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ABSTRACT

We study the rise of shadow banks in the largest consumer loan market in the US. The market share of shadow banks in originating residential mortgages nearly doubled from 2007-2015. Shadow banks gained a larger market share among less creditworthy borrowers, with a significant share of loans being originated-to-distribute to GSEs. Difference in difference tests suggest that traditional banks contracted origination activity in markets in which they faced more capital and regulatory constraints; these gaps were partly filled by shadow banks. Shadow banks with predominately online mortgage application process, "fintech" lenders, accounted for roughly a quarter of shadow bank loan originations by 2015. Relative to non-fintech shadow banks, fintech lenders serve more creditworthy borrowers and are more active in the refinancing market. They appear to use different information in setting interest rates, consistent with a big data component of technology, and charge a convenience premium of 14-16 basis points. We use a simple model to decompose the relative contribution of technology and regulation to the rise of shadow banks. We interpret the variation in mortgage rates and market shares using the model and find that increasing regulatory burden faced by traditional banks and growth of financial technology can account, respectively, for about 70% and 30% of the recent shadow bank growth.

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I. Introduction

In the last decade, the market for financial consumer products has undergone a dramatic change. Intermediation has shifted from traditional banks to less regulated shadow banks (Sunderam, 2015).[1] This change has coincided with a shift away from "brick and mortar" originators to online intermediaries.[2] Despite the scarcity of systematic evidence, regulators, policymakers, and academics have been engaged in an intense debate about the possible consequences of these developments.[3] In this paper we undertake a first systematic examination of the evolution of shadow banking in the largest consumer loan market in the US, the ten trillion dollar consumer mortgage market. We study this market to explore the economic forces which could explain the drastic change in the nature of intermediation.

We document that the market share of shadow banks in conforming mortgage origination has nearly doubled from roughly 30% to 50% from 2007-2015.[4] In the Federal Housing Administration (FHA) mortgage market, which serves less creditworthy borrowers, the change has been even more dramatic with market share of shadow banks increasing from 45% to 75% over the same period. Concurrently, "fintech" lenders, shadow banks with a predominately online mortgage application process, increased their market share rapidly, and accounted for roughly a quarter of shadow bank loan originations by 2015.

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. Banks are subject to an ever-increasing regulatory burden through heightened legal scrutiny and larger capital requirements. The increased burden has changed which products they can provide, and has increased the cost of their funding. Therefore, banks are withdrawing from markets with high regulatory costs. Shadow banks, facing substantially lower regulatory costs and related concerns, have stepped into this gap, giving rise to large gains in market share.

The second hypothesis is that the shift from traditional banks is driven by changes in technology: Fintech shadow banks have gained market share because they provide better products, or because they provide existing products more cheaply, and their technology has disrupted the mortgage market. Consider *Quicken Loans*, which has grown to the third largest mortgage lender in 2015.

[1] We use the term "shadow bank" to refer to non-bank (non-depository) lenders, consistent with the definition of the Financial Stability Board (FSB), whose members cover G20 national regulators, the International Monetary Fund, the World Bank, and the Bank of International Settlements. See also Adrian and Ashcraft (2016).
[2] Goldman Sachs Report, March 3, 2015: "The Future of Finance: The Rise of the new Shadow Bank."
[3] Bank of International Settlements, 2017: "FinTech credit. Market structure, business models and financial stability implications." http://www.bis.org/publ/cgfs_fsb1.pdf
[4] See Figures 1-3.

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 is also a more convenient and faster way for internet savvy consumers to obtain binding rate quotes and electronically provide documentation.[5] Additionally, fintech lenders may be better able to screen potential borrowers, leveraging alternative sources of information and the big data approaches inherent in technology based lending.

To examine whether increased regulatory burden is a driving force behind the decline of traditional mortgage banking, first we compare lending of banks to *all* shadow banks, irrespective of their fintech affiliation. By 2015 shadow banks originated about 50% of loans in the conforming market and 75% of loans insured by the FHA. The FHA loans allow lower income and less creditworthy households to borrow money for the purchase of a home with as little as 3.5% of the property value as down payment. The large prevalence of shadow banks' suggests that their advantage over traditional banks is especially strong in a market dominated by riskier borrowers. Traditional banks also lose market share in areas with larger minorities shares. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of less creditworthy and minority borrowers, this evidence is consistent with shadow banks expanding in segments where regulatory burden has risen substantially.

The differences between shadow and traditional banks are not limited to customer characteristics, but also extends to differences in financing of mortgages. Traditional banks' share of mortgage originations held on their balance sheet has declined since 2007, but has not declined below 30%. Shadow banks, on the other hand, primarily finance mortgages using the originate-to-distribute model, especially later in the sample. Moreover, the securitization predominantly involves products associated with government sponsored enterprises (GSE).

Next, we more directly link the rise of shadow banks to increased regulatory burden of traditional banks by focusing on three specific increases in this burden: increased capital requirements, increased regulatory burden related to mortgage servicing rights (MSR), and mortgage-related lawsuits, exploiting a differences in differences approach. We find a larger growth of shadow banks in counties in which a larger share of traditional banks had to build up capital reserves over the last decade. Additionally, regions with a larger share of lenders subject to legal actions, and a larger share of lenders involved in mortgage servicing activity also saw a larger growth in 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.

[5] https://www.nerdwallet.com/blog/mortgages/quickenloansandrocketmortgagereview/ [Accessed on 11/8/2016]

These results suggest that the lower regulatory burden provides a cost advantage to shadow banks. 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 differences in pricing, *on average,* are negligible. This average pattern hides interesting differences between loans originated by fintech and non-fintech lenders. Non-fintech lenders, which do not hold a technology advantage over traditional firms, do offer lower interest rates, suggesting that they pass some regulatory cost savings to customers. In addition, shadow banks loans are also more likely to prepay and default conditional on observables. Accounting for this higher risk further continues to suggests that, on average, shadow banks pass some regulatory cost savings to borrowers.

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

Fintech firms accounted for about a quarter of shadow bank loan originations by 2015. This simple fact suggests that on-line origination technology may have played an important role in the decline of traditional banks during the last decade. Fintech lenders serve a different segment of the mortgage market than non-fintech shadow banks. Fintech lenders are much less likely to serve less creditworthy FHA borrowers. Additionally, fintech originations are heavily tilted towards refinancing, differing from non-fintech shadow banks. One possible reason is that the more standardized tasks involved in mortgage refinancing are the best fit for fintech technology.[6]

Fintech lenders also differ from non-fintech shadow banks in loan pricing. As discussed earlier, non-fintech shadow banks offer lower interest rates than traditional banks, suggesting that they pass through a part of regulatory cost savings to customers. Fintech lenders, on the other hand, charge higher interest rates relative to traditional banks, consistent with the notion that fintech consumers are willing to pay for the convenience of transacting online. Finally, we explore whether there is indeed a difference in the technology used to set mortgage interest rates between fintech and non-fintech lenders. We find that standard variables for predicting interest rates, such as FICO and LTV, explain substantially less variation in interest rates of fintech lenders relative to non-fintech lenders. These results are consistent with the narrative that technology based lending

[6] In refinancing, the fintech lender benefits from many on-the-ground activities having already taken place at the time of purchase, such as a title check, structural examination, negotiations between buyer and seller,

uses substantially different information, potentially based on big data they obtain in addition to standard variables.

Taken together, our results suggest that two factors have contributed to the precipitous decline of traditional banks' market share in the residential mortgage market over the last decade: Additional regulatory burden faced by banks, and technology related to on-line lending platforms. To decompose the relative contribution of technology and regulation to the rise of shadow banks we present and calibrate a simple quantitative model of mortgage origination. In the model, traditional banks, non-fintech shadow banks, and fintech shadow banks compete for borrowers. To capture the stylized facts that we document, 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. We interpret the variation in mortgage rates and market shares using the model to identify the relative importance of different factors in the decline of traditional banking.

Our estimates imply that traditional banks have slightly lower shadow cost of funding and provide higher quality products than shadow banks. Despite these advantages, they lose market share during this period because of large increase in the regulatory burden after 2010. 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. We also estimate 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 70% of shadow bank growth during 2008-2015 period with advancement in on-line lending technology accounting for another 30%.

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 have 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 outside of banks. Our paper instead focuses on mortgage origination taking place outside the traditional banking system, and its accompanying regulatory structure. In this regard our paper is also related to the recent literature investigating the industrial organization of the residential mortgage market (e.g., Stanton, Wallace, and Walden 2014, 2017).

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. 2015 and 2017). Like Agarwal et. al. (2014), Lucca et. al. (2014), Granja et al. (2014), Piskorski et al (2015), Fligstein and Roehrkasse (2016), we study lawsuits 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 rely heavily 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 (e.g., Elenev et al. 2016; Hurst et al 2015; Bhutta 2012; Acharya et. al. 2011) have studied their role in income redistribution and house ownership, finding mixed results. Our paper suggests that increased regulatory burden of traditional banks combined with GSEs and FHA guarantees may 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, 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 combine and use 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 of 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 through the end of the calendar 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.[7] 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.

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-

[7] 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 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.

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.[8] 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 FHA 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 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. In particular, we use bank balance sheet data from the bank call reports, from which we calculate bank capitalization.

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[9], 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, we collected all legal actions taken by the

[8] 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.

[9] https://www.law360.com/faq

SEC regarding misconduct that led to, or arose from the financial crisis.[10] The SEC data spans 2009 through 2016. From SNL Financial, 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.[11]

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. Robustness with respect to lender classification is discussed in Section IX.

The classification of "bank" versus "shadow bank" when doing so is straightforward: a lender is a "bank" if it is a depository institution; a lender is a "shadow bank" if it is not a bank. This definition of banks is consistent with the definition of the FSB, which defines banks as "All deposit-taking corporations" and shadow banks as "credit intermediation involving entities and activities outside of the regular banking system."[12] Because our focus is mortgage origination, our measurement of shadow banking falls squarely within the FSB definition. FSB members comprise both national regulators of G20 countries, as well as international financial institutions, such as the International Monetary Fund, the World Bank, and the Bank of International Settlements, as well as, and international standard-setting and other bodies such as Basel Committee on Banking Supervision. Therefore our measurement of shadow banks has broad regulatory agreement.

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

[10] https://www.sec.gov/spotlight/enf-actions-fc.shtml
[11] https://www.snl.com/InteractiveX/Article.aspx?id=33431645
[12] http://www.fsb.org/wp-content/uploads/global-shadow-banking-monitoring-report-2015.pdf

Appendix A1 shows the list of main lenders in each of these three categories. Appendix A8 provides more details on the classification process.

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.[13] 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 directed at 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 among the top 20 lenders, 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.[14]

Shadow bank originators do not take deposits. Instead, they rely almost exclusively on making loans that are originated for sale, and earn revenue through the sale of mortgage servicing rights (MSR)—the capitalized value of future cash flows from the mortgages, a small amount of interest income between origination and sale, and servicing income.[15] Because shadow banks rely so heavily on sale of mortgages to third parties, they are particularly sensitive to the financial health of these third parties. The potential buyer depends on the originated product: 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, although after the crisis, the secondary market for most jumbo mortgages essentially vanished. As we document, traditional banks are also a purchaser of shadow bank mortgages.

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

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 declared bankruptcy or were sold to traditional banks (e.g., purchase of Countrywide Financial by Bank of America).[16] Consequently, during and in the recession following the financial crisis, shadow bank mortgage origination fell significantly. Among the 50 largest lenders, the shadow bank share of lending fell to roughly 15% in the depth of the recession. (See Appendix A7). When including smaller lenders, the shadow bank market share fell to less than 30% of total originations in 2008. This paper studies shadow banks' subsequent rise in the years following their fall and what factors might explain this rise.

C. Regulatory Changes

In the years following the financial crisis, there have been a number of regulatory changes that had a direct influence on traditional banks' mortgage origination activity. Weakened bank balance sheets in the wake of the financial crisis, combined with new capital rules under Basel III tightened regulatory capital constraints. In particular, new Basel III capital rules placed limits on the amount of MSR that banks could count towards regulatory capital requirements.[17] This rule change was proposed, finalized, and implemented between 2010 and 2015.[18] Additionally, Basel III capital requirements and changes to risk weighting placed new regulatory constraints on bank capital not faced by shadow banks. These changes applied to mortgage origination directly, as well as to other lines of business such as commercial real estate. More broadly, the passage of Dodd Frank Act in 2010 and formation of the Consumer Financial 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

There are substantial aggregate fluctuations in the amount of residential mortgages originated during the period 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 2012 before declining again.

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

This simple aggregate fact illustrates that the steady decline in traditional banking that we illustrate later is 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. Figure 1, Panel B shows the lending volume in conforming mortgages, the most popular residential loans in the US.[19] These loans conform to the Fannie Mae or Freddie Mac (GSE) requirements. In our sample, almost half of loans were loans sold to GSEs within the year (Table 1, Panel B).[20] 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 FHA. 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 15% 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. The issuance segment rose 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, which is perhaps the closest substitute for FHA loans.

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 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.

[19] 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).

[20] 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.

This growth in shadow banks was not confined to a specific segment of the residential market. In Panel B, we observe a large growth of shadow banks among conforming loans: Shadow bank share in this sector approximately 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 growth of shadow bank shares and the decline in the participation of traditional banks is even more drastic when we focus only on the largest lenders. Appendix A7 presents results for top 50 lenders. The difference in the samples reflects a relatively large market share of small shadow banks early in the sample that declined over time relative to large shadow banks. The decline in the share of shadow bank loans sold to affiliates (Figure 4, Panel B) suggests that some of these small shadow banks sold loans to traditional banks.

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 roughly 3% of residential loans. By 2015 fintech shadow bank lenders accounted for roughly 12% of loan issuance. Figure 3, which shows fintech shadow banks' share of shadow bank lending, suggests that fintech shadow banks 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. This growth has occurred in both the conforming and FHA segments (Figure 3, Panels B and 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 more than a quarter of their originated loans on balance sheets; shadow bank lenders do so rarely, holding only 7.5% on balance sheet.[21] Shadow banks sell their originated loans to government or GSEs: 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. This fact

[21] The share of loans retained on the balance sheets is likely smaller. HMDA loans not sold within the *calendar year* of origination are recorded as not sold. Therefore, some of "not sold" loans are likely sold in the next calendar year. In 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 different from their origination year. If this pattern holds in HMDA, this fully explains the 7.5% of not-sold shadow bank originations.

suggests that the lack of a depository base, and the associated government guarantees on deposits, may be responsible for the use of the originate-to-distribute model.

Figure 4 shows 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 50% of originations in 2007 to 30% in 2012, though in recent years this number has increased again to 40%. The composition of shadow bank funding has shifted dramatically. Shadow banks almost never retain originations on balance sheet, and are increasingly reliant on GSEs (Panel B). In 2007, the majority of shadow bank funding came from a bank, insurance company, and other capital, with only roughly 30% of funding coming from GSEs. By 2015, nearly 50% of shadow bank loans were sold to GSEs after origination.[22]

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, nearly 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 the vast majority of their originated loans, there is a time period between origination and sale during which time the loans are held on the balance sheet of the lender. With the Fannie Mae and Freddie Mac origination data, we observe both origination date and sale date. We investigate how the time between sale and origination differs among traditional banks, shadow banks, and within shadow banks, fintech and non-fintech shadow banks. In particular, we define $Time\_to\_Sale_{ijzt}$ of borrower *i* of lender type *j* at location *z* at time *t* (in the unit of quarters) as:

$$Time\_to\_Sale_{ijzt} = Quarters\_Between(Sale, Origination)$$

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

[22] The patterns are even more striking if we focus only on the largest lenders (Appendix A7).

$$Time\_to\_Sale_{ijzt} = \beta\ Type_j + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt}$$

Where $Type_j$ 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 in Table 2 show that the time to sale for shadow banks by roughly 0.10 quarters (9 days) shorter than time to sale of traditional banks. Within shadow banks, non-fintech shadow banks' time-to-sale is roughly 0.08 quarters (7 days) faster than traditional banks, and fintech shadow banks' time-to-sale is roughly 0.17 quarters (16 days), faster than traditional banks. These results are consistent with shadow banks having a more limited balance sheet capacity than traditional banks, which results in a faster sale.

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 sectors in which the additional regulatory burden of banks is highest.

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 3, 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 racial differences. Relative to traditional banks, 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. The lack of reported race 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

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 estimate the following linear probability specification for *all residential loans*:

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

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

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

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 $FintechLender_{ict}$ 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 (omitted category is conventional).

We estimate these specifications using two different datasets. We present results using HMDA data in Table 3, Panel B. We re-estimate the specifications using Fannie Mae and Freddie Mac data in Table 4. 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, i.e. 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.

A.1.2 Race and Income

In simple mean difference presented above, we find that shadow banks' borrowers are more likely to be low income, black, and of "unreported race." Regression results confirm that lower incomes borrowers are more likely to be shadow bank borrowers. This consumer segment has also seen most lawsuits and enforcement actions, suggesting that shadow banks are replacing traditional banks in segments in which traditional banks have experienced larger regulatory pressures.

Within shadow banks, higher income borrowers are more likely use fintech lenders, but the magnitudes are small, and the effect reverses when including year-county fixed effects. Conditioning on borrower characteristics such as income, shows that black borrowers are more likely to be shadow bank borrowers. However, because "unknown" race, and "NA" sex are much more prevalent among shadow bank borrowers, and especially fintech shadow banks, 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 as a whole are less active in the market for refinancing mortgages: a refinance is roughly 2 percentage points (pp) less likely to be a shadow bank loan than a home purchase. (Table 3). When restricting to conforming mortgage data in Table 4, we find that the difference is small and the sign depends on the regression specification.

