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Fintech, regulatory arbitrage, and the rise of shadow banks[☆]

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ABSTRACT

Shadow bank market share in residential mortgage origination nearly doubled from 2007 to 2015, with particularly dramatic growth among online "fintech" lenders. We study how two forces, regulatory differences and technological advantages, contributed to this growth. Difference in difference tests exploiting geographical heterogeneity induced by four specific increases in regulatory burden–capital requirements, mortgage servicing rights, mortgage-related lawsuits, and the movement of supervision to Office of Comptroller and Currency following closure of the Office of Thrift Supervision–all reveal that traditional banks contracted in markets where they faced more regulatory constraints; shadow banks partially filled these gaps. Relative to other shadow banks, fintech lenders serve more creditworthy borrowers and are more active in the refinancing market. Fintech lenders charge a premium of 14–16 basis points and appear to provide convenience rather than cost savings to borrowers. They seem to use different information to set interest rates relative to other lenders. A quantitative model of mortgage lending suggests that regulation accounts for roughly 60% of shadow bank growth, while technology accounts for roughly 30%.

1. Introduction

In the last decade, the consumer finance market has undergone a dramatic change. Intermediation has shifted from traditional banks to shadow banks: non-depository institutions falling outside the scope of traditional banking regulation.[1] This change has coincided with a shift away from "brick and mortar" originators to online intermediaries.[2] Despite the scarcity of systematic evidence, regulators, policymakers, and academics have been engaged in an intense debate over the potential consequences of these

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[1] We use the term "shadow bank" to refer to nonbank (nondepository) lenders, consistent with the definition of the Financial Stability Board (FSB), whose members cover G20 national regulators, the International Monetary Fund, the World Bank, and the Bank of International Settlements. See also Adrian and Ashcraft (2016).

[2] Goldman Sachs Report, March 3, 2015: "The future of finance: the rise of the new shadow bank."

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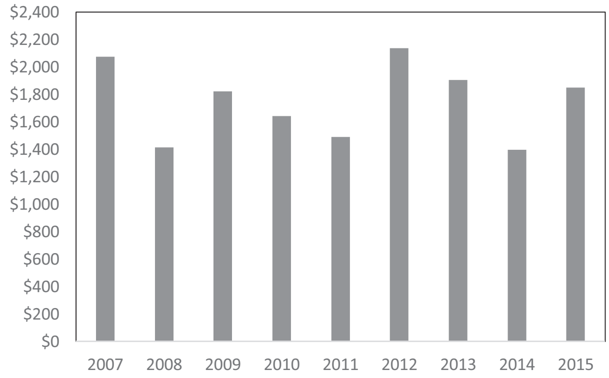
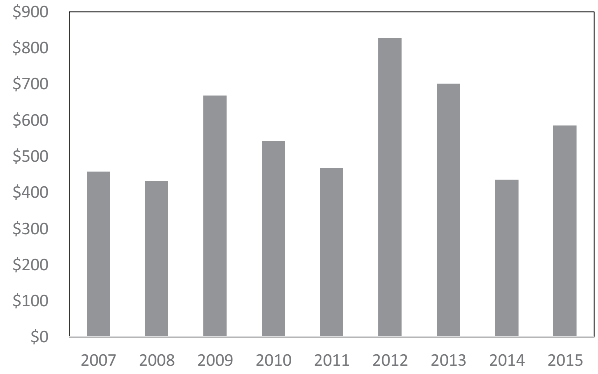
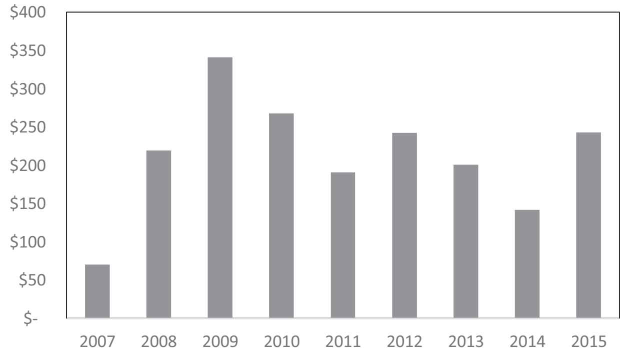


(a) All loans



(b) Conforming loans



(c) FHA loans

Fig. 1. Total residential mortgage originations. Panel A shows total dollars in billions originated between 2007 and 2015 as reported by HMDA. Panel B shows the total dollar value of originated conforming mortgages, where a mortgage is conforming if it is 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.

developments.[3] In this paper, we undertake a systematic examination of the evolution of shadow banking in the largest consumer loan market in the US, the ten trillion dollar consumer mortgage market. We seek to explore the economic forces that could explain the drastic change in the nature of intermediation.

We show that shadow banks' market share in mortgage origination has nearly doubled from roughly 30% in 2007 to 50% in 2015 (see Figs. 1–3). This growth has been particularly robust in the Federal Housing Administration (FHA) market, which serves less creditworthy borrowers, with shadow banks holding 75% market share in 2015. An important segment of growth in shadow banks were fintech lenders that primarily originate mortgages online. These lenders expanded rapidly since 2007 and accounted for a quarter of shadow bank origination in 2015.

Two broad hypotheses have attempted to explain the decline in traditional banking: increased regulatory burden on traditional banks and disruptive technology. The regulation hypothesis contends that following the financial crisis, traditional banks have been subject to increasing legal and regulatory burdens. These burdens have raised costs and limited the scope of products that traditional banks can provide, reducing lending. Shadow banks, which do not face these burdens, have gained market share by stepping into the gaps left by traditional banks.

The technology hypothesis contends that improving lending technology, particularly among new shadow bank entrants, has driven the shift away from traditional banks. Fintech shadow banks have gained market share because their technology allows them to lend more cheaply or to provide better products. For example, Quicken Loans, the third largest mortgage lender in 2015, offers the "Rocket Mortgage" product, whose application is almost entirely online and involves no human loan officer. This innovation saves labor and office space costs and is significantly more convenient according to consumer reviews.[4] Additionally, fintech lenders may be better able to screen potential borrowers, leveraging alternative sources of information and the big data approaches inherent in technology-based lending.

Our paper tests both explanations and then digs more deeply to understand the specific regulatory and

[3] Bank of International Settlements, 2017: "FinTech credit. Market structure, business models and financial stability implications." http://www.bis.org/publ/cgfs_fsb1.pdf.

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

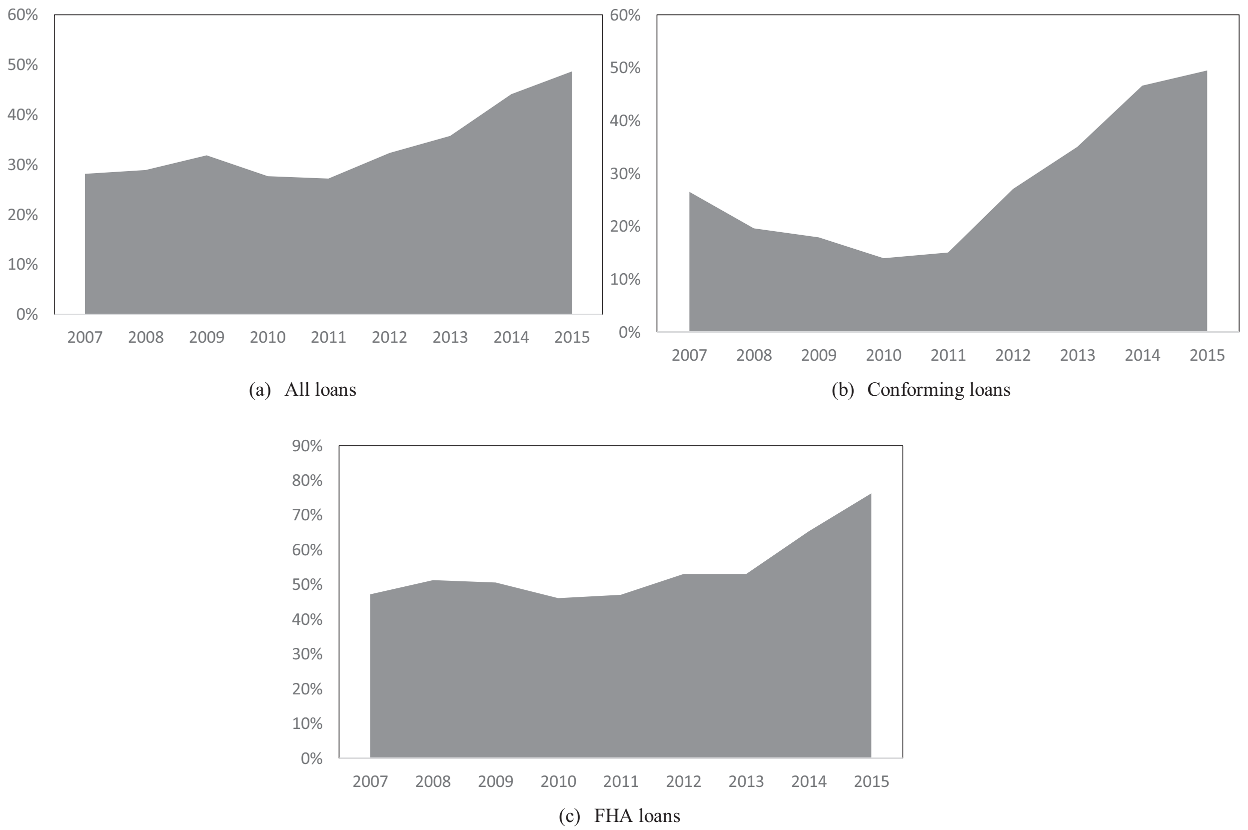


Fig. 2. Shadow bank origination shares. Panel A shows shadow bank origination shares as a fraction of total originations for all mortgages in HMDA between 2007 and 2015. Panel B shows shadow bank origination shares among conforming mortgages. Panel C shows the shadow bank origination share among FHA mortgages.

technology forces at work. Our first approach to examining whether an increased regulatory burden is a driving force behind the decline of traditional mortgage banking is to compare lending of banks to all shadow banks, irrespective of their fintech affiliation. We find that shadow banks are more likely to serve riskier, less creditworthy FHA borrowers and areas with larger minority populations. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of less creditworthy and minority borrowers, this evidence is consistent with shadow banks expanding in segments where regulatory burden has risen substantially.

Shadow banks and traditional banks also differ dramatically in mortgage financing. While traditional banks continue to hold between 30% and 50% of their originated loans on balance sheet, shadow banks finance their originations almost entirely through securitization and the originate-to-distribute model. While the private securitization market dried up following the crisis, government-sponsored enterprises (GSEs) like Fannie Mae and Freddie Mac have come to play a dominant role in guaranteeing shadow bank originations. These implicit government guarantees that shadow banks overwhelmingly rely on is another example though which regulatory activity has advantaged shadow banks.

With respect to loan pricing, we find negligible differences in traditional and shadow bank interest rates. This finding hides important heterogeneity within shadow banks, with non-fintech shadow banks offering slightly lower interest rates and fintech shadow banks offering substantially higher interest rates. We explore this heterogeneity when studying technology but conclude that that while non-fintech shadow banks pass some regulatory cost savings to borrowers, given the concurrent increase in market share of fintech shadow banks, cost advantages alone cannot explain shadow bank growth.

Finally, to link regulation and shadow bank growth more explicitly, we study the impact of four specific increases in regulatory burden: capital requirements, mortgage servicing rights (MSRs), mortgage-related lawsuits, and the movement of supervision to Office of Comptroller and Currency (OCC) following closure of the Office of Thrift Supervision (OTS), widely considered to be a lax regulator (Agarwal et al., 2014; Granja and Leuz, 2018). To avoid confounds related to credit demand differences across counties, such as differences in economic fundamentals, we exploit changes in the regulatory burden within a differences in differences framework. Our tests reveal that shadow banks gained market share and expanded lending in counties whose banks were more exposed to increases in regulatory burdens. Moreover, the

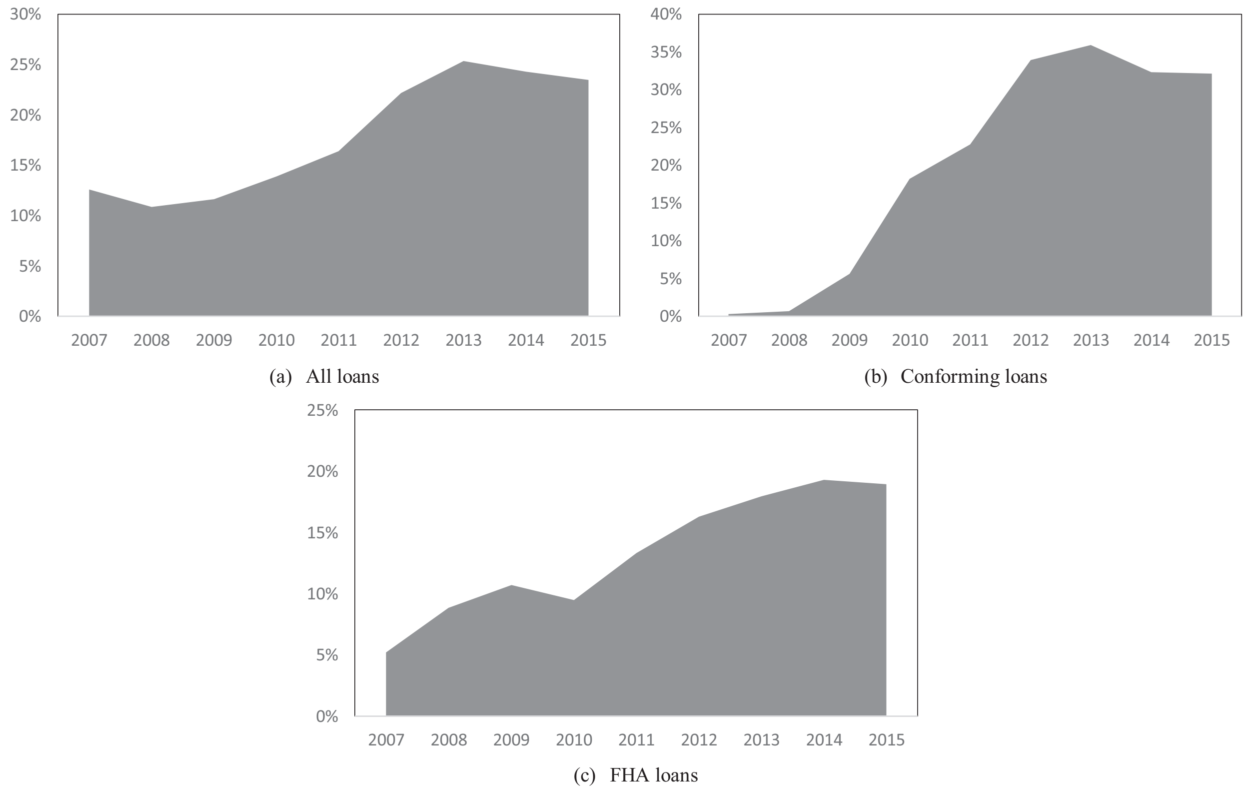


Fig. 3. Fintech origination shares of shadow bank originations. Panel A of this figure shows fintech originations as a share of shadow bank originations for all mortgages in HMDA between 2007 and 2015. Panel B shows fintech bank origination shares among shadow bank conforming originations. Panel C shows fintech share among shadow bank FHA originations (based on HMDA).

timing of specific regulatory changes is closely linked to the rise of shadow banks in exposed counties.

Concerning technology, fintech firms accounted for roughly a quarter of shadow bank loan originations in 2015. This aggregate fact suggests that online origination technology may have played an important role in the decline of traditional banks during the last decade. To assess the role of this technology, we focus on technology differences between shadow banks, which allows us to hold regulatory differences between lenders fixed. We first show that fintech lenders serve different segments of the mortgage market than non-fintech shadow banks: fintech lenders' origination activity overwhelmingly focuses on refinancing, which we speculate is a comparative advantage of online origination. Additionally, fintech lenders are less likely to serve less creditworthy FHA borrowers and higher unemployment geographies.

