The Role of Technology in Mortgage Lending

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Technology-based ("FinTech") lenders increased their market share of U.S. mortgage lending from 2% to 8% from 2010 to 2016. Using loan-level data on mortgage applications and originations, we show that FinTech lenders process mortgage applications 20% faster than other lenders, controlling for observable characteristics. Faster processing does not come at the cost of higher defaults. FinTech lenders adjust supply more elastically than do other lenders in response to exogenous mortgage demand shocks. In areas with more FinTech lending, borrowers refinance more, especially when it is in their interest. We find no evidence that FinTech lenders target borrowers with low access to finance. (*JEL* D14, D24, G21, G23)

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The U.S. residential mortgage industry is experiencing a wave of technological innovation as both start-ups and existing lenders seek ways to automate,

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simplify and speed up each step of the mortgage origination process. At the forefront of this development are FinTech lenders, which have a complete end-to-end online mortgage application and approval process that is supported by centralized underwriting operations, rather than the traditional network of local brokers or "bricks and mortar" branches. For example, *Rocket Mortgage* from Quicken Loans, introduced in 2015, provides a tool to electronically collect documentation about borrower's income, assets and credit history, allowing the lender to make approval decisions based on an online application in as little as 8 minutes.

In the aftermath of the 2008 financial crisis, FinTech lenders have become an increasingly important source of mortgage credit to U.S. households. We measure "FinTech lenders" as lenders that offer an application process that can be completed entirely online. As of December 2016, all FinTech lenders are stand-alone mortgage originators that primarily securitize mortgages and operate without deposit financing or a branch network. Their lending has grown annually by 30% from \$34bn of total originations in 2010 (2% of market) to \$161bn in 2016 (8% of market). The growth has been particularly pronounced for refinances and for mortgages insured by the Federal Housing Administration (FHA), a segment of the market which primarily serves lower income borrowers.

In this paper, we study the effects of FinTech lending on the U.S. mortgage market. Our main hypothesis is that the FinTech lending model represents a technological innovation that reduces frictions in mortgage lending, such as lengthy loan processing, capacity constraints, inefficient refinancing, and limited access to finance by some borrowers. The alternative hypothesis is that FinTech lending is not special on these dimensions, and that FinTech lenders offer services that are similar to traditional lenders in terms of processing times and scalability. Under this explanation, economic forces unrelated to technology explain the growth in FinTech lending (e.g., regulatory arbitrage or marketing).

It is important to distinguish between these explanations to evaluate the impact of technological innovation on the mortgage market. If FinTech lenders do indeed offer a substantially different product from traditional lenders, they may increase consumer surplus or expand credit supply, at least for individuals who are comfortable obtaining a mortgage online. If, however, FinTech lending is driven primarily by other economic forces, there might be little benefit to consumers. FinTech lending may even increase the overall risk of the U.S. mortgage market (e.g., due to lax screening). Studying these questions in the context of the mortgage market is informative for evaluating the broader impact of technological innovation in loan markets. Mortgage lending is arguably the market in which technology has had the largest economic impact thus far, but other loan markets may undergo similar transformations in the future.[1]

Our analysis identifies several frictions in U.S. mortgage markets and examines whether FinTech lending alleviates them. We start by examining the effect of FinTech lending on loan outcomes. We focus particularly on the time it takes to originate a loan as a measure of efficiency. FinTech lenders may be faster at processing loans than traditional lenders because online processing is automated and centralized, with less scope for human error. At the same time, this more automated approach may be less effective at screening borrowers; therefore, we also examine the riskiness of FinTech loans using data on loan defaults.

We find that FinTech lenders process mortgages faster than traditional lenders, measured by total days from the submission of a mortgage application until the closing. Using loan-level data on the near-universe of U.S. mortgages from 2010 to 2016, we find that FinTech lenders reduce processing time by about 10 days, or 20% of the average processing time. In our preferred specifications, this effect is larger for refinance mortgages (14.6 days) than purchase mortgages (9.2 days). The result holds even when we restrict the sample to nonbanks, indicating that it is not accounted for by differences in regulation.

Faster processing by FinTech lenders does not result in riskier loans. We measure loan risk using defaults on FHA mortgages, the riskiest segment of the market in recent years. We find that FinTech default rates are about 25% lower than those for traditional lenders, even when controlling for detailed loan characteristics. Interest rates are not economically significantly different. These results speak against a “lax screening” hypothesis.

We also study how FinTech lenders respond to mortgage demand shocks. Existing research documents evidence of significant capacity constraints in U.S. mortgage lending.[2] FinTech lenders may be better able to accommodate demand shocks because they collect information electronically and centralize and partially automate their underwriting operations. To empirically identify capacity constraints across lenders, we use changes in nationwide application volume as a source of exogenous variation in mortgage demand and trace out the correlation with loan processing times.

We find that FinTech lenders respond more elastically to changes in mortgage demand. A doubling of the application volume raises the loan processing time by 13.5 days (or 26%) for traditional lenders, compared to only 7.5 days for

[1] Many industry observers believe that technology will soon disrupt a wide range of loan markets including small business loans, leveraged loans, personal unsecured lending, and commercial real estate lending (Goldman Sachs Research 2015).

[2] Fuster et al. (2017b) show that increases in aggregate application volumes are strongly associated with increases in processing times and higher interest rate margins, thereby attenuating the pass-through of lower mortgage rates to borrowers. Sharpe and Sherlund (2016) and Choi et al. (2017) also find evidence of capacity constraints, which they argue alter the mix of loan applications that lenders attract.

FinTech lenders. The result is robust to including a large number of loan and borrower observables, restricting the sample to nonbanks, or using an interest rate refinancing incentive or a Bartik-style instrument to measure demand shocks. The estimated effect is larger for refinances, where FinTech lenders are particularly active. We also document that FinTech lenders reduce denial rates relative to other lenders when application volumes rise, suggesting that their faster processing is not simply due to credit rationing during peak periods.

Given that FinTech lenders particularly focus on mortgage refinances, we next study their effect on household refinancing behavior. Prior literature has shown that many U.S. households refinance too little or at the wrong times (e.g., Campbell 2006; Keys et al. 2016). FinTech lending may encourage efficient refinancing by offering a faster, less cumbersome loan process. We examine this possibility by studying the relationship between the FinTech lender market share and refinancing propensities across U.S. counties.

We find that borrowers are more likely to refinance in counties with a larger FinTech lender presence (controlling for county and time effects). An 8-percentage-point increase in the lagged market share of FinTech lenders (which corresponds to moving from the 10th percentile to the 90th percentile in 2015) raises the likelihood of refinancing by about 10% of the average. This increase in refinancing is more pronounced among borrowers estimated to benefit from refinancing based on the optimal refinancing rule of Agarwal, Driscoll, and Laibson (2013). Our findings suggest that FinTech lending, by reducing refinancing frictions, increases the pass-through of market interest rates to households.

We conduct a range of analyses to examine whether our main results reflect the endogenous matching of specific borrowers to FinTech lenders. The main identification concern is one of selection; for example, perhaps sophisticated borrowers seek out FinTech lenders, and also submit paperwork faster or are less likely to default? We conduct several auxiliary tests which in general speak against this interpretation. First, we show that our processing time and default results are robust to including or excluding a large set of borrower, loan, and geographic controls, indicating that they are not driven by selection on observables. We also find no robust evidence that FinTech penetration leads to slower processing speeds or higher defaults for other lenders, as would be expected if the pool of unobservably "fast" or low-default borrowers had simply migrated away to FinTech. Furthermore, we show that FinTech has grown most quickly in regions where mortgage processing times were previously unusually *slow*, again at odds with an explanation that FinTech lenders target "fast" borrowers. Related, in terms of our refinancing results we find that the FinTech market share is higher in geographic regions with previously slow refinancing rates; these regions have subsequently "caught up" as the FinTech share has grown. We cannot fully rule out selection effects, because our setting does not have a perfect natural experiment; however, these additional results suggest selection does not drive our key findings.

We also analyze cross-sectional patterns in who borrows from FinTech lenders. We find that FinTech borrowing is higher among more educated populations, and surprisingly among older borrowers, presumably because older borrowers are familiar with the process of obtaining a mortgage and thus more willing to borrow online. We find little evidence that FinTech lenders disproportionately target marginal borrowers with low access to finance. We find no consistent correlation between FinTech lending and local Internet usage or speed; similarly, using the entry of Google Fiber in Kansas City as a natural experiment, we find no evidence that improved Internet access increases FinTech mortgage take-up. These results mitigate concerns about a digital divide in mortgage lending.