Striking differences emerge within shadow bank loans: fintech lenders have a strong tilt towards mortgage refinancing. Among all shadow bank loans, refinance is nearly 20pp more likely to be a fintech loan (Table 3). This is the case for conforming mortgages as well: fintech lenders are especially likely to tilt their portfolio towards refinancing, being 7-8pp more likely to originate a refinance mortgage (Table 4). Interestingly, shadow banks 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 potential reason for these data patterns is that refinancing an existing mortgage is more easily standardized, and therefore a better 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 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 in 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 a 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 9pp more likely to be originated by a shadow bank. Shadow banks loans are also more likely among Veterans' Administration (VA) loans. The effect is in the opposite direction for US Department of Agricultural and Rural Housing Service (FSA/RHA) loans, with FSA/RHS loans more likely to be originated by traditional banks.

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 as their consumer credit scores or debt-to-income ratios. So FHA and VA loans may be 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 4). Borrowers with lower FICO scores, and greater debt-to-income ratios tend to be shadow bank loans, but interestingly, loans with lower loan-to-value ratios also tend to be shadow bank loans. These differences are quantitatively small: A borrower with a 100 point lower FICO score is 2 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 3 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 this alternative may explain the level of shadow bank participation GSE lending, it is unclear why the comparative advantage of the originate-to-distribute model should have been growing over time. A possible reason for this change is regulatory. Shadow banks cannot rely on government guaranteed deposits for funding, but 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 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 as well.

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-time 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 characteristics that predict shadow banks and fintech loans 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 unemployed residents. 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. Fintech lending requires a certain degree of technological sophistication on the part of borrowers. Therefore, it is surprising that fintech firms are most present in counties with less educated populations. These are univariate comparisons, however, and should be interpreted with caution.

To investigate how different geographical characteristics are associated with the market share of shadow banks and fintech lenders in a county more formally, we estimate 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

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

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

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

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 larger shadow bank shares. 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, who choose not to disclose their race in their mortgage application.

Counties with worse socioeconomic conditions also have greater penetration of shadow banks. Shadow banks have a larger share 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 1pp greater unemployment rate is associated with a 0.45pp 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 the previous findings 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 dramatically in the last decade, both in the overall market, and in the conforming mortgage market. At least two questions arise. First, how did shadow banks increase their market share: Is it because they offer cheaper mortgages? Second, are differences in pricing 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. Moreover, 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 thought experiment by estimating the following regression in the conforming loan sample, for which interest rate and credit score data is available:

$$rate_{ijzt} = \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt} \tag{5}$$

in which an observation is a mortgage i, originated by lender type j in zipcode z in quarter t. The dependent variable $rate_{ijzt}$ is the mortgage rate. $Non\,fintech\,SB_j$ is a dummy variable for whether the originator was a non-fintech shadow bank. $Fintech\,SB_j$ 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 debt to income 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 effects 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 find that brick and mortar shadow banks charge rates that are slightly, around 3bp, lower than those of 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 non-fintech shadow banks and among traditional banks that equilibrium prices are 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.

We find sizeable differences in interest rates offered by fintech firms. Fintech firms charge 13 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, reflects a 60 point difference in FICO score. The difference between fintech and non-fintech shadow banks is even larger at 14-16 basis points. We further note that this 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 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, or fintech lenders may be able to use big data techniques to better price discriminate.

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

A2). These small differences, however, should be interpreted with caution because FHA data provides less comprehensive borrower controls than the conforming loan database.

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:

$$\begin{aligned} Default_{ijzt} &= \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j + \beta_r rate_{ijzt} + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt} \qquad (6) \\ Prepayment_{ijzt} &= \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j + \beta_r rate_{ijzt} + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt} \end{aligned}$$

$Default_{ijzt}$ measures whether a mortgage *i*, originated by lender of type *j* in zipcode *z*, in quarter *t*, is at least sixty days delinquent within two years of its origination.[23] $Prepayment_{ijzt}$ is defined analogously. We control for the mortgage interest rate $rate_{ijzt}$, 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 bank conforming loans are more likely to default than traditional bank loans (Table 7, Panel A). The magnitudes are small: shadow bank borrowers default at rates about 0.02pp higher compared traditional bank borrowers, the effect equivalent to about a 3 point lower in FICO score. This effect is mostly driven by non-fintech shadow bank lenders whose borrowers default at about

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

0.023pp higher rate over the two-year period. The base rate of default within two years of origination over this time period is 0.23pp, meaning that this difference, while small in absolute terms, means that non-fintech shadow bank borrowers are about 10% more likely to default on their loans compared to traditional bank borrowers. At the same time, Column (4) of Table 7 Panel A 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 1.8% and 2.5% depending on the specification. The base rate of prepayment within two years of origination over the time period is approximately 11pp. Therefore a shadow bank loan is between 16-22% 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.

Fintech lenders exhibit even larger probability of prepayment. Relative to traditional bank loans, fintech shadow bank loans are approximately 7pp more likely to be prepaid.[24] Relative to non-fintech shadow the difference is approximately 6pp. Finally, Appendix A6 contains an analysis of the differential relationship interest rates and loan default and prepayment. The results indicate that while there is little differential relationship between interest rates and default, fintech shadow bank interest rates are significantly more correlated with prepayment. This suggests that fintech lenders' interest rates are more strongly associated with ex-post prepayment risk.

V. Rise of Shadow Banks: Capital Requirements and Regulation

What is the change in the comparative advantage of shadow banks relative to traditional banks that has allowed them to expand to such a large degree in a relatively short period of time? Increased regulation and tightening capital constraints are among the main possible differentiating factors between shadow banks and traditional banks. If regulation is driving the rise of shadow banks, we should observe the largest rise in sectors, in which the additional regulatory burden on traditional banks is highest. We investigate this idea more directly by measuring three potential sources of increased regulatory burden facing traditional banks: building capital buffers to comply with risk-based capital requirements, harsher regulatory treatment of mortgage servicing rights (MSR), and mortgage lawsuits arising out of the financial crisis. The tests are difference-in-difference in nature: we study whether counties whose traditional banks were more exposed to a specific regulatory burden experienced larger market share gains in shadow bank lending.

[24] This could in part reflect aggressive marketing efforts of the fintech lenders to induce their borrowers to keep refinancing their loans.

A.1 Capital Requirements

The Dodd-Frank act imposed minimum risk-based capital requirements on traditional banks. As a result, the average Tier 1 Risk-Based Capital ratio of US banks rose by roughly 5pp from 22% in 2008 to 27% in 2015 (4pp on asset-weighted basis). As we document, at the beginning of the great recession, traditional banks kept roughly half of their loans on their balance sheet, and took longer to dispose of the loans they eventually sold. Building up capital buffers would limit the amount of mortgage lending banks can do for portfolio reasons. We find suggestive evidence of this channel in Section IV.C, where we observe that the share of loans held for portfolio reasons declined precipitously early in the period.

Limiting the amount of portfolio loans implicitly reduces the profitability of mortgage lending for traditional banks. Traditional banks' balance sheets are to a large degree funded with government guaranteed deposits. Shadow banks, on the other hand, predominantly sell their originated loans through GSE securitization, and almost never hold them for portfolio reasons. Increased capital requirements indirectly lowered the guaranteed deposits subsidies to traditional banks, potentially contributing to the rise in shadow banks.

Here, we investigate whether banks withdrew from the mortgage market to generate adequate capital buffers over this time period, and whether this build up in capital allowed for the entry of shadow banks. Our unit of analysis is a county. We first compute in which counties banks had to build up the largest capital buffers. Consider a county c and bank b. We first calculate the change in individual bank b's Tier 1 Risk-Based Capital Ratio ($T1RBC\%$) from 2008 to 2015:

$$\Delta CR_b = T1RBC\%_{b2015} - T1RBC\%_{b2008}$$

We aggregate these to the county level by weighing banks by their share of the mortgage market in that county at the beginning of the analysis in 2008:

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

The counties with the largest change in the local capital ratio are those in which banks capital ratios grew the most. We test whether these are the areas in which shadow banks' lending share grew most in the same period:

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

$\Delta Shadow\ Bank\ Lending\ Share_c$ represents the change in the share of shadow bank market shares from 2008 to 2015. We control for other county characteristics in X_c'. Note that by computing differences, we already control for time invariant characteristics of the county akin to including county fixed effects. Ideally we would control for changes in county characteristics during the period; unfortunately these are measured by the census infrequently, so we instead control for characteristics in the year closest to 2008.

The estimates in Table 8 Panel A suggest that counties in which traditional banks increased their risk-based capital buffers by 1pp experienced a 0.54% increase in shadow bank penetration. Given the average increase in Tier-1 Risk-Based Capital ratio of 5pp, this corresponds to a 2.5% increase in shadow bank penetration. This result suggests that shadow banks indeed gained market share in areas in which traditional banks were required to raise their capital buffers

There are broadly three ways in which shadow bank market share can rise: shadow bank lending increases and traditional banks lending decreases; alternatively mortgage lending is increasing overall, and shadow banks grow faster; or, all mortgage lending declines, but the decline of shadow banks is slower. To better understand what drives the changes in market shares, we investigate the changes in the amount of lending. We construct:

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

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

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

and estimate the same specification in eq. (7) replacing the left-hand side variables.

The results in Table 8 (Columns (3)-(8)) show that the growth in capital ratios was accompanied by a contraction in bank lending and expansion in shadow bank lending. Overall, shadow banks did not quite fill the gap left by traditional banks, leading to a decline in overall mortgage lending in most affected counties. 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.

Increases in capital requirements for traditional banks were also targeted more specifically at mortgage lending. Basel III guidelines implemented by the Federal Reserve Board increased the regulatory cost of holding MSR on banks' balance sheets.[25] Because originations and mortgage servicing are complementary activities, a higher cost on servicing would also increase originations

[25] 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.

costs. The idea is that counties, in which banks relied most on MSR to bolster their regulatory capital, will be hardest hit by exit of banks and entry of shadow banks after implementation.

We calculate the origination-weighted MSR as a percent of Tier 1 capital at a county level:

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

We estimate eq. (7) replacing local capital ratio change with local MSR%.

The estimates in Table 8 Panel B support that view. A county with a 1pp greater MSR share of tier 1 capital saw 0.215pp greater shadow bank entry. In scaled terms, counties with a 1 standard deviation (2.24pp) greater MSR percentage of tier 1 capital saw roughly a 0.5pp greater increase in shadow bank share. Because mortgage servicing is largely undertaken by large banks, MSR share and the share of big banks lending are highly correlated, so controlling large banks this the effect nearly disappears. Similar to the overall effect of capital requirements, higher regulatory cost of MSR lead to an increased market share of shadow banks. Decomposing the effect, we find that it is driven by a decline in bank lending, and an increase in shadow bank lending volumes. These results suggest that Basel III results in large banks pulling back from mortgage lending, allowing shadow banks to gain market share.

Basel III was finalized in 2010, and then preceded through several steps before being implemented in 2015. To study how MSR composition of Tier-1 capital changed bank market shares over time, we estimate how the banking share evolved over time across counties as a function of counties' initial MSR share (in 2008):

$$\Delta \mathrm{BankShare}_{ct} = \beta_{0t} + \beta_{1t}\mathrm{MSR}_{c2008} + \varepsilon_{ct.} \text{ between 2008 and 2015,}$$

where $\Delta\mathrm{BankShare}_{ct}$ is the change in bank lending share between t and 2008 and MSR_{c2008} is the county weighted average MSR percent of Tier 1 Capital. This is equiavelnt to estimating regression (7) at the yearly level. The results are presented in Figure 6 where the solid line plots the estimated coefficinets β_{1t}. The results show that affected (high MSR) counties for the first few years faced lower growth in shadow bank market shares relative to unaffected counties (low MSR). That is, bank lending share is higher in high MSR counties. After Basel III was finalized in 2010, the market share of shadow banks in MSR affected regions starts increasing as traditional banks pull back, and this trend continues through 2015. The timing of the decline suggests a tighter link between the regulatory burden faced by traditional banks, and shadow bank entry.

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 less creditworthy borrowers, it may not be surprising that traditional banks tilted lending away from that sector. Because shadow bank activities are more concentrated on new originations, they escaped much of the scrutiny that full-service banks received from regulators and class action lawsuits with respect to their legacy loans.[26]

We next investigate the association between the intensity of lawsuits aimed at traditional banks and the market share of shadow banks. The idea behind this test is to investigate whether shadow banks expanded more in areas in which the legal risks increased for traditional banks. Such exposure may have limited the traditional banks' ability and willingness to serve riskier borrowers. The losses from these lawsuits have a potential knock-on effect of tightening the capital constraints of affected banks

We collect data on large mortgage lawsuit settlements against large traditional banks and shadow banks. 98% of observed lawsuits target traditional banks, likely because the subject matter often concerns activities that pure originators (shadow banks) 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 calculate exposure to mortgage settlements of county c as a weighted average of 2008 lending activity of banks in that county as follows:

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

We estimate whether a higher exposure to lawsuits in a county lead to a larger withdrawal of traditional banks by mirroring the specification in eq.(7):

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

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'. Recall that differencing already controls for time invariant county characteristics, akin to county fixed effects.

The results in Table 8 Panel C show that counties with greater exposure to lawsuit settlements saw an increase in the shadow banks' market shares. The magnitudes are substantial: consider a county with an average additional lawsuit exposure of \$18.61 billion (at the national level) relative to a county with no lawsuit exposure. The former saw an additional 6.5pp (0.351×18.61) increase in

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

shadow banks' market share before controlling for big bank market share, and a 2.3% increase after controlling for big bank market share. These results suggest that traditional banks retreated from counties that faced a larger regulatory burden. We confirm that the effect is indeed driven by a relative decline in traditional bank lending in affected (high lawsuit) counties relative to unaffected (low lawsuit) counties.

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 in Section IV point to significant differences between fintech and non-fintech lenders. Because these shadow bank lenders face the same regulations, the differences are likely driven by technology. This section attempts to shed light on economic forces driving these differences. We 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 loans. A second explanation is that fintech deliver a more convenient mortgage origination experience by requiring less effort from the borrower in the origination process.

A.1 Different Credit Models

Fintech lenders rely on technology to set mortgage interest rates, while non-fintech shadow banks potentially still rely on loan officers to do so. Online lending allows lenders to collect different types of information than would be collected by a loan officer. We want to understand whether fintech lenders' use of different information results in different mortgage pricing models. We do so by examining how much variation in interest rates is explained by standard borrower characteristics (hard information) across lenders.[27] Following Rajan, Seru, and Vig (2015), we regress:

$$rate_{izt} = \beta_1 FICO_i + \beta_2 LTV_i + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \tag{9}$$

We estimate the regressions separately for fintech and non-fintech shadow bank over the 2010-2015 period, and year by year. We use the Fannie Mae and Freddie Mac origination data, because we observe interest rates as well as information on a rich array of loan, property, and borrower

[27] In Appendix A6, we further examine whether fintech and non-fintech lenders' interest rates are better predictors of ex-post performance in terms of default and prepayment. The results suggest that fintech interest rates are better predictors of prepayment.

characteristics. The R^2 from these regressions measures the object of interest: how much of the variation in interest rates is explained the observable borrower characteristics across lender types. A large portion of variation in interest rates arises from nationwide macroeconomic effects. The contribution of these fixed effects to the R^2 does not arise from lenders' models. We therefore difference out all fixed effects, and calculate R^2 of the within regression. In other words, the reported R^2s reflect the explained variation in interest rates once removing time or time-zip average differences.

We present the results in Table 9. Fintech shadow banks use substantially less hard information than non-fintech shadow banks: The R^2 are smaller across all specifications. FICO and LTV alone can explain nearly 25% of the variation in non-fintech interest rates, but less than 16% of the variation in fintech interest rates. To ensure the pattern is robust, we estimate several specifications, using different fixed effects, including more controls, as well as polynomials of controls, to ensure our patterns do not arise because lenders use non-linear models. Even in the most saturated specifications, with the most comprehensive fixed effects and non-linear controls, the R^2 of non-fintech lenders exceed 54%, and is below 52% for fintech lenders. As Panel B shows, these differences are particularly large earlier in the sample, and have shrunk over time as the explanatory power of these variables for non-fintech shadow bank interest rates have decreased to the level of fintech shadow banks.

Comparing fintech lenders to banks, we find similar differences, with R^2 of fintech lenders being lower than traditional banks. The one exception is with the least-controlled version of the regression, where FICO and LTV alone explain roughly 16% of the variation in interest rates for both fintech shadow banks and traditional banks. These differences suggest that while both fintech shadow banks and traditional banks rely on factors besides FICO and LTV, traditional banks appear to rely on hard information beyond FICO and LTV whereas fintech shadow banks appear to rely less on hard information altogether. These results suggest that fintech lenders use substantially different information in setting mortgage interest rates than non-fintech lenders, likely by using other dimensions of "big" data, not available to other lenders.

To test the significance of the R^2 differences between fintech and non-fintech shadow banks, we bootstrap the calculation as follows: We sample with replacement from the set of originated loans. With the randomized sample, we divide the originations into fintech and non-fintech loans and rerun the interest rate regression. We do this for 100 samples. The test statistic is the t-value of the difference in R^2s across the fintech and non-fintech samples. We present the distribution of the bootstrapped R^2 in Figure 7. As can be seen, the R^2 of non-fintech lenders exceed those of fintech lenders.

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 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 14-16 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. We note, however, that at least part of this premium may also reflect relatively higher prepayment risk of these borrowers.[28]

To examine this mechanism in more detail, we focus on conforming mortgages. We divide borrowers into two groups: the dummy variable "High FICO" takes the value of 1 if the borrower's FICO score is in the top 10% of FICO scores for the origination year, and 0 otherwise. We estimate the following regression:

$$rate_{izt} = \beta_s Fintech_{bzt} + \beta_{h\times s} Fintech_{bzt} \times HighFico_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \qquad (10)$$

We are interested in the coefficient on fintech, which captures the difference in interest rates for comparable borrowers with FICO below the highest 10th percentile, and the coefficient on the interaction term, which captures the additional difference in interest rates between fintech and non-fintech lenders for High FICO borrowers.

