

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

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Abstract

This paper examines the supposed technological advantage of fintech shadow banks over traditional banks. Despite fintech's reputation for innovation and cutting-edge technology, traditional banks have invested more in digital capital and generated significantly more patents in the past decade. While fintech shadow banks could charge higher rates initially without higher defaults, this premium has decreased and reversed. However, investing in digital capital can help fintech shadow banks better withstand competition from traditional banks. Finally, fintech shadow banks have been accepting more minority borrower applications in recent years, indicating that they promote financial inclusion to circumvent direct competition from traditional banks.

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

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“[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 Consequently, for example, fintech lenders have 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.

Although fintech firms have firmly established themselves as viable competitors and 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.³ Moreover, the role of technological innovation in shaping the dynamics of the competitive landscape between fintech firms and traditional incumbents remains unexplored as fintech lenders may face challenges in the long run from incentivized mainstream banks adopting fintech to advance their business.⁴ Hence in this paper, we investigate 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 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 264 lenders in HMDA from

¹January 26, 2022, “Fintech Companies, Facing Competition From Mainstream Banks, Step Up Their Offerings”.

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

³In this vein, for example, Fuster et al. (2019) use fintech lenders as a proxy for technology innovators in the mortgage lending market.

⁴For more details, see <https://www.wsj.com/articles/fintech-competition-mainstream-banks-11642714528>.

⁵Throughout the paper, we use “fintech shadow bank” and “fintech lender” interchangeably.

the U.S. Patent and Trademark Office (USPTO) website. Of greatest surprise to us is that from 2010 to 2020, fintech lenders collectively 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 1a 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 (2016)). 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 2 shows that technology-related employees account for only approximately 2.5% of total employment in 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

⁶We 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 1b 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.

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. We conduct loan-level price and performance analysis to test these hypotheses with loans sold to Fannie Mae and Freddie Mac. 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 (i.e., 2010 – 2015), 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. We also repeat the same analysis with Federal Housing Administration-backed loans (hereafter, FHA loans) from Ginnie Mae and find the same results among these riskier loans.

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 empirical analysis using loan-level data from Fannie Mae and Freddie Mac confirms this reasoning. Specifically, fintech shadow banks with a high level of digital capital investment charge at least a 5-basis-point premium over those with low digital capital, while maintaining a 0.21% lower default rate over those with low digital capital. Such effects are more prominent among the group of borrowers likely to value fintech services more. For example, high-FICO borrowers are

shown in the literature to be less price sensitive. They 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 discount to attract those refinancing borrowers who 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 that their innovation activity is currently sub-optimal compared to traditional banks. We also repeat the same analysis with FHA loans from Ginnie Mae and find similar results among refinancing borrowers.

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. \(2018\)](#)). At the same time, 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 a 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

⁷For 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>.

Next, we directly examine whether technological investments help lenders better screen borrowers. [Cornell and Welch \(1996\)](#) argue that better screenings lead to larger dispersion of loan characteristics since banks can utilize their screening ability to give various loans to borrowers with different quality (see also, [Fisman et al. \(2017\)](#)). We use the standard deviation of loan size to capture loan dispersion and find that (1) investments in digital capital significantly increase the dispersion in loan size; (2) fintech shadow banks investing heavily in digital capital are as good at screening borrowers as traditional banks; (3) fintech shadow banks with little investments in digital capital are worse at screening borrowers than traditional banks.

Lastly, we explore whether the pattern of loan price reversal documented in this paper 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 For example, [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

⁸Our paper is also broadly related to the literature on the growth of fintech in consumer credit markets, payments, and small business lending. 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. \(2020\)](#), [Tang \(2019\)](#), [Beaumont et al. \(2022\)](#).

their findings in the early sample period while documenting a reverse trend in recent years. We attribute this pattern to fintech lenders' lack of continuous technological innovation. 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. On the credit supply side, [Jagtiani et al. \(2021\)](#) find fintech lenders have greater market shares in places with lower credit scores and higher mortgage denial rates; [Allen et al. \(2022\)](#) find that fintech lenders are more responsive to increased mortgage demand caused by natural disasters than traditional banks. Compared to the existing literature, 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. To our best 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.

Second, this paper relates to recent works examining banking regulation's effects in the post-crisis era. For example, [DAcunto and Rossi \(2022\)](#) document a substantial mortgage loan redistribution since 2011 due to post-crisis financial regulation. [Begley and Srinivasan \(2022\)](#) show that small banks grew faster than fintech lenders in the mortgage market after big banks retreated due to regulatory burdens. On the corporate loan market, [Irani et al. \(2021\)](#) find that less-capitalized banks reduce loan retention and give non-banks the chance to step in. We also 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.

Third, our paper is also related to the growing strand of literature on the role of fintech in financial inclusion. On the one hand, fintech may help promote financial inclusion through increased competition with incumbents. For example, [Parlour et al. \(2022\)](#) show that fintech competition in payment services promotes financial inclusion at the expense of consumers with a strong bank preference. [Erel and Liebersohn \(2022\)](#) find that fintech is used more in Zip codes with fewer bank branches, lower income, and more minority households (see also, e.g., [Cornelli et al. \(2022\)](#)). On the other hand, fintech may hinder

financial inclusion through statistical or taste-based discrimination, [Fuster et al. \(2022\)](#) find that minority borrowers will be less likely to gain when lenders use machine learning to screen borrowers (see also, e.g., [Bartlett et al. \(2022\)](#)). [Fei \(2021\)](#) find fintech lenders create a more negative rating gap between minority and non-minority borrowers, suggesting taste-based discrimination. We add nuance to the literature by showing suggestive evidence of fintech improving financial inclusion as a result of circumventing direct competition from traditional banks.

Our paper also provides new evidence to complement recent works on how financial technology is reshaping the financial industry. [Jiang, He, Yin, and Xu \(2022b\)](#) show that the entry of fintech prompts banks to invest more in information technologies (see also, e.g., [Vives and Ye \(2021\)](#), [Pierri and Timmer \(2022\)](#)). [Jiang, Yu, and Zhang \(2022a\)](#) find that digital disruption has shifted tech-savvy consumers preference from branch services to digital services. Banks respond by closing costly branches, serving consumers remotely, and exploiting market power on non-tech savvy customers. [Jiang, Tang, Xiao, and Yao \(2021\)](#) 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 over time.

Finally, our paper also adds insight to the innovation literature. Most papers to date study firm innovation activities by utilizing patent-based metrics (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 institution 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 HMDA 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 (here-

after 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

Finally, we extend our loan pricing and performance analysis to FHA loans, which is a riskier segment of the US mortgage market. To this end, we collect monthly loan-level performance data from Ginnie Mae MBS from January 2012 to December 2020 with a focus on FHA loans. Ginnie Mae MBS also details origination and performance records, enabling us to define dependent and control variables in a similar manner as in FMFM data.¹⁰ Merging the lender classification list with the FHA data set equips us with 72 unique lenders, among which are 53 traditional banks and 19 are fintech shadow banks.¹¹

⁹As a robustness check, we validate our main findings in Section 3.4 using the 2017 version of the lender classifications. Table 1 lists lenders and their classifications based on the 2017 version.

¹⁰The construction of binary variable *Loan Default* requires loan delinquency records within two years of origination, so our sample starts from 2012 when complete 24-month records first become available. Following Fuster et al. (2019), we also control for indicators on whether a loan’s loan-to-value ratio or debt-to-income ratio is missing.

¹¹We exclude lenders that set higher bars on credit scores for FHA borrowers. The 72 lenders command a market share greater than 60% among loans securitized into Ginnie Mae MBS.

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.¹² 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.¹³ 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 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 and 3,323 patents granted to 10 out of 35 FMFM lenders¹⁴. 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 \(2016\)](#)). 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.

¹²For a complete list of research datasets provided by the USPTO, see: <https://www.uspto.gov/ip-policy/economic-research/research-datasets>.

¹³The following USPTO website provides all assignment records for each firm: <https://assignment.uspto.gov/patent/index.html>.

¹⁴Table 1 details the lenders in our HMDA and FMFM sample with non-zero patents and their classifications.

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. labor market.¹⁵ 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]*.¹⁶

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 observa-

¹⁵For more details, see <https://www.statista.com/statistics/272783/linkedin-membership-worldwide-by-country>.

¹⁶As 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.

tions 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 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 FMFM sample contains approximately 18.2 million mortgage loans originating during the sample period from January 2010 through December 2020. Table 3 presents the summary statistics of loan characteristics for FMFM loans. 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%).

