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ABSTRACT

We study the rise of fintech and non-fintech shadow banks in the residential lending market. The market share of shadow banks in the mortgage market has nearly tripled from 2007-2015. Shadow banks gained a larger market share among less creditworthy borrowers, with a tilt towards refinancing mortgages. Shadow banks were significantly more likely to enter markets where traditional banks faced more regulatory constraints. This suggests that traditional banks retreated from markets with a larger regulatory burden, and that shadow banks filled this gap. Fintech firms accounted for almost a third of shadow bank loan originations by 2015. To isolate the role of technology in the decline of traditional banking, we focus on technology differences between shadow banks, holding the regulatory differences between different lenders fixed. Analyzing fintech firms' entry and pricing decisions, we find some evidence that fintech lenders possess technological advantages in determining corresponding interest rates. More importantly, the online origination technology appears to allow fintech lenders to originate loans with greater convenience for their borrowers. Among the borrowers most likely to value convenience, fintech lenders command an interest rate premium for their services. We use a simple model to decompose the relative contribution of technology and regulation to the rise of shadow banks. This simple quantitative assessment indicates that increasing regulatory burden faced by traditional banks and financial technology can account, respectively, for about 55% and 35% of the recent shadow bank growth.

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I. Introduction

In the last decade, the market for financial consumer products has undergone a dramatic change. Intermediation has shifted away from traditional banks to shadow banks, which have a substantially lower regulatory burden because they are not funded with deposits. This change has coincided with a shift away from "brick and mortar" originators to online intermediaries.[1] These developments have generated an intense debate and have resulted in significant concerns among regulators and market participants. Despite the rapidly increasing market share of fintech and non-fintech shadow banks, there is little systematic analysis of this change.

We study the rise of fintech and non-fintech shadow banks in the largest consumer loan market in the US, the residential lending market, which has been at the center of this drastic change. As we document,[2] the market share of shadow banks[3] in the mortgage market has nearly tripled from 14% to 38% from 2007-2015. In the Federal Housing Administration (FHA) mortgage market, which serves less creditworthy borrowers, the market share of shadow banks increased by a staggering seven fold during the same period, from 20% to 75% of the market. In the mortgage market, "fintech," lenders, have increased their market share from about 5% to 15% in conforming mortgages and to 20% in FHA mortgages during the same period. The aggregate numbers, however, hide substantial differences across markets. Therefore, the comparative advantage that shadow banks and fintech firms hold over traditional banks does not extend equally to all parts of the mortgage market. In fact, simple summary statistics suggest that fintech firms focus on somewhat different part of the market than the traditional shadow banks.

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

The second hypothesis is that the shift from traditional banks is driven by changes in technology. Fintech shadow banks have disrupted the market, because they provide better products, or provide existing products more cheaply. Consider Quicken Loans, which has grown to the third largest mortgage lender in 2015. The Quicken "Rocket Mortgage" application is done mostly online,

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

resulting in substantial labor and office space savings for Quicken Loans. The "Push Button. Get Mortgage" approach[4] is also more convenient and faster for internet savvy consumers. Last, fintech shadow banks might be better able to screen potential borrowers using big data approaches inherent in technology based lending, benefitting some segments of consumers, and possibly hurting others.

Our first cuts of the data are based on the simple idea that we should observe the largest decline of traditional banks in areas in which their relative disadvantage to shadow bank entrants is highest. If we observe increased entry of shadow banks in a certain sector, for example, in FHA mortgages, we infer that shadow banks hold an advantage in that sector. Since regulation is the main differentiating factor between shadow bank and traditional banks, such results suggest that these are the sectors in which the additional regulatory burden of banks is highest. To study the role of technology, we compare the entry of fintech shadow banks to the entry of non-fintech shadow banks, which are subject to the same regulation, but differ in the technology they use.

To examine whether it is plausible that the increased regulatory burden was the driving force behind the decline of traditional banking, we examine the entry of all shadow banks, irrespective of their fintech affiliation. While the market share of shadow banks in the mortgage market has nearly tripled from 2007-2015, the growth has been especially explosive in the FHA segment where in 2015 shadow banks accounted for about 75% of all FHA originations. This differential growth is strong evidence that shadow banks' advantage over traditional banks has grown especially quickly in the market with riskier borrowers. This evidence is consistent with the narrative that this is the segment in which the regulatory burden in has risen substantially because of a "series of costly lawsuits brought by the federal government surrounding these loans."[5]

Shadow banks have also expanded in the conforming loan market. While the growth has not been as explosive as is the riskier FHA market, their market share of conforming mortgages has risen from 15% in 2007 to 43% in 2015. One might therefore infer that shadow banks generally focus on the less creditworthy, lower income parts of borrowers. To examine that intuition, we look within the conforming sector. Contrary to the intuition suggested by FHA loans, we find only weak evidence that shadow banks grow more aggressively among lower income or less creditworthy borrowers within the conforming sector. They do, however, seem to enter areas with larger shares of minorities. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of minority borrowers, it may not be surprising that banks are retreating from that sector somewhat. This evidence suggests that the regulatory distinction between FHA and conforming

[4] https://www.nerdwallet.com/blog/mortgages/quickenloansandrocketmortgagereview/ [Accessed on 11/8/2016]
[5] http://www.wsj.com/articles/banksnolongermakethebulkofusmortgages1478079004 [Accessed on 11/8/2016]

loans is driving the difference in entry rates of shadow banks, rather than a specific specialization of shadow banks on low income borrowers.

The differences between shadow and traditional banks are not limited to customer characteristics. Sector shadow banks have gained larger market shares in the refinancing market relative to financing house purchases directly. One possible reason for this segmentation is that traditional banks are also substantially more likely to hold loans on their own balance sheet than shadow banks. Approximately one fourth of traditional banks loans in HMDA are held on their own balance sheet. For shadow banks, the share is closer to 5%. Because refinancing loans held on the balance sheet cuts directly into a bank's profit, their incentives to refinance are smaller. In addition, shadow banks might be better at refinancing because they can avoid labor-intensive "purchase" activity.

Our results suggest that the rise of shadow banks in the mortgage market is importantly driven by their lower regulatory burden. In other words, shadow banks find it cheaper to originate mortgages. We next examine if these cost advantages are passed through to consumers: i.e. is the change we observe in the market limited to quantities, or is it also reflected in prices of mortgages. We find that if differences in pricing do exist, they are on average negligible. We later show that the average interest rate differences hide some interesting variation in the pricing of the loans.

To more directly link the rise of shadow banks to an increased regulatory burden of traditional banks, we focus on three potential sources for this increase: Capital requirements, mortgage-related enforcement actions, and mortgage lawsuits. Unlike shadow banks, traditional banks are deposit taking institutions, and are thus subject to capital requirements, which do not bind shadow banks. If capital requirements are the constraint that increases the cost of extending mortgages for traditional banks, we should see larger entry of shadow banks in places in which capital requirement constraints are more binding. Indeed, we find a larger growth of shadow banks in counties in which capital constraints have tightened more in the last decade. We collect data on enforcement actions directed at depositary institutions (i.e. not shadow banks) as well as mortgage related lawsuits. We find that areas in which a larger share of lenders have been subject to enforcement and legal actions are also areas in which we see a larger entry 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.

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

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

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

Fintech shadow banks have disrupted the market, either because they provide better products, or because they provide existing products more cheaply. If fintech lenders offer a better experience for the customers, they should potentially be able to charge more for originating mortgages. Conversely, if the main consequence of fintech is to lower costs for the lender, then one would expect fintech lenders to potentially pass-through some of the cost savings to the borrowers. Recall that shadow banks on average charge similar interest rates as traditional banks. Within shadow banks, on the other hand, we find that fintech firms charge on average higher interest rates, suggesting that fintech consumers are willing to pay for the convenience of transacting online. Notably, the fintech interest rate premium is lower for the least creditworthy (low FICO) borrowers and higher for the most creditworthy borrowers. These results suggest that fintech lenders are able to price discriminate between different groups of borrowers when competing with brick and mortar shadow banks.

Fintech shadow banks might also be better able to screen potential borrowers using big data approaches or better statistical models inherent in technology based lending. Better mortgages would suggest that fintech firms are able to better price mortgage risk or price discriminate among borrowers, either by combining existing data, or by using other dimensions of data, not available to brick and mortar lenders. If this is true, we expect to observe variation in interest rates explain more of the variation in subsequent performance for fintech loans relative to non-fintech loans. We find evidence that is consistent with fintech lenders using hard information differentially relative to non-fintech lenders. Interest rates explain more variation in prepayment outcomes, the dominant risk in our data, across borrowers for fintech loans relative to non-fintech loans. These results suggest that fintech lenders do take some advantage of technology in setting mortgage interest rates.

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

We use a simple model to decompose the relative contribution of technology and regulation to the rise of shadow banks. We calibrate the model every year from 2008 onwards to see how the funding costs, quality, and regulatory impediments of traditional banks have changed over the period. Traditional banks have slightly lower shadow cost of funding and provide higher quality products than shadow banks. Despite this, they lose market share during this period because of a large increase in the intensity of regulatory burden after 2010 passage of the Dodd-Frank Act. We find 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. This finding is consistent with evidence in Fuster, Lo and Willen (2017), who find evidence of an increased legal and regulatory burden over 2008-2014. Using this simple model, we find that increasing regulatory burden can account for about 55% of shadow bank growth during 2008-2015 period with technology accounting for another 35%.

II. Related Literature

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

The Structure of the Residential Mortgage Market

Many papers have studied the changing structure of the mortgage origination chain, with particular attention paid to the originate-to-distribute model and the costs and benefits thereof (e.g., Berndt and Gupta 2009, Piskorski et al. 2010, Keys et al. 2010 and 2013, Purnanandam 2011). The focus has primarily been on the run-up to the financial crisis, rather than on the immediate aftermath and recovery following the crisis. As we document, shadow bank lenders tilt towards the originate-to-distribute model, and we document the steady rebirth of these practices. In the aftermath of the crisis, the primary risk event is not default, but rather prepayment, and we find that mortgages originated by primarily originate-to-distribute lenders—shadow banks—prepay with significantly higher probability.

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

Banking Regulation and GSEs

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

Because shadow banks are so dependent on GSEs and FHA guarantees, our paper relates to literature studying GSEs and their role in mortgage lending. GSEs were established to promote housing ownership, particularly in underserved areas, and a number of papers (Hurst et al 2015, Bhutta 2014, Acharya et. al. 2011) have studied their role in income redistribution and house ownership, finding mixed results. Our paper suggests that government policies of increased regulatory burden of traditional banks combined with GSEs and FHA guarantees have contributed greatly to the rise of the shadow banking sector. We find that shadow banks do provide credit to underserved and higher-risk borrowers who may otherwise be excluded from traditional bank lending, but that these loans tend to perform more poorly.

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 first that fintech lenders appear able to make use of big-data to better screen borrowers and set interest rates that better predict ex-post loan performance. Philippon (2015) documents that advances in financial technology have failed to reduce intermediation costs. In that spirit, our paper shows fintech lenders in fact offer higher interest rates than non-fintech lenders. However, consumers' willingness to use more expensive fintech lenders may also reflect more convenient services offered by these lenders.

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

III. Data and Lender Classification

III.A Description of Datasets

We use and combine the following datasets in our paper.

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

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

[6] The dataset does not include adjustable-rate mortgage loans, balloon mortgage loans, interest-only mortgage loans, mortgage loans with prepayment penalties, government-insured mortgage loans, Home Affordable Refinance Program (HARP) mortgage loans, Refi Plus™ mortgage loans, and non-standard mortgage loans. Also excluded are loans that do not reflect current underwriting guidelines, such as loans with originating LTV's of over 97%, and mortgage loans subject to long-term standby commitments, those sold with lender recourse or subject to other third-party risk-sharing arrangements, or were acquired by Fannie Mae on a negotiated bulk basis.

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-rate mortgages originating between January 1999 and September 2015 and purchased by Freddie Mac. Also included are 15- and 20-year fixed-rate mortgages originating between January 2005 and September 2015. The monthly loan performance data runs until March 2016 for all the loans provided.[7] Combining the Fannie Mae and Freddie Mac datasets gives us coverage of the majority of conforming loans issued in the United Sates during the period of our study.

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

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

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

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

which we calculate bank capitalization. We use two other measures in addition to bank capital to measure bank regulatory burdens. As in Lucca et. al. (2014), we obtain a regional measure of bank regulator activity by examining enforcement actions brought by the primary banking regulators: The Federal Reserve, the FDIC, the OCC, and the (no-longer active) OTS. Regulators use enforcement actions to discipline banks that receive poor examination reports, and the formal enforcement actions are disclosed to the public.[8][9][10] Like Lucca et. al., we focus on the harshest enforcement actions: Cease and Desist orders, Prompt Corrective Action Directives, and Termination and Suspension of Deposit Insurance. We extend the period covered by the data through 2015.

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

III.B Lender Classification

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

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

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

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

Aggregate fluctuations in lending volume were not uniform across different sectors of the residential mortgage market, possibly because of differential government intervention.[14] Figure 1, Panel B shows the lending volume in the most popular residential loans in the US[15], conforming mortgages. These loans conform to the Fannie Mae or Freddie Mac (Government Sponsored Enterprises, GSE). In our sample almost half of loans were loans sold to GSEs within the year (Table 1, Panel B).[16] Because of its size, the conforming residential market volumes largely mirror

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

[15] 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).

[16] 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.

those of the market as a whole. The makeable difference arises at the beginning of the crisis; the conforming market suffered only a small decline in loan issuance in 2008.

Figure 1, Panel C presents loan volumes insured by the Federal Housing Authority (FHA loans). The FHA loans allow lower income and less creditworthy households to borrow money at often below private market rates for the purchase of a home that they would not otherwise be able to afford. Usually borrowers with FHA loans finance only about 3.5% of the property value through a down payment with the rest being financed with an FHA loan. These loans account for approximately 14% 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 differ substantially from the conforming mortgages. This segment grew increase in the issuance of FHA loans from $70 billion in 2007, and peaked in 2009 at over $340 billion. This dramatic growth reflects among other things the disappearance of the private subprime lending market to which FHA loans are the closest substitute.

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

Despite these large fluctuations in the aggregate amount of residential mortgage originations, the *share* of shadow banks has been steadily increasing over time. Figure 2 shows that the share of 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 nearly tripled, growing from about 15% in 2007 to more than 38% in 2015. While there were some signs of a shift to shadow banks early in the sample, the majority of the growth in the total market takes place after 2011.

This growth in shadow banks was not confined to a specific segment of the residential market. We observe a large growth of shadow banks among conforming loans: shadow bank share in this sector more than doubled, reaching about 42 percent in 2015, with the largest growth occurring after 2013. Figure 2, Panel C, shows that the growth of shadow banks in the FHA loan market has been explosive: the shadow bank origination share grew from about 20% in 2007 to about 75% in 2015. The large expansion of shadow banks started earlier than in the conforming market, as early as 2010. Note that the share of shadow banks grew both in the period of rising volumes from 2007 to 2009, as well as declining volumes from 2010 to 2014. These aggregate data suggest a structural shift has taken place in who lends in this market.