The results presented in Table 10 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 credit score fintech borrowers pay approximately 0.6 basis points more than borrowers in the ordinary credit score range do for fintech loans. This difference is roughly equivalent to the interest rate difference associated with a 3.5 point FICO differential. Relative to the baseline difference of 11.5 basis points, this estimate corresponds to a 4% increase in the

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

premium of fintech over non-fintech rates. The results suggest that borrowers most likely to value convenience might be willing to pay for the convenience offered by fintech lenders.

The differences become larger in the later part of the sample, between the years 2014 and 2015. As we show in the model below, it was in these years where consumers' appreciation for fintech convenience was at its highest, likely to do technological improvements. Over this period, we find a 17 basis point difference between fintech and non-fintech loans for the lower 90 percentile of FICO scores, with an additional 1.1 basis point difference for the highest FICO scores.

To summarize, we find some evidence that fintech lenders use different technology in determining mortgage rates. In addition, online originations offer convenience, which borrowers appear to value. Among the most price sensitive borrowers, fintech loans have lower interest rates. In contrast, among the borrowers most likely to value convenience, fintech lenders are able to command a premium for their services. It is worth noting though that our evidence is also consistent with the notion that different technology of setting interest rate may have allowed fintech lenders to better price discriminate borrowers.

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

The shadow bank market share in the overall mortgage market grew by more than 20pp in 2008 to 2015 period. Of this increase, about 9pp 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 allows us 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, 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 from lender i is:

$$u_{ib} = -\alpha r_i + q_i + \epsilon_{ib} \tag{11}$$

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 entry 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 changing a bank's marginal cost, regulatory burdens may also reduce traditional banks' activity on the extensive margin. For example, binding capital requirements, risk constrains, or lawsuits may sometimes prevent a traditional bank from lending to a given borrower altogether. We capture this type of regulatory burden through parameter γ_b. If lender i is a bank, its probability of lending to a specific borrower is scaled by a factor γ_b. A higher γ_b captures a relatively unconstrained bank; a lower γ_b captures a relatively constrained bank. γ_b shocks are i.i.d. across lender-borrower pairs. Denote a lender's market share she would have obtained without regulatory burdens as s_i; the actual market share is then $\gamma_i s_i$. These constraints do not affect shadow banks, i.e. for non-fintech and fintech lenders, $\gamma_n = \gamma_f = 1$.

Conditional on being present in a market, a lender sets its interest rate r_i to maximize its expected profit:

$$(r_i - \rho_i)\gamma_i s_i \tag{12}$$

which is a function of the spread it charges over its financing cost and the probability that its offer is accepted.

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

$$\pi_i = (r_i - \rho_i)\gamma_i s_i F - c_i \tag{13}$$

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 ((11) 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 ((12) 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. ((13) equals zero for all lenders i)

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

$$s_i(r_i, q_i; \{r_j, q_j\}) = \frac{\exp(-\alpha r_i + q_i)}{\sum_{j=1}^{N} \exp(-\alpha r_j + q_j)} \tag{14}$$

Recall that the actual market shares of firms depend on their regulatory burden. 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:

$$S_b = \frac{\gamma_b N_b \exp(-\alpha r_b + q_b)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{15}$$

$$S_n = \frac{N_n \exp(-\alpha r_n + q_n)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{16}$$

$$S_f = \frac{N_f \exp(-\alpha r_f + q_f)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)} \tag{17}$$

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 burden of 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.

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 burdens 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,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 $\mathrm{r_{bt}} - \mathrm{y_t}$ 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:

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

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

We next turn to calibrating the differences in quality of services between these lenders using optimal consumer choice (aggregate market share) equations (15)-(17). 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 $(\mathrm{r_{ft}} - \mathrm{r_{nt}})$, 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 $(\mathrm{r}_{\mathrm{it}} - \widetilde{\rho_{it}} - y_t)$ times the quantity of loans $\gamma_{\mathrm{it}} \mathrm{s}_{\mathrm{it}} \mathrm{F}_{\mathrm{t}}$:

$$c_{it} = (\mathrm{r}_{\mathrm{it}} - \widetilde{\rho_{it}} - y_t)\gamma_{\mathrm{it}} \mathrm{s}_{\mathrm{it}} \mathrm{F}_{\mathrm{t}}$$

C. Results

The results of the calibration are shown in Figure 8. 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; for instance, 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.

The answer lies with regulatory burden changing over time -- our estimates suggest that the 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 indicating a progressive recovery of traditional bank mortgage lending. It is not until after 2011 that banks' regulatory position starts deteriorating substantially. We note that the 2011-2015 period of substantial deterioration in our calibrated measure of regulatory burden corresponds to the period of implementation of the Dodd-Frank Act, development of Basel III rules changing the treatment of MSR from the perspective of capital requirements, the establishment of the Consumer Financial Protection Bureau, and increased mortgage lawsuit activity targeted at traditional banks. These results suggest 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.[29]

Recall the findings in Section V.A.2 in which we study the effects of Basel III changing the treatment of MSR from the perspective of capital requirements (Figure 6). The estimates from Figure 6 suggested that 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 patterns obtained in Figure 8 from our model are remarkably similar to those in Figure 6. It is worth noting that this is despite the fact that the model uses a different type of variation than what was exploited earlier.

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 Decomposition

As we document, the shadow bank market share in overall mortgage market grew by more than 20pp in the 2008 to 2015 period. Of this increase, about 9pp are attributable to the growth in fintech

[29] 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. These findings are also consistent with Gete and Reher (2017) who present evidence suggesting that the 2014 U.S. liquidity coverage ratio (LCR) rules has led to a higher FHA market share for nonbanks.

firms. We use our simple calibrated model to infer how much of this growth is attributable to an increased regulatory burden and how much to technology improvements.

First, we ask how the 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, setting up a baseline. We do so by setting both bank regulatory burden 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 9 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 14pp, including a 2.5 percentage point growth occurring in the fintech sector (Figure 9). 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 mortgage sector would have developed if the regulatory constraints would not have tightened, but the technology revolution of fintech had 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 6pp in market share, with non-fintech shadow banks losing roughly 1 percentage point in market share (Figure 9). Therefore, technology alone is responsible for approximately 70% of gains of fintech firms, and 25% of shadow bank growth overall.

The 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. Robustness

This section describes a number of robustness checks concerning lender classification, sample selection, and other concerns that might impact inferences from our earlier analysis.

A. Classification

The classification of a lender as bank or shadow bank is straightforward and based on whether the lender is a depository institution. This classification essentially entirely overlaps with the lender's primary regulator, although we verify this manually. The classification of a shadow bank lender as fintech or non-fintech is potentially more subjective. To overcome any subjectivity in the classification, we utilize multiple independent research assistants (RAs) to cross-validate the classifications; the RAs together with the authors arrive at substantively similar classifications. Where there is disagreement, we take a conservative approach and classify the lender as non-fintech.

Notably, the main classification of fintech versus non-fintech is based on visiting the websites at the time of writing the paper. A potential shortcoming of this approach is that a lender classified as fintech at the time of writing the paper may have operated as a non-fintech at some point during the sample period. To address this concern, we use a web service called the Internet Archive Wayback Machine,[30] which since 2001 has periodically archived websites. This allows us to visit historical versions of the lenders' websites to verify that they were indeed fintech or non-fintech lenders during the sample period. When examining the largest fintech and non-fintech lenders, we find that nearly all lenders classified as fintech in 2016 would have been classified as fintech between 2008 and 2010, and all lenders classified as non-fintech in 2016 would have been non-fintech in 2008-2010.[31]

Finally, we note that while HMDA identifies all originators, the Fannie Mae and Freddie Mac datasets only identify sellers which have comprised at least 1% of total sales to the GSE within a given quarter. On average there are between 15 and 20 uniquely identified Fannie/Freddie lenders in a given quarter. In our sample period, we identify 55 unique lenders comprising between 50% and 85% of the entire market share in a given quarter. As we will discuss next, the qualitative inferences in the paper do not change when we only isolate the sample to the largest lenders.

The entire classification procedure is described in detail in online Appendix A8.

B. Sample Selection

We rerun the tests on a number of samples. In particular, we (1) restrict the HMDA data to the top 50 lenders, (2) look only at retail originations in the Fannie Mae and Freddie Mac data, (3) exclude

[30] https://archive.org/web/

[31] The wayback machine does not allow us to fully verify that the historical on-line application process would result in a firm offer rate, since the archived on-line pages of lenders are inactive. However, we note that our results are robust to restricting the fintech classification to largest market participants that account for vast majority of fintech lending in our sample and that were known to offer firm offer rates through their on-line lending platforms during our entire sample period.

Quicken Loans from the sample, and (4) run the tests on the 2010-2013 (rather than 2010-2015) sample. In all cases the results are substantively unchanged.

Top 50 Lenders. We rerun all tests involving HMDA data, which includes borrower and geographic characteristics, as well as market share changes, looking only at the largest 50 lenders as of 2010. This restriction makes the HMDA data more comparable to the Fannie Mae and Freddie Mac data, in that it focuses only on the largest lenders. Appendix A7 shows market shares of fintech and non-fintech shadow banks, as well as the buyers of their loans. When restricting the sample to the top 50 lenders, the results are qualitatively unchanged.

Retail Originations. The Fannie Mae and Freddie Mac data identify by name the largest *sellers* to the respective GSE, rather than the originator directly. Therefore, one worry is that we are comparing retail lending, in which the originator and the seller are the same entity, to wholesale lending, in which the seller is bundles loans originated by other entities. Fintech lenders are almost entirely retail lenders, while many non-fintech lenders are wholesale lenders. To address concerns that our results are driven by differences in wholesale and retail lending, we restrict our Fannie Mae and Freddie Mac sample to only retail originations and rerun our tests. With this restriction, the results are unchanged.

Excluding Quicken Loans. The largest online lender is, by far, Quicken Loans. In order to test whether the findings regarding fintech shadow banks are restricted to Quicken Loans only, we rerun a number of tables excluding Quicken Loans sales from the sample. Appendix A9 shows key tables from these results. While excluding Quicken Loans substantially reduces the power of our tests, we find on the restricted sample that most substantive results hold: Fintech still appears to specialize in refinances; Fintech lenders are significantly faster that banks in selling originated loans (though not statistically significantly so); Fintech shadow banks charge significantly higher interest rates than non-fintech shadow banks, and the interest rates they charge are significantly less-explained by borrower observable characteristics. Having said that, fintech lenders excluding Quicken do not charge as high rates relative to non-fintech lenders as they did in Table 6. Consequently, shadow banks all together as a group, excluding Quicken, appear to charge lower, not higher, rates than banks.

2010-2013 Sample. We restrict the sample period to 2010-2013 to test whether the results are driven by financial technology that has only recently improved. The results are unchanged.

D. Other Robustness

To conclude this section, we highlight a number of other robustness checks. First, while we show that Fintech lenders charge significantly higher interest rates, it is possible that they compensate borrowers with lower origination fees or points. While comprehensive data is not available on origination fees, manual investigation appears to show that this is not the case; in fact, online reviews often cite high origination fees as a problem regarding Quicken Loans. See Appendix A4 for details.

Second, we run similar tests on the FHA dataset to test whether interest rates differ significantly. A drawback of this analysis is that we do not observe borrower credit score, so there may be uncontrolled-for correlation between the creditworthiness of borrowers and their selection into fintech or non-fintech borrowing. With this caveat, unlike in the conforming loans analysis, we find that fintech lenders charge slightly lower interest rates. Lower interest rates being charged to this riskiest segment of borrowers is consistent with idea that these borrowers do not value the convenience that lower-risk borrowers value, and rather, fintech lenders are able to pass on cost savings to this segment of borrowers.

Finally, we test whether there are differential relationships between interest rates and loan performance across lender types. If a lender's model more accurately prices risk, there interest rate should be more reflective of the probability of default or prepayment. This test follows the test used in Rajan, Seru, and Vig (2015), and is described in detail in Appendix A6. We find no differential relationship between interest rates and default across lender types, but do find that fintech interest rates are significantly more predictive of prepayment than other lender types.

X. Conclusion

The residential mortgage market has changed dramatically in the years following the financial crisis and the 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.

Shadow bank lenders' market share among all residential mortgage lending has grown from roughly 30% in 2007 to 50% in 2015. We argue that traditional banks face regulatory restrictions that have led them to retreat from this market. Shadow banks, which face substantially lower regulatory constraints, have filled this gap. This phenomenon is largest among the high-risk, low-creditworthiness FHA borrower segment, as well as among high unemployment and high-minority areas; loans that traditional banks may be unable hold on constrained and highly monitored balance sheets. Second, there has been significant geographical heterogeneity and shadow banks are significantly more likely to expand their market shares in those markets where banks faced the most regulatory constraints. Our quantitative assessment indicates that increasing these constraints can account for about 70% of the recent shadow bank growth.

Fintech lenders, for which the origination process takes place nearly entirely online, have grown from roughly 3% market share in 2007 to 12% market share in 2015, representing a significant fraction of shadow bank market share growth. We identify two forces associated with online technology. Fintech lenders make use of different information to set interest rates, which they acquire through the lending process. 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. Our model suggests that 30% of the recent shadow bank growth is due to the disruption caused by online origination.

Finally, we conclude by cautioning against a normative interpretation of our results. While the regulation of the traditional banking sector is potentially responsible the rise of shadow banks, it is unclear whether this shift in mortgage origination is problematic. On the one hand, because shadow banks originate-to-distribute, rather than hold mortgages on their balance sheets, they may be preferred as originators from the perspective of banking system stability. This is especially so since shadow banks do not rely on guaranteed deposits as a direct source of financing. On the other hand, while fintech lenders have the potential to address ongoing regulatory challenges raised by Philippon (2016), in their current state, fintech and non-fintech shadow bank lenders funding is tightly tethered to the ongoing operation of GSEs and the FHA – institutions plagued by political economy surrounding implicit and explicit government guarantees. How these considerations weigh against each other and impact 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	Shadow Banks Fintech
% Conventional	76.9%	83.2%	64.31%	62.0%	74.3%
% FHA	15.8%	11.0%	25.33%	26.9%	18.7%
% Other	7.3%	5.8%	10.36%	11.1%	7.0%
Count	46,431,132	30,943,694	15,487,438	12,575,694	2,911,744

Panel B: Loan disposition based on 2007-2015 HMDA

	All Lenders	Traditional Banks	Shadow Banks	Shadow Banks Non-Fintech	Shadow Banks Fintech
Not Sold	23.32%	31.15%	7.50%	6.80%	10.53%
Sold To:					
Fannie Mae	23.37%	23.68%	22.80%	20.25%	33.85%
Freddie Mac	14.63%	17.58%	8.84%	8.25%	11.35%
Ginnie Mae	10.55%	9.12%	13.47%	13.19%	14.66%
Private Securitization	0.68%	0.76%	0.49%	0.57%	0.15%
Commercial Bank	9.50%	5.38%	17.71%	19.19%	11.29%
Ins/CU/Mortgage Bank	5.93%	2.44%	12.89%	12.34%	15.26%
Affiliate Institution	4.75%	6.70%	0.88%	0.99%	0.44%
Other	7.26%	3.19%	15.43%	18.42%	2.49%
Count	46,431,132	30,943,694	15,487,438	12,575,694	2,911,744

Table 2: Time Between Origination and Sale

Table 2 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 2015. 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^{***}	-0.100^{***}	-	-	-	-
	(-52.77)	(-52.67)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0812^{***}	-0.0803^{***}	-	-
	-	-	(-39.12)	(-39.37)	-	-
Fintech Shadow Bank	-	-	-0.180^{***}	-0.173^{***}	-0.0846^{***}	-0.0842^{***}
	-	-	(-63.17)	(-60.18)	(-28.21)	(-26.84)
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	4075985	4071465	4075985	4071465	1187390	1185846
R^2	0.0349	0.0491	0.0368	0.0507	0.0603	0.0931

Table 3: 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)-(2)), a non-fintech shadow bank (Columns (3)-(4)), a fintech lender among all lenders (Columns (5)-(6)), or a fintech lender among shadow banks (Columns (7)-(8)) on borrower characteristics over the period 2007-2015. Odd columns include year fixed effects. Even columns include year-county fixed effects. 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	30,943,694	15,487,438	12,575,694	2,911,744	2,300,721	2,182,654	1,670,680	511,974
Median Income	$83,000	$79,000	$78,000	$82,000	$89,000	$80,000	$79,000	$82,000
Male	66.98%	67.61%	68.94%	61.87%	65.64%	65.94%	69.01%	55.92%
Race								
Native American	0.52%	0.50%	0.50%	0.50%	0.59%	0.57%	0.56%	0.62%
Asian	5.21%	5.79%	6.09%	4.50%	5.63%	5.50%	5.79%	4.55%
African American	4.72%	5.59%	5.85%	4.48%	4.83%	6.34%	6.80%	4.86%
Native Hawaiian	0.36%	0.42%	0.43%	0.34%	0.36%	0.45%	0.49%	0.33%
White	78.04%	76.47%	77.76%	70.90%	77.10%	74.93%	78.17%	64.38%
Other/Unknown	11.15%	11.23%	9.36%	19.27%	11.49%	12.19%	8.19%	25.26%
Loan Purpose								
Home improvement	6.34%	0.68%	0.78%	0.22%	9.80%	1.14%	1.35%	0.47%
Refinancing	60.40%	52.69%	47.26%	76.13%	44.67%	47.44%	40.87%	68.88%