Importantly, we find that fintech shadow banks charge significantly higher interest rates than both non-fintech shadow banks and traditional banks. The combination of high interest rates and growing market shares suggests an increasing consumer demand for fintech services as the technology improves. These results suggest that fintech entry in this market is not only driven by cost saving technology. We also find significant differences in information used to set mortgage interest rates between fintech and non-fintech lenders. Standard variables for predicting interest rates, such as FICO and loan-to-value ratio (LTV), explain substantially less variation in interest rates of fintech lenders relative to non-fintech lenders. In other words, technology-based lending uses different information, potentially based on big data, in addition to standard pricing variables.

Taken together, our results suggest that both increased regulatory burdens and technological improvements have contributed to the decline of traditional banks' market share. To decompose their relative contributions, we calibrate a simple quantitative model of mortgage origination. In the model, traditional banks, non-fintech shadow banks, and fintech shadow banks compete for borrowers. To capture the conventional facts that we document, these lenders differ on three dimensions: regulatory burden, convenience, and costs of making loans. Pricing, firm entry, and markups are determined endogenously for each type of lender. We interpret the variation in mortgage rates and market shares using the model to identify the relative importance of different factors in the decline of traditional banking.

Our estimates imply that traditional banks have slightly lower shadow cost of funding and provide higher quality products than shadow banks. Despite these advantages, they lose market share during this period because of increasing regulatory burdens after 2010. This period coincides with the adoption of a number of new regulatory initiatives concerning bank capital requirements and stricter regulatory oversight. We also estimate a substantial increase in perceived quality of online origination platforms by borrowers occurring between 2009 and 2012. Putting these effects together, we find that increasing regulatory burden can account for about 60% of shadow bank growth during 2008–2015 period, advancement in online lending technology accounting for another 30%, and the balance coming from other sources.

2. 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.

2.1. The structure of the residential mortgage market

Many papers have studied the 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, 2013; Purnanandam, 2011). The focus has primarily been on the run-up to the financial crisis rather than on the immediate aftermath and recovery following the crisis.

Bank-like activities taking place outside of traditional deposit-taking institutions have attracted considerable attention in the literature and at federal banking regulators (see Adrian and Ashcraft, 2016 for an exhaustive summary). The literature (e.g., Bord and Santos, 2012) has primarily focused on the maturity transformation role of banks taking place outside of banks. Our paper instead focuses on mortgage origination taking place outside the traditional banking system and its accompanying regulatory structure. In this regard our paper is also related to the recent literature investigating the industrial organization of the residential mortgage market (e.g., Stanton et al., 2014, 2018).

2.2. Banking regulation and GSEs

Our paper relates to a large literature examining the role of government programs undertaken during the financial crisis (e.g., Mayer et al., 2014; Haughwout et al., 2016; Agarwal et al., 2015, 2017). Like Agarwal et al. (2014), Lucca et al. (2014), Granja et al. (2017), Piskorski et al. (2015), Fligstein and Roehrkasse (2016), Granja and Leuz (2018), we study lawsuits arising out of the financial crisis, capital constraints, and the closure of the OTS. We make use of geographical heterogeneity in regulatory burden to show that shadow banks, facing relatively lower regulatory pressure in heavily regulated markets, gain market share.

Because shadow banks rely heavily on GSEs and FHA guarantees, our paper relates to literature studying GSEs and their role in mortgage lending. GSEs were established to promote housing ownership, particularly in underserved areas, and a number of papers (e.g., Elenev et al., 2016; Hurst et al., 2016; Acharya et al., 2011) have studied their role in income redistribution and house ownership, finding mixed results. Our paper suggests that increased regulatory burden of traditional banks combined with GSEs and FHA guarantees may have contributed greatly to the rise of the shadow banking sector.

2.3. 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 show that fintech lenders appear to use substantially different methods to set interest rates. Philippon (2015) shows 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. In this regard, Fuster et al. (2018) study how technology impacts frictions in the mortgage origination process, such as slow processing times, capacity constraints, and refinancing. They show that fintech lenders process mortgage applications faster and adjust supply more elastically than other lenders in response to mortgage demand shocks, which suggests that technological innovation may have improved the efficiency of financial intermediation in the mortgage market. Bartlett et al. (2018) study the role of fintech lenders in alleviating discrimination in mortgage markets. They find evidence that suggests that such lenders make the mortgage lending markets more accessible to African American and Hispanic borrowers and provide these borrowers with fairer pricing.

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

3. Data and lender classification

3.1. Description of data sets

We combine and use the following data sets in our paper.

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

Fannie Mae and Freddie Mac single-family loan performance data: The Fannie Mae and Freddie Mac data sets provide origination and performance data on a subset of these GSEs' 30-year, fully amortizing, full documentation, single-family, conforming fixed-rate mortgages that are the predominant conforming contract type in the US.[5] This loan-level monthly panel data has detailed information on a rich array of loan, property, and borrower characteristics (e.g., interest rates, location of the property, borrower credit scores, LTV ratios) and monthly payment history (e.g., delinquent or not, prepaid). The loans in our data were acquired between January 1, 2000, and October 2015. The monthly performance data runs through June 2016. Combining the Fannie Mae and Freddie Mac data sets gives us coverage of the majority of conforming loans issued in the United Sates during the period of our study.

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

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

Regulatory burden of depository institution data: In studying the market share of shadow banks we investigate whether shadow banks are likely to enter areas where the traditional banking system faces heightened regulatory scrutiny. We draw on a number of data sources to measure these regulatory burdens between 2006 and 2015. In particular, we use bank balance sheet data from the bank call reports, from which we calculate bank capitalization.

Lawsuit settlements data: Finally, following Piskorski et al. (2015) and Fligstein and Roehrkasse (2016), we collect lawsuit settlements arising out of the financial crisis brought against banks, lenders, and mortgage servicers. We construct a timeline of settlements and settlement amounts by year and bank by aggregating data from a number of sources. From Law360,[6] a news service that covers all aspects of litigation, we collect data on lawsuit settlements associated with residential mortgage-backed securities (RMBS), mortgage foreclosures, fraud, deceptive lending, securitization, refinancing, and robo-signing. The Law360 data spans 2008 through 2016. From the Securities and Exchange Commission (SEC), we collected all legal actions taken by the SEC regarding misconduct that led to or arose from the financial crisis.[7] The SEC data spans 2009 through 2016. From SNL Financial, now a part of S&P Global Intelligence, we collect a timeline of major bank settlements arising out of the financial crisis between 2011 and 2015.[8]

3.2. Lender classification

Central to this paper is the classification of mortgage lenders as banks or shadow banks and within shadow banks as fintech or non-fintech. We perform this classification manually. The Fannie Mae, Freddie Mac, and FHA data identify each loan's originator if the originator was among the top 50 originators in the reporting period. HMDA identifies all originators. We classify the identified lenders in the Fannie Mae, Freddie Mac, and FHA data. Additionally, we classify the largest lenders in HMDA that are not identified in the Fannie, Freddie, or FHA data so that our classified sample covers 80% of total originations by value in 2010. Robustness with respect to lender classification is discussed in Section 10.

A lender is a "bank" if it is a depository institution; a lender is a "shadow bank" otherwise. This definition commands broad regulatory agreement: it is consistent with the definition of the FSB, which defines banks as "[*a*]ll deposit-taking corporations" and shadow banks as "credit intermediation involving entities and activities outside of the regular banking system."[9] Because our focus is mortgage origination, our measurement of shadow banking falls squarely within the FSB definition. FSB members comprise both national regulators of G20 countries, as well as international financial institutions, such as the International Monetary Fund, the World Bank, and the Bank of International Settlements, as well as international standard-setting and other bodies such as the Basel Committee on Banking Supervision.

The classification of fintech and non-fintech is more subjective: we classify a lender as a fintech lender if it has

[5] The data set 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 nonstandard mortgage loans. Also excluded are loans that do not reflect current underwriting guidelines, such as loans with originating LTVs over 97% and mortgage loans subject to long-term standby commitments, those sold with lender recourse or subject to other third-party risk-sharing arrangements, or were acquired by Fannie Mae on a negotiated bulk basis.

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

[7] https://www.sec.gov/spotlight/enf-actions-fc.shtml.

[8] https://www.snl.com/InteractiveX/Article.aspx?id=33431645.

[9] http://www.fsb.org/wp-content/uploads/global-shadow-banking-monitoring-report-2015.pdf.

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 Online Appendix A.4). 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.

While we consider the possibility of "fintech traditional banks," we find no banks fitting our criteria among the nation's largest bank lenders. More details on this are discussed in Online Appendix A.7, where we additionally confirm the historical accuracy of our classifications using the "Wayback Machine" to view archived webpages. Conversations with senior bankers confirm our finds and suggest a hesitancy to adopt automated lending technology, due to the existence of legacy systems and processes, and, in line with the themes of this paper, a concern over regulatory scrutiny in the wake of robo-signing scandals.[10]

Online Appendix A.1 shows the list of main lenders in each of these three categories. Online Appendix A.7 provides more details on the classification process.

4. Institutional background

This section provides an overview of the institutional details and history of shadow banking before and after the financial crisis.

4.1. History of shadow banking in the retail mortgage market

While this paper focuses on shadow bank mortgage origination after the crisis, we note that shadow banks a large market share before the crisis. Goldman Sachs estimates that among the top 20 lenders, shadow banks originated roughly 30% of all mortgages for the years 2004–2006. The shadow bank lending was heavily concentrated: Countrywide Financial alone accounted for more than half of the shadow bank originations.[11]

Shadow bank originators rely almost exclusively on making loans that are originated for sale to third parties The identity of the third party depends on the originated product: Fannie Mae and Freddie Mac buy conforming loans; Ginnie Mae buys loans by the FHA or Veterans Administration (VA). Private securitizers bought nonconforming jumbo or subprime mortgages.

Precrisis shadow banks were particularly active in these nonagency markets, which essentially vanished during the crisis. Because shadow banks are so reliant on secondary markets for their originations, shadow bank lenders like Countrywide and New Century found themselves unable to secure additional financing when the secondary market for nonconforming subprime and jumbo loans dried up in 2007. As a result, many shadow bank lenders declared bankruptcy or were sold to traditional banks.[12] Consequently, during the financial crisis and the following recession, shadow bank mortgage origination fell significantly. In the depths of the recession, shadow bank market share among the 50 largest lenders fell to roughly 15%. (See Online Appendix A.6). Even including smaller lenders, the shadow bank market share fell to less than 30% in 2008.

MSR : Mortgage serving ratio. it refers to the borrower's gross monthly income that goes towards repaying all property loans, including the loan being applied for.

4.2. Regulatory changes

Following the financial crisis, a number of regulatory changes have had a direct influence on traditional banks' mortgage origination activity. Weakened bank balance sheets combined with new capital rules under Basel III led to tightened regulatory capital constraints. In particular, Basel III changed risk-weighted capital requirements and placed limits on banks counting MSRs toward their regulatory capital requirement.[13] The MSR rule change was proposed, finalized, and implemented between 2010 and 2015.[14] At the same time, lawsuits arising from conduct prior and during to the crisis fell heavily on the surviving lenders, which were overwhelmingly banks. Additionally, the OTS, which had overseen failed lenders like Countrywide and Washington Mutual and had a reputation for lax oversight, was closed, and its duties folded into the OCC, Federal Deposit Insurance Corporation (FDIC), Federal Reserve, and newly formed Consumer Financial Protection Bureau (CFPB).

5. The rise of shadow banks and fintech

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

5.1. Aggregate facts

Residential lending volume fluctuated significantly between 2007 and 2015. Fig. 1, Panel A shows the value of new US residential mortgages as reported in HMDA by year of their origination. In 2007 the originations reached over \$2 trillion; in 2008 it declined to less than \$1.4 trillion, only to peak at almost \$2.2 trillion in 2012 before declining again. Fig. 1, Panel B shows the lending volume in conforming mortgages, the most popular residential loans in

[10] See, for example, https://diginomica.com/2017/10/12/fintech-risk-aversion-culture-shock/,https://letstalkpayments.com/why-banks-should-not-be-held-responsible-for-slow-innovation-adoption/https://www.americanbanker.com/opinion/regulatory-ambiguity-is-slowing-bank-adoption-of-cloud-serviceshttps://thefinancialbrand.com/65069/america-us-banking-digital-innovation-trends/.

[11] GS Report, pg. 51.

[12] http://www.charlotteobserver.com/news/business/banking/article9151889.html, accessed April 15, 2017.

[13] GS Report, pg 54.

[14] See https://deepblue.lib.umich.edu/bitstream/handle/2027.42/110908/1213_Shakespeare_March2016.pdf.

Table 1
Residential mortgage lending: traditional versus shadow banks.
Table 1 provides shows loan type and disposition by lender type. 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

more details on the data in panel a

	All lenders	Traditional banks	Shadow banks	Shadow banks	
				Non-fintech	Fintech
% Conventional	76.9%	83.2%	64.31%	62.0%	74.3%
% FHA	15.8%	11.0%	25.33%	26.9%	18.7%
% Other	7.3%	5.8%	10.36%	11.1%	7.0%
Count	46,431,132	30,943,694	15,487,438	12,575,694	2,911,744

Panel B: Loan disposition based on 2007–2015 HMDA

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

the US.[15] Over this time period, almost half of loans were loans sold to GSEs within the year.[16]

Fig. 1, Panel C presents volumes of FHA-insured loans. FHA loans allow lower income and less creditworthy households to borrow money, often at below-private-market rates, for the purchase of a home that they would not otherwise be able to afford. FHA borrowers typically make only a 3.5% down payment, with the FHA loan financing the balance. These loans account for approximately 15% of our sample (Table 1, Panel A, Column 1) and are the second most popular loan segment in the United States. Aggregate trends in FHA loan volumes differ substantially from conforming mortgage trends. The issuance segment rose from $70 billion in 2007 to peak in 2009 at over $340 billion. This dramatic growth reflects the disappearance of the private subprime lending market, which was the closest substitute for many FHA loans.

Despite these large fluctuations in the aggregate amount of residential mortgage originations, the share of shadow banks has been steadily increasing over time. Fig. 2 shows that the share of mortgages originated by shadow banks across different markets. Panel A shows that among all loans reported in the HMDA data, the share of shadow banks has increased from roughly 30% in 2007 to 50% in 2015, with the majority of the growth taking place after 2011.