In the FHA market, fintech shadow banks charge a slightly higher rate than traditional banks do (3.94 % vs 3.90%) while the default rate for fintech loans is 0.83% higher than that for traditional loans, as suggested by Table 13.

The evidence from the two markets 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 refinancing borrowers.

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 the 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 1a 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 in 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, reaching 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.¹⁷ 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 intriguing since fintech firms are generally viewed as 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

¹⁷To 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 1b is qualitatively similar to that documented in Figure 1a using the unfiltered patent data.

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, 2016; 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.¹⁸ Table 2 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 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 indicate further 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.¹⁹

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

¹⁸Section 2.3 provides a detailed description of our digital capital measure.

¹⁹One may wonder what non-tech-focused employees fintech lenders hire. Figure IA.4 plots a word cloud of all the non-tech-focused employees hired by fintech lenders. Non-tech-related job positions are defined as those that 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]. Surprisingly, the most popular position is loan officer, suggesting that fintech lenders may not be as different from traditional banks as we thought.

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:

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

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, 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 4, the positive and significant coefficient of *Fintech* 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* in Columns (2) and (3) suggest that the price pre-

mium 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* 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* in Figure 3a. 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* for 2020 even turns negative.²⁰

Table 14 repeats our above analysis with FHA loan data originating from 2012 to 2020. Similarly, we find that fintech shadow banks charged a 2.4 bps higher rate than traditional banks over the last decade, as reported by the positive and significant coefficient of *Fintech* in Column 1 of Table 14. However, the coefficients of *Fintech* in Columns (2) and (3) suggest that the price premium mainly comes from the early period (2011–2015). More importantly, the coefficient of *Fintech* in Column (3) becomes insignificant, suggesting that fintech lenders were not able to charge price premiums in the late period (2016–2020). These results confirm that our above findings also existed in riskier loans.

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

²⁰Table IA.1 and Figure IA.2a report qualitatively similar results using the 2017 classification list, thus verifying that our findings are not sensitive to the choice of classification method.

in the long run.²¹ 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:

$$\begin{aligned} \text{Loan Price}_{i,j,z,t} = & \alpha + \beta_1 \text{High DC Fintech}_{j,t} + \beta_2 \text{Low DC Fintech}_{j,t} \\ & + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \quad (2)$$

where $\text{Loan Price}_{i,j,z,t}$ is the interest rate of mortgage i originated by lender j in zip code z at time t , $\text{High DC Fintech}_{j,t}$ 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 $\text{Low DC Fintech}_{j,t}$ 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, $\text{Digital Capital}_{j,t}$ 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.

Columns (2) and (4) of Table 5 report the regression results of Equation (2) using $\text{Ln}(1+\text{DC})$ 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* and *Low DC Fintech* based on $\text{Ln}(1+\text{DC})$ (or *Scaled DC*). We find that fintech lenders' pricing edge has been shrinking in recent years, even for those actively

²¹Figures IA.1a and IA.3 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 1a and 2.

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* 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:

$$\begin{aligned} \text{Loan Price}_{i,j,z,t} = & \alpha + \beta_1 \text{Fintech}_j + \beta_2 \text{Digital Capital}_{j,t} \\ & + \beta_3 \text{Fintech}_j \times \text{Digital Capital}_{j,t} + X_{i,t} \Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \quad (3)$$

where $\text{Loan Price}_{i,j,z,t}$ 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; $\text{Digital Capital}_{j,t}$ 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 $\text{Fintech} \times \text{Digital Capital}$ (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 5 reject the null hypothesis. Instead, we find that the coefficient of $\text{Fintech} \times \text{Digital Capital}$ (β_3) is positive and significant using either $\text{Ln}(1+DC)$ 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.

One concern of using FMFM data is that it only identifies the largest 50 lenders for all the loans sold to Fannie Mae and Freddie Mac. To mitigate this concern, we also repeat our above analysis with originated loans in HMDA that cover all types of purchased loans (e.g., FHA, VA, USDA, and FMFM) and identify all lenders. HMDA started to make the price information publicly available in 2018. Panel A of Table 12 reports the price regression results using HMDA loan data originating from 2018 to 2020. The negative coefficient estimate of *Fintech* in Column (1) suggests that fintech lenders are offering a cheaper price than traditional banks in the period of 2018–2020. We also decompose the *Fintech* dummy into *High Scaled DC Fintech* and *Low Scaled DC Fintech* based on whether a fintech passes the average level of digital capital investments. Column (2) shows that the coefficient estimate of *Low Scaled DC Fintech* is more negative than that of *High Scaled DC Fintech*, suggesting that innovation plays a positive role in price competition. Further, the positive and significant coefficient of *Fintech* $\times$ *Scaled DC* also suggests that fintech lenders in the HMDA sample are not investing optimally in digital capital. Panel B of 12 repeats the same analysis in Panel A with FMFM loan data from 2018 to 2020.²² The results in Panel B are qualitatively similar to those in Panel A, suggesting that our findings are not driven by changes in specification or the types of loans.

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:

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

where $Loan\ Default_{i,j,z,t}$ measures the default status of mortgage i originated by lender j

²²Unlike FMFM data, HMDA does not disclose borrowers' credit scores and only discloses county-level location information and year-level information. Therefore, the specification in this table does not control for borrowers' credit scores and includes county-by-year fixed effects.

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 6 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 and avoid the covid year 2020. The coefficient of *Fintech* 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* 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* 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 borrower and loan characteristics coefficients in all three regressions are consistent with results from prior literature. For example, the loan-to-value and debt-to-income ratios are positively associated with the loan default rate, while FICO scores negatively predict loan default.²³ To visualize the time trend, we rerun Equation (4) by year and plot the yearly coefficients of *Fintech* in Figure 3b. 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.

Table 15 repeats our above analysis with FHA loan data originating from 2011 to 2020. Similarly, we consider loans made only up to 2017, as we need at least two full years to evaluate the mortgage delinquency status and avoid the covid year 2020. We also find that fintech loans performed worse than traditional bank loans over the last decade, as reported by the positive and significant coefficient of *Fintech* in Column 1 of Table 15. However, the

²³Panel B of Table IA.1 reports the regression results using the 2017 version of lender classification. The coefficient of *Fintech* 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.

coefficients of *Fintech* in Columns (2) and (3) suggest that the loan default rate increased from 0.38% in the early period (2011–2014) to 0.74% in the late period (2015–2017). These results confirm that fintech loans also perform much worse over time in the riskier FHA loan sample.

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:

$$\begin{aligned} \text{Loan Default}_{i,j,z,t} = & \alpha + \beta_1 \text{High DC Fintech}_{j,t} + \beta_2 \text{Low DC Fintech}_{j,t} \\ & + \beta_3 \text{Loan Price}_{i,j,z,t} + X_{i,t} \Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \quad (5)$$

where $\text{Loan Default}_{i,j,z,t}$ 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. $\text{High DC Fintech}_{j,t}$ 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; $\text{Low DC Fintech}_{j,t}$ 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 7 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* are positive and significant, the coefficient of *High DC Fintech* 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 5a (respectively, 5b) display the yearly coefficients of *High DC Fintech* (β_1) and *Low DC Fintech* (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:

$$\begin{aligned} \text{Loan Default}_{i,j,z,t} = & \alpha + \beta_1 \text{Fintech}_j + \beta_2 \text{Digital Capital}_{j,t} \\ & + \beta_3 \text{Fintech}_j \times \text{Digital Capital}_{j,t} \\ & + \beta_4 \text{Loan Price}_{i,j,z,t} + X_{i,t} \Phi + \delta_{z,t} + \epsilon_{i,j,z,t} \end{aligned} \quad (6)$$

where $\text{Loan Default}_{i,j,z,t}$ 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; $\text{Digital Capital}_{j,t}$ 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 7 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 $\text{Fintech} \times \text{Digital Capital}$ (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 fintech shadow banks underinvest in innovation compared to traditional banks.

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, IN-

TELLIGENCE, DATABASE, OPERATOR, COMPUTER]. Table IA.3 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*, *Low DC Fintech*, $Fintech \times Digital Capital$) 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).²⁴ Panel A of Table IA.2 reports the regression results on loan price competition. The coefficient of *Fintech* in Column (1) 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.2a continues to find a similar time trend of loan price competition. Moreover, if we compare the coefficient of *High DC Fintech* to that of *Low DC Fintech* as shown in Columns (2) and (4) of Table IA.2, 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 $Fintech \times Digital Capital$ in Columns (3) and (5) of Table IA.2 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.2, we document qualitatively similar results on loan performance using the 2017 lender classification, except that the coefficient of *Low DC Fintech* 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 8, 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 8, 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

²⁴Table 1 lists all lenders based on the 2017 version of the lender classification list.