Taken together, our results suggest that recent technological innovations are improving the efficiency of the U.S. mortgage market. We find that FinTech lenders process mortgages more quickly without increasing loan risk, respond more elastically to demand shocks, and increase the propensity to refinance, especially among borrowers that are likely to benefit from it. We find, however, little evidence that FinTech lending is more effective at allocating credit to otherwise constrained borrowers.

Our results do not necessarily predict how FinTech lending will evolve in the future. FinTech lenders are nonbanks who securitize most of their mortgages—their growth could be affected by regulatory changes or reforms to the housing finance system. Some uncertainty surrounds how the increased popularity of machine learning techniques, which FinTech lenders may be using more intensely, will influence the quantity and distribution of credit.[3] Related to this issue, although we find no evidence FinTech lenders select the highest-quality borrowers ("cream skim"), which could reduce credit for other borrowers, these results could change as technology-based lending becomes more widespread. Lastly, FinTech lenders use a less personalized loan process that relies on hard information, which could reduce credit to borrower applications that rely on soft information.

Our research contributes to several strands of the literature. Although a large body of research has studied residential mortgage lending (see Campbell 2013 and Badarinza et al. 2016 for surveys), much of the recent work focuses on securitization and the lending boom prior to the U.S. financial crisis.[4] Our paper instead focuses on how technology affects mortgage lending after the crisis. Most closely related to this paper, Buchak et al. (2018) study the recent growth in the share of nonbank mortgage lenders, including FinTech lenders. Although there is some overlap between the descriptive parts of our analyses, the two papers are otherwise strongly complementary. Buchak et al. (2018) focus

[3] Bartlett et al. (2017) and Fuster et al. (2017a) study these issues in the context of the mortgage market.

[4] See, for example, Mian and Sufi (2009), Keys et al. (2010), Purnanandam (2010), Acharya et al. (2013), or Jiang et al. (2014). Aside from this paper, research focusing on mortgage lending in the post-crisis environment includes that of D'Acunto and Rossi (2017), DeFusco et al. (2017), and Gete and Reher (2018).

on explaining the growth of nonbank lending, using reduced-form analysis and a calibrated structural model. Our paper focuses on how technology affects frictions in the mortgage origination process, such as slow processing times, capacity constraints, and slow or suboptimal refinancing.[5]

Our findings inform research on the role of mortgage markets in the transmission of monetary policy (e.g., Beraja et al. 2019; Di Maggio et al. 2017). If lenders constrain the pass-through of interest rates (Agarwal et al. 2017; Drechsler et al. 2017; Fuster et al. 2017b; Scharfstein and Sunderam 2016), or borrowers are slow to refinance (Andersen et al. 2015; Agarwal et al. 2015), changes in risk-free interest rates will not be fully reflected in mortgage rates and originations. Our findings suggest that technology may be easing these frictions, potentially improving monetary policy pass-through in mortgage markets.

Finally, our paper contributes to a growing literature on the role of technology in finance (see Philippon 2016 for an overview), and a broader literature on how new technology can lead to productivity growth (see, e.g., Syverson 2011; Collard-Wexler and De Loecker 2015). In our case, the "productivity" or "efficiency" measures we consider are processing times, supply elasticity, default and refinancing propensities, and we are the first to document that FinTech lending appears to lead to improvements along these dimensions.

1. Who Is a FinTech Lender?

1.1 Defining FinTech lenders

A central feature of our study is the distinction between FinTech mortgage originators and other lenders. While many mortgage lenders are adopting new technologies to varying degrees, it is clear that some lenders are at the forefront of using technology to fundamentally streamline and automate the mortgage origination process. The defining features of this business model are an end-to-end online mortgage application platform and centralized mortgage underwriting and processing augmented by automation.[6]

How does the FinTech business model affect the mortgage origination process in practice?[7] Online applications mean that a borrower can be approved

5 We also study loan defaults and mortgage pricing in a similar way to Buchak et al. (2018), but focus on the riskier FHA segment of the market; they primarily study loans insured by Fannie Mae and Freddie Mac.

6 The discussion of institutional details in this section draws on extensive conversations with mortgage industry professionals, market analysts within the Federal Reserve, and other industry experts. For more detail on how technology is reshaping the mortgage market, see Oliver Wyman (2016), *The Economist* (2016), Goodman (2016), Goldman Sachs Research (2015), and Housing Wire (2015, 2017).

7 Obtaining a purchase mortgage involves three main steps (see e.g., Freddie Mac 2016). (1) An initial application and preapproval—a preapproval letter is nonbinding, but is indicative of a borrower's credit capacity and is often required to make an offer on a home. (2) Processing and underwriting, which is usually undertaken after a property has been identified and sale price agreed upon. This step involves verification of all supporting documentation, often involving many interactions between the processor, loan officer, and borrower and can take from 1 to 2 days to several weeks or more (known as the "turn time"). (3) Closing, when the funds and property deed

for a loan without talking to a loan officer or visiting a physical location. The online platform is able to directly access the borrower's financial account statements and tax returns to electronically collect information about assets and income. Other supporting documents can be uploaded electronically, rather than by being sent piecemeal by mail, fax or email.[8] This automates a labor-intensive process, speeds up information transfer, and can improve accuracy by, for example, eliminating transcription errors (Goodman 2016; Housing Wire 2015). The online platform also allows borrowers to customize their mortgage based on current lender underwriting standards and real-time pricing.

Supporting and complementing this online application process, FinTech mortgage lenders have developed "back-end" processes to automatically analyze the information collected during the application. For example, borrower information is compared with employment databases, property records, and marriage and divorce records; additionally, algorithms can examine whether recent bank account deposits are consistent with the borrower's paystubs. Optical character recognition and pattern recognition software can be used to process documents uploaded by the borrower and flag missing or inconsistent data. These systems make the mortgage underwriting process more standardized and repeatable, and may help identify fraud (Goodman 2016).

This approach does not eliminate the role of human underwriters, but does make mortgage processing less labor intensive. In contrast with more hub-and-spoke loan origination operations that put loan officers and underwriters in branches, FinTech lenders centralize their processing operations, which allows for labor specialization in the underwriting process. Lenders have told us anecdotally that this makes it easier to train new workers and to adjust labor supply in response to demand shocks.

However, a more automated approach to mortgage underwriting may also come with important disadvantages. For example, poorly designed online platforms may confuse borrowers or lead to errors, and a lack of personal interaction may impede the transmission of soft information, resulting in less effective borrower screening or credit rationing.[9] Our empirical analysis examines both the benefits and costs of the FinTech mortgage lending model.

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are transferred. FinTech lenders partially automate the first two steps and allow them to be completed online. Recently, some lenders have also digitized the third and final step by creating an electronic mortgage note (e.g., see Quicken Loans 2017a).

[8] FinTech lenders also offer email and phone support. The key distinction to traditional lenders is that borrowers can process the entire application without using paper forms, email, or phone support. In practice, the degree of automation is much larger among FinTech lenders relative to other lenders, even if some FinTech borrowers communicate via email or over the phone with their lender.

[9] A substantial academic literature has emphasized the role of soft versus hard information in lending (e.g., Petersen and Rajan 2002; Stein 2002).

We emphasize that automation and online applications are not entirely new.[10] For example, many lenders in recent years have allowed borrowers to initiate a mortgage application online. However, the online application is often just a first step before directing applicants to speak to a loan officer who then initiates a more traditional loan application process. Similarly, although online mortgage rate comparison services, such as LendingTree and BankRate, have been a feature of the mortgage market for many years, these services simply provide information and connect borrowers and lenders; they do not automate the mortgage origination process or put it online.

The emergence of several stand-alone FinTech firms as major lenders over the last few years is a strong indicator that fundamental change is underway. These firms are at the technological frontier and focus exclusively on the new business model. In contrast, established lenders with branch-based mortgage origination processes face significant obstacles in recalibrating their operations away from branches and loan officers. For this reason, the vanguard of FinTech lenders is composed of nonbanks, which do not have access to deposit finance and therefore do not retain originated loans on balance sheet. Like other nonbanks, the vast majority of FinTech lenders sell their loans through established channels supported by government guarantee programs (FHA, VA, Fannie Mae, and Freddie Mac).

That said, a significant and growing number of mortgage lenders are at present incorporating aspects of the "FinTech model," and the current distinction between FinTech originators and other firms, including banks, may be temporary. The current market structure presents a window of opportunity to study the impact of FinTech on mortgage origination, and to draw inferences about what is likely to happen to the mortgage industry as a whole as these technologies diffuse more broadly.