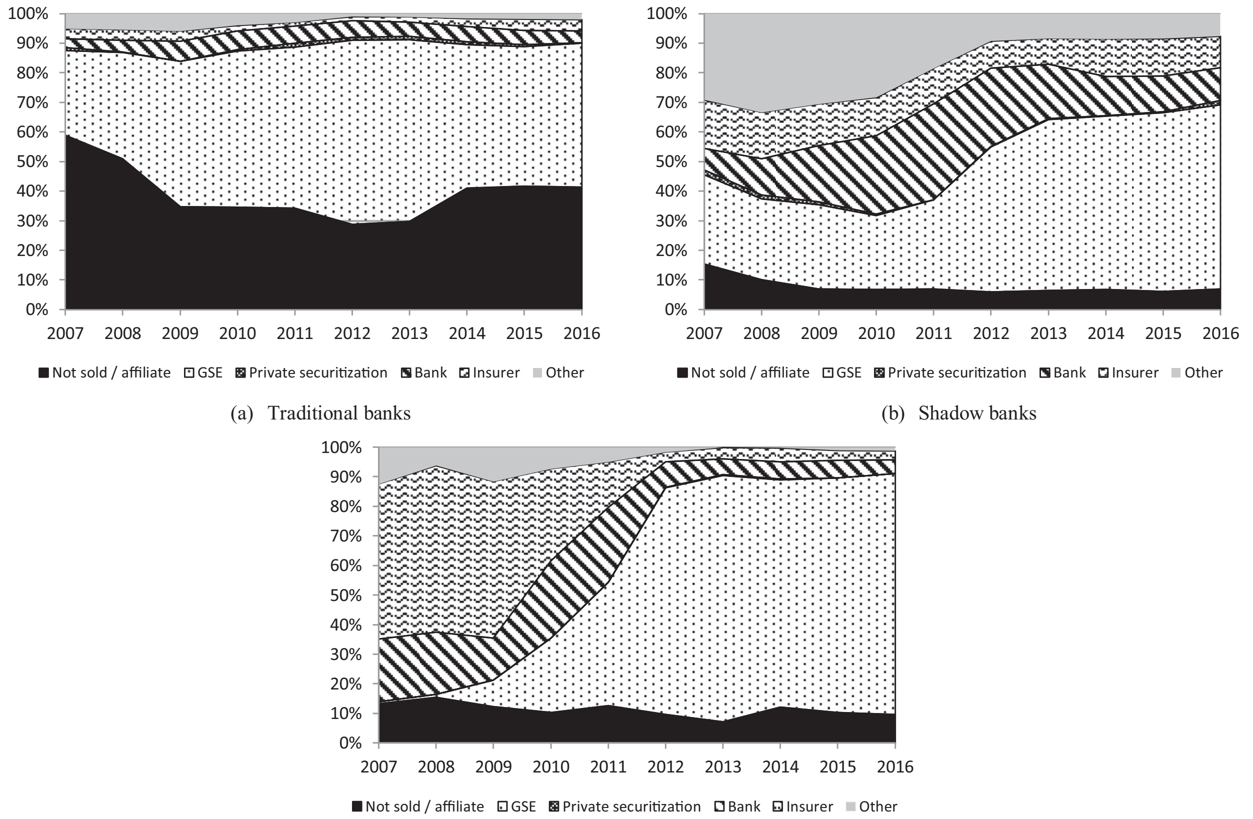
This growth in shadow banks was not confined to a specific segment of the residential market. Panel B shows that among conforming loans, the shadow bank share approximately doubled from 25% in 2007 to 50% in 2015 with the majority of the growth occurring after 2011. Panel C, shows that among FHA loans, the shadow bank origination share grew from about 45% in 2007 to about an astounding 75% in 2015. 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.[17]

The rise in shadow banks has coincided with a shift away from brick-and-mortar originators to online intermediaries. Here, we show the extent of this shift in the residential mortgage market. Fintech originations accounted for roughly 3% of residential loans and grew to 12% by 2015. Fig. 3, which shows fintech shadow banks' share of

[15] Prior to the Great Recession, private nonconforming (nonagency) 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.

[17] Online Appendix A.7 presents results for top 50 largest lenders. The difference in the samples reflects a relatively large market share of small shadow banks early in the sample that declined over time relative to large shadow banks. The decline in the share of shadow bank loans sold to affiliates (Fig. 4, Panel B) suggests that some of these small shadow banks sold loans to traditional banks.



(a) Traditional banks (b) Shadow banks

(c) Fintech lenders

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

shadow bank lending, reveals that fintech shadow banks account for a substantial part of the expansion of shadow bank lending. Fig. 3, Panel A shows that fintech share of shadow bank lending grew especially in 2009–2013 period. This growth is in both the conforming and FHA segments (Fig. 3, Panels B and C).

5.2. Financing of shadow banks

Accompanying these market share changes have been shifts in the source of traditional and shadow bank financing. Table 1, Panel B shows that between 2007 and 2015, traditional banks have held more than 30% of originated mortgages, while shadow banks retain, at most, 7.5%.[18] In addition to these level differences, traditional banks and shadow banks' financing patterns evolved very differently over time. Fig. 4 shows the time trends of loan financing among traditional banks, shadow banks, and fintech lenders, respectively. While private securitization accounted for the bulk of shadow bank purchasers precrisis, this market collapsed prior to the start of our period of interest. At the start of our study, neither traditional nor shadow banks had access to this source of financing. Panel A shows that the share of bank loans held on balance sheet has been roughly stable, fluctuating from 50% in 2007 to 30% in 2012, before increasing again to 40%. This contrasts significantly with changes in shadow bank financing. As Panel B shows, shadow banks have grown increasingly reliant on GSEs: in 2007, only 30% of their funding came from GSEs. By 2015, nearly 50% of shadow bank loans were sold to GSEs after origination.[19]

Significant changes are also apparent for fintech shadow banks. As Panel C shows, before 2010, fintech lenders sold most of their mortgages to insurance companies. From 2010 onward, fintech lenders started shifting their sales

Government sponsored enterprises = GSEs

[18] The share of loans retained on the balance sheets is likely smaller. HMDA loans not sold within the calendar year of origination are recorded as not sold. Therefore, some of “not sold” loans are likely sold in the next calendar year. In the Fannie Mae and Freddie Mac data set (which records both date of origination and date of sale), roughly 9% of shadow bank loans are sold in a year that is different from their origination year. If this pattern holds in HMDA, this fully explains the 7.5% of not sold shadow bank originations.

[19] The patterns are even more striking if we focus only on the largest lenders (Online Appendix A.7).

Table 2
Time between origination and sale.
Table 2 shows the results of the time-to-sale regression for quarters between origination and sale, using Fannie Mae and Freddie Mac origination data from 2010 to 2015. Columns (1) and (2) compare shadow banks to traditional banks for the entire sample of lenders. Columns (3) and (4) compare present the results with shadow banks broken out by fintech and non-fintech lenders. Columns (5) and (6) compare fintech shadow banks to non-fintech shadow banks among the shadow bank sample only. Columns (1), (3), and (5) have quarter fixed effects and no other controls. Columns (2), (4), and (6) have borrower and loan controls and zip-quarter fixed effects. The left-hand-side variable is in quarters since origination. Its mean among all lenders is 0.46, or approximately 41 days; its mean among shadow bank lenders is 0.40, or approximately 36 days. Standard errors are clustered at the zip-quarter level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Qtrs to sale	(2) Qtrs to sale	(3) Qtrs to sale	(4) Qtrs to sale	(5) Qtrs to sale	(6) Qtrs to sale
Sample	All lenders				Shadow banks only	
Shadow bank	−0.103***	−0.100***	–	–	–	–
	(−52.77)	(−52.67)	–	–	–	–
Non-fintech shadow bank	–	–	−0.0812***	−0.0803***	–	–
	–	–	(−39.12)	(−39.37)	–	–
Fintech shadow bank	–	–	−0.180***	−0.173***	−0.0846***	−0.0842***
	–	–	(−63.17)	(−60.18)	(−28.21)	(−26.84)
Borrower and loan controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	4,075,985	40,71,465	4,075,985	4,071,465	1,187,390	1,185,846
R^2	0.0349	0.0491	0.0368	0.0507	0.0603	0.0931

toward GSEs, and by 2015, nearly 80% of loans originated by fintech lenders were loans financed by some underlying government guarantee. Overall, these results suggest that shadow banks, and fintech shadow banks in particular, grew increasingly reliant on government guarantees in the form of GSEs and FHA insurance relative to traditional banks, which instead rely on government-guaranteed deposits for funding.

In addition to differences between traditional banks and shadow banks in how their originated mortgages are ultimately financed, we also show significant variation in financing patterns, even conditional on the mortgages being sold. In particular, among conforming loans sold to the GSEs, we study the length of time the mortgage is held on the originator's balance sheet. We define $Time\_to\_Sale_{ijzt}$ of borrower i of lender type j at location z at time t (in the unit of quarters) as

$$Time\_to\_Sale_{ijzt} = Quarters\,Between(Sale, Origination) \tag{1}$$

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

$$Time\_to\_Sale_{ijzt} = \beta\,Type_j + X\prime_i\Gamma + \delta_{zt} + \epsilon_{ijzt}, \tag{2}$$

where $Type_j$ is bank, shadow bank, fintech, or non-fintech. X_i is a vector of loan controls, and δ_{zt} are zip-time fixed effects. The results in Table 2 show that the time-to-sale for shadow banks by roughly 0.10 quarters (9 days) shorter than time-to-sale of traditional banks. Within shadow banks, non-fintech shadow banks' time-to-sale is roughly 0.08 quarters (7 days) faster than traditional banks, and fintech shadow banks' time-to-sale is roughly 0.17 quarters (16 days), faster than traditional banks. These results are consistent with shadow banks having a more limited balance sheet capacity than traditional banks, which results in a faster sale. Without additional data, it is hard to assess whether fintech lender's even faster time is driven by technological advantages, or greater balance sheet constraints, or a combination of both. These findings are certainly consistent with Fuster et al. (2018) who find that fintech lenders process mortgage applications faster.

6. Loan-level differences between traditional banks, shadow banks, and fintech

This section shows differences in loans and borrower characteristics among lender types. We first examine characteristics of loans and borrowers within and across geographic markets. We then study pricing and performance differences across lender types. These facts will provide suggestive evidence on the role of regulation and technology in the decline of traditional banks that we study in greater detail in following sections.

6.1. The characteristics of non-fintech and fintech shadow bank borrowers and loans

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

6.1.1. Descriptive statistics

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

(Table 3, Panel A). Compared with traditional banks, shadow bank borrowers have approximately $4,000 lower annual incomes on average. This difference became more pronounced in the recent period, growing to $9,000 by 2015. Among shadow bank borrowers, those using fintech firms report slightly higher incomes.

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

6.1.2. Borrower and loan characteristics

We now frame our analysis with the observation that if shadow banks are engaging in regulatory arbitrage, they should be most active among borrowers and geographies where traditional banks face the greatest regulatory burdens. Moreover, to the extent that fintech shadow banks are exploiting technological advantages, they should be most active among those best able to use the technology and those for whom the technology offers the greatest benefits.

We analyze both individual loan-level differences within a given market as well differences in market share at the geographical level. On the individual level, we estimate the following linear probability specification:

$$Lender\_Type_{ict} = X_i'\Gamma + \delta_{ct} + \epsilon_{ict}. \tag{3}$$

Each observation is a residential mortgage i in county c originated in time t. We first estimate the regression first on the sample of all residential loans, where $Lender\_Type_{ict}$ is an indicator variable taking the value 100 if the originator is a shadow bank, and 0 otherwise, meaning the coefficients are in units of percentage points. We next estimate the regression only among shadow bank loans in which case $Lender\_Type_{ict}$ is an indicator taking the value 100 if the originator is a fintech shadow bank, and 0 otherwise. X_i is a vector of borrower and loan characteristics, such as borrower income, race, loan purpose, or loan type. Both specifications include county x time fixed effects δ_{ct} to compare borrowers within a market at the same time.

We estimate these specifications separately using HMDA data and Fannie Mae and Freddie Mac data. The broader HMDA data gives insight into the overall mortgage market over certain characteristics such as borrower race and loan financing. The narrower Fannie and Freddie data are limited to FRM loans but contain more detailed credit information and loan term information.

While the above specification provides insight at the individual level within a given market, we also study market-level differences at the county level. Fig. 5 shows significant heterogeneity in the county-level shadow bank penetration in 2015, ranging from less than 10% to more than 80%. It is these differences that this section seeks to

Table 3
Shadow bank, fintech presence, and the borrower and loan characteristics: all loans.

Table 3 presents descriptive statistics for borrowers and loans by lender type. Panel A summarizes differences in borrower demographics in accepted mortgage applications as reported in the HMDA data. Columns (1)–(4) compare cover the period 2007–2015. Columns (5)–(8) cover the 2015. Columns (1) and (2) and (5) and (6) compare traditional and shadow banks; Columns (3) and (4) and (7) and (8) compare non-fintech and fintech shadow banks. Panel B shows the result of Eq. (3), a linear probability model regressing whether the lender is a shadow bank, Columns (1) and (2); a non-fintech shadow bank, Columns (3) and (4); a fintech lender among all lenders, Columns (5) and (6); or a fintech lender among shadow banks, Columns (7) and (8), on borrower characteristics over the period 2007–2015. Odd columns include year fixed effects. Even columns include year-county fixed effects. For race dummies, the base category is White; for sex dummies, the base is Male. For loan purpose dummies, the base is Purchase. For purchaser dummies, the base is Not sold. For type dummies, the base is Conventional. Coefficients are in percent. 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	Shadow banks		Traditional banks	Shadow banks	Shadow banks	
			Non-fintech	Fintech			Non-fintech	Fintech
Count	30,943,694	15,487,438	12,575,694	2,911,744	2,300,721	2,182,654	1,670,680	511,974
Median income	$83,000	$79,000	$78,000	$82,000	$89,000	$80,000	$79,000	$82,000
Male	66.98%	67.61%	68.94%	61.87%	65.64%	65.94%	69.01%	55.92%
Race								
Native American	0.52%	0.50%	0.50%	0.50%	0.59%	0.57%	0.56%	0.62%
Asian	5.21%	5.79%	6.09%	4.50%	5.63%	5.50%	5.79%	4.55%
African American	4.72%	5.59%	5.85%	4.48%	4.83%	6.34%	6.80%	4.86%
Native Hawaiian	0.36%	0.42%	0.43%	0.34%	0.36%	0.45%	0.49%	0.33%
White	78.04%	76.47%	77.76%	70.90%	77.10%	74.93%	78.17%	64.38%
Other/Unknown	11.15%	11.23%	9.36%	19.27%	11.49%	12.19%	8.19%	25.26%
Loan purpose								
Home improvement	6.34%	0.68%	0.78%	0.22%	9.80%	1.14%	1.35%	0.47%
Refinancing	60.40%	52.69%	47.26%	76.13%	44.67%	47.44%	40.87%	68.88%

(continued on next page)

Table 3
(continued)