Table 3 [continued]

Panel B: Regressions (HMDA)

	(1) Shadow Bank	(2) Shadow Bank	(3) Non-Fintech	(4) Non-Fintech	(5) Fintech	(6) Fintech	(7) Fintech	(8) Fintech
Sample	All Lenders						Shadow Banks Only	
Income (000s)	-0.00857***	-0.00673***	-0.00692***	-0.00468***	-0.00165***	-0.00206***	0.00138***	-0.00197***
	(0.0000462)	(0.0000453)	(0.0000440)	(0.0000431)	(0.0000266)	(0.0000266)	(0.000107)	(0.000106)
Loan Amount (000s)	0.00835***	0.000881***	0.00931***	0.000910***	-0.000965***	-0.0000288	-0.0152***	-0.00511***
	(0.0000392)	(0.0000423)	(0.0000373)	(0.0000402)	(0.0000226)	(0.0000249)	(0.0000799)	(0.0000895)
Race (Omitted Category = White)								
Native American	-0.227**	-1.362***	-0.821***	-2.028***	0.593***	0.666***	1.170***	1.879***
	(0.0877)	(0.0861)	(0.0835)	(0.0820)	(0.0506)	(0.0506)	(0.138)	(0.136)
Asian	3.923***	1.204***	4.384***	1.498***	-0.461***	-0.294***	-3.313***	-2.288***
	(0.0276)	(0.0283)	(0.0263)	(0.0269)	(0.0159)	(0.0166)	(0.0414)	(0.0421)
Black	0.405***	0.296***	0.338***	0.346***	0.0676***	-0.0501**	0.000883	0.171***
	(0.0300)	(0.0304)	(0.0285)	(0.0290)	(0.0173)	(0.0179)	(0.0448)	(0.0456)
Hawaiian	1.363***	-0.696***	1.630***	-0.774***	-0.267***	0.0776	-0.798***	0.680***
	(0.103)	(0.101)	(0.0980)	(0.0961)	(0.0594)	(0.0593)	(0.153)	(0.151)
Unknown	7.438***	5.663***	3.716***	1.958***	3.723***	3.705***	5.309***	5.925***
	(0.0292)	(0.0286)	(0.0278)	(0.0272)	(0.0168)	(0.0168)	(0.0407)	(0.0400)
NA	-24.98***	-20.46***	-26.68***	-22.71***	1.706***	2.247***	-6.432***	-4.702***
	(0.816)	(0.794)	(0.776)	(0.756)	(0.470)	(0.467)	(1.463)	(1.429)
Sex (Omitted Category = Male)								
Female	0.163***	-0.113***	-0.204***	-0.535***	0.366***	0.422***	0.896***	1.110***
	(0.0146)	(0.0143)	(0.0139)	(0.0136)	(0.00841)	(0.00838)	(0.0225)	(0.0220)
Unknown	-4.636***	-4.091***	-8.296***	-7.846***	3.660***	3.755***	15.78***	15.33***
	(0.0375)	(0.0366)	(0.0357)	(0.0348)	(0.0216)	(0.0215)	(0.0556)	(0.0545)
NA	16.27***	16.38***	19.76***	19.74***	-3.487***	-3.362***	-8.278***	-8.503***
	(0.734)	(0.715)	(0.699)	(0.681)	(0.424)	(0.420)	(0.709)	(0.692)
Purpose (Omitted Category = Purchase)								
Home Improvement	-13.26***	-12.18***	-12.25***	-11.40***	-1.011***	-0.782***	-6.862***	-5.399***
	(0.0327)	(0.0323)	(0.0311)	(0.0307)	(0.0189)	(0.0190)	(0.116)	(0.114)
Refinance	-2.056***	-1.792***	-7.965***	-7.839***	5.908***	6.047***	18.24***	18.14***
	(0.0143)	(0.0141)	(0.0136)	(0.0134)	(0.00823)	(0.00831)	(0.0212)	(0.0213)
Purchaser (Omitted Category = Held)								
Fannie Mae	20.65***	19.04***	15.66***	13.96***	4.995***	5.082***	-5.948***	-4.915***
	(0.0188)	(0.0187)	(0.0179)	(0.0178)	(0.0109)	(0.0110)	(0.0414)	(0.0415)
Ginnie Mae	19.46***	19.03***	12.96***	12.51***	6.504***	6.520***	-5.474***	-5.567***
	(0.0333)	(0.0326)	(0.0316)	(0.0310)	(0.0192)	(0.0192)	(0.0515)	(0.0512)
Freddie Mac	8.171***	7.333***	7.620***	6.654***	0.551***	0.679***	-9.832***	-8.992***
	(0.0212)	(0.0210)	(0.0202)	(0.0199)	(0.0122)	(0.0123)	(0.0485)	(0.0484)
Farmer Mac	64.94***	59.91***	65.85***	59.75***	-0.903	0.159	-21.07***	-16.13***
	(1.094)	(1.067)	(1.041)	(1.015)	(0.631)	(0.627)	(1.097)	(1.075)
Private Securitization	9.693***	8.028***	11.82***	10.11***	-2.123***	-2.081***	-16.40***	-15.03***
	(0.0751)	(0.0735)	(0.0715)	(0.0700)	(0.0433)	(0.0432)	(0.142)	(0.142)
Bank	48.21***	46.72***	42.39***	40.79***	5.824***	5.923***	-13.54***	-13.08***
	(0.0255)	(0.0253)	(0.0243)	(0.0240)	(0.0147)	(0.0149)	(0.0424)	(0.0429)
Insr or Fnce Co.	57.96***	56.34***	43.68***	41.76***	14.29***	14.57***	-3.679***	-2.688***
	(0.0298)	(0.0294)	(0.0284)	(0.0280)	(0.0172)	(0.0173)	(0.0444)	(0.0448)
Affiliate	-2.121***	-3.004***	-1.137***	-1.920***	-0.983***	-1.084***	-13.48***	-12.39***
	(0.0327)	(0.0325)	(0.0311)	(0.0309)	(0.0189)	(0.0191)	(0.107)	(0.107)
Other	58.01***	55.87***	57.20***	54.89***	0.807***	0.972***	-20.90***	-20.12***
	(0.0279)	(0.0276)	(0.0265)	(0.0263)	(0.0161)	(0.0163)	(0.0432)	(0.0439)
Loan Type (Omitted Category = Conventional)								
FHA	9.418***	9.242***	9.085***	8.938***	0.332***	0.304***	-1.755***	-1.972***
	(0.0249)	(0.0245)	(0.0237)	(0.0233)	(0.0143)	(0.0144)	(0.0301)	(0.0299)
VA	2.331***	3.189***	2.717***	3.237***	-0.386***	-0.0475*	-1.909***	-1.713***
	(0.0361)	(0.0360)	(0.0344)	(0.0343)	(0.0209)	(0.0212)	(0.0461)	(0.0464)
FSA/RHS	-3.036***	-0.660***	-0.205***	2.484***	-2.832***	-3.144***	-5.681***	-6.684***
	(0.0566)	(0.0563)	(0.0538)	(0.0536)	(0.0326)	(0.0331)	(0.0760)	(0.0766)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year x County FE	No	Yes	No	Yes	No	Yes	No	Yes
N	43138392	43138392	43138392	43138392	43138392	43138392	14340698	14340698
R^2	0.241	0.281	0.223	0.265	0.059	0.074	0.133	0.178

Table 4: Shadow Bank Presence and the Borrower and Loan Characteristics: Conforming Loans

Table 4 shows the results of a linear probability model, specifications (1) and (2), regressing whether the lender is a shadow bank (Columns (1)-(2)), a non-fintech shadow bank (Columns (3)-(4)), a fintech lender among all lenders (Columns (5)-(6)), or a fintech lender among shadow banks (Columns (7)-(8)) on individual characteristics, using the pooled Fannie Mae and Freddie Mac Data for the period 2010-2015. Odd columns include quarter fixed effects only; even columns include zip-quarter fixed effects. Loan purpose dummies (Refinance, Investment/Second Home) use Purchase and Primary Residence as the base category. 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) Non-Fintech	(4) Non-Fintech	(5) Fintech	(6) Fintech	(7) Fintech	(8) Fintech
Sample			All Lenders				Shadow Banks Only	
Loan Amount	0.0000100***	0.00000748***	0.0000103***	0.00000846***	-0.000000292***	-0.000000975***	-0.0000122***	-0.0000104***
	(90.27)	(55.75)	(99.88)	(67.29)	(-5.04)	(-14.19)	(-52.91)	(-37.45)
Loan Term (Months)	0.0436***	-0.00237***	0.0321***	-0.000162	0.0115***	-0.00221***	0.00515***	-0.0176***
	(212.38)	(-10.78)	(168.56)	(-0.80)	(116.49)	(-20.48)	(10.18)	(-30.33)
Loan-to-Value	-0.0608***	-0.0414***	-0.0400***	-0.0295***	-0.0208***	-0.0119***	-0.0392***	-0.0293***
	(-58.29)	(-38.33)	(-41.31)	(-29.35)	(-39.71)	(-21.43)	(-17.58)	(-12.62)
Debt-to-Income	0.0606***	0.0517***	0.0268***	0.0225***	0.0338***	0.0292***	0.102***	0.0780***
	(41.09)	(35.71)	(19.48)	(16.60)	(45.73)	(39.44)	(32.92)	(25.84)
FICO	-0.0186***	-0.0207***	0.000627	-0.00167***	-0.0192***	-0.0191***	-0.0519***	-0.0416***
	(-51.68)	(-59.23)	(1.90)	(-5.15)	(-93.99)	(-94.54)	(-71.09)	(-58.69)
Investment/Secondary Property	-1.333***	-2.431***	-0.0902*	-0.772***	-1.243***	-1.659***	-3.359***	-4.226***
	(-30.50)	(-54.68)	(-2.22)	(-18.63)	(-56.08)	(-71.48)	(-37.47)	(-46.32)
Refinance	-0.623***	1.503***	-2.484***	-0.822***	1.862***	2.326***	8.083***	6.832***
	(-21.90)	(51.08)	(-93.23)	(-30.19)	(133.10)	(141.09)	(138.63)	(105.76)
First-Time Buyer	-5.805***	-4.725***	-1.808***	-0.847***	-3.997***	-3.878***	-11.79***	-11.78***
	(-139.23)	(-113.69)	(-45.56)	(-21.40)	(-213.31)	(-200.91)	(-148.39)	(-147.96)
Has Mtg. Insurance	1.282***	0.900***	0.597***	0.349***	0.685***	0.551***	2.637***	2.023***
	(27.64)	(19.91)	(13.83)	(8.27)	(27.47)	(22.19)	(28.96)	(22.73)
Zip x Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
N	8480852	8480851	8480852	8480851	8480852	8480851	1946017	1946017
R^2	0.0709	0.135	0.0404	0.101	0.0364	0.0736	0.0581	0.162

Table 5: Shadow Bank and Fintech Penetration and Regional Characteristics

Table 5 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

	All	Shadow Bank		Fintech	
Median Values	Counties	Bottom Quartile	Top Quartile	Bottom Quartile	Top Quartile
Median Household Income	$45,114.00	$44,587.00	$46,949.00	$48,160.00	$41,101.00
Population Density	42.7	35.6	44.1	55.3	19.1
% with less than 12th grade education	13.10%	11.80%	15.35%	10.80%	17.00%
% with Bachelor degree or higher	18.20%	17.70%	18.20%	20.00%	15.40%
% African American	2.10%	1.06%	2.83%	1.35%	1.81%
% Hispanic	3.74%	2.40%	8.80%	3.39%	4.07%
Unemployment Rate	7.00%	6.40%	7.50%	6.30%	7.20%
% living in Same House >= 1 year	86.90%	87.60%	86.19%	86.74%	87.25%
Herfindahl	0.09761	0.14843	0.07831	0.11564	0.11421
# Lenders	39.00	29.00	50.00	45.00	22.00
% of FHA Origination loans	16.28%	12.50%	18.71%	13.58%	17.76%
Population	25930.00	20913.00	33417.00	34184.00	13472.00
% with less than 35K salary	26.70%	27.10%	25.70%	24.80%	29.95%

Table 5 [continued]

Panel B: Regressions

	(1) % Shadow Banks	(2) % Shadow Banks	(3) % Shadow Banks	(4) % Fintech	(5) % Fintech	(6) % Fintech
Med HH Income	0.000199***	0.000159***	0.000135***	-0.0000368***	-0.0000309**	0.00000211
	(0.0000224)	(0.0000221)	(0.0000231)	(0.00000944)	(0.00000951)	(0.00000955)
Pop Den	-0.000620***	-0.000606***	-0.000665***	-0.000256***	-0.000258***	-0.000229***
	(0.000146)	(0.000143)	(0.000144)	(0.0000616)	(0.0000614)	(0.0000597)
% Edu < 12th	0.186***	0.147**	0.192***	0.0817***	0.0874***	0.0780***
	(0.0469)	(0.0458)	(0.0462)	(0.0197)	(0.0197)	(0.0191)
% >= Bachelors	0.0743*	0.0459	-0.0263	-0.00912	-0.00493	0.0522***
	(0.0339)	(0.0331)	(0.0350)	(0.0143)	(0.0142)	(0.0145)
% African American	0.0511***	0.0414**	0.0376*	0.0219***	0.0233***	0.0302***
	(0.0151)	(0.0147)	(0.0149)	(0.00634)	(0.00633)	(0.00617)
% Hispanic	0.259***	0.268***	0.239***	0.0860***	0.0846***	0.0979***
	(0.0170)	(0.0166)	(0.0169)	(0.00714)	(0.00713)	(0.00698)
Unemp Rate	0.450***	0.321***	0.252***	-0.119***	-0.100***	0.00145
	(0.0631)	(0.0623)	(0.0654)	(0.0265)	(0.0268)	(0.0271)
Same home >= 1yr	-0.100*	-0.0493	-0.0565	0.114***	0.106***	0.0872***
	(0.0444)	(0.0435)	(0.0440)	(0.0187)	(0.0187)	(0.0182)
% FHA	0.288***	0.259***	0.271***	0.0744***	0.0788***	0.0848***
	(0.0213)	(0.0209)	(0.0210)	(0.00894)	(0.00897)	(0.00870)
Herfindahl	-	-19.81***	-	-	2.922***	-
	-	(1.549)	-	-	(0.666)	-
# Lenders	-	-	0.0584***	-	-	-0.0355***
	-	-	(0.00605)	-	-	(0.00250)
Constant	12.15**	14.83***	12.47**	-2.647	-3.042	-2.845
	(4.124)	(4.026)	(4.065)	(1.735)	(1.732)	(1.682)
N	3131	3131	3131	3131	3131	3131
R^2	0.256	0.293	0.277	0.176	0.181	0.226

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

Table 6 shows the results of regression (5) using Fannie Mae and Freddie Mac loans from 2010-2015. 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)	(2)	(3)	(4)	(5)	(6)
	Interest Rate	Interest Rate	Interest Rate	Interest Rate	Interest Rate	Interest Rate
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	0.00665***	0.00714***	-	-	-	-
	(5.19)	(8.33)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0281***	-0.0242***	-	-
	-	-	(-20.48)	(-27.42)	-	-
Fintech Shadow Bank	-	-	0.143***	0.129***	0.163***	0.144***
	-	-	(87.68)	(101.99)	(91.09)	(113.17)
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	8485573	8480376	8485573	8480376	1946802	1943693
R^2	0.598	0.808	0.601	0.811	0.585	0.807

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

Table 7 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	0.0196^{***}	0.0208^{***}	-	-	-	-
	(3.90)	(4.11)	-	-	-	-
Non-Fintech Shadow Bank	-	-	0.0116^{*}	0.0236^{***}	-	-
	-	-	(2.15)	(4.34)	-	-
Fintech Shadow Bank	-	-	0.0557^{***}	0.00795	0.0307^{*}	-0.0286^{*}
	-	-	(4.66)	(0.67)	(2.33)	(-2.04)
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	1151439	1149115
R^2	0.000359	0.0112	0.000362	0.0112	0.000609	0.0348

Panel B: Prepayment

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid	(5) Prepaid	(6) Prepaid
Sample	All Lenders				Shadow Banks Only	
Shadow Bank	2.469^{***}	1.823^{***}	-	-	-	-
	(20.31)	(23.38)	-	-	-	-
Non-Fintech Shadow Bank	-	-	1.456^{***}	0.713^{***}	-	-
	-	-	(10.71)	(8.94)	-	-
Fintech Shadow Bank	-	-	7.054^{***}	6.757^{***}	5.675^{***}	6.358^{***}
	-	-	(34.50)	(34.23)	(26.48)	(30.27)
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	1151439	1149115
R^2	0.0566	0.151	0.0571	0.152	0.0594	0.155

Table 8: Regulatory Activity and Shadow Bank Market Shares

Table 8 shows the result of regressions (7) and (8) 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. Columns (1) and (2) show changes in shadow bank market share from 2008 to 2015. Columns (3)-(4) show changes in all lending from 2008 to 2015 as a fraction of all 2008 lending; Columns (5)-(6) show changes in bank lending from 2008 to 2015 as a fraction of all 2008 lending; Columns (7)-(8) show changes in shadow bank lending from 2008 to 2015 as a fraction of all 2008 lending. All columns include county level census demographic controls; Columns (2), (4), (6), and (8) include the 2008 share of big bank lending. The left-hand-side variable is in units of percent. t-statistics 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
	(8.331)	(7.956)	(-1.776)	(-2.154)	(-4.377)	(-4.509)	(2.285)	(1.772)
Big Bank Share	-	17.7***	-	57.0***	-	13.9*	-	43.1***
	-	(8.157)	-	(6.643)	-	(2.344)	-	(9.390)
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
	(3.536)	(0.358)	(0.473)	(-2.537)	(-1.791)	(-3.136)	(3.156)	(-0.675)
Big Bank Share	-	18.0***	-	71.3***	-	24.8***	-	46.6***
	-	(7.563)	-	(7.683)	-	(3.851)	-	(9.376)
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
	(7.163)	(2.214)	(-0.966)	(-2.682)	(-4.099)	(-4.123)	(3.464)	(0.282)
Big Bank Share	-	21.2***	-	40.9***	-	8.1	-	32.7***
	-	(8.314)	-	(3.815)	-	(1.101)	-	(5.767)
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 9: Determinants of Interest Rates

Table 9 shows the R^2 of observables for different specifications of regression (9). 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 2015 for the banks shadow bank, non-fintech, and fintech subsamples. Non-linear controls include third-order polynomials of all observables. Tests of significance of R^2 are bootstrapped. Panel B shows year-by-year regressions with (linear) FICO, LTV controls and Quarter FE only.