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).

Further, we also repeat our analyses from Sections 3.2 and 3.3 with FHA refinance loans. Table 16 reports the loan price results using FHA refinance loan data originating from 2012 to 2020. We also decompose the *Fintech* dummy into *High Scaled DC Fintech* and *Low Scaled DC Fintech* based on whether a fintech passes the average level of digital capital investments. Column (2) shows that the coefficient estimate of *Low Scaled DC Fintech* is less positive than that of *High Scaled DC Fintech*, suggesting that innovation plays a positive role in price competition. Table 17 reports the loan performance results using FHA refinance loan data originating from 2012 to 2017. The coefficient of *High Scaled DC Fintech* in Columns (2) and (4) is negative and statistically significant, while the coefficient of *Low Scaled DC Fintech* in Columns (2) and (4) is positive and statistically significant. These results suggest that loans originated by fintech shadow banks with high digital capital performed better than traditional bank loans, while loans originated by fintech shadow banks with low digital capital performed worse. These results confirm the earlier findings that digital capital investments play an important role in screening refinance borrowers.²⁵

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)).²⁶ Literature has suggested several reasons

²⁵We also did the same analyses for FHA new purchase loans and found the results do not exist for new purchase loans.

²⁶For 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/>).

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 9, 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.²⁷

4.2 Does innovation help improve loan screening?

Cornell and Welch (1996) predict that better screening would increase the dispersion in lending: i.e., loan officers increase the variance of loan characteristics with better signals of borrower quality. We follow the existing literature and use the natural logarithm of the standard deviation of loan size to capture loan dispersion (Fisman et al. (2017), Lim and Nguyen (2021)). To test whether innovation help improves loan screening of mortgage lenders, we regress loan dispersion against our fintech indicators and digital capital measures. Table 10 reports the empirical results. While the coefficients of *High DC Fintech* are positive and insignificant in Columns (1) and (3), the coefficients of *Low DC Fintech* are negative and significant. These results suggest that fintech shadow banks investing heavily in digital capital are as good at screening borrowers as traditional banks. In con-

²⁷For 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>.

trast, fintech shadow banks with little investments in digital capital are worse at screening borrowers than traditional banks. The positive and significant coefficients of $\ln(1+DC)$ and *Scaled DC* in Columns (2) and (4) suggest that investing in digital capital does help lenders more effectively screen borrowers. Lastly, the positive and significant coefficient of $Fintech \times Scaled DC$ in Column (4) suggests that fintech shadow banks are underinvesting in digital capital compared to traditional banks.

4.3 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.²⁸ Indeed, the summary statistics of Home Mortgage Disclosure Act (HMDA) data displayed in Panel A of Table 11 reflect that minority borrowers exhibit much stronger demand for fintech lenders than for traditional banks.²⁹ Panel A of Figure 6 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 11 documents that approximately 34% of loans originated by fintech shadow banks are to minority borrowers compared to 22% of those originated by traditional banks over the past decade. In addition, Panel B of Figure 6 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

²⁸Several 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 traditional financial institutions would have otherwise rejected. 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.

²⁹Minority demand is measured as the ratio of minority borrowers' application volume over the number of total applications.

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 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 regarding loan price and loan performance. The effect is strongest among high-FICO 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 post-crisis 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 similar 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 to increase 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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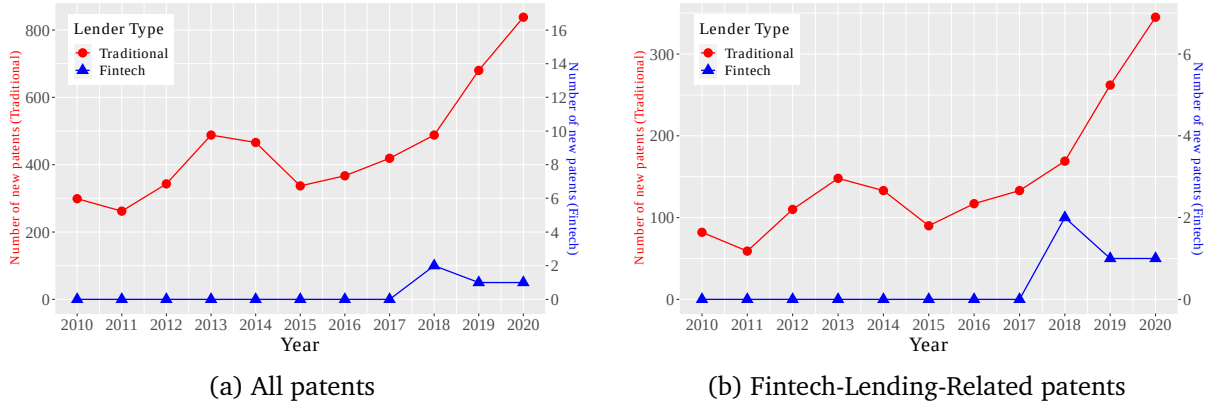


Figure 1: Patents over time (HMDA)

Figure 1a plots the annual number of new patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. Figure 1b 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]. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. Patent data are obtained from the USPTO.

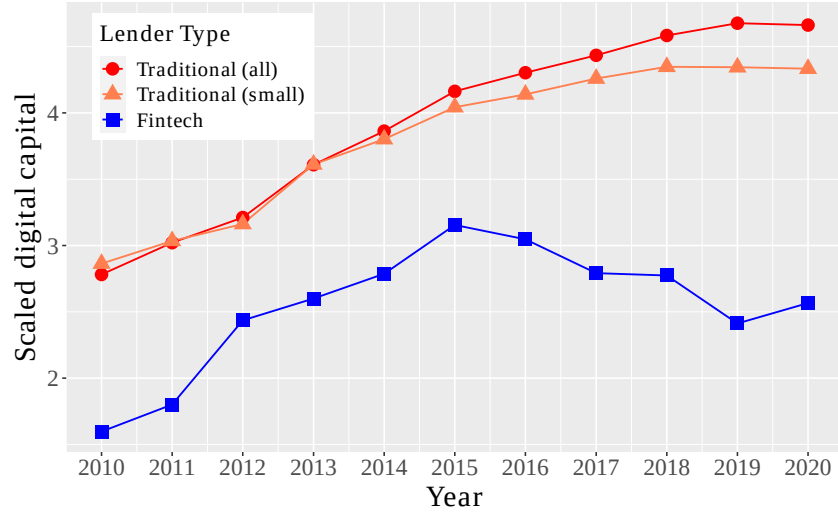
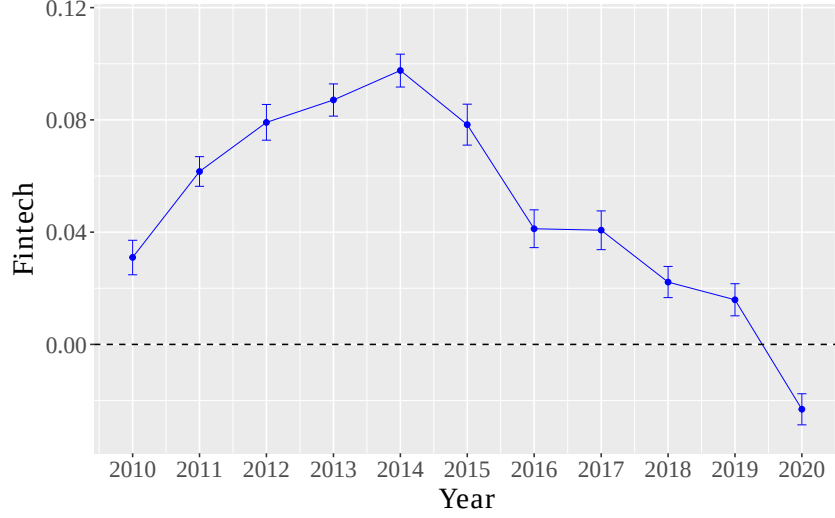
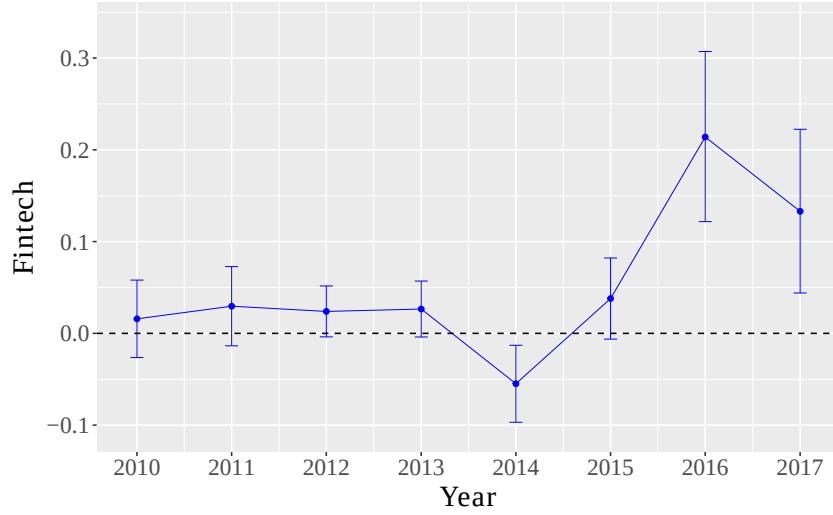


Figure 2: Scaled digital capital over time (HMDA)

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). The classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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, 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]) over the total number of employees identified on LinkedIn.