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

Moreover, the fintech share of shadow bank lending has slowly increased over time, especially in 2009-2013 period.

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

C. Financing of Shadow Banks

We conclude this section by presenting a few basic facts on the financing side of shadow bank residential mortgage lending. Panel B of Table 1 shows that traditional banks tend to hold almost a quarter of their originated loans on balance sheet, shadow bank lenders do so rarely, at approximately 5%. This fact 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. Shadow banks sell their originated loans to government or government sponsored enterprises: Fannie Mae, Ginnie Mae, Freddie Mac, or Farmer Mac. Fannie Mae and Freddie Mac are the purchasers of conforming loans, while Ginnie Mae is the primary purchaser of FHA loans. Moreover, whereas banks hardly ever sell their loans to other banks, this is a reasonably common practice for shadow banks, which do so with more than 10% of the loans they originate.

Figure 4 confirms this inference by showing the time trends of loan disposition among traditional banks, shadow banks, and fintech lenders, respectively. Panel A shows that bank loans are overwhelmingly either held on balance sheet by the originator or affiliate of the originator, or sold to GSEs. Banks have been shifting towards holding fewer loans on balance sheet, moving from holding roughly 60% of originations in 2007 to 30% in 2012, though in recent years this number has increased again to 40%. Contrast this with Panel B, which shows that shadow banks almost never retain originations on balance sheet, and are increasingly reliant on GSEs. The composition of shadow bank funding has shifted dramatically: In 2007, shadow banks were funded primarily with bank, insurance company, and other capital, with only 30% of funding coming from GSEs. By 2015, roughly 85% of shadow bank loans were sold to GSEs after origination. They also increasingly sell to other banks.

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

V. Regulatory Burden: Traditional Banks versus Shadow Banks

This rise of shadow banks at the expense of traditional banking is consistent with the idea that traditional banks retreated from markets with a larger regulatory burden, and that shadow banks filled this gap. In this section, we analyze in greater detail the residential lending activity of shadow banks relative to traditional banks. 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 bank entrants is highest. Since regulation is the main differentiating factor between shadow bank and traditional banks, such results suggest that these are the sectors in which the additional regulatory burden of banks is highest. We then analyze the pricing and performance of shadow bank loans relative to observationally similar loans issued by traditional banks. Finally, we link the rise of shadow banks to specific three specific sources for this increase: capital requirements, mortgage-related enforcement actions, and mortgage lawsuits

A. Descriptive Statistics

A.1 Borrower and Loan Characteristics within Geographic Markets

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

Compared with traditional banks, shadow bank borrowers have approximately \$4,000 lower annual incomes on average. This difference became more pronounced in the recent period growing to \$15,000 by 2015. We do not observe dramatic differences in race across borrowers. Shadow banks have a slightly lower proportion of borrowers reporting as white and a larger proportion of borrowers reporting to be African-American (in 2015). The most striking difference is that shadow banks' borrowers report "other" or "unknown race" far more often than traditional lenders. Presumably, some borrowers may choose not to report their race when lenders cannot easily observe it, especially in the context of online lending.

We examine which markets shadow banks enter in the next section. Here, we more formally analyze which types of borrowers obtain mortgages from traditional versus shadow banks in a given market, by estimating the following linear probability specification:

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

in which an observation is a residential mortgage i in county c originated in year t. $Shadow\_Lender_{ict}$ is an indicator variable that take takes a value 1 if the residential mortgage was originated by a shadow bank and 0 otherwise. X_i is a vector of borrower and loan characteristics, such as borrower income and race, the purpose of the loan (omitted category is home purchase) or loan type loan type (omitted category is conventional). We also include county x time fixed effect δ_{ct} so that we compare borrowers in the same market, at the same point in time. Panel B of Table 2 displays the results.

In simple mean difference earlier, we find that shadow banks' borrowers are more likely to be low income, black, and "unreported race" borrowers. Consistent with simple mean differences, borrowers with lower incomes are more likely to be shadow bank borrowers. Conditioning on borrower characteristics such as income, however, shows that black borrowers are less likely to be shadow bank borrowers. These results do not necessarily imply that shadow banks' borrowers are more likely lower income whites: "unknown" race, and "NA" sex are much more likely to be shadow bank borrowers.

The most significant differences between traditional and shadow banks do not arise on borrower characteristics captured in the HMDA data. For example, shadow banks are much more active in the market for refinancing mortgages: a refinance is roughly 5 percentage points more likely to be a shadow bank loan than a home purchase. Shadow banks are even less likely to finance home improvement loans. One possible reason is that shadow banks might be better at refinancing because they can avoid labor-intensive "purchase" activity such as a title check, structural examination, negotiations between buyer and seller, having already taken place at the time of purchase.

Shadow banks are also substantially more likely to originate loans across segments, in which government intervention is meant to increase mortgage access. Aggregate data, presented in Figure 2 indicate that the FHA market, which serves less creditworthy borrowers, experienced large growth of shadow banks. Even conditional on borrower characteristics such as income and race, shadow banks are substantially more active in the FHA market: a FHA loan is 7 percentage points more likely to be originated by a shadow bank. Shadow banks loans are also more likely among US Veterans (VA) loans, and US Department of Agriculture and Rural Housing Service (RHA) loans.

There are several reasons why shadow bank participation may be more likely in such programs. One reason may be that the HMDA data does not include detailed borrower attributes such as their consumer credit scores or debt-to-income ratios. So FHA, VA, and RHA loans are simply a proxy for creditworthiness of borrowers. We explore this explanation further in the conforming mortgage data below. Second, these types of loans are tied to the originate-to-distribute model, which is more prevalent among shadow banks. The results in Table 2, Panel B 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. Third is that the rise of shadow bank is linked to government subsidies. Shadow banks that cannot rely on government guaranteed deposits for funding appear to be very reliant on government guarantees in the form of GSEs and FHA insurance. Last, the GSEs mortgage segment, especially FHA, were subject to several enforcement actions and lawsuits that had specifically targeted traditional banks' so, it may not be surprising that banks are retreating from that sector somewhat. We examine this channel in more detail in Section V.B.

One way to examine whether the expansion of shadow banks is driven by their expansion in the less creditworthy segment is to take advantage of Fannie Mae and Freddie Mac data, which contain more detailed credit information than HMDA data we examined above. This limits our inquiry to the sample of conforming FRMs. We estimate which types of borrowers obtain *conforming* mortgages from traditional versus shadow banks in a given market, by reestimating regression (1) and present the results in Table 3.

The results show differences between loans originated by traditional banks and shadow banks in the conforming market. There are some differences in the creditworthiness of borrowers who are more likely to use shadow banks. Borrowers with lower FICO scores, and greater debt-to-income ratios tend within a market tend to be shadow bank loans, though interestingly, loans with lower loan-to-value ratios also tend to be shadow bank loans. These differences, however, are quantitatively very small: a borrower with a 100 point higher FICO score is 0.5 percentage points more likely a shadow bank borrower. Similarly, larger mortgages tend to be shadow bank originations, but the effect is quantitatively small.

We find larger differences in the purpose for these mortgages. Confirming our finding from the HMDA data, shadow banks focus on refinancing, rather than originating than a home purchase, especially cash-out refinances are significantly more likely to be handled by shadow banks, with small differences in the other direction for non-cash-out refinances. Shadow bank loans are also much more likely to be for primary residence mortgages, rather than investment properties or second homes.

A.2 Shadow Bank Expansion across Geographic Markets

In the previous section, a substantial part of the analysis is focused within a specific geographic market. In this section, we analyze differences in the shadow bank penetration across geographic markets. This comparison 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 the distribution of shadow bank market share in residential lending across counties in the US based on HMDA. There is a significant heterogeneity in the county-level shadow bank penetration ranging from less than 10% to more than 80%. Panel A of Table 4 shows geographical differences at the county level between areas with a low (bottom 25%) and high (top 25%) share of shadow banks. Counties with a large shadow bank presence have more minorities and worse socioeconomic conditions. The median income for a high-shadow bank area is lower than that for a low shadow-bank area; there are more African American and Hispanic residents, and a greater percentage of residents earning below $35 thousand per year. Interestingly, shadow banks are also more predominant in areas with significantly lower lending concentration as measured by a Herfindahl Index, and with more unique lenders on average.

To shed more light on this issue we next investigate how different geographical characteristics are associated with the market share of shadow banks in a county. In particular, at the county level we regress:

$$\%Shadow\_Bank\_Loans_c = X_c'\Gamma + \epsilon_c \tag{2}$$

where 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 (based on HMDA).

Panel B of Table 4 shows these results. Across the specifications, we confirm the insight from the simple descriptive statistics above: counties with have more minorities and worse socioeconomic conditions have greater penetration of shadow banks. This is the case in counties with more high-school, non-college educated residents, and counties with more African American and Hispanic residents have more shadow banks. Recall that we do not find large differences in the share of African American and Hispanic borrowers when looking at individual borrower data, but we found that borrowers who do not declare race more likely borrowed from a shadow banks. The county level result suggest that shadow banks are tilted towards minority borrowers, but that these borrowers may frequently choose not to disclose their race in their mortgage application.

Moreover, there is a strong positive association between the unemployment rate and shadow bank penetration: In the baseline specification, a 1% greater unemployment rate is associated with a 0.5% greater penetration of shadow banks. Interestingly, while shadow banks tilt their lending to serve FHA borrowers within a market, this does not manifest at the county level. Rather, it appears the shadow banks' tilt towards FHA loans occurs within counties. Finally, confirming descriptive statistics areas with more shadow banks tend to have less banking concentration and a larger number of unique lenders.

A.3 Loan Pricing: Are Shadow Banks Cheaper?

As we document, the market share of shadow banks in US residential mortgages has grown explosively in the last decade, both in the overall market, and in the conforming mortgage market. At least two questions arise. How did shadow banks increase their market share: is it because they offer cheaper mortgages? If traditional banks are indeed suffering from an increased regulatory burden, is the cost of this burden passed through to consumers by charging more? We present differences between shadow banks and traditional banks charged on observationally similar borrowers by estimating the following regression to study these differences in the conforming loan sample for which interest rate data is available:

$$rate_{izt} = \beta Shadow\_Bank_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \tag{3}$$

in which an observation is a mortgage i, originated in zipcode z in quarter t. The dependent variable $rate_{izt}$ is the mortgage rate. The independent variable of interest, $Shadow\_Bank_{izt}$ is a dummy variable for whether the originator was as shadow bank. We control for borrower characteristics such as FICO and loan-to-value in X_i. Last, to compare pricing of mortgages in the same market, at the same point in time, we include zipcode x quarter fixed effect δ_{zt}. This fixed effect controls for differences in supply and demand conditions across markets, as well as any regulatory differences across markets that may explain the entry of shadow banks. The results are presented in Table 5.

We find no significant difference between shadow bank interest rates and traditional bank interest rates with all borrower and loan controls and zip-quarter fixed effects. In other words, shadow banks gained a substantial market share without charging on average lower prices than traditional banks. This finding suggests that borrowers perceive mortgages as homogenous products, so Bertrand style competition forces prices to equate. Alternatively, there is enough competition among shadow banks and among traditional banks that prices are pushed very close, even if consumers perceive these as differentiated, lenders do not have substantial market power to extract surplus, at least across these groups.

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

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

A.4 Loan Performance

Shadow banks could also "underprice" loans to borrowers 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 whether shadow bank borrowers are more likely to exhibit worse performance holding their characteristics, and importantly, interest rate fixed, using the following specifications:

$$\begin{aligned} Default_{izt} &= \beta Shadow\_Bank_{izt} + \beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \\ Prepayment_{izt} &= \beta Shadow\_Bank_{izt} + \beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \end{aligned} \tag{4}$$

$Default_{izt}$ measures whether a mortgage *i*, originated in zipcode *z*, in quarter *t*, is delinquent within two years of its origination.[17] $Prepayment_{izt}$ is defined analogously. We control for the mortgage interest rate $rate_{izt}$, borrower and mortgage characteristics, X_i. We compare mortgage performance within a market at the same point in time, using zipcode x quarter fixed effects δ_{zt}.

Shadow banks loans are more likely to default than traditional bank loans (Table 6, Panel A). The magnitudes are small: shadow bank borrowers' default rates are roughly equivalent to traditional bank borrowers with a 4 point lower in FICO score. We find larger differences in loan prepayment (Table 6, Panel B). Shadow bank loans are more likely to be prepaid, with coefficients ranging roughly between 1.5% and 3% depending on the specification. The base rate of prepayment within two years of origination over the time period is approximately 11%. Therefore a shadow bank loan

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

is between 12-25% more likely to be prepaid than a comparable traditional bank loan in the same market, with the same borrower characteristics, and with the same interest rate. In other words, shadow banks expansion was partially achieved by charging similar interest rates, to borrowers with similar default rates, but drawing a pool of borrowers which is more likely to prepay mortgages.

B. Rise of Shadow Banks: Capital Requirements and Regulation

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

B.1 Capital Requirements

Shadow banks predominantly sell their originated loans to government or government sponsored agencies, and unlike traditional banks, almost never hold them for portfolio reasons. This fact suggests that unlike traditional banks that can also rely on government guaranteed deposits for funding, shadow banks are very reliant on government guarantees in the form of GSEs and FHA insurance. One possibility is that increased capital requirements indirectly lowered the relative subsidies available through government guaranteed deposits, partially contributing to the rise in shadow banks. We investigate whether capital constraints of traditional banks had a role to play in the rise of shadow banking by examining whether shadow banks expanded more in areas where traditional banks suffered significant tightening of their capital constraints during the recent crisis.

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

$$\delta CR_{b2016} = \frac{Equity_{b2015}}{Assets_{b2015}} - \frac{Equity_{b2006}}{Assets_{b2006}}$$

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

$$\Delta Local\ Capital\ Ratio_c = 100\times \sum_{b\in c} \delta CR_{b2006} \frac{Deposits_{bc2006}}{\sum_{d\in c} Deposits_{dc2006}}$$

We estimate whether a tightening of their capital constraints led to a larger growth of shadow banks in a county using the cross-sectional specification:

$$\Delta Shadow\ Bank\ Lending\ Share_c = \beta_0 + \beta_1 \Delta Local\ Capital\ Ratio_c + X_c'\Gamma + \epsilon_c, \qquad (5)$$

in which $\Delta Shadow\ Bank\ Lending\ Share_c$ represents the change in the share of shadow bank market shares from 2007 to 2015. We control for other county characteristics in X_c'.[18]

The estimates in Table 7 suggest that the counties with traditional banks whose capital ratios decreased by 1% saw increased entry of shadow banks by 0.36%. In scaled terms, a one standard deviation decrease in bank capital ratios corresponds to a 1.2 standard deviation increase in shadow bank lending share. This is consistent with the prediction that shadow banks enter local lending markets in which traditional banks, which rely on capital to meet regulatory requirements, were experiencing tightening of capital constraint.