Panel B: regressions (HMDA)								
	(1) Shadow bank	(2) Shadow bank	(3) Non-fintech	(4) Non-fintech	(5) Fintech	(6) Fintech	(7) Fintech	(8) Fintech
Sample	All lenders						Shadow banks only	
Income (000 s)	−0.00857***	−0.00673***	−0.00692***	−0.00468***	−0.00165***	−0.00206***	0.00138***	−0.00197***
	(0.0000462)	(0.0000453)	(0.0000440)	(0.0000431)	(0.0000266)	(0.0000266)	(0.000107)	(0.000106)
Loan amount (000 s)	0.00835***	0.000881***	0.00931***	0.000910***	−0.000965***	−0.0000288	−0.0152***	−0.00511***
	(0.0000392)	(0.0000423)	(0.0000373)	(0.0000402)	(0.0000226)	(0.0000249)	(0.0000799)	(0.0000895)
Race (Omitted category = White)								
Native American	−0.227**	−1.362***	−0.821***	−2.028***	0.593***	0.666***	1.170***	1.879***
	(0.0877)	(0.0861)	(0.0835)	(0.0820)	(0.0506)	(0.0506)	(0.138)	(0.136)
Asian	3.923***	1.204***	4.384***	1.498***	−0.461***	−0.294***	−3.313***	−2.288***
	(0.0276)	(0.0283)	(0.0263)	(0.0269)	(0.0159)	(0.0166)	(0.0414)	(0.0421)
Black	0.405***	0.296***	0.338***	0.346***	0.0676***	−0.0501**	0.000883	0.171***
	(0.0300)	(0.0304)	(0.0285)	(0.0290)	(0.0173)	(0.0179)	(0.0448)	(0.0456)
Hawaiian	1.363***	−0.696***	1.630***	−0.774***	−0.267***	0.0776	−0.798***	0.680***
	(0.103)	(0.101)	(0.0980)	(0.0961)	(0.0594)	(0.0593)	(0.153)	(0.151)
Unknown	7.438***	5.663***	3.716***	1.958***	3.723***	3.705***	5.309***	5.925***
	(0.0292)	(0.0286)	(0.0278)	(0.0272)	(0.0168)	(0.0168)	(0.0407)	(0.0400)
NA	−24.98***	−20.46***	−26.68***	−22.71***	1.706***	2.247***	−6.432***	−4.702***
	(0.816)	(0.794)	(0.776)	(0.756)	(0.470)	(0.467)	(1.463)	(1.429)
Sex (Omitted category = Male)								
Female	0.163***	−0.113***	−0.204***	−0.535***	0.366***	0.422***	0.896***	1.110***
	(0.0146)	(0.0143)	(0.0139)	(0.0136)	(0.00841)	(0.00838)	(0.0225)	(0.0220)
Unknown	−4.636***	−4.091***	−8.296***	−7.846***	3.660***	3.755***	15.78***	15.33***
	(0.0375)	(0.0366)	(0.0357)	(0.0348)	(0.0216)	(0.0215)	(0.0556)	(0.0545)
NA	16.27***	16.38***	19.76***	19.74***	−3.487***	−3.362***	−8.278***	−8.503***
	(0.734)	(0.715)	(0.699)	(0.681)	(0.424)	(0.420)	(0.709)	(0.692)
Purpose (Omitted category = Purchase)								
Home improvement	−13.26***	−12.18***	−12.25***	−11.40***	−1.011***	−0.782***	−6.862***	−5.399***
	(0.0327)	(0.0323)	(0.0311)	(0.0307)	(0.0189)	(0.0190)	(0.116)	(0.114)
Refinance	−2.056***	−1.792***	−7.965***	−7.839***	5.908***	6.047***	18.24***	18.14***
	(0.0143)	(0.0141)	(0.0136)	(0.0134)	(0.00823)	(0.00831)	(0.0212)	(0.0213)
Purchaser (Omitted category = Held)								
Fannie Mae	20.65***	19.04***	15.66***	13.96***	4.995***	5.082***	−5.948***	−4.915***
	(0.0188)	(0.0187)	(0.0179)	(0.0178)	(0.0109)	(0.0110)	(0.0414)	(0.0415)
Ginnie Mae	19.46***	19.03***	12.96***	12.51***	6.504***	6.520***	−5.474***	−5.567***
	(0.0333)	(0.0326)	(0.0316)	(0.0310)	(0.0192)	(0.0192)	(0.0515)	(0.0512)
Freddie Mac	8.171***	7.333***	7.620***	6.654***	0.551***	0.679***	−9.832***	−8.992***
	(0.0212)	(0.0210)	(0.0202)	(0.0199)	(0.0122)	(0.0123)	(0.0485)	(0.0484)
Farmer Mac	64.94***	59.91***	65.85***	59.75***	−0.903	0.159	−21.07***	−16.13***
	(1.094)	(1.067)	(1.041)	(1.015)	(0.631)	(0.627)	(1.097)	(1.075)
Private securitization	9.693***	8.028***	11.82***	10.11***	−2.123***	−2.081***	−16.40***	−15.03***
	(0.0751)	(0.0735)	(0.0715)	(0.0700)	(0.0433)	(0.0432)	(0.142)	(0.142)
Bank	48.21***	46.72***	42.39***	40.79***	5.824***	5.923***	−13.54***	−13.08***
	(0.0255)	(0.0253)	(0.0243)	(0.0240)	(0.0147)	(0.0149)	(0.0424)	(0.0429)
Insr or Fnce co.	57.96***	56.34***	43.68***	41.76***	14.29***	14.57***	−3.679***	−2.688***
	(0.0298)	(0.0294)	(0.0284)	(0.0280)	(0.0172)	(0.0173)	(0.0444)	(0.0448)
Affiliate	−2.121***	−3.004***	−1.137***	−1.920***	−0.983***	−1.084***	−13.48***	−12.39***
	(0.0327)	(0.0325)	(0.0311)	(0.0309)	(0.0189)	(0.0191)	(0.107)	(0.107)
Other	58.01***	55.87***	57.20***	54.89***	0.807***	0.972***	−20.90***	−20.12***
	(0.0279)	(0.0276)	(0.0265)	(0.0263)	(0.0161)	(0.0163)	(0.0432)	(0.0439)
Loan Type (Omitted category = Conventional)								
FHA	9.418***	9.242***	9.085***	8.938***	0.332***	0.304***	−1.755***	−1.972***
	(0.0249)	(0.0245)	(0.0237)	(0.0233)	(0.0143)	(0.0144)	(0.0301)	(0.0299)
VA	2.331***	3.189***	2.717***	3.237***	−0.386***	−0.0475*	−1.909***	−1.713***
	(0.0361)	(0.0360)	(0.0344)	(0.0343)	(0.0209)	(0.0212)	(0.0461)	(0.0464)
FSA/RHS	−3.036***	−0.660***	−0.205***	2.484***	−2.832***	−3.144***	−5.681***	−6.684***
	(0.0566)	(0.0563)	(0.0538)	(0.0536)	(0.0326)	(0.0331)	(0.0760)	(0.0766)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year x County FE	No	Yes	No	Yes	No	Yes	No	Yes
N	43,138,392	43,138,392	43,138,392	43,138,392	43,138392	43,138,392	14,340,698	14,340,698
R^2	0.241	0.281	0.223	0.265	0.059	0.074	0.133	0.178

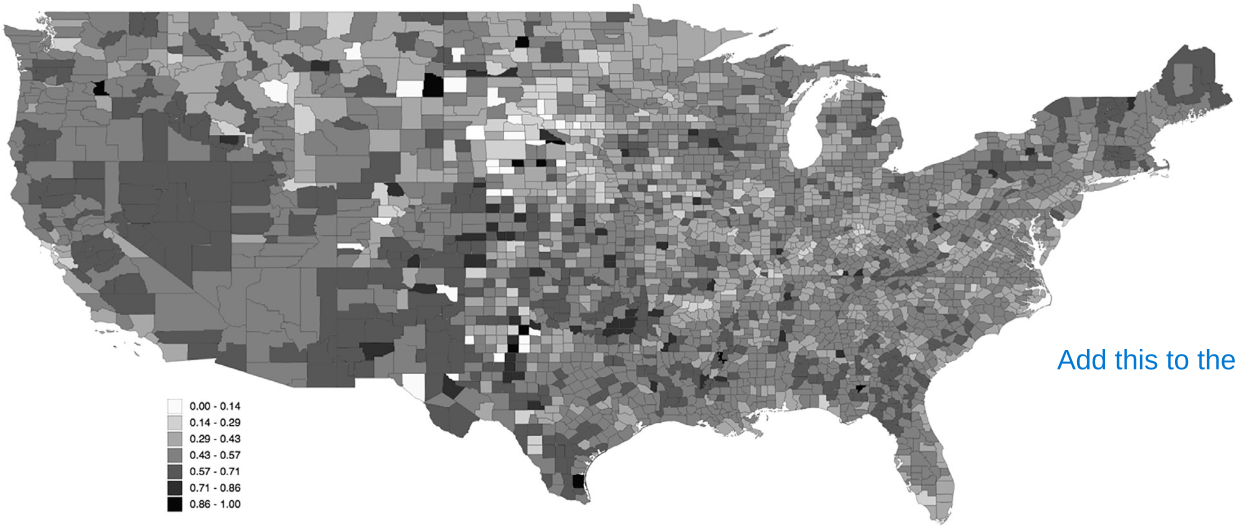


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Fig. 5. Regional shadow banking penetration. Fig. 5 shows the county-level percentage of mortgages originated by shadow bank lenders as of 2015. Calculations are based on HMDA data.

understand. To that end, we estimate the following regression of 2015 market share on county characteristics:

$$\%Lender\_Type\_Loans_c = X_c'\Gamma + \epsilon_c. \tag{4}$$

In parallel with the individual-level analysis, we study both shadow bank penetration as a share of all loans and fintech penetration as a share of shadow bank loans. That is, we use as left-hand side variables both

$$\%Shadow\_Bank\_Loans_c = \frac{\sum_{i\in nshshadow} Dollars\ Originated_{ic}}{\sum_{i\in all} Dollars\ Originated_{ic}}, \tag{5}$$

and

$$\%Fintech\_Loans_c = \frac{\sum_{i\in nfintech} Dollars\ Originated_{ic}}{\sum_{i\in shadow} Dollars\ Originated_{ic}}. \tag{6}$$

The individual-level results are shown in Table 3, Panel B for HMDA and Table 4 for the Fannie Mae and Freddie Mac data; the market-level results are shown in Table 5, with Panel A showing average differences and Panel B showing the regressions. The individual and geographical results, broadly similar, are presented below.

6.1.2.1. Race, income, and credit scores. Concerning race and income, Table 3, Panel B, Column (2) shows that within markets, lower income borrowers and racial minorities are more likely to be shadow bank borrowers. Table 5, Panel B, Columns (1)-(3) show that this result holds across markets: counties with greater shares of African American and Hispanic residents see significantly higher shadow bank market share. Additionally, counties with higher unemployment rates and fewer high school graduates see significantly higher shadow bank market share. As a consumer segment, economically disadvantaged and minority borrowers as have seen more mortgage-related lawsuits, and therefore we interpret these findings as shadow banks focusing on segments in which traditional banks face greater regulatory scrutiny. The Fannie Mae and Freddie Mac data in Table 4 reveals that among GSE borrowers, while shadow bank borrowers tend to have slightly lower FICO scores and slightly higher debt-to-income ratios, they also have lower loan-to-value ratios. Thus, while shadow bank borrowers tend to have lower incomes overall, within the GSE segment, they are not clearly more or less creditworthy.

Comparing fintech shadow banks to brick-and-mortar shadow banks, we do not find robust differences in incomes among individuals but do find that counties with lower unemployment rates see significantly greater fintech market penetration. Concerning race, we find the interesting result that borrowers reporting unknown race are significantly more likely to be fintech borrowers. This suggests that online borrowers are more circumspect in reporting their race when a loan officer cannot easily observe it. Within GSE loans, we once again find ambiguous differences in borrower riskiness and credit quality, with borrowers having lower FICO scores, greater debt-to-income ratios, and lower loan-to-value ratios being more likely to be fintech borrowers.[20]

6.1.2.2. Loan purpose: purchase versus refinancing. We find striking differences between lender types regarding the purpose of mortgage originations, particularly as between fintech and other lender types. Among individual shadow

[20] Simple descriptive statistics in Panel A of Table 5 suggests that consumer characteristics that predict shadow banks and fintech loans in a given market also predict across market variation in shadow bank and fintech penetration. Counties with a large shadow bank presence have more minorities and worse socioeconomic conditions: there are more African American and Hispanic residents and a greater percentage of unemployed residents. Interestingly, shadow banks are also more predominant in areas with significantly lower lending concentration as measured by a Herfindahl index and with more unique lenders on average. Fintech lending requires a certain degree of technological sophistication on the part of borrowers. Therefore, it is surprising that fintech firms are most present in counties with less educated populations. These are univariate comparisons, however, and should be interpreted with caution.

Table 4
Shadow bank presence and the borrower and loan characteristics: conforming loans.
Table 4 shows the results of a linear probability model, Eq. (3), regressing whether the lender is a shadow bank, Columns (1) and (2); a non-fintech shadow bank, Columns (3) and (4)); a fintech lender among all lenders, Columns (5) and (6); or a fintech lender among shadow banks, Columns (7) and (8), on individual characteristics, using the pooled Fannie Mae and Freddie Mac Data for the period 2010–2015. Odd columns include quarter fixed effects only; even columns include zip-quarter fixed effects. Loan purpose dummies (Refinance, Investment/Second home) use Purchase and Primary residence as the base category. Coefficients are in percents. Standard errors are clustered by zip-quarter; *t*-statistics in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

	(1) Shadow bank	(2) Shadow bank	(3) Non-fintech	(4) Non-fintech	(5) Fintech	(6) Fintech	(7) Fintech	(8) Fintech
Sample	All lenders						Shadow banks only	
Loan amount	0.0000100***	0.00000748***	0.0000103***	0.00000846***	−0.000000292***	−0.000000975***	−0.0000122***	−0.0000104***
	(90.27)	(55.75)	(99.88)	(67.29)	(−5.04)	(−14.19)	(−52.91)	(−37.45)
Loan term (Months)	0.0436***	−0.00237***	0.0321***	−0.000162	0.0115***	−0.00221***	0.00515***	−0.0176***
	(212.38)	(−10.78)	(168.56)	(−0.80)	(116.49)	(−20.48)	(10.18)	(−30.33)
Loan-to-value	−0.0608***	−0.0414***	−0.0400***	−0.0295***	−0.0208***	−0.0119***	−0.0392***	−0.0293***
	(−58.29)	(−38.33)	(−41.31)	(−29.35)	(−39.71)	(−21.43)	(−17.58)	(−12.62)
Debt-to-income	0.0606***	0.0517***	0.0268***	0.0225***	0.0338***	0.0292***	0.102***	0.0780***
	(41.09)	(35.71)	(19.48)	(16.60)	(45.73)	(39.44)	(32.92)	(25.84)
FICO	−0.0186***	−0.0207***	0.000627	−0.00167***	−0.0192***	−0.0191***	−0.0519***	−0.0416***
	(−51.68)	(−59.23)	(1.90)	(−5.15)	(−93.99)	(−94.54)	(−71.09)	(−58.69)
Investment/Secondary property	−1.333***	−2.431***	−0.0902*	−0.772***	−1.243***	−1.659***	−3.359***	−4.226***
	(−30.50)	(−54.68)	(−2.22)	(−18.63)	(−56.08)	(−71.48)	(−37.47)	(−46.32)
Refinance	−0.623***	1.503***	−2.484***	−0.822***	1.862***	2.326***	8.083***	6.832***
	(−21.90)	(51.08)	(−93.23)	(−30.19)	(133.10)	(141.09)	(138.63)	(105.76)
First-time buyer	−5.805***	−4.725***	−1.808***	−0.847***	−3.997***	−3.878***	−11.79***	−11.78***
	(−139.23)	(−113.69)	(−45.56)	(−21.40)	(−213.31)	(−200.91)	(−148.39)	(−147.96)
Has mortgage insurance	1.282***	0.900***	0.597***	0.349***	0.685***	0.551***	2.637***	2.023***
	(27.64)	(19.91)	(13.83)	(8.27)	(27.47)	(22.19)	(28.96)	(22.73)
Zip x Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
N	8480852	8480851	8480852	8480851	8480852	8480851	1946017	1946017
R^2	0.0709	0.135	0.0404	0.101	0.0364	0.0736	0.0581	0.162

bank borrowers, Table 3, Panel B, Column (8) shows that a refinance is nearly 20% more likely to be a fintech loan. Table 4 shows that this is the case for conforming mortgages as well, with a conforming refinance being 7%−8% more likely to be a fintech loan. Consistent with this finding, first-time borrowers are significantly less likely to be fintech borrowers. Table 5 confirms this result across markets, which shows that counties where many residents have lived in the same home for more than a year see significantly greater fintech penetration. These are counties where many residents are likely candidates for mortgage refinancing.

These loan purpose differences are less stark looking at shadow banks as whole. Table 3 shows that when examining shadow banks as a whole, a refinance is roughly 2% less likely to be a shadow bank loan than a home purchase, which is mirrored in the GSE results in Table 4. Additionally, the share of residents living in their home for more than a year is not significantly predictive of shadow bank penetration, whereas it was predictive of fintech penetration.

These robust results linking refinance and fintech shadow banks in particular lead us to speculate that fintech technology is particularly well suited toward mortgage refinancing rather than new purchases. In refinancing, many activities, such as a title check, structural examination, and negotiations between buyer and seller, already took place at the time of purchase, leaving less nonstandardized work for the fintech lender to do. These somewhat nonstandardized activities may be less-well suited to technological comparative advantages of a fintech lender.

6.1.2.3. Financing: portfolio loans, GSEs, and government programs. We find that shadow banks are substantially more likely to originate loans in segments in which government intervention is meant to increase mortgage access. Table 3 confirms results suggested by our aggregate data. Shadow banks are much more active in the FHA market: an FHA loan is 9% more likely to be originated by a shadow bank. Shadow banks loans are also more likely among VA loans. The effect is in the opposite direction for US Department of Agricultural and Rural Housing Service (FSA/RHS) loans, with FSA/RHS loans more likely to be originated by traditional banks.

One explanation for why shadow banks are so active in these programs may be measurement: HMDA data does not include detailed borrower attributes, such as their consumer credit scores or debt-to-income ratios, so a loan having an FHA and VA guarantee may proxy for creditworthiness of borrowers, and shadow banks may focus on less creditworthy borrowers. Our results discussed above using the GSE data, however, did not find economically significant differences in borrower creditworthiness or risk. Table 4 shows that a borrower with a 100-point higher FICO score is only 2 percentage points less likely to be a shadow bank borrower.

The second reason why government-guaranteed originations are more likely to be shadow bank mortgages is that these types of loans are tied to the

Table 5
Shadow bank and fintech penetration and regional characteristics.