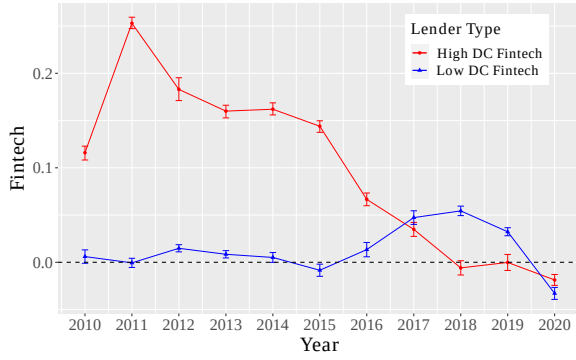
(a) Loan price over time



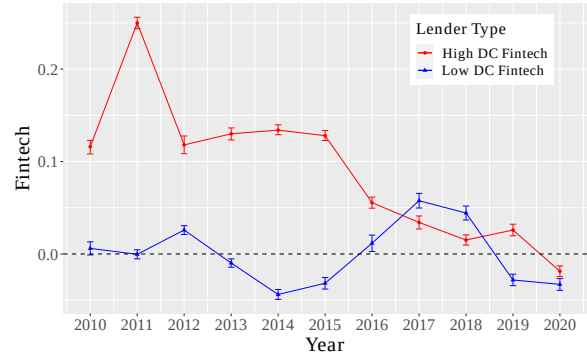
(b) Loan performance over time

Figure 3: Loan price and Performance over time

Figure 3a plots the coefficient of *Fintech* (i.e., β_1) by estimating the following regression for each year: $Loan Price_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Figure 3b plots the coefficient of *Fintech* (i.e., β_1) by estimating the following regression for each year: $Loan Default_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Definitions of all variables are detailed in Table 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. Loan origination data are from FMFM. The error bars denote 95% confidence intervals.



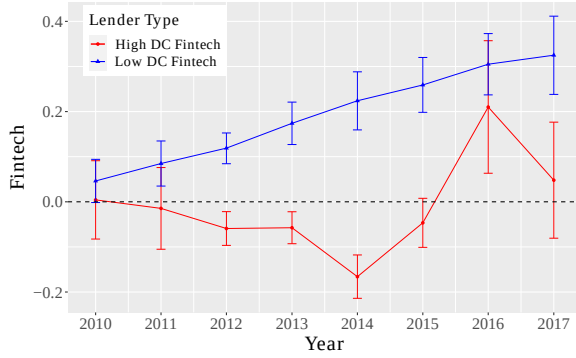
(a) Mean of $\ln(1+DC)$ as cutoff



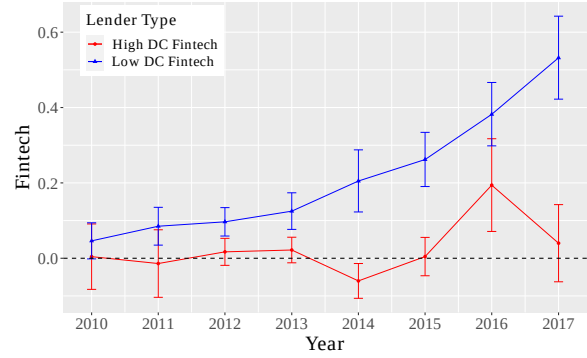
(b) Mean of *Scaled DC* as cutoff

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: $Loan Price_{i,j,z,t} = \alpha + \beta_1 High DC Fintech_j + \beta_2 Low DC Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Definitions of fintech-related variables are detailed in Table 5. 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 3 and Table 2, respectively. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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.



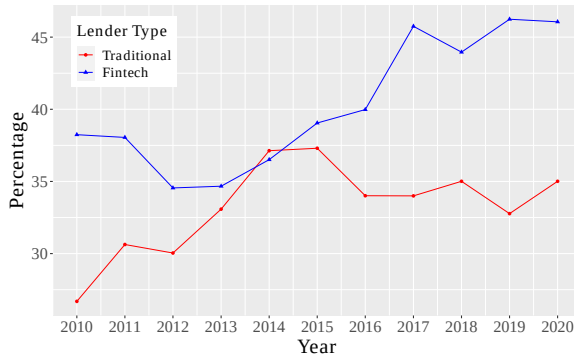
(a) Mean of $\ln(1+DC)$ as cutoff



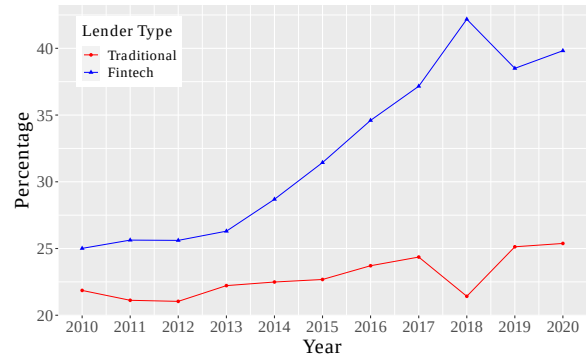
(b) Mean of *Scaled DC* as cutoff

Figure 5: Effects of digital capital on loan default over time

Figure 5 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: $Loan Default_{i,j,z,t} = \alpha + \beta_1 High DC Fintech_j + \beta_2 Low DC Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Definitions of fintech-related variables are detailed in Table 5. 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 3 and Table 2, respectively. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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.



(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 6: Impact of fintech on HMDA minority loans applications and originations

Figure 6 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. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. Mortgage application data are obtained from HMDA.

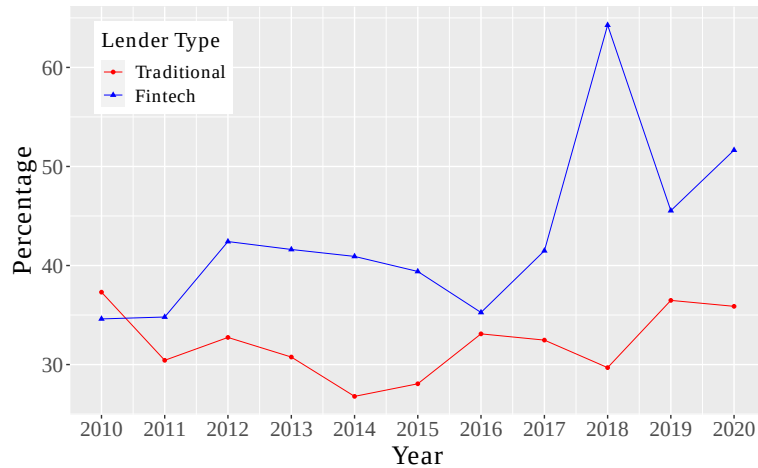


Figure 7: Impact of fintech on HMDA minority loans in acceptance rate

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 non-white. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. Mortgage application and origination data are obtained from HMDA.

Table 1: HMDA Lenders with patents

This table lists HMDA traditional banks and fintech shadow banks with patents. We follow [Buchak et al. \(2019\)](#) in classifying fintech shadow banks and traditional banks. * denotes the list of traditional banks and fintech shadow banks that appear in the FMFM sample based on the 2017 version of the lender classification in [Buchak et al. \(2018\)](#); † denotes the list of traditional banks and fintech shadow banks that appear in the FMFM sample based on the 2019 version of the lender classification in [Buchak et al. \(2019\)](#).