B.2 Regulatory Oversight

The descriptive statistics suggest that shadow banks tilt their lending to markets with more minorities and worse socioeconomic conditions. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of minority borrowers, it may not be surprising that traditional banks retreated from that sector somewhat. Because shadow bank activities are more concentrated on new originations, they escape much of the scrutiny that full-service banks' receive from regulators and class action lawsuits with respect to their legacy loans.[19]

We next investigate the impact of lawsuits aimed at traditional banks on the entry of shadow banks. The idea behind this test is to investigate whether shadow banks expanded more in areas that were dominated by traditional banks that became significantly exposed to the crisis area mortgage liability and lawsuit risk. Such exposure may have limited the traditional banks' ability and willingness to serve riskier borrowers.

We collect data on large mortgage lawsuit settlements against large lenders, both traditional and shadow bank. 98% of observed lawsuits target traditional banks, as the subject matter of the lawsuits often concerns activities that pure originators do not engage in, such as securitization. Denote a bank b's accumulated lawsuit settlements between 2006 and 2015, in billions as L_b. We

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

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

calculate exposure to mortgage settlements of county c as a weighted average of 2006 lending activity of banks in that county as follows:[20]

$$\Delta Lawsuit\ Exposure_c = 100 \times \sum_{b \in c} L_b \frac{Originations_{bc2006}}{\sum_{d \in c} Originations_{dc2006}}$$

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

$$\Delta Shadow\ Bank\ Lending\ Share_c = \beta_0 + \beta_1 \Delta Local\ Lawsuit\ Exposure_c + X_c' \Gamma + \epsilon_c \qquad (6)$$

in which $\Delta Shadow\ Bank\ Lending\ Share_c$ represents the change in the share of shadow bank market shares from 2007 to 2015. We control for other county characteristics in X_c'. Table 8 shows the corresponding results. We find that counties with greater exposure to lawsuit settlements saw more entry of shadow bank lenders, suggesting that traditional banks retreated from counties that faced a larger regulatory burden. The magnitudes are substantial: consider a county where banks have mean additional lawsuit exposure of $18.61 billion (at the national level) relative to a county with no lawsuit exposure. The former saw an additional 5.2 percentage points (0.28*18.61) entry of shadow banks. This amounts to an additional 20% increase in shadow bank share relative to the mean increase of 25.77 percentage points.

Another way to measure the regulatory burden faced by traditional banks is to examine enforcement actions brought against them. We collect data on enforcement actions of agencies that regulate depository institutions and not shadow bank lenders: OCC, FDIC, OTS, and Federal Reserve.[21] Following Lucca et. al. (2014) we focus on the initiation dates of the harshest formal enforcement actions: Cease and desist orders, prompt corrective action directives, and terminations or suspensions of deposit insurance.

We define enforcement intensity in county c in year t, $EA\_Intensity_{ct}$, as the total number of enforcement actions brought by these agencies divided by the number of active banks in the same county and year. To examine whether shadow banks, being outside these regulators' purview, disproportionately enter regions following spells of particularly high enforcement activity, we estimate the following specification:

$$\Delta Shadow\ Bank\ Lending\ Share_{ct} = \beta_0 + \beta_1 EA\_Intensity_{\mathrm{ct-1}} + X_{ct}' \Gamma + \delta_t + \delta_c + \epsilon_{ct} \qquad (7)$$

[20] We weigh lawsuits by lending activity, not deposits, because shadow bank lenders do not have deposits.
[21] OCC regulates national banks; the OTS (now folded into the OCC but active for part of our sample period) regulates Thrifts; the Federal Reserve and FDIC regulate state member and non-member banks.

The results in Table 9 indicate that counties in which traditional banks experienced more enforcement action saw more entry by shadow banks in the following year. The mean number of enforcement actions bank in a county-year is 2.24 with a standard deviation of 17.7. A coefficient of 0.06 implies that a one standard deviation increase in enforcement actions per bank is associated with roughly a 1 percentage point increase in shadow bank lending per year. This is meaningful relative to the mean growth rate of shadow bank lending per year, which is 2.86 percentage points. These findings suggest that a greater regulatory burden falling on traditional banks is associated with greater entry from shadow bank lenders.

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 Role of Technology: The Rise of Fintech

The rise in shadow banks has coincided with a shift away from "brick and mortar" originators to online intermediaries. The quintessential example is Quicken Loans, which grew to be the second largest retail mortgage lender in the U.S, and the largest lender in (VA) and FHA loans.[22] The lending process occurs with no human interaction except a brief closing meeting with a Quicken Loans representative that could take place in a local coffee shop or the borrower's home. From a regulatory perspective, fintech banks are just another example of shadow banks. The difference between fintech lenders and other shadow banks is in their use of financial technology and on-line access in their lending process.

To shed light on the role that technology may have played in the rise of shadow banks, we focus on technology differences *between* shadow banks. Examining the role of technology within shadow banks allows us to hold the regulatory differences between different lenders fixed. First, we collect the information on a shadow bank's online presence, to classify their lending operations as fintech or non-fintech. We then examine in which markets fintech firms have grown faster than non-fintech shadow banks.

A. Descriptive Statistics

A.1 Borrower and Loan Characteristics within Geographic Markets

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

We begin our descriptive analysis by examining differences between fintech borrowers and other 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 both shadow bank lending overall, and fintech lending, had already substantially expanded (Table 10, Panel A). Fintech borrowers have slight higher incomes than non-fintech borrowers. The results on race are difficult to interpret, because a large share of borrowers do not report race: approximately one quarter of fintech borrowers do not report race in 2015. The reported racial composition shifts between the two samples over time, so little can be said from simple descriptive statistics.

To analyze more formally an association between borrower and loan attributes and fintech lending, we estimate the following linear probability specification at the individual level:

$$Fintech\_Lender_{ict} = X_i'\Gamma + \delta_{ct} + \epsilon_{ict} \quad (8)$$

in which an observation is a residential mortgage issued by a shadow bank i in county c originated in year t. The dependent variable $FintechLender_{ict}$ measures whether the originator was a fintech lender. X_i is a vector of borrower and loan characteristics, such as borrower income and race, the purpose of the loan (omitted category is home purchase) or loan type loan type (omitted category is conventional). We also include county x time fixed effect δ_{ct} so that we compare borrowers in the same market, at the same point in time. Table 10, Panel B displays the results.

Consistent with simple means, higher income borrowers are more likely to borrow through fintech lenders, but the magnitudes are small. The differences in the racial composition are also fairly small with the exception of Asian borrowers who are substantially less likely to borrow from fintech firms. Recall that a large share of borrowers do not disclose race, so these differences have to be interpreted with caution. As was the case with shadow bank versus traditional bank loans, there are striking differences concerning loan purposes. A refinance is more than 20% more likely to be a fintech loan.

The HMDA data does not include detailed borrower attributes such as their consumer credit scores or debt-to-income ratios. To shed light on these attributes, we take advantage of Fannie Mae and Freddie Mac data and explore differences in these characteristics in the sample of conforming FRMs. For that purpose we run a regression of the form (8) and present the results in Table 11.

While there are some differences in loan characteristics, such as loan amount, term, loan-to-value, and debt-to-income, the most striking differences emerge from loan purpose and property type variables. In particular, in line with our evidence from HMDA data, refinances of all types are seven to ten percent more likely to be fintech-originated. Further, mortgages on primary residences are also most likely to be fintech refinances. Finally, first-time buyers are significantly less likely to be fintech customers.

One could rationalize these findings based on tasks involved in mortgage refinancing as being better suited for fintech technology. Refinancing an existing mortgage is more mechanical than originating a mortgage for a new purchase. In particular, 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.2 Fintech Expansion across Geographic Markets

Next, we analyze differences across the fintech shadow bank penetration at the county level. This comparison will allow us to explore differences in other household attributes such as education and unemployment rates that are not available to us at the borrower level.

Panel A of Table 12 shows geographical differences at the county level between areas with a low (bottom 25%) and high (top 25%) share of fintech shadow bank lenders. Median household incomes tend to be lower in areas where fintech lenders are most active; they are also most active in areas with lower population densities and lower levels of education. These are univariate patterns. To shed more light on this issue we next investigate how different geographical characteristics are associated with the market share of fintech lenders in a county. In particular, at the county level we regress:

$$\%Fintech\_Loans_c = X_c'\Gamma + \epsilon_c \qquad (9)$$

where X_c is a vector of county level characteristics. Panel B of Table 12 shows these results. Columns (1) is the baseline specification; Columns (2) and (3) include measures of lending competition: The Herfindahl concentration measure for (2) and the number of unique lenders for column (3).

There are several large and consistent factors associated with a greater penetration of fintech. First, once we control for other factors, counties where there are more residents with bachelors' degrees see significantly more penetration from fintech lenders. This is not surprising since access to fintech lending requires a certain degree of technological sophistication on the part of borrowers. Second, while we find that shadow banks are on average more likely to be found in counties with greater minority populations, the opposite is true for fintech lenders among shadow banks: Counties with greater minority populations see less penetration by such lenders. Third, counties with lower unemployment rates see more entry of fintech lenders, though this effect varies significantly depending on competition controls. Fourth, we also see greater fintech penetration among counties where a greater fraction of the population that has lived in the same home for over a year. This is consistent with findings we report below, that fintech lenders specialize in refinancing. Fifth, a greater share of FHA loans in a county predicts strongly greater penetration of fintech lenders. And finally, we find counties with greater lending concentration and fewer unique lenders see more fintech penetration.

A.3 How Expensive are Fintech Loans?

We next turn to differences in interest rates between fintech and non-fintech shadow banks charged on observationally similar borrowers. One view is that technology allows fintech shadow banks to extend cheaper loans, because lending online results in less labor, and other costs, associated with making loans. If this is the case, one would expect fintech firms to pass some of the savings to their consumers. Such differential pricing might explain the large rise of fintech market share in the conforming and FHA market. Lending online could also lead to product differentiation: because online loans do not require a visit with a physical mortgage officer they may save time and be more convenient also from consumers' perspective. To better understand the differential pricing of fintech firms and shadow banks, we estimate the following in the conforming FRM sample of shadow bank loans, for which we have price data:

$$rate_{izt} = \beta Fintech_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt}. \quad (10)$$

Where $rate_{ict}$ is the interest rate charged on mortgage i, at zipcode z, originated in quarter t. $Fintech_{izt}$ is a dummy variable for whether the originator was a fintech lender, X_i is a vector of borrower controls, including FICO and loan-to-value, and δ_{zt} is a zipcode x time fixed effect.

The results show sizeable differences in interest rates offered on conforming loans comparing fintech and non-fintech firms. Fintech firms charge 11 basis points greater interest rates than non-fintech shadow banks to observably similar borrowers in the same zip code in the same quarter. This is equivalent to roughly a 2.5% premium over the mean non-fintech interest rate, or, alternatively, would reflect a a 60 point difference in FICO score.[23] We further note that this interest premium is unlikely to be explained by differences in origination fees between fintech and non-fintech lenders (see Appendix A4).

Overall, this pricing evidence suggests that more creditworthy and arguably wealthier fintech borrowers pay a premium for fintech loans. One possible reason is that this represents a premium for convenience. Alternatively, higher income borrowers who are attracted to fintech are less price elastic.

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

Recall that on average shadow banks charge very similar interest rates as traditional banks in the conforming loan market (Section V.A.3). The results of this section showing a substantial interest premium charged by fintech lenders point towards a more nuanced "segmented market" view of the shadow bank expansion in the conforming market. Fintech shadow banks offer higher rates (both relative to non-fintech and traditional banks) in the segment of high income and creditworthy borrowers who may value convenience. At the same time non-fintech shadow banks charge lower rates (both relative to fintech lenders and traditional banks) and attract less creditworthy and potentially more price sensitive borrowers. Indeed, consistent with this view we verify that, controlling for other observables, non-fintech shadow bank charge rates that are about 2.9 basis points lower relative to traditional banks while fintech shadow banks charger rates that are about 9.7 basis points higher compared to traditional banks. Given their respective market shares, the combined effect of these differences implies no average difference in interest rates charged by shadow banks relative to traditional bank lenders.[24]

A.4 Loan Performance

As we found in the previous section, shadow banks' loans are more likely to be refinanced relative to traditional banks loans, but we found almost no differences related to defaults. Here we examine whether there are differences in loan performance estimating a corresponding fintech specification by focusing on shadow bank loans:

$$\begin{aligned} Default_{izt} &= \beta Fintech_{izt} + \beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \\ Prepayment_{izt} &= \beta Fintech_{izt} + \beta_r rate_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \end{aligned} \tag{11}$$

$Default_{izt}$ measures whether a mortgage i, originated in zipcode z, in quarter t, is delinquent within two years of its origination.[25] $Prepayment_{izt}$ is defined analogously. We control for the mortgage interest rate $rate_{izt}$, borrower and mortgage characteristics, X_i. We compare mortgage performance within a market at the same point in time, using zipcode x quarter fixed effects δ_{zt}.

Panel A of Table 14 show the results for default. Fintech loans are less likely to default than non-fintech loans within the same zip code, which were originated in the same quarter with the same characteristics. Fintech loans are roughly 0.04% less likely to default than non-fintech loans. This is equivalent to a 6.3 point difference in FICO score. The base rate of default within two years of origination over this time period is 0.23%, meaning that this difference, while small in absolute

[24] Since about 80% of shadow banks are non-fintech in the conforming loan sample these relative differences in interest rates amount to essentially no difference in average rates charged by shadow banks and traditional banks: 0.80*(-2.9)+0.2*(9.7) ≈ -0.36 basis points (consistent with the estimates in Table 5).

[25] We therefore restrict loans to have two years of performance, reducing our sample to loans originated between 2010 and 2013.

terms, means that fintech loans are roughly 20% less likely to default than non-fintech loans. However, the result only arises when controlling for interest rates, suggesting that for a given interest rate, fintech lenders are able to attract borrowers of higher quality, or equivalently, that borrowers of a fixed quality are willing to accept higher interest rates from fintech lenders.

Panel B of Table 14 show the results for prepayment. Fintech loans are 2% more likely to be prepaid than non-fintech loans. Once controlling for interest rates, these differences shrink to roughly 1%. The base rate of prepayment within two years of origination during this time period is approximately 11%, so this the difference before controlling for interest rates makes fintech loans roughly 20% more likely to prepay with the difference shrinking to roughly 10% after controlling for interest rates.

