech shadow banks. Hence, without changes in regulatory burden and technology, we can account for only about 5% of shadow bank lending growth during this period.

Second, we investigate how much shadow growth can be explained by rising regulatory burden placed on traditional banks without any technology improvements. We do so by setting fintech quality q_f to their 2008 levels, but let regulatory burden parameter to evolve as estimated. We find that in this case total shadow bank growth reaches approximately 14 percentage points, including a 2.5 percentage point growth occurring in the fintech sector (Figure 8). Hence, without technological improvements, we can account for about 70% of growth in shadow bank lending.

Last, we examine the role of technology. We ask how the residential mortgage sector would have developed if the regulatory constraints would not have tightened, but the technology revolution of fintech has taken place. We therefore fix the regulatory burden parameter of traditional banks at the level of 2008. We find that technological improvements lead to fintech gaining roughly 6 percentage points in market share, with non-fintech shadow banks losing roughly 1 percentage point in market share (Figure 8). Therefore, technology alone is responsible for approximately 70% of gains of fintech firms, and 25% of shadow bank growth overall.

The increase in 2.5% increase in fintech arising from increased regulation alone, combined with the 6% increase in fintech arising from increased technology alone leaves 0.5% residual growth in fintech. This suggests that the 0.5% residual arose as a consequence of an interaction between technology improvements occurring at the same time as incumbents, the traditional banks, were suffering from increased regulatory burden.

IX. Conclusion

The residential mortgage market has changed dramatically in the years following the financial crisis and great recession. Our paper documents two important aspects of this transformation: The rise of shadow bank lenders on one hand and the rise of fintech lenders on the other. By comparing the lending patterns and growth of shadow bank lenders, we demonstrate shadow bank lenders expand their market shares among borrower segments and geographical areas in which regulatory burdens and tightening capital constraints have made lending more difficult for traditional, deposit-taking banks.

Shadow bank lenders' market share among all residential mortgage lending has grown from roughly 30% in 2007 to 50% in 2015. We argue that shadow bank lenders possess regulatory advantages that have contributed to this growth. First, shadow bank lenders' growth has been most dramatic among the high-risk, low-creditworthiness FHA borrower segment, as well as among low-income and high-minority areas, making loans that traditional banks may be unable hold on constrained and highly monitored balance sheets. Second, there has been significant geographical heterogeneity in bank capital ratios, regulator enforcement actions, and lawsuits arising from mortgage lending during the financial crisis, and we show that shadow banks are significantly more likely to expand their market shares in those markets where banks have faced the most regulatory and capital constraints.

Fintech lenders, for which the origination process takes place nearly entirely online, have grown from roughly 5% market share in 2007 to 12% market share in 2015, and represent a significant fraction of shadow bank market share growth. By comparing lenders fintech and non-fintech shadow banks, we compare lenders who face similar regulatory regimes, thus isolating the role of technology. First, we find some evidence that fintech lenders appear to use different models (and possibly data) to set interest rates. Second, the ease of online origination appears to allow fintech lenders to charge higher rates, particularly among the lowest-risk, and presumably least price sensitive and most time sensitive borrowers.

Finally, we conclude by pointing out that while fintech lenders have the potential to address ongoing regulatory challenges raised by Philippon (2016), in their current state, fintech lenders are tightly tethered to the ongoing operation of GSEs and the FHA as a source of capital. While fintech lenders may bring better services and pricing to the residential lending market, they appear to be intimately reliant on the political economy surrounding implicit and explicit government guarantees. How changes in political environment impacts the interaction between various lenders remains an area of future research.

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Table 1: Residential Mortgage Lending: Traditional versus Shadow Banks

Panel A reports the types of loans types made by different lenders between 2007 and 2015. Loan types are Conventional, FHA, or Other, which includes VA and FSA/RHS (Farm Service Agency and Rural Housing Service) loans. Conventional loans are all loans that are not FHA or VA/FSA/RHS loans. Column (1) reports the composition of loans made by all lenders; Column (2) reports those made by traditional banks; Column (3) reports those made by shadow banks. Column (4) reports those made by non-fintech Shadow Banks, and Column (5) Reports those made by fintech Shadow Banks. Panel B reports to which type of entity the originating entity sold the loan. Loans not sold within one year are "Not Sold." Columns are the same as in Panel A.

Panel A: Loan types based on 2007-2015 HMDA

	All Lenders	Traditional Banks	Shadow Banks	Shadow Banks	
				Non-Fintech	Fintech
% Conventional	76.9%	83.2%	64.31%	62.3%	72.4%
% FHA	15.8%	11.0%	25.33%	26.5%	20.6%
% Other	7.3%	5.8%	10.36%	11.21%	7.0%
Count	46,431,132	30,865,082	15,487,438	12,342,588	3,144,850

Panel B: Loan disposition based on 2007-2015 HMDA

	All Lenders	Traditional Banks	Shadow Banks	Shadow Banks	
				Non-Fintech	Fintech
Not Sold	23.32%	31.15%	7.50%	6.83%	10.13%
Sold To:					
Fannie Mae	23.37%	23.68%	22.80%	20.23%	32.91%
Freddie Mac	14.63%	17.58%	8.84%	8.24%	11.17%
Ginnie Mae	10.55%	9.12%	13.47%	12.96%	15.48%
Private Securitization	0.68%	0.76%	0.49%	0.56%	0.22%
Commercial Bank	9.50%	5.38%	17.71%	19.38%	11.13%
Ins/CU/Mortgage Bank	5.93%	2.44%	12.89%	12.47%	14.53%
Affiliate Institution	4.75%	6.70%	0.88%	1.00%	0.43%
Other	7.26%	3.19%	15.43%	18.34%	4.00%
Count	46,431,132	30,865,082	15,487,438	12,342,588	3,144,850

Table 2: Shadow Bank, Fintech Presence and the Borrower and Loan Characteristics: All Loans

Panel A summarizes differences in borrower demographics in accepted mortgage applications as reported in the HMDA data. Columns (1)-(4) compare cover the period 2007-2015. Columns (5)-(8) cover the 2015. Columns (1)-(2) and (5)-(6) compare traditional and shadow banks; Columns (3)-(4) and (7)-(8) compare non-fintech and fintech shadow banks. Panel B shows the result of Regressions (1) and (2), a linear probability model regressing whether the lender is a shadow bank (Columns (1)-(4)) or fintech (Columns (5)-(8)) on borrower characteristics over the period 2007-2015. Columns (1)-(2) and (5)-(6) include year fixed effects; Columns (3)-(4) and (7)-(8) include year-county fixed effects. Columns (2), (4), (6), and (8) include dummy variables for loan type. For race dummies, the base category is White; for sex dummies, the base is Male. For loan purpose dummies, the base is Purchase. For purchaser dummies, the base is Not Sold. For type dummies, the base is Conventional. Standard errors (in parentheses) are clustered at the county-year level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary statistics based on (HMDA)

	2007-2015				2015			
	Traditional	Shadow	Shadow Banks		Traditional	Shadow	Shadow Banks	
	Banks	Banks	Non-Fintech	Fintech	Banks	Banks	Non-Fintech	Fintech
Count	30,865,082	15,487,438	12,342,588	3,144,850	2,290,400	2,182,654	1,633,520	549,134
Median Income	$83,000	$79,000	$78,000	$82,000	$89,000	$80,000	$79,000	$81,000
Male	66.99%	67.61%	68.91%	62.51%	65.64%	65.94%	68.96%	56.95%
Race								
Native American	0.52%	0.50%	0.51%	0.49%	0.60%	0.57%	0.56%	0.60%
Asian	5.22%	5.79%	6.13%	4.47%	5.63%	5.50%	5.79%	4.63%
African American	4.72%	5.59%	5.81%	4.72%	4.85%	6.34%	6.76%	5.10%
Native Hawaiian	0.36%	0.42%	0.43%	0.34%	0.36%	0.45%	0.50%	0.33%
White	78.04%	76.47%	77.70%	71.66%	77.08%	74.93%	78.10%	65.51%
Other/Unknown	11.14%	11.23%	9.42%	18.32%	11.49%	12.19%	8.28%	23.84%

Table 2 [continued]

Panel B: Regressions (HMDA)

