Do Fintech Shadow Banks Compete with Technological Advantages? Evidence from Mortgage Lending

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Abstract

Contrary to common perceptions, we find that fintech shadow banks do not possess technological advantages over traditional banks, which have had significantly more patent output and technology-based talent (digital capital) acquisitions over the past decade. Consequently, although fintech shadow banks could charge a higher rate than traditional banks without incurring higher defaults early on, this premium has been shrinking drastically and recently has completely reversed. Highlighting the importance of technological innovation, we find evidence suggesting that fintech shadow banks investing heavily in digital capital can better withstand competition from traditional banks. Further analysis reveals that compared to traditional banks, fintech shadow banks overall underinvest in digital capital, and providing convenient services alone is not sufficient to sustain premium pricing in the long term. Finally, fintech shadow banks appear to have begun accepting more minority borrower applications only later in the sample period, suggesting that fintech lenders improve financial inclusion to circumvent direct competition from traditional banks.

Keywords: Fintech, Shadow Bank, Mortgage lending, Patent, Digital capital, Competition
JEL classification: G21, G23, O31

"[Fintechs] are all racing each other to introduce additional products. The question really is what things are on fintech companies' road maps that will continue to set them apart?"

—Alex Johnson, fintech research director at Cornerstone Advisors, reported by *Wall Street Journal*.[1]

1 Introduction

Disruptive technology is revolutionizing the financial industry. Many new startups have thrived on new business opportunities by bringing technological advancements to the traditional sector.[2] As a result, for example, fintech lenders rapidly increased their shares in the U.S. mortgage market from 2% in 2010 to 14% in 2020 (Berg et al. (2021)). On the flip side, traditional incumbents have been under enormous pressure to withstand possible displacements and respond to disruptive technology arising from these fintech competitors. Though fintech firms have firmly established themselves as viable competitors, they may also face challenges in the long run from mainstream banks, especially those with a strong willingness to adopt fintech to advance their business.[3]

Technological prowess is undoubtedly one of the key determinants of whether financial firms can continuously compete in the fintech era. Although fintech firms are by default assumed to be very innovative or disruptive players in the product market, little is known about whether they indeed possess technological advantages differentiating them from traditional market players.[4] Moreover, the role of technological innovation in shaping the dynamics of the competition landscape between fintech firms and traditional incumbents remains unexplored. Hence in this paper, we address these questions by depicting the U.S. mortgage lending market as an example.

To begin with, we attempt to quantify the innovation activity of fintech shadow banks

[1] January 26, 2022, "Fintech Companies, Facing Competition From Mainstream Banks, Step Up Their Offerings".

[2] Statista estimates that as of December 2020, there were about 8,775 fintech firms in the U.S.

[3] For more details, see https://www.wsj.com/articles/fintech-competition-mainstream-banks-11642714528.

[4] In this vein, for example, Fuster et al. (2019) use fintech lenders as a proxy for technology innovators in the mortgage lending market.

and traditional banks in the mortgage lending market.[5] Patent-based measures are widely used in the innovation literature. We collect patent data for all lenders in our sample from the U.S. Patent and Trademark Office (USPTO) website. Of greatest surprise to us is that from 2010 to 2020, fintech lenders as a whole had only 4 patents granted, with all of these 4 patents belonging exclusively to just one firm (Quicken Loans), while traditional banks collectively produced more than 4,900 new patents during the same period. The time-series pattern plotted in Figure 1 is also striking. No single fintech lender had any patents before 2018, while in 2010 alone, almost 200 patents were granted to traditional banks. More importantly, the number of newly granted patents for traditional banks has grown significantly over time and had reached more than 800 in 2020.[6]

These findings from patent data seem to conflict with the common perception that fintech firms hold a technological edge. One justification is that fintech innovations are often built upon open-sourced code and software and are thus less likely to be patentable (see, e.g., Massarotto (2015)). Additionally, the real value of fintech may not be to invent new and disruptive technology but to introduce available technology in the mortgage origination process to make it more efficient. If this is the case, fintech shadow banks' technological innovations may not be captured by patent granting data.

To explore these possibilities, we follow Tambe et al. (2020) to construct firm-level intangible digital capital each year as an alternative measure of fintech innovativeness. Using IT employment data from LinkedIn, Tambe et al. (2020) find that digital capital explains and predicts the high productivity of superstar firms in the digital era. We argue that this measure is well suited for our study since digital capital is likely to capture the two possibilities mentioned above because to either develop new origination models or merely implement existing financial technology, firms will have to invest in technology-related talent acquisition. Lending further support to our findings on patent grants, Table 1 shows that technology-related employees account for only approximately 2.5% of total employment in

[5] Throughout the paper, we use "fintech shadow bank" and "fintech lender" interchangeably.

[6] We ensure the difference is not entirely driven by the fact that many patents filed by traditional banks can be irrelevant to fintech lending technology by requiring patents granted to traditional banks to have at least one of the following keywords in its description: "data", "mortgage", or "lending'. Figure IA.1 shows that the number of filtered patents owned by traditional banks is reduced to 1,648 under this criterion but is still significantly larger than the number for their fintech counterparts within the same technological space.

fintech shadow banks while the average percentage is over 3.9% for traditional banks, with a rapid increase in recent years. One may be concerned that the higher ratio of technology-related bank employees might come from nonlending divisions. To address this concern, we compare fintech shadow banks and small banks with fewer than 1,000 employees on LinkedIn, given that small banks are presumably more likely to focus on the mortgage lending business. We continue to find that fintech shadow banks have lower technology-related employees in percent terms, thus rejecting the possibility that non-mortgage-lending divisions drive our findings.

This evidence from patents and digital capital casts serious doubt on whether fintech shadow banks have technological advantages over traditional banks. Our findings point in the opposite direction: traditional banks have started responding to the stiff competition induced by fintech by rapidly increasing their investments in technological innovations. As noted in Fuster et al. (2019) as well, "In the long run, it is unclear whether technology-based lending will remain dominated by nonbanks or whether commercial banks will be able to use technology to regain market share in the mortgage market". Along this line of reasoning, we hypothesize that fintech shadow banks may lose their comparative edge in the long run, given their lack of disruptive technology and that traditional banks will, in turn, catch up on this dimension. Indeed, this is what we find in the data. Specifically, although fintech shadow banks were able to charge a higher loan price than traditional banks without the cost of higher defaults in the first half of the sample period, this premium has been shrinking drastically and even completely reversed in recent years. Moreover, the default rate of fintech loans has been worse than that of traditional bank loans since 2015.

If technological advantage is at the center of mortgage market competition in the fintech era, we expect fintech shadow banks that invest heavily in technological innovation to be more likely to withstand competition from traditional banks. In contrast, those with little investment may need to offer discounts and extend their business to borrowers with higher credit risk to maintain their market shares. Our findings confirm this reasoning. Specifically, fintech shadow banks with high digital capital charge at least a 5-basis-point premium over those with low digital capital, and such effects are more prominent among the group of borrowers who are likely to value fintech services more. For example, high-FICO borrowers are shown in the literature to be less price sensitive and can be particularly attracted to features of loan services other than price, such as convenience. In addition, refinancing borrowers are more likely to choose fintech shadow banks, as these borrowers prefer faster closings and already have mortgage origination experience and thus are less dependent on face-to-face interactions. Indeed, we find that fintech shadow banks with large digital capital investments are able to price discriminate among those types of borrowers. However, fintech shadow banks with low digital capital need to offer a significant price discount to attract those refinancing borrowers who would naturally prefer fintech lenders. Further analysis also reveals that the marginal benefit of investing in additional digital capital is significantly higher for fintech shadow banks, stressing the fact that their innovation activity is currently suboptimal in comparison to that of traditional banks.

It seems puzzling that fintech shadow banks were able to enjoy a price premium early on although they do not hold technological advantages. Several recent papers have shown that costly legal and regulatory burdens after the financial crisis significantly limited traditional banks' lending ability (e.g., Buchak et al. (2018)) while fintech lenders were able to grow fast without the concern of heavy regulation. In addition, fintech shadow banks may win a temporary edge, especially in relatively underserved regions, by introducing the new business model of online processing to the market. The idea is that borrowers living in regions with fewer bank branches would probably find themselves more constrained in obtaining mortgage services. As a result, borrowers in these underserved regions are more likely to adopt fintech services even though they are a more expensive option. To test this hypothesis, we collect data on the number of bank branches at the 3-digit zip code level to proxy for borrowers' willingness to pay for fintech services. In line with our reasoning, we find that fintech shadow banks charge a higher premium in regions with less concentrated bank branches. However, this price premium for fintech shadow banks in underserved regions has declined over time. This is likely because traditional banks also started to offer online services over time, given that online origination services can be replicated.[7]

We next explore whether the pattern of loan price reversal documented in this paper

[7]For example, Bank of America launched its Digital Mortgage Experience to guide clients through the mortgage process via the bank's mobile app in 2017. For more details, please see https://www.bizjournals.com/charlotte/news/2018/04/11/bank-of-america-launches-digital-mortgage.html.

relates to fintech shadow banks' strategic response to competition. A few recent works (e.g., Bartlett et al. (2022) and Di Maggio et al. (2022)) document that by transforming the loan origination process from human to machine, fintech shadow banks can help reduce bias-induced discrimination arising from in-person interactions. If fintech shadow banks indeed enter the market with disruptive algorithms to better interpret alternative data, we would expect them to extend more credit to minority borrowers from the very beginning. We find that even though minority borrowers present strong demand for fintech loans, fintech shadow banks did not increase their approval rate for minority borrowers at a much higher rate until later in the sample period. This finding indicates that fintech shadow banks likely improved financial inclusion due to their strategic adjustment to the intense competition exerted by traditional banks. That is, fintech shadow banks choose to lend more loans to underserved minority groups, among which the direct competition from traditional banks is less intense. This strategic shift further echoes the concern over whether fintech shadow banks truly offer innovative technology.

Our paper contributes to several strands of the literature. First, our paper connects to the burgeoning literature on fintech lenders in the mortgage market.[8] Related to ours, Buchak et al. (2018) study the early growth of shadow banks, including fintech shadow banks from 2010 to 2015. They find that fintech shadow banks charge a higher rate than traditional banks for providing convenience to high-quality borrowers. Our study confirms their findings in the early sample period while documenting a reverse trend in recent years. We argue that the lack of continuous technological innovation is likely the driving factor. In addition, Fuster et al. (2019) view fintech lenders as a proxy for advanced technological players and study the role of technology in the mortgage market competition. They find that fintech lenders process mortgage loan applications faster than traditional banks do and argue that technology helps reduce friction in the mortgage origination process. Our paper unveils a novel distinction between financial technology and fintech lenders. Although technology is critical in determining competition with respect to loan price and performance, many fintech shadow banks do not exhibit technological advantages over traditional banks.

[8] Our paper is also broadly related to the literature on the growth of fintech in various consumer credit markets. See, for example, Bartlett et al. (2022), Chiu et al. (2018), D'Acunto et al. (2021), Di Maggio and Yao (2021), He et al. (2020), Parlour et al. (2020), and Tang (2019).

Second, this paper is related to recent works examining banking regulation's effects in the post-crisis era. For example, D'Acunto and Rossi (2021) document a substantial mortgage loan redistribution since 2011 as a result of post-crisis financial regulation. Begley and Srinivasan (2021) show that small banks grew faster than fintech lenders in the mortgage market after big banks retreated due to regulatory burdens. We show that the fast-growing market shares of fintech shadow banks are likely to be driven by their differences in regulatory burdens rather than by their differences in technological innovations. To our knowledge, we document for the first time in the literature that fintech lenders are less innovative than traditional banks and technologically disadvantaged in relation to them.

Our paper provides new evidence to complement recent works on how financial technology is reshaping the financial industry. Jiang et al. (2021) study how incumbents change their hiring and innovation strategy in response to the technology shock. Chen et al. (2019) find that public financial firms have filed more patent applications than fintech startups. We show that traditional banks invest more heavily in technology than fintech shadow banks do. Our results underscore that instead of fintech startups outgrowing incumbent firms, it is more likely to be the case that existing leading market players respond to the wake-up call sent from those fintech startups by altering their business models through adoption, acquisition, and the invention of innovative technology. We believe the framework that we document in the mortgage market can be generalized to other financial sectors regarding how they strategically adopt disruptive technology.

Finally, our paper also adds insight to the innovation literature. Most papers utilize patent-based metrics to study innovation activity by firms (e.g., Aghion et al. (2005), Nanda and Rhodes-Kropf (2013), and Seru (2014)). While patent output has delivered valuable insights about corporate innovation in general, we find that it may fall short in capturing innovation activities in the fintech era (e.g., Tambe et al. (2020)). For example, Lerner et al. (2020) document that the recent surge in financial patenting was driven by IT firms and others outside of the financial sector. Using intangible digital capital as an alternative measure of innovation, we are able to quantify fintech innovation activity for mortgage lenders. Relying on this measure, we document strong evidence that fintech shadow banks with more digital capital can better withstand competition from traditional banks.

The remainder of the paper is organized as follows. Section 2 describes our data sets and key variable construction. In Section 3, we introduce our empirical methodology and present our main findings. Section 4 provides further discussions, and Section 5 concludes.

2 Data and key variables

2.1 Mortgage data and lender classification

We first collected loan application data disclosed by U.S. mortgage lenders under the Home Mortgage Disclosure Act (hereafter HMDA) from January 2010 to December 2020. HMDA data covers a majority of home mortgage applications across the United States. The data set spans a wide range of loan and borrower characteristics, including loan purpose, loan type, loan amount, loan originator, loan origination year, loan outcome, borrower's race, income, gender, census tract, etc.

To classify mortgage lenders as traditional banks or fintech shadow banks, we use the lender classification list shared by Buchak et al. (2019) in their 2019 update. Specifically, a lender is classified as a "bank" if it is a depository institution and as a "fintech shadow bank" if it is a non-depository institutions falling outside the scope of traditional banking regulation and has a strong online presence with most of its mortgage applications processed without human involvement. This classification method was introduced in Buchak et al. (2018), and in the current 2019 version, they revised the classification list to include more lenders, updating the status of certain shadow banks and considering the possibility of traditional banks being fintech banks. Since we are particularly interested in understanding whether and how mainstream banks have reacted to the fintech revolution, we exclude non-fintech shadow banks throughout the paper. By combining subsidiaries, excluding wholesalers, and merging the lender classification list to the HDMA data set, we are able to identify 312 lenders unique HMDA lenders, of which 270 are traditional banks and 42 are fintech shadow banks.

To further understand the implication on loan pricing and performance, we obtain loan-level origination and performance data from Fannie Mae and Freddie Mac (hereafter FMFM) for the period between January 2010 and December 2020. FMFM discloses detailed origination and performance records for a representative subset of single-family mortgage loans on a monthly basis. The data cover a rich array of key variables, such as the interest rate, loan-to-value ratio, current loan status, borrower FICO scores, and loan payment status. Our primary dependent variable of interest is the pricing strategy, i.e., loan origination rate ($Loan\,Price$). In addition, we examine the post-origination loan performance by constructing a binary variable $Loan\,Default$, which is equal to 100 if the loan experienced delinquency for at least 60 consecutive days within two years after origination and 0 otherwise. Following the literature, we also include a set of control variables, including the loan amount, loan term, loan-to-value, debt-to-income, and FICO score, which have been shown to significantly affect loan price and performance. Note that in each reporting period, only loans originated by lenders ranked among the top 50 originators are revealed by FMFM. Therefore, with a similar lender classification process, we are able to identify 35 unique lenders, of which 22 are traditional banks and the remaining 13 are fintech shadow banks in the FMFM data.[9]

2.2 USPTO patent filing data

Patent-based metrics are widely used to capture firm innovation activities (e.g., Aghion et al. (2005), Nanda and Rhodes-Kropf (2013), and Seru (2014)). We collect patent data for all lenders in our sample from the USPTO website.[10] We follow the innovation literature to focus on utility patents. We first conduct a fuzzy name match between lenders and patent owners using the Patent Assignment Dataset. We then manually search each lender from the USPTO website to avoid any potential omissions.[11] The official Patent Assignment Dataset and the USPTO website provide information on the type of assignment for each assignment record. For financial firms, many of their assignment records are security interests and liens. These types of assignment records track borrowers' activities of pledging patents as collateral to financial firms. We exclude those patents, as they do not reflect the innovation

[9]As a robustness check, we validate our main findings in Section 3.4 using the 2017 version of the lender classifications. Table IA.3 lists lenders and their classifications based on the 2017 version.