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 2: 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, 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])). The classifications of fintech shadow banks and traditional banks are detailed in Table 1. Patent data are obtained from the USPTO, and the employee data used to construct digital capital are manually collected from LinkedIn.

	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
<i>Panel A: HMDA lenders</i>																
<i># of new patent</i>	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
<i>Has-new-patent</i>	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
<i>Scaled DC (%)</i>	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
<i>Panel B: FMFM lenders</i>																
<i># of new patent</i>	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
<i>Has-new-patent</i>	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
<i>Scaled DC (%)</i>	385	4.44	3.53	0.00	21.72	3.66	143	3.66	2.43	4.02	242	4.90	4.24	3.36	1.24***	3.25
<i>Panel C: FHA lenders</i>																
<i># of new patent</i>	792	5.79	0.00	0.00	432	36.73	209	0.02	0.00	0.17	583	7.86	0.00	42.63	7.84***	2.66
<i>Has-new-patent</i>	792	0.10	0.00	0.00	1.00	0.30	209	0.01	0.00	0.12	583	0.13	0.00	0.34	0.12***	4.91
$\ln(1+DC)$	792	3.48	3.04	0.00	9.37	2.16	209	2.85	2.48	1.53	583	3.71	3.30	2.30	0.85***	4.97
<i>Scaled DC (%)</i>	792	3.89	2.84	0.00	25.00	3.55	209	2.69	1.92	2.95	583	4.32	3.58	3.65	1.64***	5.83

Table 3: Summary statistics for all variables over 2010–2020 (FMFM)

This table reports FMFM loan origination data summary statistics 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. The classifications of fintech shadow banks and traditional banks are detailed in Table 1.

	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	100	7.88	2,132,765	0.94	0	100	9.64	10,378,655	0.56	0	100	7.47
Loan amount (000s)	18,258,918	234.79	7	1403	116.58	4,896,163	247.96	11	1403	116.77	13,362,755	229.97	7	1403	116.14
Term (month)	18,258,918	309.06	60	551	80.81	4,896,163	309.08	85	366	79.52	13,362,755	309.06	60	551	81.28
FICO	18,252,553	759.02	431	850	43.46	4,895,209	753.83	527	844	45.78	13,357,344	760.92	431	850	42.42
OLTV (%)	18,258,918	70.65	1	96	17.17	4,896,163	70.57	2	96	16.68	13,362,755	70.68	1	96	17.35
DTV (%)	18,254,519	33.16	1	65	9.71	4,895,687	34.10	1	64	9.58	13,358,832	32.81	1	65	9.73
Investment/Second	18,258,918	0.11	0	1	0.32	4,896,163	0.10	0	1	0.30	13,362,755	0.12	0	1	0.32
Refinance	18,258,918	0.56	0	1	0.50	4,896,163	0.66	0	1	0.47	13,362,755	0.52	0	1	0.50
FTHB	18,258,820	0.14	0	1	0.34	4,896,155	0.10	0	1	0.30	13,362,665	0.15	0	1	0.36
Insurance	18,258,918	0.20	0	1	0.40	4,896,163	0.21	0	1	0.41	13,362,755	0.19	0	1	0.39

Table 4: 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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; * $p < 0.05$, ** $p < 0.01$, ***

Dependent variable	<i>Loan Price</i>		
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
<i>Fintech</i>	0.035*** (3.94)	0.077*** (10.40)	0.010 (1.17)
Loan amount	-0.190*** (-31.50)	-0.167*** (-39.00)	-0.225*** (-32.45)
Loan term (Months)	0.003*** (27.55)	0.004*** (28.96)	0.003*** (16.17)
FICO	-0.002*** (-25.02)	-0.002*** (-34.79)	-0.002*** (-19.79)
Original Loan to Value Ratio (LTV)	0.003*** (18.32)	0.003*** (19.81)	0.004*** (14.20)
Debt-To-Income (DTI)	0.002*** (22.70)	0.002*** (19.40)	0.002*** (16.45)
Investment/Secondary property	0.328*** (29.51)	0.293*** (24.31)	0.375*** (34.16)
Refinance	0.099*** (11.61)	0.092*** (6.90)	0.100*** (12.39)
First-time buyer	-0.009*** (-2.89)	-0.006** (-2.31)	-0.011* (-2.09)
Has mortgage insurance	-0.018* (-1.97)	0.030*** (5.84)	-0.058*** (-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 5: 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, 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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	<i>Loan Price</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	0.035*** (3.94)		-0.032 (-1.35)		-0.024 (-1.42)
<i>High Ln(1+DC) Fintech</i>		0.054*** (3.71)			
<i>Low Ln(1+DC) Fintech</i>		0.013** (2.03)			
<i>Ln(1+DC)</i>			-0.001 (-1.24)		
<i>Fintech × Ln(1+DC)</i>			0.012** (2.40)		
<i>High Scaled DC Fintech</i>				0.052*** (4.44)	
<i>Low Scaled DC Fintech</i>				-0.000 (-0.01)	
<i>Scaled DC</i>					-0.005*** (-4.26)
<i>Fintech × Scaled DC</i>					0.009*** (4.33)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip × 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 6: **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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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	<i>Loan Default</i>		
Sample period	Full (2010–2017)	Early (2010–2013)	Late (2014–2017)
	(1)	(2)	(3)
<i>Fintech</i>	0.081** (2.70)	0.013 (1.66)	0.100** (2.38)
Original Interest Rate	0.632*** (9.59)	0.426*** (9.98)	0.860*** (11.14)
Loan amount	-0.139*** (-7.76)	-0.174*** (-18.39)	-0.097** (-2.86)
Loan term (Months)	-0.001*** (-4.40)	-0.000** (-2.61)	-0.002*** (-7.35)
FICO	-0.015*** (-15.56)	-0.011*** (-16.02)	-0.018*** (-15.05)
Original Loan to Value Ratio (LTV)	0.001 (1.39)	0.001*** (3.62)	-0.000 (-0.18)
Debt-To-Income (DTI)	0.011*** (11.79)	0.009*** (9.70)	0.015*** (12.28)
Investment/Secondary property	-0.334*** (-8.27)	-0.192*** (-11.93)	-0.526*** (-10.06)
Refinance	0.023 (1.04)	0.061* (2.10)	-0.079*** (-3.13)
First-time buyer	0.015 (0.78)	-0.034** (-2.33)	0.034 (1.17)
Has mortgage insurance	0.198*** (5.72)	0.059*** (4.53)	0.274*** (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 7: 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. Definitions of fintech-related variables are detailed in Table 5. Definitions of control variables are detailed in Table 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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	<i>Loan Default</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	0.081** (2.70)		0.527*** (3.59)		0.255*** (3.92)
<i>High Ln(1+DC) Fintech</i>		-0.059 (-1.24)			
<i>Low Ln(1+DC) Fintech</i>		0.212*** (8.65)			
<i>Ln(1+DC)</i>			0.000 (0.10)		
<i>Fintech × Ln(1+DC)</i>			-0.083** (-2.67)		
<i>High Scaled DC Fintech</i>				-0.021 (-0.58)	
<i>Low Scaled DC Fintech</i>				0.253*** (6.31)	
<i>Scaled DC</i>					0.001 (0.35)
<i>Fintech × Scaled DC</i>					-0.020** (-2.54)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip × 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 8: 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. Definitions of fintech-related variables are detailed in Table 5. Definitions of control variables are detailed in Table 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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 Default				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Fintech</i>	0.032*** (2.64)		-0.067*** (-2.76)		-0.043** (-2.41)	0.037*** (3.31)		0.190*** (3.37)		0.080** (2.35)
<i>High Ln(1+DC) Fintech</i>		0.058*** (2.93)					-0.007 (-0.45)			
<i>Low Ln(1+DC) Fintech</i>		0.005 (0.53)					0.075*** (5.37)			
<i>Ln(1+DC)</i>			-0.002 (-1.67)					0.001 (0.61)		
<i>Fintech × Ln(1+DC)</i>			0.017*** (3.02)					-0.029** (-2.74)		
<i>High Scaled DC Fintech</i>				0.053*** (3.46)					0.006 (0.42)	
<i>Low Scaled DC Fintech</i>				-0.011 (-1.23)					0.083*** (4.15)	
<i>Scaled DC</i>					-0.007*** (-6.64)					-0.000 (-0.12)
<i>Fintech × Scaled DC</i>					0.012*** (6.57)					-0.005 (-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
<i>R</i> 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