	(1) Shadow Bank	(2) Shadow Bank	(3) Shadow Bank	(4) Shadow Bank	(5) Fintech	(6) Fintech	(7) Fintech	(8) Fintech
Income (000s)	-0.00931***	-0.00857***	-0.00752***	-0.00673***	0.00180***	0.00116***	-0.00189***	-0.00263***
	(0.0000462)	(0.0000462)	(0.0000453)	(0.0000453)	(0.000110)	(0.000110)	(0.000108)	(0.000109)
Loan Amount (000s)	0.00781***	0.00835***	0.000511***	0.000881***	-0.0156***	-0.0158***	-0.00484***	-0.00472***
	(0.0000392)	(0.0000392)	(0.0000423)	(0.0000423)	(0.0000821)	(0.0000824)	(0.0000921)	(0.0000923)
Race (Omitted Category = White)								
Native American	0.102	-0.227**	-1.050***	-1.362***	0.473***	0.535***	1.333***	1.379***
	(0.0879)	(0.0877)	(0.0863)	(0.0861)	(0.143)	(0.143)	(0.141)	(0.141)
Asian	3.669***	3.923***	0.940***	1.204***	-3.542***	-3.705***	-2.491***	-2.605***
	(0.0276)	(0.0276)	(0.0283)	(0.0283)	(0.0426)	(0.0427)	(0.0434)	(0.0434)
Black	1.152***	0.405***	1.024***	0.296***	0.195***	0.342***	0.0645	0.258***
	(0.0299)	(0.0300)	(0.0304)	(0.0304)	(0.0460)	(0.0462)	(0.0468)	(0.0470)
Hawaiian	1.568***	1.363***	-0.486***	-0.696***	-1.244***	-1.176***	0.461**	0.539***
	(0.103)	(0.103)	(0.101)	(0.101)	(0.158)	(0.158)	(0.155)	(0.155)
Unknown	7.485***	7.438***	5.692***	5.663***	5.101***	5.057***	5.735***	5.708***
	(0.0292)	(0.0292)	(0.0286)	(0.0286)	(0.0420)	(0.0420)	(0.0413)	(0.0413)
NA	-25.13***	-24.98***	-20.60***	-20.46***	8.516***	8.486***	10.04***	10.03***
	(0.817)	(0.816)	(0.796)	(0.794)	(1.509)	(1.509)	(1.473)	(1.473)
Sex (Omitted Category = Male)								
Female	0.444***	0.163***	0.129***	-0.113***	0.870***	0.765***	1.032***	0.975***
	(0.0145)	(0.0146)	(0.0142)	(0.0143)	(0.0230)	(0.0232)	(0.0226)	(0.0227)
Unknown	-4.637***	-4.636***	-4.083***	-4.091***	14.76***	14.76***	14.19***	14.19***
	(0.0376)	(0.0375)	(0.0367)	(0.0366)	(0.0573)	(0.0573)	(0.0562)	(0.0561)
NA	16.07***	16.27***	16.14***	16.38***	-6.864***	-6.903***	-7.058***	-7.093***
	(0.736)	(0.734)	(0.716)	(0.715)	(0.731)	(0.731)	(0.714)	(0.714)
Purpose (Omitted Category = Purchase)								
Home Improvement	-14.28***	-13.26***	-13.23***	-12.18***	-6.111***	-6.429***	-4.317***	-4.685***
	(0.0325)	(0.0327)	(0.0321)	(0.0323)	(0.119)	(0.120)	(0.117)	(0.117)
Refinance	-2.935***	-2.056***	-2.705***	-1.792***	19.41***	19.13***	19.48***	19.14***
	(0.0139)	(0.0143)	(0.0138)	(0.0141)	(0.0212)	(0.0219)	(0.0213)	(0.0219)
Purchaser (Omitted Category = Held)								
Fannie Mae	20.18***	20.65***	18.53***	19.04***	-5.535***	-5.770***	-4.434***	-4.707***
	(0.0188)	(0.0188)	(0.0186)	(0.0187)	(0.0423)	(0.0427)	(0.0424)	(0.0428)
Ginnie Mae	25.40***	19.46***	25.08***	19.03***	-4.868***	-3.980***	-5.032***	-4.009***
	(0.0266)	(0.0333)	(0.0262)	(0.0326)	(0.0487)	(0.0531)	(0.0487)	(0.0528)
Freddie Mac	7.663***	8.171***	6.791***	7.333***	-9.324***	-9.549***	-8.414***	-8.659***
	(0.0212)	(0.0212)	(0.0209)	(0.0210)	(0.0497)	(0.0500)	(0.0496)	(0.0499)
Farmer Mac	62.95***	64.94***	59.04***	59.91***	-24.45***	-21.73***	-20.05***	-16.81***
	(1.096)	(1.094)	(1.069)	(1.067)	(1.130)	(1.131)	(1.108)	(1.109)
Private Securitization	10.30***	9.693***	8.604***	8.028***	-13.98***	-13.76***	-12.56***	-12.27***
	(0.0752)	(0.0751)	(0.0736)	(0.0735)	(0.146)	(0.146)	(0.146)	(0.146)
Bank	50.08***	48.21***	48.66***	46.72***	-14.36***	-14.11***	-14.01***	-13.68***
	(0.0247)	(0.0255)	(0.0244)	(0.0253)	(0.0435)	(0.0437)	(0.0440)	(0.0442)
Insr or Fnce Co.	60.07***	57.96***	58.43***	56.34***	-4.623***	-4.443***	-3.697***	-3.448***
	(0.0292)	(0.0298)	(0.0288)	(0.0294)	(0.0456)	(0.0458)	(0.0459)	(0.0461)
Affiliate	-1.883***	-2.121***	-2.698***	-3.004***	-13.67***	-13.68***	-12.64***	-12.65***
	(0.0327)	(0.0327)	(0.0324)	(0.0325)	(0.110)	(0.110)	(0.111)	(0.111)
Other	59.84***	58.01***	57.70***	55.87***	-20.02***	-19.83***	-19.10***	-18.82***
	(0.0273)	(0.0279)	(0.0271)	(0.0276)	(0.0444)	(0.0446)	(0.0451)	(0.0452)
Loan Type (Omitted Category = Conventional)								
FHA	-	9.418***	-	9.242***	-	-0.544***	-	-0.913***
	-	(0.0249)	-	(0.0245)	-	(0.0311)	-	(0.0309)
VA	-	2.331***	-	3.189***	-	-2.436***	-	-2.401***
	-	(0.0361)	-	(0.0360)	-	(0.0476)	-	(0.0479)
FSA/RHS	-	-3.036***	-	-0.660***	-	-5.460***	-	-6.648***
	-	(0.0566)	-	(0.0563)	-	(0.0783)	-	(0.0790)
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
Year x County FE	No	No	Yes	Yes	No	No	Yes	Yes
N	43138392	43138392	43138392	43138392	14340698	14340698	14340698	14340698
R^2	0.238	0.241	0.278	0.281	0.128	0.128	0.173	0.173

Table 3: Shadow Bank Presence and the Borrower and Loan Characteristics: Conforming Loans

Table 3 shows the results of a linear probability model, specifications (1) and (2), regressing whether the lender is a shadow bank (Columns (1)-(2)) or a fintech lender among shadow banks (Columns (3)-(4)) on individual characteristics, using the pooled Fannie Mae and Freddie Mac Data for the period 2010-2013. Columns (1) and (3) include quarter fixed effects only; Columns (2) and (4) includes zip-quarter fixed effects. Loan purpose dummies (Cash-out refinance, Non-Cash-out Refinance, and Unspecified Refinance) use Purchase as the base category. Property type dummies (Investment and Second Home) use Primary Residence as the base category. The left-hand-side variable has mean 17. Standard errors are clustered by zip-quarter; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Shadow Bank	(2) Shadow Bank	(3) Fintech	(4) Fintech
Loan Amount	0.0000101***	4.14e-06***	-8.26e-06***	-1.19e-06
	(20.02)	(14.33)	(-7.45)	(-1.65)
Loan Term (Months)	0.0220***	-0.0107***	0.0281***	0.00243
	(28.29)	(-17.90)	(19.59)	(1.80)
Loan-to-Value	-0.0831***	-0.0501***	0.0490***	0.0261***
	(-28.20)	(-30.70)	(8.36)	(7.04)
Debt-to-Income	0.0640***	0.0422***	0.103***	0.0825***
	(28.89)	(22.70)	(16.21)	(14.62)
FICO	0.000819	-0.00631***	-0.0664***	-0.0460***
	(1.30)	(-11.10)	(-44.67)	(-35.42)
Purpose (Omitted Category = Purchase)				
Cash-Out Refinance	0.698***	0.916***	13.4***	9.44***
	(7.07)	(11.86)	(67.06)	(51.00)
Non-Cash-Out Refinance	-0.809***	0.0488	14.8***	9.80***
	(-6.15)	(0.53)	(44.73)	(37.68)
Unspecified Refinance	44.0*	41.1*	-1.85	4.68***
	(2.38)	(2.36)	(-1.89)	(4.67)
Property Type (Omitted Category = Primary Residence)				
Investment	1.23***	-0.376***	-1.17***	-1.08***
	(12.15)	(-4.43)	(-4.33)	(-4.33)
Secondary	-2.28***	-3.16***	-0.401	-4.18***
	(-19.81)	(-36.28)	(-1.44)	(-17.38)
First-Time Buyer	-3.97***	-3.83***	-7.85***	-8.51***
	(-53.29)	(-64.02)	(-32.94)	(-42.09)
Has Mtg. Insurance	0.900***	0.527***	0.0273	-0.511**
	(11.66)	(7.67)	(0.13)	(-3.06)
Zip x Quarter FE	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No
N	6523711	6523402	956634	954478
R^2	0.0162	0.0727	0.106	0.244

Table 4: Time Between Origination and Sale

Table 4 shows the results of the time-to-sale regression for quarters between origination and sale, using Fannie Mae and Freddie Mac origination data from 2010 to 2013. Columns (1)-(2) compare shadow banks to traditional banks for the entire sample of lenders. Columns (3)-(4) compare present the results with shadow banks broken out by fintech and non-fintech lenders. Columns (5)-(6) compare fintech shadow banks to non-fintech shadow banks among the shadow bank sample only. Columns (1), (3), and (5) have quarter fixed effects and no other controls. Columns (2), (4), and (6) have borrower and loan controls and zip-quarter fixed effects. The left-hand-side variable is in quarters since origination. Its mean among all lenders is 0.46, or approximately 41 days; its mean among shadow bank lenders is 0.40, or approximately 36 days. Standard errors are clustered at the zip-quarter level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Qtrs to Sale	(2) Qtrs to Sale	(3) Qtrs to Sale	(4) Qtrs to Sale	(5) Qtrs to Sale	(6) Qtrs to Sale
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	-0.103***	-0.0960***	-	-	-	-
	(-38.81)	(-36.04)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0836***	-0.0797***	-	-
	-	-	(-27.59)	(-26.73)	-	-
Fintech Shadow Bank	-	-	-0.157***	-0.149***	-0.0432***	-0.0402***
	-	-	(-37.15)	(-35.31)	(-8.56)	(-7.18)
Borrower and Loan Controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	3199775	3196090	3199775	3196090	596062	594984
R^2	0.0147	0.0298	0.0155	0.0299	0.0433	0.0842

Table 5: Shadow Bank and Fintech Penetration and Regional Characteristics

Panel A summarizes demographic differences between counties with low and high shares of shadow bank lending in 2015. Shadow bank and fintech share is calculated from accepted HMDA acceptances. Demographic information comes from the American Community Survey, while Herfindahl, Numbers of Lenders, and Percentage of FHA loans is calculated from HMDA. Column (1) shows statistics for all counties. Column (2) shows statistics for counties in the bottom 25% of shadow bank share. Column (3) shows statistics for counties in the top 25% of shadow bank share. Column (3) shows statistics for counties in the bottom 25% of fintech share. Column (4) shows statistics for counties in the top 25% of fintech share. Panel B shows the results of regressions (3) and (4) where the share of shadow banks (Columns (1)-(3)) or fintech (Columns (4)-(6)) in a county is regressed on county characteristics. Columns (1) and (4) are the baseline specification. Columns (2) and (5) include the county-level Herfindahl measure. Columns (3) and (6) include the number of unique lenders within a county. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary Statistics