[10]For a complete list of research datasets provided by the USPTO, see: https://www.uspto.gov/ip-policy/economic-research/research-datasets.

[11]The following USPTO website provides all assignment records for each firm: https://assignment.uspto.gov/patent/index.html.

activities originated by a given financial firm.

For the period 2010 through 2020, there were 4,987 patents in total granted to 26 out of 312 HMDA lenders[12] and 3,323 patents granted to 10 out of 35 FMFM lenders[13]. Surprisingly, only 1 out of these lenders is a fintech shadow bank, and all the others are traditional banks. To the extent that patents are commonly viewed as a proxy for a firm's innovation activities, this seems to suggest that most fintech shadow banks should not be considered innovative players at all. One possible justification could be that most fintech innovations are built upon open-sourced code and software and thus are unlikely to be patentable (see, e.g., Massarotto (2015)). In addition, the real value of fintech may not be the invention of new disruptive technology but rather the introduction of available technology into the mortgage market to improve the origination process. If so, the innovativeness of each mortgage lender may not be well measured by the patent data.

2.3 Digital capital based on LinkedIn data

To overcome the possibility that classic innovation measures may fail to capture mortgage lenders' fintech innovation activities, we follow Tambe et al. (2020) to construct a firm-level intangible digital capital measure as an alternative proxy of technology innovation. By extracting IT employment data from LinkedIn, Tambe et al. (2020) find that the value of digital capital to firm productivity began to rise from 2010 onward, coinciding with the wave of recent technology innovations, including mobile technology, big data, data science, and artificial intelligence (AI). We argue that digital capital can help capture fintech innovation because regardless of whether the technology is built in-house or not, firms have to invest in technology-based human capital acquisitions to implement it.

As a leading platform providing professional networking, LinkedIn allows professionals to create personal profiles by posting their educational background and employment history. According to Statista, there were approximately 180 million members of LinkedIn located in the U.S. as of July 2021, thus reflecting a fairly representative sample of the overall U.S. la-

[12] Table IA.1 details the lenders in our HMDA sample with non-zero patents and their classifications.

[13] Table IA.2 details all the lenders in our FMFM sample and their classifications.

bor market.[14] To measure digital capital for mortgage lenders every year, we first attempt to identify lenders on LinkedIn based on company names, official website, location, and any other useful information disclosed both on LinkedIn and in the mortgage database. The search identifies 264 (35) HMDA (FMFM) lenders that have at least one active employee on LinkedIn. Next, we manually collect all employee records for every identified lender. Since our primary focus is digital talent, we create the following keyword list to identify "IT"- or "data"-related job positions: *[IT, DATA, SOFTWARE, DATABASE, PROGRAMMER, INTELLIGENCE, COMPUTE, ANALYTIC, ENGINEER, DEVELOPER, TECHNICIAN, ARCHITECT, DIGITAL, OPERATION, SCIENTIST, STRATEGIST, INTERNET, SOLUTION, FRAUD, AUTOMATION]*.[15]

To create the measure of digital capital at the lender–year level, we track the complete employment history to ensure that all relevant employees who are currently employed and those who previously worked for this employer are included. The whole process yields over 2 million employment records and results in a panel of 2,904 HMDA lender–year observations and 385 FMFM lender–year observations. After we merge the FMFM data, there are 18.2 million loans with non-missing digital capital information. We use the natural log of 1 plus the raw number of tech-related employees (denoted as $Ln(1 + DC)$) and scaled digital capital (denoted as $Scaled\ DC$, where the number of tech-focused employees is scaled by the firm's total number of employees on LinkedIn in a given year) as our main variables. To the best of our knowledge, this is the first paper to estimate fintech innovations based on intangible digital capital by utilizing LinkedIn employment data.

The digital capital measure has several distinct features. First of all, as argued by Tambe et al. (2020), digital capital can better capture the intensity of a firm's technological advancement than traditional physical capital can (e.g., IT hardware spending) in the digital era because an increasing number of firms have started to use cloud computing services for their daily operations during this period. Second, the measure helps us better quantify the innovation activities in the mortgage lending markets. For example, while almost

[14] For more details, see https://www.statista.com/statistics/272783/linkedins-membership-worldwide-by-country.

[15] As a robustness check, in Section 3.4, we replicate our main findings using two alternative keyword lists, with one more conservative and the other more inclusive.

none of the fintech shadow banks have any patents, all of them need to acquire tech-based employment to keep the business going.

2.4 Summary statistics

Our final sample contains approximately 18.2 million mortgage loans originating during the sample period from January 2010 through December 2020. Table 2 presents the summary statistics of loan characteristics. Contrary to what Buchak et al. (2018) find, fintech shadow banks on average charge a rate 0.1% lower than traditional banks when more recent sample periods are included, at about 3.97%. Similarly, the default rate is higher for loans originated by fintech shadow banks than those originated by traditional banks (0.80% vs. 0.54%). The evidence thus raises concerns on whether fintech shadow banks are able to continuously charge a premium over time. In addition, fintech is more attractive to certain types of mortgage borrowers, such as borrowers who are refinancing their homes.

3 Empirical analysis

3.1 Are fintech shadow banks more innovative than traditional banks?

Technological innovation is often viewed as the backbone of maintaining a competitive edge in the long term. To check whether fintech lenders are more innovative than traditional banks, we first count the number of newly granted patents for each fintech shadow bank and traditional bank, which is a standard measure to proxy for firm innovation activities in the existing literature (see, e.g., Aghion et al. (2005), Nanda and Rhodes-Kropf (2013), and Seru (2014)).

The finding of a greatest surprise to us is there are only 4 patents in total granted to fintech shadow banks from 2010 to 2020, while around 5,000 patents were granted to traditional banks in the same period. Moreover, these 4 patents all belong to just one fintech shadow bank (i.e., Quicken Loans). In contrast, 26 traditional banks were granted at least one patent from 2010 to 2020. In addition, Figure 1 plots the number of newly granted patents for both fintech shadow banks and traditional banks every year from 2010 to 2020. On the one hand, fintech firms had zero patents before Quicken Loans was granted 2 patents in 2018 and 1 patent in each of the years 2019 and 2020. On the other hand, about 300 patents were granted to traditional banks in 2010 alone. More importantly, the number of newly granted patents for traditional banks has grown significantly over the past decade and reached more than 800 in 2020. Thus, the results based on the number of patents seem to suggest that fintech shadow banks are not as innovative as traditional banks.[16] Despite the fact that fintech lenders had little market presence before 2010 (i.e., less than 2% of the market share), one may argue that those fintech lenders may have entered the market with technology already in place. In an untabulated analysis, we reject this possibility, as we do not find any patents ever granted to fintech shadow banks prior to 2010.

The collective findings are quite intriguing since fintech firms are generally viewed as very innovative or disruptive players in the product market. For example, Fuster et al. (2019) use fintech shadow banks as a proxy for technology innovation in the mortgage lending market. However, our patent data seem to suggest that this conventional wisdom could be unfounded. Is it possible that patents fail to capture fintech shadow banks' innovation activity? For example, many recent disruptive technologies such as artificial intelligence or machine learning algorithms are based mainly on open-source code or software and thus may not be easily patentable (Massarotto, 2015; Lerner and Tirole, 2005). In addition, it could be the case that fintech shadow banks' business model is to compete by making the origination process more efficient or to provide customers with a better service experience. If this is the case, the real value of fintech shadow banks lies not in their invention of new disruptive technology but in their introduction of existing advanced technology into the mortgage market. Both factors could contribute to the fact that we do not observe patent granting from fintech shadow banks.

To explore these possibilities, we follow Tambe et al. (2020) to construct firm-level intangible digital capital each year to capture firm innovation in fintech.[17] Table 1 summarizes the innovation output for fintech shadow banks and traditional banks. On average, tech-focused employees account for approximately 2.5% of the total employment among

[16] To mitigate the impact of irrelevant patents, we further require patents containing at least one of the keywords "data", "mortgage", or "lending". The time-series trend plotted in Figure IA.1 is qualitatively similar to that documented in Figure 1 using the unfiltered patent data.

[17] Section 2.3 provides a detailed description of our digital capital measure.

fintech shadow banks over the past decade, while the fraction of tech-based employment is around 3.9% among traditional banks. Figure 2 plots the time-series pattern of the scaled digital capital measure, which is the ratio of tech-based employment over total employment for both fintech shadow banks and traditional banks. Traditional banks have dominated fintech lenders in all years, and traditional banks have significantly increased their investments in technology over time. This pattern seems to further indicate that traditional banks (at least some of them) have started responding to the compelling threat from their fintech counterparts and the disruptive technology that they have brought.[18]

One may argue that the higher percentage of tech-related employees among traditional banks may be affected by the innovation activities carried out by other business divisions within banks. To mitigate this concern, we select a sample of small banks that have fewer than 1,000 employees, given that their services are more likely to focus exclusively on mortgage lending. We continue to find that small banks have more tech-based employment in percent terms than fintech lenders do, thus alleviating this concern.

3.2 Implication on loan price

If fintech shadow banks have not stayed at the vanguard of technology innovation, can they continue to charge higher rates in the long run?

Using the FMFM data from 2010 to 2015, Buchak et al. (2018) find that fintech lenders are able to charge rates more than 10 basis points (bps) higher than those charged by traditional banks. However, we have documented that traditional banks have significantly increased their investment in technology over time, possibly to combat the threat from fintech lenders. As a result, it is natural to ask whether fintech shadow banks are able to continuously charge higher rates over time.

To answer this question, we extend the FMFM loan-level data to 2020 and conduct the following regression:

$$Loan\ Price_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \tag{1}$$

[18] One may wonder what non-tech-focused employees fintech lenders hire. Figure IA.5 plots a word cloud of all the non-tech-focused employees hired by fintech lenders. Surprisingly, the most popular position is loan officer, suggesting that fintech lenders may not be as different from traditional banks as we thought.

where $Loan\,Price_{i,j,z,t}$ is the interest rate of mortgage loan i originated by lender j in zip code z at quarter t; $Fintech_j$ is a dummy variable equal to 1 if lender j is a fintech shadow bank and 0 otherwise; $X_{i,t}$ includes an array of borrower and loan characteristics, including loan amount, loan term, borrower credit score (i.e., FICO score), loan-to-value ratio (LTV), debt-to-income ratio (DTI), second property indicator, refinance indicator, first-time buyer indicator (FTHB), and mortgage insurance indicator; and $\delta_{z,t}$ are zip code times quarter fixed effects. The borrower and loan characteristics and fixed effects are expected to control for differences in supply and demand conditions across markets that affect loan prices. Standard errors are clustered at the zip code and quarter level.

As reported in Column 1 of Table 3, the positive and significant coefficient of $Fintech_j$ confirms that fintech shadow banks indeed charge a 3.5 bps higher rate than their traditional bank counterparts in the extended sample period. The finding is qualitatively in line with the result of Buchak et al. (2018), albeit much smaller in magnitude. The reason for the smaller magnitude is that fintech lenders' price premium has been reduced over time. Specifically, the coefficients of $Fintech_j$ in Columns (2) and (3) suggest that the price premium dropped from 7.7 bps in the early period (2010–2015) to 1.0 bps in the late period (2016–2020). More importantly, the coefficient of $Fintech_j$ in Column (3) becomes insignificant, suggesting that the price premium of fintech lenders has become insignificantly in the late period (2016–2020). The coefficients of borrower and loan characteristics in all three regressions are mostly consistent with findings from prior literature. For example, the loan term, loan-to-value ratio, and debt-to-income ratio are positively correlated with the loan price, while the FICO score and mortgage insurance indicator negatively predict the loan price. We further visualize the time trend by rerunning Equation (1) for every year and plotting the yearly coefficients of $Fintech_j$ in Figure 3. Starting from 2010, the premium that fintech shadow banks were able to charge steadily increased until 2015. At its peak year of 2015, fintech shadow banks were able to charge a rate 9 bps higher than that charged by their traditional bank counterparts. However, this momentum stopped and started to reverse in the second half of the sample period, and the coefficient of $Fintech_j$

for 2020 even turns negative.[19]

3.2.1 The role of innovation in loan price competition

Two combined forces may help explain the time-series trend documented in Section 3.2. On the one hand, although fintech shadow banks can enjoy a price premium by introducing technology into the mortgage lending market, they lack truly disruptive technology, measured in terms of either patents or digital capital, to maintain their pricing advantage in the long run.[20] On the other hand, we also observe that traditional banks have been rapidly increasing their investment in technology innovation and digital capital acquisition over time. Such technological catch-up by traditional banks may further dampen fintech lenders' early premium, especially given that banks have more resources to compete, including cheap access to funding, large client bases, and a local presence and network.

According to this line of reasoning, dedication to technology investment can be crucial for fintech shadow banks to continuously charge a premium. To check this conjecture, we estimate the following regression:

$$\begin{aligned} Loan\,Price_{i,j,z,t} = \alpha &+ \beta_1 High\,DC\,Fintech_{j,t} + \beta_2 Low\,DC\,Fintech_{j,t} \\ &+ X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \tag{2}$$

where $Loan\,Price_{i,j,z,t}$ is the interest rate of mortgage i originated by lender j in zip code z at time t, $High\,DC\,Fintech_{j,t}$ is a dummy variable that equals 1 if lender j is a fintech shadow bank with an above-average level of digital capital among all fintech lenders at time t and zero otherwise, and $Low\,DC\,Fintech_{j,t}$ is a dummy variable that equals 1 if lender j is a fintech shadow bank with a below-average level of digital capital among all fintech shadow banks at time t and zero otherwise. Defined in Section 2.3, $Digital\,Capital_{j,t}$ is the number of tech-related employees of lender j at time t, $X_{i,t}$ includes borrower and mortgage characteristics, and $\delta_{z,t}$ indicates zip code by quarter fixed effects.

[19] Table IA.4 and Figure IA.6 report qualitatively similar results using the 2017 classification list, thus verifying that our findings are not sensitive to the choice of classification method.

[20] Figures IA.2 and IA.4 plot the number of newly granted patents and the percentage of tech-focused employees for traditional banks and fintech lenders in the FMFM loan sample, where the time-series pattern is similar to those plotted in Figures 1 and 2.

Columns (2) and (4) of Table 4 report the regression results of Equation (2) using $Ln(1+DC)$ and $Scaled\ DC$ as our measure of digital capital, respectively. In line with our conjecture, the loan price charged by $High\ DC$ fintech shadow banks shows on average a 5 bps premium over the price charged by traditional banks, while fintech lenders with $Low\ DC$ cannot price with any premium. The results suggest that investment in innovation seems to be the key driver of whether fintech shadow banks are able to maintain their market competitiveness. To examine the role of innovation in loan price competition over time, we estimate Equation (2) for every year. Figure 4a (or 4b) plots the yearly coefficients of $High\,DC\,Fintech_{j,t}$ and $Low\,DC\,Fintech_j$ based on $Ln(1+DC)$ (or $Scaled\ DC$). We find that fintech lenders' pricing edge has been shrinking in recent years, even for those actively investing in digital capital. The results support the notion that traditional banks have started to catch up with fintech firms by means of substantial investments in technology. Interestingly, we find that the coefficient of $Low\,DC\,Fintech_{j,t}$ is negative for eight out of the ten years, suggesting that these fintech shadow banks were dominated by their innovative counterparts and traditional banks throughout the sample period. The evidence presented here also validates that digital capital helps separate high-quality fintech shadow banks from low-quality ones.