Panel A: R^2 of Pooled Regressions, 2010-2015

Specification				Full Sample		Shadow Bank Sample		
Controls	Quarter FE	Zip-Quarter FE	Lender FE	Bank	Shadow Bank	Non-Fintech	Fintech	(Non-Fintech – Fintech)
FICO, LTV	Y	N	N	0.159	0.234	0.249	0.159	0.090***
FICO, LTV	N	Y	N	0.0888	0.103	0.109	0.0837	0.0253***
All	Y	N	N	0.547	0.558	0.586	0.519	0.067***
All	N	Y	N	0.507	0.476	0.500	0.465	0.035***
Non-Linear	Y	N	N	0.588	0.596	0.621	0.563	0.058***
Non-Linear	N	Y	N	0.553	0.521	0.544	0.513	0.031***
Non-Linear	N	Y	Y	0.559	0.533	0.542	0.520	0.022***

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	0.184	0.194	0.156
2011	0.203	0.385	0.405	0.156
2012	0.157	0.330	0.368	0.099
2013	0.154	0.240	0.242	0.182
2014	0.177	0.181	0.186	0.188
2015	0.170	0.202	0.220	0.177

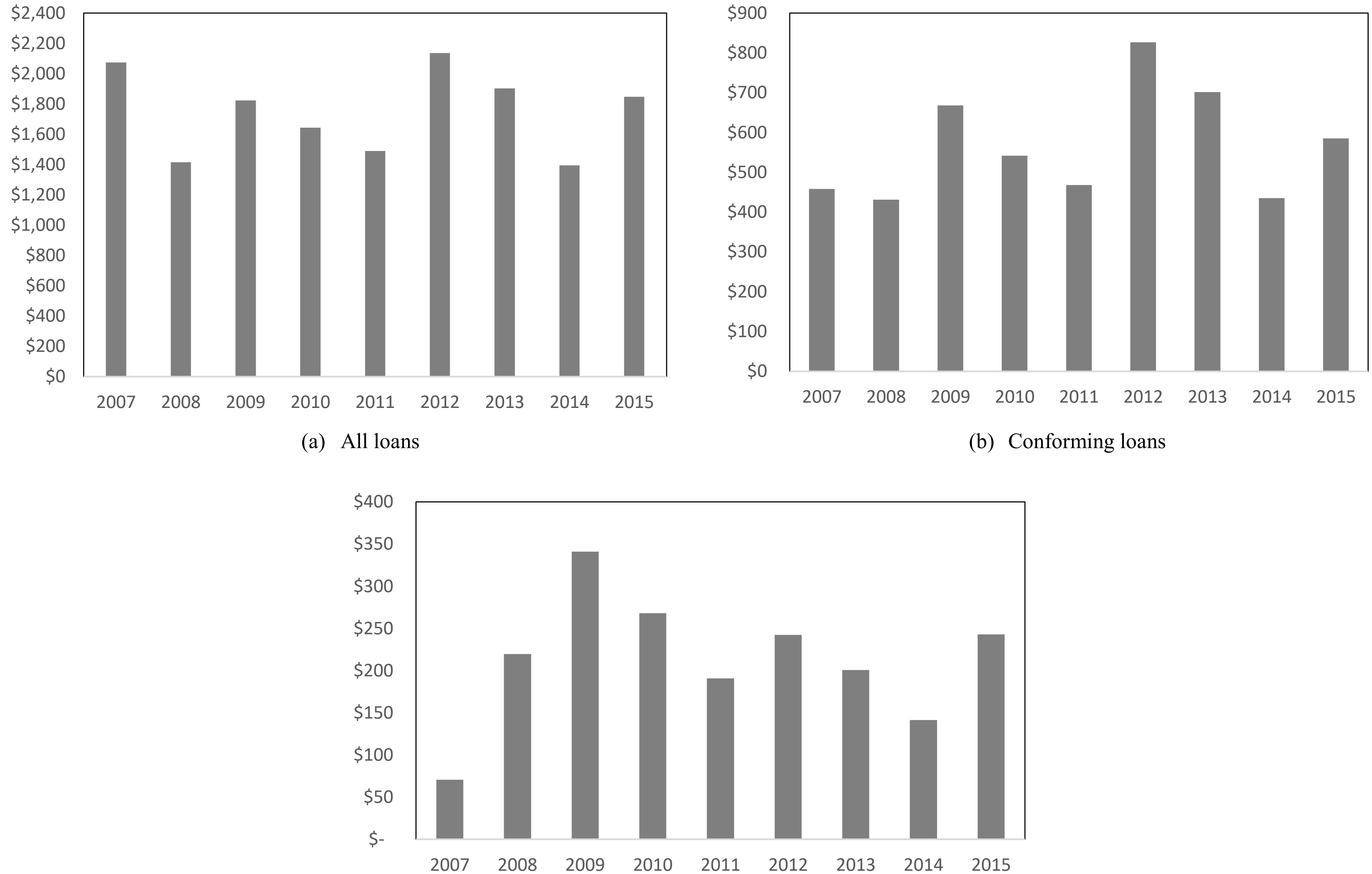
Table 10: Fintech Cost and Convenience

Table 10 shows the results of regression (10). Data is from Fannie Mae and Freddie Mac Shadow Bank originations between 2010 and 2015. High FICO is a dummy variable for borrowers with FICO in the top decile for the year. Columns (1)-(2) show the results for the full sample, 2010-2015. Columns (3)-(4) show the results for the early period, 2010-2013. Columns (5)-(6) show the results for the late sample, 2014-2015. All columns include borrower and loan controls. Columns (1), (3), and (5) include quarter fixed effects; Columns (2), (4), and (6) include quarter-zip 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; t-statistics are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Full (2010-2015)		Early (2010-2013)		Late (2014-2015)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Rate	Rate	Rate	Rate	Rate	Rate
Fintech	0.156***	0.143***	0.140***	0.122***	0.172***	0.166***
	(121.33)	(112.12)	(77.41)	(70.28)	(99.07)	(97.99)
High FICO x Fintech	0.00574***	0.00338*	0.00905***	0.00770***	0.0111***	0.00948***
	(3.59)	(2.16)	(4.08)	(3.55)	(5.32)	(4.55)
Borrower and Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	1946017	1943693	1151009	1149115	795008	794578
R^2	0.792	0.808	0.826	0.841	0.682	0.698

Figure 1: Total Residential Mortgage Originations

Panel A shows total dollars in billions 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.



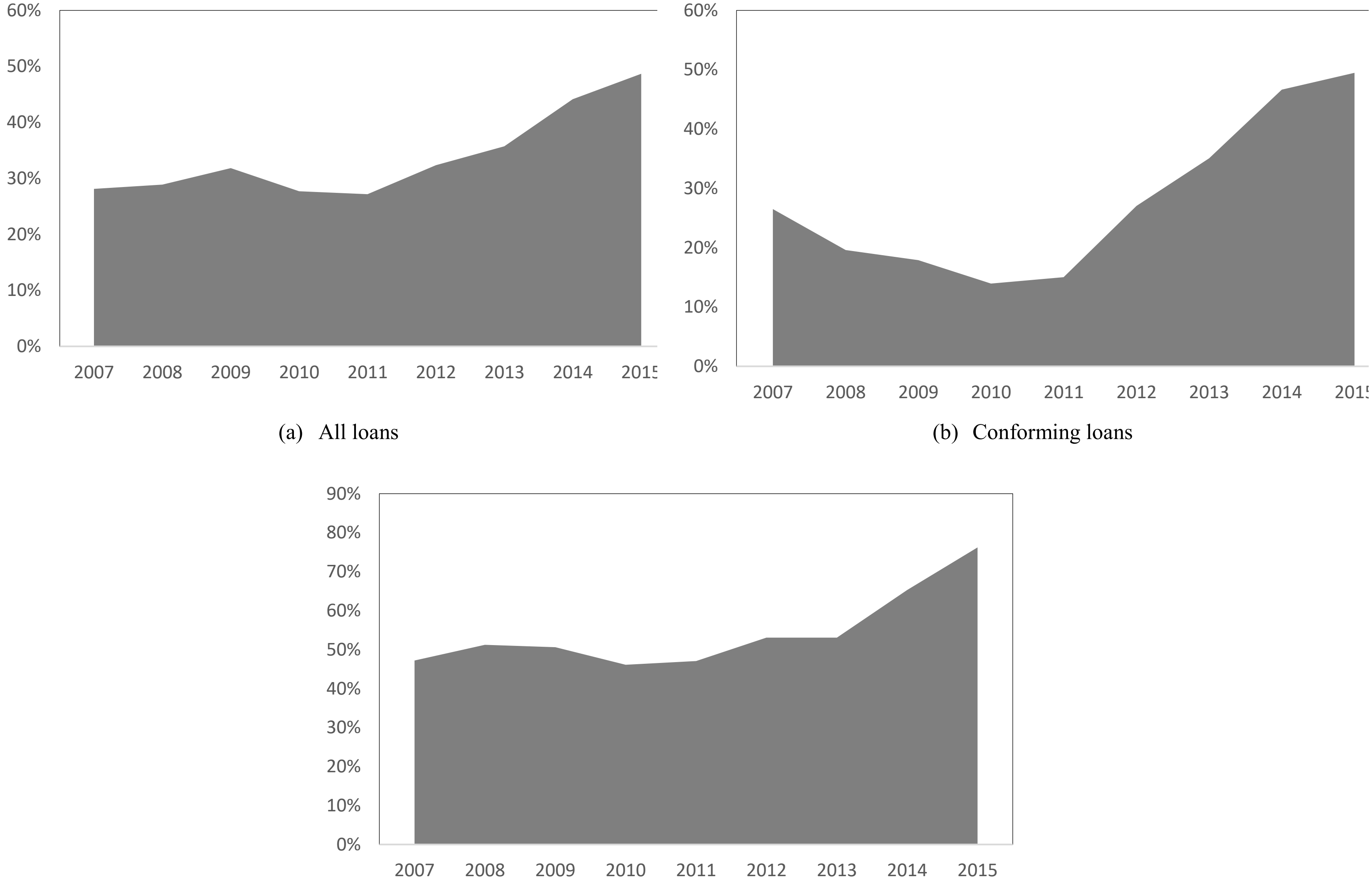
(a) All loans

(b) Conforming loans

(c) FHA loans

Figure 2: Shadow Bank Origination Shares

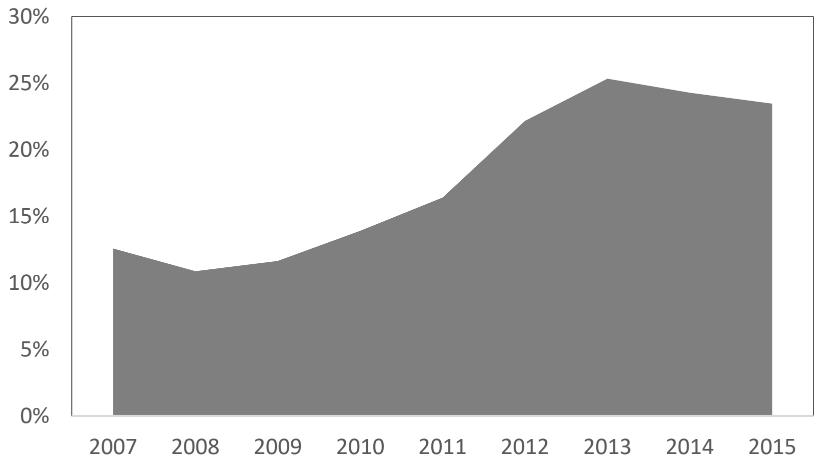
Panel A shows shadow bank origination shares as a fraction of total originations for all mortgages in HMDA between 2007 and 2015. Panel B shows shadow bank origination shares among conforming mortgages. Panel C shows the shadow bank origination share among FHA mortgages.



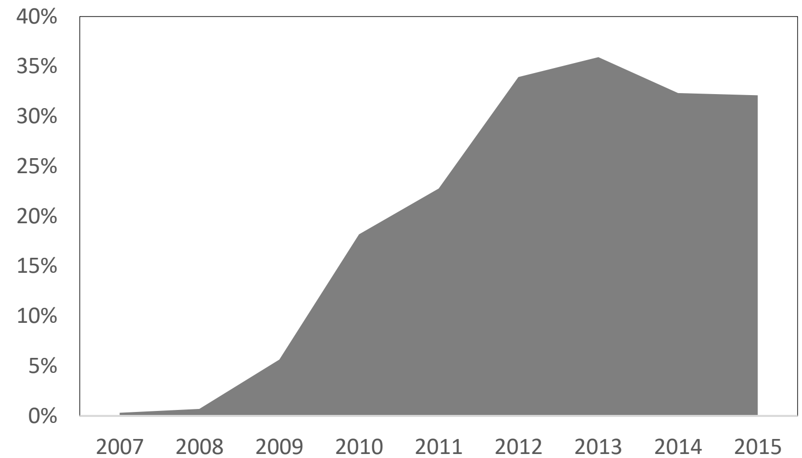
(c) FHA loans

Figure 3: Fintech Origination Shares of Shadow Bank Originations

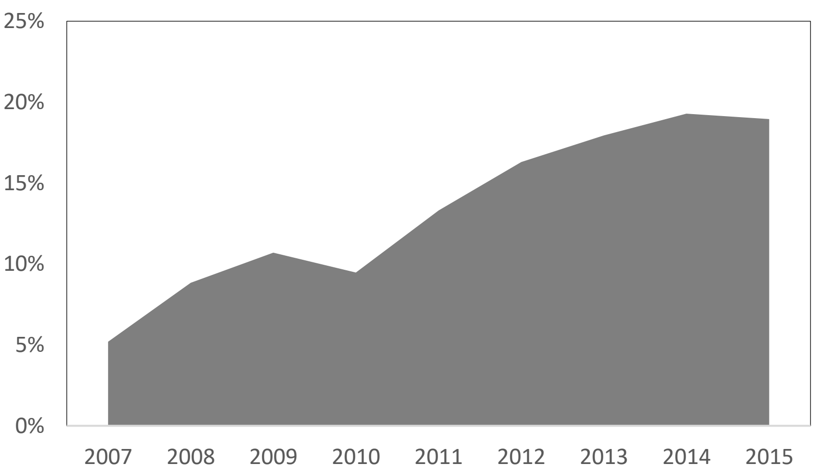
Panel A of this figure shows fintech originations as a share of shadow bank originations for all mortgages in HMDA between 2007 and 2015. Panel B shows fintech bank origination shares among shadow bank conforming originations. Panel C shows fintech share among shadow bank FHA originations (based on HMDA).