Median Values	All Counties	Shadow Bank Bottom Quartile	Shadow Bank Top Quartile	Fintech Bottom Quartile	Fintech Top Quartile
Median Household Income	$45,114.00	$44,607.00	$45,530.50	$49,800.50	$41,704.50
Population Density	42.7	35.4	37.6	77.1	18.0
% with less than 12th grade education	13.10%	11.80%	15.70%	11.75%	13.80%
% with Bachelor degree or higher	18.20%	17.90%	17.60%	21.60%	16.20%
% African American	2.10%	1.10%	2.55%	2.45%	1.06%
% Hispanic	3.74%	2.61%	7.04%	6.02%	2.65%
Unemployment Rate	7.00%	6.20%	7.40%	6.80%	6.70%
% living in Same House >= 1 year	86.90%	87.46%	86.40%	85.55%	87.73%
Herfindahl	0.09761	0.15188	0.08286	0.07116	0.15845
# Lenders	39.00	29.00	40.00	69.00	17.50
% of FHA Origination loans	16.28%	12.16%	19.84%	17.10%	14.81%
Population	25930.00	20370.50	25676.50	52826.00	11058.00
% with less than 35K salary	26.70%	27.05%	26.50%	23.50%	29.40%

Table 5 [continued]

Panel B: Regressions

	(1) % Shadow Banks	(2) % Shadow Banks	(3) % Shadow Banks	(4) % Fintech	(5) % Fintech	(6) % Fintech
Med HH Income	0.000157***	0.0000797*	0.0000775*	-0.000391***	-0.000280***	-0.000156***
	(0.0000326)	(0.0000315)	(0.0000337)	(0.0000399)	(0.0000376)	(0.0000389)
Pop Den	-0.000675**	-0.000649**	-0.000731***	0.000305	0.000240	0.000461
	(0.000213)	(0.000203)	(0.000211)	(0.000257)	(0.000240)	(0.000241)
% Edu < 12th	0.256***	0.182**	0.264***	-0.0149	0.0527	-0.0490
	(0.0681)	(0.0653)	(0.0674)	(0.0831)	(0.0776)	(0.0777)
% >= Bachelors	0.102*	0.0478	-0.0223	-0.245***	-0.142*	0.132*
	(0.0493)	(0.0472)	(0.0511)	(0.0602)	(0.0564)	(0.0590)
% African American	0.0347	0.0161	0.0179	0.0210	0.0466	0.0665**
	(0.0219)	(0.0210)	(0.0218)	(0.0267)	(0.0249)	(0.0250)
% Hispanic	0.251***	0.268***	0.227***	-0.0663*	-0.0857**	0.00674
	(0.0247)	(0.0236)	(0.0246)	(0.0300)	(0.0280)	(0.0282)
Unemp Rate	0.621***	0.374***	0.376***	-0.954***	-0.534***	-0.189
	(0.0917)	(0.0888)	(0.0955)	(0.115)	(0.109)	(0.113)
Same home >= 1yr	-0.0191	0.0782	0.0350	0.477***	0.394***	0.332***
	(0.0645)	(0.0620)	(0.0642)	(0.0792)	(0.0740)	(0.0743)
% FHA	0.662***	0.605***	0.641***	-0.0909*	-0.0128	-0.0245
	(0.0309)	(0.0297)	(0.0307)	(0.0392)	(0.0368)	(0.0368)
Herfindahl	-	-37.89***	-	-	68.40***	-
	-	(2.208)	-	-	(3.206)	-
# Lenders	-	-	0.0721***	-	-	-0.216***
	-	-	(0.00883)	-	-	(0.0102)
Constant	13.69*	18.81**	14.10*	30.44***	16.28*	27.75***
	(5.996)	(5.741)	(5.934)	(7.350)	(6.894)	(6.870)
N	3131	3131	3131	3096	3096	3096
R^2	0.244	0.310	0.260	0.128	0.240	0.239

Table 6: Shadow Bank and Fintech Mortgage Rates: Conforming Loans

This table shows the results of regression (5) using Fannie Mae and Freddie Mac loans from 2010-2013. Columns (1)-(2) test differences between shadow banks and traditional banks. Columns (3)-(4) split shadow banks into fintech and non-fintech lenders and compare interest rates across all lenders. Columns (5)-(6) test differences in fintech rates within shadow banks. Columns (1), (3), and (5) quarter fixed effects and no other controls. Columns (2), (4), (6) have quarter times zip fixed effects and borrower controls. Standard errors are clustered at the zip-quarter level. Interest rates are quoted in percent. The mean interest rate over the sample period is 4.74. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate	(5) Interest Rate	(6) Interest Rate
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	-0.0178***	-0.00436***	-	-	-	-
	(-9.41)	(-3.35)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0568***	-0.0359***	-	-
	-	-	(-27.20)	(-25.92)	-	-
Fintech Shadow Bank	-	-	0.120***	0.105***	0.154***	0.118***
	-	-	(54.95)	(63.83)	(57.07)	(68.26)
Borrower and Loan Controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6527612	6523402	6527612	6523402	956967	954478
R^2	0.643	0.826	0.645	0.827	0.665	0.842

Table 7: Shadow Bank Presence and Loan Performance: Conforming Loans

Panels A and B show the results of regression (6) for Default and Prepayment, respectively using Fannie Mae and Freddie Mac performance data from 2010 to 2013. Prepayment is defined as the loan being prepaid within two years of origination. Default is defined as the loan status becoming 60-days past due within two years of origination. Columns (1)-(2) test differences between shadow banks and traditional banks. Columns (3)-(4) split shadow banks into fintech and non-fintech lenders and compare performance across all lenders. Columns (5)-(6) test differences in fintech performance within shadow banks. Columns (1), (3), and (5) quarter fixed effects and no other controls. Columns (2), (4), (6) have quarter times zip fixed effects and borrower controls. The left-hand-side variable is in percent. Its mean for defaults over the sample period is 0.23. Its mean for prepayments over the sample period is 11. Standard errors are clustered at the zip-quarter level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Default

	(1) Defaulted	(2) Defaulted	(3) Defaulted	(4) Defaulted	(5) Defaulted	(6) Defaulted
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	0.0260***	0.0341***	-	-	-	-
	(4.74)	(6.19)	-	-	-	-
Non-Fintech Shadow Bank	-	-	0.0174**	0.0395***	-	-
	-	-	(2.89)	(6.49)	-	-
Fintech Shadow Bank	-	-	0.0564***	0.00906	0.0220	-0.0949***
	-	-	(4.71)	(0.77)	(1.62)	(-6.16)
Borrower and Loan Controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6527612	6523402	6527612	6523402	956967	954478
R^2	0.000360	0.0115	0.000362	0.0112	0.000641	0.0415

Panel B: Prepayment

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid	(5) Prepaid	(6) Prepaid
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	3.56***	2.39***	-	-	-	-
	(26.94)	(27.69)	-	-	-	-
Non-Fintech Shadow Bank	-	-	2.56***	1.06***	-	-
	-	-	(16.73)	(11.50)	-	-
Fintech Shadow Bank	-	-	7.11***	6.73***	4.62***	3.64***
	-	-	(35.06)	(34.40)	(21.18)	(16.77)
Borrower and Loan Controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6527612	6527612	6527612	6523402	956967	954478
R^2	0.0570	0.0570	0.0573	0.152	0.0619	0.171

Table 8: Regulatory Activity and Shadow Bank Market Shares

Table 8 shows the result of regression (7) The regression is at the county level. Panel A measures regulatory activity using changes in bank capital ratios. Panel B measures regulatory activity using banks MSR assets as a fraction of Tier 1 Capital. Panel C measures regulatory activity using lawsuit exposure. Column 1 looks at 2008 to 2015 changes in all lending as a fraction of 2008 lending. Columns (2)-(5) look at changes in bank, shadow bank, non-fintech, and fintech lending as a fraction total 2008 lending. All columns include county level controls including the 2008 share of big banks. The left-hand-side variable is in units of percent, with a mean value of 25.77. Standard errors are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Capital Ratios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔSB Share	ΔSB Share	ΔAll	ΔAll	ΔBank	ΔBank	ΔSB	ΔSB
ΔCapital Ratio	0.539***	0.510***	-0.453	-0.547*	-0.766***	-0.789***	0.313*	0.241
	(0.0647)	(0.0641)	(0.255)	(0.254)	(0.175)	(0.175)	(0.137)	(0.136)
Big Bank Share		17.7***	-	57.0***	-	13.9*	-	43.1***
		(2.17)	-	(8.58)	-	(5.93)	-	(4.59)
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3095	3095	3095	3095	3095	3095	3095	3095
R^2	0.082	0.101	0.055	0.069	0.072	0.073	0.053	0.079

Panel B: Mortgage Servicing Rights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔSB Share	ΔSB Share	ΔAll	ΔAll	ΔBank	ΔBank	ΔSB	ΔSB
MSR	0.215***	0.0234	0.112	-0.647*	-0.292	-0.555**	0.404**	-0.0918
	(0.0608)	(0.0653)	(0.237)	(0.255)	(0.163)	(0.177)	(0.128)	(0.136)
Big Bank Share	-	18.0***	-	71.3***	-	24.8***	-	46.6***
	-	(2.38)	-	(9.28)	-	(6.44)	-	(4.97)
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3095	3095	3095	3095	3095	3095	3095	3095
R^2	0.064	0.081	0.057	0.074	0.069	0.073	0.056	0.082

Panel C: Lawsuit Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔSB Share	ΔSB Share	ΔAll	ΔAll	ΔBank	ΔBank	ΔSB	ΔSB
Lawsuits	0.351***	0.124*	-0.200	-0.633**	-0.582***	-0.668***	0.381***	0.035
	(0.049)	(0.056)	(0.207)	(0.236)	(0.142)	(0.162)	(0.110)	(0.124)
Big Bank Share	-	21.2***	-	40.9***	-	8.1	-	32.7***
	-	(2.55)	-	(10.72)	-	(7.36)	-	(5.67)
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3117	3117	3120	3120	3120	3120	3120	3120
R^2	0.067	0.087	0.050	0.054	0.064	0.064	0.049	0.059

Table 11: Relationship Between Interest Rate and Performance

Panels A and B show the coefficients on mortgage interest rate for probit regressions (9) and (10), respectively. Data is Fannie Mae and Freddie Mac performance data for loans originated by Shadow Banks between 2010 and 2013. A mortgage is in default if it is more than 60-days past due within two years of origination; A mortgage is prepaid if it is prepaid within two years of origination. All regressions include year fixed effects. Regressions with controls include all controls in earlier loan-level Fannie Mae and Freddie Mac Regressions; * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*.