Are fintech shadow banks currently underinvesting in innovation? The answer is probably yes, as their patent output and digital capital acquisition lag behind those of their traditional bank counterparts. We have documented that fintech shadow banks with higher digital capital earn a rate premium on average, but how does the marginal benefit to fintech shadow banks from increasing digital capital in terms of the loan price compare with the benefit to traditional banks? We investigate this question by estimating the following regression:

$$\begin{aligned} Loan\,Price_{i,j,z,t} =& \alpha + \beta_1 Fintech_j + \beta_2 Digital\,Capital_{j,t} \\ &+ \beta_3 Fintech_j \times Digital\,Capital_{j,t} + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \tag{3}$$

where $Loan\,Price_{i,j,z,t}$ is the interest rate of mortgage i originated by lender j in zip code z at time t; $Fintech_j$ is a dummy variable equal to 1 if lender j is a fintech shadow bank and

0 otherwise; $Digital\,Capital_{j,t}$ measures the amount of digital capital owned by lender j at time t as defined in Section 2.3; $X_{i,t}$ includes borrower and mortgage characteristics; and $\delta_{z,t}$ indicates zip code by quarter fixed effects.

The null hypothesis is that the coefficient of $Fintech_j \times Digital\,Capital_{j,t}$ (β_3) should be insignificant if fintech shadow banks currently invest in innovation at a level as efficient as that of traditional banks. The results reported in Columns (3) and (5) of Table 4 reject the null hypothesis. Instead, we find that the coefficient of $Fintech_j \times Digital\,Capital_{j,t}$ (β_3) is positive and significant using either $Ln(1 + DC)$ or $Scaled\ DC$, indicating that the benefit of investing in an additional unit of digital capital is larger for fintech shadow banks than for traditional banks. The marginal cost of investing in digital capital (i.e., hiring one more software engineer at the market price) should be similar among most lenders, regardless of their type. Therefore compared to traditional banks, fintech shadow banks are not investing up to their optimal level.

3.3 How do fintech loans perform over time?

Buchak et al. (2018) find that fintech conforming-loan borrowers had default rates very similar to those of traditional bank borrowers between 2010 and 2015. Moreover, Fuster et al. (2019) document that fintech default rates are about 25% lower than those for traditional lenders on riskier FHA mortgages. How did fintech loans perform in our extended sample period? To answer this question, we estimate the following regression:

$$Loan\,Default_{i,j,z,t} = \alpha + \beta_1 Fintech_j + \beta_2 Loan\,Price_{i,j,z,t} + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \qquad (4)$$

where $Loan\,Default_{i,j,z,t}$ measures the default status of mortgage i originated by lender j in zip code z at time t. The default status is a binary variable equal to 100 if a loan experienced delinquency for at least 60 consecutive days within two years after origination and 0 otherwise. $Fintech_j$ is a dummy variable equal to 1 if lender j is a fintech shadow bank and 0 otherwise; $X_{i,t}$ includes borrower and mortgage characteristics; and $\delta_{z,t}$ indicates zip code by quarter fixed effects.

Table 5 reports the regression results of estimating Equation (4) for the period from

2010 to 2020. We consider loans made only up to 2017, as we need at least two full years to evaluate the mortgage delinquency status. We find that the coefficient of $Fintech_j$ in Column (1) is positive and significant, suggesting that fintech loans are more likely to enter default than loans originated by traditional banks in the extended sample period. The magnitude of β_1 is small but not negligible. On average, the default rate of fintech loans is 0.08% (or 14.3% higher than the sample average default rate), higher than that of traditional bank loans. The coefficient of $Fintech_j$ in Column (2) is close to zero (i.e., 0.01%) and not statistically significant for the sample period from 2010 to 2013. However, the magnitude of the coefficient of $Fintech_j$ increases significantly to 0.10% for the second half of the sample period (reported in Column (3)), suggesting that fintech loans perform much worse over time. The coefficients of borrower and loan characteristics in all three regressions are consistent with results from prior literature. For example, the loan-to-value ratio and debt-to-income ratio are positively associated with the loan default rate, while FICO scores negatively predict loan default.[21] To visualize the time trend, we rerun Equation (4) by year and plot the yearly coefficients of $Fintech_j$ in Figure 5. In line with the result in Buchak et al. (2018), fintech borrowers had default rates very similar to those of traditional bank borrowers early on. However, fintech loans have exhibited significantly higher default rates since 2015.

3.3.1 The role of innovation in loan performance

The results presented in Section 3.2.1 show that fintech shadow banks investing more in digital capital are able to charge higher rates. Does fintech shadow banks' investment in technology innovations also positively affect their loan performance? To answer this question, we estimate the following regression:

$$\begin{aligned} Loan\,Default_{i,j,z,t} = \alpha &+ \beta_1 High\,DC\,Fintech_{j,t} + \beta_2 Low\,DC\,Fintech_{j,t} \\ &+ \beta_3 Loan\,Price_{i,j,z,t} + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \tag{5}$$

[21] Panel B of Table IA.4 reports the regression results using the 2017 version of lender classification. The coefficient of $Fintech_j$ changes from significantly negative in early periods (reported in Column (2)) to insignificantly negative in later periods (reported in Column (3)), suggesting that fintech loans have performed worse over time.

where $Loan\,Default_{i,j,z,t}$ measures the default status of mortgage i originated by lender j in zip code z at time t. The default status is a binary variable equal to 100 if a mortgage is delinquent for at least two consecutive months within two years of its origination and 0 otherwise. $High\,DC\,Fintech_{j,t}$ is a dummy variable equal to 1 if lender j is a fintech shadow bank with an above-average level of digital capital among all fintech shadow banks at time t and zero otherwise; $Low\,DC\,Fintech_{j,t}$ is a dummy variable equal to 1 if lender j is a fintech shadow bank with a below-average level of digital capital among all fintech shadow banks at time t and zero otherwise; $X_{i,t}$ includes borrower and mortgage characteristics; and $\delta_{z,t}$ indicates zip code by quarter fixed effects.

Columns (2) and (4) of Table 6 report the regression results of Equation (4) for loans originated between 2010 and 2017 using $Ln(1 + DC)$ and $Scaled\ DC$, respectively, as our measure of digital capital. While the coefficient of $Low\,DC\,Fintech_{j,t}$ are positive and significant, the coefficient of $High\,DC\,Fintech_{j,t}$ is negative and insignificant. These results suggest that investing in digital capital does help fintech shadow banks more effectively screen borrowers, thus leading to better loan performance. Figure 6a (respectively, 6b) display the yearly coefficients of $High\,DC\,Fintech_{j,t}$ (β_1) and $Low\,DC\,Fintech_{j,t}$ (β_2) based on $Ln(1 + DC)$ (respectively, $Scaled\ DC$). At the beginning of the sample period, loans originated by high-DC fintech shadow banks performed at least as well as those originated by traditional banks, while they have underperformed more recently. Loans originated by fintech shadow banks with little technology innovation underperformed in all years.

We next estimate the marginal benefits to loan performance from increasing digital capital for fintech shadow banks in comparison to the benefits from traditional banks' technological investment by conducting the following regression:

$$\begin{aligned} Loan\,Default_{i,j,z,t} =& \alpha + \beta_1 Fintech_j + \beta_2 Digital\,Capital_{j,t} \\ &+ \beta_3 Fintech_j \times Digital\,Capital_{j,t} \\ &+ \beta_4 Loan\,Price_{i,j,z,t} + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \tag{6}$$

where $Loan\,Default_{i,j,z,t}$ measures the default status of mortgage i originated by lender j in zip code z at time t. The default status is a binary variable equal to 100 if a mortgage is delinquent for at least two consecutive months within two years of its origination and 0 otherwise. $Fintech_j$ is a dummy variable equal to 1 if lender j is a fintech shadow bank and 0 otherwise; $Digital\,Capital_{j,t}$ measures the amount of digital capital owned by lender j at time t as defined in Section 2.3; $X_{i,t}$ includes borrower and mortgage characteristics; and $\delta_{z,t}$ indicates zip code by quarter fixed effects.

Columns (3) and (5) of Table 6 report the regression results of Equation (6) using $Ln(1 + DC)$ and $Scaled\ DC$, respectively, as our measure of digital capital. The negative and significant coefficient of $Fintech_j \times Digital\,Capital_{j,t}$ (β_3) suggests that the marginal benefit of digital capital investments for loan performance is higher among fintech shadow banks than among traditional banks. The overall findings again imply that compared to traditional banks, fintech shadow banks underinvest in innovation.

3.4 Robustness checks

We perform a battery of tests to check the robustness of our main findings.

First, we use two alternative keyword lists to reconstruct our digital capital measure. The first alternative list is more conservative, keeping only [IT, DATA] from the current keyword list. The second alternative list is more inclusive with the following keywords: [IT, DATA, ANALYST, SPECIALIST, OPERATIONS, ENGINEER, DATA, SYSTEMS, TECHNOLOGY, DEVELOPER, SECURITY, RISK, SOFTWARE, TECHNICIAN, TECHNICAL, NETWORK, SYSTEM, PROGRAM, ARCHITECT, DIGITAL, CONTROL, PROGRAMMER, ANALYTICS, INTELLIGENCE, DATABASE, OPERATOR, COMPUTER]. Table IA.6 reports the regression results on loan price and loan performance based on digital capital constructed using the two aforementioned lists. All coefficients of our key variables (i.e., $High\,DC\,Fintech_{j,t}$, $Low\,DC\,Fintech_{j,t}$, $Fintech_j \times Digital\,Capital_{j,t}$) remain largely unchanged, indicating that our main findings are not sensitive to the choices of keywords used to construct the digital talent measure.

Next, we repeat our analyses from Sections 3.2 and 3.3 based on the 2017 version of the lender classification list used in Buchak et al. (2018).[22] Panel A of Table IA.5 reports the regression results on loan price competition. The coefficient of $Fintech_j$ in Column (1)

[22]Table IA.3 lists all lenders based on the 2017 version of the lender classification list.

of the loan price regression is around 5 bps, which is slightly larger than the magnitude documented using the 2019 lender classification, while Figure IA.6 continues to find a similar time trend of loan price competition. Moreover, if we compare the coefficient of $High\,DC\,Fintech_j$ to that of $Low\,DC\,Fintech_j$ as shown in Columns (2) and (4) of Table IA.5, we continue to find that the loan price premium charged by fintech shadow banks is driven mainly by those heavily investing in digital capital. Lastly, the positive and significant coefficients of $Fintech_j \times Digital\,Capital_{j,t}$ in Columns (3) and (5) of Table IA.5 suggest that the marginal benefit of investing in digital capital for the loan price is higher for fintech shadow banks than for traditional banks. As reported in Panel B of Table IA.5, we document qualitatively similar results on loan performance using the 2017 lender classification, except that the coefficient of $Low\,DC\,Fintech_j$ becomes insignificant in Column (4). In other words, our main findings are robust to the choice of lender classification.

Last, we also repeat our analyses from Sections 3.2 and 3.3 in two subgroups of borrowers that likely prefer fintech services, i.e, High-FICO borrowers and refinancing borrowers. High-FICO borrowers are defined as borrowers whose FICO scores are in the top decile for the origination year. The results for high-FICO borrowers reported in Panel A of Table 7, indeed confirm that fintech shadow banks are able to charge high-FICO borrowers a premium. Moreover, we show that high-FICO borrowers are sensitive to technology as they are only willing to pay a premium for fintech shadow banks with high digital capital. Reported in Panel B in Table 7, the coefficient of $High\ DC\ Fintech$ ($Low\ DC\ Fintech$) is positive (negative), suggesting that refinancing borrowers value (discount) fintech shadow banks that have invested heavily (little) in digital capital. In addition, compared to traditional bank loans, the bad performance of fintech loans is also largely driven by fintech shadow banks with low digital capital. Notably, loans originated by high-DC fintech shadow banks perform better among borrowers who value the fintech service more (i.e., high-FICO borrowers and refinancing borrowers).

4 Further discussions

4.1 Pay for convenience?

The traditional lending model relies on loan officers interacting with borrowers. The soft information collected through customer interaction plays a key role in facilitating better loan service and origination decisions (Petersen (2004), Agarwal and Hauswald (2010)). Unlike traditional banks, fintech lenders automate the application process and make it available entirely online (Berg et al. (2020)).[23] Literature has suggested several reasons why borrowers may choose fintech lenders over traditional banks, such as convenience and shorter processing time.

In this section, we directly test the value of fintech lending using local bank concentration as a direct measure of borrowers' willingness to pay for convenience. The idea is that borrowers living in regions with fewer bank branches would probably find themselves more constrained in obtaining mortgage services. As a result, borrowers in such underserved regions should be more likely to choose fintech lenders given that the latter can provide services entirely online.

To test this hypothesis, we interact the log number of bank branches at the 3-digit zip code level with the fintech dummy. As shown in Table 8, the coefficient of the interaction term is negative and significant, suggesting that fintech shadow banks indeed charge higher rates in regions with less concentrated branches. Moreover, we find that the price premium charged by fintech shadow banks in underserved regions drops over time when we compare the coefficient estimates of the interaction term in the late period (2016–2020) to those in the early period (2010–2015). The finding is likely due to the fact that traditional banks also started to offer online services later on in the sample period.[24]

[23] For example, Rocket Mortgage (formerly known as Quicken Loans) emphasizes on its website that "Convenient online access makes it easy to achieve your financial and homeownership goals". (https://www.rocketmortgage.com/).

[24] For example, Bank of America launched its Digital Mortgage Experience to guide clients through the mortgage process via the bank's mobile app in 2017. For more details, please see https://www.bizjournals.com/charlotte/news/2018/04/11/bank-of-america-launches-digital-mortgage.html.

4.2 Financial inclusion over time

A long-standing discussion among academics and policymakers regards the high cost and limited availability of credit for minority borrowers. The emergence of fintech lending may help alleviate the issue as it shifts the mortgage process from man to machine.[25] Indeed, the summary statistics of Home Mortgage Disclosure Act (HMDA) data displayed in Panel A of Table 9 reflect that minority borrowers exhibit much stronger demand for fintech lenders than for traditional banks.[26] Panel A of Figure IA.8 further reveals that minority borrowers' demand for fintech lenders has been increasing steadily over time. This high demand possibly reflects the fact that minority borrowers view fintech firms as less biased lenders from which they are more likely to obtain access to credit.

While systematically examining the role of fintech lenders in reducing racial discrimination is beyond the scope of this paper, at a glance, it seems that fintech lenders have been accommodating minority borrowers' high credit demand. Specifically, Panel B of Table 9 documents that approximately 34% of loans originated by fintech shadow banks are to minority borrowers in comparison to 22% of those originated by traditional banks over the past decade. In addition, Panel B of Figure IA.8 exhibits that fintech shadow banks have significantly increased their fraction of loans to nonwhite borrowers from approximately 25% in 2010 to over 40% in 2020 while this figure for traditional banks has remained relatively stable at 22% over the past decade.

However, further analysis of mortgage approval data unveils the reason for this improvement in financial inclusion among fintech lenders. As documented in Figure 7, fintech shadow banks did not begin to approve minority borrowers at a much higher rate until later in the sample period. If fintech shadow banks indeed entered the market with disruptive technology capable of better processing alternative data, we should observe that

[25] Several recent works have contributed to this discussion. For example, Bartlett et al. (2022) find that algorithmic lenders do reduce rate disparities by over a third. Similarly, Di Maggio et al. (2022) show that the underwriting model of Upstart Network, a fintech platform, improves credit inclusion by funding borrowers who would otherwise have been rejected by traditional financial institutions. However, decision-making relying purely on algorithms can also lead to inadvertent discrimination. For example, Fuster et al. (2022) find that more sophisticated statistical techniques, such as machine learning, while better predicting the probability of mortgage default, can impose more severe financial exclusion on Black and Hispanic borrowers.