<i>Panel B: Refinance Sample</i>										
Dependent variable	<i>Loan Price</i>					<i>Loan Default</i>				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Fintech</i>	0.023* (1.71)		-0.074*** (-3.46)		-0.059*** (-2.83)	0.082** (2.05)		0.521*** (3.65)		0.363*** (3.71)
<i>High Ln(1+DC) Fintech</i>		0.048*** (2.58)					-0.055 (-1.13)			
<i>Low Ln(1+DC) Fintech</i>		-0.022*** (-2.65)					0.265*** (5.48)			
<i>Ln(1+DC)</i>			-0.002 (-1.52)					-0.003 (-1.39)		
<i>Fintech × Ln(1+DC)</i>			0.016*** (3.37)					-0.081*** (-2.79)		
<i>High Scaled DC Fintech</i>				0.043** (2.60)					-0.037 (-0.88)	
<i>Low Scaled DC Fintech</i>				-0.026*** (-2.82)					0.313*** (4.89)	
<i>Scaled DC</i>					-0.006*** (-4.93)					-0.003 (-0.94)
<i>Fintech × Scaled DC</i>					0.013*** (5.92)					-0.030*** (-3.17)
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	0.821	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 9: 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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	<i>Loan Price</i>		
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
<i>Fintech</i>	0.098*** (4.99)	0.152*** (4.65)	0.049** (2.40)
$\ln(1+Branch)$	0.021*** (6.80)	0.022*** (7.53)	0.019*** (4.71)
$Fintech \times \ln(1+Branch)$	-0.012*** (-3.46)	-0.015** (-2.63)	-0.007* (-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 10: **Loan size dispersion and digital capital: Fintech shadow bank vs. traditional bank (HMDA)**

This table shows the regression results of loan size dispersion using HMDA loans from 2010 to 2020. The dependent variable is the natural logarithm of the standard deviation of the loan amount (size). Definitions of fintech-related variables are detailed in Table 5. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include lender and year fixed effects. Standard errors are clustered at the lender level; t statistics are in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Dependent variable	<i>Ln(Loan size standard deviation)</i>			
	(1)	(2)	(3)	(4)
<i>Fintech</i>		-0.046 (-0.97)		-0.186*** (-5.35)
<i>High Ln(1+DC) Fintech</i>	0.083 (1.04)			
<i>Low Ln(1+DC) Fintech</i>	-0.122*** (-6.30)			
<i>Ln(1+DC)</i>		0.082*** (10.61)		
<i>Fintech × Ln(1+DC)</i>		-0.008 (-0.47)		
<i>High Scaled DC Fintech</i>			0.123 (1.72)	
<i>Low Scaled DC Fintech</i>			-0.142*** (-8.72)	
<i>Scaled DC</i>				0.014*** (6.62)
<i>Fintech × Scaled DC</i>				0.029*** (3.73)
Year and Lender FE	Yes	Yes	Yes	Yes
R^2	0.499	0.529	0.500	0.508
Observations	2,276	2,276	2,276	2,276

Table 11: **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*. The classifications of fintech shadow banks and traditional banks are detailed in Table 1.

Time period	Fintech Sample			Traditional Bank Sample		
	2010–2020	2010–2015	2016–2020	2010–2020	2010–2015	2016–2020
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Loan application sample</i>						
White Borrower	59.49%	63.69%	55.41%	68.02%	68.61%	65.96%
Nonwhite Borrower	40.51%	36.31%	44.59%	31.98%	31.39%	34.04%
Female Borrower	24.22%	23.35%	25.06%	24.56%	23.89%	26.85%
Purchase Loan	31.90%	28.76%	34.96%	34.74%	33.09%	40.45%
Improvement Loan	0.51%	0.32%	0.70%	6.60%	5.40%	10.75%
Refinancing Loan	67.33%	70.92%	63.83%	57.00%	61.50%	41.37%
Conventional Loan	66.78%	67.70%	65.89%	78.04%	75.98%	85.20%
FHA Loan	21.36%	22.69%	20.08%	14.48%	16.41%	7.75%
VA Loan	10.50%	8.36%	12.58%	5.76%	5.67%	6.09%
FSA/RHS Loan	1.35%	1.24%	1.46%	1.72%	1.94%	0.96%
Approval Rate	53.55%	53.57%	53.52%	46.04%	45.56%	47.69%
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
<i>Panel B: Originated loan sample</i>						
White Borrower	67.25%	73.07%	61.58%	77.70%	78.36%	75.50%
Nonwhite Borrower	32.75%	26.93%	38.42%	22.30%	21.64%	24.50%
Female Borrower	26.30%	25.77%	26.81%	26.11%	25.42%	28.41%
Purchase Loan	32.54%	29.70%	35.31%	31.57%	28.67%	41.19%
Improvement Loan	0.45%	0.26%	0.63%	5.93%	4.70%	9.99%
Refinancing Loan	66.75%	70.04%	63.54%	61.29%	66.63%	43.62%
Conventional Loan	71.48%	70.55%	72.38%	84.72%	83.31%	89.39%
FHA Loan	18.12%	20.66%	15.65%	8.83%	10.27%	4.05%
VA Loan	9.42%	7.55%	11.23%	5.52%	5.42%	5.85%
FSA/RHS Loan	0.99%	1.24%	0.75%	0.94%	1.01%	0.70%
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

Table 12: Loan price competition with digital capital: Fintech shadow bank vs. traditional bank (HMDA)

This table shows the results of eqs. (1) to (3) using HMDA loans from 2018 to 2020. The dependent variable is the *Loan Price*, which is the raw loan origination rate (in percent). Definitions of fintech-related variables are detailed in Table 5. Definitions of control variables are detailed in Table 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include county by year fixed effects. Standard errors are clustered at the county level; *t* statistics are in parentheses; **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

<i>Panel A: All HMDA loans</i>			
Dependent variable	<i>Loan Price</i>		
	(1)	(2)	(3)
<i>Fintech</i>	-0.059*** (-11.63)		-0.089*** (-17.32)
<i>High Scaled DC Fintech</i>		-0.042*** (-7.92)	
<i>Low Scaled DC Fintech</i>		-0.080*** (-14.89)	
<i>Scaled DC</i>			0.001* (1.92)
<i>Fintech</i> × <i>Scaled DC</i>			0.005*** (6.71)
Borrower and loan controls	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
<i>R</i> ²	0.628	0.629	0.629
Observations	5,148,215	5,148,215	5,148,215
<i>Panel B: FMFM Loans</i>			
Dependent variable	<i>Loan Price</i>		
	(1)	(2)	(3)
<i>Fintech</i>	-0.090*** (-17.08)		-0.160*** (-24.55)
<i>High Scaled DC Fintech</i>		-0.062*** (-11.11)	
<i>Low Scaled DC Fintech</i>		-0.139*** (-22.31)	
<i>Scaled DC</i>			0.002** (2.46)
<i>Fintech</i> × <i>Scaled DC</i>			0.010*** (11.91)
Borrower and loan controls	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
<i>R</i> ²	0.664	0.666	0.665
Observations	3,882,543	3,882,543	3,882,543

Table 13: Summary statistics for all variables over 2012–2020 (FHA)

This table reports the summary statistics of FHA loan origination data for all lenders, fintech shadow banks, and traditional banks from 2012 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); *OLTV indicator* is a dummy variable equal to 1 if the OLTV record is non-missing; *DTI* is the ratio of the borrower's monthly debt over her monthly income (in percent); *DTI indicator* is a dummy variable equal to 1 if the DTI record is non-missing; *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; *Down payment* is a dummy variable equal to 1 if the borrower receives gift funds for the loan Down Payment; *Number of borrowers* is the number of borrowers on the loan; *Property type* is the number of living units of the property. The classifications of fintech shadow banks and traditional banks are detailed in Table 1.