Panel A: Default

	No Controls		Controls	
	Rate	Pseudo R2	Rate	Pseudo R2
Bank	0.454***	0.0363	0.188***	0.124
Shadow Bank	0.472***	0.0440	0.164***	0.135
Non-Fintech	0.479***	0.0481	0.190***	0.144
Fintech	0.446***	0.0315	0.0855*	0.116

Panel B: Prepayment

	No Controls		Controls	
	Rate	Pseudo R2	Rate	Pseudo R2
Bank	0.251***	0.0528	0.564***	0.111
Shadow Bank	0.294***	0.0367	0.758***	0.0972
Non-Fintech	0.206***	0.0441	0.680***	0.113
Fintech	0.691***	0.0517	1.038***	0.0945

Table 12: Interest Rates and Performance Differentials

Table 12 shows the results of probit regression (11) for the Fannie Mae and Freddie Mac data for loans originated by Shadow Banks between 2010 and 2013. A loan is prepaid if it is prepaid within two years of origination. Columns (1)-(2) have no controls; Columns (3)-(4) include borrower and loan controls. All specifications have year fixed effects. Columns (2) and (4) additionally have a fintech dummy, not shown; t-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Default

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid
Rate	0.472***	0.472***	0.164***	0.175***
	(35.31)	(35.01)	(9.43)	(10.02)
Rate x Fintech	-	0.000220	-	-0.0181***
	-	(0.06)	-	(-4.59)
Borrower and Loan Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	956967	956967	956628	956628
Pseudo R^2	0.0440	0.0440	0.135	0.136

Panel B: Prepayment

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid
Rate	0.285***	0.262***	0.749***	0.731***
	(101.72)	(87.32)	(192.69)	(177.33)
Rate x Fintech		0.128***		0.0869***
		(20.89)		(13.69)
Borrower and Loan Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	956967	956967	956634	956634
Pseudo R^2	0.0372	0.0376	0.0976	0.0977

Table 13: Determinants of Interest Rates

Table 13 shows the R^2 of observables for different specifications of regression (12). Data is from Fannie Mae and Freddie Mac. Fixed effects are differenced out so that their effects are not included in the total sum of squares. Panel A shows pooled regressions between 2010 and 2013 for the banks shadow bank, non-fintech, and fintech subsamples. Non-linear controls include third-order polynomials of all observables. Panel B shows year-by-year regressions with (linear) FICO, LTV controls and Quarter FE only.

Panel A: R^2 of Pooled Regressions, 2010-2013

Specification				Full Sample		Shadow Bank Sample	
Controls	Quarter FE	Zip-Quarter FE	Lender FE	Bank	Shadow Bank	Non-Fintech	Fintech
FICO, LTV	Y	N	N	0.158	0.289	0.303	0.139
FICO, LTV	N	Y	N	0.081	0.087	0.086	0.070
All	Y	N	N	0.535	0.586	0.619	0.437
All	N	Y	N	0.490	0.463	0.495	0.374
Non-Linear	Y	N	N	0.575	0.623	0.653	0.484
Non-Linear	N	Y	N	0.535	0.510	0.542	0.425
Non-Linear	N	Y	Y	0.543	0.514	0.540	0.435

Panel B: R^2 of Year-By-Year Regressions, FICO, LTV, & Quarter FE

	Full Sample		Shadow Bank Sample	
Year	Bank	Shadow Bank	Non-Fintech	Fintech
2010	0.128	0.194	0.205	0.156
2011	0.203	0.398	0.420	0.156
2012	0.157	0.355	0.379	0.099
2013	0.158	0.235	0.237	0.182
2014	0.176	0.178	0.184	0.179
2015	0.172	0.194	0.218	0.173

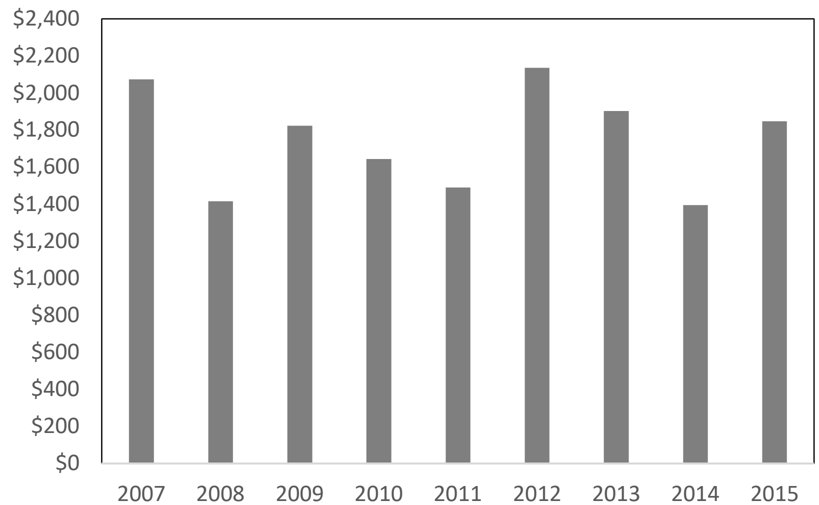
Table 14: Fintech Cost and Convenience

Table 14 shows the results of regression (13). Data is from Fannie Mae and Freddie Mac Shadow Bank originations between 2010 and 2013. High FICO is a dummy variable for borrowers with FICO score at origination greater than 800. Columns (1)-(2) do not include other borrower and loan controls (aside from FICO and a High FICO dummy, not shown). Columns (3)-(4) include borrower and loan controls. Columns (1) and (3) include quarter fixed effects only; Columns (2) and (4) include zip-quarter fixed effects. The left-hand-side variable is in percent terms; the mean is 4.18. Standard errors are clustered at the zip-quarter level; standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

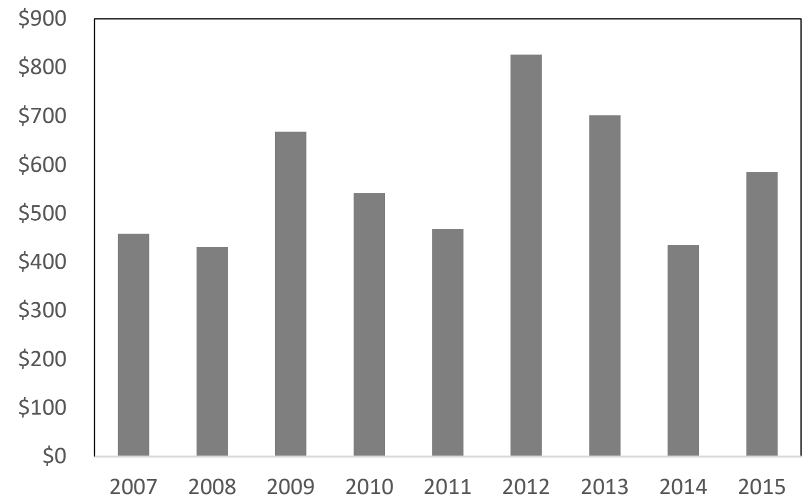
	(1) Rate	(2) Rate	(3) Rate	(4) Rate
Fintech	0.135^{***}	0.120^{***}	0.136^{***}	0.116^{***}
	(136.53)	(51.73)	(73.89)	(66.68)
High FICO x Fintech	0.0122^{***}	0.0116^{***}	0.00766^{***}	0.00576^{***}
	(5.38)	(5.54)	(4.26)	(3.32)
Borrower and Loan Controls	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No
N	956832	954677	956634	954478
R^2	0.685	0.718	0.826	0.842

Figure 1: Total Residential Mortgage Originations

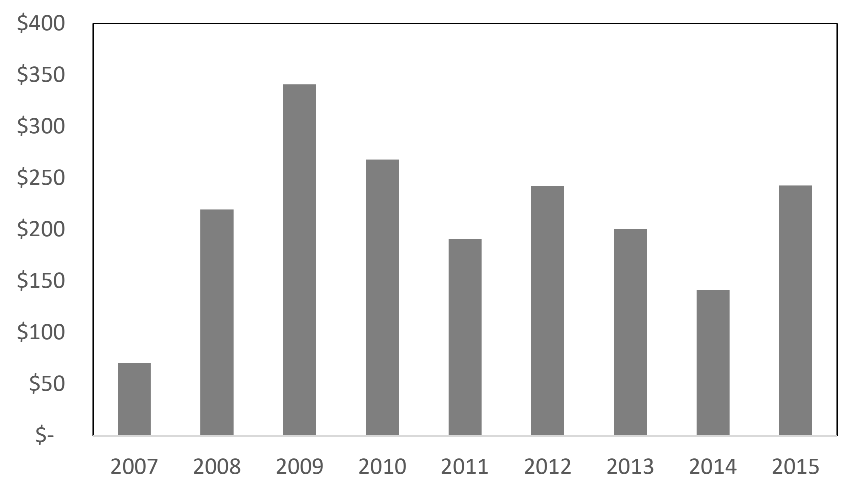
Panel A shows total dollars originated between 2007 and 2015 as reported by HMDA. Panel B shows the total dollar value of originated conforming mortgages, where a mortgage is conforming if it is (1) conventional and reported as sold to Fannie Mae or Freddie Mac in HMDA. Note that if the mortgage is sold to Fannie Mae or Freddie Mac more than a year after origination it is not reported as sold and hence not counted in Panel B. Panel C shows total dollars of FHA originations.