1.2 Classifying FinTech lenders

For our empirical analysis, we classify an originator as a FinTech lender if they enable a mortgage applicant to obtain a preapproval online. We believe this classification distinguishes FinTech lenders from more traditional mortgage originators that may use "online applications" for marketing purposes but still require interaction with a loan officer.

Our classification should be viewed as a proxy, since an online application platform is only one dimension of the FinTech "model." Even so, it is an important component, and is also easily measurable in a consistent way across a large number of mortgage lenders. In practice, the set of lenders classified as FinTech by our approach matches up well with firms considered by industry observers and media to be at the frontier of technology-based mortgage lending.

[10] More generally, the use of information technology in mortgage lending and servicing is not a recent phenomenon (see, e.g., LaCour-Little 2000 for a discussion of developments in the 1990s).

It also quite closely matches with the independent classification by Buchak et al. (2018).[11]

We implement our classification by first compiling lists of the top-100 nonbank lenders for purchase loans and for refinancings over the analysis period.[12] The resultant list includes 135 lenders. We then manually initiate a mortgage application with each lender and analyze whether it is possible to obtain a preapproval online. Most lenders halt the online application prior to the preapproval and ask the borrower to directly contact a loan officer or broker. We classify the lender as a FinTech lender if we are able to continue with the online process until we get to the preapproval decision that is based on a hard credit check of the applicant's credit score.

Our final classification is based on an analysis completed in June 2017. To construct a panel, we go back in time using a database that archives Web sites ("Wayback Machine"). Using the database from 2010 to 2017, we evaluate at which point in time a lender appears to have adopted their qualifying online lending process. We cannot always conduct a full evaluation because online application processes often rely on a technological process that evaluates information in real time. However, we can use the archived Web site to evaluate when a lender adopted an application which resembles the qualifying application in 2017. We use this information to determine the year in which a lender adopted a FinTech lending model. We corroborate our results using industry reports.[13]

FinTech lenders exhibit several other distinguishing characteristics relative to their competitors. For example, FinTech firms typically require a Social Security number and conduct a hard credit check online, unlike most traditional mortgage originators we classified. FinTech lenders also tend to orient their marketing efforts around their Web site or mobile phone app. In particular, FinTech lender advertisements emphasize the functionality and ease of use of their Web site or app, and direct borrowers to those platforms. Other lenders may include their Web site in their marketing material but do not emphasize it to the same degree, and may primarily use it for "lead generation."

Figure 1 plots the number of FinTech lenders by year based on our classification. The number increases from two firms in 2010 to 18 lenders by 2017. In Table 1 we list the top-20 lenders in 2016, along with other FinTech lenders in the data in that year. The three largest originators identified as FinTech lenders are Quicken, LoanDepot.com, and Guaranteed Rate. All of the primary

[11] Our classification and empirical analysis closely follows the methodology in our proposal to the RFS FinTech initiative submitted on March 15, 2017. Our proposal was submitted before we and Buchak et al. (2018) became aware of each others' work and predates the first public version of their working paper.

[12] We also examined several top depository bank lenders, but did not classify any of them as FinTech through 2016 (although some began offering online preapprovals in 2017). As discussed above, entrenched bank business models may slow their ability to integrate new technology into their existing branch-based mortgage origination process.

[13] We find no instance of a lender that stopped offering online processing during the analysis period.

Figure 1
Number of FinTech mortgage lenders (according to our classification) over time

analyses in this paper use this classification, although we have verified that our main results are robust to the alternative classification of Buchak et al. (2018).[14]

Table 2 provides summary statistics of mortgage originations and applications, in total and by lender type, based on data collected under the Home Mortgage Disclosure Act (HMDA). HMDA data report characteristics of individual residential mortgage applications and originations from the vast majority of U.S. banks and nonbanks. Data include the identity of the lender, loan amount, property location, borrower income, race, and gender, though not credit score or loan-to-value (LTV) ratio.

Based on known local conforming loan limits, we impute whether each loan has "jumbo" status and thus cannot be securitized by Fannie Mae, Freddie Mac, or Ginnie Mae. The processing time of loan applications, one of our main outcome variables of interest, can only be computed from a restricted version of the data available to users within the Federal Reserve.[15] We include loans with application dates between January 2010 and June 2016.[16]

14 Our classification is similar to the one proposed by Buchak et al. (2018). There are only minor differences with respect to the classification of a few smaller lenders.

15 This restricted version of the data records the exact date the lender receives an application, as well as the date on which the application was resolved (e.g., origination of the loan or denial or withdrawal of the application). The publicly available HMDA data only contain the year. All other variables are the same.

16 We end the sample in June. For applications submitted later in the year, processing times may be biased downward because only applications for which an action (origination, denial, etc.) was taken by the end of 2016 are included in the HMDA data available at the time of writing.

Table 1
FinTech and top-20 mortgage originators in 2016, based on the Home Mortgage Disclosure Act (HMDA)

Rank	Type of lender	Lender name	Volume (bn)	Market share (%)	FinTech since
1	Bank	Wells Fargo	132.58	6.62	
2	FinTech	Quicken Loans	90.55	4.52	2010
3	Bank	JPMorgan Chase	75.52	3.77	
4	Bank	Bank Of America	60.24	3.01	
5	FinTech	Loandepot.com	35.94	1.80	2016
6	Mtg	Freedom Mortgage	32.17	1.61	
7	Bank	US Bank	30.69	1.53	
8	Mtg	Caliber Home Loans	27.94	1.40	
9	Bank	Flagstar	27.31	1.36	
10	Mtg	United Shore	22.93	1.15	
11	Bank	Citibank	21.73	1.09	
12	FinTech	Guaranteed Rate	18.44	0.92	2010
13	Mtg	Finance of America	17.63	0.88	
14	Mtg	Fairway Independent	16.10	0.80	
15	Bank	USAA Federal Savings	15.52	0.78	
16	Mtg	Guild Mortgage	15.07	0.75	
17	Mtg	Stearns Lending	14.93	0.75	
18	Bank	Suntrust Mortgage	14.77	0.74	
19	Bank	Primelending	13.87	0.69	
20	Mtg	Nationstar Mortgage	13.50	0.67	
…					
23	FinTech	Movement Mortgage	11.61	0.58	2014
39	FinTech	Everett Financial (Supreme)	7.62	0.38	2016
534	FinTech	Avex Funding (Better.com)	0.49	0.02	2016

Bank = Depository Institution, Mtg = Nonbank Mortgage Lender, FinTech = FinTech Lender. Market share is based on dollar volume of originations in HMDA. This table reports all lenders classified as Fintech at the end of 2016. Our classification also identified 12 additional nonbank lenders who began offering an online application platform in the first half of 2017, after the end of our HMDA sample period: FBC Mortgage Inc.; RPM Mortgage Inc.; ARK-LA-TEX Financial Services (Benchmark Mortgage); Envoy Mortgage; Skyline Financial Corp.; Evergreen Moneysource Mortgage; American Neighborhood Mortgage; Mortgage Investors Group; 21st Mortgage Corp; Amerisave Mortgage Corp.; Homeward Residential Inc. and American Internet Mortgage.

In terms of basic risk characteristics, nonbank lenders originate loans to borrowers with relatively low income and a high loan amount to income (LTI) ratio relative to banks. In keeping with this fact, nonbank lenders also originate a much higher share of FHA and VA loans, although this is less pronounced for FinTech lenders than for other types of nonbanks. Nonbanks also originate fewer jumbo mortgages, which are more difficult to securitize or sell. Notably, FinTech lenders originate many more refinance loans (as opposed to loans used for a home purchase) than either banks and other nonbank lenders.[17]

The table also shows that FinTech lenders have shorter average processing times than either banks or other nonbank lenders. In the next section, we study whether this result persists after controlling for loan characteristics and location-time fixed effects. In Section 6 we study differences in borrower and location characteristics between FinTech and non-FinTech mortgages more systematically, building on Table 2.

17 As also noted by Buchak et al. (2018), FinTech lenders have a higher fraction of applications where applicant race or gender is missing. We understand this is because borrowers can complete online applications without being required to provide this information. See Section 6 for additional discussion.