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

Panel A: summary statistics

Median values	All counties	Shadow bank		Fintech	
		Bottom quartile	Top quartile	Bottom quartile	Top quartile
Median household income	$45,114.00	$44,587.00	$46,949.00	$48,160.00	$41,101.00
Population density	42.7	35.6	44.1	55.3	19.1
% with less than 12th grade education	13.10%	11.80%	15.35%	10.80%	17.00%
% with bachelor degree or higher	18.20%	17.70%	18.20%	20.00%	15.40%
% African American	2.10%	1.06%	2.83%	1.35%	1.81%
% Hispanic	3.74%	2.40%	8.80%	3.39%	4.07%
Unemployment rate	7.00%	6.40%	7.50%	6.30%	7.20%
% living in same house ≥ 1 year	86.90%	87.60%	86.19%	86.74%	87.25%
Herfindahl	0.09761	0.14843	0.07831	0.11564	0.11421
# Lenders	39.00	29.00	50.00	45.00	22.00
% of FHA origination loans	16.28%	12.50%	18.71%	13.58%	17.76%
Population	25930.00	20913.00	33417.00	34184.00	13472.00
% with less than 35 K salary	26.70%	27.10%	25.70%	24.80%	29.95%

Panel B: regressions

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

originate-to-distribute model, which shadow banks necessarily follow. The results in Table 3 show that even conditioning on borrower and loan characteristics, sold loans are more likely to be 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. These results confirm the aggregate results on financing discussed earlier and highlight the importance of GSE financing for shadow bank growth.

6.2. Loan pricing and performance

6.2.1. Loan pricing: are traditional banks more expensive?

We now turn to interest rate differences between lender types. A potential explanation for the growth of shadow banks and fintech is that they have lower costs and gain market share by offering cheaper mortgages: shadow bank lenders benefit from lower regulatory cost, and fintech shadow banks additionally benefit from

Table 6
Shadow bank and fintech mortgage rates: conforming loans.
Table 6 shows the results of Eq. (7) using Fannie Mae and Freddie Mac loans from 2010–2015. Columns (1) and (2) test differences between shadow banks and traditional banks. Columns (3) and (4) split shadow banks into fintech and non-fintech lenders and compare interest rates across all lenders. Columns (5) and (6) test differences in fintech rates within shadow banks. Columns (1), (3), and (5) quarter fixed effects and no other controls. Columns (2), (4), (6) have quarter times zip fixed effects and borrower controls. Standard errors are clustered at the zip-quarter level. Interest rates are quoted in percent. The mean interest rate over the sample period is 4.74. t-statistics in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

	(1) Interest rate	(2) Interest rate	(3) Interest rate	(4) Interest rate	(5) Interest rate	(6) Interest rate
Sample	All lenders				Shadow banks only	
Shadow bank	0.00665***	0.00714***	–	–	–	–
	(5.19)	(8.33)	–	–	–	–
Non-fintech shadow bank	–	–	−0.0281***	−0.0242***	–	–
	–	–	(−20.48)	(−27.42)	–	–
Fintech shadow bank	–	–	0.143***	0.129***	0.163***	0.144***
	–	–	(87.68)	(101.99)	(91.09)	(113.17)
Borrower and loan controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	8,485,573	8,480,376	8,485,573	8,480,376	1,946,802	1,943,693
R^2	0.598	0.808	0.601	0.811	0.585	0.807

cost-reducing technology. The alternative explanation is that regulations restrict banks on the quantity side, while better technology increases the quality of fintech offerings, allowing fintech lenders to gain market share while charging equal or higher rates. Studying differences in loan pricing helps to resolve this question.

We focus on the conforming loan sample, which reports interest rate and FICO score and test whether rates offered to observationally equivalent borrowers differ by lender type. In particular, we estimate the following regression:

$$rate_{ijzt} = \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt}, \tag{7}$$

where an observation is a mortgage i, originated by lender type j in zip code z in quarter t. The dependent variable, $rate_{ijzt}$ is the mortgage rate in percentage points. $Non\,fintech\,SB_j$ is a dummy variable for whether the originator was a non-fintech shadow bank. $Fintech\,SB_j$ is a dummy variable for whether the originator was a fintech shadow bank. We control for borrower characteristics such as FICO, loan-to-value ratio, and debt to income in X_i. To compare rates in the same market at the same point in time, we include zip code times quarter fixed effects δ_{zt}. These fixed effects absorb differences in supply and demand conditions across markets, including regulatory differences across markets. Table 6 shows the results.

Overall, we find negligible differences between traditional bank and shadow bank interest rates, with each type's rates falling within one basis point of each other. However, there is significant heterogeneity within shadow bank types. Non-fintech lenders charge rates that are around three basis points lower than those of traditional banks This difference in rates suggests that consumers perceive some product differentiation. However, traditional and non-fintech shadow banks appear to compete enough to keep these prices close in equilibrium. This quantitatively small difference serves as evidence against regulatory cost advantages being the primary driver of shadow bank growth.

While non-fintech shadow banks offer slightly lower rates than traditional banks, we find that fintech shadow banks offer significantly higher interest rates. Fintech firms charge 13 basis points more than traditional banks to observably similar borrowers in the same zip code and quarter. This is equivalent to a 60 point difference in FICO score. Within shadow banks, the difference is even larger at 14-16 basis points.[21] Overall, this pricing evidence suggests borrowers pay a significant premium for fintech loans. Therefore, we conclude that the growth of fintech market share cannot be explained by fintech gaining market share by passing lower costs onto borrowers. Rather, the answer lies in differing consumer tastes between fintech and non-fintech offerings.

6.2.2. Loan performance

We next investigate loan performance, noting that in addition to offering higher interest rates on average, a lender may price differentially by giving loans at similar interest rates to worse performing borrowers. We first clarify some institutional details regarding lenders' exposure to GSE loan performance. 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 account for variation in interest rates induced by these fees. The one exception is that originators may fear legal liability for riskier loans (e.g., suits by GSEs for violations of representation of warranties). The more relevant aspect of performance for originators is prepayment. Since

[21] We further note that this premium is unlikely to be explained by differences in origination fees between fintech and non-fintech lenders (see Online Appendix A.4).

prepayment risk is not insured by the GSEs, investors may want to require a higher interest rates on loans with higher prepayment risk. We therefore examine both dimensions of loan performance.

With this in mind, we estimate differences in performance across lender types by running the following regressions:

$$\begin{aligned} Default_{ijzt} &= \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j \\ &\quad + \beta_r rate_{ijzt} + X\prime_i \Gamma + \delta_{zt} + \epsilon_{ijzt}, \\ Prepayment_{ijzt} &= \beta_1 Non\,fintech\,SB_j + \beta_2 Fintech\,SB_j \\ &\quad + \beta_r rate_{ijzt} + X\prime_i \Gamma + \delta_{zt} + \epsilon_{ijzt}. \end{aligned} \tag{8}$$

$Default_{ijzt}$ measures whether a mortgage i, originated by lender of type j in zip code z, in quarter t, is at least 60 days delinquent within two years of its origination. We therefore restrict loans to have two years of performance. This reduces our sample to loans originated between 2010 and 2013. $Prepayment_{ijzt}$ is defined analogously. We control for the mortgage interest rate $rate_{ijzt}$ and borrower and mortgage characteristics, X_i. We compare mortgage performance within a market at the same point in time, using zip code x quarter fixed effects δ_{zt}.

Shadow bank conforming loans are more likely to default than traditional bank loans (Table 7, Panel A). The magnitudes are small: shadow bank borrowers default at rates about 0.02% higher than traditional bank borrowers, the effect equivalent to about a three points lower FICO score. This effect is mostly driven by non-fintech shadow bank lenders whose borrowers default at about 0.023% higher rate over the two-year period. The results for fintech loans indicate that fintech conforming borrowers have very similar default rates as traditional bank borrowers.

We find larger absolute differences in loan prepayment (Table 7, Panel B). Shadow bank loans are more likely to be prepaid, with coefficients ranging roughly between 1.8% and 2.5% depending on the specification. The base rate of prepayment within two years of origination over the time period is approximately 11%, meaning that a shadow bank loan is between 16% and 22% more likely to be prepaid than a comparable traditional bank loan. Relative to traditional banks, fintech lenders exhibit an even larger probability of prepayment, with fintech shadow bank loans approximately 7% more likely to be prepaid. These results, taken together, suggest that indeed, shadow bank loans are slightly riskier to investors ex-post, even conditional on interest rates, but only from a prepayment perspective. This is consistent with earlier findings that shadow banks target a riskier segment of the market.

7. Rise of shadow banks: regulatory arbitrage

Having documented differences between banks and shadow banks that suggest an underlying regulatory cause, this section directly ties the growth of shadow banks to four measures of regulatory burden that fell primarily on traditional banks: building capital buffers to comply with risk-based capital requirements, harsher regulatory treatment of MSRs, mortgage lawsuits arising out of the financial crisis, and the dissolution of the OTS and the folding of its regulatory duties into OCC and other regulators.

The tests are difference in difference in nature. In particular, we study whether counties whose traditional banks were more exposed to a specific regulatory burden experienced larger market share gains in shadow bank lending. We first describe the construction and justification of the four measures of and then describe the regression specifications, which follow parallel approaches, before presenting the results.

7.1. Capital requirements

The Dodd-Frank Act imposed minimum risk-based capital requirements on traditional banks. As a result, the average tier 1 risk-based capital ratio of US banks rose by roughly 5% from 22% in 2008 to 27% in 2015 (4% on asset-weighted basis). As we show, at the beginning of the Great Recession, traditional banks kept roughly half of their loans on their balance sheet and took longer to dispose of the loans they eventually sold. Banks focusing on building capital buffers may do so at the expense of less balance sheet mortgage lending.

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

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

$$\Delta CR_b = T1RBC\%_{b2015} - T1RBC\%_{b2008}. \tag{9}$$

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

$$\Delta Local\,capital\,ratio_c = 100 \times \sum_{b \in c} \Delta CR_b \frac{Originations_{bc2008}}{\sum_{d \in c} Originations_{dc2008}}. \tag{10}$$

The counties with the largest change in the local capital ratio are those in which banks capital ratios grew the most. Our hypothesis is that these counties saw greater shadow bank market share and lending growth.

7.2. Mortgage servicing rights

Some changes to capital requirements specifically targeted mortgage lending. Basel III guidelines implemented by the Federal Reserve Board increased the regulatory cost of holding MSR on banks' balance sheets. In particular, the

Table 7
Shadow bank presence and loan performance: conforming loans.
Table 7 shows the results of Eq. (8) for loan outcomes using Fannie Mae and Freddie Mac performance data from 2010 to 2013. Panel A shows the results for default. Panel B shows the results for prepayment. Prepayment is defined as the loan being prepaid within two years of origination. Default is defined as the loan status becoming 60 days past due within two years of origination. Columns (1)-(2) test differences between shadow banks and traditional banks. Columns (3)-(4) split shadow banks into fintech and non-fintech lenders and compare performance across all lenders. Columns (5)-(6) test differences in fintech performance within shadow banks. Columns (1), (3), and (5) quarter fixed effects and no other controls. Columns (2), (4), (6) have quarter times zip fixed effects and borrower controls. The left-hand-side variable is in percent. Its mean for defaults over the sample period is 0.23. Its mean for prepayments over the sample period is 11. Standard errors are clustered at the zip-quarter level; *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: Default

	(1) Defaulted	(2) Defaulted	(3) Defaulted	(4) Defaulted	(5) Defaulted	(6) Defaulted
Sample	All lenders				Shadow banks only	
Shadow bank	0.0196***	0.0208***	-	-	-	-
	(3.90)	(4.11)	-	-	-	-
Non-fintech shadow bank	-	-	0.0116*	0.0236***	-	-
	-	-	(2.15)	(4.34)	-	-
Fintech shadow bank	-	-	0.0557***	0.00795	0.0307*	−0.0286*
	-	-	(4.66)	(0.67)	(2.33)	(-2.04)
Borrower and loan controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6,527,612	6,523,402	6,527,612	6,523,402	1,151,439	1,149,115
R^2	0.000359	0.0112	0.000362	0.0112	0.000609	0.0348

Panel B: Prepayment

	(1) Prepaid	(2) Prepaid	(3) Prepaid	(4) Prepaid	(5) Prepaid	(6) Prepaid
Sample	All lenders				Shadow banks only	
Shadow bank	2.469***	1.823***	-	-	-	-
	(20.31)	(23.38)	-	-	-	-
Non-fintech shadow bank	-	-	1.456***	0.713***	-	-
	-	-	(10.71)	(8.94)	-	-
Fintech shadow bank	-	-	7.054***	6.757***	5.675***	6.358***
	-	-	(34.50)	(34.23)	(26.48)	(30.27)
Borrower and loan controls	No	Yes	No	Yes	No	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	6,527,612	6,523,402	6,527,612	6,523,402	1,151,439	1,149,115
R^2	0.0566	0.151	0.0571	0.152	0.0594	0.155

rule change increased the risk weighting of MSR assets for purpose of capital requirements. The Federal Reserve Board issued the final rule implementing these guidelines in 2013.[22] Because origination and servicing are complementary activities, a higher cost of servicing reduces the attractiveness of origination. As with the capital ratio measure, we calculate the origination-weighted MSR as a percent of tier 1 capital at a county level:

$$MSR\%_c = 100 \times \sum_{b \in c} MSR\%_{b2008} \frac{Originations_{bc2008}}{\sum_{d \in c} Originations_{dc2008}}. \tag{11}$$

The counties with the largest ex-ante MSR percent of tier 1 capital are those in which banks relied most heavily on MSR assets to bolster their regulatory capital. Our hypothesis is that these counties saw greater shadow bank market share after implementation.

7.3. Regulatory oversight

The descriptive statistics suggest that shadow banks tilt their lending to markets with more minorities and worse socioeconomic conditions. Given that several enforcement actions and lawsuits had specifically targeted banks' treatment of less creditworthy borrowers, it may not be surprising that traditional banks tilted lending away from that sector. Because shadow bank activities are concentrated on origination, rather than holding and servicing, they escaped much of the scrutiny that full-service banks received from regulators and class action lawsuits with respect to their legacy loans.

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

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

We collect data on large mortgage lawsuit settlements against large traditional banks and shadow banks. Ninety-eight percent of observed lawsuits target traditional banks. Denote a bank b's accumulated lawsuit settlements between 2008 and 2015, in billions as L_b. As before, we calculate exposure to mortgage settlements of county c as a weighted average of 2008 lending activity of banks in that county as follows:

$$\Delta Lawsuit\ exposure_c = 100 \times \sum_{b \in c} L_b \frac{Originations_{bc2008}}{\sum_{d \in c} Originations_{dc2008}}. \tag{12}$$

The counties with a high exposure to lawsuits are those counties whose most active banks received the most mortgage-related lawsuits. Our hypothesis is that these counties saw greater shadow bank market share and lending growth.

7.4. Office of thrift supervision closure

Dodd Frank dissolved the Office of Thrift Supervision in 2011, and its regulatory duties were folded into the OCC, FDIC, Federal Reserve, and CFPB. Prior to its dissolution, the OTS supervised several institutions that experienced financial-crisis era notable failures such as Countrywide, Washington Mutual, and AIG. Importantly for our analysis, the OTS was regarded as a lax regulator. It was understaffed relative to the number of institutions it supervised and to attract more resources, marketed itself as lax to potential lenders, which would in turn bring funds to the agency (see also Agarwal et al., 2014; Granja and Leuz, 2018).[23]

We investigate whether counties that previously saw a large share of originations regulated by the OTS in 2008, prior to its closure, saw greater growth in shadow bank lending between 2008 and 2015 and particularly between 2011 and 2015, following its closure. We calculate the county-level exposure to this shock as follows:

$$\text{OTS\%}_c = 100 \times \frac{OTS\ regulated\ originations_{c2008}}{Total\ originations_{c2008}}. \tag{13}$$

Counties with higher share of OTS regulated originations in 2008 receive a relatively larger shock when the OTS is dissolved and its duties folded into the supervision of the OCC, FDIC, Federal Reserve, or CPBF. Our hypothesis is that these counties saw greater shadow bank market share and lending growth, as the banks in these counties adjust to stricter regulatory supervision.