B. Rise of Fintech Lenders: Better Screening Models, Convenience, and Cost Savings

The descriptive results point to significant differences between fintech and non-fintech lenders This section attempts to shed light on economic forces behind these differences. Because our comparison is across shadow bank lenders, the differences are unlikely driven by regulation. We therefore consider two explanations for the role of technology in the rise of fintech lenders. One explanation is that fintech lenders make use of more data and use better models to price their loans. A second explanation is that fintech, by requiring less effort from the borrower in the origination process, deliver a more convenient mortgage origination experience.

B.1 Better Credit Models

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

$$P(default_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \tag{12}$$

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + X_i'\Gamma + \delta_t) \tag{13}$$

where r_i is the interest rate on the loan. Panel A of Table 15 presents the results for default. While the coefficients on interest rate are all positive, there is little difference among them, and little difference among the explanatory power of the repressors. The coefficient for non-fintech shadow banks without other controls is 0.507 versus 0.506 for fintech. Including controls, the coefficients become 0.211 and 0.170, respectively.

As we discuss above, these loans have substantially higher differences in prepayment risk. Panel B of Table 15 shows the results. There are striking differences in the no-controls results: Non-fintech shadow banks, the coefficient on interest rate is negative. This result in not surprising, once we consider the absence of credit risk controls. Borrowers in good financial condition are the most likely to prepay, and interest rates for good borrowers are lower. Therefore, there are two opposing forces in setting interest rates with respect to prepayment: Prepayment is bad for the investor, but those borrowers who are able to prepay are less likely to default. However, with fintech borrowers, the coefficient, while low in magnitude, is actually positive, suggesting that for fintech loans, the larger prepayment risk dominates the interest rate decision. Once adding controls, interest rates are positively associated with prepayment risk. More importantly, fintech lenders' interest rates are more positively related to prepayment.

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

$$P(prepay_{it}) = \Phi(\beta_0 + \beta_1 r_i + \beta_2 r_i \times Fintech_b + X_i'\Gamma + \delta_t) \quad (14)$$

The results are presented in Table 16. 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 better pricing models that are more reflective of prepayment risk. Two important caveats need to be considered, however. First, for fintech lenders to care about better pricing, investors who buy these loans need to be aware that such lenders are able to better price prepayment risk and be willing pay a premium for these loans. Second, a stronger association between interest rates and subsequent prepayment on fintech loans may also reflect selection of borrowers who select into fintech lenders.

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

$$rate_{izt} = \beta_1 FICO_i + \beta_2 LTV_i + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \quad (15)$$

We present the results in Table 17. Fintech shadow banks use substantially less hard information than non-fintech shadow banks: the R^2 are smaller across all specifications. These results suggest that fintech lenders do set interest rates differently from non-fintech lenders either by combining existing data, or by using other dimensions of data, not available to other lenders.

B.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 roughly 11 basis points higher than non-fintech interest rates. At same time we found some evidence that among the lowest segment, FHA borrowers, fintech interest rates were roughly seven basis points lower than non-fintech interest rates for otherwise similar borrowers. These differences are consistent with low-quality, lower income FHA borrowers being price sensitive and with a low value of convenience, and high-quality conventional borrowers being less price sensitive and willing to pay for convenience. Bolstering this interpretation is the fact that in terms of default, among conforming borrowers with the same interest rate, fintech borrowers are less likely to default. This suggests that conforming borrowers of equal quality pay a premium for fintech loans. We note, however, that at least part of this premium may also reflect relatively higher prepayment risk of these borrowers.[26]

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

$$rate_{izt} = \beta_s Fintech_{bzt} + \beta_{h\times s} Fintech_{bzt} \times HighFico_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt} \tag{16}$$

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

The results presented in Table 18 show that fintech borrowers with the highest credit ratings pay an even greater premium for fintech loans, relative to other borrowers with the same characteristics. The highest Fico score fintech borrowers pay approximately 1.5 basis points more than borrowers in the ordinary Fico range do for fintech loans. This difference is roughly equivalent to the interest rate difference associated with a 7.5 point FICO differential. Relative to

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

the baseline difference of 9.2 basis points, this estimate corresponds to a 15% increase in the premium of fintech over non-fintech rates. Including zip times quarter fixed effects reduces the effect to roughly 0.4 basis points, which is still significant and corresponds to a 5% increase in premium. The results suggest that indeed, those borrowers most likely to value convenience are willing to pay for the convenience offered by fintech lenders.

To summarize, we find some evidence that fintech lenders use technological advantages in determining corresponding interest rates. In addition, fintech originations may provide a larger convenience, which their borrowers value. Among the most price sensitive borrowers, fintech loans have lower interest rates, among the borrowers most likely to value convenience, fintech lenders are able to command a premium for their services.

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

The shadow bank market share in conforming loan market grew by more than 33 percentage points in 2007 to 2015 period.[27] Of this increase, about 11.7 percentage points are attributable to the growth in fintech firms. The evidence presented above suggests that the rise of shadow banks and fintech firms at the expense of traditional banks was driven both by differences in regulatory burden across these types of institutions, as well as differences in the perceived convenience, quality, and other services offered by different types of lenders. In this section, we present a simple quantitative model, which we use to assess the relative contribution of regulation and technology to the rise of shadow banks and fintech.

A. Model Framework

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

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

A.1 Demand:

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

Borrower b's utility from choosing mortgage i is:

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

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. Depositors' 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:

Lender i is differ in quality of service q_i and in the marginal costs of providing a mortgage, ρ_i, which can reflect their shadow cost of financing. Operating within a market entails a fixed cost c_i, such as the cost of basic regulatory registrations, offices, support staff, and offices. Lenders are identical within type, so that the lender side of the economy is parameterized by each type's quality $q_i \in \{q_b, q_n, q_f\}$, funding cost $\rho_i \in \{\rho_b, \rho_n, \rho_f\}$, entry costs $c_i \in \{c_b, c_n, c_f\}$

In addition to impacting a bank's marginal cost, regulatory impediments may also reduce traditional banks' activity on the extensive margin. That is, binding capital requirements, risk constrains, enforcement actions, or lawsuits may sometimes prevent a traditional bank from lending to a borrower altogether. We capture this type of regulatory burden by γ_b, by assuming that if lender i is a bank, it will be unable to lend to a borrower with probability $1 - \gamma_b \in [0,1]$. These shocks are assumed to be independent and identically distributed across borrowers. These constraints do not affect shadow banks, i.e. non-fintech and fintech lenders, $\gamma_n = \gamma_f = 1$

Denote a lender's market share she would have obtained without regulatory impediments as s_i; the actual market share is then $\gamma_i s_i$. Conditional on being present in a market, a lender sets its interest rate r_i to maximize its expected profit, which is a function of the spread it charges over its financing cost and the probability that its offer is accepted:

$$(r_i - \rho_i)\gamma_i s_i$$

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

$$\pi_i = (r_i - \rho_i)\gamma_i s_i F - c_i$$

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
2) Lenders set interest rates, to maximize profits, taking market structure and the pricing decisions of other lenders as given
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

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

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

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

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

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

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

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 have to 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 impediments of traditional banks have changed over the period.

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

Additionally, we make the following normalizations: First, we measure quality and funding costs relative to banks, so that $\widetilde{\rho_b} = q_b = 0$. Notice from the expression for market share that this normalization on q_b is without loss of generality, and the normalization on $\widetilde{\rho_b}$ amounts to a scaling on the preference parameter α. Note also that by writing $\gamma_b = \exp(-q_b^r)$, bank regulatory impediment changes and bank quality changes relative to other lender types are not separately identifiable. Therefore, we set $\gamma_b = 1$ in 2008 and allow it to change thereafter, and calculate q_n in 2008 and hold it fixed, assuming that bank and non-fintech service quality did not change relative to each other. These normalizations leave observed fintech quality, q_b, and bank regulatory impairment, $1 - \gamma_b$, as well as funding and fixed costs to evolve through time.

Given the normalization that $\widetilde{\rho_b} = 0$, with observed individual bank market share s_b and bank mortgage rate r_b, we back out the preference parameter over interest rates, α, from the bank's first-order condition. Together with α, the fintech and non-fintech first-order conditions pin down $\widetilde{\rho_n}$ and $\widetilde{\rho_f}$ in each year. Next, observed aggregate market shares allow us to solve for implicit qualities and regulatory impediments. Finally, the zero-profit condition gives each firm type's fixed operating costs.

C. Results

The results of the calibration are shown in Figure 6. Our estimates imply that non-fintech shadow banks offer lower quality services than traditional banks. Obtaining a mortgage from her primary bank is more convenient for the borrower; it does not involve search, the borrower can make automatic payments from linked accounts, and the bank offers other convenient banking services such of checking accounts. The simultaneous rise of fintech market share and higher prices of fintech mortgages imply that fintech is gaining market share through increased quality and convenience of providing mortgages online. Our estimates suggest fintech quality increases dramatically, reaching parity with traditional banks by 2011, and surpassing it thereafter.

Our estimates imply that the expansion of fintech would have been even larger if it were not for its rising marginal (funding) costs. Fintech funding costs rise initially to roughly 20 basis points above bank and non-fintech funding costs, and stay at this increased level after 2011 suggesting that the funding for these new entrants became scarcer as they grew. While fintech funding costs exceed that of other shadow banks, shadow bank marginal costs of funding still slightly exceeded those of traditional banks, which have access to a large (and subsidized) deposit base. These results are not surprising given that banks and shadow banks charge similar interest rates. Rates are a markup over funding costs that depends on market shares. Neither the rate differential nor relative market shares of individual lenders underwent significant changes during this period, implying that relative funding costs could not have changed dramatically.

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

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

The last interesting result to note is that, in addition to shadow funding costs, the fixed costs of fintech lending have increased over time, suggesting increasing barriers to entry in this sector.

High entry costs in this sector are consistent with a rise in intellectual property and software development costs that the entry of new competitors requires, as well as potential un-modeled economies of scale in this sector.

D. Regulatory Burden and Technology: A Simple Decomposition

We recall that the shadow bank market share in conforming mortgage market grew by more than 33 percentage points in 2007 to 2015 period. Of this increase, about 11.7 percentage points are attributable to the growth in fintech firms. We use our simple calibrated model to infer how much of this growth is attributable to an incased regulatory burden and how much to technology improvements.

First, we ask how the conforming mortgage sector would have developed if the regulatory burden of traditional banks were frozen at the level of 2008, and the technological progress would not have taken place. We do so by setting both bank regulatory burden $1 - \gamma_b$ 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 7 suggest that non-fintech shadow banks would have gained approximately 3 percentage point market share between 2008 and 2015, with essentially no growth in fintech. Hence, without changes in regulatory burden and technology, we can account for only about 10% 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 $\mathrm{q_f}$ 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 18.2 percentage points, including a 1.1 percentage point growth occurring in the fintech sector (Figure 7). Hence, without technological improvements, we can account for about 55% of growth in shadow bank lending.

Last, we examine the role of technology. We ask how the residential mortgage sector would have developed if the regulatory constraints would not have tightened, but the technology revolution of fintech has taken place. We therefore fix the regulatory burden parameter of traditional banks at the level of 2008. We find that technological improvements lead to fintech gaining roughly 9.1 percentage points in market share, with non-fintech shadow banks gaining 2.5 percentage points in market share (Figure 7). Therefore, technology alone is responsible for approximately 78% of gains of fintech firms, and 35% of shadow bank growth overall.

The increase in 1.1% increase in fintech arising from increased regulation alone, combined with the 9.1% increase in fintech arising from increased technology alone leaves 1.5% residual growth in fintech. This suggests that the 1.5% residual arose as a consequence of an interaction between technology improvements occurring at the same time as incumbents, the traditional banks, were suffering from increased regulatory burden.

IX. Conclusion

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

Shadow bank lenders' market share among all residential mortgage lending has grown from 15% in 2007 to 38% in 2015. We argue that shadow bank lenders possess regulatory advantages that have contributed to this growth. First, shadow bank lenders' growth has been most dramatic among the high-risk, low-creditworthiness FHA borrower segment, as well as among low-income and high-minority areas, making loans that traditional banks may be unable hold on constrained and highly monitored balance sheets. Second, there has been significant geographical heterogeneity in bank capital ratios, regulator enforcement actions, and lawsuits arising from mortgage lending during the financial crisis, and we show that shadow banks are significantly more likely to enter in those markets where banks have faced the most regulatory constraints.

Fintech lenders, for which the origination process takes place nearly entirely online, have grown from roughly 4% market share in 2007 to 13% market share in 2015, and represent a significant fraction of shadow bank market share growth. By comparing lenders fintech and non-fintech shadow banks, we compare lenders who face similar regulatory regimes, thus isolating the role of technology. First, we find some evidence that fintech lenders appear to use different models (and possibly data) to set interest rates. Second, the ease of online origination appears to allow fintech lenders to charge higher rates, particularly among the lowest-risk, and presumably least price sensitive and most time sensitive borrowers.