[26] Minority demand is measured as the ratio of minority borrowers' application volume over the number of total applications.

they started extending more credit to minority borrowers from their time of entry. Instead, the evidence suggests that fintech lenders began to strategically approve more credit to underserved minority groups, among whom direct competition from traditional banks is mild, as a way to maintain a market presence in the later sample period. One adverse consequence of doing so is higher credit risk, as the marginal applications approved by the fintech shadow banks are more likely unqualified. Such strategic adjustment casts further doubt on whether fintech shadow banks truly offer innovative technology.

5 Conclusion

This paper explores the emergence of fintech in the mortgage lending market over the past decade. While fintech shadow banks were able to charge a higher loan price than traditional banks without incurring a higher default rate in the early 2010s, this price premium has been shrinking quickly and even completely reversed in recent years.

We find two joint forces that help to explain this pattern. On the one hand, surprisingly, we uncover that fintech shadow banks lack technological advantages, given that most of them have never produced patents. Additionally, using technology-related employment to proxy for intangible digital capital, we yield a similar conclusion: fintech shadow banks underinvest in tech-related talent acquisition, accounting for only approximately 2.5% of their total employment. On the other hand, traditional banks have responded strongly by significantly increasing both their patent output and their intangible digital capital, thus outcompeting their fintech counterparts over time.

Highlighting the importance of technological innovation, we present evidence suggesting that fintech shadow banks investing heavily in digital capital can better withstand the competition from traditional banks in terms of loan price and loan performance. The effect is strongest among high-FICO borrowers, and refinancing borrowers, who value fintech services most. Further analysis reveals that the marginal benefit of investing in additional digital capital is significantly higher for fintech lenders, stressing the fact that their innovation activity is currently suboptimal in comparison to that of traditional banks.

The costly postcrisis regulatory burden on traditional banks and the unique business model of entirely online processing may have given fintech shadow banks a temporary edge early on. However, their price premium from providing convenient services alone is not sustainable, as traditional banks started to offer online services later on as well. We also find that over time, fintech shadow banks have expanded their customer base to underserved minority borrowers, among whom the direct competition from traditional banks is mild. While these efforts improve financial inclusion, one potential consequence is increased credit risk, as the marginal applications approved by the fintech lenders are more likely unqualified. Such strategic adjustment casts further doubts on whether fintech shadow banks truly offer innovative technology.

Importantly, our results highlight a new framework to study how technology can eventually reshape traditional industries. Instead of fintech startups outgrowing incumbents, it is more likely to be the case that existing leaders respond to the wake-up call sent from those fintech startups and then alter their business models by adopting, acquiring, and inventing innovative technologies. We believe the framework that we document in this paper can shed light on other financial sectors that are currently exposed to fintech.

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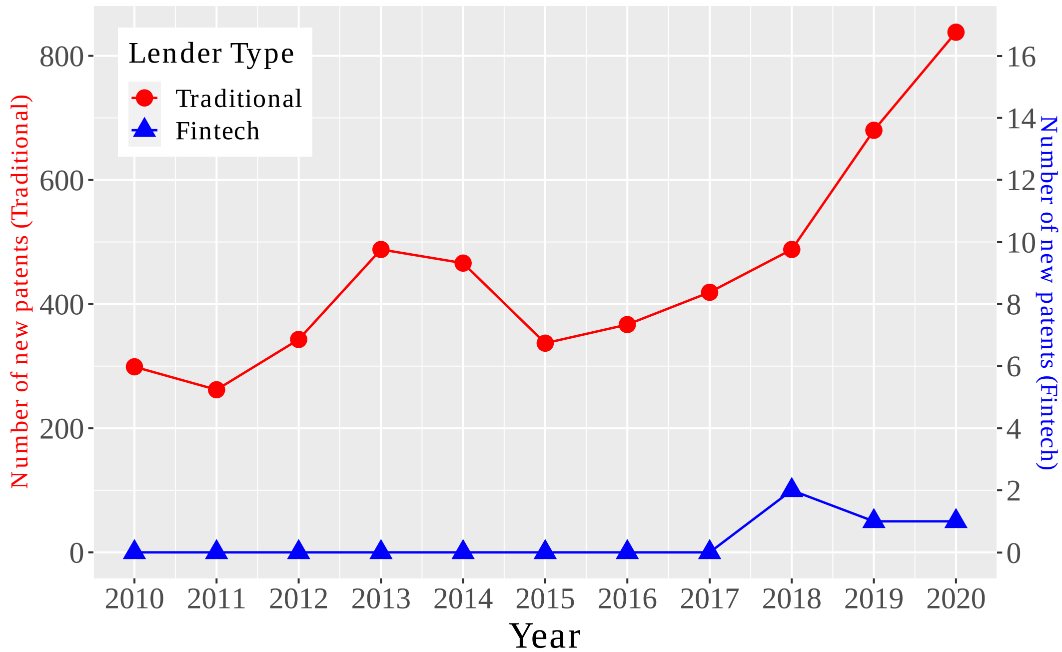


Figure 1: **Patents over time (HMDA)**

Figure 1 plots the annual number of new patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Patent data are obtained from the USPTO.

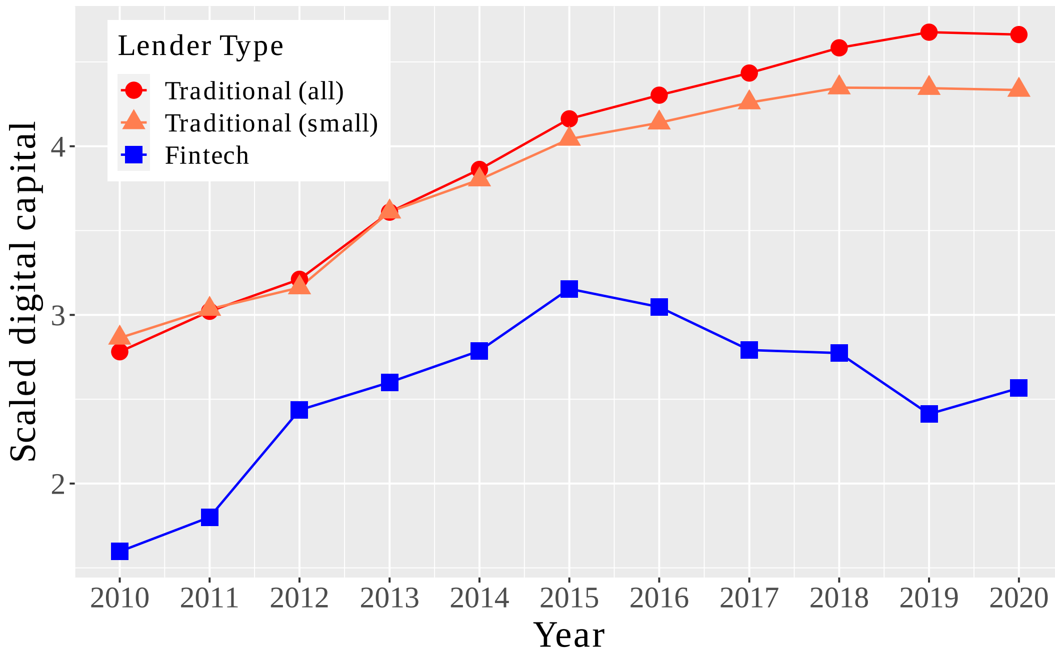


Figure 2: **Scaled digital capital over time (HMDA)**

Figure 2 plots the average annual scaled digital capital of fintech shadow banks, all traditional banks, and small traditional banks (i.e., banks with fewer than 1,000 employees on LinkedIn). We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Scaled digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any of the following keywords: [IT, data, software, database, programmer, intelligence, computer]) over the total number of employees identified on LinkedIn.

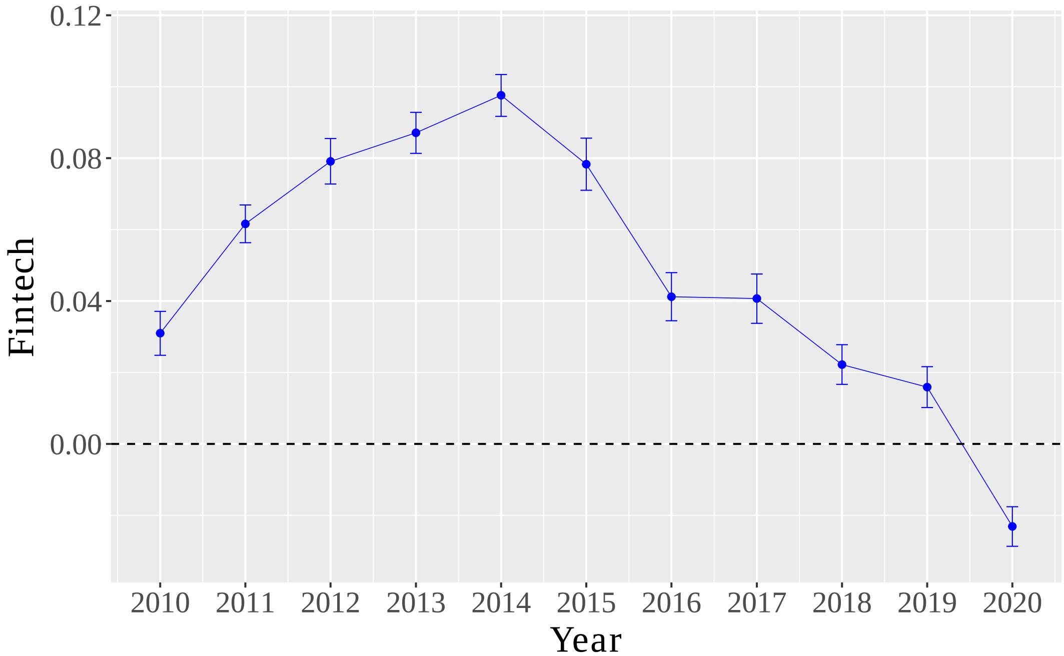
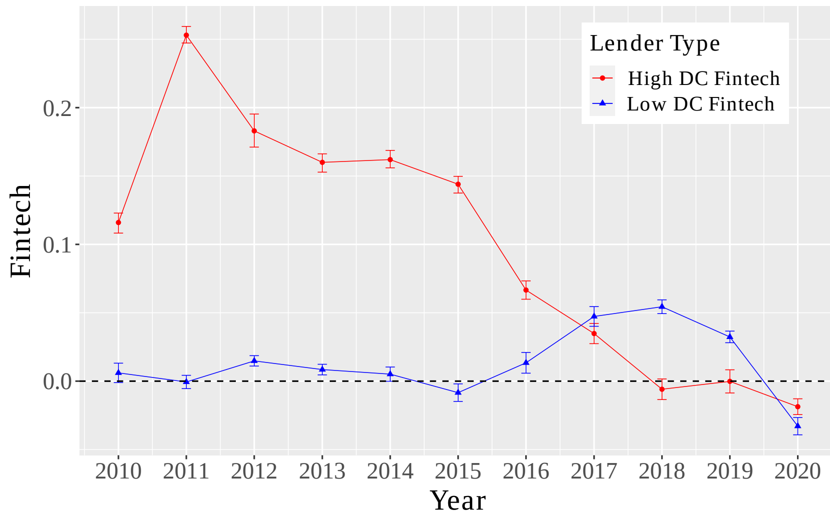
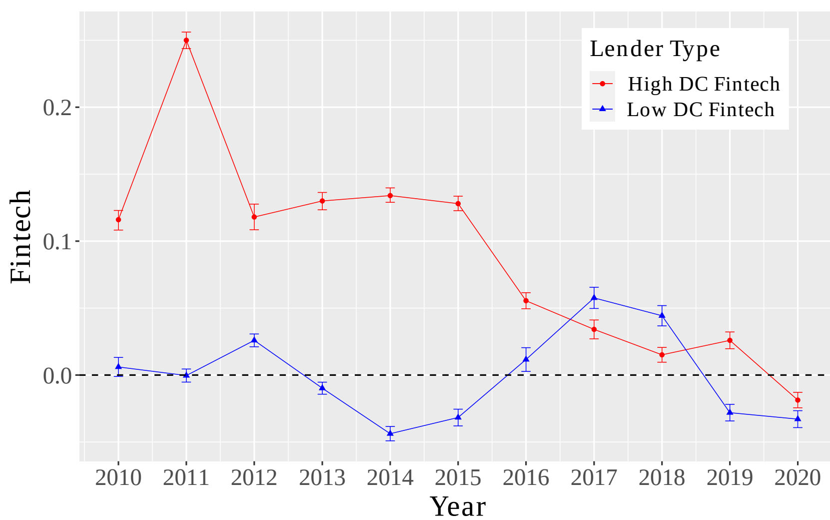


Figure 3: **Loan price over time**

Figure 3 plots the coefficient of $Fintech_j$ (i.e., β_1) by estimating the following regression for each year: $Loan\,Price_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Price$ is the loan rate at origination (in percent); $Fintech$ is a dummy variable equal to 1 if the loan is originated by a fintech shadow bank; X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan amount, term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator, and insurance indicator. Definitions of all control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from FMFM. The error bars denote 95% confidence intervals.



(a) Mean of $Ln(1 + DC)$ as cutoff



(b) Mean of $Scaled\ DC$ as cutoff

Figure 4: **Effects of digital capital on loan price over time**

Figure 4 plots coefficients of $High\ (Low)\ DC\ Fintech$ (i.e., β_1 (β_2)) by estimating the following regression (traditional banks as the benchmark) for each year: $Loan\ Price_{i,j,z,t} = \alpha + \beta_1 High\ DC\ Fintech_j + \beta_2 Low\ DC\ Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Price$ is the loan rate at origination (in percent); $High\ (Low)\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has digital capital above (below) the mean across all fintech lenders; X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan amount, term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator and insurance indicator. Panels (a) and (b) use $Ln(1+DC)$ and $Scaled\ DC$ as the measure of digital capital, respectively. Definitions of control variables and digital capital measures are detailed in Table 2 and Table 1, respectively. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from FMFM, and the employee data used to construct digital capital are manually collected from LinkedIn. The error bars denote the corresponding 95% confidence intervals.