Table 2
Descriptive statistics by lender type, HMDA data, 2010 - mid-2016

	Banks		Nonbank lenders Non-FinTech		Nonbank lenders FinTech		All lenders	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Originated mortgages								
Applicant income	121	86.00	102	82.00	102	84.00	115	84.00
Loan amount / income	1.96	1.80	2.46	2.40	2.34	2.19	2.13	2.00
Home purchase	0.34	0	0.52	1	0.22	0	0.38	0
Refinancing	0.66	1	0.48	0	0.78	1	0.62	1
Jumbo	0.05	0	0.02	0	0.02	0	0.04	0
Loan type:								
Conventional	0.86	1	0.61	1	0.71	1	0.78	1
FHA	0.09	0	0.28	0	0.20	0	0.15	0
VA	0.05	0	0.11	0	0.09	0	0.07	0
Owner occupied	0.88	1	0.92	1	0.92	1	0.89	1
Male	0.67	1	0.69	1	0.59	1	0.68	1
Female	0.25	0	0.27	0	0.26	0	0.26	0
No coapplicant	0.45	0	0.52	1	0.50	0	0.48	0
Race:								
White	0.79	1	0.78	1	0.68	1	0.78	1
Black/African American	0.04	0	0.06	0	0.05	0	0.05	0
Asian	0.05	0	0.07	0	0.04	0	0.06	0
Other	0.01	0	0.01	0	0.01	0	0.01	0
Unknown	0.11	0	0.09	0	0.22	0	0.11	0
Processing time	53.04	45.00	50.20	40.00	42.58	37.00	51.71	43.00
Observations	32,751,662		14,742,227		2,306,237		49,800,126	
All applications								
Loan outcome								
Originated	0.64	1	0.58	1	0.66	1	0.62	1
Approved, not accepted	0.04	0	0.05	0	0.03	0	0.04	0
Denied	0.20	0	0.16	0	0.27	0	0.19	0
Withdrawn	0.09	0	0.15	0	0.03	0	0.11	0
Closed for incompleteness	0.03	0	0.06	0	0.01	0	0.04	0
Processing time	47.16	40.00	46.98	35.00	40.11	35.00	46.80	38.00
Observations	51,448,444		25,604,501		3,473,506		80,526,451	

This table contains summary statistics of HMDA data by lender type, for loan applications from January 2010 through June 2016. “Banks” are depository institutions, “Nonbank lenders” are nonbank mortgage lenders, and “FinTech” lenders are classified according to Section 2. In the first part of the table, summary statistics are calculated for originated mortgages only. In the second part of the table, statistics are calculated for all applications, which include applications that ended up being originated, approved by the lender but not accepted by the borrower, denied, withdrawn by the applicant before a decision was made, or closed for incompleteness. “Applicant Income” is in thousands of USD and does not include missing values. “Loan amount / income“ (LTI) is loan amount divided by applicant income; LTI is winsorized at the 0.5% level and does not include missing values. “Jumbo” is an indicator for the loan amount being greater than the applicable FHFA Conforming Loan Limit. “Owner Occupied” is an indicator for the property being the borrower’s principal dwelling. “No Coapplicant” is an indicator for no coapplicant provided for the loan. Race: “Other” is an indicator for applicant race being American Indian, Alaskan, Hawaiian, or Pacific Islander. “Unknown” is an indicator for race being unreported or “Not Applicable”. “Processing Time” is the number of days between application date and action date of a loan. Loan outcomes: “Originated” are applications that were successfully originated. “Approved, Not Accepted” are applications where the application was approved, but not accepted by applicant. “Denied” are applications that were denied by originator. “Withdrawn” are applications that were withdrawn by the applicant before a credit decision was made. “Closed for Incompleteness” are applications where the application file was closed for incompleteness.

2. Is FinTech Lending Faster?

Our first research question is whether FinTech lenders are able to process mortgage applications more quickly than other lenders. We measure processing time by the number of days between application and origination date, as in

Fuster et al. (2017b). We estimate the following ordinary least squares (OLS) regression using loan-level HMDA data:

$$\text{Processing Time}_{ijct} = \delta_{ct} + \beta \text{FinTech}_j + \gamma \text{Controls}_{ijct} + \epsilon_{ijct}, \quad (1)$$

where Processing Time_{ijct} is for loan i issued by lender j in census tract c for an application received in month t, FinTech_j is an indicator variable equal to 1 for FinTech lenders and zero otherwise, δ_{ct} is a vector of census-tract-month fixed effects, and Controls_{ijct} includes loan and borrower controls.[18] We winsorize the top and the bottom 1% of processing times and cluster standard errors at the lender level.

Our regression includes a large number of observable loan and borrower characteristics to control for factors other than lender efficiency that may affect processing time (e.g., local laws, housing market conditions, the complexity of the loan, borrower, and property, and the speed of obtaining a property appraisal). We expect that our rich set of controls should account well for these factors. In particular, census-tract-month fixed effects control in a highly disaggregated way for common geographic and time variation in processing times. We conduct the analysis separately for home purchase mortgages and refinances because the latter do not require the homeowner to move and the application process is simpler.

2.1 Processing time results

Panel A of Table 3 presents the results for purchase mortgages. In Column 1, we find that FinTech lenders process loans 7.9 days faster than non-FinTech lenders. This effect is large, corresponding to 15% of average home purchase processing time of 52 days. The result is slightly larger in magnitude and remains statistically significant when we include loan and borrower controls (Column 2), census tract-month fixed effects (Column 3), and both (Column 4, where the estimated effect corresponds to 18% of the average processing time). The results are also robust to dropping deposit-taking banks from the sample (Column 5), which suggests that the results are not driven by regulatory factors or the different funding model of banks.

Panel B of Table 3 finds even larger effects for refinances. Across specifications, FinTech lenders process mortgages 9.2 to 14.8 days faster than other lenders. The effect corresponds to 17%-29% of the average refinance loan processing time of 51 days. Again, the result is robust to comparing FinTech lenders only to other nonbanks, which suggests that it is not driven by regulation or funding. The FinTech advantage for refinance loans might be larger because

18 The control variables are the natural logarithm of borrower income, the natural logarithm of total loan amount, indicator variables for race and gender, an indicator variable for coapplicants, an indicator variable for whether a preapproval was requested, indicator variables for the occupancy and lien status of the loan, indicator variables for property type, indicator variables for whether the loan is insured by the FHA or the Department of Veterans Affairs (VA), an indicator variable for loans above the conforming loan limit (i.e., jumbo loans), and an indicator variable in case applicant income is missing.

Table 3
FinTech lenders and processing times: Loan-level results

A. Purchase loans	(1)	(2)	(3)	(4)	(5)
FinTech lender	−7.93***	−9.43***	−8.31***	−9.20***	−7.45***
	(2.22)	(2.84)	(1.79)	(2.30)	(1.65)
log(applicant income)		−0.55***		−0.81***	−0.18
		(0.20)		(0.11)	(0.24)
log(loan amount)		4.47***		5.22***	7.07***
		(0.52)		(0.35)	(0.96)
FHA		0.65		−0.11	−0.96*
		(0.44)		(0.33)	(0.53)
VA		1.68		1.25	1.26
		(1.26)		(1.05)	(1.50)
Jumbo		3.17***		5.32***	6.18***
		(1.23)		(0.76)	(1.49)
Observations	19,159,345	19,159,345	18,146,785	18,146,785	6,841,626
R^2	.00	.02	.26	.28	.36
Census tract-month	No	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes	Yes
Sample	All lenders	All lenders	All lenders	All lenders	Nonbanks
B. Refinance loans	(1)	(2)	(3)	(4)	(5)
FinTech lender	−9.99***	−13.64***	−11.17***	−14.75***	−9.20***
	(2.46)	(2.35)	(2.08)	(2.20)	(1.93)
log(applicant income)		0.04		−0.16	−0.23
		(0.34)		(0.26)	(0.36)
log(loan amount)		4.74***		4.32***	1.62**
		(0.50)		(0.47)	(0.67)
FHA		5.83***		5.40***	5.20***
		(1.98)		(1.78)	(1.59)
VA		1.70		2.03	1.53
		(2.60)		(2.16)	(2.28)
Jumbo		7.06***		7.32***	9.40***
		(1.01)		(0.94)	(0.52)
Observations	30,616,247	30,616,247	29,843,262	29,843,262	7,674,028
R^2	.01	.10	.21	.27	.32
Census tract-month	No	No	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes	Yes
Sample	All lenders	All lenders	All lenders	All lenders	Nonbanks