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

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Table 1: Residential Mortgage Lending: Traditional versus Shadow Banks

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

Panel A: Loan types based on 2007-2015 HMDA

	All Lenders	Traditional Banks	Shadow Banks	Shadow Banks	
				Non-Fintech	Fintech
% Conventional	78.8%	82.7%	67.01%	63.9%	72.4%
% FHA	13.6%	10.9%	21.71%	22.7%	20.0%
% Other	7.5%	6.3%	11.18%	13.3%	7.5%
Count	28,075,783	21,149,870	6,925,913	4,388,723	2,537,190

Panel B: Loan disposition based on 2007-2015 HMDA

	All Lenders	Traditional Banks	Shadow Banks	Shadow Banks	
				Non-Fintech	Fintech
Not Sold	19.07%	23.68%	5.03%	4.00%	6.80%
Sold To:					
Fannie Mae	28.94%	28.68%	29.73%	26.10%	36.01%
Freddie Mac	19.03%	20.48%	14.59%	16.48%	11.32%
Ginnie Mae	13.91%	12.03%	19.64%	20.86%	17.52%
Private Securitization	0.48%	0.55%	0.28%	0.29%	0.26%
Commercial Bank	3.35%	0.70%	11.42%	12.05%	10.33%
Ins/CU/Mortgage Bank	3.10%	1.09%	9.26%	5.29%	16.12%
Affiliate Institution	8.13%	10.78%	0.06%	0.09%	0.00%
Other	3.99%	2.02%	10.00%	14.84%	1.63%
Count	28,075,783	21,149,870	6,925,913	4,388,723	2,537,190

Table 2: Shadow Bank 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)-(2) compare Traditional and Shadow Banks for the period 2007-2015. Columns (3)-(4) compare Traditional and Shadow Banks for 2015. Panel B shows the result of Regression (1), a linear probability model regressing whether the lender is a Shadow Bank on borrower characteristics over the period 2007-2015. Columns (1)-(2) include year fixed effects; Columns (3)-(4) include year-county fixed effects. Columns (2) and (4) include dummy variables for loan type. For race dummies, the base category is White; for sex dummies, the base is Male. For loan purpose dummies, the base is Purchase. For purchaser dummies, the base is Not Sold. For type dummies, the base is Conventional. Standard errors (in parentheses) are clustered at the county-year level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary statistics based on (HMDA)

	2007-2015		2015	
	Traditional Banks	Shadow Banks	Traditional Banks	Shadow Banks
Count	21,149,870	6,925,913	1,640,611	1,389,608
Median Applicant Income	\$86,000	\$81,099	\$95,000	\$80,714
Male	69.93%	62.70%	66.32%	64.14%
Race				
Native American	0.56%	0.48%	0.53%	0.68%
Asian	7.80%	5.14%	8.23%	5.36%
African American	5.53%	4.97%	5.14%	6.68%
Native Hawaiian	0.50%	0.36%	0.41%	0.50%
White	75.36%	72.14%	73.82%	71.24%
Other/Unknown	10.23%	16.91%	11.87%	15.55%

Table 2 [continued]

Panel B: Regressions (HMDA)

	(1) Shadow Bank	(2) Shadow Bank	(3) Shadow Bank	(4) Shadow Bank
Income (000s)	-0.00590***	-0.00561***	-0.00515***	-0.00484***
	(0.000227)	(0.000223)	(0.000197)	(0.000191)
Loan Amount (000s)	-5.96e-06	0.000486	-0.00123**	-0.000875*
	(0.000479)	(0.000481)	(0.000423)	(0.000423)
Race (Omitted Category = White)				
Native American	-0.714**	-0.762**	-1.76***	-1.83***
	(0.254)	(0.256)	(0.257)	(0.259)
Asian	1.83***	1.97***	1.22***	1.33***
	(0.404)	(0.402)	(0.332)	(0.330)
Black	-1.76***	-1.98***	-0.219	-0.472***
	(0.127)	(0.122)	(0.121)	(0.118)
Hawaiian	0.545	0.530	-0.599***	-0.662***
	(0.294)	(0.291)	(0.167)	(0.164)
Unknown	3.95***	3.97***	3.90***	3.90***
	(0.149)	(0.148)	(0.138)	(0.138)
NA	-1.40	-0.769	-1.42	-0.806
	(2.27)	(2.20)	(2.28)	(2.21)
Sex (Omitted Category = Male)				
Female	0.0116	-0.209***	0.120***	-0.0737*
	(0.0397)	(0.0392)	(0.0316)	(0.0315)
Unknown	-0.321	-0.324	-0.153	-0.154
	(0.203)	(0.203)	(0.203)	(0.203)
NA	6.33**	5.59**	6.46**	5.81**
	(2.23)	(2.16)	(2.23)	(2.16)
Purpose (Omitted Category = Purchase)				
Home Improvement	-4.76***	-4.04***	-.515***	-4.46***
	(0.207)	(0.201)	(0.198)	(0.189)
Refinance	4.47***	5.04***	4.08***	4.64***
	(0.157)	(0.156)	(0.151)	(0.149)
Purchaser (Omitted Category = Held)				
Fannie Mae	16.6***	17.0***	15.7***	16.1***
	(0.442)	(0.457)	(0.437)	(0.452)
Ginnie Mae	23.2***	18.8***	22.7***	18.3***
	(0.442)	(0.372)	(0.444)	(0.364)
Freddie Mac	9.70***	10.2***	9.07***	9.54***
	(0.397)	(0.405)	(0.391)	(0.399)
Farmer Mac	25.5*	24.5*	20.2*	19.4
	(10.1)	(10.1)	(10.2)	(10.2)
Private Securitization	7.58***	7.61***	6.94***	7.00***
	(0.777)	(0.776)	(0.757)	(0.755)
Bank	72.4***	71.2***	70.5***	69.3***
	(0.792)	(0.823)	(0.791)	(0.821)
Insr or Fnce Co.	70.9***	69.4***	69.6***	68.2***
	(0.453)	(0.449)	(0.414)	(0.404)
Affiliate	-2.94***	-3.06***	-3.99***	-4.09***
	(0.197)	(0.196)	(0.204)	(0.203)
Other	57.5***	57.0***	55.1***	54.5***
	(0.754)	(0.754)	(0.726)	(0.727)
Loan Type (Omitted Category = Conventional)				
FHA	-	7.19***	-	7.03***
	-	(0.313)	-	(0.306)
VA	-	0.633	-	1.24***
	-	(0.356)	-	(0.325)
FSA/RHS	-	4.87***	-	4.72***
	-	(0.321)	-	(0.284)
Year FE	Yes	Yes	No	No
Year x County FE	No	No	Yes	Yes
N	28112712	28112712	28112712	28112712
R^2	0.262	0.263	0.285	0.286

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

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

	(1) Shadow Bank	(2) Shadow Bank
Loan Amount	0.00000930***	0.00000255***
	(82.28)	(18.40)
Loan Term (Months)	0.0119***	-0.00920***
	(53.62)	(-38.35)
Loan-to-Value	-0.0939***	-0.0514***
	(-86.73)	(-45.78)
Debt-to-Income	0.0826***	0.0534***
	(54.98)	(35.85)
FICO	0.000991**	-0.00578***
	(2.59)	(-15.31)
Purpose (Omitted Category = Purchase)		
Cash-Out Refinance	0.784***	0.867***
	(19.39)	(21.62)
Non-Cash-Out Refinance	-0.884***	-0.318***
	(-26.82)	(-9.44)
Unspecified Refinance	41.74**	38.63**
	(2.75)	(2.74)
Property Type (Omitted Category = Primary Residence)		
Investment	0.752***	-0.690***
	(12.97)	(-11.84)
Secondary	-2.880***	-3.505***
	(-45.81)	(-52.32)
First-Time Buyer	-4.021***	-3.933***
	(-94.02)	(-90.95)
Has Mtg. Insurance	1.146***	0.887***
	(23.37)	(18.37)
Zip x Quarter FE	No	Yes
Quarter FE	Yes	No
N	6391930	6391929
R^2	0.0114	0.0575

Table 4: Shadow Bank Penetration and Regional Characteristics

Panel A summarizes demographic differences between counties with low and high shares of Shadow Bank lending in 2015. Shadow Bank share is calculated from accepted HMDA applications. 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. Panel B shows the results of regression (2), where the share of Shadow Banks in a county is regressed on county characteristics. Column (1) is the baseline specification. Column (2) includes the county-level Herfindahl measure. Column (3) includes the number of unique lenders within a county. t-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary Statistics

Median Values	All Counties	Bottom Quartile Shadow Bank	Top Quartile Shadow Bank
Median Household Income	$44,850.50	$46,293.50	$44,432.00
Population Density	46.3	36.5	39.7
% with less than 12th grade education	51.20%	50.75%	49.60%
% with Bachelor degree or higher	17.30%	17.60%	17.50%
% African American	2.20%	1.00%	2.60%
% Hispanic	3.50%	2.40%	6.40%
Unemployment Rate	8.80%	7.95%	9.30%
% living in Same House >= 1 year	86.85%	87.25%	86.14%
Herfindahl	0.04197	0.06058	0.03517
# Lenders	33.00	27.00	38.00
% of FHA Origination loans	18.18%	18.26%	18.40%
Population	21157.00	16019.00	22079.00
% with less than 35K salary	20.20%	19.10%	21.10%

Table 4 [continued]

Panel B: Regressions

	(1) % Shadow Banks	(2) % Shadow Banks	(3) % Shadow Banks
Med HH Income	0.0000626***	0.0000187	0.00000791
	(0.0000142)	(0.0000139)	(0.0000146)
Pop Den	-0.000259***	-0.000245***	-0.000261***
	(0.0000678)	(0.0000650)	(0.0000662)
% Edu < 12th	-0.301***	-0.320***	-0.288***
	(0.0233)	(0.0223)	(0.0227)
% >= Bachelors	-0.365***	-0.389***	-0.422***
	(0.0293)	(0.0281)	(0.0290)
% African American	0.0861***	0.0721***	0.0749***
	(0.00852)	(0.00821)	(0.00837)
% Hispanic	0.132***	0.121***	0.120***
	(0.00885)	(0.00851)	(0.00870)
Unemp Rate	0.516***	0.329***	0.269***
	(0.0398)	(0.0398)	(0.0438)
Same home >= 1yr	-8.203**	-3.528	-1.442
	(2.927)	(2.821)	(2.910)
% FHA	-0.00577	0.00456	0.00382
	(0.0118)	(0.0113)	(0.0115)
Herfindahl	-	-44.26***	-
	-	(2.697)	-
# Lenders	-	-	0.138***
	-	-	(0.0112)
Constant	40.03***	43.58***	34.90***
	(2.835)	(2.727)	(2.799)
N	3073	3073	3073
R^2	0.173	0.240	0.212

Table 5: Shadow Bank Presence and Mortgage Rates: Conforming Loans

This table shows the results of regression (3) using Fannie Mae and Freddie Mac loans from 2010-2013. 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. 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)
	Interest Rate	Interest Rate	Interest Rate	Interest Rate
Shadow Bank	-0.0145***	-0.0176***	-0.00130	-0.00214
	(-5.19)	(-6.83)	(-0.65)	(-1.15)
Borrower and Loan Controls	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No
N	6396762	6396654	6391929	6391821
R^2	0.573	0.593	0.758	0.767

Table 6: Shadow Bank Presence and Loan Performance: Conforming Loans

Panels A and B show the results of regression (4) 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) include no borrower or loan controls. Columns (3)-(4) include borrower and loan controls except for the interest rate. Columns (5)-(6) include borrower and loan controls including the interest rate. Columns (1), (3), (5) include quarter fixed effects only; Columns (2), (4), (6) include zip-quarter fixed effects. 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 Regressions

	(1) Defaulted	(2) Defaulted	(3) Defaulted	(4) Defaulted	(5) Defaulted	(6) Defaulted
Shadow Bank	0.0234***	0.0333***	0.0300***	0.0290***	0.0303***	0.0296***
	(4.19)	(5.95)	(5.50)	(5.24)	(5.56)	(5.34)
Borrower and Loan Controls	No	No	Yes	Yes	Yes	Yes
Interest Rate	No	No	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6396762	6396654	6391929	6391821	6391929	6391821
R^2	0.000320	0.00407	0.00467	0.00798	0.00497	0.00828

Panel B: Prepayment Regressions

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid	(5) Prepaid	(6) Prepaid
Shadow Bank	2.77***	1.51***	2.35***	1.47***	2.36***	1.48***
	(22.34)	(19.75)	(22.30)	(19.57)	(21.40)	(18.44)
Borrower and Loan Controls	No	No	Yes	Yes	Yes	Yes
Interest Rate	No	No	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6396762	6396654	6391929	6391821	6391929	6391821
R^2	0.136	0.214	0.154	0.223	0.159	0.228

Table 7: Regional Evidence: Change in the Traditional Bank Capitalization and the Shadow Bank Penetration

Table 7 shows the results of regression (5) over the time period 2006 to 2015 at the county level. Column (1) does not include local demographic controls while Column (2) does. The left-hand-side variable is in units of percent, with a mean value of 25.77. ; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Δ Shadow Bank Lending Share	(2) Δ Shadow Bank Lending Share
Δ Local Capital Ratio, 2006-2015	-0.360***	-0.334***
	(0.0647)	(0.0627)
% Less than High School	-	-0.143*
	-	(0.0605)
% BA or Higher	-	-0.703***
	-	(0.0819)
Unemployment Rate	-	0.275**
	-	(0.0939)
% In Same House	-	-29.26***
	-	(6.236)
Percent Black	-	-2.582
	-	(2.057)
Percent Hispanic	-	16.09***
	-	(2.292)
Population Density	-	-0.000000741
	-	(0.000000723)
Median Income	-	0.0000539
	-	(0.0000305)
Cons	22.49***	49.29***
	(0.243)	(5.417)
N	2483	2483
R^2	0.012	0.079

Table 8: Regional Evidence: Exposure of Traditional Banks to the Crisis Area Lawsuits and the Shadow Bank Penetration

Table 8 shows the results of regression (6) over the time period 2006 to 2015 at the county level. Column (1) does not include local demographic controls while Column (2) does. The left-hand-side variable is in units of percent, with a mean value of 25.77. The weighted lawsuit exposure measure is in billions of dollars, weighted by the lawsuit target's share of lending in the county as of 2006. Its mean is 18.61; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Δ Shadow Bank Lending Share	(2) Δ Shadow Bank Lending Share
Weighted Lawsuit Exposure ($B)	0.286***	0.371***
	(0.030310)	(0.026)
% Less than High School	-	-0.078
	-	(0.053)
% BA or Higher	-	-0.623***
	-	(0.077)
Unemployment Rate	-	-0.198**
	-	(0.076)
% In Same House	-	0.020
	-	(0.054)
Percent Black	-	0.031
	-	(0.019)
Percent Hispanic	-	0.088***
	-	(0.020)
Population Density	-	-0.000**
	-	(0.000)
Median Income	-	-0.000**
	-	(0.000)
Cons	-	34.929***
	-	(4.851)
N	2900	2823
R^2	0.030	0.119

Table 9: Regional Evidence: Regulatory Enforcement Intensity and the Shadow Bank Penetration

Table 9 shows the result of regression (7). The regression is at the county-year level between 2006 and 2015. Columns (1)-(2) do not include other economic controls. Columns (3)-(4) include local changes in house prices and gross state product. Columns (1) and (3) include year fixed effects only; Columns (2) and (4) include year and county fixed effects. The left-hand-side variable is in units of percent; its mean is 2.86. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Δ Shadow Bank Lending Share	(2) Δ Shadow Bank Lending Share	(3) Δ Shadow Bank Lending Share	(4) Δ Shadow Bank Lending Share
$EA\_Intensity_{ct-1}$	0.0197	0.0597***	0.0190	0.0589***
	(1.59)	(3.91)	(1.52)	(3.84)
$\Delta House\_Price_{ct}$	-	-	0.0179	0.0372*
	-	-	(1.31)	(2.48)
ΔGSP_{st}	-	-	0.0445	0.0697
	-	-	(1.43)	(1.90)
County FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	27831	27831	27831	27831
R^2	0.299	0.336	0.300	0.337

Table 10: Fintech Lender 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)-(2) compare fintech non-fintech and fintech shadow bank lenders for the period 2007-2015. Columns (3)-(4) compare non-fintech and fintech shadow bank lenders for 2015. Panel B shows the result of regression (8), a linear probability model regressing whether the lender is a fintech lender on borrower characteristics over the period 2007-2015. Columns (1)-(2) include year fixed effects; Columns (3)-(4) include year-county fixed effects. Columns (2) and (4) include dummy variables for loan type. For race dummies, the base category is White; for sex dummies, the base is Male. For loan purpose dummies, the base is Purchase. For purchaser dummies, the base is Not Sold. For type dummies, the base is Conventional. Standard errors (in parentheses) are clustered at the county-year level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary statistics based on (HMDA)