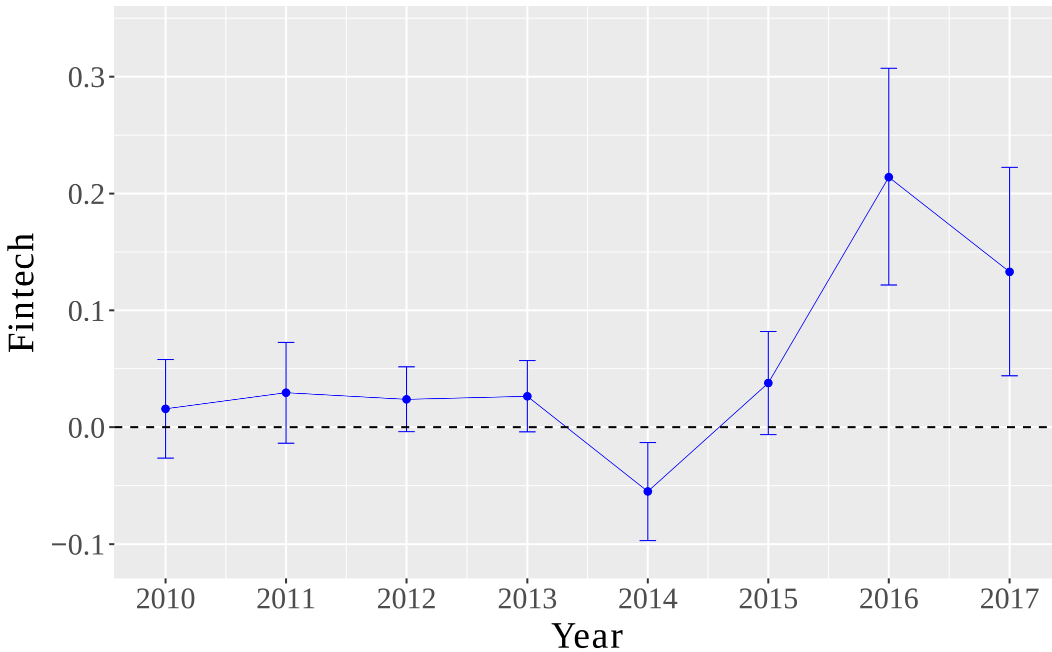
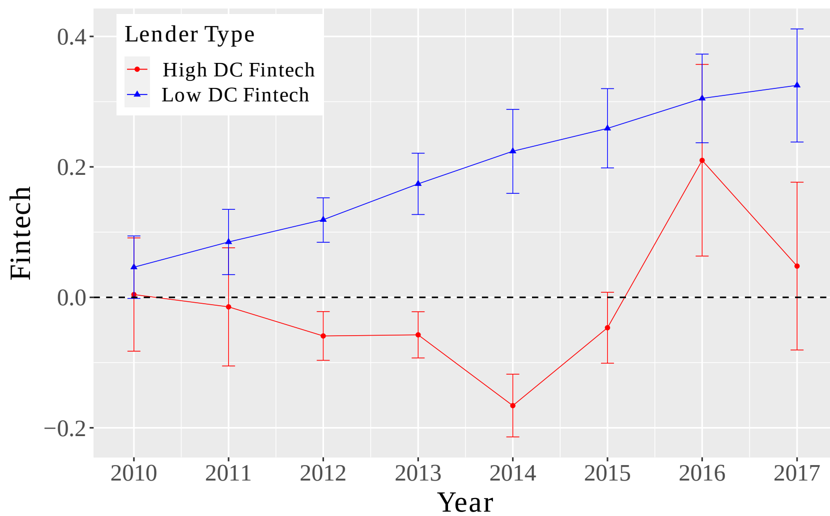
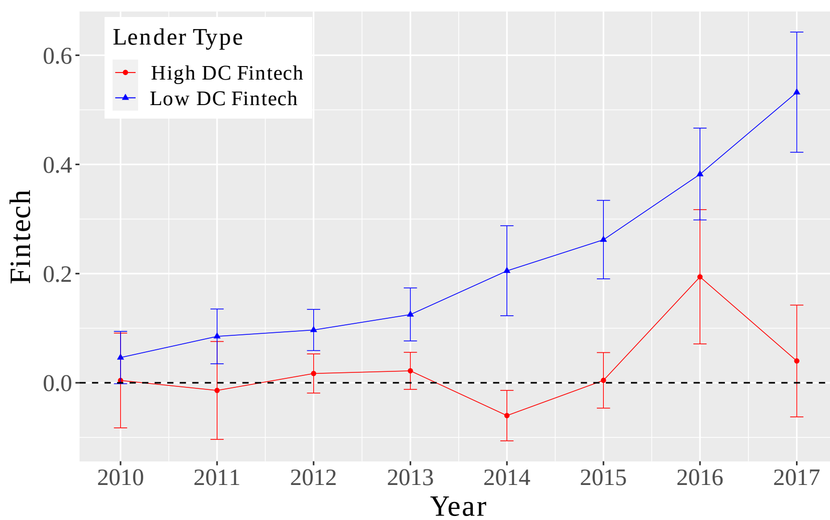


Figure 5: **Loan performance over time**

Figure 5 plots the coefficient of $Fintech$ (i.e., β_1) by estimating the following regression for each year: $Loan\,Default_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Default$ is a binary variable equal to 100 if a mortgage is delinquent at least two consecutive months within two years of its origination; $Fintech$ lender is a dummy variable taking value of 1 if the loan is originated by a fintech shadow bank; X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan price, loan amount, term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator, and insurance indicator. Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from FMFM . The error bars denote the corresponding 95% confidence intervals.



(a) Mean of $Ln(1 + DC)$ as cutoff



(b) Mean of $Scaled\ DC$ as cutoff

Figure 6: **Effects of digital capital on loan default over time**

Figure 6 plots the coefficients of $High$ (Low) DC $Fintech$ (i.e., β_1 (β_2)) by estimating the following regression (with traditional banks as the benchmark) for each year: $Loan\,Default_{i,j,z,t} = \alpha + \beta_1 High\,DC\,Fintech_j + \beta_2 Low\,DC\,Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Default$ is a binary variable equal to 100 if a mortgage is delinquent at least two consecutive months within two years of its origination; $High$ (Low) DC $Fintech$ is dummy variable taking value of 1 if the loan is originated by a fintech shadow bank with digital capital above (below) the mean of all fintech lenders; and X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan amount, term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator, and insurance indicator. Panels (a) and (b) use $Ln(1 + DC)$ and $Scaled\ DC$ as the measure of digital capital, respectively. Definitions of control variables and digital capital measures are detailed in Table 2 and Table 1, respectively. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from FMFM, and the employee data used to construct digital capital are manually collected from LinkedIn. The error bars denote the corresponding 95% confidence intervals.

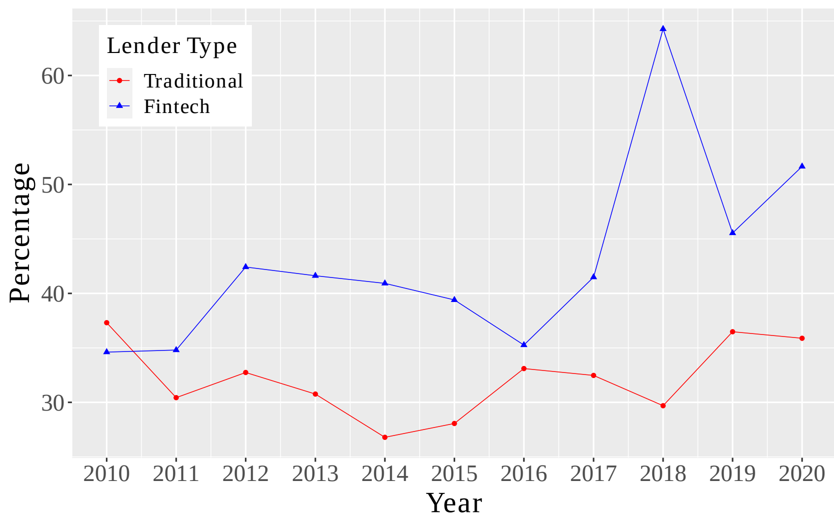


Figure 7: **Impact of fintech on HMDA minority loans in acceptance rate**

Figure 7 reports the annual acceptance rate of minority loans by fintech shadow banks and traditional banks from 2010 to 2020. The acceptance rate of minority loans is defined as the number of originated loans for minority borrowers over the minority borrower application volume. Minority borrowers are defined as borrowers whose reported race is nonwhite. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Mortgage application and origination data are obtained from HMDA.

Table 1: **Summary statistics for patents and digital capital over 2010–2020**

This table reports the summary statistics of innovation proxies for all lenders, fintech shadow banks, and traditional banks from 2010 to 2020. The number of observations, mean, min, max, and standard deviation of the following variables are displayed: *# of new patent* is the number of new patents granted to each lender; *Has-new-patent* is a dummy variable equal to 1 if a lender obtains at least one new patent in a given year; $Ln(1+DC)$ is the logarithm of one plus digital capital; $Scaled\ DC$ is the digital capital scaled by the total number of employees (in percent). Digital capital is measured as the number of tech-related employees (i.e., employees with job positions containing any word in [IT, data, software, database, programmer, intelligence, computer]). We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Patent data are obtained from the USPTO, and the employee data used to construct digital capital are manually collected from LinkedIn.

Panel A: HMDA lenders

	All lenders						Fintech shadow bank				Traditional bank				Subsample Difference	
	Obs.	Mean	Median	Min	Max	STD	Obs.	Mean	Median	STD	Obs.	Mean	Median	STD	Mean	t-statistics
# of new patent	2,904	1.72	0.00	0.00	432.00	19.51	407	0.01	0.00	0.12	2,497	2.00	0.00	21.03	1.99*	1.91
Has-new-patent	2,904	0.04	0.00	0.00	1.00	0.20	407	0.01	0.00	0.09	2,497	0.05	0.00	0.21	0.04***	3.76
$Ln(1+DC)$	2,904	2.65	2.48	0.00	9.37	1.87	407	2.04	1.79	1.59	2,497	2.75	2.64	1.89	0.71***	7.17
$Scaled\ DC$ (%)	2,904	3.74	2.53	0.00	40.74	4.09	407	2.54	1.54	3.32	2,497	3.94	2.72	4.17	1.39***	6.41

Panel B: FMFM lenders

	All lenders						Fintech shadow bank				Traditional bank				Subsample Difference	
	Obs.	Mean	Median	Min	Max	STD	Obs.	Mean	Median	STD	Obs.	Mean	Median	STD	Mean	t-statistics
# of new patent	385	11.76	0.00	0.00	432.00	52.04	143	0.03	0.00	0.20	242	18.69	0.00	64.70	18.66***	3.45
Has-new-patent	385	0.18	0.00	0.00	1.00	0.39	143	0.02	0.00	0.14	242	0.28	0.00	0.45	0.26***	6.70
$Ln(1+DC)$	385	4.48	4.09	0.00	9.37	2.26	143	3.78	3.64	1.35	242	4.89	4.67	2.58	1.11***	4.79
$Scaled\ DC$ (%)	385	4.44	3.53	0.00	21.72	3.66	143	3.66	2.43	4.02	242	4.9	4.24	3.36	1.24***	3.25

Table 2: **Summary statistics for all variables over 2010–2020**

This table reports the summary statistics of FMFM loan origination data for all lenders, fintech shadow banks, and traditional banks from 2010 to 2020. The number of observations, mean, min, max, and standard deviation of the following variables are displayed: *Loan price* is the origination rate in percent; *Loan default* is a binary variable equal to 100 if a mortgage is delinquent for at least two consecutive months within two years of its origination; *loan amount* is the amount of money on the loan at origination (in thousands); *Loan term* is the loan term at origination (in months); *FICO* is the borrower's raw FICO score at origination; *OLTV* is the ratio of the loan amount over the property value (in percent); *DTV* is the ratio of the borrower's monthly debt over her monthly income (in percent); *investment/second* is a dummy variable equal to 1 if the loan property occupancy status at origination is classified as a second home or an investment property; *Refinance* is a dummy variable equal to 1 if the loan purpose is to refinance; *FTHB* is a dummy variable equal to 1 if the borrower of the loan qualifies as a first-time home buyer; *Insurance* is a dummy variable equal to 1 if mortgage insurance is attached to the loan. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2.

	All lenders					Fintech shadow bank					Traditional bank				
	Obs.	Mean	Min	Max	STD	Obs.	Mean	Min	Max	STD	Obs.	Mean	Min	Max	STD
Loan price (%)	18,258,918	3.97	1.62	7.25	0.70	4,896,163	3.78	1.75	6.62	0.76	13,362,755	4.04	1.62	7.25	0.67
Loan default (%)	12,511,420	0.63	0.00	100.00	7.88	2,132,765	0.94	0.00	100.0	9.64	10,378,655	0.56	0.00	100.00	7.47
Loan amount (000s)	18,258,918	234.79	7.00	1403.00	116.58	4,896,163	247.96	11.00	1403.00	116.77	13,362,755	229.97	7.00	1403.00	116.14
Term (month)	18,258,918	309.06	60.0	551.0	80.81	4,896,163	309.08	85.00	366.00	79.52	13,362,755	309.06	60.00	551.00	81.28
FICO	18,252,553	759.02	431.00	850.00	43.46	4,895,209	753.83	527.00	844.00	45.78	13,357,344	760.92	431.00	850.00	42.42
OLTV (%)	18,258,918	70.65	1.00	96.00	17.17	4,896,163	70.57	2.00	96.00	16.68	13,362,755	70.68	1.00	96.00	17.35
DTV (%)	18,254,519	33.16	1.00	65.00	9.71	4,895,687	34.10	1.00	64.00	9.58	13,358,832	32.81	1.00	65.00	9.73
Investment/Second	18,258,918	0.11	0.00	1.00	0.32	4,896,163	0.10	0.00	1.00	0.30	13,362,755	0.12	0.00	1.00	0.32
Refinance	18,258,918	0.56	0.00	1.00	0.50	4,896,163	0.66	0.00	1.00	0.47	13,362,755	0.52	0.00	1.00	0.50
FTHB	18,258,820	0.14	0.00	1.00	0.34	4,896,155	0.10	0.00	1.00	0.30	13,362,665	0.15	0.00	1.00	0.36
Insurance	18,258,918	0.20	0.00	1.00	0.40	4,896,163	0.21	0.00	1.00	0.41	13,362,755	0.19	0.00	1.00	0.39

Table 3: **Loan price competition over time: Fintech shadow bank vs. traditional bank**

This table shows the results of eq. (1) using Fannie Mae and Freddie Mac loans from 2010 to 2020. The dependent variable is the $Loan\,Price$, which is the raw loan origination rate (in percent). $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Dependent variable	$Loan\ Price$		
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
$Fintech$	0.035***	0.077***	0.010
	(3.94)	(10.40)	(1.17)
Loan amount	-0.190***	-0.167***	-0.225***
	(-31.50)	(-39.00)	(-32.45)
Loan term (Months)	0.003***	0.004***	0.003***
	(27.55)	(28.96)	(16.17)
Borrower Credit Score at Origination	-0.002***	-0.002***	-0.002***
	(-25.02)	(-34.79)	(-19.79)
Original Loan to Value Ratio (LTV)	0.003***	0.003***	0.004***
	(18.32)	(19.81)	(14.20)
Debt-To-Income (DTI)	0.002***	0.002***	0.002***
	(22.70)	(19.40)	(16.45)
Investment/Secondary property	0.328***	0.293***	0.375***
	(29.51)	(24.31)	(34.16)
Refinance	0.099***	0.092***	0.100***
	(11.61)	(6.90)	(12.39)
First-time buyer	-0.009***	-0.006**	-0.011*
	(-2.89)	(-2.31)	(-2.09)
Has mortgage insurance	-0.018*	0.030***	-0.058***
	(-1.97)	(5.84)	(-6.97)
Zip $\times$ Year-quarter FE	Yes	Yes	Yes
R^2	0.816	0.800	0.819
Observations	18,247,961	9,721,509	8,526,452

Table 4: **Loan price competition with digital capital: Fintech shadow bank vs. traditional bank**

This table shows the results of eqs. (1) to (3) using Fannie Mae and Freddie Mac loans from 2010 to 2020. The dependent variable is the $Loan\,Price$, which is the raw loan origination rate (in percent). $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $High$ (Low) $Ln(1+DC)$ $Fintech$ or $Scaled\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has a corresponding measure of digital capital above (below) the average across all fintech lenders. $Ln(1+DC)$ is the logarithm of one plus digital capital, and $Scaled\ DC$ is the digital capital scaled by total number of employees (in percent). Digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any word in [IT, data, software, database, programmer, intelligence, computer]). Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p<0.05,^{**}p<0.01,^{***}p<0.001$.