(a) All loans



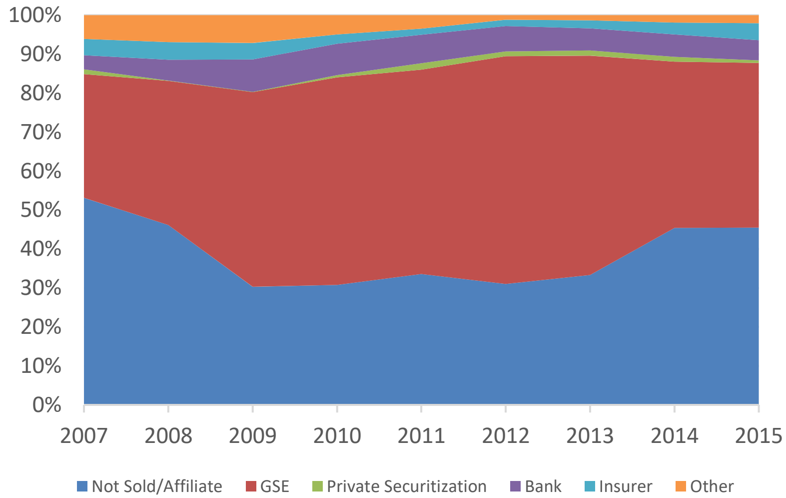
(b) Conforming loans



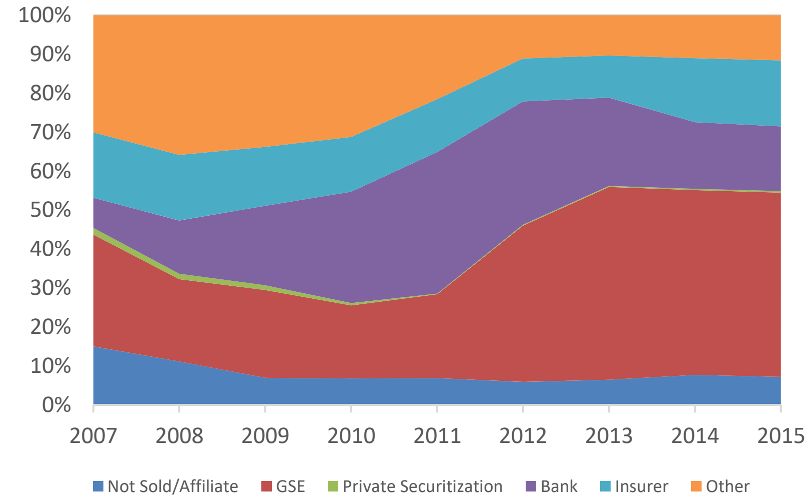
(c) FHA loans

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

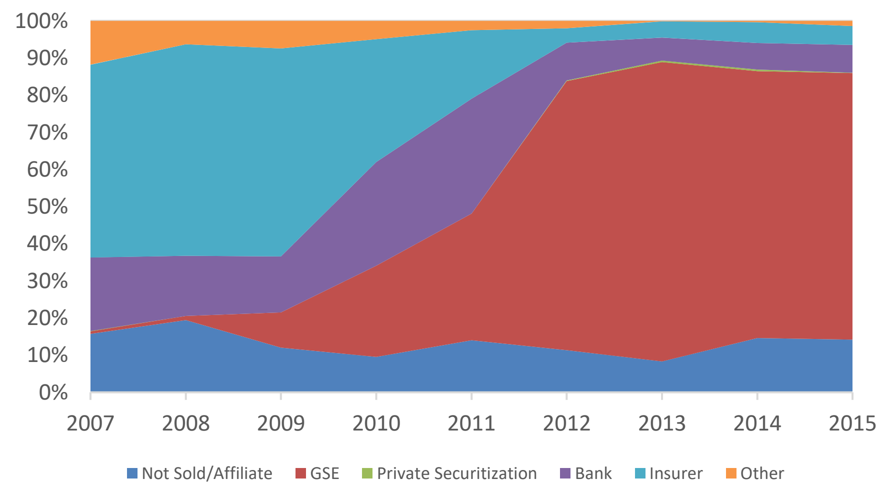
Figure 4 shows the percentage of originated loans by originator type sold to various entities within the calendar year of origination (including loans not sold). Panel A shows the buyer composition of traditional bank originations; Panel B shows the buyer composition of all shadow bank originations; Panel C shows the buyer composition of fintech shadow bank originations. Loans categorized as "unsold" are not sold within the calendar year of origination, although they may be sold some time later. The GSE category pools Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac. Calculations are based on HMDA data.



(a) Traditional banks



(b) Shadow banks



(c) Fintech lenders

Figure 5: Regional Shadow Banking Penetration

Figure 5 shows the county-level percentage of mortgages originated by shadow bank lenders as of 2015. Calculations are based on HMDA data.

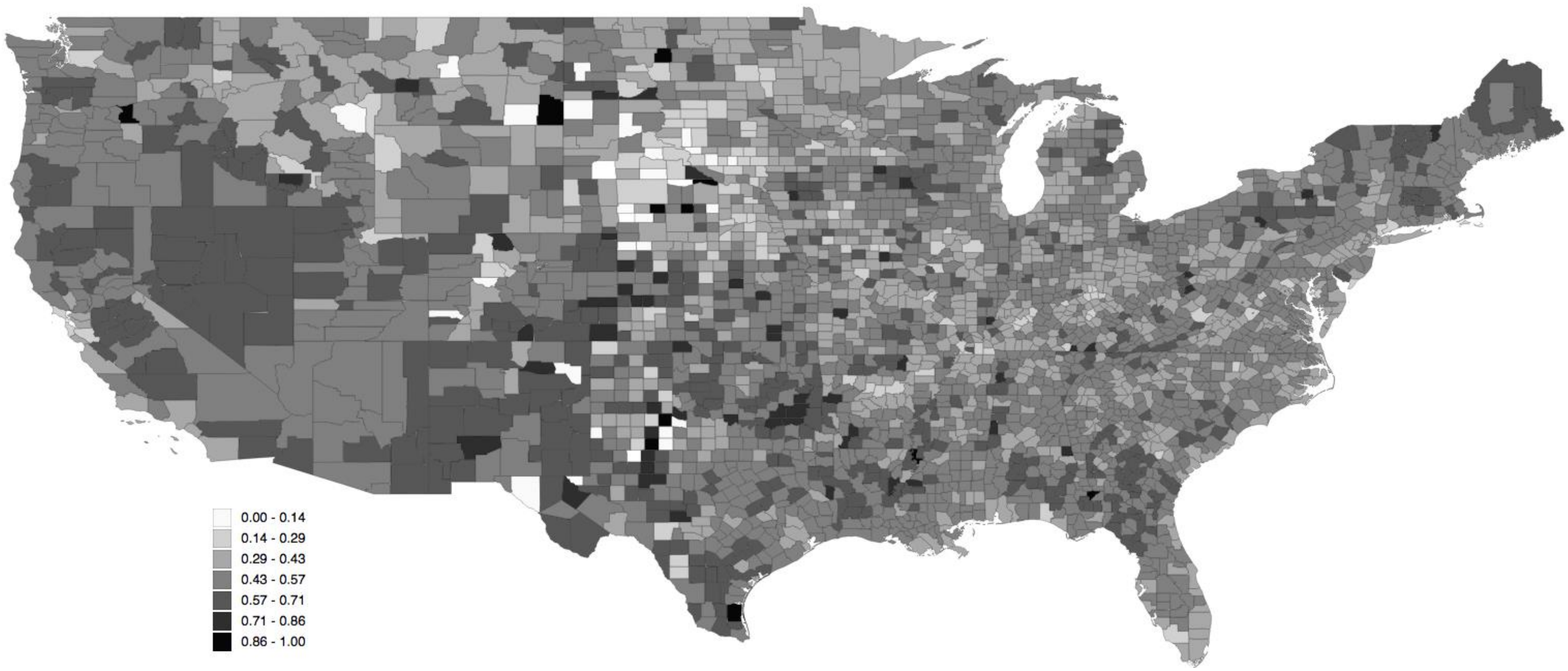


Figure 6: Mortgage Servicing Rights and Bank Shares over Time

Figure 6 shows the year-by-year relationship between the change in traditional bank market share within a county since 2008 and the 2008 MSR composition of bank Tier 1 Capital within the county. In particular, it is the coefficient β_{1t} from the regression $\Delta BankShare_{ct} = \beta_{0t} + \beta_{1t}MSR_{c2008} + \varepsilon_{ct.}$ between 2008 and 2015, where $\Delta BankShare_{ct}$ is the change in bank lending share between t and 2008 and MSR_{c2008} is the county weighted average MSR percent of Tier 1 Capital. This is regression (7) run at the yearly level. The solid line plot the estimated coefficinets β_{1t}; the dotted lines denote 95% confidence intervals

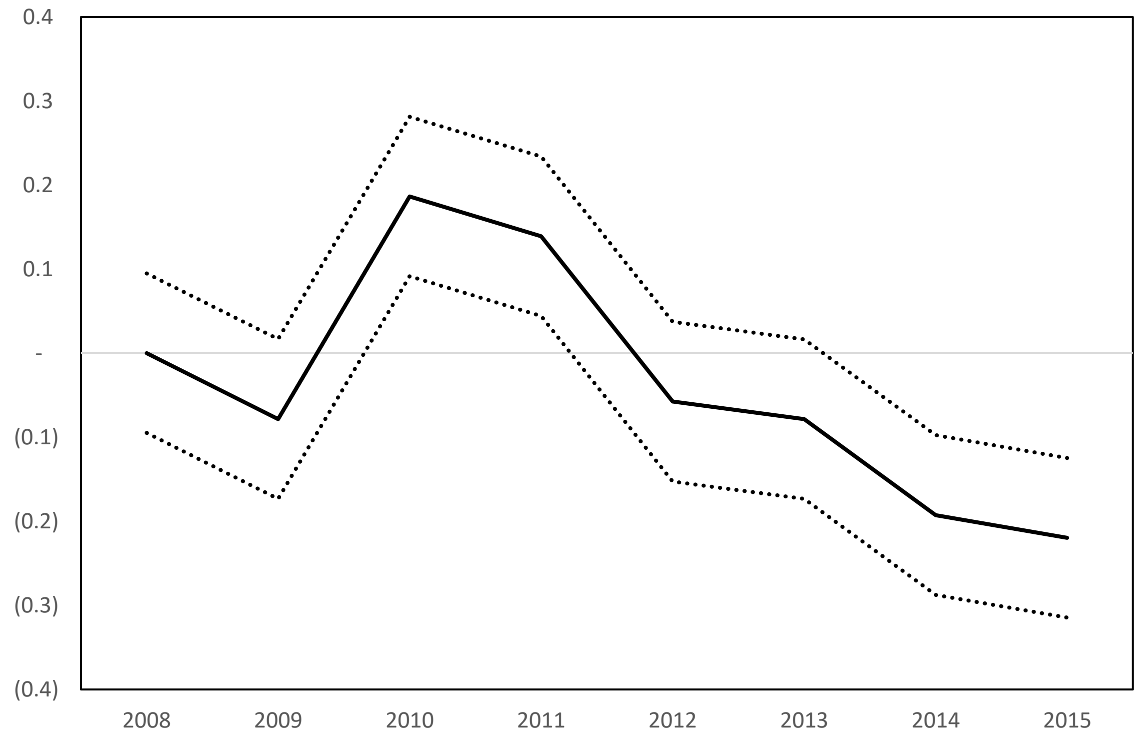
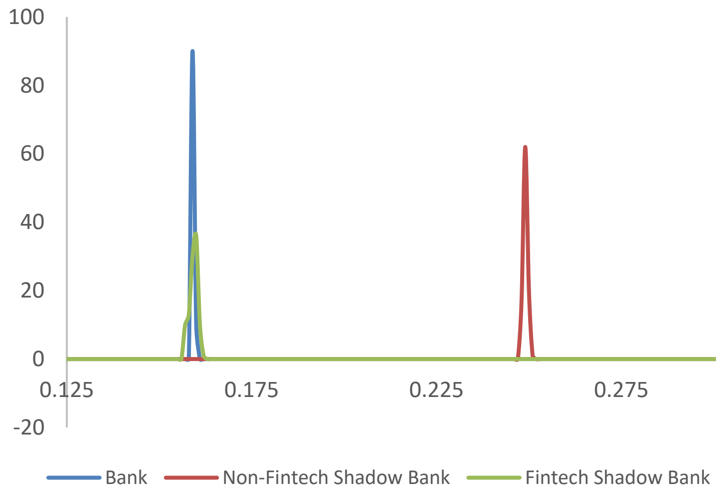
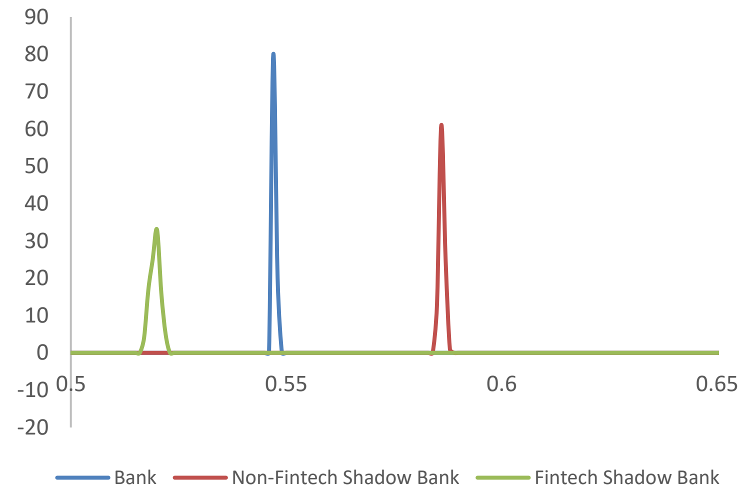


Figure 7: Distribution of Bootstrapped R-squares

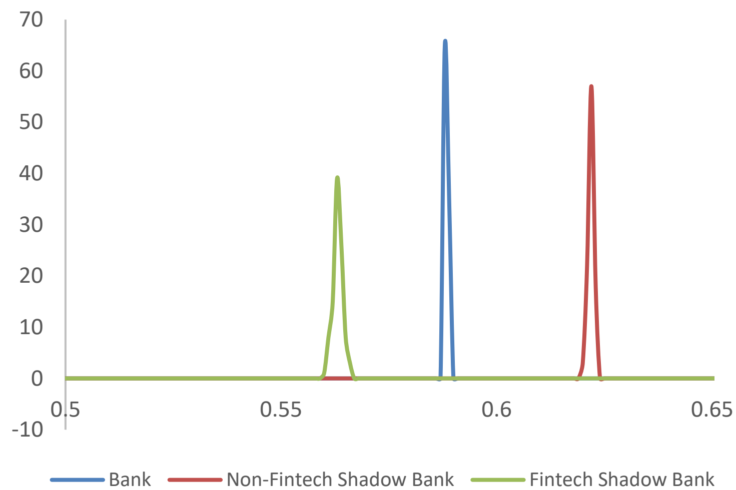
This figure shows the distribution of bootstrapped R-squares, corresponding to the determinants of interest rates. Each bootstraped sample selects a random sample of originations with replacement, reruns the interest rate regression, and records the R-squares. The bootstrap is run on 100 random samples. Panel A shows a model of interest rates with FICO, LTV, and quarter fixed effects. Panel B shows a model of interest rates with all (linear) observables and quarter fixed effects. Panel C shows a model of all observables with up to third-degree terms included.



(a) LTV, FICO, Quarter FE



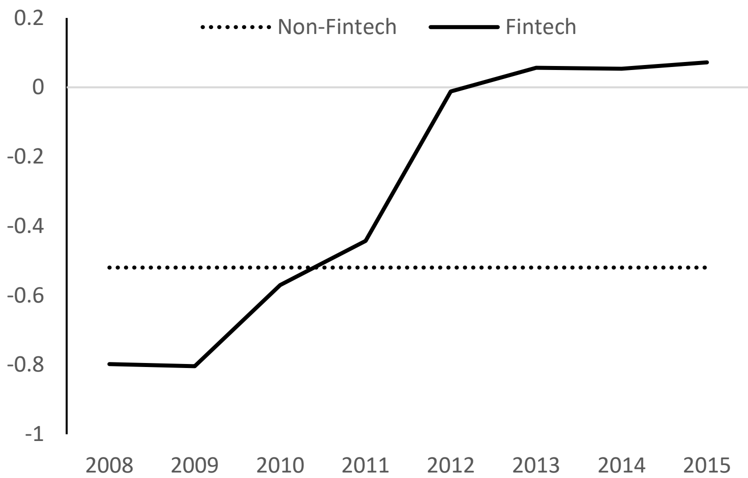
(b) All controls, Quarter FE



(c) All controls (non-linear), Quarter FE

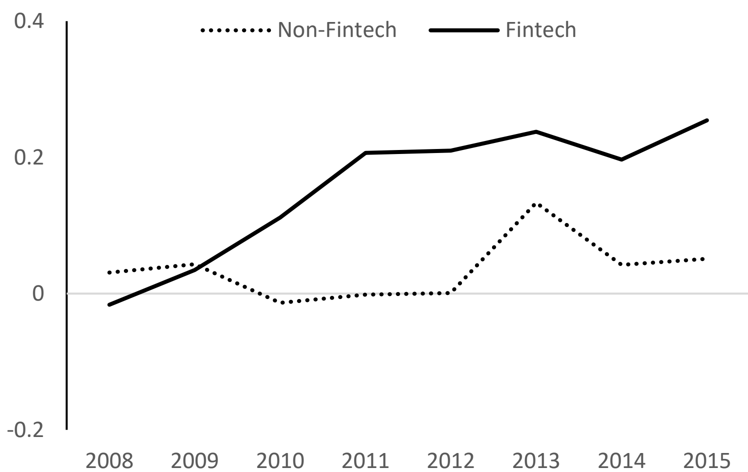
Figure 8: Calibrated Characteristics of Lenders

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 face by traditional banks implied by our model relative to 2008 level. A higher value of the parameter implies a *lower* regulatory burden level. 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.