	2007-2015		2015	
	Non-Fintech	Fintech	Non-Fintech	Fintech
Count	4,388,723	2,537,190	893,022	496,586
Median Applicant Income	$80,000	$83,000	$80,000	$82,000
Male	60.57%	66.38%	69.35%	54.77%
Race				
Native American	0.47%	0.51%	0.75%	0.55%
Asian	4.36%	6.49%	5.99%	4.22%
African American	4.83%	5.21%	7.37%	5.44%
Native Hawaiian	0.33%	0.40%	0.58%	0.35%
White	70.65%	74.73%	75.12%	64.25%
Other/Unknown	19.36%	12.67%	10.19%	25.19%

Table 10 [continued]

Panel B: Regressions (HMDA)

	(1) Fintech	(2) Fintech	(3) Fintech	(4) Fintech
Income (000s)	0.0129***	0.0106***	0.00523***	0.00304***
	(0.00116)	(0.00115)	(0.000605)	(0.000588)
Loan Amount (000s)	-0.0175***	-0.0181***	0.00316***	0.00365***
	(0.00172)	(0.00172)	(0.000747)	(0.000730)
Race (Omitted Category = White)				
Native American	-3.02***	-2.68***	-0.558*	-0.247
	(0.362)	(0.357)	(0.277)	(0.276)
Asian	-8.32***	-8.78***	-5.15***	-5.43***
	(0.581)	(0.579)	(0.410)	(0.413)
Black	0.815*	1.29***	-2.11***	-1.55***
	(0.331)	(0.322)	(0.241)	(0.230)
Hawaiian	-4.85***	-4.54***	-0.447	-0.166
	(0.389)	(0.382)	(0.275)	(0.274)
Unknown	3.19***	3.12***	3.72***	3.71***
	(0.277)	(0.276)	(0.226)	(0.225)
NA	2.71	2.62	4.12	3.96
	(4.40)	(4.40)	(3.79)	(3.78)
Sex (Omitted Category = Male)				
Female	2.46***	2.13***	2.31***	1.97***
	(0.0987)	(0.0905)	(0.0604)	(0.0626)
Unknown	2.18***	2.16***	20.3***	20.2***
	(0.452)	(0.453)	(0.361)	(0.362)
NA	8.35	8.00	3.81	3.32
	(5.62)	(5.61)	(5.46)	(5.46)
Purpose (Omitted Category = Purchase)				
Home Improvement	-21.4***	-22.4***	-18.0***	-18.9***
	(0.787)	(0.809)	(0.960)	(0.960)
Refinance	24.5***	23.5***	22.8***	21.9***
	(0.438)	(0.451)	(0.344)	(0.350)
Purchaser (Omitted Category = Held)				
Fannie Mae	-9.32***	-11.1***	-7.74***	-9.46***
	(0.875)	(0.940)	(0.593)	(0.636)
Ginnie Mae	-8.46***	-4.62***	-8.67***	-4.78***
	(0.899)	(0.832)	(0.615)	(0.624)
Freddie Mac	-22.6***	-24.2***	-20.0***	-21.6***
	(1.21)	(1.23)	(0.891)	(0.898)
Farmer Mac	-34.9***	-35.8***	-33.6***	-34.5***
	(4.67)	(4.59)	(8.53)	(8.42)
Private Securitization	-4.25*	-4.68**	-4.81***	-5.30***
	(1.77)	(1.75)	(1.24)	(1.22)
Bank	-7.43***	-6.68***	-6.18***	-5.37***
	(1.02)	(1.03)	(0.734)	(0.743)
Insr or Fnce Co.	25.0***	25.3***	24.2***	24.4***
	(1.23)	(1.22)	(0.828)	(0.827)
Affiliate	-37.1***	-37.2***	-28.6***	-28.6***
	(1.16)	(1.13)	(0.828)	(0.838)
Other	-29.7***	-29.5***	-25.5***	-25.3***
	(1.16)	(1.15)	(0.754)	(0.755)
Loan Type (Omitted Category = Conventional)				
FHA	-	-4.01***	-	-3.90***
	-	(0.556)	-	(0.375)
VA	-	-9.19***	-	-10.2***
	-	(0.725)	-	(0.429)
FSA/RHS	-	-20.2***	-	-19.5***
	-	(0.892)	-	(0.545)
Year FE	Yes	Yes	No	No
Year x County FE	No	No	Yes	Yes
N	6598684	6598684	6598684	6598684
R^2	0.199	0.202	0.286	0.288

Table 11: Fintech Lender Presences and the Borrower and Loan Characteristics: Conforming Loans

This table shows the results of a linear probability model, regressing whether the lender is a fintech lender on individual characteristics, using the pooled Fannie Mae and Freddie Mac Data for the period 2010-2013. Column (1) includes quarter fixed effects only; Column includes zip-quarter fixed effects. Loan purpose dummies (Cash-out refinance, Non-Cash-out Refinance, and Unspecified Refinance) use Purchase as the base category. Property type dummies (Investment and Second Home) use Primary Residence as the base category. The left-hand-side variable is in percent and has mean 26. Standard errors are clustered by zip-quarter; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Fintech	(2) Fintech
Loan Amount	-0.00000661***	0.000000759*
	(-23.08)	(2.24)
Loan Term (Months)	0.0410***	0.00610***
	(93.06)	(12.86)
Loan-to-Value	0.0341***	0.00506*
	(13.99)	(2.00)
Debt-to-Income	0.0408***	0.0383***
	(11.07)	(10.92)
FICO	-0.0314***	-0.0226***
	(-32.34)	(-24.39)
Purpose (Omitted Category = Purchase)		
Cash-Out Refinance	9.226***	7.214***
	(100.54)	(82.21)
Non-Cash-Out Refinance	13.44***	10.26***
	(152.47)	(117.27)
Unspecified Refinance	2.254***	1.815
	(4.33)	(1.65)
Property Type (Omitted Category = Primary Residence)		
Investment	-0.747***	-0.826***
	(-5.37)	(-5.98)
Secondary	0.715***	-2.842***
	(3.91)	(-14.89)
First-Time Buyer	-5.056***	-6.000***
	(-38.41)	(-48.54)
Has Mtg. Insurance	1.118***	0.890***
	(7.96)	(6.72)
Zip x Quarter FE	No	Yes
Quarter FE	Yes	No
N	1,015,205	1,015,205
R^2	0.167	0.284

Table 12: Fintech Penetration and Regional Characteristics

Panel A summarizes demographic differences between counties with low and high shares of fintech shadow bank lending in 2015. Fintech share is calculated from accepted HMDA applications. 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 fintech share. Column (3) shows statistics for counties in the top 25% of fintech Bank share. Panel B shows the results of regression (2), where the share of fintech in a county is regressed on county characteristics. Column (1) is the baseline specification. Column (2) includes the county-level Herfindahl measure. Column (3) includes the number of unique lenders within a county. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Summary Statistics

Median Values	All Counties	Bottom Quartile Fintech	Top Quartile Fintech
Median Household Income	$44,850.50	$48,377.50	$41,903.00
Population Density	46.3	45.55	33.5
% with less than 12th grade education	51.20%	48.30%	52.70%
% with Bachelor degree or higher	17.30%	19.20%	16.60%
% African American	2.20%	1.40%	1.80%
% Hispanic	3.50%	3.75%	2.90%
Unemployment Rate	8.80%	7.90%	9.00%
% living in Same House >= 1 year	86.85%	86.10%	87.60%
Herfindahl	0.04197	0.04465	0.04753
# Lenders	33.00	34.00	28.00
% of FHA Origination loans	18.18%	17.24%	19.15%
Population	21157.00	22105.50	13790.50
% with less than 35K salary	20.20%	17.60%	22.90%

Table 12 [continued]

Panel B: Regressions

	(1) % Fintech	(2) % Fintech	(3) % Fintech
Med HH Income	-0.000278***	-0.000172***	-0.0000979***
	(0.0000286)	(0.0000271)	(0.0000279)
Pop Den	0.000373**	0.000339**	0.000380**
	(0.000137)	(0.000127)	(0.000127)
% Edu < 12th	0.130**	0.169***	0.0776
	(0.0469)	(0.0437)	(0.0435)
% >= Bachelors	0.233***	0.288***	0.419***
	(0.0591)	(0.0550)	(0.0554)
% African American	-0.141***	-0.105***	-0.102***
	(0.0172)	(0.0161)	(0.0160)
% Hispanic	-0.166***	-0.138***	-0.125***
	(0.0179)	(0.0167)	(0.0167)
Unemp Rate	-0.783***	-0.335***	0.0271
	(0.0804)	(0.0780)	(0.0838)
Same home >= 1yr	0.570***	0.459***	0.349***
	(0.0591)	(0.0552)	(0.0557)
% FHA	0.176***	0.158***	0.151***
	(0.0237)	(0.0221)	(0.0221)
Herfindahl	-	110.3***	-
	-	(5.276)	-
# Lenders	-	-	-0.463***
	-	-	(0.0215)
Constant	-12.06*	-20.72***	5.311
	(5.722)	(5.337)	(5.358)
N	3081	3073	3073
R^2	0.144	0.255	0.260

Table 13: Fintech Lender Presence and Mortgage Rates: Conforming Loans

This table shows the results of regression (10) using Fannie Mae and Freddie Mac loans from 2010-2013. 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. The left-hand-side variable is in percent terms; the mean is 4.18. Standard errors are clustered at the zip-quarter level. Interest rates are quoted in percent. *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate
Fintech	0.148***	0.128***	0.125***	0.110***
	(25.68)	(25.96)	(32.14)	(31.84)
Borrower and Loan Controls	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No
N	1,015,605	1,015,012	1,015,205	1,014,612
R^2	0.554	0.591	0.750	0.765

Table 14: Fintech Lender Presence and Loan Performance

Panels A and B show the results of regression (11) 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) include no borrower or loan controls. Columns (3)-(4) include borrower and loan controls except for the interest rate. Columns (5)-(6) include borrower and loan controls including the interest rate. Columns (1), (3), (5) include quarter fixed effects only; Columns (2), (4), (6) include zip-quarter fixed effects. 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 Regressions

	(1) Defaulted	(2) Defaulted	(3) Defaulted	(4) Defaulted	(5) Defaulted	(6) Defaulted
Fintech	0.0492**	0.0228	-0.00121	-0.0111	-0.0367*	-0.0432**
	(3.27)	(1.44)	(-0.08)	(-0.70)	(-2.45)	(-2.70)
Borrower and Loan Controls	No	No	Yes	Yes	Yes	Yes
Interest Rate	No	No	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	1,015,605	1,015,012	1,015,205	1,014,612	1,015,205	1,014,612
R^2	0.000429	0.0184	0.00547	0.0228	0.00581	0.0231

Panel B: Prepayment Regressions

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid	(5) Prepaid	(6) Prepaid
Fintech	2.37***	1.74***	2.80***	1.91***	1.83***	1.02***
	(10.47)	(11.32)	(12.37)	(12.63)	(8.59)	(8.18)
Borrower and Loan Controls	No	No	Yes	Yes	Yes	Yes
Interest Rate	No	No	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	1,015,605	1,015,012	1,015,205	1,014,612	1,015,205	1,014,612
R^2	0.174	0.259	0.189	0.267	0.195	0.273

Table 15: Relationship Between Interest Rate and Performance

Panels A and B show the coefficients on mortgage interest rate for probit regressions (12) and (13), 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
Non-Fintech	0.507***	0.0507	0.211***	0.143
Fintech	0.506***	0.0423	0.170***	0.127

Panel B: Prepayment

	No Controls		Controls	
	Rate	Pseudo R2	Rate	Pseudo R2
Non-Fintech	-0.305***	0.0434	0.358***	0.119
Fintech	0.125***	0.0445	0.601***	0.127

Table 16: Performance Differentials for Prepayment

Table 16 shows the results of probit regression (14) 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid
Rate	-0.173***	-0.274***	0.346***	0.260***
	(-123.20)	(-98.36)	(177.55)	(84.00)
Rate x Fintech	-	0.122***	-	0.104***
	-	(41.99)	-	(35.88)
Borrower and Loan Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,396,763	6,396,763	6,391,919	6,391,919
Pseudo R^2	0.0428	0.0432	0.0910	0.0913

Table 17: Determinants of Interest Rates

Table 17 shows the coefficients on FICO and LTV for different specifications of regression (15). Data is from Fannie Mae and Freddie Mac between 2010 and 2013. The non-fintech subset is run on non-fintech originations only; the fintech subset is run on fintech originations only. The left column's results have quarter fixed effects only; the right column's results have zip-quarter fixed effects. The top rows of regressions have no controls aside from FICO and LTV; the bottom rows of the regressions have all Fannie Mae and Freddie Mac Controls. Standard errors are clustered at the zip-quarter level; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	No Other Controls, Quarter FE Only			No Other Controls, Zip-Quarter FE		
Subset	FICO	LTV	R2	FICO	LTV	R2
Non-Fintech	-0.00206***	0.00628***	0.620	-0.00207***	0.00486***	0.728
Fintech	-0.00236***	0.00386***	0.365	-0.00214***	0.00338***	0.450

	Full Controls, Quarter FE Only			Full Controls, Zip-Quarter FE		
Subset	FICO	LTV	R2	FICO	LTV	R2
Non-Fintech	-0.00187***	0.00219***	0.826	-0.00179***	0.00243***	0.852
Fintech	-0.00198***	0.00325****	0.545	-0.00186***	0.00287***	0.591

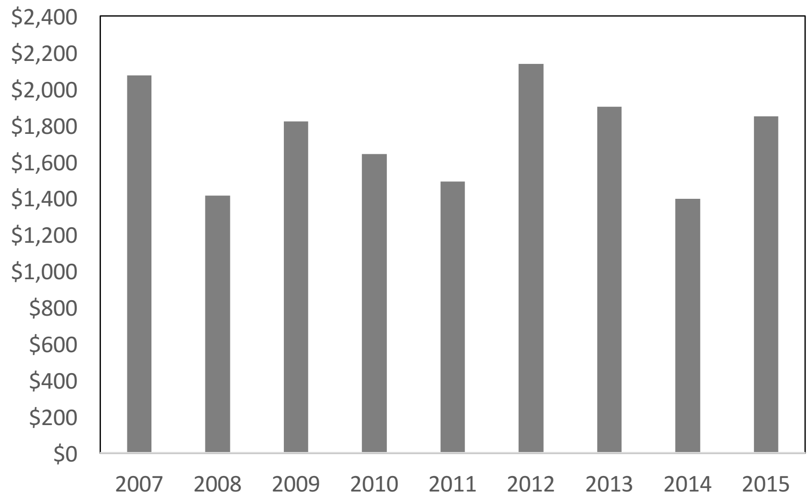
Table 18: Fintech Cost and Convenience

Table 18 shows the results of regression (16). Data is from Fannie Mae and Freddie Mac Shadow Bank originations between 2010 and 2013. High FICO is a dummy variable for borrowers with FICO score at origination greater than 800. Columns (1)-(2) do not include other borrower and loan controls (aside from FICO and a High FICO dummy, not shown). Columns (3)-(4) include borrower and loan controls. Columns (1) and (3) include quarter fixed effects only; Columns (2) and (4) include zip-quarter fixed effects. The left-hand-side variable is in percent terms; the mean is 4.18. Standard errors are clustered at the zip-quarter level; standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