Dependent variable	$Loan\,Price$				
	(1)	(2)	(3)	(4)	(5)
$Fintech$	0.035***		-0.032		-0.024
	(3.94)		(-1.35)		(-1.42)
$High\ Ln(1+DC)\ Fintech$		0.054***			
		(3.71)			
$Low\ Ln(1+DC)\ Fintech$		0.013**			
		(2.03)			
$Ln(1+DC)$			-0.001		
			(-1.24)		
$Fintech \times\ Ln(1+DC)$			0.012**		
			(2.40)		
$High\ Scaled\ DC\ Fintech$				0.052***	
				(4.44)	
$Low\ Scaled\ DC\ Fintech$				-0.000	
				(-0.01)	
$Scaled\ DC$					-0.005***
					(-4.26)
$Fintech \times Scaled\ DC$					0.009***
					(4.33)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.816	0.816	0.816	0.816	0.816
Observations	18,247,961	18,247,961	18,247,961	18,247,961	18,247,961

Table 5: **Loan performance competition over time: Fintech shadow bank vs. traditional bank**

This table shows the results of eq. (4) using Fannie Mae and Freddie Mac loans from 2010 to 2020. The dependent variable is $Loan\ Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$.

Dependent variable	$Loan\ Default$		
Sample period	Full (2010–2017)	Early (2010–2013)	Late (2014–2017)
	(1)	(2)	(3)
$Fintech$	0.081**	0.013	0.100**
	(2.70)	(1.66)	(2.38)
Original Interest Rate	0.632***	0.426***	0.860***
	(9.59)	(9.98)	(11.14)
Loan amount	-0.139***	-0.174***	-0.097**
	(-7.76)	(-18.39)	(-2.86)
Loan term (Months)	-0.001***	-0.000**	-0.002***
	(-4.40)	(-2.61)	(-7.35)
Borrower Credit Score at Origination	-0.015***	-0.011***	-0.018***
	(-15.56)	(-16.02)	(-15.05)
Original Loan to Value Ratio (LTV)	0.001	0.001***	-0.000
	(1.39)	(3.62)	(-0.18)
Debt-To-Income (DTI)	0.011***	0.009***	0.015***
	(11.79)	(9.70)	(12.28)
Investment/Secondary property	-0.334***	-0.192***	-0.526***
	(-8.27)	(-11.93)	(-10.06)
Refinance	0.023	0.061*	-0.079***
	(1.04)	(2.10)	(-3.13)
First-time buyer	0.015	-0.034**	0.034
	(0.78)	(-2.33)	(1.17)
Has mortgage insurance	0.198***	0.059***	0.274***
	(5.72)	(4.53)	(6.55)
Borrower and loan controls	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes
R^2	0.021	0.011	0.027
Observations	12,502,438	7,474,845	5,027,593

Table 6: **Loan performance competition with digital capital: Fintech shadow bank vs. traditional bank**

This table shows the results of eqs. (4) to (6) using Fannie Mae and Freddie Mac loans from 2010 to 2020. The dependent variable is the $Loan\ Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $High\ (Low)\ Ln(1+DC)\ Fintech$ or $Scaled\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has a corresponding measure of digital capital above (below) the average across all fintech lenders. $Ln(1+DC)$ is the logarithm of one plus digital capital, and $Scaled\ DC$ is the digital capital scaled by total number of employees (in percent). Digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any word in [IT, data, software, database, programmer, intelligence, computer]). Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$.

Dependent variable	$Loan\ Default$				
	(1)	(2)	(3)	(4)	(5)
$Fintech$	0.081**		0.527***		0.255***
	(2.70)		(3.59)		(3.92)
$High\ Ln(1+DC)\ Fintech$		-0.059			
		(-1.24)			
$Low\ Ln(1+DC)\ Fintech$		0.212***			
		(8.65)			
$Ln(1+DC)$			0.000		
			(0.10)		
$Fintech \times\ Ln(1+DC)$			-0.083**		
			(-2.67)		
$High\ Scaled\ DC\ Fintech$				-0.021	
				(-0.58)	
$Low\ Scaled\ DC\ Fintech$				0.253***	
				(6.31)	
$Scaled\ DC$					0.001
					(0.35)
$Fintech \times Scaled\ DC$					-0.020**
					(-2.54)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.021	0.021	0.021	0.021	0.021
Observations	12,502,438	12,502,438	12,502,438	12,502,438	12,502,438

Table 7: **Loan price and performance competition: High-FICO and refinancing borrowers**

This table shows the competition pattern of loan price (Panel A) and performance (Panel B) between fintech shadow banks and traditional banks for high- and low-FICO loans. High-FICO (low-FICO) loans are defined as loans applied for by borrowers whose FICO scores are in the top (bottom) decile. In Panel A, the dependent variable is $Loan\,Price$, which is the raw loan origination rate (in percent). In Panel B, the dependent variable is $Loan\,Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $High$ (Low) $Ln(1+DC)$ $Fintech$ or $Scaled\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has a corresponding measure of digital capital above (below) the average across all fintech lenders. $Ln(1+DC)$ is the logarithm of one plus digital capital, and $Scaled\ DC$ is the digital capital scaled by total number of employees (in percent). Digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any word in [IT, data, software, database, programmer, intelligence, computer]). Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from Fannie Mae and Freddie Mac, and the employment data used to construct digital capital are manually collected from LinkedIn. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p<0.05,^{**}p<0.01,^{***}p<0.001$.

Panel A: High-FICO Sample

Dependent variable	*Loan Price*					*Loan Performance*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Fintech$	0.032***		-0.067***		-0.043**	0.037***		0.190***		0.080**
	(2.64)		(-2.76)		(-2.41)	(3.31)		(3.37)		(2.35)
$High\ Ln(1+DC)\ Fintech$		0.058***					-0.007			
		(2.93)					(-0.45)			
$Low\ Ln(1+DC)\ Fintech$		0.005					0.075***			
		(0.53)					(5.37)			
$Ln(1+DC)$			-0.002					0.001		
			(-1.67)					(0.61)		
$Fintech \times\ Ln(1+DC)$			0.017***					-0.029**		
			(3.02)					(-2.74)		
$High\ Scaled\ DC\ Fintech$				0.053***					0.006	
				(3.46)					(0.42)	
$Low\ Scaled\ DC\ Fintech$				-0.011					0.083***	
				(-1.23)					(4.15)	
$Scaled\ DC$					-0.007***					-0.000
					(-6.64)					(-0.12)
$Fintech \times Scaled\ DC$					0.012***					-0.005
					(6.57)					(-1.13)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip × Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.834	0.835	0.834	0.835	0.835	0.027	0.027	0.027	0.027	0.027
Observations	1,706,176	1,706,176	1,706,176	1,706,176	1,706,176	1,183,984	1,183,984	1,183,984	1,183,984	1,183,984

Panel B: Refinace Sample										
Dependent variable			*Loan Price*					*Loan Default*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Fintech$	0.023*		-0.074***		-0.059***	0.082**		0.521***		0.363***
	(1.71)		(-3.46)		(-2.83)	(2.05)		(3.65)		(3.71)
$High\ Ln(1+DC)\ Fintech$		0.048***					-0.055			
		(2.58)					(-1.13)			
$Low\ Ln(1+DC)\ Fintech$		-0.022***					0.265***			
		(-2.65)					(5.48)			
$Ln(1+DC)$			-0.002					-0.003		
			(-1.52)					(-1.39)		
$Fintech \times\ Ln(1+DC)$			0.016***					-0.081***		
			(3.37)					(-2.79)		
$High\ Scaled\ DC\ Fintech$				0.043**					-0.037	
				(2.60)					(-0.88)	
$Low\ Scaled\ DC\ Fintech$				-0.026***					0.313***	
				(-2.82)					(4.89)	
$Scaled\ DC$					-0.006***					-0.003
					(-4.93)					(-0.94)
$Fintech \times Scaled\ DC$					0.013***					-0.030***
					(5.92)					(-3.17)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.821	0.821	0.821	0.821	0.821	0.025	0.025	0.025	0.025	0.025
Observations	10,252,708	10,252,708	10,252,708	10,252,708	10,252,708	6,980,218	6,980,218	6,980,218	6,980,218	6,980,218

Table 8: **Loan price competition over time: High versus low bank concentration**

This table shows the impact of bank concentration on the competition pattern between fintech shadow banks and traditional banks. The dependent variable is $Loan\,Price$, which is the raw loan origination rate (in percent). $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $Ln(1 + Branch)$ is defined as logarithm of one plus the number of branches within a zip-3 code area. Definitions of control variables are detailed in Table 2. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Loan origination data are from Fannie Mae and Freddie Mac, and branch distribution data are provided by Federal Financial Institution Examination Council. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$.

Dependent variable		$Loan\ Price$	
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
$Fintech$	0.098***	0.152***	0.049**
	(4.99)	(4.65)	(2.40)
$Ln(1 + Branch)$	0.021***	0.022***	0.019***
	(6.80)	(7.53)	(4.71)
$Fintech \times Ln(1 + Branch)$	-0.012***	-0.015**	-0.007*
	(-3.46)	(-2.63)	(-1.79)
Borrower and loan controls	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
R^2	0.809	0.792	0.814
Observations	18,247,997	9,721,528	8,526,469

Table 9: **Summary statistics for HMDA data over 2010–2020**

This table compares loan characteristics of HMDA data between fintech shadow banks and traditional banks for the applied loan sample (Panel A) and the loan origination sample (Panel B) from 2010 to 2020. Loan characteristics reported include *Borrower race*, *Borrower gender*, *Loan purpose*, *Loan type*, *Action taken*, *Borrower income*, and *Loan amount*. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2.

Panel A: Applied loan sample

	Fintech Sample			Traditional Bank Sample		
Time period	2010–2020	2010–2015	2016–2020	2010–2020	2010–2015	2016–2020
	(1)	(2)	(3)	(4)	(5)	(6)
Borrower race						
White	59.49%	63.69%	55.41%	68.02%	68.61%	65.96%
Nonwhite	40.51%	36.31%	44.59%	31.98%	31.39%	34.04%
Borrower gender						
Female	24.22%	23.35%	25.06%	24.56%	23.89%	26.85%
Loan purpose						
Purchase	31.90%	28.76%	34.96%	34.74%	33.09%	40.45%
Improvement	0.51%	0.32%	0.70%	6.60%	5.40%	10.75%
Refinancing	67.33%	70.92%	63.83%	57.00%	61.50%	41.37%
Loan type						
Conventional	66.78%	67.70%	65.89%	78.04%	75.98%	85.20%
FHA	21.36%	22.69%	20.08%	14.48%	16.41%	7.75%
VA	10.50%	8.36%	12.58%	5.76%	5.67%	6.09%
FSA/RHS	1.35%	1.24%	1.46%	1.72%	1.94%	0.96%
Action taken						
Approved/Origianted	53.55%	53.57%	53.52%	46.04%	45.56%	47.69%
Other characteristics						
Income (000s)	$103.71	$102.86	$104.51	$120.21	$114.00	$141.34
Loan amount (000s)	$233.57	$219.51	$247.24	$220.53	$209.35	$259.31
Observations	21,569,317	10,637,278	10,932,039	94,290,390	73,190,205	21,100,185

Panel B: Originated loan sample						
	Fintech Sample			Traditional Bank Sample		
Time period	2010–2020	2010–2015	2016–2020	2010–2020	2010–2015	2016–2020
	(1)	(2)	(3)	(4)	(5)	(6)
Borrower race						
White	67.25%	73.07%	61.58%	77.70%	78.36%	75.50%
Nonwhite	32.75%	26.93%	38.42%	22.30%	21.64%	24.50%
Borrower gender						
Female	26.30%	25.77%	26.81%	26.11%	25.42%	28.41%
Loan purpose						
Purchase	32.54%	29.70%	35.31%	31.57%	28.67%	41.19%
Improvement	0.45%	0.26%	0.63%	5.93%	4.70%	9.99%
Refinancing	66.75%	70.04%	63.54%	61.29%	66.63%	43.62%
Loan type						
Conventional	71.48%	70.55%	72.38%	84.72%	83.31%	89.39%
FHA	18.12%	20.66%	15.65%	8.83%	10.27%	4.05%
VA	9.42%	7.55%	11.23%	5.52%	5.42%	5.85%
FSA/RHS	0.99%	1.24%	0.75%	0.94%	1.01%	0.70%
Other characteristics						
Income (000s)	$107.05	$105.13	$108.93	$129.18	$122.29	$151.25
Loan amount (000s)	$241.56	$222.35	$260.27	$230.56	$216.16	$278.28
Observations	11,549,357	5,698,112	5,851,245	43,411,918	33,349,086	10,062,832

Internet Appendix to "Do Fintech Shadow Banks Compete with Technological Advantages? Evidence from Mortgage Lending"

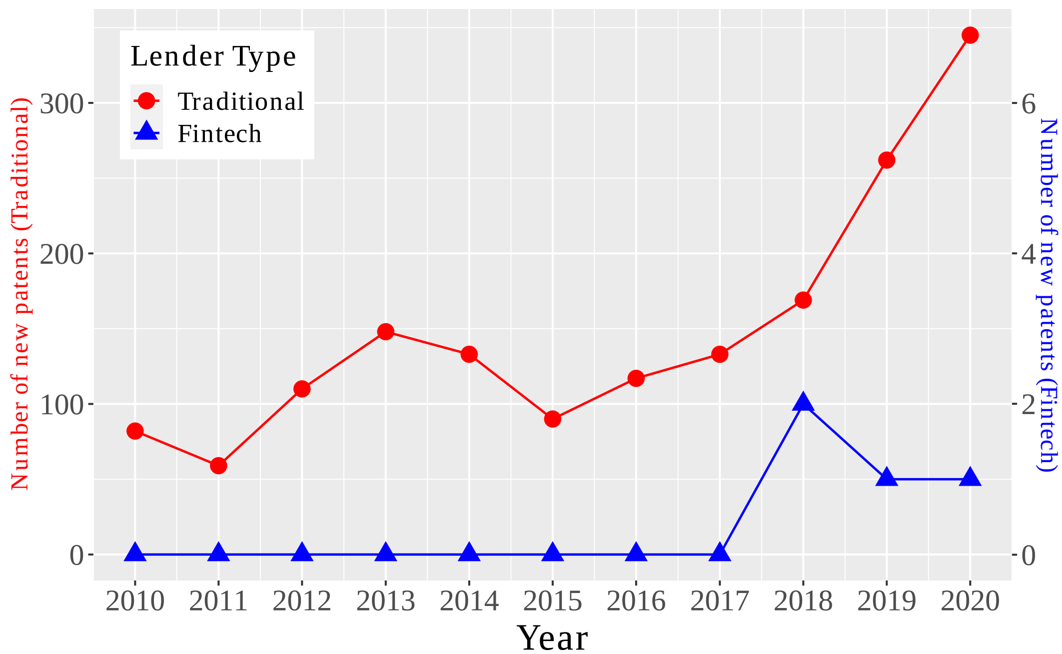


Figure IA.1: **Fintech-Lending-Related patents over time (HMDA)**

Figure IA.1 plots the annual number of new fintech lending–related patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. Fintech lending–related patents are defined as patents whose abstracts contain at least one of the following keywords: [mortgage, lending, data]. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Patent data are obtained from the USPTO.