	All lenders					Fintech shadow bank					Traditional bank				
	Obs.	Mean	Min	Max	STD	Obs.	Mean	Min	Max	STD	Obs.	Mean	Min	Max	STD
Loan price (%)	3,927,106	3.91	1.0	6.75	0.54	1,225,863	3.94	1.75	6.38	0.6	2,701,243	3.9	1.0	6.75	0.51
Loan default (%)	3,108,344	3.69	0.0	100.0	18.84	714,368	4.63	0.0	100.0	21.02	2,393,976	3.4	0.0	100.0	18.13
Loan amount (000s)	3,927,106	181.85	2.0	1446.0	99.92	1,225,863	189.36	11.0	1446.0	106.35	2,701,243	178.43	2.0	1427.0	96.67
Term (month)	3,927,106	348.42	55.0	362.0	42.54	1,225,863	342.57	55.0	361.0	51.38	2,701,243	351.08	96.0	362.0	37.55
FICO	3,737,804	691.85	300.0	850.0	49.31	1,206,116	676.26	300.0	850.0	49.15	2,531,688	699.27	300.0	850.0	47.62
OLTV (%)	3,927,106	88.89	0.0	125.0	18.98	1,225,863	84.5	0.0	124.97	22.79	2,701,243	90.88	0.0	125.0	16.6
OLTV indicator	3,927,106	0.97	0.0	1.0	0.18	1,225,863	0.95	0.0	1.0	0.22	2,701,243	0.97	0.0	1.0	0.16
DTI (%)	3,927,106	28.6	0.0	65.0	19.7	1,225,863	33.03	0.0	65.0	18.62	2,701,243	26.59	0.0	65.0	19.84
DTI indicator	3,927,106	0.72	0.0	1.0	0.45	1,225,863	0.8	0.0	1.0	0.4	2,701,243	0.69	0.0	1.0	0.46
Refinance	3,927,106	0.36	0.0	1.0	0.48	1,225,863	0.54	0.0	1.0	0.5	2,701,243	0.29	0.0	1.0	0.45
FTHB	3,927,106	0.48	0.0	1.0	0.5	1,225,863	0.34	0.0	1.0	0.47	2,701,243	0.55	0.0	1.0	0.5
Down payment	3,927,106	0.13	0.0	1.0	0.33	1,225,863	0.09	0.0	1.0	0.29	2,701,243	0.14	0.0	1.0	0.35
# of borrowers	3,927,086	1.41	1.0	5.0	0.52	1,225,863	1.41	1.0	5.0	0.51	2,701,223	1.41	1.0	5.0	0.52
Property type	3,927,103	1.03	1.0	4.0	0.2	1,225,860	1.02	1.0	4.0	0.17	2,701,243	1.03	1.0	4.0	0.21

Table 14: Loan price competition over time: Fintech shadow bank vs. traditional bank (FHA)

This table shows the results of eq. (1) using Ginnie Mae MBS loans from 2012 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. All columns include state by year-month fixed effects. Standard errors are clustered at the state by year-month level; *t* statistics are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Dependent variable	<i>Loan Price</i>		
Sample period	Full (2012–2020)	Early (2012–2015)	Late (2016–2020)
	(1)	(2)	(3)
<i>Fintech</i>	0.024*** (7.46)	0.052*** (17.58)	-0.004 (-0.80)
Loan amount	-0.126*** (-62.82)	-0.124*** (-60.25)	-0.135*** (-50.35)
Loan term (Months)	0.003*** (184.75)	0.003*** (195.73)	0.002*** (127.37)
Borrower credit score at origination	-0.001*** (-77.70)	-0.001*** (-69.35)	-0.002*** (-82.59)
Original loan to value ratio (LTV)	0.003*** (43.62)	0.001*** (19.36)	0.002*** (27.98)
Non-missing LTV	-0.237*** (-39.05)	-0.125*** (-19.56)	-0.191*** (-22.25)
Debt-to-income ratio (DTI)	0.001*** (19.39)	0.001*** (17.09)	0.001*** (9.26)
Non-missing DTI	-0.004 (-0.97)	-0.038*** (-9.07)	0.010** (2.28)
Refinance	0.102*** (33.27)	0.140*** (36.07)	0.002 (0.60)
First-time buyer	0.042*** (29.41)	0.022*** (16.72)	0.065*** (27.75)
Downpayment	0.102*** (25.82)	0.055*** (13.72)	0.135*** (22.57)
Number of borrowers	0.008*** (12.82)	0.002*** (2.97)	0.014*** (13.97)
Property type	0.016*** (9.83)	0.019*** (11.42)	0.016*** (5.88)
State $\times$ Year-month FE	Yes	Yes	Yes
R^2	0.559	0.525	0.631
Observations	3,737,781	2,248,056	1,489,725

Table 15: **Loan performance competition over time: Fintech shadow bank vs. traditional bank (FHA)**

This table shows the results of eq. (4) using Ginnie Mae MBS loans from 2012 to 2017. 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. All columns include state by year-month fixed effects. Standard errors are clustered at the state by month level; t statistics are in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Dependent variable	<i>Loan Default</i>		
Sample period	Full (2012–2017)	Early (2012–2014)	Late (2015–2017)
	(1)	(2)	(3)
<i>Fintech</i>	0.672*** (13.47)	0.690*** (14.28)	0.739*** (8.84)
Origination rate	1.693*** (37.12)	1.328*** (24.76)	1.882*** (24.60)
Loan amount	0.615*** (14.50)	0.659*** (13.63)	0.359*** (5.10)
Loan term (Months)	-0.001*** (-4.37)	-0.000 (-0.33)	0.000 (0.43)
Borrower credit score at origination	-0.034*** (-73.66)	-0.027*** (-69.69)	-0.049*** (-64.81)
Original loan to value ratio (LTV)	0.022*** (13.91)	0.009*** (4.67)	0.024*** (9.33)
Non-missing LTV	-2.835*** (-18.24)	-1.661*** (-7.97)	-2.939*** (-11.99)
Debt-to-income ratio (DTI)	0.062*** (35.24)	0.050*** (24.51)	0.077*** (28.17)
Non-missing DTI	-2.314*** (-29.99)	-1.888*** (-20.78)	-3.448*** (-28.14)
Refinance	-0.054 (-1.32)	0.043 (0.93)	-0.750*** (-9.52)
First-time buyer	0.260*** (7.55)	0.051 (1.26)	0.627*** (10.88)
Downpayment	0.999*** (19.28)	0.834*** (12.78)	1.042*** (12.55)
Number of borrowers	-1.739*** (-69.08)	-1.452*** (-53.36)	-2.318*** (-52.71)
Property type	-0.323*** (-5.84)	-0.324*** (-4.78)	-0.219** (-2.32)
State $\times$ Year-month FE	Yes	Yes	Yes
R^2	0.027	0.014	0.042
Observations	2,929,283	1,823,247	1,106,036

Table 16: Loan price competition with digital capital: Fintech shadow bank vs. traditional bank (FHA, refinance loans)

This table shows the results of eqs. (1) to (3) using Ginnie Mae MBS refinance loans from 2012 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, 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include state by year-month fixed effects. Standard errors are clustered at the state by year-month level; *t* statistics are in parentheses; **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

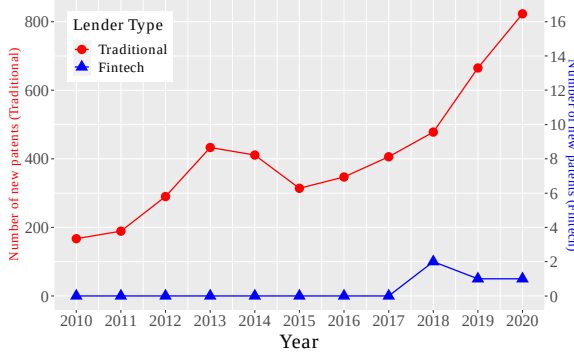
Dependent variable	<i>Loan price</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	0.045*** (13.90)		0.051*** (7.06)		0.054*** (9.82)
<i>High Ln(1+DC) Fintech</i>		0.047*** (14.08)			
<i>Low Ln(1+DC) Fintech</i>		0.037*** (9.94)			
<i>Ln(1+DC)</i>			0.007*** (12.05)		
$\widehat{Fintech} \times Ln(1+DC)$			-0.000 (-0.39)		
<i>High Scaled DC Fintech</i>				0.047*** (13.68)	
<i>Low Scaled DC Fintech</i>				0.039*** (10.80)	
<i>Scaled DC</i>					0.005*** (6.44)
$\widehat{Fintech} \times Scaled DC$					-0.004*** (-5.10)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
State $\times$ Year-month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.552	0.552	0.553	0.552	0.552
Observations	1,247,880	1,247,880	1,247,880	1,247,880	1,247,880

Table 17: Loan performance competition with digital capital: Fintech shadow bank vs. traditional bank (FHA, refinance loans)