7.5. The differential effect of regulation

With our four measures of regulatory burdens defined, we now describe the basic specification. There are two outcome variables of interest, the change in shadow bank market share between 2008 and 2015 and the growth in shadow bank lending between 2008 and 2015 as a share of all 2008 lending. That is, we examine both:

$$\Delta Shadow\ bank\ share = 100 \times \left[\frac{Shadow\ originations_{c2015}}{All\ originations_{c2015}} - \frac{Shadow\ originations_{c2008}}{All\ originations_{c2008}} \right], \tag{14}$$

$$\Delta Shadow\ bank\ lending = 100 \times \left[\frac{Shadow\ originations_{c2015} - Shadow\ originations_{c2008}}{All\ originations_{c2008}} \right]. \tag{15}$$

Examining changes in market share allows us to analyze changes in shadow bank lending separately from changes in overall market size; examining changes in lending levels additionally allows us to answer whether changes in shadow bank market share arises merely because banks reduce lending and shadow bank lending stays constant or whether shadow banks actually actively expand lending in the face of regulatory gaps. The two specifications we consider are

$$\Delta Shadow\ bank\ share_c = \beta_0 + \beta_1 \text{Regulation}_c + X'_c\Gamma + \epsilon_c, \tag{16}$$

And analogously,

$$\Delta Shadow\ bank\ lending_c = \beta_0 + \beta_1 \text{Regulation}_c + X'_c\Gamma + \epsilon_c, \tag{17}$$

where Regulation_c is one of the aforementioned measures of county-level regulation, changes in capital ratios, MSR percentage of tier 1 capital, lawsuit exposure, or OTS share. To facilitate comparison between these measures, we first standardize by dividing by the cross-sectional standard deviation. Thus, coefficients can be interpreted as percent changes in market share of lending volume for a one standard deviation change in the regulation variable. We control for other county characteristics in X'_c, including demographics and traditional bank share in 2008. Because counties are of very heterogeneous size with respect to lending activity, we run weighted least squares regressions weighted by 2008 originations.

The results, shown in Table 8, Panel A, indicate significant and economically meaningful associations between shadow bank activity and our measures of bank regulatory

[23] For example, Countrywide, which was regulated by the OCC, switched regulators to the OTS. According to a report by the Washington Post, "critics in government and industry said Countrywide's shift from OCC oversight to that of OTS was evidence of a 'competition in laxity' among regulators eager to attract business." http://www.washingtonpost.com/wp-dyn/content/article/2008/11/22/AR2008112202213.html.

Table 8
Regulatory activity and shadow bank market shares.
Table 8 shows the result of the regressions specified by Eqs. (16) and (17). The regression is at the county level. Panel A, Columns (1)–(4) regress percent changes in county-level shadow bank market share on four measures of regulatory exposure. Columns (5)–(8) regress percent changes in county-level shadow bank lending volume on four measures of regulatory exposure. All columns include demographic controls. Δ Capital ratio is the 2008 lending-weighted change in bank capital ratios between 2008 and 2015. % MSR is the lending-weighed 2008 fraction of MSR assets of tier-1 capital. Lawsuit exposure is the lending-weighted exposure to mortgage-related lawsuits. % OTS is the share of mortgage originations regulated by the OTS in 2008. Panel B shows the results of using 2006–2008 capital ratio changes to instrument for 2008–2015 changes. Column (1) is the first stage; Columns (2) and (4) are the reduced form regressions. Columns (3) and (5) are the second stage regressions. The *F*-statistic of the instrument is 48.68. All regulatory variables are standardized, so coefficients can be interpreted as percent change in shadow bank share for a one standard deviation change in the regulatory measure. *t*-statistics are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Panel A: regulation and market share changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Shadow bank share				Δ Shadow bank lending			
Δ Capital ratio	3.358***	–	–	–	3.412***	–	–	–
	(16.601)	–	–	–	(8.160)	–	–	–
% MSR	–	1.902***	–	–	–	1.939***	–	–
	–	(9.403)	–	–	–	(4.739)	–	–
Lawsuit exposure	–	–	2.034***	–	–	–	6.494***	–
	–	–	(10.898)	–	–	–	(17.921)	–
% OTS	–	–	–	1.215***	–	–	–	5.209***
	–	–	–	(4.759)	–	–	–	(10.333)
County controls	Y	Y	Y	Y	Y	Y	Y	Y
N	3094	3094	3094	3094	3094	3094	3094	3094
R^2	0.211	0.164	0.172	0.147	0.327	0.318	0.378	0.336

Panel B: 2006–2008 capital ratio change as instrument

	(1)	(2)	(3)	(4)	(5)
	ΔCR (2008–2015) first stage	Δ Shadow bank share		Δ Shadow bank lending	
ΔCapital ratio (2008-2015) (Fit)	–	–	9.634***	–	8.241***
	–	–	(8.270)	–	(3.838)
ΔCapital ratio (2006-2008)	−0.238***	−2.289***	–	−1.958***	–
	(−11.270)	(−9.201)	–	(−3.888)	–
County controls	Y	Y	Y	Y	Y
N	3,094	3094	3094	3094	3094
R^2	0.215	0.163	−0.036	0.316	0.298

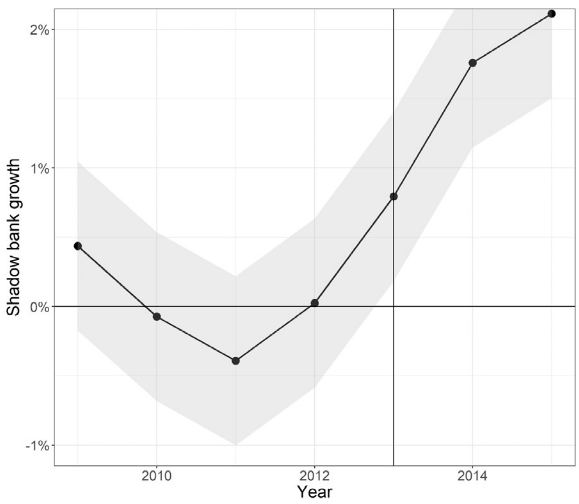
burden.[24] A one standard deviation increase in capital ratio changes is associated with a 3.4% rise in shadow bank market share (Column 1) and a 3.4% rise in shadow bank lending activity (Column 5). Similarly, a one standard deviation increase in MSR assets is associated with approximately a 1.9% rise in shadow bank market share (Column 2) and a 1.9% rise in shadow bank lending activity (Column 6). Likewise, a one standard deviation increase in lawsuit exposure is associated with a 2.0% rise in shadow bank market share (Column 3) and a 6.5% rise in shadow bank lending activity (Column 7). Finally, a one standard deviation increase in OTS lending share is associated with a 1.2% rise in shadow bank market share (Column 4) and a 5.2% rise in shadow bank lending activity (Column 8). These numbers are all economically meaningful relative to the mean increase in shadow bank market share of roughly 20% and the mean increase in shadow bank lending activity of 27%.

These results, taken together, suggest that shadow banks gained the most market share in counties whose banks were exposed to the greatest regulatory pressure. Notably, they show that shadow banks are gaining market share relative to banks, so our results are not simply picking up counties with better or worse economic fundamentals but are rather associated with differential impacts across banks and shadow banks. Moreover, the results are not merely driven by banks exiting lending, but rather, shadow banks are expanding into these markets.

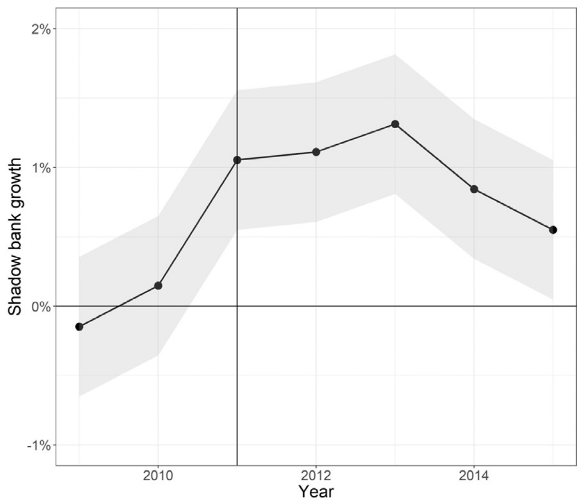
To provide more credence to our interpretation of the results, we examine the exact timing of these market share changes for the two measures with definitive event dates. In particular, the MSR rule was finalized in 2013, and the OTS shut down in 2011. We therefore run the following panel event study:

$$\begin{aligned} \mathit{Shadow\,bank\,share}_{ct} = \gamma_t + \gamma_c + \beta(\mathit{High\,reg}_c \times \mathit{Year}) \\ + (X_c \times \mathit{Year})'\Gamma + \epsilon_{ct}, \end{aligned} \tag{18}$$

[24] To provide a visual of the variation in the data coming from these four measures of regulatory exposure, Online Appendix A.9 shows binned scatter plots of shadow bank market share versus the four measures of regulatory exposure. These plots show that the positive relationship tends to be robust through many values of the regulatory exposure measures.



(a) High MSR counties relative to other counties



(b) High OTS counties relative to other counties

Fig. 6. Mortgage servicing rights, OTS shares, and bank shares over time. Fig. 6 shows the year-by-year relationship in the county-level shadow bank market share for counties in the top quintile of MSR assets (a) or the top quintile of OTS originations (b). Shadow bank market shares in high MSR and high OTS counties are compared with other counties. Coefficients are estimated from the difference in difference regression specified in Eq. (18), $\text{ShadowBankShare}_{ct} = \gamma_t + \gamma_c + \beta\ (\text{Year} \times \text{High}) + (\text{Year} \times X_c)\Gamma + \varepsilon_{ct}$. The shaded regions denote 95% confidence intervals. The rule implementing the MSR guidelines was finalized in 2013. The OTS dissolved in 2011.

where High reg_c is defined as a county falling in the top quintile for either MSR % of tier one capital or OTS origination share. We allow for year and county fixed effects and allow coefficients on county-level controls to vary by year. Fig. 6 shows the difference in difference coefficient β by year. In particular, we compare the shadow bank shares in counties with high MSR (Fig. 6a) or high OTS origination (Fig. 6b) to other counties over time. Notice that the large relative jump in high MSR county shadow bank share occurs in 2013, the year when the rule is finalized, and the large relative jump in high OTS county shadow bank share occurs in 2011, when the OTS closes. The timing of when the effects in market shares show up lines up well with the timing of the events, consistent with arguments made in this section.

7.6. Robustness: instrumenting for capital ratio increase

To further isolate the effect that the rebuilding of regulatory capital had on bank lending, which may be endogenously related to loan demand, we instrument for capital ratio increases between 2008 and 2015 with capital ratio decreases between 2006 and 2008. Our hypothesis is that counties whose banks saw the largest capital decreases during the crisis are the counties whose banks had rebuild their capital reserves the most following the crisis at the expense of mortgage origination. In other words, we test whether counties whose banks were induced to increase capital between 2008 and 2015 due to capital decreases between 2006 and 2008 saw increase shadow bank market share and lending activity.

The results in Table 8, Panel B confirm this intuition. First, Column (1) shows that as expected, there is a significant negative relationship between capital ratio decreases in from 2006 to 2008 and capital ratio increases from 2008 to 2015. Columns (2) and (4) show the reduced form results that capital ratio decreases between 2006 and 2008 are associated with greater shadow bank market share growth and shadow bank lending activity, respectively. Columns (3) and (5), the second stage regressions, confirm the results shown in Table 8, Panel A that increases in bank capitalization between 2008 and 2015 are associated with greater shadow bank entry.

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.

8. The rise of fintech lenders: the role of technology

The descriptive results in Section 6 point to significant differences between fintech and non-fintech lenders. Because these shadow bank lenders face the same regulations, the differences are likely driven by technology. This section attempts to shed light on economic forces driving these differences. We consider two explanations for the role of technology in the rise of fintech lenders. One explanation is that fintech lenders make use of more data and different models to price their loans. A second explanation is that fintech delivers a more convenient mortgage origination experience by requiring less effort from the borrower in the origination process.

8.1. Different credit models

Fintech lenders rely on technology to set mortgage interest rates, while non-fintech shadow banks potentially still rely on loan officers to do so. Online lending

Table 9
R^2 of different specifications explaining interest rates.
Table 9 shows the R^2 of observables for different specifications of the regression specified by Eq. (19). Data is from Fannie Mae and Freddie Mac. Fixed effects are differenced out so that their effects are not included in the total sum of squares. The table shows pooled regressions between 2010 and 2015 for the banks shadow bank, non-fintech, and fintech subsamples. Nonlinear controls include third-order polynomials of all observables. Tests of significance of R^2 differences follow Erickson and Whited (2002). *** denotes significance at the 1% level.

Panel A: R^2 of pooled regressions, 2010-2015

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

allows lenders to collect different types of information than would be collected by a loan officer. We want to understand whether fintech lenders' use of different information results in different mortgage pricing models. We do so by examining how much variation in interest rates is explained by standard borrower characteristics (hard information) across lenders. Following Rajan et al. (2015), we regress:

$$rate_{izt} = \beta_1 FICO_i + \beta_2 LTV_i + X_i'\Gamma + \delta_{zt} + \epsilon_{izt}. \tag{19}$$

We estimate the regressions separately for fintech and non-fintech shadow bank over the 2010-2015 period and year by year. We use the Fannie Mae and Freddie Mac origination data, because we observe interest rates as well as information on a rich array of loan, property, and borrower characteristics. The R^2 from these regressions measures the object of interest: how much of the variation in interest rates is explained by the observable borrower characteristics across lender types. A large portion of variation in interest rates arises from nationwide macroeconomic effects and not from lenders' models. We therefore difference out fixed effects and calculate R^2 of the within regression.

We present the results in Table 9. Fintech shadow banks use substantially less hard information than non-fintech shadow banks: the R^2s are smaller across all specifications. FICO and LTV alone can explain nearly 25% of the variation in non-fintech interest rates but less than 16% of the variation in fintech interest rates. We test for the significance of the R^2 differences following the method in is Erickson and Whited (2002) and find that the differences are significant beyond the 1% significance level in all cases.

To ensure the pattern is robust, we estimate several specifications, using different fixed effects, including more controls, as well as polynomials of controls, to ensure our patterns do not arise because lenders use nonlinear models. Even in the most saturated specifications, with the most comprehensive fixed effects and nonlinear controls, the R^2 of non-fintech lenders exceed 54% and is below 52% for fintech lenders.[25] These results suggest that fintech lenders use substantially different information in setting mortgage interest rates than non-fintech lenders, likely by using other dimensions of "big" data, not available to other lenders.