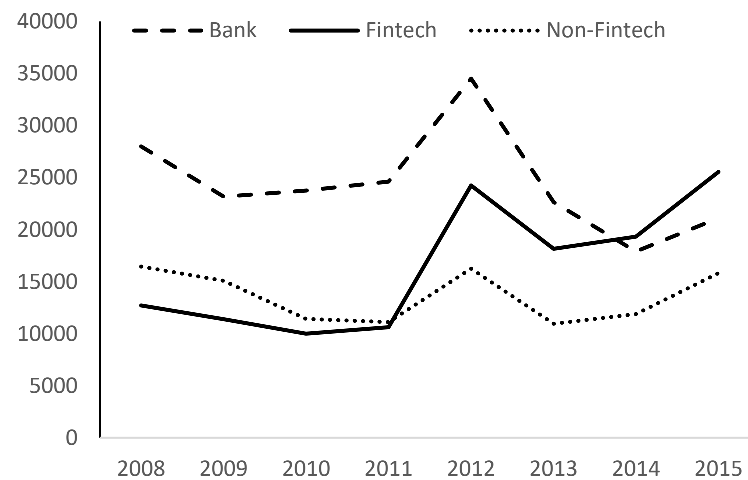


(a) Lender's quality

(b) Regulatory burden



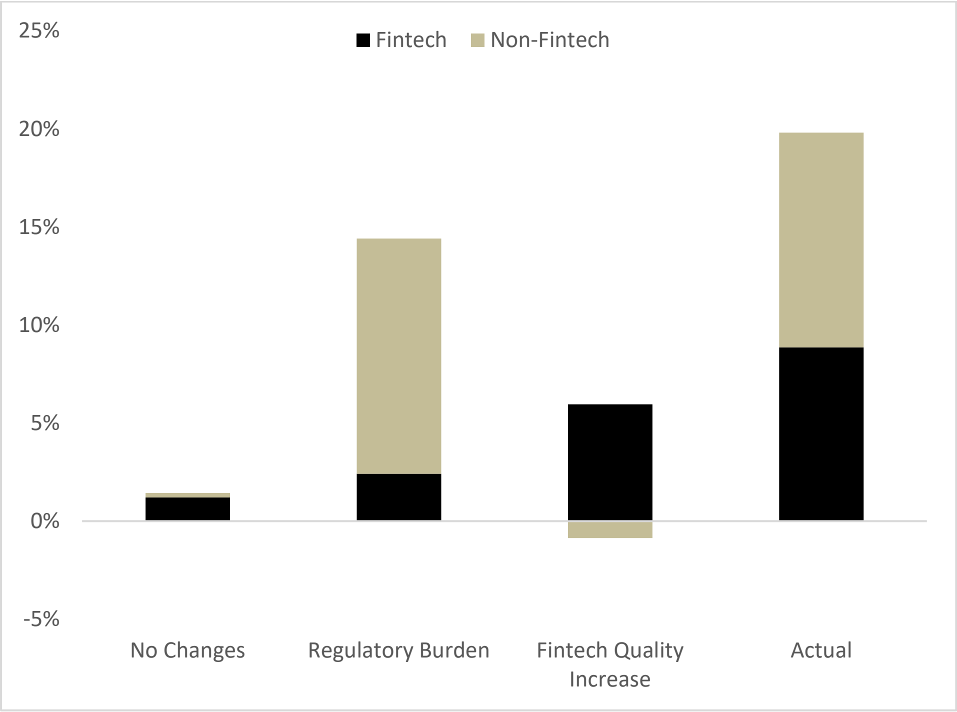
(c) Funding costs



(d) Fixed costs

Figure 9: Counterfactuals for the Change in the Shadow Bank Market Share Implied by our Model

This figure shows predicted changes in shadow bank market share in the overall mortgage market 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[32]

Panel A: List of Largest Shadow Banks

Name	Bank or Shadow Bank	Fintech or Non-Fintech
Amerisave Mortgage	Shadow Bank	Fintech
Cashcall Inc	Shadow Bank	Fintech
Guaranteed Rate Inc	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
Homebridge Financial Services	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

[32] This list is partial and includes the largest lenders. The full list comprises 550 lenders that accounted for 80% of mortgage lending market share as of 2010.

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 or Shadow Bank
Ally Bank	Bank
Bank of America	Bank
BOK Financial	Bank
Branch Banking and Trust Company	Bank
Capital One	Bank
Citibank	Bank
Citimortgage	Bank
Colorado FSB	Bank
Everbank	Bank
FHLB Chicago	Bank
Fidelity Bank	Bank
Fifth Third Mortgage	Bank
First Republic Bank	Bank
Flagstar Bank FSB	Bank
Fremont Bank	Bank
Homestreet Bank	Bank
HSBC Bank	Bank
JPMorgan Chase	Bank
MB Bank	Bank
Metlife Home Loans	Bank
Mortgage Stanley Private Bank	Bank
MUFG Bank	Bank
Navy FCU	Bank
NY Community Bank	Bank
PNC Bank	Bank
Redwood Credit Union	Bank
Regions Bank	Bank
Union Savings Bank	Bank
US Bank	Bank
USAA FSB	Bank
Wells Fargo Bank	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) Rate	(2) Rate	(3) Rate	(4) 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)	(2)	(3)	(4)
	Rate	Rate	Rate	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,[33] 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[34] relative to other lenders. Several lenders, including Quicken Loans, provide closing cost estimators for purchases and refinances.[35] 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[36] 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.[37]

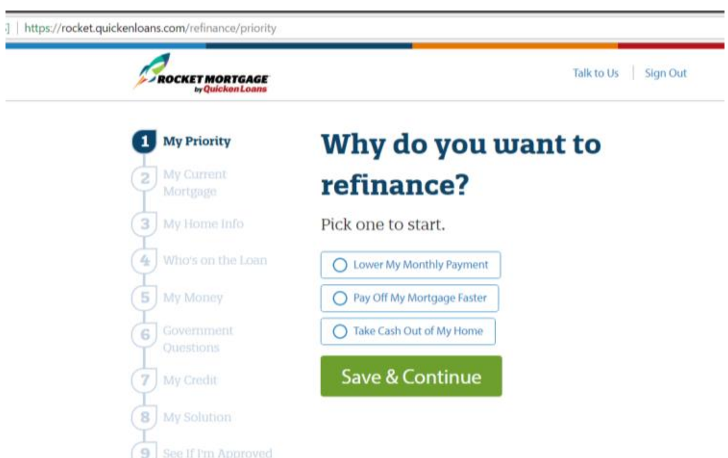
[33] https://www.zillow.com/mortgage-learning/closing-costs/ (Accessed March 7, 2017)
[34] https://www.consumeraffairs.com/finance/quicken_loans_mortgage.html
[35] https://www.quickenloans.com/my-mortgage/calculator#!/purchase/question/purchase-price (Accessed March 7, 2017)
[36] https://www.bankofamerica.com/mortgage/closing-costs-calculator/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

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 10



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

Figure 11

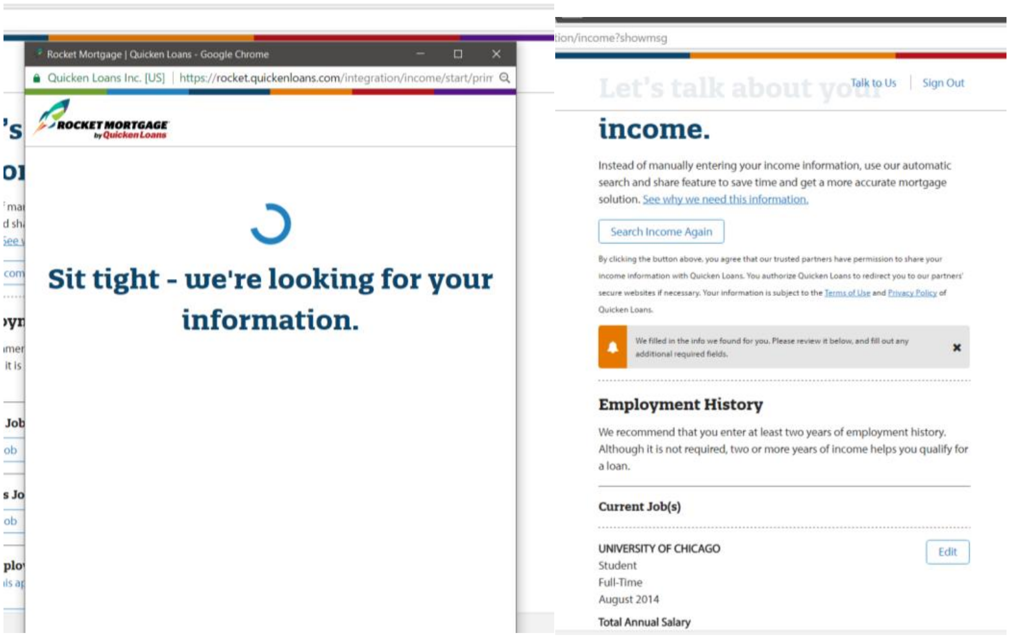
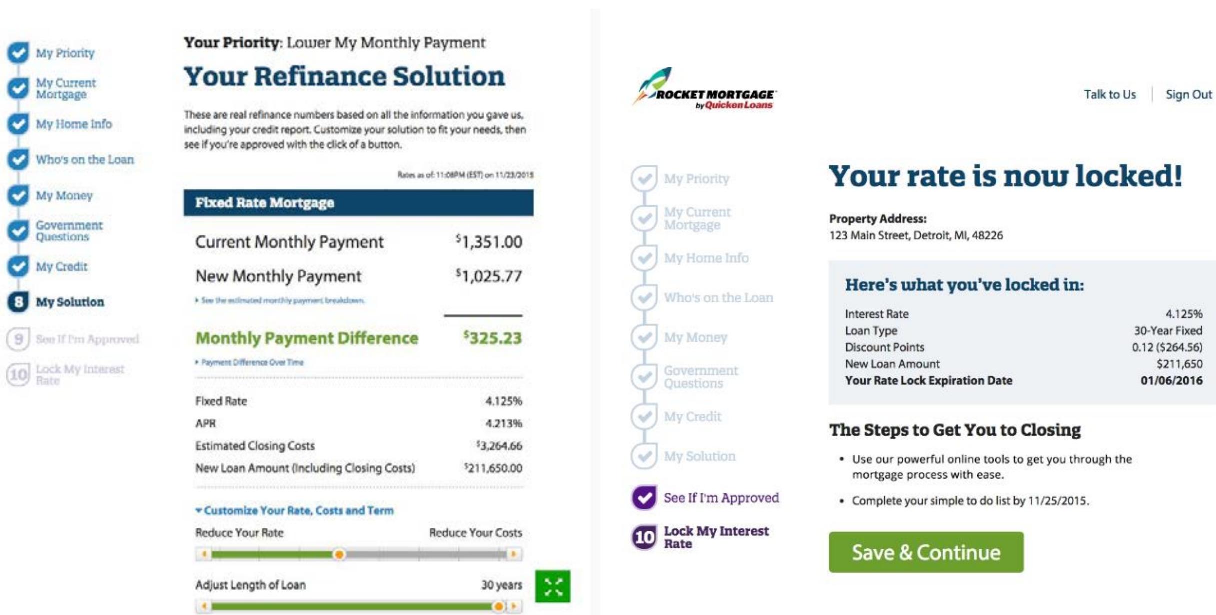


Figure 12



From TechCrunch.com

Appendix A6: Interest rate and Performance of Fintech and Non-Fintech

We test whether 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:

$$P(default_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \quad (18)$$

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \quad (19)$$

where r_i is the interest rate on the loan. Panel A of Table A6.1 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 0.487 versus 0.446 for fintech. Including controls, the coefficients become 0.190 and 0.087, 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 A6.1 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:

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + \beta_2 r_i \times Fintech_b + X_i'\Gamma + \delta_t) \quad (20)$$

The results are presented in Table A6.2. The results in column (4) show that there are important differences in how the interest rates fintech lenders charge on loans relate to the subsequent prepayment of borrowers relative other shadow banks. This evidence is consistent with fintech lenders using different 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 different selection of borrowers into fintech lenders.

Table A6.1: Relationship Between Interest Rate and Performance

Panels A and B show the coefficients on mortgage interest rate for probit regressions (18) and (19), 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	0.451***	0.0364	0.188***	0.124
Shadow Bank	0.479***	0.0426	0.170***	0.135
Non-Fintech	0.487***	0.0454	0.190***	0.142
Fintech	0.446***	0.0315	0.087*	0.115

Panel B: Prepayment

	No Controls		Controls	
	Rate	Pseudo R2	Rate	Pseudo R2
Bank	0.248***	0.0528	0.561***	0.111
Shadow Bank	0.297***	0.0384	0.740***	0.0973
Non-Fintech	0.218***	0.0454	0.666***	0.110
Fintech	0.697***	0.0523	1.045***	0.0953

Table A6.2: Interest Rates and Performance Differentials

This table shows the results of probit regression (20) 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

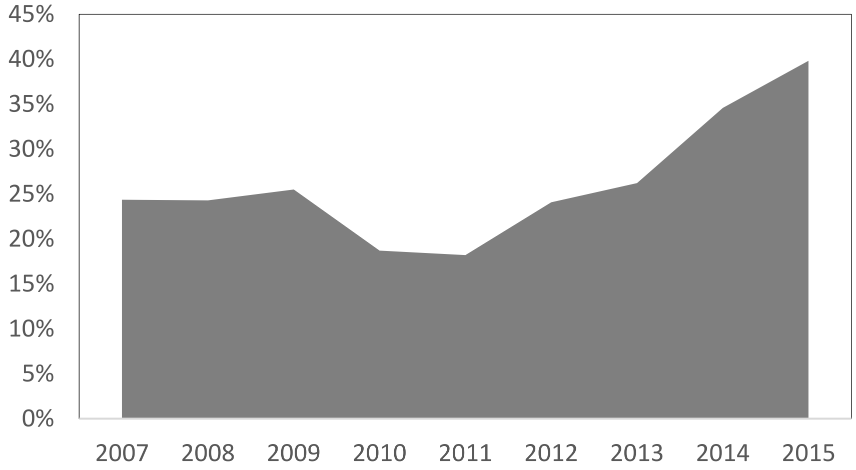
	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid
Rate	0.479***	0.479***	0.170***	0.178***
	(38.29)	(37.99)	(10.63)	(11.04)
Rate x Fintech	-	0.00144	-	-0.0142***
	-	(0.41)	-	(-3.73)
Borrower and Loan Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1151439	1151439	1151003	1151003
Pseudo R^2	0.0426	0.0427	0.135	0.136

Panel B: Prepayment

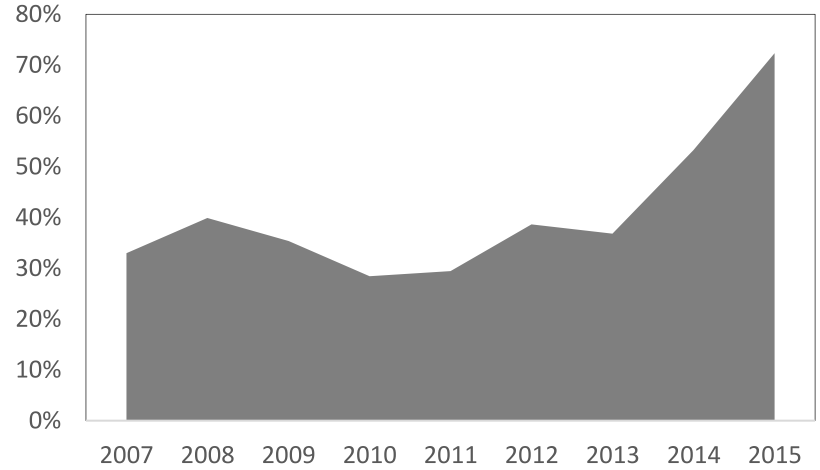
	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid
Rate	0.297***	0.280***	0.740***	0.724***
	(114.51)	(106.40)	(208.34)	(201.21)
Rate x Fintech	-	0.0308***	-	0.0262***
	-	(37.70)	-	(30.73)
Borrower and Loan Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1151439	1151439	1151009	1151009
Pseudo R^2	0.0384	0.0395	0.0973	0.0980

Appendix A7: Shadow Bank Trends among Top 50 Lenders

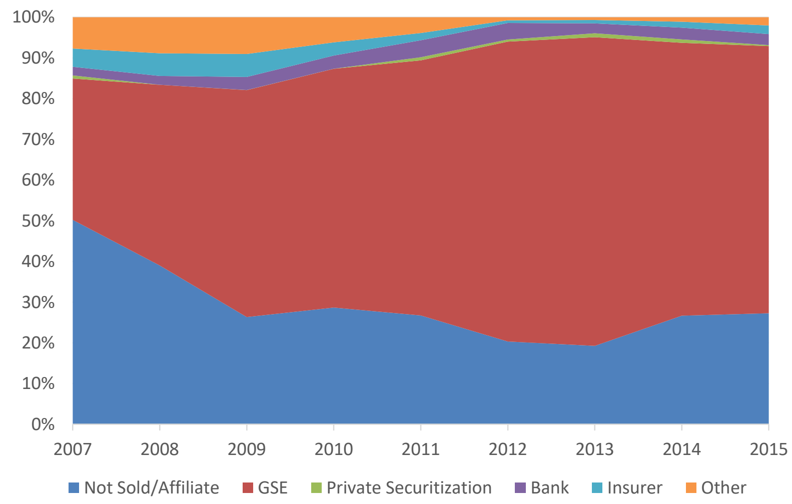
Panel A shows the shadow bank share among mortgage originations by top 50 lenders (based on HMDA origination volume). Panel B shows the corresponding shadow bank origination share among FHA loans. Panel C shows the disposition of mortgages among shadow banks in this large-lender sample. The GSE category pools Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac. Calculations are based on HMDA data.



(a) All loans



(b) FHA loans



(c) Loan disposition

Appendix A8: Lender Classification

Lenders are classified into one of three mutually exclusive categories: (1) Traditional Banks, (2) Non-Fintech Shadow Banks, and (3) Fintech Shadow Banks. The classification procedure is summarized in the following steps:

1. Is the lender a traditional bank or a shadow bank?
    a. If the lender is a traditional bank, this is its classification.
    b. If the lender is a shadow bank, proceed to step 2:
2. Is the shadow bank a fintech shadow bank or a non-fintech shadow bank?

This appendix provides details regarding steps one and two: (1) the determination of whether a lender is a traditional bank or a shadow bank, and (2) the determination of whether a shadow bank is a fintech shadow bank or a non-fintech shadow bank.[39]

Traditional Banks versus Shadow Banks

A lender is a traditional bank if it is a depository institution; otherwise, the lender is a shadow bank. We argue that this is a sensible definition for our paper because whether a lender is subject to most banking regulation is determined by its status as deposit-taking or not, and one of our primary goals is to explore the role that banking regulation has played in the mortgage market. Whether a non-depository institution has a funding relationship to a depository institution is not our primary concern; rather, we are interested in why lending activities have been pushed outside the traditional banking system.

The Fannie Mae and Freddie Mac data identify by name sellers who have comprised at least 1% of sales to the GSE within a given quarter. There are on average between 15 and 20 uniquely identified lenders in a given quarter. As market shares change through time, the composition of identified lenders shifts, which results in a greater number of identified lenders. Over our sample period, we identify 55 unique lenders comprising between 50% and 85% market share in a given quarter. See Figures A.8.1 Panels (A) and (B). These lenders are classified as traditional or shadow banks manually based on their status as a depository institution.