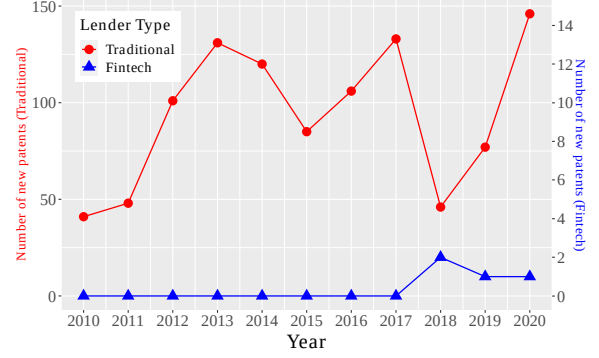
This table shows the results of eqs. (4) to (6) using Ginnie Mae MBS refinance loans from 2012 to 2017. The dependent variable is the *Loan Default*, which is a binary variable equal to 100 if a loan is delinquent for at least two consecutive months within two years of its origination. *Fintech* is a 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, 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 3 and the classifications of fintech shadow banks and traditional banks are detailed in Table 1. The employment data used to construct digital capital are manually collected from LinkedIn. All columns include state by year-month fixed effects. Standard errors are clustered at the state by year-month level; *t* statistics are in parentheses; **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Dependent variable	<i>Loan Default</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	0.515*** (10.43)		1.924*** (9.94)		1.490*** (11.25)
<i>High Ln(1+DC) Fintech</i>		0.319*** (5.72)			
<i>Low Ln(1+DC) Fintech</i>		1.168*** (14.26)			
<i>Ln(1+DC)</i>			-0.049*** (-5.23)		
$\hat{Fintech} \times Ln(1+DC)$			-0.266*** (-7.61)		
<i>High Scaled DC Fintech</i>				0.339*** (6.02)	
<i>Low Scaled DC Fintech</i>				1.050*** (13.50)	
<i>Scaled DC</i>					0.040*** (2.64)
$\hat{Fintech} \times Scaled DC$					-0.141*** (-6.74)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
State $\times$ Year-month FE	Yes	Yes	Yes	Yes	Yes
<i>R</i> ²	0.025	0.025	0.025	0.025	0.025
Observations	974,349	974,349	974,349	974,349	974,349

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



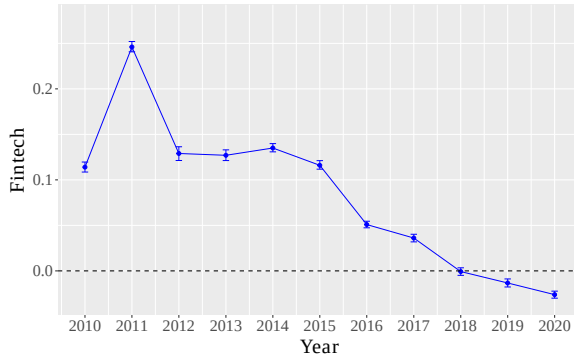
(a) Total New Patents over time



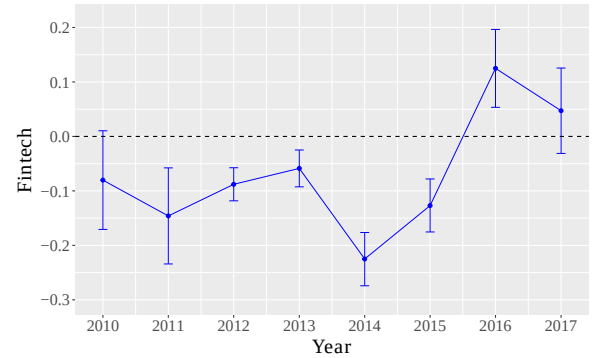
(b) Fintech-Lending-Related patents over time

Figure IA.1: Total New Patents and Fintech-Lending-Related patents over time (FMFM)

Figure IA.1a plots the annual number of new patents granted to fintech shadow banks and traditional banks in our sample from 2010 to 2020. Figure IA.1b 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]. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. Patent data are obtained from the USPTO.



(a) Loan price over time



(b) Loan performance over time

Figure IA.2: Loan price and Performance over time (2017 classification)

Figure IA.2a 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 Table 1: $Loan\ Price_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Figure IA.2b 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 Table 1: $Loan\ Default_{i,j,z,t} = \alpha + \beta_1 Fintech_j + X_{i,t}\Phi + \delta_{z,t} + \epsilon_{i,j,z,t}$. Definitions of all variables are detailed in Table 3. Loan origination data are from FMFM. The error bars denote 95% confidence intervals.

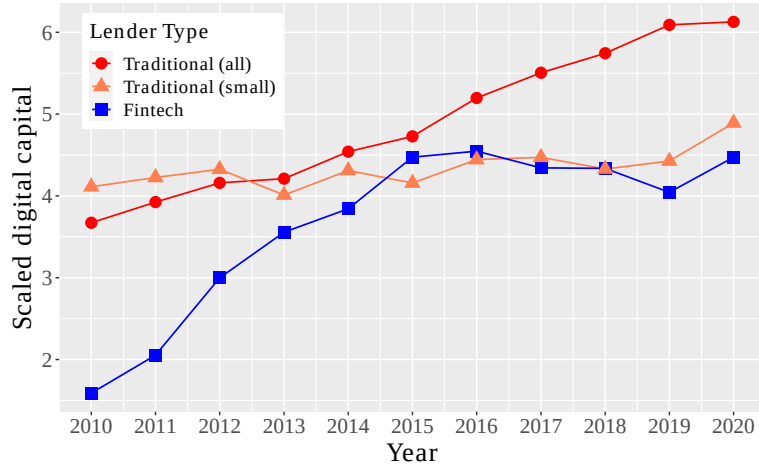


Figure IA.3: Scaled digital capital over time (FMFM)

Figure IA.3 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). The classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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.4: Word cloud of non-tech-related job positions for fintech shadow bank

Figure IA.4 plots the word cloud of non-tech-related job positions for fintech shadow banks. The classification of fintech shadow banks is detailed in Table 1.

Table IA.1: 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 3. 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

<i>Panel A: Loan Price Regressions</i>			
Dependent variable	<i>Loan Price</i>		
Sample period	Full (2010–2020)	Early (2010–2015)	Late (2016–2020)
	(1)	(2)	(3)
<i>Fintech</i>	0.048*** (3.92)	0.130*** (12.17)	0.003 (0.34)
Controls	Yes	Yes	Yes
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
<i>Panel B: Loan Performance Regressions</i>			
Dependent variable	<i>Loan Default</i>		
Sample period	Full (2010–2017)	Early (2010–2013)	Late (2014–2017)
	(1)	(2)	(3)
<i>Fintech</i>	-0.029** (-2.17)	-0.093*** (-8.21)	-0.019 (-1.11)
Controls	Yes	Yes	Yes
Zip $\times$ 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.2: 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. Definitions of control variables are detailed in Table 3. 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

<i>Panel A: Loan Price Regressions</i>					
Dependent variable	<i>Loan Price</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	0.048*** (3.92)		0.032 (0.54)		0.014 (0.44)
<i>High Ln(1+DC) Fintech</i>		0.056*** (4.10)			
<i>Low Ln(1+DC) Fintech</i>		-0.004 (-0.29)			
<i>Ln(1+DC)</i>			-0.002* (-1.70)		
<i>Fintech × Ln(1+DC)</i>			0.002 (0.26)		
<i>High Scaled DC Fintech</i>				0.054*** (4.04)	
<i>Low Scaled DC Fintech</i>				0.010 (0.58)	
<i>Scaled DC</i>					-0.004*** (-2.73)
<i>Fintech × Scaled DC</i>					0.006* (1.74)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip × 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

<i>Panel B: Loan Performance Regressions</i>					
Dependent variable	<i>Loan Default</i>				
	(1)	(2)	(3)	(4)	(5)
<i>Fintech</i>	-0.029 (-0.71)		-0.012 (-0.07)		-0.024 (-0.24)
<i>High Ln(1+DC) Fintech</i>		-0.045 (-0.91)			
<i>Low Ln(1+DC) Fintech</i>		0.070* (1.80)			
<i>Ln(1+DC)</i>			0.001 (0.21)		
<i>Fintech × Ln(1+DC)</i>			-0.003 (-0.08)		
<i>High Scaled DC Fintech</i>				-0.042 (-0.82)	
<i>Low Scaled DC Fintech</i>				0.039 (0.96)	
<i>Scaled DC</i>					0.007** (2.15)
<i>Fintech × Scaled DC</i>					-0.005 (-0.33)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes
Zip × 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.3: 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*. Panel B reports the results of eqs. (4) to (6), and the dependent variable is *Loan Default*. 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 3. Loan origination data are from FMFM. The sample period is from 2010 to 2020. The classifications of fintech shadow banks and traditional banks are detailed in Table 1. 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; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

[illegible]

[illegible]