(a) All loans



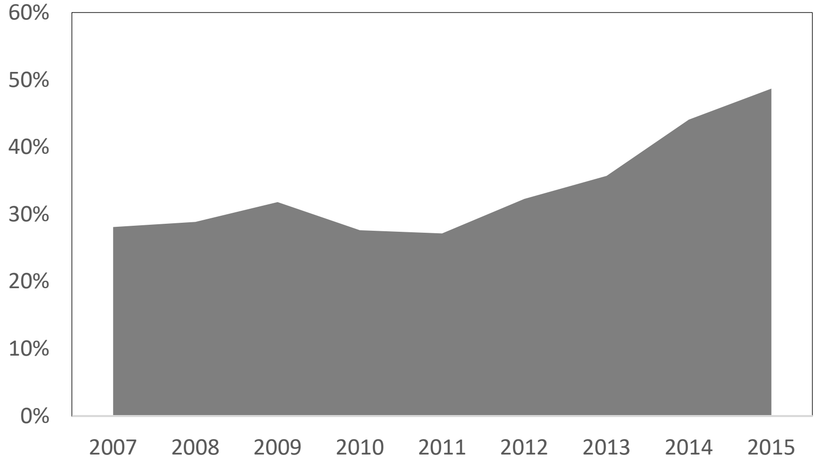
(b) Conforming loans



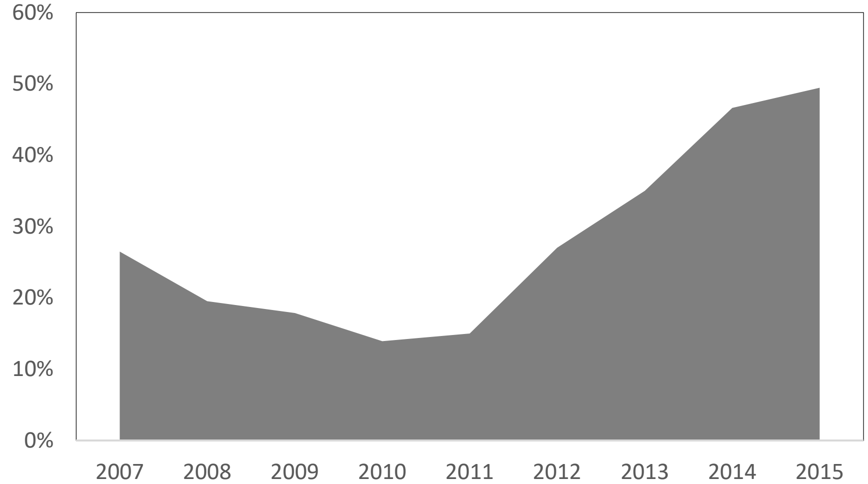
(c) FHA loans

Figure 2: Shadow Bank Origination Shares

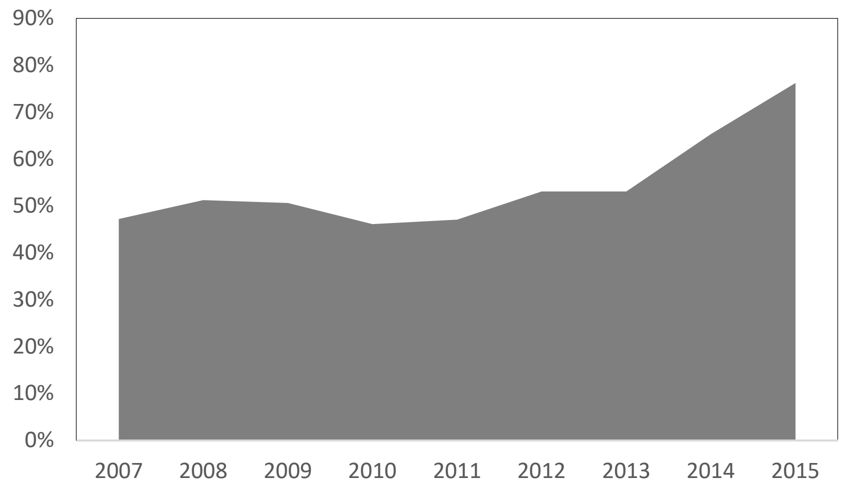
Panel A shows shadow bank origination shares as a fraction of total originations for all mortgages in HMDA between 2007 and 2015. Panel B shows shadow bank origination shares among conforming mortgages. Panel C shows the shadow bank origination share among FHA mortgages.



(a) All loans



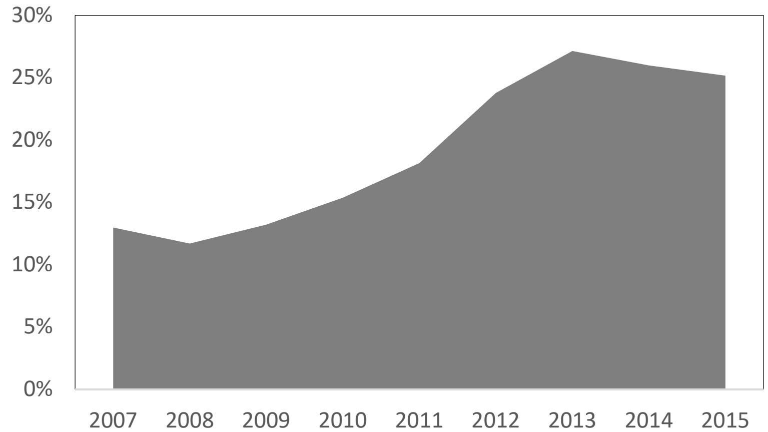
(b) Conforming loans



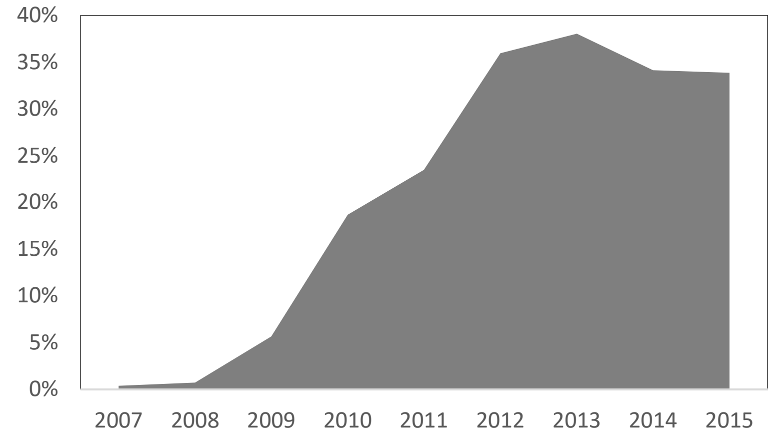
(c) FHA loans

Figure 3: Fintech Origination Shares of Shadow Bank Originations

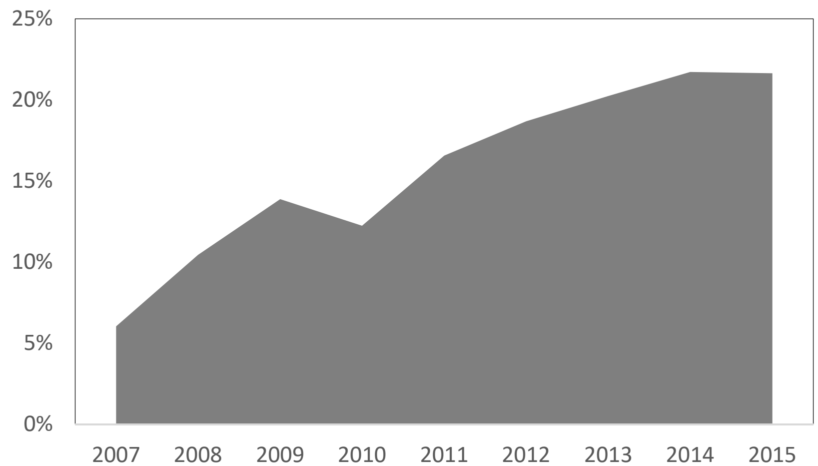
Panel A of this figure shows fintech originations as a share of shadow bank originations for all mortgages in HMDA between 2007 and 2015. Panel B shows fintech bank origination shares among shadow bank conforming originations. Panel C shows fintech share among shadow bank FHA originations (based on HMDA).



(a) All loans



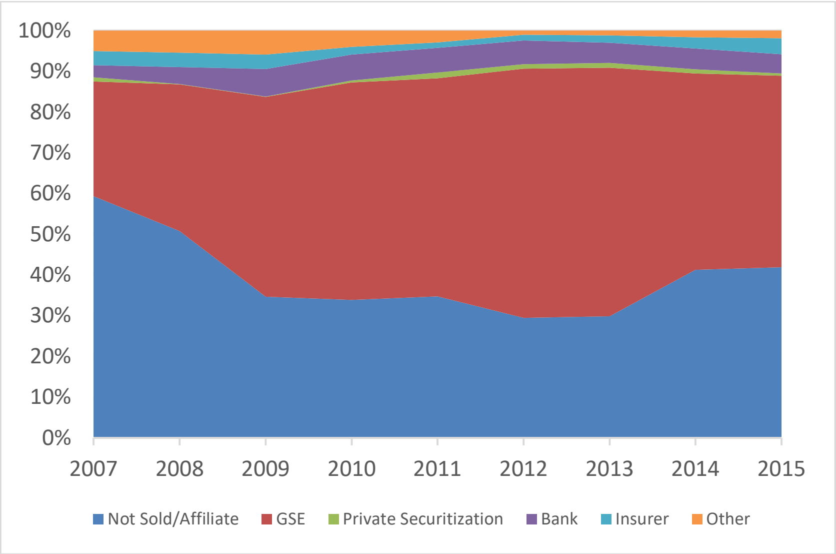
(b) Conforming loans



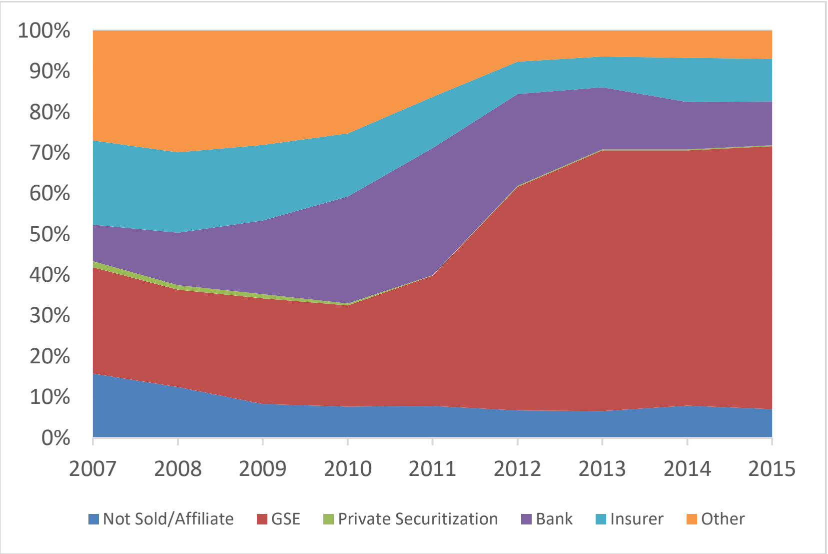
(c) FHA loans

Figure 4: Disposition of Loans among Traditional Banks, Shadow Banks, and Fintech Lenders

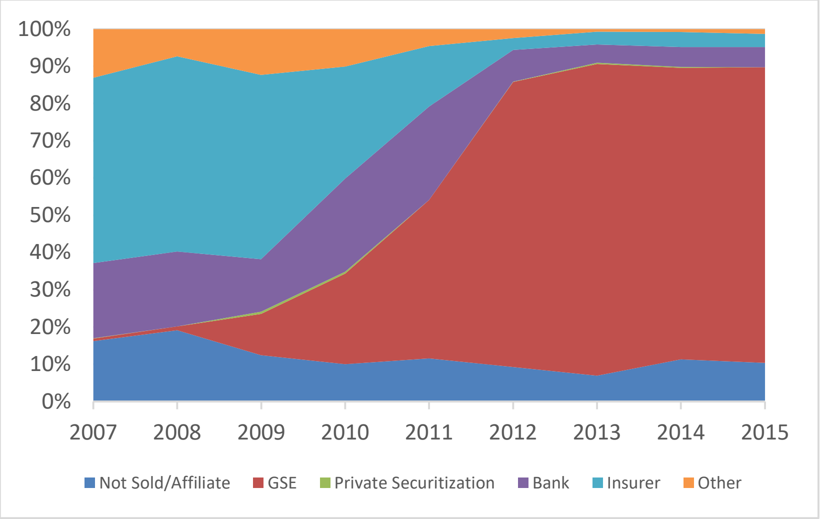
This figure shows disposition of loans among traditional banks (panel a), shadow banks (panel b), and fintech lenders (panel c) based on HMDA data.