This table reports regressions of loan processing time (in days) on an indicator variable identifying FinTech lenders, census tract-month fixed effects, loan controls and borrower controls. Data source: HMDA. The sample consists of originated purchase loans in panel A and refinancing loans in panel B with application dates from 2010 to 2016Q2. Displayed loan controls include the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans and jumbo loans. Suppressed loan controls include applicant race, gender, whether the loan has a coapplicant, whether a preapproval was obtained, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Column 5 excludes bank lenders. Standard errors reported in parentheses are clustered by lender. *$p < .1$; **$p < .05$; ***$p < .01$.

refinances offer more scope for automation than home purchase loans. For example, purchase loans always require an appraisal, which is administered locally and is not (yet) automated. This interpretation is consistent with the fact that FinTech lending growth has been larger for refinances relative to home purchase loans.[19]

[19] In unreported results we also rerun these regressions restricting the sample to FHA- or VA-insured loans, because anecdotally, underwriting is less amenable to automation for these loans, possibly constraining the advantages of FinTech lenders. Indeed, we find for refinances that the FinTech lender advantage is lower by 3 days (relative to a

While these regressions capture average effects, it is instructive to study the entire distribution of processing times across lender types. We do so in Figure A.1 in the Internet Appendix, where we plot the cumulative distributions of processing times for both purchase and refinance mortgages, after accounting for census-tract-month fixed effects and loan characteristics. For purchase mortgages the advantage of FinTech lenders comes primarily from the right tail (i.e., few loans have very long processing times), while for refinances the entire distribution is shifted to the left. This again suggests that efficiency gains may be easier to realize for refinances.

2.2 Additional analysis

One potential concern is that our processing time results are affected by endogenous matching between borrowers and lenders. For instance, if younger borrowers are more likely to use FinTech lenders and also tend to submit their paperwork faster, FinTech lenders would appear to process mortgages more quickly, even if they do not have an inherent technological advantage. Alternatively, FinTech lenders may attract the most complex mortgage applications, which would attenuate the estimated FinTech processing time advantage.

We emphasize that the coefficient on FinTech lenders is robust across specifications and samples. If FinTech lenders matched with borrowers or loan types that are easier to process, then adding the control variables should attenuate the estimated coefficient; instead, the coefficient tends to get larger with additional controls. To the extent that unobservable factors that make some borrowers faster than others are also correlated with observables, this is a first piece of evidence that our results are unlikely to be driven by endogenous matching or other unobserved variables, but instead represent the direct effect of FinTech lending on processing times.

To investigate further, we test whether the FinTech processing time advantage is driven by "fast borrowers" migrating to FinTech lenders. We implement this test in two stages. In the first stage, we predict the probability that each loan is originated by a FinTech lender as a function of loan and borrower characteristics. We then include this predicted probability as an explanatory variable in a second stage analysis of processing times among non-FinTech mortgages. If non-FinTech lenders lose their faster customers to FinTech lenders, non-FinTech processing times should have increased disproportionately for borrower and loan types with high FinTech penetration (as measured by a high first-stage probability).

Table A.1 in the Internet Appendix shows the second-stage results. In our baseline specification, we find a positive effect of the predicted FinTech probability on non-FinTech processing times. This is consistent with selection,

sample of nongovernment or "conventional" loans). However, we detect no corresponding difference in FinTech lenders' processing time advantage among new purchase loans.

although the coefficient is not nearly large enough to explain our earlier processing time results.[20] In addition, the coefficient of interest flips sign once we control for lender-by-census tract fixed effects to allow for the possibility that FinTech lenders have a high market share in areas where traditional lenders are slow (Columns 2 and 4 of the table). In sum, it does not appear that selection effects could easily explain the large processing time differences we document.

Furthermore, as a direct test of whether FinTech lenders match with "fast" borrowers, we study whether FinTech originators have gained the highest market share in geographic locations where processing times were shortest ex ante, measured in 2010 prior to the growth in FinTech. Section 6 presents these results. To preview the key result, we in fact find the opposite; FinTech lenders have become popular in locations where processing times were originally *slow* conditional on observables. This is inconsistent with an "endogenous selection" interpretation of our processing time estimates, and in fact suggests that slow processing by traditional lenders may be a driver of the growth in FinTech lending.

Summing up, our results suggest that FinTech mortgage lenders are roughly 20% faster at processing mortgage originations than other lenders; the estimated effects range from 7.5 to 9.4 days for purchase mortgages and 9.2 to 14.7 days for refinances. Several pieces of evidence suggest that this finding is not due to endogenous borrower-lender matching or other omitted variable biases.[21]

3. Is FinTech More Efficient or Just Less Careful?

Fast FinTech processing speeds could simply be a product of less careful screening of borrowers, rather than greater efficiency.[22] We test this "lax screening" hypothesis by studying the ex post performance of FinTech loans compared to similar mortgages from other lenders. We focus on FHA lending, which has been the riskiest segment of the mortgage market in recent years and where we are therefore most likely to detect differences in loan risk.[23] We

[20] For instance, the coefficient of 1.7 in Column 1 of Table A.1 means that moving from the 1st to the 99th percentile in predicted FinTech propensity, corresponding to a difference of 0.335, increases expected processing time by 0.57 days. This is less than one-tenth of the processing time advantage of FinTech lenders as estimated in Table 3. Magnitudes are similar in Column 3, which limits the sample to refinances.

[21] As a "reality check," our estimates seem roughly comparable to industry-based estimates of the processing-time advantage of technology-based lending. For instance, Quicken Loans (2017b) claims that importing income and asset information through their online platform reduces average client mortgage processing time by 12 days. Although it is not clear exactly how this statistic is calculated, it is interesting that it is in the same ballpark as our estimates of the processing time advantage of FinTech lenders.

[22] For instance, using proprietary lender data, LaCour-Little (2007) documents that prior to the financial crisis, processing times were shortest for nonagency nonprime mortgages. This category of loans subsequently experienced extremely high default rates during the crisis.

[23] FHA mortgages require a down payment of as little as 3.5% and are generally made to borrowers with low credit scores who do not qualify for a prime conforming loan. That FHA loans are government guaranteed limits the credit risk for the lender. However, the lender is not fully indemnified against risk, because the FHA can refuse to compensate the lender for credit losses in cases of fraud or other defects in mortgage underwriting. FHA lenders

use two separate sources of public data on FHA mortgage defaults: segment level data extracted from the FHA Neighborhood Watch Early Warning System (“FHA NW data”) and FHA loan-level data from Ginnie Mae (“FHA Ginnie Mae data”). To our knowledge, this is the first academic study to make systematic use of either of these data sources.[24]

3.1 Analysis of default rates in FHA NW data

The FHA NW data report originations and default rates by lender at the national level and by state and metropolitan statistical area (MSA). The data are available for all FHA loans as well as certain subcategories including home purchase mortgages, refinances, and mortgages originated in underserved census tracts.[25] The data generally covers the period 2015:Q3 to 2017:Q3, although state and national data for all loans (not broken down by loan type) are available over a longer sample period from 2012:Q3 to 2017:Q3.

Default rates are calculated as the share of loans that become at least 90 days delinquent or are the subject of an FHA insurance claim within a specific time horizon after origination. The data include rates at 1-year (“1-year default”) and 2-year (“2-year default”) horizons. To control for geographic variation in default rates we scale a lender’s default rate in each location by the overall default rate in that area. As an alternative to raw default rates, the data also contain the “supplementary performance metric” (SPM), which scales a lender’s default rate by a benchmark default rate defined based on the credit score distribution of the underlying mortgages. Again, we then take the ratio of the lender’s SPM to the overall SPM in the area. The SPM is only available at the state and national level and at a 2-year horizon after origination (“mix-adjusted 2-year default”).

Our analysis focuses on the difference in default rates between FinTech lenders and other lenders. We compute the difference by taking the weighted average of FinTech relative default rates using origination volume by region and lender as weights and subtracting one. This measure yields zero if there are no differences in default rates between FinTech lenders and other lenders. We use a difference-in-means test to examine the null hypothesis that FinTech lenders’ default rates are the same as other lenders’.

Table 4 reports the results. Column 1 presents the relative difference in default rates for FinTech lenders using 1-year default as the default measure. In panel A,

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have also paid out large legal settlements on FHA loans because of breaches of the False Claims Act and other laws. As a result of these risks, many large bank lenders have withdrawn from FHA lending or wound back their participation in the market (see, e.g., *Wall Street Journal* 2015).

[24] The FHA Ginnie Mae data are similar to the loan-level data made available by government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac. These are analyzed by Buchak et al. (2018), who find little difference in default probabilities between FinTech and other lenders (for origination vintages 2010-2013). The main drawback of the GSE data is that these prime mortgages have experienced very low default rates for recent vintages (as they are significantly less risky than FHA loans) so that it may be difficult to detect differences across lenders.