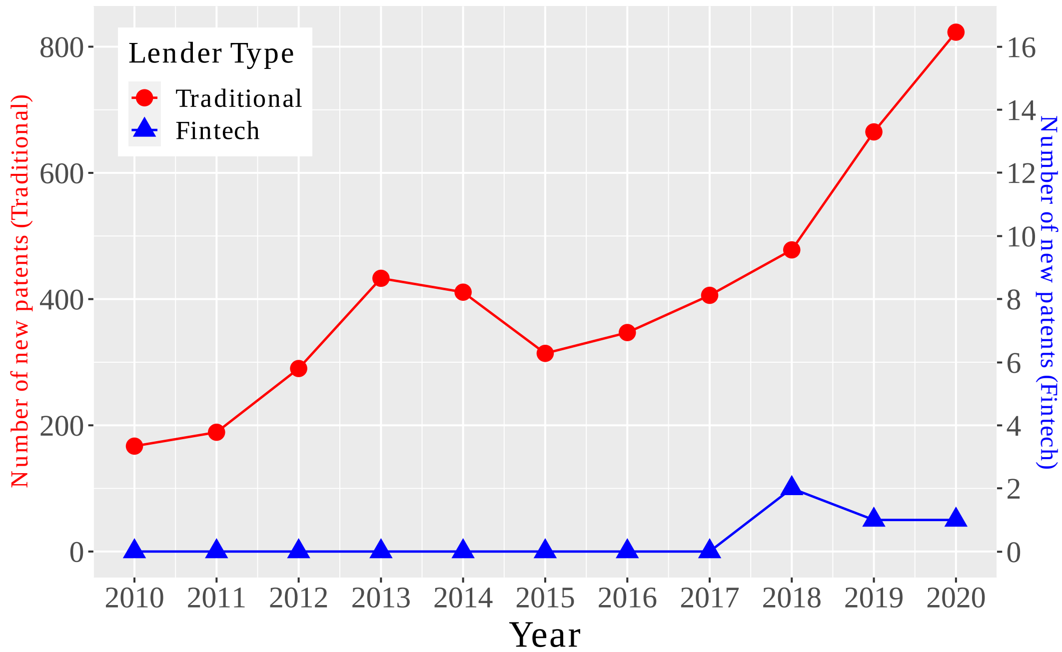


Figure IA.2: **Patents over time (FMFM)**

Figure IA.2 plots the annual number of new patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Patent data are obtained from the USPTO.

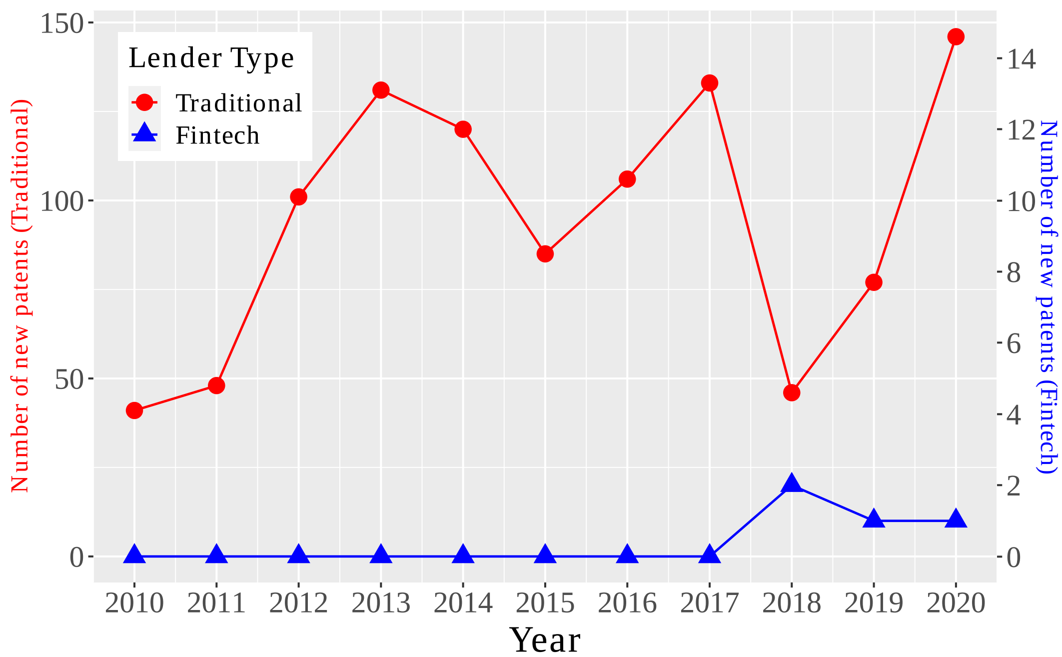


Figure IA.3: **Fintech-Lending-Related patents over time (FMFM)**

Figure IA.3 plots the annual number of new fintech lending–related patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. Fintech lending–related patents are defined as patents whose abstracts contain at least one of the following keywords: [mortgage, lending, data]. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Patent data are obtained from the USPTO.

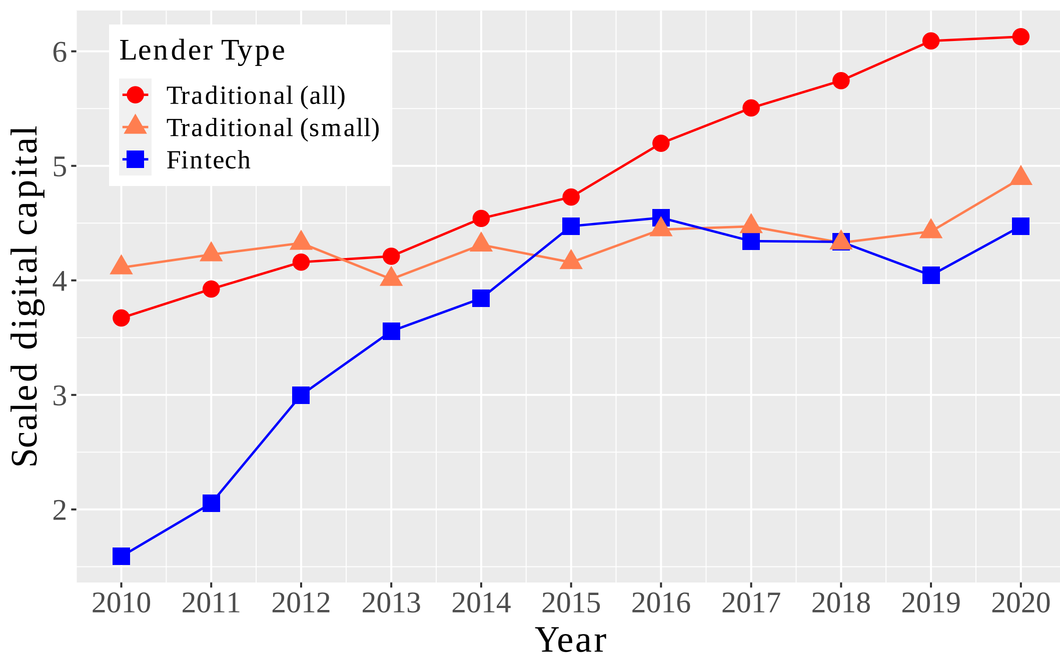


Figure IA.4: **Scaled digital capital over time (FMFM)**

Figure IA.4 plots the average annual scaled digital capital of fintech shadow banks, all traditional banks, and small traditional banks (i.e., banks with fewer than 1,000 employees on LinkedIn). We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Scaled digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any of the following keywords: [IT, data, software, database, programmer, intelligence, computer]) over the total number of employees identified on LinkedIn.

Figure IA.5: **Word cloud of non-tech-related job positions for fintech lenders**

Figure IA.5 plots the l of fintech shadow banks. We follow Buchak et al. (2019) in classifying fintech shadow banks. Non-tech-related job positions are defined as those do not contain any of the following keywords: [IT, DATA, INTERNET, INTELLIGENCE, SOFTWARE, PROGRAMMER, ENGINEER, ANALYST, DEVELOPER, TECHNICIAN, ARCHITECT, SCIENTIST, STRATEGIST, RISK, FRAUD, SOLUTION, AUTOMATION, OPERATION, SPECIALIST, SECURITY, CONTROL, NETWORK, SYSTEM, RESEARCH, SERVER, EXPERT, VIRTUAL, VISUALIZATION, TELECOM, LOGIST, APPLICATION, MACHINE].

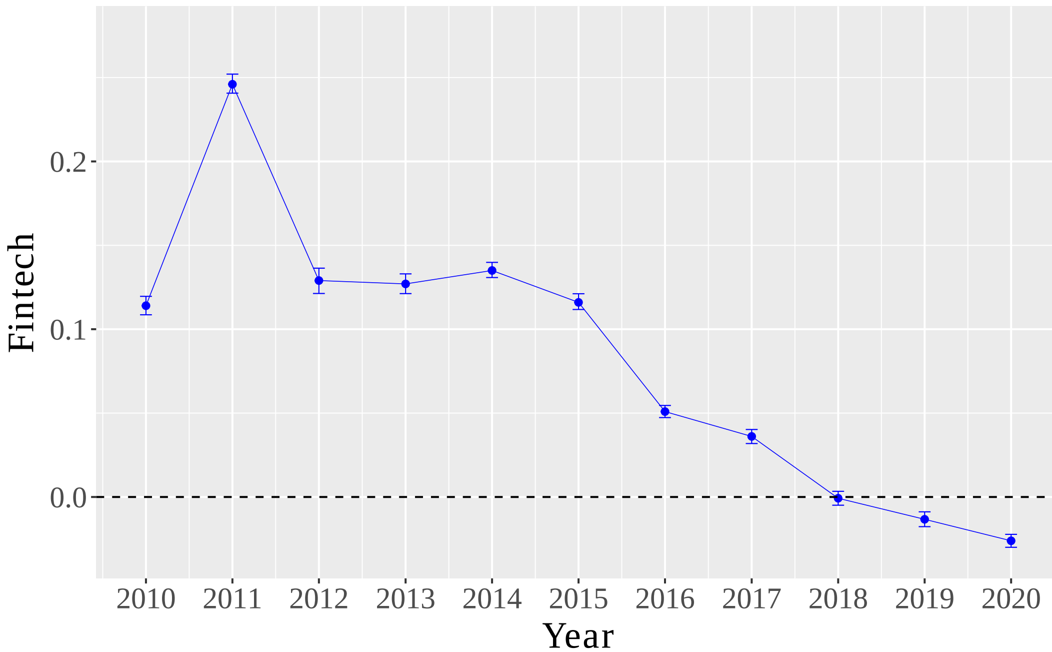


Figure IA.6: **Loan price over time (2017 classification)**

Figure IA.6 plots the coefficient of $Fintech_j$ (i.e., β_1) by estimating the following regression for each year based on the 2017 version of the lender classification in Buchak et al. (2018) (detailed in Table IA.3): $Loan\,Price_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Price$ is the loan rate at origination (in percent); $Fintech$ is a dummy variable equal to 1 if the loan is originated by a fintech shadow bank; X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan amount, loan term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator, and insurance indicator. Definitions of all control variables are detailed in Table 2. Loan origination data are from FMFM . The error bars denote 95% confidence intervals.

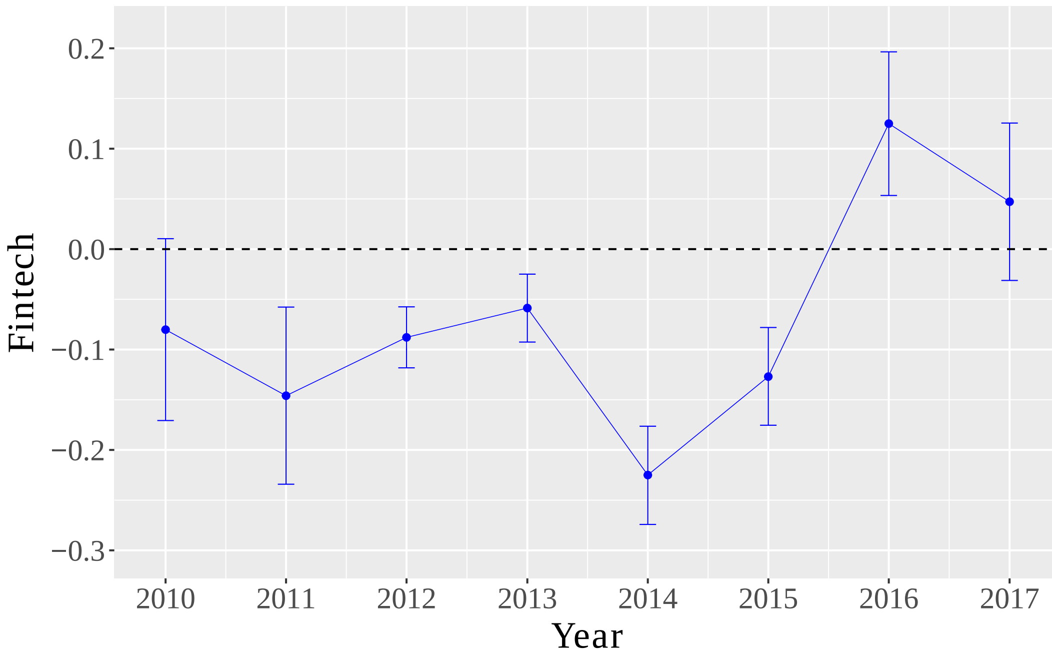
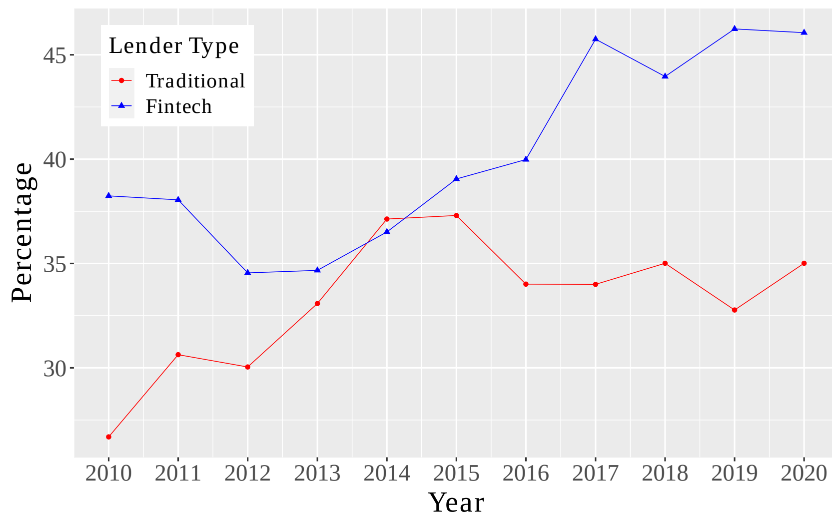
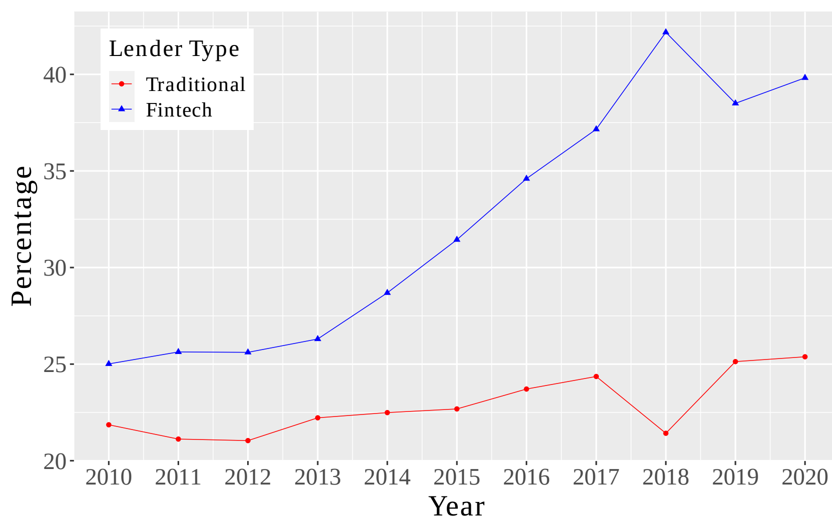


Figure IA.7: **Loan performance over time (2017 classification)**

Figure IA.7 plots the coefficient of $Fintech$ (i.e., β_1) by estimating the following regression for each year based on the 2017 version of the lender classification in Buchak et al. (2018) (detailed in Table IA.3): $Loan\,Default_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$, where $Loan\ Default$ is a binary variable equal to 100 if a mortgage is delinquent at least two months within two years of its origination; $Fintech$ is a dummy variable taking value of 1 if the loan is originated by a fintech shadow bank; X includes quarter by zip code fixed effects and controls for borrower and loan characteristics including loan price, loan amount, term, FICO, OLTV, DTV, investment/second property indicator, refinance indicator, FTHB indicator, and insurance indicator. Definitions of control variables are detailed in Table 2. Loan origination data are from FMFM . The error bars denote the corresponding 95% confidence intervals.