(a) Traditional banks



(b) Shadow banks



(c) Fintech lenders

Figure 5: Regional Shadow Banking Penetration

This shows the county-level shadow bank penetration as of 2015 using HMDA data.

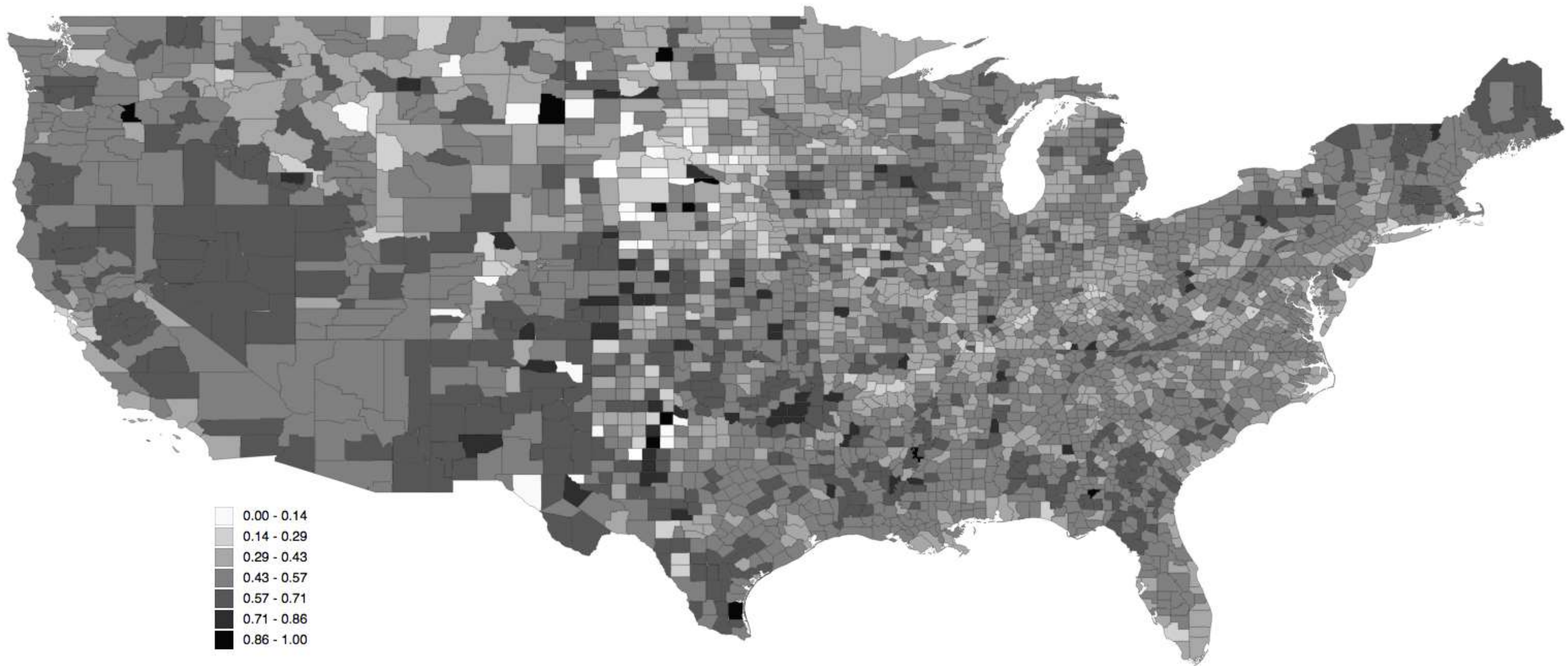


Figure 6: Mortgage Service Rights and Bank Shares over Time

This figure shows the coefficents on MSR from the regression of $\Delta BankShare_{ct} = \beta_{0t} + \beta_{1t} MSR_{c2008} + \varepsilon_{ct.}$ between 2008 and 2015. This corresponds to Regression (7) run as a repeated cross-section year-by-year. $\Delta BankShare_{ct}$ is the change in bank lending share between t and 2008. The solid line is the coefficient estimate; the dotted lines denote 95% confidence intervals.

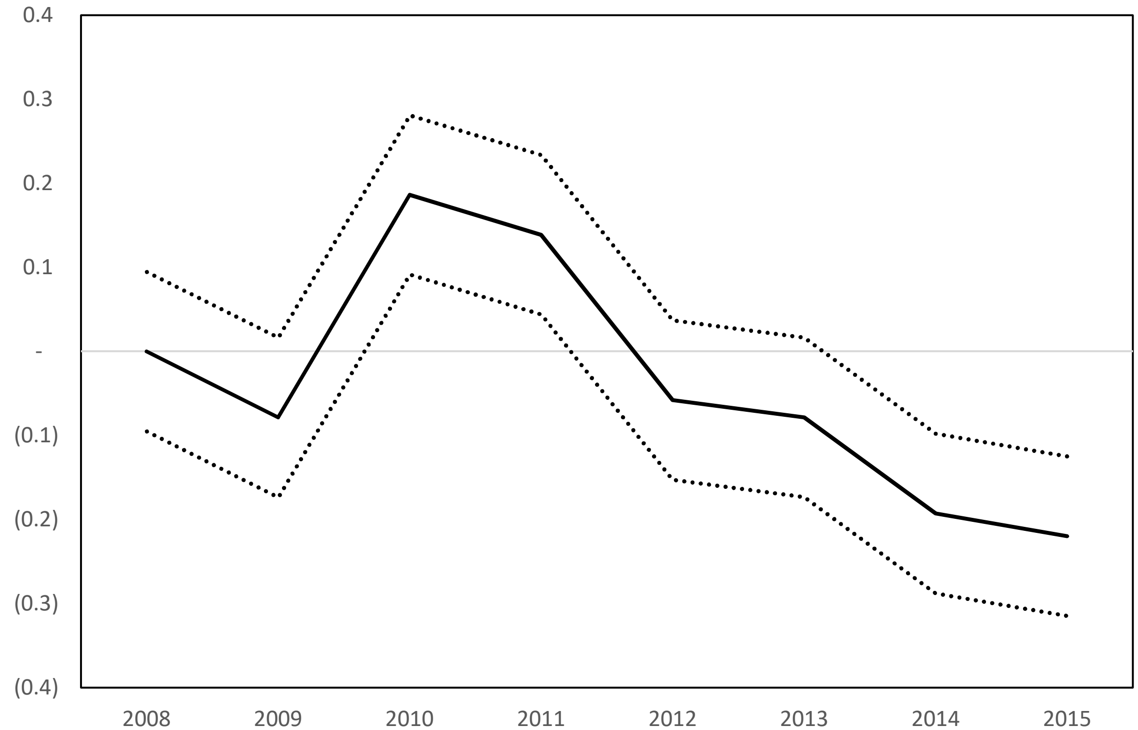
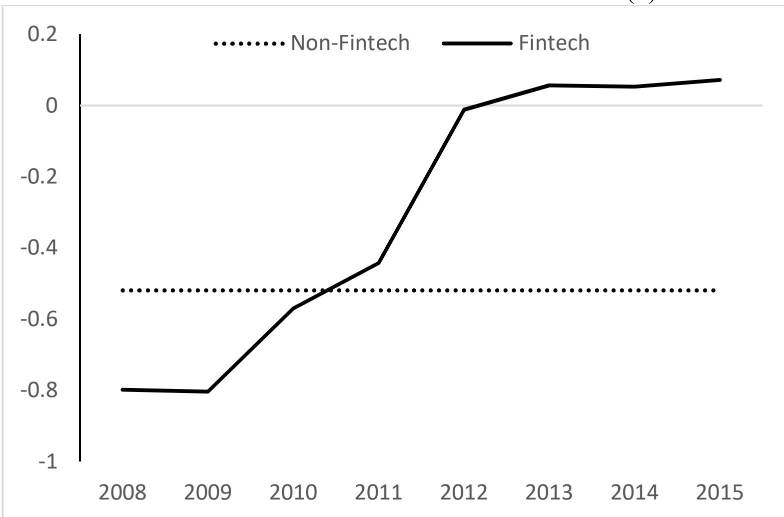
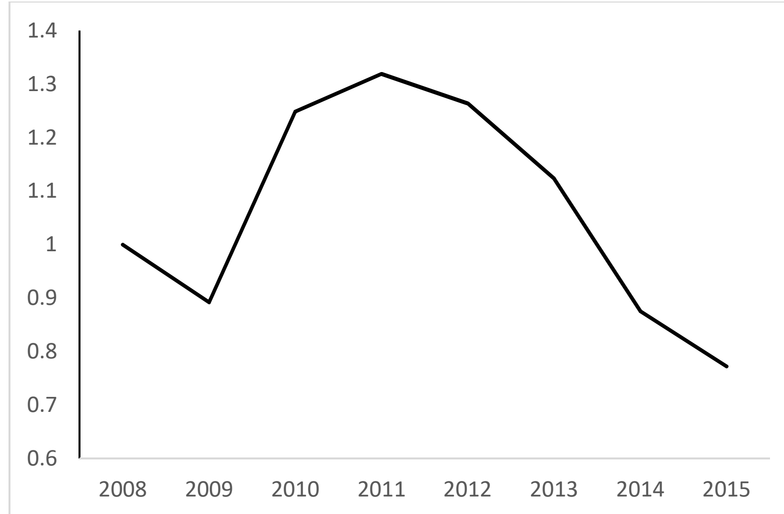