[25] A census tract is considered underserved by the FHA based on an administrative classification derived from median income and the share of minority households.

Table 4
Default rate for FinTech lenders, FHA loans (% deviation from region)

	Default definition		
	1-year default	2-year default	Mix-adjusted 2-year default
A. All FHA loans			
State level	−35.0***	−35.8***	−25.5***
	(3.8)	(3.9)	(4.5)
MSA level	−35.3***	−36.2***	
	(2.4)	(2.6)	
B. High market share regions only (loans in top quartile markets by lender):			
State level	−24.7***	−23.4***	−11.7
	(8.4)	(8.6)	(9.9)
MSA level	−19.8***	−20.5***	
	(6.0)	(6.1)	
C. Disaggregated by purchase versus refinancing (all loans, state level)			
Purchase	−14.8***	−17.1***	−10.1*
	(3.6)	(4.3)	(5.9)
Refinancing	−30.6***	−27.5***	−40.3***
	(2.6)	(3.5)	(2.4)
D. Disaggregated by neighborhood socioeconomic status (all loans, state level)			
Underserved (low income/minority)	−33.5***	−32.4***	−25.3***
	(4.5)	(4.4)	(4.4)
Not underserved	−36.8***	−36.5***	−25.4***
	(3.6)	(3.9)	(4.3)
E. All FHA loans: longer time series			
National level	−44.7***	−45.6***	−32.7***
	(4.8)	(4.5)	(5.7)
State level	−45.4***	−46.1***	−33.4***
	(3.2)	(3.1)	(3.9)

This table reports weighted average percent difference in default rate between mortgages from FinTech lenders and all FHA mortgages originated in same time period and market (MSA, state, or national market). Values less than zero indicate lower default rates for FinTech lenders. These statistics are calculated as the weighted average of $compare_{ir} = (default\,rate_{ir}/default\,rate_r) - 1$ across FinTech lenders i and regions r, weighting by lender origination volume. In practice we calculate this weighted average by regressing $compare_{ir}$ on a constant term using weighted least squares. Default definition is default within first year, default within first 2 years, or the "mix-adjusted" default rate, which is based on the supplementary performance metric, an adjusted default rate, which takes into account the credit score distribution of originations (see text for details). Sample period 2015:Q3 to 2017:Q3, except for panel E, where sample period is 2012:Q3 to 2017:Q3. Data are extracted from the FHA NW Early Warning System portal in December 2017. Robust standard errors in parentheses; standard errors are clustered by state in a state-level regression using the longer time series (panel E). $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

we find that loans originated by FinTech lenders are 35% less likely to default than comparable loans from non-FinTech lenders. The coefficient is almost unchanged when using MSA-level data instead of state-level data or using the 2-year default rate instead of the 1-year default rate (Column 2). The coefficient remains statistically significant, albeit slightly smaller (-25.5%), when using the SPM mix-adjusted default rate as the outcome variable (Column 3). We find quantitatively similar results when restricting the sample to high-market share regions (panel B), when considering home purchase loans or refinances separately (panel C), for loans to underserved neighborhoods (panel D), and when considering a longer sample period (panel E). Overall, we find no evidence that FinTech loans are risker than non-FinTech loans; in fact, they appear to default less often.

3.2 Loan-level analysis of FHA default rates

We complement this evidence with a loan-level analysis of data on FHA mortgages securitized into Ginnie Mae MBS. The main advantage of the Ginnie Mae data relative to the FHA NW data is that they include a rich set of loan and borrower characteristics (e.g., the borrower's credit score and the loan-to-value ratio). This allow us to investigate whether FinTech lenders target specific borrower types based on their riskiness and whether differences in default rates can be explained by differences in observable characteristics. A disadvantage of the Ginnie Mae data is that they only include the identity of the *MBS issuer*, not the mortgage originator. Hence, the data do not perfectly identify which loans come from FinTech lenders. However, the issuer and originator are typically the same and a comparison to HMDA suggests mismeasurement is concentrated among small lenders.[26]

Our sample consists of data from September 2013 (when the Ginnie Mae data first become available) until May 2017. We restrict the sample to 30-year fixed-rate mortgages, which are by far the most common FHA loan type. We estimate the following OLS regression:

$$\text{Default}_{ijst} = \alpha + \beta \text{FinTech}_j + \gamma \text{Controls}_{ijst} + \epsilon_{ijst}, \tag{2}$$

where Default_{ijst} on loan i by lender j in state s originated in month t is an indicator variable equal to 1 if a loan ever becomes delinquent for 90 days or more over our observation period, FinTech_j is an indicator variable equal to 1 for FinTech issuers, and Controls_{ijst} is a broad set of control variables, such as origination month or state-by-origination month fixed effects, loan purpose fixed effects, and other loan controls including borrower FICO score, loan-to-value (LTV) ratio and debt-to-income (DTI) ratio.[27] We cluster standard errors at the issuer-origination month level.

Table 5 presents the results. Column 1 controls for origination-month fixed effects only and finds that FinTech borrowers are 1.29 percentage points less likely to default than non-FinTech borrowers, equivalent to 35% of the overall default rate of 3.65%. This result is very similar to the estimates based on FHA NW data. Column 2 adds loan purpose fixed effects. The effect declines to 0.91 percentage points, or 27%, but remains statistically significant. This result reflects the fact that FinTech lenders issue more refinance mortgages than home purchase mortgages, and that over this period, refinances tend to be less risky (especially those not involving cash-out). In Column 3, we add further loan-level controls, such as FICO and the LTV ratio. This has only a

[26] For some small FinTech lenders, the number of MBS-issued loans is substantially smaller than their number of originated loans in HMDA, implying that they sell a significant portion of their loans to other firms before issuance. The effect on identifying FinTech loans should be limited given that this issue primarily affects smaller lenders.

[27] Other loan controls include the log of the loan amount and indicators for the number of borrowers, the property type, whether the borrower received down payment assistance, and for whether a loan's FICO, LTV, or DTI are missing.

Table 5
FHA mortgage default regressions based on Ginnie Mae data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FinTech	-1.29^{***}	-0.97^{***}	-0.93^{***}	-1.51^{***}	-0.79^{***}		-0.91^{***}
	(0.33)	(0.30)	(0.27)	(0.46)	(0.16)		(0.29)
FinTech share						-0.10	
						(1.43)	
FT × FT share							-1.70
							(2.05)
FICO			-0.04^{***}	-0.05^{***}	-0.03^{***}	-0.04^{***}	-0.04^{***}
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTV			0.04^{***}	0.07^{***}	0.03^{***}	0.04^{***}	0.04^{***}
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
DTI			0.06^{***}	0.07^{***}	0.04^{***}	0.06^{***}	0.06^{***}
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Purpose FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	No	No	No	Yes	No
State FEs	No	No	No	No	No	Yes	No
Month × state FEs	No	No	Yes	Yes	Yes	No	Yes
Loan controls	No	No	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	3.65	3.65	3.65	4.00	2.73	3.65	3.65
R^2	.02	.02	.04	.05	.03	.04	.04
Observations	4,097,569	4,097,568	4,097,544	2,966,644	1,130,881	4,097,548	4,097,544
Loan sample	All	All	All	Purch.	Refi	All	All

Table reports regressions of indicator for a loan ever entering 90+ day delinquency on an indicator variable identifying FinTech issuers (or the state-level FinTech market share, demeaned by month; or the interaction of the FinTech indicator with FinTech market share), state-by-origination month fixed effects, loan controls and borrower controls. Coefficients are expressed in percentage points. The sample consists of FHA-insured 30-year fixed-rate mortgages originated over June 2013 to May 2017, obtained from Ginnie Mae MBS monthly loan-level disclosures. Displayed loan controls include the borrower FICO score, the loan-to-value (LTV) ratio and the debt-to-income (DTI) ratio. Suppressed loans controls include loan purpose type, the log of the loan amount, and indicators for the number of borrowers, the property type, whether the borrower received down payment assistance, and for whether FICO, LTV, or DTI are missing. Standard errors reported in parentheses are clustered by issuer. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

small incremental effect on the coefficient of interest, implying that FinTech lenders do not originate loans that are less risky based on these observable characteristics. Columns 4 and 5 split the sample by loan purpose; the effect is slightly larger for home purchase mortgages, but is also sizable for refinances.[28]

3.3 Interpretation and cream skimming

Our analysis of default rates finds no evidence that FinTech lenders originate riskier mortgages. In fact, in the FHA market we find the opposite result. The difference in default rates varies across specifications but is statistically

[28] Table A.2 in the Internet Appendix repeats these regressions using default within one or two years after origination as the outcome variable. This allows us to see whether the default advantages of FinTech lenders are particularly pronounced early in the life cycle of a loan, and also to ensure that the findings in our main table are not driven by composition effects or differential prepayments. The results in Column 3 — our preferred specification — indicate that the size of the effect relative to average default rates is even larger over the first 1 and 2 years (in both cases, FinTech loans have about a 36% lower default rate than others). As discussed below, this is consistent with FinTech lenders being better at screening, though it could also reflect better loan servicing. In further (unreported) regressions, we find that effect size is fairly stable if we repeat the regressions for each loan origination year 2013-2017, or use a sample of mortgages guaranteed by the Department of Veterans Affairs (VA), which are also in the Ginnie Mae data.

significant in almost all of them and the magnitude is economically large—default rates for FinTech-originated loans are about 25% lower in Column 3 of Table 5, which includes the largest set of controls, and ranges between 10% and 40% in the other specifications. The results are robust to using two different data sets and to different sets of loan, borrower and location controls.