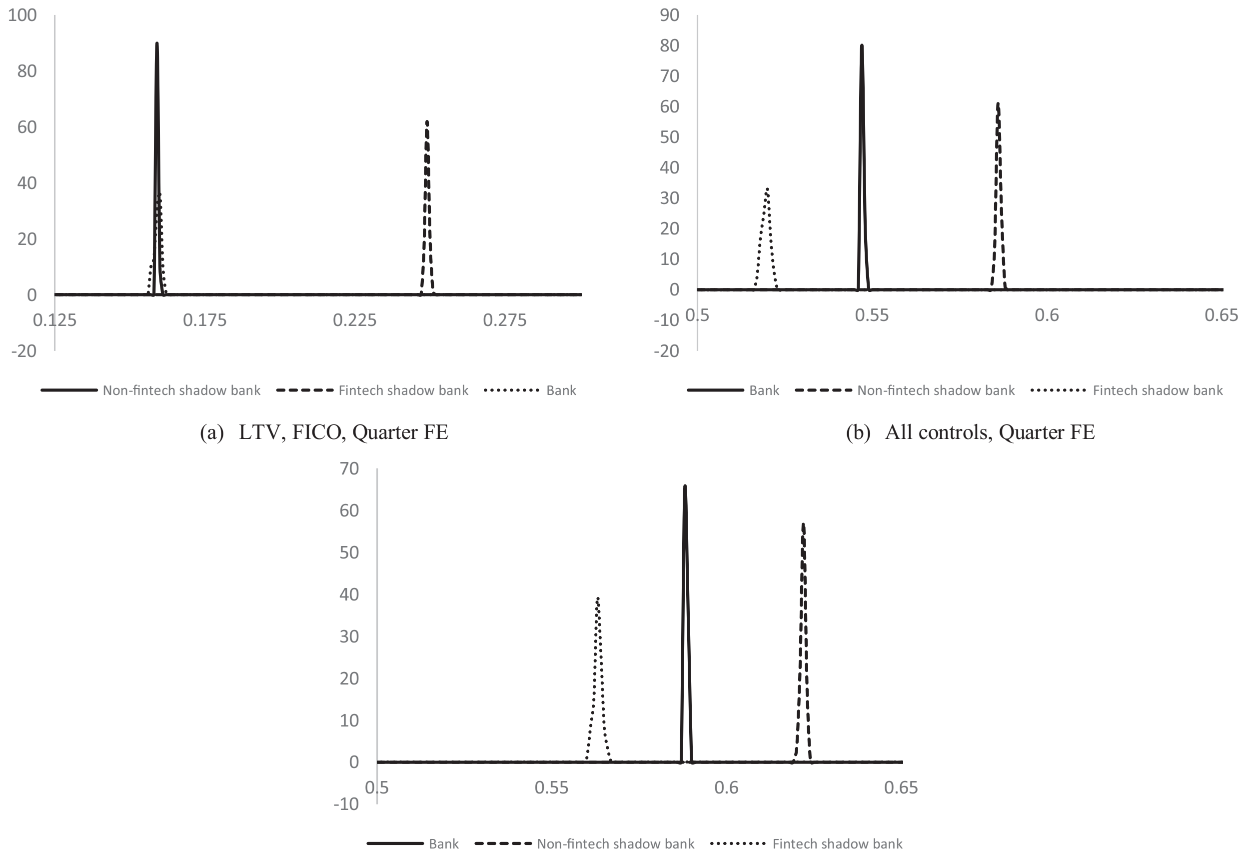
As an additional robustness test of significance, we bootstrap the calculation as follows: we sample with replacement from the set of originated loans. With the randomized sample, we divide the originations into fintech and non-fintech loans and rerun the interest rate regression. We do this for 100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

Finally, we further examine whether fintech and non-fintech lenders' interest rates are better predictors of ex-post performance in terms of default and prepayment. This analysis rests on the observation that if lenders are using more or better data to set interest rates, these interest rates should be more correlated with ex-post performance. Online Appendix A.5 presents the results together with a detailed discussion. In short, we find little difference regarding default, which is not surprising as GSE lenders have little economic exposure to defaults. We find large differences regarding prepayment, where investors do have economic exposure, finding the coefficient on interest rate to be two to four times larger than non-fintech interest rates. This finding is consistent with fintech interest rates being better predictors of ex-post performance. However, these findings should be interpreted with caution since borrowers more likely to refinance might select fintech lenders for loans.

8.2. Convenience and cost savings

Next, we consider the possibility that fintech's origination model also allows for lower cost or more convenient originations. Fintech can potentially lower origination costs though its automated process and can offer more

[25] In unreported tests we also examine year-by-year differences in R^2 between fintech and non-fintech lenders and find lower R^2 for fintech lenders in all years. The R^2s for non-fintech lenders have grown smaller over time, suggesting that these lenders may also be adopting more sophisticated pricing models.



(a) LTV, FICO, Quarter FE

(b) All controls, Quarter FE

(c) All controls (nonlinear), Quarter FE

Fig. 7. Distribution of bootstrapped R^2. Fig. 7 shows the distribution of bootstrapped R^2s, corresponding to the determinants of interest rates. Each bootstraped sample selects a random sample of originations with replacement, reruns the interest rate regression, and records the R^2s. The bootstrap is run on 100 random samples. Panel A shows a model of interest rates with FICO, LTV, and quarter fixed effects. Panel B shows a model of interest rates with all (linear) observables and quarter fixed effects. Panel C shows a model of all observables with up to third-degree terms included.

convenient originations more quickly through the borrower's home computer. To the extent that borrower willingness to pay is correlated with observable characteristics like FICO score or income, fintech lenders may be able to price discriminate.

Earlier results in Section 6.2.1 showed that that fintech interest rates were 14–16 basis points higher than non-fintech interest rates among conforming loans. At the same time, Online Appendix Section A.2 shows suggestive evidence that among FHA borrowers, an economically disadvantaged segment, that fintech interest rates were roughly three basis points lower than non-fintech interest rates for otherwise similar borrowers. Comparing across segments, these differences are consistent with low income FHA borrowers being price sensitive with low willingness to pay for convenience, with higher income conforming borrowers being more willing to pay for convenience.

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

$$rate_{izt} = \beta_s Fintech_{bzt} + \beta_{h\times s} Fintech_{bzt} \times High\,Fico_{izt} + X_i'\Gamma + \delta_{zt} + \epsilon_{izt}. \quad (20)$$

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

The results presented in Table 10 show that fintech borrowers with the highest credit ratings pay an even greater premium for fintech loans, relative to other borrowers with the same characteristics. The highest credit score fintech borrowers pay approximately 0.6 basis points more than borrowers in the ordinary credit score range do for fintech loans. This difference is roughly equivalent to the interest rate difference associated with a 3.5 point FICO differential. Relative to the baseline difference of 15 basis points, this estimate corresponds to a 4% increase in the premium of fintech over non-fintech rates. The results suggest that borrowers most likely to value convenience might be

Table 10
Fintech cost and convenience.
Table 10 shows the results of the regression specified by Eq. (20). Data are from Fannie Mae and Freddie Mac Shadow Bank originations between 2010 and 2015. High FICO is a dummy variable for borrowers with FICO in the top decile for the year. Columns (1) and (2) show the results for the full sample, 2010–2015. Columns (3) and (4) show the results for the early period, 2010–2013. Columns (5) and (6) show the results for the late sample, 2014–2015. All columns include borrower and loan controls. Columns (1), (3), and (5) include quarter fixed effects; Columns (2), (4), and (6) include quarter-zip fixed effects. The left-hand-side variable is in percent terms; the mean is 4.18. Standard errors are clustered at the zip-quarter level; t-statistics are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Full (2010–2015)		Early (2010–2013)		Late (2014–2015)	
	(1) Rate	(2) Rate	(3) Rate	(4) Rate	(5) Rate	(6) Rate
Fintech	0.156***	0.143***	0.140***	0.122***	0.172***	0.166***
	(121.33)	(112.12)	(77.41)	(70.28)	(99.07)	(97.99)
High FICO x Fintech	0.00574***	0.00338*	0.00905***	0.00770***	0.0111***	0.00948***
	(3.59)	(2.16)	(4.08)	(3.55)	(5.32)	(4.55)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip x Quarter FE	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	No	Yes	No	Yes	No
N	1,946,017	1,943,693	1,151,009	1,149,115	795,008	794,578
R^2	0.792	0.808	0.826	0.841	0.682	0.698

willing to pay for the convenience offered by fintech lenders. This interpretation is also consistent with findings of Fuster et al. (2018) who show that fintech lenders process mortgage applications about 20% faster than other lenders and that in areas with more fintech lending, borrowers refinance more, especially when it is in their interest to do so.

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

To summarize, we find some suggestive evidence that fintech lenders use different technology in determining mortgage rates. In addition, fintech lenders offer convenience, which borrowers appear to value. Among the most price sensitive borrowers, fintech loans have lower interest rates. In contrast, among the borrowers most likely to value convenience, fintech lenders are able to command a premium for their services. An alternative explanation, which we do not rule out, is that fintech's technology may allow for better price discrimination of borrowers.

9. Decomposing effects of regulation and technology: a quantitative framework

The shadow bank market share in the overall mortgage market grew by more than 20% in 2008 to 2015 period. Of this increase, about 9% are attributable to the growth in fintech firms. Our analysis so far suggests that regulatory burdens on traditional banks benefited all shadow banks, but that fintech shadow banks additionally benefited from technological improvements. This section presents a simple model to quantitatively evaluate the contribution of regulation and technology to the overall decline of traditional banks in this sector.

9.1. Model framework

Three types of lenders compete for mortgage borrowers: banks, non-fintech shadow banks ("non-fintech"), and fintech shadow banks ("fintech"). These lenders differ on three dimensions: regulatory burden; convenience, modeled as a difference in quality; and differences in the cost of making loans. Pricing, firm entry, and markups are determined endogenously for each type of lender.

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

9.1.1. Demand

Borrower b's utility from choosing mortgage from lender i is

$$u_{ib} = -\alpha r_i + q_i + \epsilon_{ib.} \tag{21}$$

Borrowers' utility declines in the mortgage rate with $\alpha > 0$ measuring interest rate sensitivity. Borrowers also derive utility from nonprice attributes of lenders: $q_i + \epsilon_{ib}$ (Egan et al., 2017). Nonprice attributes represent convenience, quality, and other services offered by the lender. For example, banks offer checking accounts and other financial services that other lender types do not, while fintech lenders offer the convenience of at-home origination that other lender types do not. q_i captures these type-specific quality differences. Individual borrowers' preferences across individual lenders can also differ idiosyncratically: Bank of America may have a particularly desirable branch location for a particular borrower; *Quicken*'s online interface may be especially appealing to another particular borrower. 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 et al., 1995) that ϵ_{ib} is independent and identically distributed (i.i.d.) type 1 extreme value.

9.1.2. Supply

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

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

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

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

$$(r_i - \rho_i)\gamma_i s_i, \tag{22}$$

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

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

$$\pi_i = (r_i - \rho_i)\gamma_i s_i F - c_i. \tag{23}$$

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

9.1.3. 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 (Eq. (21) holds for all borrowers b).
2) Lenders set interest rates to maximize profits, taking market structure and the pricing decisions of other lenders as given (Eq. (22) holds for all lenders i).
3) There is free entry: the number of firms of each type N_b, N_n, N_f is set such that profits of all firms are zero. (Eq. (23) equals zero for all lenders i).

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

$$s_i\left(r_i, q_i; \{r_j, q_j\}\right) = \frac{\exp(-\alpha r_i + q_i)}{\sum_{j=1}^{N} \exp\left(-\alpha r_j + q_j\right)}. \tag{24}$$

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

$$S_b = \frac{\gamma_b N_b \exp(-\alpha r_b + q_b)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)}, \tag{25}$$

$$S_n = \frac{N_n \exp(-\alpha r_n + q_n)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)}, \tag{26}$$

$$S_f = \frac{N_f \exp(-\alpha r_f + q_f)}{\gamma_b N_b \exp(-\alpha r_b + q_b) + N_n \exp(-\alpha r_n + q_n) + N_f \exp(-\alpha r_f + q_f)}. \tag{27}$$

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

$$r_i^* - \rho_i = \frac{1}{\alpha}\frac{1}{1 - s_i}. \tag{28}$$

Last, the free entry condition can be written as

$$\left(r_i^* - \rho_i\right)\gamma_i s_i\left(r_i^*, q_i; \left\{r_j, q_j\right\}\right)F - c_i = 0. \tag{29}$$

9.2. Calibration

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

We aggregate data to the zip-year level and calibrate to observed data in the mean zip for each year. In other words, each year we observe the number of firms of each type (N_b, N_n, N_f), the market share of each lender type (S_n, S_f, N_b), the pricing of each lender type (r_b, r_n, r_f), and the market size F.[26] We measure costs relative to the ten-year government yield, y_t. That is, we measure $\tilde{\rho}_i = \rho_i - y_t$. We calibrate the model to obtain model primitives, each type's quality $q_i \in \{q_b, q_n, q_f\}$, funding cost $\rho_i \in \{\rho_b, \rho_n, \rho_f\}$, entry costs $c_i \in \{c_b, c_n, c_f\}$, and consumer price sensitivity α.

Additionally, we make the following normalizations: first, we measure quality and funding costs relative to banks, $\tilde{\rho}_b = q_b = 0$. Setting $q_b = 0$ plays a similar role

[26] A data limitation is that we do not see fintech interest rates in the data until 2010 because Quicken Loans is not yet large enough to be reported by name in the Fannie Mae and Freddie Mac data. We assume that the 2010 gap between bank and fintech interest rates is similar in 2008 and 2009. When we restrict the model to only 2010 onwards, it does not alter the results because most effects of regulation and technological growth occurred after 2010.

to setting the share of outside good in demand in Berry (1994) and Berry et al. (1995). We further assume not only that banks differ from non-fintech lenders in the quality of their service, but that the relative difference in service provision between brick and mortar lenders did not change during the period. Further, we measure the change in regulatory burdens relative to 2008, so we set $\gamma_b = 1$ in 2008 and allow it to change thereafter.

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

$$\alpha_t = \frac{1}{r_{bt} - y_t} \frac{1}{1 - s_{it}}. \tag{30}$$

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

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

$$\tilde{\rho}_{nt} = (r_{nt} - y_t) - \frac{1}{\alpha_t} \frac{1}{1 - s_{nt}}, \tag{31}$$

$$\tilde{\rho}_{ft} = (r_{ft} - y_t) - \frac{1}{\alpha_t} \frac{1}{1 - s_{ft}}. \tag{32}$$

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

We next turn to calibrating the differences in quality of services between these lenders using optimal consumer choice (aggregate market share) Eqs. (25)–(27). Recall that we set $q_b = 0$, so the service quality is relative to banks. We first calibrate the service quality of non-fintech shadow banks, q_n. The regulatory burden is normalized relative to 2008, i.e., $\gamma_{b,08} = 1$, so we can derive an expression for $q_n$as a function of observed interest rates, market shares, and price sensitivity, a, in 2008, which we calibrated above:

$$q_n = \alpha_{08}\left(r_{n,08} - r_{b,08}\right) + \log\left(\frac{s_{n,08}}{s_{b,08}}\right). \tag{33}$$

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

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

$$q_{ft} = \alpha_t (r_{ft} - r_{nt}) + \log\left(\frac{s_{ft}}{s_{nt}}\right) + q_n. \tag{34}$$

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

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

$$\log \gamma_{bt} = \alpha_t (r_{bt} - r_{nt}) + \log\left(\frac{s_{bt}}{s_{nt}}\right) + q_n. \tag{35}$$

Intuitively, given differences in quality and rates offered by traditional and non-fintech shadow banks, a smaller market share of traditional banks implies that there is a larger regulatory burden, $1 - \gamma_{bt}$, which prevents them from lending more. A limitation of this calibration is that we only calibrate the differences in technology between banks and fintech shadow banks. Overall improvements in technology, which also benefit traditional banks, would affect the size of the market rather than market shares. In other words, if bank technology also improves over time, our calibration only measures this improvement relative to fintech shadow banks. As we discuss in Section 3.2, however, our searching revealed little by way of "fintech banks", and so this understatement is likely minimal.