Figure 7: Calibrated Characteristics of Lenders

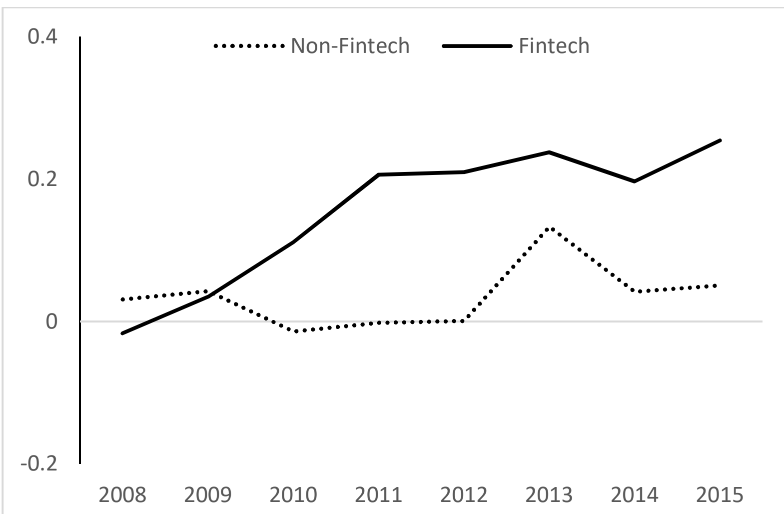
This figure presents the model parameters discussed in Section VII.C. Panel (a) shows lender quality characteristics for fintech and non-fintech shadow banks relative to traditional bank. Panel (b) shows the evolution of regulatory burden implied by our model and data. Panel (c) shows funding costs for fintech and non-fintech shadow banks and relative to traditional bank. Panel (d) shows fixed costs of traditional banks, and fintech and non-fintech shadow banks.



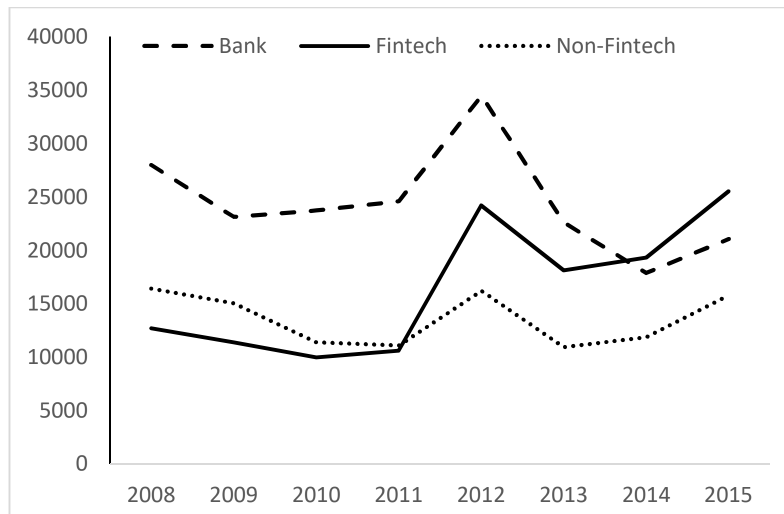
(a) Lender's quality



(b) Regulatory environment



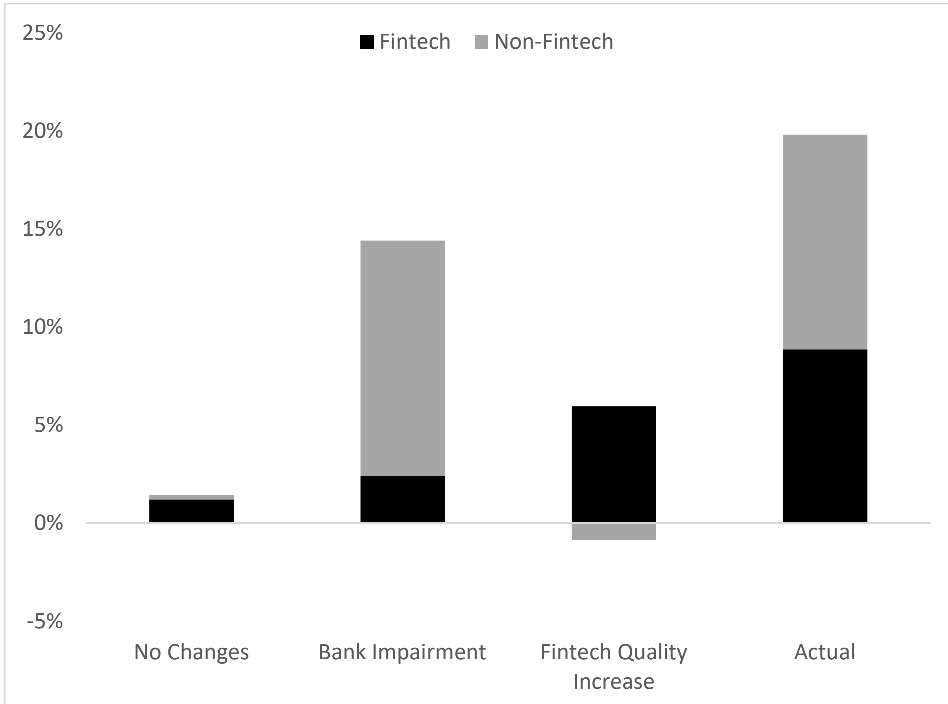
(c) Funding costs



(d) Fixed costs

Figure 8: Counterfactuals for the Change in the Shadow Bank Market Share Implied by our Model

This figure shows predicted changes in shadow bank market share between 2008 and 2015, broken down between non-fintech and non-fintech entrants, for three counterfactuals regarding fintech quality and bank regulatory impairment. "No Changes" fixes both fintech quality to its 2008 and bank regulatory burden parameter to 0. "Regulatory Impairment" has fixed fintech quality and allows bank regulatory burden to vary as calibrated. "Fintech Quality Increase" fixes bank regulatory burden and allows fintech quality to vary as in the data. "Actual" shows the actual changes in our data.



On-Line Appendix:

Appendix A1: Classification of Lenders

Panel A: List of Largest Shadow Banks

Name	Bank Type	Fintech or Non-Fintech
Amerisave Mortgage	Shadow Bank	Fintech
Cashcall Inc	Shadow Bank	Fintech
Guaranteed Rate Inc	Shadow Bank	Fintech
Homebridge Financial Services	Shadow Bank	Fintech
Homeward Residential	Shadow Bank	Fintech
Movement Mortgage	Shadow Bank	Fintech
Quicken Loans	Shadow Bank	Fintech
Academy Mortgage	Shadow Bank	Non-Fintech
AmCap Mortgage LTD	Shadow Bank	Non-Fintech
American Neighborhood Mtg	Shadow Bank	Non-Fintech
American Pacific Mortgage	Shadow Bank	Non-Fintech
Amerifirst Financial Corp	Shadow Bank	Non-Fintech
Amerihome Mortgage	Shadow Bank	Non-Fintech
Ark-LA-TEX Fin Svcs.	Shadow Bank	Non-Fintech
Bay Equity	Shadow Bank	Non-Fintech
Broker Solutions	Shadow Bank	Non-Fintech
Caliber Home Loans	Shadow Bank	Non-Fintech
Chicago Mortgage Solutions	Shadow Bank	Non-Fintech
CMG Mortgage	Shadow Bank	Non-Fintech
Ditech Financial	Shadow Bank	Non-Fintech
Fairway Independent Mortgage	Shadow Bank	Non-Fintech
Franklin American Mortgage	Shadow Bank	Non-Fintech
Freedom Mortgage	Shadow Bank	Non-Fintech
Greenlight Financial	Shadow Bank	Non-Fintech
Guild Mortgage	Shadow Bank	Non-Fintech
Impact Mortgage	Shadow Bank	Non-Fintech
LoanDepot.com	Shadow Bank	Non-Fintech
Mortgage Research Center	Shadow Bank	Non-Fintech
Nationstart Mortgage	Shadow Bank	Non-Fintech
Newday Financial	Shadow Bank	Non-Fintech
Pacific Union Financial	Shadow Bank	Non-Fintech
PennyMac Loan Services	Shadow Bank	Non-Fintech
PHH Mortgage	Shadow Bank	Non-Fintech
Plaza Home Mortgage	Shadow Bank	Non-Fintech
Primary Residential Mortgage Inc.	Shadow Bank	Non-Fintech
PrimeLending	Shadow Bank	Non-Fintech
Primelending Plainscapital	Shadow Bank	Non-Fintech
Prospect Mortgage	Shadow Bank	Non-Fintech
Provident Funding	Shadow Bank	Non-Fintech
Sierra Pacific Mortgage	Shadow Bank	Non-Fintech
Sovereign Lending Group	Shadow Bank	Non-Fintech
Stearns Lending	Shadow Bank	Non-Fintech
Stonegate Mortgage	Shadow Bank	Non-Fintech
Suntrust Mortgage	Shadow Bank	Non-Fintech
Sunwest Mortgage Company	Shadow Bank	Non-Fintech
United Shore Financial Services	Shadow Bank	Non-Fintech
Walker and Dunlop	Shadow Bank	Non-Fintech

Panel B: List of Largest Traditional Banks

Name	Bank Type
Allay Bank	Traditional Bank
Bank of America	Traditional Bank
BOK Financial	Traditional Bank
Branch Banking and Trust Company	Traditional Bank
Capital One	Traditional Bank
Citibank	Traditional Bank
Citimortgage	Traditional Bank
Colorado FSB	Traditional Bank
Everbank	Traditional Bank
FHLB Chicago	Traditional Bank
Fidelity Bank	Traditional Bank
Fifth Third Mortgage	Traditional Bank
First Republic Bank	Traditional Bank
Flagstar Bank FSB	Traditional Bank
Fremont Bank	Traditional Bank
Homestreet Bank	Traditional Bank
HSBC Bank	Traditional Bank
J.P. Morgan Madison Avenue Securities Trust	Traditional Bank
JPMorgan Chase	Traditional Bank
MB Bank	Traditional Bank
Metlife Home Loans	Traditional Bank
Mortgage Stanley Private Bank	Traditional Bank
MUFG Bank	Traditional Bank
Navy FCU	Traditional Bank
NY Community Bank	Traditional Bank
PNC Bank	Traditional Bank
Redwood Credit Union	Traditional Bank
Regions Bank	Traditional Bank
Union Savings Bank	Traditional Bank
US Bank	Traditional Bank
USAA FSB	Traditional Bank
Wells Fargo Bank	Traditional Bank