(a) Number of applications by minority borrowers/number of applications by all borrowers



(b) Number of originated loans to minority borrowers/number of originated loans to all borrowers

Figure IA.8: **Impact of fintech on HMDA minority loans applications and originations**

Figure IA.8 reports the time-series pattern of fintech shadow banks and traditional banks on minority mortgage loans from 2010 to 2020. Panel A exhibits the share of loan applied for by minority borrowers, which is a ratio defined as the number of loans applied for by minority borrowers over the application volume for all borrowers. Panel B plots the percentage of originated loans for minority borrowers, which is a ratio defined as the number of originated loans to minority borrowers over the total number of loans originated. Minority borrowers are defined as borrowers whose reported races is nonwhite. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks and provide details in Table IA.2. Mortgage application data are obtained from HMDA.

Table IA.1: HMDA Lenders with patents

This tables lists HMDA traditional banks and fintech shadow banks with patents. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks.

Name	Classification
American Bank	Traditional Bank
Bank of Ann Arbor	Traditional Bank
Bank of America	Traditional Bank
CitiMortgage	Traditional Bank
Citizens Bank	Traditional Bank
Dollar Bank	Traditional Bank
Fifth Third Bank	Traditional Bank
First Niagara Bank	Traditional Bank
Harris Bank	Traditional Bank
HSBC Bank	Traditional Bank
ING Bank	Traditional Bank
J.P. Morgan Chase Bank	Traditional Bank
KeyBank	Traditional Bank
Marshall & Ilsley Bank	Traditional Bank
Morgan Stanley Credit	Traditional Bank
Union Bank	Traditional Bank
People's United Bank	Traditional Bank
PNC Bank	Traditional Bank
Provident Bank	Traditional Bank
Regions Bank	Traditional Bank
San Diego County Credit Union	Traditional Bank
Sovereign Bank	Traditional Bank
Suntrust Bank	Traditional Bank
U.S. Bank	Traditional Bank
Wells Fargo Bank	Traditional Bank
Zions First Bank	Traditional Bank
Quicken Loans	Fintech Shadow Bank

Table IA.2: FMFM Lender classification list (2019 version)

This tables lists all traditional banks and fintech shadow banks included in our sample and their patent grant status over the period from 2010 to 2020. We follow Buchak et al. (2019) in classifying fintech shadow banks and traditional banks.

Traditional Bank		Fintech Shadow Bank	
Name	New patent	Name	New patent
Ally Bank	NO	AmeriSave Mortgage	NO
Bank of America	YES	Cashcall	NO
Branch Banking and Trust	NO	Eagle Home Mortgage	NO
CitiMortgage	NO	Guaranteed Rate	NO
Citizens Bank	NO	Guild Mortgage	NO
Colorado Federal Savings Bank	NO	Impac Mortgage	NO
Fifth Third Bank	YES	LoanDepot	NO
Flagstar Bank Home loans	NO	Movement Mortgage	NO
Fremont Bank	NO	New Penn Financial	NO
HSBC Bank	YES	Newrez	NO
J.P. Morgan Chase Bank	YES	Pennymac Loan Services	NO
MetLife Home Loans	NO	PHH Mortgage	NO
New York Community Bank	NO	Quicken Loans	YES
PNC Bank	YES		
Redwood Credit Union	NO		
Regions Bank	YES		
Sovereign Bank	NO		
Suntrust Bank (including Suntrust Mortgage)	YES		
U.S. Bank	YES		
Union Savings Bank	NO		
USAA Federal Savings Bank	NO		
Wells Fargo Bank	YES		

Table IA.3: FMFM Lender classification list (2017 version)

This tables lists all traditional banks and fintech shadow banks based on the 2017 version of the lender classification in Buchak et al. (2018) and their patent grant status over the period from 2010 to 2020.

Traditional Bank		Fintech Shadow Bank	
Name	New patent	Name	New patent
Ally Bank	NO	Amerisave Mortgage	NO
Bank of America	YES	Cashcall	NO
Branch Banking and Trust	NO	Guaranteed Rate	NO
CitiMortgage	NO	Movement Mortgage	NO
Colorado Federal Savings Bank	NO	Quicken Loans	YES
Fifth Third Mortgage	NO		
Flagstar Bank Home Loans	NO		
Fremont Bank	NO		
HSBC Bank	YES		
J.P. Morgan Chase Bank	YES		
Metlife Home Loans	NO		
New York Community Bank	NO		
PNC Bank	YES		
Redwood Credit Union	NO		
Regions Bank	YES		
USAA Fedral Savings Bank	NO		
Wells Fargo Bank	YES		

Table IA.4: **Loan price and performance competition over time: Fintech shadow banks vs. traditional banks (2017 classification)**

This table shows the competition pattern of loan price and performance over the period from 2010 to 2020 between fintech shadow banks and traditional banks using the 2017 version of the lender classification in Buchak et al. (2018). Panel A reports the results of eq. (1), and the dependent variable is $Loan\,Price$, which is the raw loan origination rate (in percent). Panel B reports the results of eq. (4), and the dependent variable is $Loan\,Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. Definitions of control variables are detailed in Table 2. Loan origination data are from FMFM . All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Panel A: Loan Price Regressions			
Dependent variable		$Loan\ Price$	
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
$Fintech$	0.048***	0.130***	0.003
	(3.92)	(12.17)	(0.34)
Loan amount	-0.195***	-0.171***	-0.235***
	(-30.24)	(-40.37)	(-30.06)
Loan term (Months)	0.003***	0.004***	0.003***
	(29.81)	(29.03)	(17.60)
Borrower Credit Score at Origination	-0.002***	-0.002***	-0.002***
	(-24.97)	(-36.00)	(-19.32)
Original Loan to Value Ratio (LTV)	0.003***	0.003***	0.004***
	(18.55)	(21.40)	(13.53)
Debt-To-Income (DTI)	0.002***	0.002***	0.002***
	(22.70)	(19.15)	(14.84)
Investment/Secondary property	0.324***	0.290***	0.372***
	(28.68)	(23.65)	(33.53)
Refinance	0.104***	0.089***	0.116***
	(11.45)	(6.49)	(15.21)
First-time buyer	-0.008**	-0.007**	-0.009
	(-2.38)	(-2.56)	(-1.52)
Has mortgage insurance	-0.013	0.030***	-0.051***
	(-1.49)	(5.98)	(-5.86)
Zip $\times$ Year-quarter FE	Yes	Yes	Yes
R^2	0.810	0.799	0.814
Observations	15,243,518	8,589,270	6,654,248

Panel B: Loan Performance Regressions			
Dependent variable		$Loan\ Default$	
Sample period	Full (2010–2017)	Early (2010–2013)	Late (2014–2017)
	(1)	(2)	(3)
$Fintech$	-0.029**	-0.093***	-0.019
	(-2.17)	(-8.21)	(-1.11)
Original Interest Rate	0.608***	0.421***	0.836***
	(49.82)	(38.28)	(36.00)
Loan amount	-0.145***	-0.173***	-0.111***
	(-21.07)	(-26.38)	(-7.43)
Loan term (Months)	-0.001***	-0.000***	-0.001***
	(-16.02)	(-4.10)	(-14.72)
Borrower Credit Score at Origination	-0.014***	-0.011***	-0.017***
	(-99.41)	(-90.98)	(-67.96)
Original Loan to Value Ratio (LTV)	0.001***	0.001***	0.001
	(4.49)	(7.79)	(1.53)
Debt-To-Income (DTI)	0.011***	0.010***	0.015***
	(42.73)	(35.58)	(27.66)
Investment/Secondary property	-0.329***	-0.193***	-0.527***
	(-31.54)	(-17.85)	(-27.09)
Refinance	0.030***	0.071***	-0.079***
	(3.88)	(8.39)	(-5.75)
First-time buyer	0.017	-0.037***	0.040**
	(1.61)	(-3.20)	(2.29)
Has mortgage insurance	0.193***	0.059***	0.262***
	(19.52)	(5.79)	(16.56)
Zip × Year-quarter FE	Yes	Yes	Yes
R^2	0.021	0.012	0.028
Observations	10,923,782	6,636,663	4,287,119

Table IA.5: **Role of fintech innovation in loan price and performance competition (2017 classification)**

This table studies the role of fintech innovation in the loan price and performance competition between fintech shadow banks and traditional banks using the 2017 version of the lender classification in Buchak et al. (2018). Panel A reports the results of eqs. (1) to (3), and the dependent variable is $Loan\,Price$, which is the raw loan origination rate (in percent). Panel B reports the results of eqs. (4) to (6), and the dependent variable is $Loan\,Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $High$ (Low) $Ln(1 + DC)$ $Fintech$ or $Scaled\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has a corresponding measure of digital capital above (below) the average across all fintech lenders. $Ln(1 + DC)$ is the logarithm of one plus digital capital, and $Scaled\ DC$ is the digital capital scaled by total number of employees (in percent). Digital capital is defined as the number of tech-related employees (i.e., employees with job positions containing any word in [IT, data, software, database, programmer, intelligence, computer]). Definitions of control variables are detailed in Table 2. Loan origination data are from FMFM, and the employment data used to construct digital capital are manually collected from LinkedIn. The sample period is from 2010 to 2020. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Panel A: Loan Price Regressions

Dependent variable	$Loan\,Price$				
	(1)	(2)	(3)	(4)	(5)
$Fintech$	0.048***		0.032		0.014
	(3.92)		(0.54)		(0.44)
$High\ Ln(1 + DC)\ Fintech$		0.056***			
		(4.10)			
$Low\ Ln(1 + DC)\ Fintech$		-0.004			
		(-0.29)			
$Ln(1 + DC)$			-0.002*		
			(-1.70)		
$Fintech \times\ Ln(1 + DC)$			0.002		
			(0.26)		
$High\ Scaled\ DC\ Fintech$				0.054***	
				(4.04)	
$Low\ Scaled\ DC\ Fintech$				0.010	
				(0.58)	
$Scaled\ DC$					-0.004***
					(-2.73)
$Fintech \times Scaled\ DC$					0.006*
					(1.74)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.810	0.810	0.810	0.810	0.810
Observations	15,243,518	15,243,518	15,243,518	15,243,518	15,243,518

Panel B: Loan Performance Regressions					
Dependent variable			*Loan Default*		
	(1)	(2)	(3)	(4)	(5)
Fintech	-0.029		-0.012		-0.024
	(-0.71)		(-0.07)		(-0.24)
High $Ln(1+DC)$ *Fintech*		-0.045			
		(-0.91)			
Low $Ln(1+DC)$ *Fintech*		0.070^{*}			
		(1.80)			
$Ln(1+DC)$			0.001		
			(0.21)		
Fintech $\times$ $Ln(1+DC)$			-0.003		
			(-0.08)		
High Scaled DC Fintech				-0.042	
				(-0.82)	
Low Scaled DC Fintech				0.039	
				(0.96)	
Scaled DC					0.007^{**}
					(2.15)
Fintech $\times$ *Scaled DC*					-0.005
					(-0.33)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes
R^2	0.021	0.021	0.021	0.021	0.021
Observations	10,923,610	10,923,610	10,923,610	10,923,610	10,923,610

Table IA.6: **Loan price and performance competition: Alternative digital capital construction methods**

This table studies the role of fintech innovation in the loan price and performance competition between fintech shadow banks and traditional banks based on alternative digital capital construction methods. Panel A reports the results of eqs. (1) to (3), and the dependent variable is $Loan\,Price$, which is the raw loan origination rate (in percent). Panel B reports the results of eqs. (4) to (6), and the dependent variable is $Loan\,Default$, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. $Fintech$ is a dummy variable equal to 1 if the loan originator is a fintech shadow bank. $High\ (Low)\ Ln(1+DC)\ Fintech$ or $Scaled\ DC\ Fintech$ is a dummy variable equal to 1 if the loan was originated by a fintech shadow bank that has a corresponding measure of digital capital above (below) the average across all fintech lenders. $Ln(1+DC)$ is the logarithm of one plus digital capital, and $Scaled\ DC$ is the digital capital scaled by total number of employees (in percent). Digital capital is defined as the number of tech-related employees whose positions are either based on the most conservative keyword list, i.e., [IT, DATA], or from the most inclusive keyword list, i.e., [IT, DATA, ANALYST, SPECIALIST, OPERATIONS, ENGINEER, DATA, SYSTEMS, TECHNOLOGY, DEVELOPER, SECURITY, RISK, SOFTWARE, TECHNICIAN, TECHNICAL, NETWORK, SYSTEM, PROGRAM, ARCHITECT, DIGITAL, CONTROL, PROGRAMMER, ANALYTICS, INTELLIGENCE, DATABASE, OPERATOR, COMPUTER]. Definitions of control variables are detailed in Table 2. Loan origination data are from FMFM, and the employment data used to construct digital capital are manually collected from LinkedIn. The sample period is from 2010 to 2020. All columns include quarter by zip code fixed effects. Standard errors are clustered at the zip code and quarter level; t statistics are in parentheses; $^{*}p<0.05,^{**}p<0.01,^{***}p<0.001$.

Panel A: Loan Price Regressions

Dependent variable	*Loan Price*							
	Alternative keyword list 1				Alternative keyword list 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Fintech$		-0.027		-0.020		-0.021		-0.002
		(-1.30)		(-1.38)		(-0.90)		(-0.19)
$High\ Ln(1+DC)\ Fintech$	0.063^{***}				0.053^{***}			
	(4.89)				(3.80)			
$Low\ Ln(1+DC)\ Fintech$	0.007				0.012^{*}			
	(0.95)				(1.80)			
$Ln(1+DC)$		-0.001				-0.001		
		(-1.21)				(-1.31)		
$Fintech \times\ Ln(1+DC)$		0.012^{**}				0.009^{*}		
		(2.57)				(1.91)		
$High\ Scaled\ DC\ Fintech$			0.061^{***}				0.041^{***}	
			(5.19)				(4.05)	
$Low\ Scaled\ DC\ Fintech$			0.005				0.026^{**}	
			(0.68)				(2.30)	
$Scaled\ DC$				-0.011^{***}				-0.004^{***}
				(-5.69)				(-4.88)
$Fintech \times Scaled\ DC$				0.020^{***}				0.005^{***}
				(4.72)				(4.24)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.816	0.816	0.816	0.816	0.816	0.816	0.816	0.816
Observations	18,247,961	18,247,961	18,247,961	18,247,961	18,247,961	18,247,961	18,247,961	18,247,961

Panel B: Loan Performance Regressions								
Dependent variable	*Loan Default*							
	Alternative keyword list 1				Alternative keyword list 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Fintech$		0.390***		0.315***		0.565***		0.222***
		(3.61)		(5.04)		(3.33)		(3.55)
$High\ Ln(1+DC)\ Fintech$	-0.059				-0.046			
	(-1.24)				(-1.02)			
$Low\ Ln(1+DC)\ Fintech$	0.212***				0.220***			
	(8.65)				(8.76)			
$Ln(1+DC)$		0.001				0.001		
		(0.26)				(0.28)		
$Fintech \times\ Ln(1+DC)$		-0.066**				-0.084**		
		(-2.38)				(-2.54)		
$High\ Scaled\ DC\ Fintech$			-0.033				0.050	
			(-0.77)				(1.00)	
$Low\ Scaled\ DC\ Fintech$			0.218***				0.106**	
			(8.10)				(2.52)	
$Scaled\ DC$				0.003				0.002
				(0.62)				(1.28)
$Fintech \times Scaled\ DC$				-0.058***				-0.013**
				(-2.85)				(-2.74)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip $\times$ Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
Observations	12,502,438	12,502,438	12,502,438	12,502,438	12,502,438	12,502,438	12,502,438	12,502,438