Our findings speak directly against the "lax screening" hypothesis. If anything, they suggest that the automated technologies used by FinTech lenders may screen borrowers more effectively than the labor-intensive methods used by other lenders (e.g., because the automated systems directly check databases of original source documents, reducing the possibility of fraud). This reasoning has been emphasized by industry experts (e.g., Goodman 2016), and to our knowledge we provide the first systematic evidence consistent with it.

That said, FinTech lenders could achieve better loan performance through several possible channels, representing a mix of treatment and selection effects. First, FinTech lenders may be able to target or attract low-risk borrowers ex ante. Our regression results indicate this is not occurring on observable dimensions of risk (e.g., FICO, LTV), although it is possible that there is advantageous selection on unobservable dimensions. Second, as discussed above, FinTech lenders may be able to better screen loan applications to correct errors or identify deliberate fraud. Third, FinTech lenders may be able to use technology to service their loans more effectively ex post (e.g., communicate more quickly with delinquent borrowers through online channels).

Selection or "cream skimming" of low-risk borrowers by FinTech lenders could in principle have negative consequences for other borrowers, or for the government. For example, cream skimming could lead to ex ante credit rationing by weakening the credit quality of the remaining borrower pool—a mechanism explored by Mayer et al. (2013) in the context of private subprime mortgage lending. Alternatively, it could shift costs to the government if private and public lenders compete for borrowers, an argument that has been made in the context of FinTech lenders like SoFi in the student loan market.[29]

In the current context of the mortgage market, however, it is unlikely that cream skimming by FinTech lenders has economically significant effects. The reason is that during our analysis period, nearly all risky mortgages in the United States are government insured at a preset price by the FHA or other government agencies, such as the Department of Veterans Affairs. Consequently, cream skimming by FinTech lenders is unlikely to materially affect credit access for remaining borrowers, who will still qualify for government insurance.

Even so, we estimate two specifications to investigate possible cream-skimming effects. First, we test whether a higher FinTech market share in a location leads to lower overall mortgage default risk in that location, as opposed to FinTech lenders just selecting the lowest-default borrowers from a fixed pool.

[29] See, for example, Lorin (2015).

We also test whether the default advantage of FinTech lenders diminishes as their market share increases. If the distribution of risky borrowers is unchanged by the presence of FinTech lenders, then as their market share increases in an area their performance advantage will diminish, as they expand to riskier borrowers.

We present the results, based on the Ginnie Mae data used earlier, in Columns 6 and 7 of Table 5. Column 6 estimates the direct effect of FinTech state-level market share on default. Although the point estimate is negative, the effect is economically small and statistically insignificant, implying that that there is no discernable effect of an increased FinTech footprint on overall defaults for local borrowers. Given the large standard errors on the estimate, it would be interesting to revisit this analysis in the future when more data are available. Column 7 adds the interaction of the FinTech lender dummy and local FinTech market share. The coefficient on the interaction term is negative, which would imply that the better default performance of FinTech mortgages is *more* pronounced in regions where FinTech has a larger market share, but the effect is not statistically significant. On the other hand, in panel B of Table 4, we find a smaller FinTech default advantage in high market-share regions, although again the difference is not statistically significant, and even in these locations, FinTech default rates remain lower than the market as a whole.

While somewhat mixed, we find no evidence of a robust positive relation between market share and marketwide default risk, or that the lower default rate of FinTech lenders disappears in locations where their market share is high. In sum, the findings suggest that the lower default rate associated with FinTech lending is not simply due to positive selection of low-risk borrowers. More generally, although we cannot fully disentangle the channels by which FinTech lenders achieve lower default rates, our results clearly speak against the view that automation or the lack of a local physical presence has led FinTech lenders to be *less* effective in borrower screening and monitoring than traditional lenders.

3.4 Are FinTech lenders charging higher interest rates?

We can also use the Ginnie Mae FHA loan-level data to test whether FinTech lenders charge higher or lower mortgage interest rates conditional on observables. Table A.3 in the Internet Appendix shows the results. We find that FinTech interest rates are 2.3 bp lower overall. Splitting the sample by loan purpose, the effect is 7.5 bp for purchase mortgages and effectively zero for refinances.[30] While these differences are small in magnitude, the direction of the effect is consistent with the Buchak et al. (2018) estimates for FHA loans

[30] These coefficients are not particularly stable if we allow them to vary over time: in some time periods the FinTech coefficient is positive and significant, but over others it is negative and significant. A potential explanation is that movements in market interest rates may be reflected at different times on rates on originated loans between FinTech and other lenders because of differences in processing times. The Ginnie Mae data, or the GSE data used by Buchak et al. (2018), do not easily allow one to cleanly control for this.

(although they are cautious in drawing inferences from their results because their FHA data set includes fewer loan-level controls than the data used here). However, it contrasts with Buchak et al. (2018)'s finding that FinTech lenders charge higher rates for GSE mortgages. One possible explanation that could account for both sets of results, and is in line with some of Buchak et al. (2018)'s other evidence, is that lower-income borrowers, who are more likely to obtain FHA loans, are more price sensitive and less willing to pay a premium for convenience.

4. Is FinTech Lending More Elastic?

Next we study whether FinTech lenders are better able to accommodate shocks to mortgage demand. Mortgage application volumes in the United States fluctuate enormously over time, primarily due to movements in interest rates that can lead to "refinancing waves." There is also substantial cross-sectional variation in demand for new mortgages, for example, because of differential housing market trends.

Managing volatility in mortgage applications is a key challenge for lenders. If a lender receives more applications than their underwriting process can accommodate, their processing times increase and they risk losing money (and future business) due to loans not closing in a timely manner. Figure 2, which is similar to evidence in Fuster et al. (2017b), illustrates two main points. First, as shown in panel (a), there is large variation in the level of monthly applications, with the peak level being almost 3 times as high as the trough. Application volume closely comoves with borrowers' average incentive to refinance, here proxied by the difference between the average coupon rate on outstanding mortgages and the 10-year Treasury yield. Second, panel (b) shows that fluctuations in median processing times are sizable (from a low of 37 days to a high of 51 days), and that processing times are strongly positively correlated with total mortgage applications.[31]

By automating, centralizing and standardizing much of the underwriting process, FinTech lenders may conceivably increase the short-run elasticity of lending supply in response to demand shocks. However, testing whether capacity constraints are less binding for FinTech lenders presents a clear empirical challenge: the volume of applications a lender receives is endogenous. For example, lenders may solicit applications when processing constraints are slack and discourage applications when processing times are expected to be long. Both behaviors would attenuate the relationship between applications and processing time, and obfuscate differences across lenders.

[31] One exception occurs between October and December 2015 when processing times increase even though applications decrease. This is most likely due to the implementation of new loan disclosure rules ("TILA-RESPA Integrated Disclosure," or TRID) on October 3, 2015. These new rules required many lenders to adjust their underwriting processes, resulting in delays. For more details, see, for example, Light (2015).