The HMDA data identifies all loan originators. We classify 551 lenders so as to cover 80% origination market share as of 2010. HMDA identifies the lender's primary regulator, which provides a useful first-cut regarding depository versus non-depository institutions. For OCC, OTS, and NCUA-regulated lenders, all lenders were classified as banks. The FRS regulates both

[39] Note that we do not classify traditional banks as "fintech traditional banks" or "non-fintech traditional banks."

traditional banks and shadow banks, so these lenders were manually classified. For FDIC regulated lenders, Merrimack Mortgage Company was classified as a shadow bank because it did not have deposits. It accounts for 0.12% of FDIC loans. For HUD regulated lenders, Homeowners Mortgage Enterprise, Liberty Mortgage Corporation, Morgan Stanley Credit Corp, and Prosperity Mortgage Company were categorized as banks. This made up 0.30% of HUD loans. For CFPB regulated loans, Suntrust Mortgage was classified as a shadow bank and made up 2.57% of CFPB loans. The following table summarizes the classifications by regulator in HMDA.

Regulatory Agency	Classification distribution
OCC	100.00% Bank 0.00% Shadow Bank
FRS	62.92% Bank 37.08% Shadow Bank
FDIC	99.88% Bank 0.12% Shadow Bank
OTS	100.00% Bank 0.00% Shadow Bank
NCUA	100.00% Bank 0.00% Shadow Bank
HUD	0.30% Bank 99.70% Shadow Bank
CFPB	97.43% Bank 2.57% Shadow Bank

Fintech Shadow Banks versus Non-Fintech Shadow Banks

Among shadow bank lenders, a lender is "fintech" if the loan application process is entirely online and the potential borrower is able to obtain a firm, contractual rate quote without interacting with a human loan officer. Fintech lenders' websites typically include automated tools to collect and verify information including the applicant's work and financial assets automatically. See Figure A.8.2 Panel A. This classification focuses on the front-end, consumer-interaction aspect of fintech, although lenders with this automated interface empirically appear to also bring more (or at least non-standard) data into the interest rate decision relative to lenders with less sophisticated consumer-facing platforms.

Many lenders have online forms that allow borrowers to submit an application online. Under our classification rule, having such a form is *not* sufficient for a lender to be a fintech lender. For example, Figure A.8.2 Panel B shows the website of Home Point Financial. While the site allows users to begin the application process online, it explicitly states "After you have finished," that the company will "contact you to: Guide you through the loan process… Complete your loan application package… Help you select the best program and interest rate." Because this lender does not allow the borrower to receive a firm, contractual rate quote online, it is not a fintech lender. Where the correct classification is ambiguous, our approach is to be conservative with respect to classifying a lender as fintech: Ambiguous cases are treated as non-fintech shadow banks.

The classification process for fintech shadow banks versus non-fintech shadow banks is done by hand, using multiple independent RAs to verify the classifications. The primary classification is based on visiting lenders' websites and reading reviews as of 2016 and 2017. In order to ensure that lender types are stable through time, we make use of archived versions of the lenders' websites though the Wayback Machine,[40] which periodically saves timestamped snapshots of websites. The following table provides links to archived sites of some of the largest fintech and non-fintech lenders in our classification:

Lender	Link	Date	Notes
Fintech Lenders			
QuickenLoans	https://web.archive.org/web/20000301152531/http://rockloans.com/	2000	
CashCall	https://web.archive.org/web/20080201145127/http://cashcall.com/	2008	
Guaranteed Rate	https://web.archive.org/web/20080105084749/http://www.guaranteedrate.com:80/	2008	
Amerisave	https://web.archive.org/web/20081121145731/http://www.amerisavemortgage.com/aboutus.cfm	2008	
Homeward	https://web.archive.org/web/20120725213830/http://ahmsi3.com:80/servicing/home.asp#	2012	Note[41]
Movement	https://web.archive.org/web/20130205223025/http://www.movementmortgage.com:80/refinance/	2013	Note[42]
Summit Mortgage	https://web.archive.org/web/20130901000000*/http://summit-mortgage.com/	2007	
Non-Fintech Lenders			
Franklin American		2010	Note[43]
Ditech	https://web.archive.org/web/20100314055607/http://ditech.com	2010	Note[44]
Nationstar	https://web.archive.org/web/20090217131827/http://www.nationstarmtg.com	2010	
Allied	https://web.archive.org/web/20100819213036/http://alliedmortgagecorp.com	2010	
Academy	https://web.archive.org/web/20100306021159/http://academymortgage.com:80/	2010	

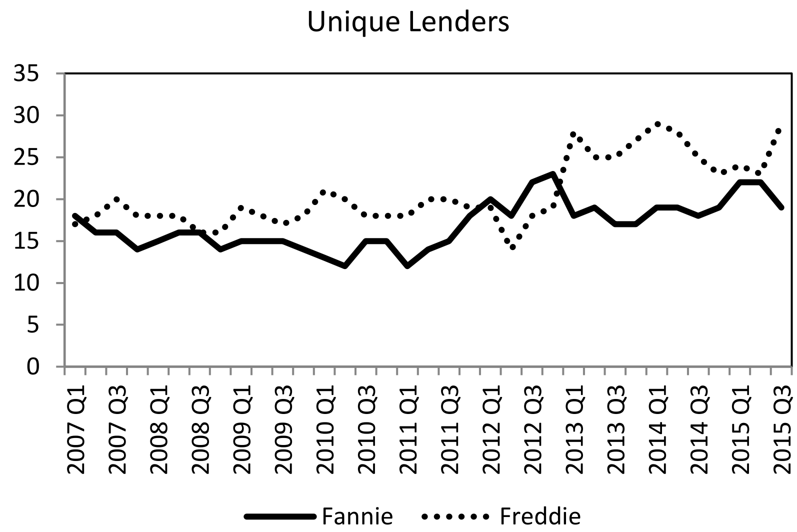
The results of this check are that the classifications are stable and robust over time. In almost all cases, lenders classified as fintech in 2016-2017 would have been classified as fintech lenders in 2010 or earlier; Movement Mortgage and Summit Mortgage, which we classify as fintech lenders now are ambiguous; while they had sophisticated online presences, especially for the time (and

[40] https://archive.org/web/, accessed 7/13/2017.
[41] In 2012, Homeward Residential was an online *servicer*, and did not appear to originate mortgages.
[42] The current website, "movement.com" was held by another owner; "movementmortgage.com" comes online in 2013.
[43] No viewable site in or prior to 2010.
[44] Has (and continues to have as of 2017) an online application that directs user to a human loan officer.

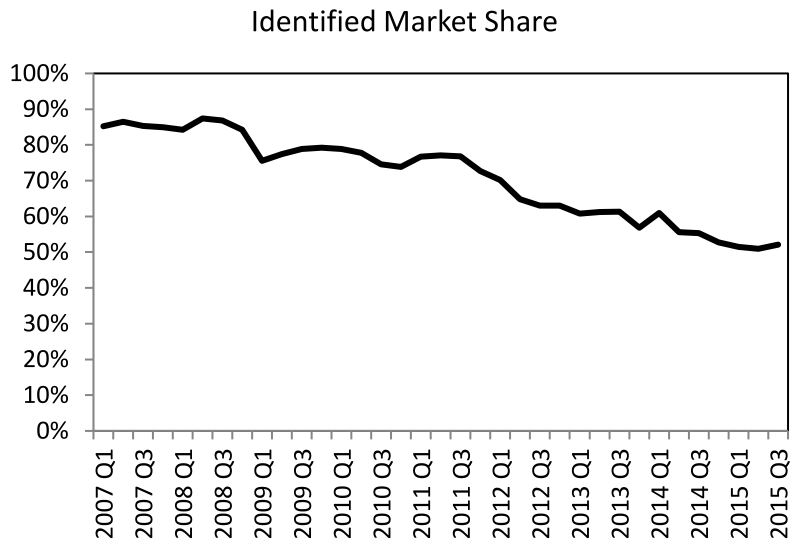
held out their technology as a reason to borrow from them), their application process appears to involve a human loan officer at some point. In all cases, lenders classified as non-fintech in 2016-2017 would have been classified as non-fintech in 2010.

Figure A.8.1: Identified Lenders in Fannie Mae and Freddie Mac

Panel (A) shows the number of unique identified lenders in the Fannie Mae and Freddie Mac data per quarter. Panel (B) shows the total market share of sales to the GSEs by the identified lenders.



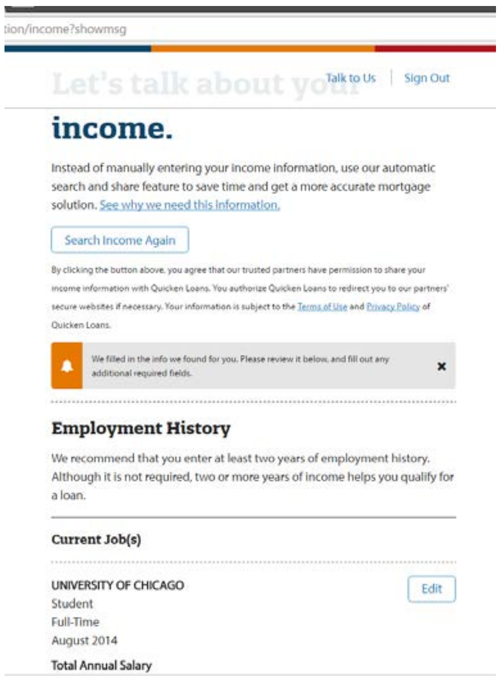
Panel (A): Unique Identified Lenders



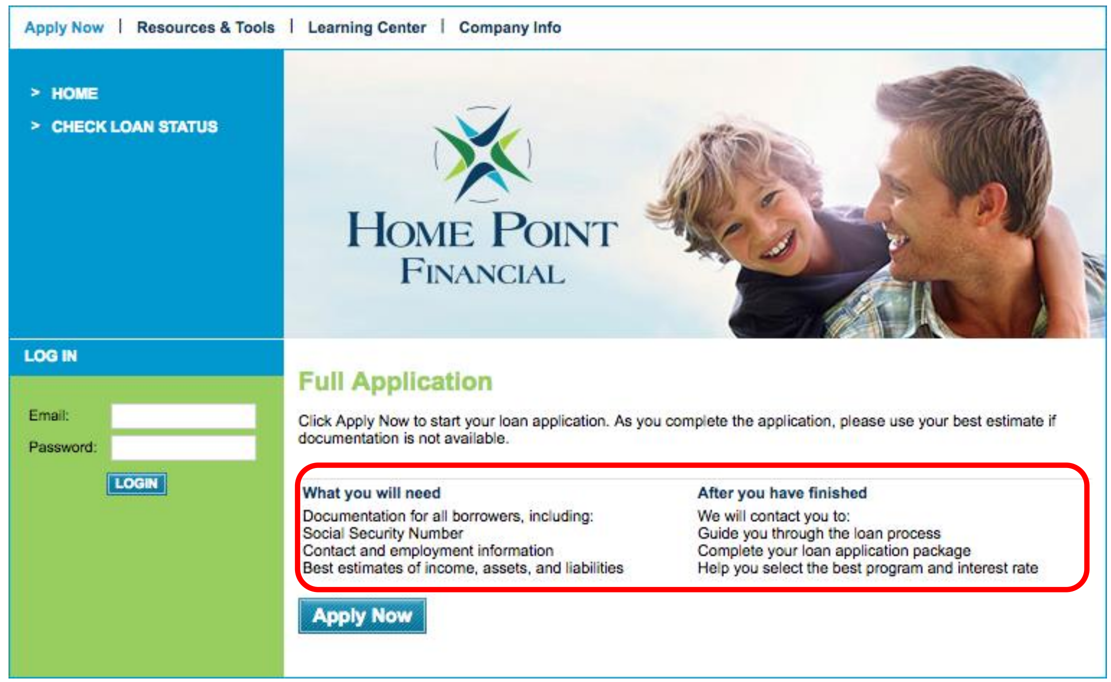
Panel (B): Market Share of Identified Lenders

Figure A.8.2: The Fintech and Non-Fintech Loan Process

Panel (A) shows part of the loan application process for a fintech lender (Quicken Loans). Note that the lender's technology automatically retrieves the borrower's employment history. Panel (B) shows part of the loan application process for a non-fintech lender. Note that despite having an "online" application, the application process requires the applicant to interact with a human loan officer after initially submitting her contact information.



Panel A: A fintech lender



Panel B: A non-fintech lender's site (highlighting added for emphasis).

Appendix A9: Excluding Quicken Loans

Table A9.1 shows Table 4: Loan Characteristics of Conforming Loans, excluding Quicken Loans from the sample. Table A9.2 shows Table 2: Time Between Origination and Sale: Conforming Loans, excluding Quicken Loans from the sample. Table A9.3 shows Table 6: Shadow Bank and Fintech Mortgage Rates: Conforming Loans, excluding Quicken Loans from the Sample.

Table A9.1: Loan Characteristics of Conforming Loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Shadow Bank	Shadow Bank	Non-Fintech	Non-Fintech	Fintech	Fintech	Fintech	Fintech
Sample	All Lenders						Shadow Banks Only	
Loan Amount	0.0000115***	0.00000824***	0.0000108***	0.00000849***	0.000000692***	-0.000000251***	0.00000185***	-0.000000993***
	(105.85)	(62.45)	(100.41)	(64.96)	(38.31)	(-10.89)	(20.46)	(-8.73)
Loan Term (Months)	0.0385***	-0.00202***	0.0355***	-0.00178***	0.00299***	-0.000238***	0.0135***	-0.00127***
	(193.43)	(-9.49)	(178.99)	(-8.38)	(147.10)	(-17.69)	(125.38)	(-20.21)
Loan-to-Value	-0.0478***	-0.0375***	-0.0434***	-0.0373***	-0.00447***	-0.000225	-0.00552***	0.00654***
	(-47.10)	(-35.77)	(-43.15)	(-35.90)	(-24.40)	(-1.18)	(-5.65)	(6.66)
Debt-to-Income	0.0303***	0.0265***	0.0325***	0.0312***	-0.00218***	-0.00466***	-0.0109***	-0.0211***
	(21.12)	(18.85)	(22.89)	(22.38)	(-8.49)	(-18.18)	(-8.20)	(-16.67)
FICO	-0.00359***	-0.00828***	-0.00384***	-0.00775***	0.000254***	-0.000528***	-0.000140	-0.000202
	(-10.24)	(-24.24)	(-11.06)	(-22.86)	(4.57)	(-9.59)	(-0.53)	(-0.81)
Cash-Out Refinance	-1.372***	-0.382***	-1.647***	-0.581***	0.275***	0.199***	1.443***	0.745***
	(-36.67)	(-10.35)	(-44.38)	(-15.84)	(46.94)	(34.70)	(46.87)	(25.79)
Non-Cash-Out Refinance	-2.214***	0.601***	-2.656***	0.308***	0.442***	0.293***	2.355***	1.180***
	(-70.64)	(18.39)	(-85.65)	(9.51)	(80.21)	(49.40)	(90.94)	(42.20)
Unspecified Refinance	40.61**	39.58**	40.70**	39.92**	-0.0834	-0.335	0.651***	0.345***
	(2.65)	(2.66)	(2.67)	(2.72)	(-0.41)	(-0.74)	(3.86)	(4.80)
Investment	0.877***	-0.361***	0.709***	-0.323***	0.168***	-0.0375***	1.050***	0.159***
	(16.30)	(-6.74)	(13.33)	(-6.11)	(16.30)	(-3.58)	(21.93)	(3.40)
Secondary	-2.210***	-3.306***	-2.122***	-3.190***	-0.0874***	-0.115***	0.147**	-0.180**
	(-35.93)	(-51.14)	(-34.81)	(-49.73)	(-9.17)	(-11.31)	(2.78)	(-3.28)
First-Time Buyer	-3.003***	-2.269***	-2.852***	-2.081***	-0.151***	-0.188***	-0.0756**	-0.499***
	(-72.41)	(-54.97)	(-69.24)	(-50.70)	(-27.14)	(-32.42)	(-2.83)	(-18.73)
Has Mtg. Insurance	1.108***	0.607***	0.986***	0.472***	0.122***	0.135***	0.545***	0.323***
	(24.36)	(13.72)	(21.89)	(10.76)	(16.07)	(17.94)	(15.46)	(9.63)
Zip x Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
N	8104117	8104116	8104117	8104116	8104117	8104116	1569282	1569282
R^2	0.0502	0.119	0.0519	0.118	0.0140	0.0613	0.0782	0.240

Table A9.2: Time Between Origination and Sale: Conforming Loans

	(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	-0.0846***	-0.0831***	-	-	-	-
	(-39.82)	(-40.01)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0816***	-0.0809***		
	-	-	(-39.24)	(-39.57)		
Fintech Shadow Bank	-	-	-0.154***	-0.134***	-0.0301*	-0.0121
	-	-	(-11.41)	(-10.22)	(-2.14)	(-0.87)
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	3844312	3839732	3844312	3839732	955717	953784
R^2	0.0314	0.0465	0.0316	0.0466	0.0593	0.103

Table A9.3: Shadow Bank and Fintech Mortgage Rates: Conforming Loans

	(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	-0.0273***	-0.0235***	-	-	-	-
	(-20.03)	(-26.72)	-	-	-	-
Non-Fintech Shadow Bank	-	-	-0.0280***	-0.0240***		
	-	-	(-20.33)	(-27.04)		
Fintech Shadow Bank	-	-	0.00156	-0.00260	0.0462***	0.00670**
	-	-	(0.49)	(-1.02)	(13.81)	(3.03)
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	8485573	8480376	8485573	8480376	1946802	1943693
R^2	0.598	0.808	0.601	0.811	0.585	0.807