Appendix A2: Shadow Bank Presence and Mortgage Rates: FHA Loans

This table shows the results of regression (3) using FHA loans from 2008-2015. Columns (1)-(2) have no borrower and loan controls. Columns (3)-(4) have borrower and loan controls. Columns (1) and (3) have quarter fixed effects. Columns (2) and (4) have zip-quarter fixed effects. Standard errors are clustered at the zip-quarter level. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)	(4)
	Rate	Rate	Rate	Rate
Shadow Bank	0.0341***	0.0337***	0.0413***	0.0373***
	(0.000698)	(0.000815)	(0.000645)	(0.000759)
Borrower and Loan Controls	No	No	Yes	Yes
Quarter FE	Yes	No	Yes	No
Quarter x Zip FE	No	Yes	No	Yes
N	2280859	2280859	2280858	2280858
R^2	0.557	0.653	0.676	0.743

Appendix A3: Fintech Loan Presence and Mortgage Rates: FHA Loans

This table shows the results of regression (10) using FHA loans from 2008-2015. Columns (1)-(2) have no borrower and loan controls. Columns (3)-(4) have borrower and loan controls. Columns (1) and (3) have quarter fixed effects. Columns (2) and (4) have zip-quarter fixed effects. Standard errors are clustered at the zip-quarter level. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Rate	(2) Rate	(3) Rate	(4) Rate
Fintech	-0.113^{***}	-0.0989^{***}	-0.0515^{***}	-0.0398^{***}
	(0.000938)	(0.00133)	(0.000850)	(0.00120)
Borrower and Loan Controls	No	No	Yes	Yes
Quarter FE	Yes	No	Yes	No
Quarter x Zip FE	No	Yes	No	Yes
N	1035740	1035740	1035739	1035739
R^2	0.528	0.683	0.623	0.741

Appendix A4: Fintech Origination Fees

We briefly provide evidence on mortgage origination fees, which we do not observe in our dataset. In particular, a concern is that while fintech lenders offer higher rates on average, they may offer these higher rates in exchange for lower fixed costs at origination. Closing costs are typically 1-5% of the mortgage balance,[35] and cover costs associated with closing the transaction such as legal and processing fees paid to the originator.

Anecdotally, fintech lenders do not appear to offer lower origination fees. On the contrary, their fees appear on the high end of the typical range. For example, on consumer review sites, a common complaint regarding Quicken Loans, the largest fintech lender in our data, is it high origination fees[36] relative to other lenders. Several lenders, including Quicken Loans, provide closing cost estimators for purchases and refinances.[37] For the purchase of a $200,000 home with a 20% down payment in Illinois, the calculator estimates an origination fee of $8,648, which is 5.4% of the principal balance at origination. Bank of America provides a similar tool[38] and estimates origination fees of $8,659. Bankrate.com, which gathers closing cost information on the largest lenders within each state, reports that average closing costs in Illinois for a similar loan are $2,079.[39]

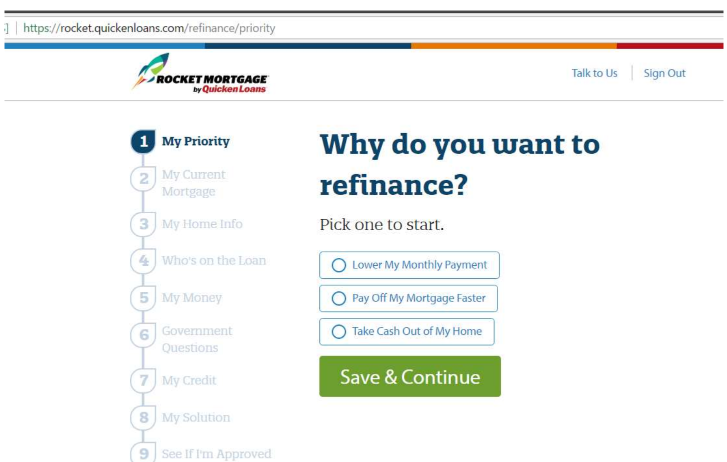
[35] https://www.zillow.com/mortgage-learning/closing-costs/ (Accessed March 7, 2017)
[36] https://www.consumeraffairs.com/finance/quicken_loans_mortgage.html
[37] https://www.quickenloans.com/my-mortgage/calculator#!/purchase/question/purchase-price (Accessed March 7, 2017)
[38] https://www.bankofamerica.com/mortgage/closing-costs-calculator/ (Accessed March 7, 2017)
[39] http://www.bankrate.com/finance/mortgages/closing-costs/illinois.aspx (Accessed March 7, 2017)

Appendix A5: The Origination Process at Quicken Loans

To illustrate the degree of automation offered by fintech lenders, this section walks through the process on Quicken Loans, the largest fintech lender, that the borrower must take in order to get a firm loan offer. The process is designed to take place entirely online with no human interaction necessary until closing. What follows combines screenshots from Quicken Loans' flagship online product, Rocket Mortgage, accessed on March 7, 2017, and screenshots from a TechCrunch.com November 24, 2015 review of the product.[40]

The system guides the borrower through a series of online questions regarding the borrowers need and financial situation. (Figure 1). As the user clicks through the questionnaire, the system automatically gathers income and asset information using the borrower's social security number. (Figure 2). With the borrower's consent, the system performs a credit check and proposes mortgage terms, which the borrower can lock in online (Figure 3).

Figure 1



[40] https://techcrunch.com/2015/11/24/this-could-be-the-mortgage-industrys-iphone-moment/, Accessed (March 7, 2017).

Figure 2

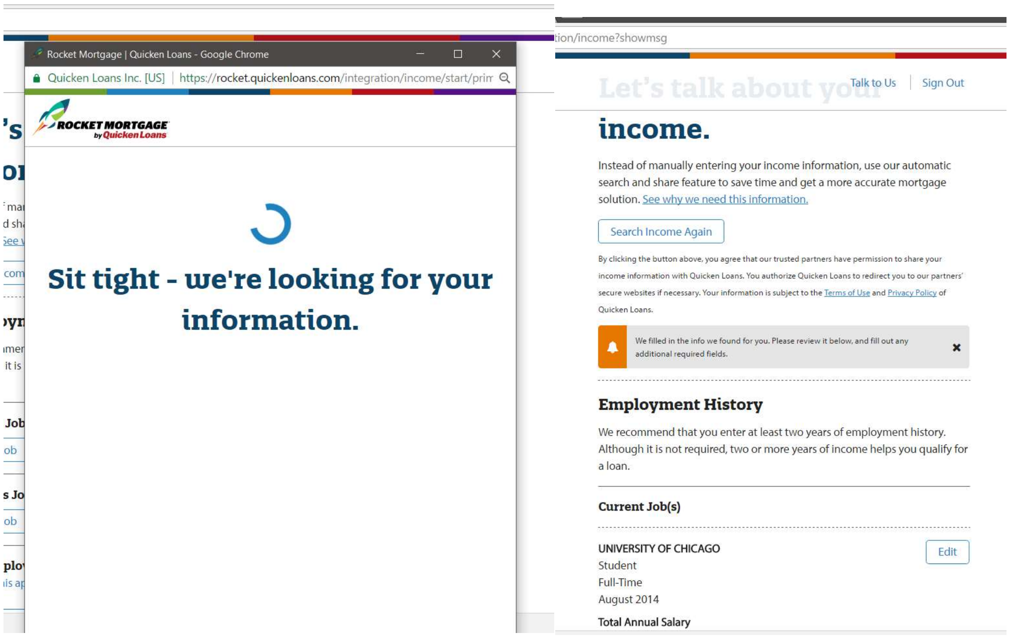
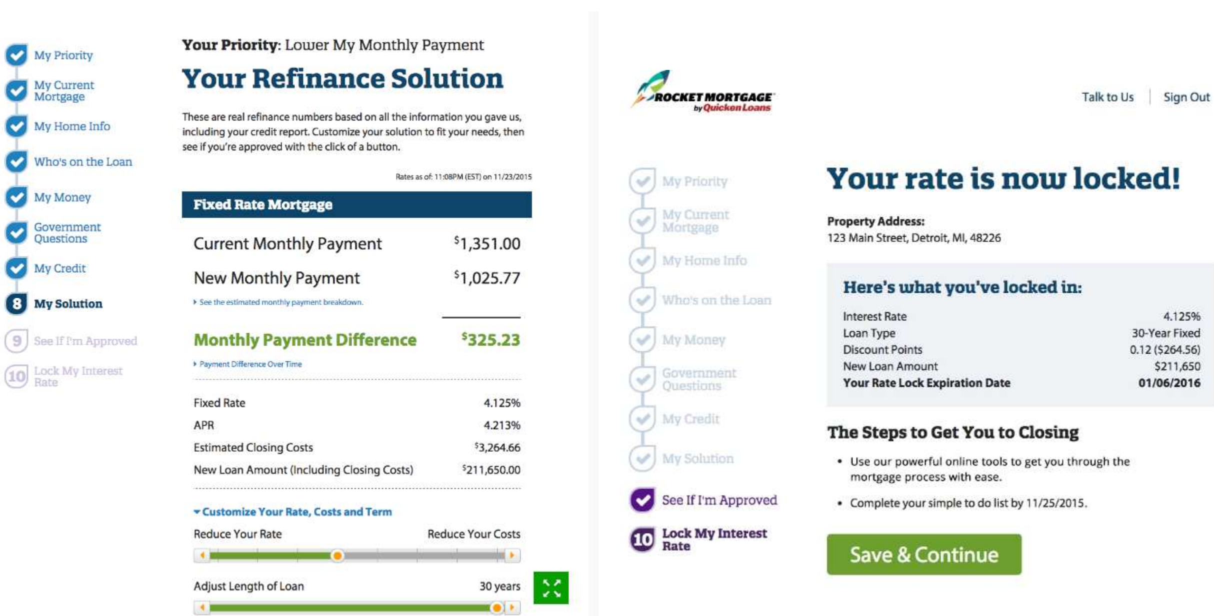


Figure 3



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