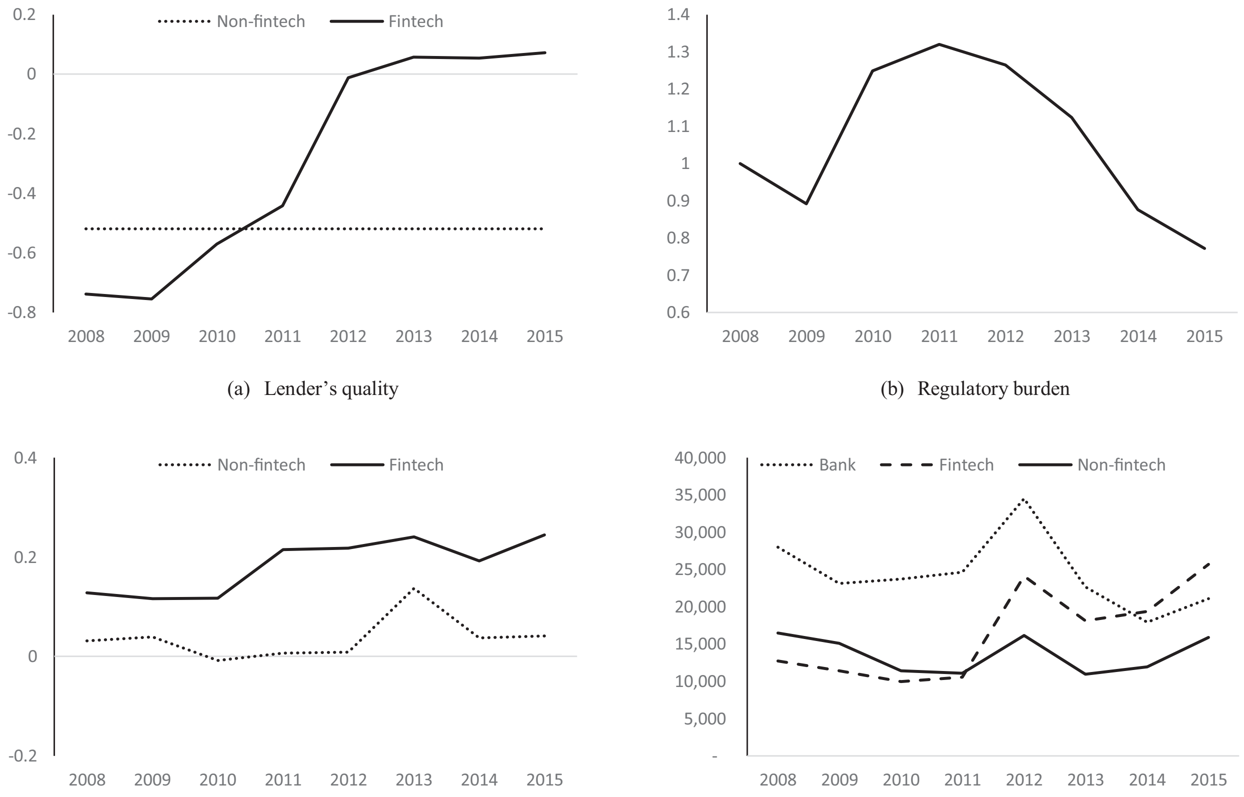
Finally, the zero-profit condition implies that the fixed costs lenders face have to equal their profits, i.e., the margin on individual loans ($r_{it} - \tilde{\rho}_{it} - y_t$) times the quantity of loans $\gamma_{it} s_{it} F_t$:

$$c_{it} = (r_{it} - \tilde{\rho}_{it} - y_t)\gamma_{it} s_{it} F_t. \tag{36}$$

9.3. Results

The results of the calibration are shown in Fig. 8. Our estimates imply that non-fintech shadow banks offer lower quality services than traditional banks. Obtaining a mortgage from her primary bank is more convenient for the borrower; for instance, it does not involve search, the borrower can make automatic payments from linked accounts, and the bank offers other convenient banking services such as checking accounts. The simultaneous rise of fintech market share and higher prices of fintech mortgages imply that fintech is gaining market share through increased quality and convenience of providing mortgages online. Our estimates suggest fintech quality increases dramatically, reaching parity with traditional banks by 2012 and surpassing it thereafter.

Our estimates suggest 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)



(a) Lender's quality

(b) Regulatory burden

(c) Funding costs

(d) Fixed costs

Fig. 8. Calibrated characteristics of lenders. Fig. 8 presents the model parameters discussed in Section 9.3. Panel A shows lender quality characteristics for fintech and non-fintech shadow banks relative to traditional bank. Panel B shows the evolution of regulatory burden face by traditional banks implied by our model relative to 2008 level. A higher value of the parameter implies a lower regulatory burden level. Panel C shows funding costs for fintech and non-fintech shadow banks and relative to traditional bank. Panel D shows fixed costs of traditional banks, and fintech and non-fintech shadow banks.

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. We also do not find that entry costs of banks increased dramatically.

This leaves the rising regulatory burden to explain the growth of shadow banks. While the burden rose overall, between 2008 and 2010, in the aftermath of the crisis, banks' ability to lend appears to increase slightly, indicating a progressive recovery of traditional bank mortgage lending. This suggests that the dissolution of the private securitization market that occurred early in our sample did not play a large role in the growth of shadow bank market share. It is not until after 2011 that banks' regulatory position starts deteriorating substantially. We note that the 2011–2015 period of substantial deterioration in our calibrated measure of regulatory burden corresponds to the period of implementation of the Dodd-Frank Act, development of Basel III rules changing the treatment of MSR from the perspective of capital requirements, the establishment of the Consumer Financial Protection Bureau, and increased mortgage lawsuit activity targeted at traditional banks. These results suggest that rather than operating on the intensive margin of increasing the funding costs of traditional banks, new regulations reduce banks' abilities to lend function primarily through an extensive margin channel.[27]

Recall the findings in Section 7.1 in which we study the effects of Basel III changing the treatment of MSR from the perspective of capital requirements (Fig. 6). The estimates from Fig. 6 suggested that banks' initially benefit from their regulatory position, and it is only after 2010 that their exposure to this regulatory shock begins to take hold. The patterns obtained in Fig. 8 from our model are remarkably similar to those in Fig. 6 despite the regression and model exploiting different types of variation.

We conclude by noting that the fixed costs of fintech lending have increased over time, suggesting increasing barriers to entry in this sector. High entry costs in

[27] These findings are consistent with evidence in Fuster, Lo, and Willen (2017), who find evidence of an increased legal and regulatory burden over 2008-2014. They argue that an important part of this trend may reflect increased loan servicing costs and the changed treatment of servicing rights under revised capital regulations. These findings are also consistent with Gete and Reher (2017), who present evidence suggesting that the 2014 US liquidity coverage ratio (LCR) rules has led to a higher FHA market share for nonbanks.

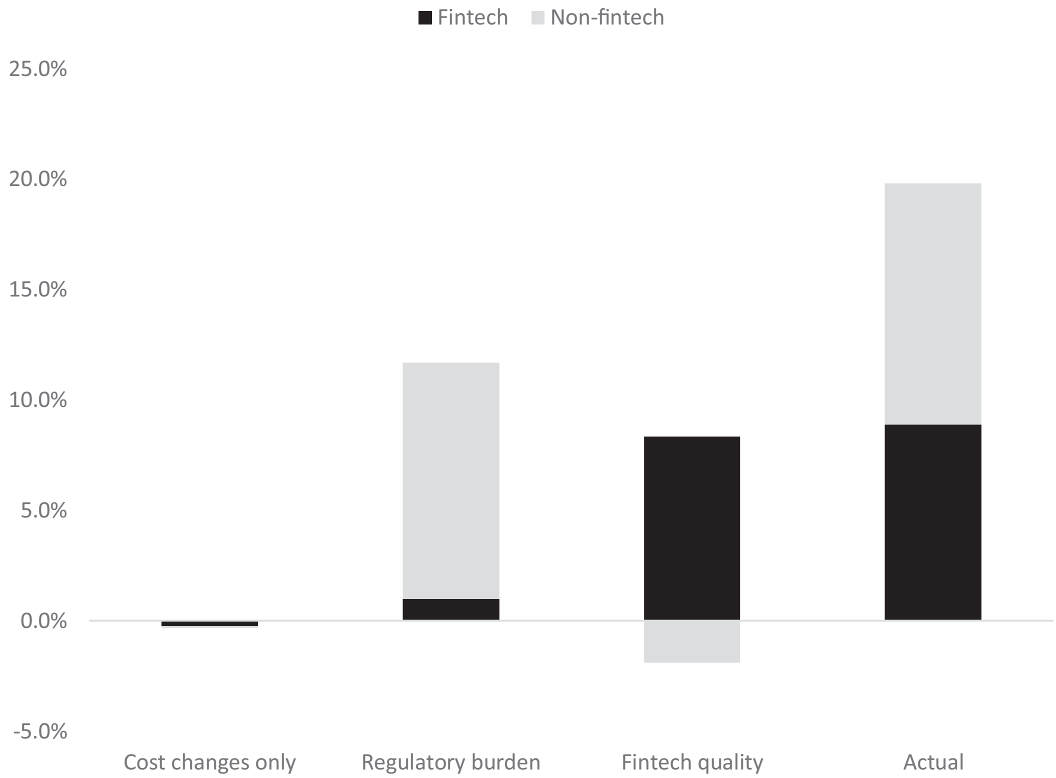


Fig. 9. Counterfactuals for the change in the shadow bank market share implied by our model. Fig. 9 shows predicted changes in shadow bank market share in the overall mortgage market between 2008 and 2015, broken down between non-fintech and non-fintech entrants, for three counterfactuals regarding fintech quality and bank regulatory impairment. "No changes" fixes both fintech quality to its 2008 and bank regulatory burden parameter to zero. "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.

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 unmodeled economies of scale in this sector.

9.4. Regulatory burden and technology: a decomposition

We conclude by using the calibrated model to infer how much of the growth in shadow banking and fintech is attributable to an increased regulatory burden and how much is attributable to technological improvements. First, we ask how the mortgage sector would have developed if the regulatory burden of traditional banks were frozen at the level of 2008 and the technological progress would not have taken place, setting up a baseline. We do so by setting both bank regulatory burden γ_b and fintech quality q_f to their 2008 levels. We allow other fitted parameters to evolve as calibrated and report the growth of non-fintech and fintech shadow banks. Our estimates presented in Fig. 9 suggest that both fintech and non-fintech shadow banks would have approximately zero growth between 2008 and 2015.

Next, we investigate how much shadow growth can be explained by rising regulatory burden placed on traditional banks without any technology improvements. We do so by setting fintech quality q_f to their 2008 levels but let regulatory burden parameter to evolve as estimated. We find that in this case total shadow bank growth reaches approximately 12%, including a 1% growth occurring in the fintech sector (Fig. 9). Hence, without technological improvements, we can account for about 60% of growth in shadow bank lending.

Finally, we examine the role of technology. We ask how the mortgage sector would have developed if the regulatory constraints would not have tightened, but the technological improvements in fintech had taken place. We therefore fix the regulatory burden parameter of traditional banks at the level of 2008. We find that technological improvements lead to fintech gaining roughly 8.3% in market share, with non-fintech shadow banks losing roughly 2% in market share (Fig. 9) as their fintech competitors improve their offerings. Therefore, technology alone is responsible for approximately 90% of gains of fintech firms and 30% of shadow bank growth overall. The 12% shadow bank growth due to regulatory changes and 6% shadow bank growth due to technological changes leaves roughly 2% unexplained by the model.

10. Robustness

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

10.1. Classification

While we describe the classification process in detail in Online Appendix A.7, we highlight here several important robustness checks. First, while the classification of bank versus nonbank is straightforward, the classification of fintech versus non-fintech involves some subjective judgment. To overcome any subjectivity in the classification, we utilize multiple independent research assistants (RAs) to cross-validate the classifications; the Ras, together with the authors, arrive at substantively similar classifications. Where there is disagreement, we take a conservative approach and classify the lender as non-fintech.

Second, while the primary classification is based on visiting websites at the time of writing, we verify that these classifications are appropriate at the start of the sample period. We view archived versions of the lenders' websites through a webservice called the Internet Archive Wayback Machine,[28] which has, since 2001, periodically archived historical websites. When examining the largest lenders, we verify that nearly all lenders classified as fintech in 2016 would have been fintech between 2008 and 2010, and all lenders classified as non-fintech in 2016 would have been non-fintech in 2008–2010.[29] Additionally, we find that no large traditional banks would have been classified as fintech in either time period.

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

10.2. Sample selection

We rerun the tests on a number of samples. In particular, we (1) restrict the HMDA data to the top 50 lenders, (2) look only at retail originations in the Fannie Mae and Freddie Mac data, (3) exclude Quicken Loans from the sample, and (4) run the tests on the 2010–2013 (rather than 2010–2015) sample. In all cases the results are substantively unchanged.

Top 50 lenders. We rerun all tests involving HMDA data, which includes borrower and geographic characteristics, as well as market share changes, looking only at the largest 50 lenders as of 2010. This restriction makes the HMDA data more comparable to the Fannie Mae and Freddie Mac data, in that it focuses only on the largest lenders. Online Appendix A.6 shows market shares of fintech and non-fintech shadow banks as well as the buyers of their loans. When restricting the sample to the top 50 lenders, the results are qualitatively unchanged.

Retail originations. The Fannie Mae and Freddie Mac data identify by name the largest sellers to the respective GSE rather than the originator directly. While most fintech lend are retail lenders and sell their own originations, many non-fintech sellers are wholesale lenders that purchase loans from other originators, bundle them, and sell them to GSEs. To address concerns that our results are driven by differences in wholesale and retail lending, we restrict our Fannie Mae and Freddie Mac sample to only retail originations and rerun our tests. With this restriction, the results are unchanged.

Excluding Quicken Loans. Quicken Loans is the largest fintech lender. To test whether the findings regarding fintech shadow banks are restricted to Quicken Loans only, we rerun a number of tables excluding Quicken Loans sales from the sample. Online Appendix A.8 shows key tables from these results. While excluding Quicken Loans substantially reduces the power of our tests, we find on the restricted sample that most substantive results hold: fintech still appears to specialize in refinances; Fintech lenders are significantly faster that banks in selling originated loans (though not statistically significantly so); Fintech shadow banks charge significantly higher interest rates than non-fintech shadow banks, and the interest rates they charge are significantly less-explained by borrower observable characteristics. Having said that, fintech lenders, excluding Quicken, do not charge as high rates relative to non-fintech lenders as they did in Table 6. Consequently, shadow banks all together as a group, excluding Quicken, appear to charge lower, not higher, rates than banks.

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

11. Other robustness

To conclude this section, we highlight three other robustness checks. First, while we show that fintech lenders charge significantly higher interest rates, it is possible that they compensate borrowers with lower origination fees or points. While comprehensive data is not available on origination fees, manual investigation appears to show that this is not the case; in fact, online reviews often cite high origination fees as a problem regarding Quicken Loans. See Online Appendix A.3 for details.

Second, we run similar tests on the FHA data set to test whether interest rates differ significantly. A drawback of this analysis is that we do not observe borrower credit score, so there may be uncontrolled-for correlation between the creditworthiness of borrowers and their selection into fintech or non-fintech borrowing. With this

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

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

caveat, unlike in the conforming loans analysis, we find that fintech lenders charge slightly lower interest rates, which is consistent with our interpretation of fintech lenders charging high rates for price insensitive consumers valuing convenience and passing lower costs on to price sensitive consumers.

Third, most tables cluster standard errors by geographical area cross time to account for correlated shocks within a market. For robustness, we also calculate standard errors clustering by lender times time to account for within-lender shocks. The significance of the main results is unaffected.

12. Conclusion

The residential mortgage market has changed dramatically in the years following the financial crisis and the Great Recession. Our paper shows two important aspects of this transformation: the rise of shadow bank lenders on one hand and the rise of fintech lenders on the other.

Shadow bank lenders' market share among all residential mortgage lending has grown from roughly 30% in 2007 to 50% in 2015. We argue that traditional banks have faced greater regulatory restrictions since the crisis and have consequently reduced mortgage lending. Shadow banks, not subject to these restrictions, have partially filled the gap. Shadow banks dominate in market segments that are subject to greater regulatory scrutiny: low income, minority, and FHA borrowers. Additionally, shadow banks have gained the most market share in geographical areas where banks have been subject to more regulatory constraints, and their growth coincides with the timing of specific regulatory changes. Our quantitative assessment indicates that these regulatory differences can explain roughly 60% of the documented shadow bank growth.

Fintech lenders' market share has grown from roughly 3% in 2007 to 12% in 2015, representing a significant fraction of shadow bank market share growth. We identify two forces associated with online technology. Fintech lenders make use of different information to set interest rates, which they acquire through the lending process. Second, the ease of online origination appears to allow fintech lenders to charge higher rates, particularly among the lowest-risk, and presumably least price sensitive and most time sensitive borrowers. Our model suggests that 30% of the recent shadow bank growth is due to the disruption caused by online origination.

We conclude by cautioning against a normative interpretation of our results. While the regulation of the traditional banking sector is potentially responsible the rise of shadow banks, it is unclear whether this shift in mortgage origination is problematic. Because shadow banks do not rely on guaranteed deposits as a source of direct financing, they may be preferred as originators from the perspective of banking system stability. Fintech lenders, for their part, appear to offer products that consumers value greatly may have the potential to address ongoing regulatory challenges raised by Philippon (2016). On the other hand, fintech and non-fintech shadow banks alike rely extensively on the ongoing operation of GSEs and the FHA–institutions plagued by political economy concerns surrounding implicit and explicit government guarantees (e.g., Admati et al., 2018). How these considerations weigh against each other and impact the interaction between various lenders remains an area of future research.

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