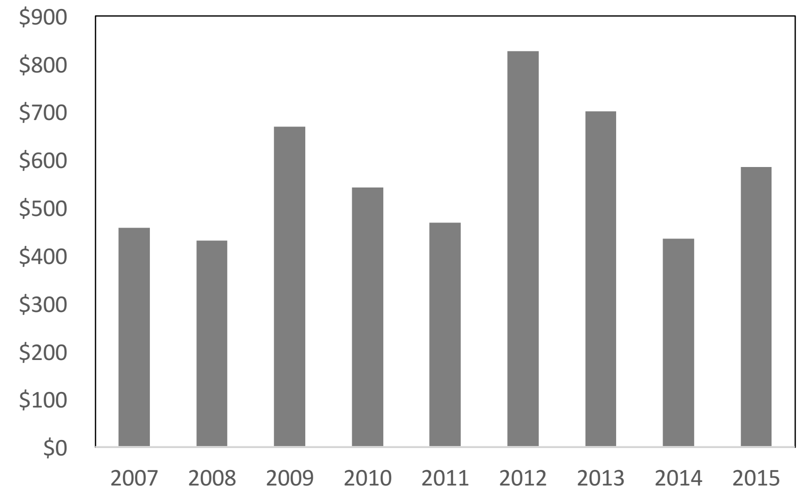
	(1) Rate	(2) Rate	(3) Rate	(4) Rate
Fintech	0.192***	0.125***	0.092***	0.114***
	(0.005)	(0.003)	(0.004)	(0.002)
High FICO x Fintech	0.047***	0.022***	0.014***	0.004*
	(0.003)	(0.002)	(0.002)	(0.002)
Borrower and Loan Controls	No	No	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No
N	983,709	983,709	983,495	983,495
R^2	0.589	0.708	0.804	0.847

Figure 1: Total Residential Mortgage Originations

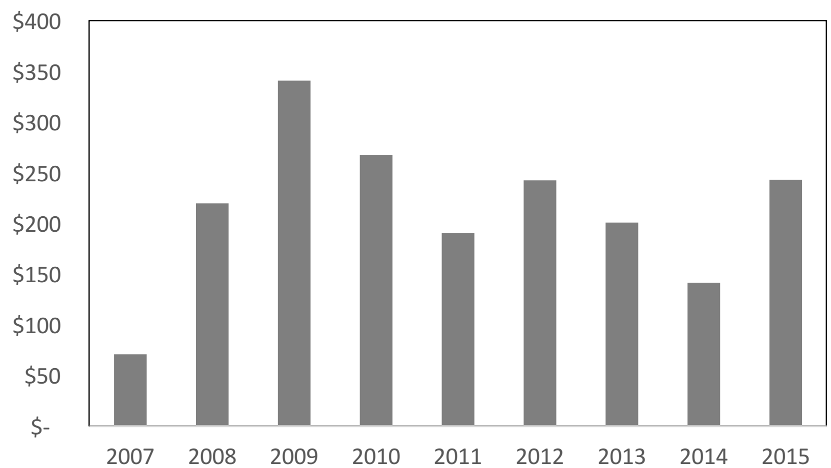
Panel A shows total dollars originated between 2007 and 2015 as reported by HMDA. Panel B shows the total dollar value of originated conforming mortgages, where a mortgage is conforming if it is (1) conventional and reported as sold to Fannie Mae or Freddie Mac in HMDA. Note that if the mortgage is sold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



(a) All loans



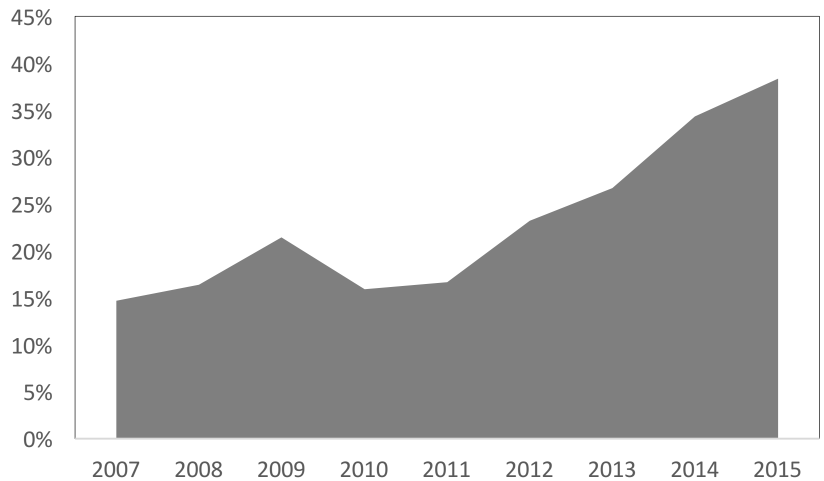
(b) Conforming loans



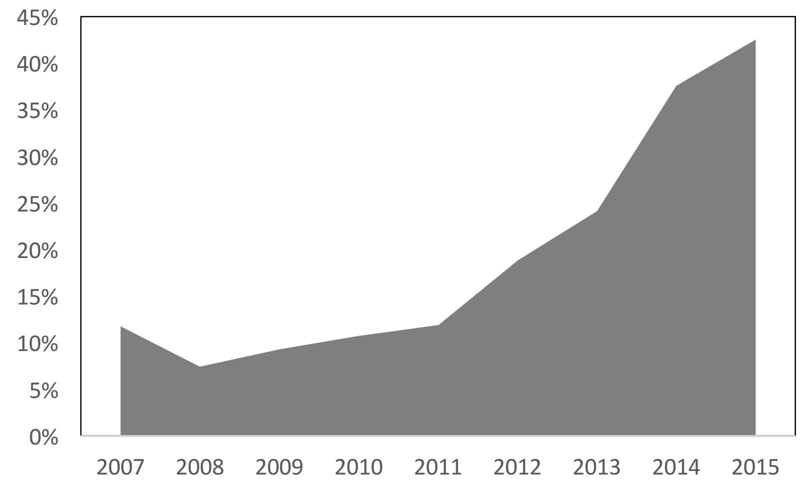
(c) FHA loans

Figure 2: Shadow Bank Origination Shares

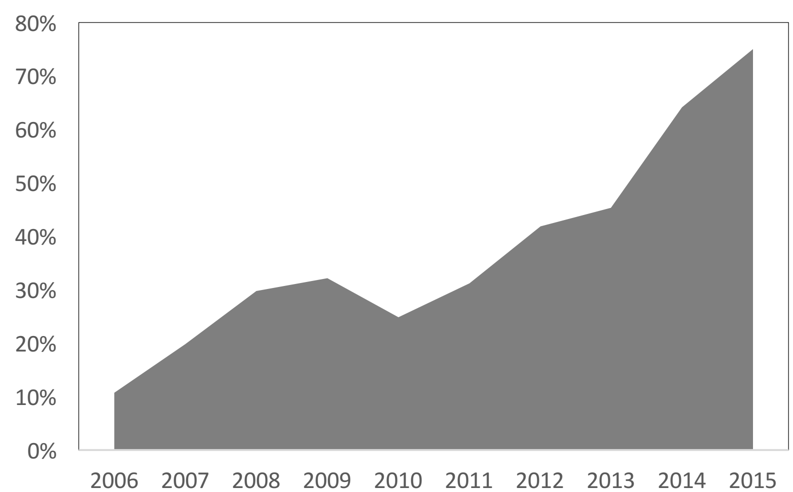
Panel A shows shadow bank origination shares as a fraction of total originations for all mortgages in HMDA between 2007 and 2015. Panel B shows shadow bank origination shares among conforming mortgages. Panel C shows the shadow bank origination share among FHA mortgages.



(a) All loans



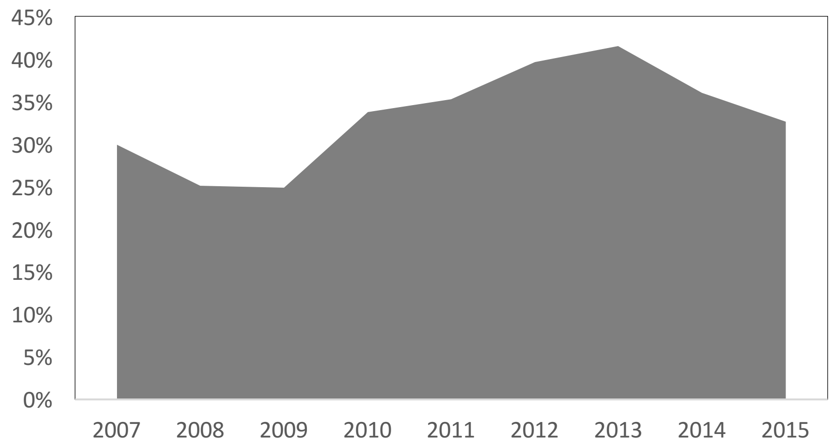
(b) Conforming loans



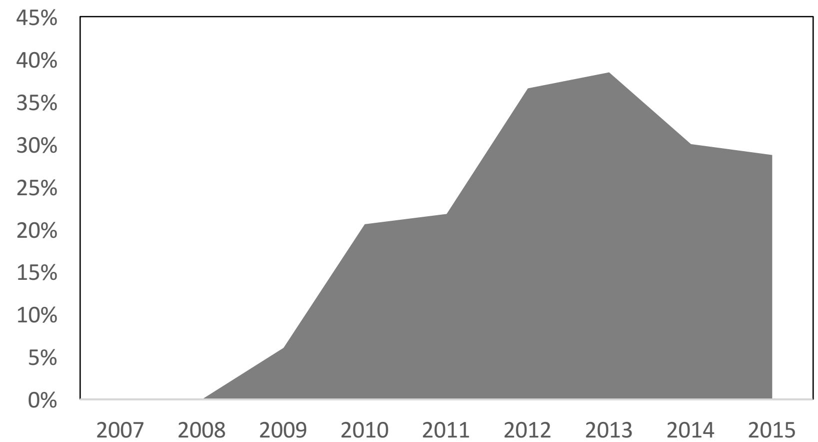
(c) FHA loans

Figure 3: Fintech Origination Shares of Shadow Bank Originations

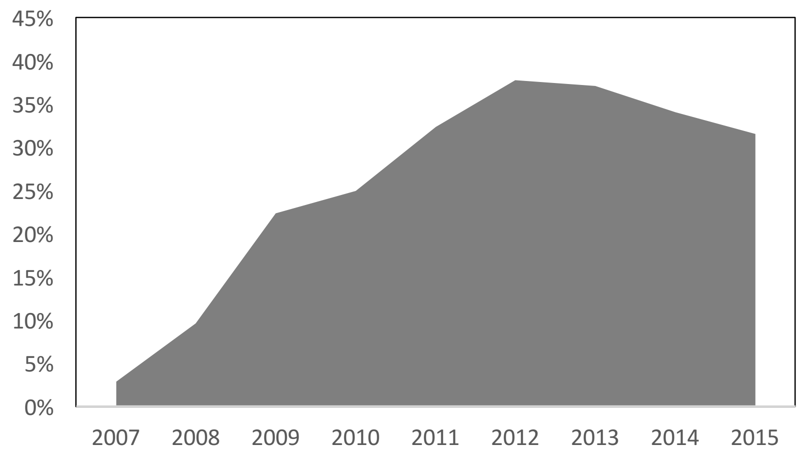
Panel A of this figure shows fintech originations as a share of shadow bank originations for all mortgages in HMDA between 2007 and 2015. Panel B shows fintech bank origination shares among shadow bank conforming originations. Panel C shows fintech share among shadow bank FHA originations (based on HMDA).



(a) All loans



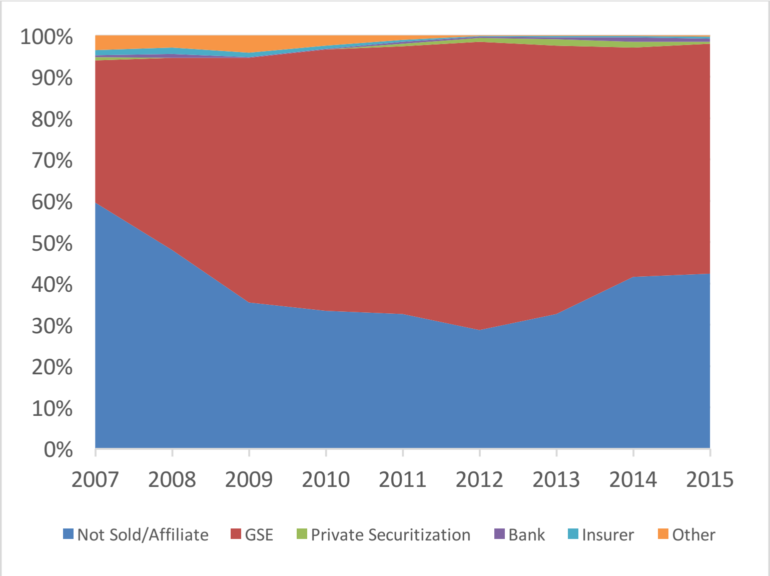
(b) Conforming loans



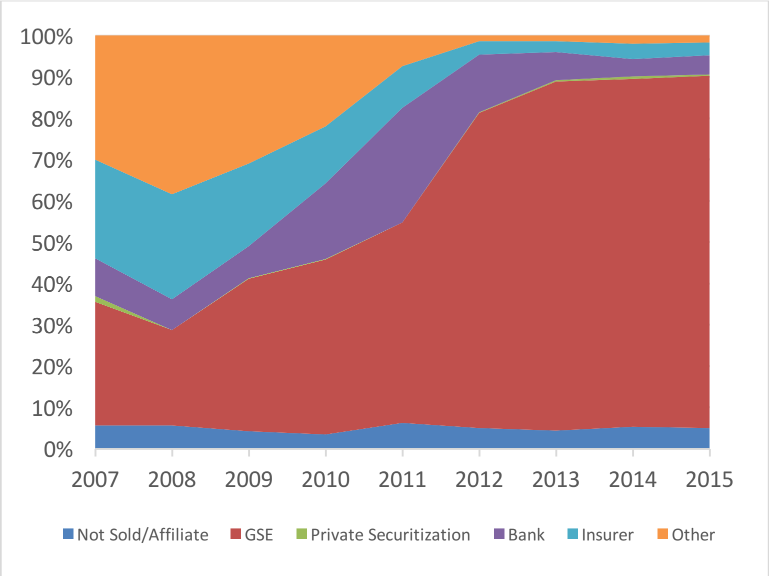
FHA loans

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

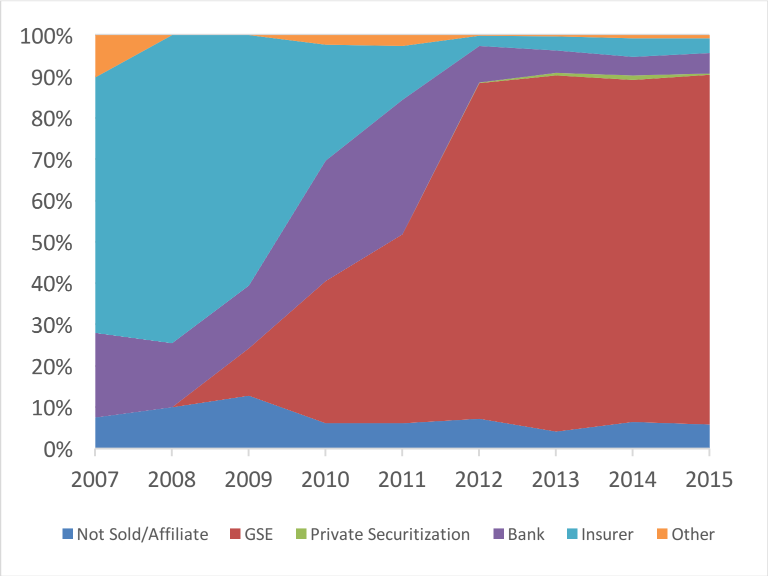
This figure shows disposition of loans among traditional banks (panel a), shadow banks (panel b), and fintech lenders (panel c) based on HMDA data.



(a) Traditional banks



(b) Shadow banks



(c) Fintech lenders

Figure 5: Regional Shadow Banking Penetration

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

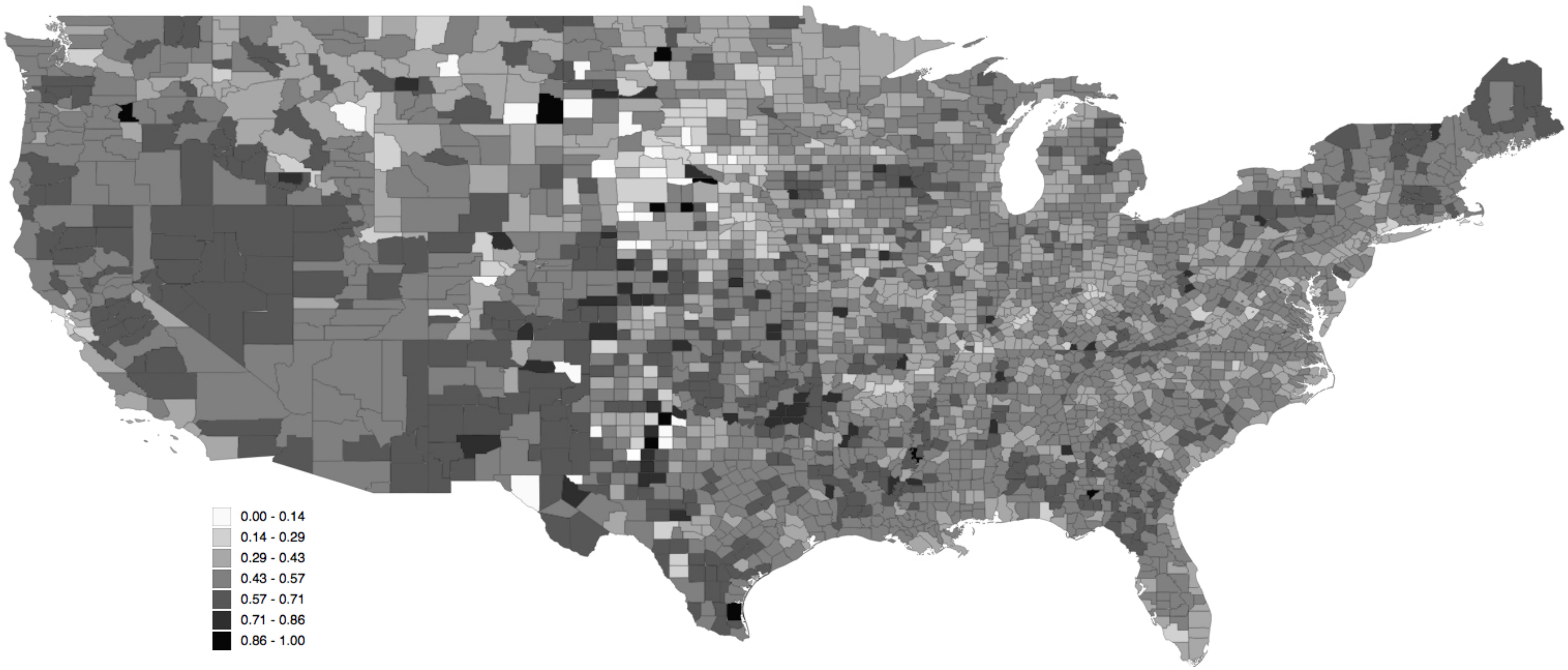


Figure 6: Calibrated Characteristics of Lender

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

(a) Lender's quality

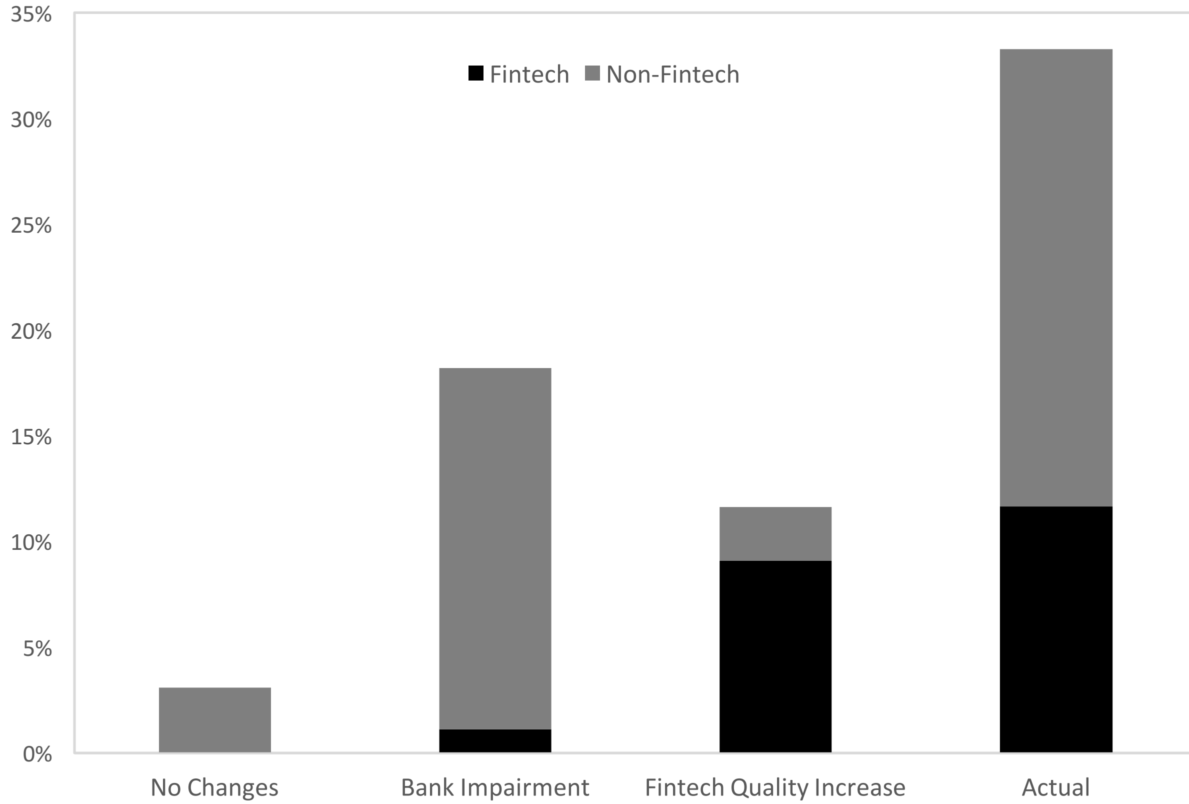
(b) Regulatory burden

(c) Funding costs

(d) Fixed costs

Figure 7: Counterfactuals for the Change in Shadow Bank Market Share in Implied by our Model

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



On-Line Appendix:

Appendix A1: Classification of Lenders

Panel A: List of Shadow Banks

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

Panel B: List of Traditional Banks

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

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

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

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

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

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

	(1)	(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,[28] 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[29] relative to other lenders. Several lenders, including Quicken Loans, provide closing cost estimators for purchases and refinances.[30] 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[31] 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.[32]

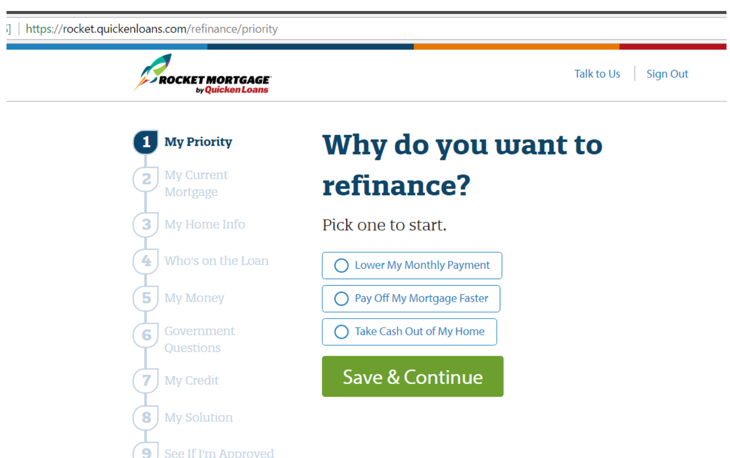
[28] https://www.zillow.com/mortgage-learning/closing-costs/ (Accessed March 7, 2017)
[29] https://www.consumeraffairs.com/finance/quicken_loans_mortgage.html
[30] https://www.quickenloans.com/my-mortgage/calculator#!/purchase/question/purchase-price (Accessed March 7, 2017)
[31] https://www.bankofamerica.com/mortgage/closing-costs-calculator/ (Accessed March 7, 2017)
[32] 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.[33]

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

Figure 1



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

Figure 2

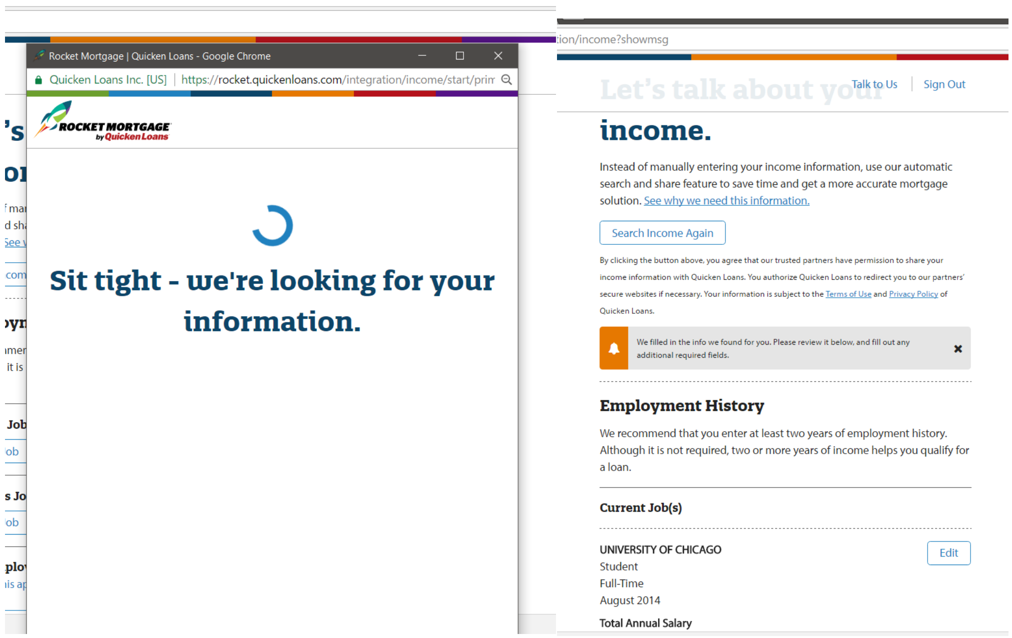
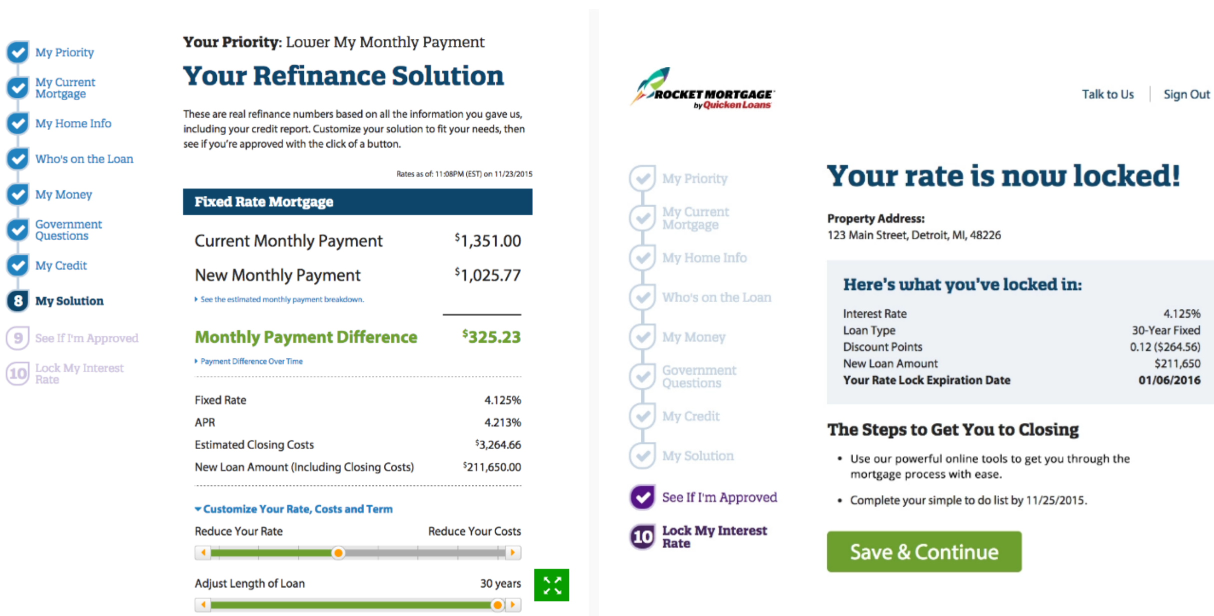


Figure 3



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