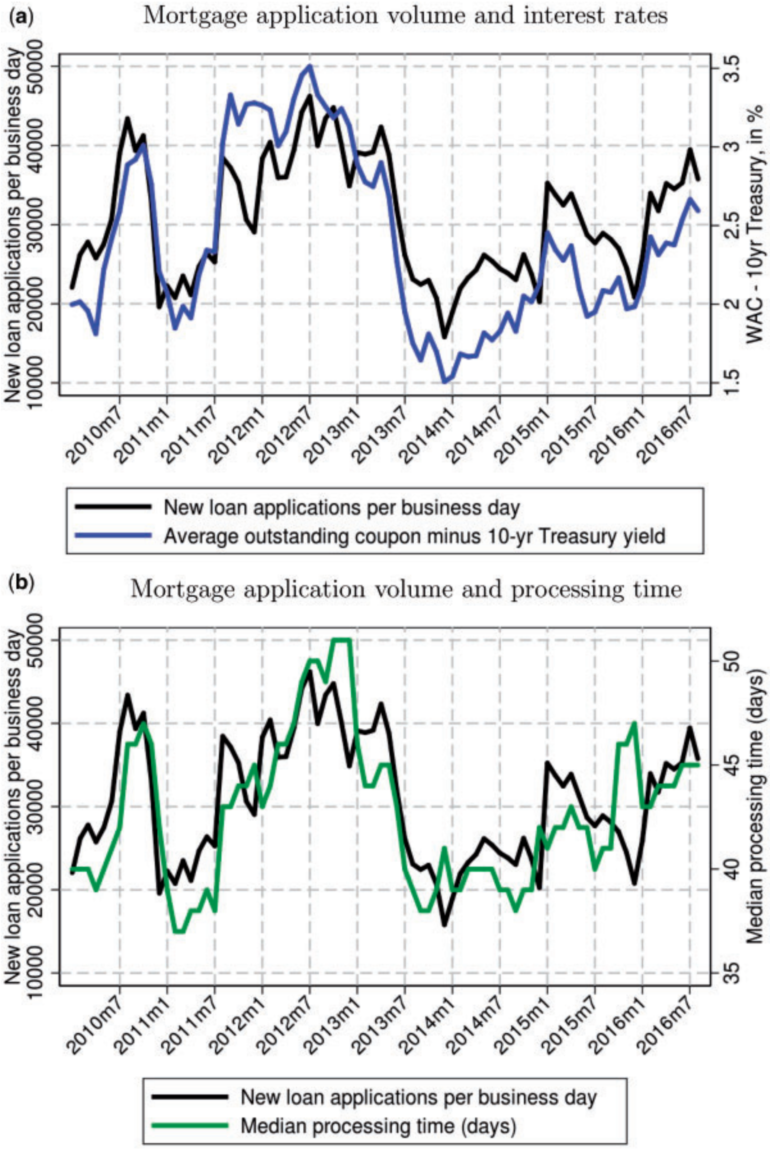

Figure 2
Application volume, interest rate, and processing time
This figure shows the evolution of the number of applications for new loans in HMDA that result in loan originations (divided by the number of business days in a given month), plotted against (a) a proxy for borrowers' refinancing incentive (the difference between the average coupon on outstanding mortgages and the 10-year Treasury-bond yield), and (b) the median processing time for new loan applications that result in loan originations and were submitted in the same month.

Table 6
Elasticity of processing time with respect to aggregate application volume: FinTech versus other lenders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(app. vol.)	11.76***	13.42***	18.79***	13.38***	8.88***	13.60***	10.55***
	(1.37)	(1.52)	(2.30)	(1.34)	(1.46)	(2.80)	(2.14)
ln(app. vol.)	−7.55***	−6.12***	−9.51***	−7.45***	−2.08	−4.45**	−4.48*
× FinTech	(2.17)	(1.81)	(2.19)	(2.07)	(1.60)	(2.25)	(2.35)
Observations	49,775,550	49,774,855	30,615,102	80,495,607	17,023,266	8,925,769	29,047,814
R^2	.14	.20	.25	.17	.21	.17	.17
Loan controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census tract FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	No	Yes	Yes	Yes	Yes	Yes	Yes
Application sample	Originated	Originated	Refi	All	Originated	Refi	All
Lender sample	All	All	All	All	Nonbanks	Nonbanks	Nonbanks

Table reports regressions of loan processing time (in days) on the log of aggregate monthly application volume, an interaction with the FinTech indicator, loan controls, lender fixed effects, census-tract fixed effects, and calendar month fixed effects. Data source: HMDA. The sample is restricted to application dates from 2010 to 2016:Q2. Columns 1, 2, and 5 include all originated loans; Columns 3 and 6 include originated refinancing loans; and Columns 4 and 7 include all applications (including denied and withdrawn applications). The sample of lenders includes all lender types in Columns 1–4 and nonbanks only in Columns 5–7. Loan controls include the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans, and jumbo loans, applicant race, gender, whether the loan has a coapplicant, whether a preapproval was obtained, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Columns 4 and 7 also include indicators for whether a loan was denied or withdrawn. Standard errors reported in parentheses are clustered by lender. $*p<.1$; $**p<.05$; $***p<.01$.

4.1 Demand shocks and processing time

We identify differences in supply elasticity by exploiting demand shocks that vary application volumes independent of firm-specific conditions. We use time-series variation in *total* applications, which is primarily determined by macroeconomic factors, in particular long-term interest rates, and is plausibly exogenous to the capacity contraints any individual lender faces. We test whether FinTech mortgage processing times are less sensitive to variation in total application volume by estimating the following regression using loan-level HMDA data from 2010 through June of 2016:

$$\text{Processing Time}_{ijct} = \gamma \,\text{Applications}_t + \beta \,\text{Applications}_t \times \text{FinTech}_j + \alpha_j + \delta_c + \theta \text{Controls}_{it} + \epsilon_{ijct}, \tag{3}$$

where Processing Time_{ijct} is the number of days between application and closing for mortgage i from lender j in census tract c and application month t, Applications_t is the log of aggregate mortgage applications in month t, FinTech_j is an indicator variable equal to 1 for FinTech lenders, α_j and δ_c are vectors of lender and census-tract fixed effects, and Controls_{it} includes borrower and loan controls similar to Table 3 as well as dummies for loan purpose (purchase versus refinancing) and calendar month dummies to account for seasonality. Standard errors are clustered by lender.

Table 6 presents the results. The first two columns consider all originated loans; Column 1 controls only for lender dummies, and Column 2 includes additional controls for loan and borrower characteristics, location, and month.

We find that FinTech lenders are about half as sensitive to aggregate mortgage application volumes as other lenders. Quantitatively, a 10% rise in overall application volume increases processing time by 1.3 days for non-FinTech lenders but only 0.7 days for FinTech firms (based on Column 2). Column 3 restricts the sample to refinances, the market where FinTech lenders specialize and where interest rates matter most for demand. We find that processing times for refinances are more sensitive to aggregate volumes, but again FinTech lenders are only half as sensitive. Column 4 considers all applications, including denied and withdrawn applications; again, the results are similar. All results are statistically significant at the 1% level. Columns 5–7 repeat the prior three specifications but restrict the sample to nonbanks. The degree to which FinTech lenders are less sensitive to aggregate applications is not as large in this sample but the magnitudes are still economically meaningful. FinTech lenders are 20%–40% less sensitive to aggregate volumes relative to nonbanks; the key coefficients are statistically significant at the standard 5% and 10% levels in Columns 6 and 7, respectively, though not in Column 5 (p-value = .19).[32]

Figure 3 visually illustrates the differential sensitivity of FinTech lender processing times to application volume. This binned scatter plot confirms that FinTech lenders have shorter processing times on average, as already shown in Section 2. More importantly, processing time for FinTech lenders is also less sensitive to demand for new mortgages compared to banks and (to a lesser extent) other nonbank lenders. This lower sensitivity is particularly apparent at the highest levels of application volume (when aggregate application volume exceeds 1.2 million mortgages per month).

4.2 Alternative demand shocks and processing time

We repeat the analysis using the weighted average coupon on the universe of fixed-rate MBS less the 10-year Treasury yield ("Refi Incentive") as our measure of mortgage demand, instead of log application volume.[33] Our findings, presented in panel A of Table A.4 in the Internet Appendix, are similar to those discussed above. A higher refinancing incentive is significantly correlated with longer processing times across specifications, but processing times for FinTech lenders are significantly less sensitive, if anything by a larger proportion than in our main results. The consistency with our earlier findings is sensible given that we show in Figure 2 that refinancing incentives are the key determinant of mortgage application volume. The specification does, however, address any concerns that our earlier results are affected by idiosyncratic shocks to individual large lenders that are large enough to influence aggregate applications.

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32 In unreported results, we consider specifications with time fixed effects and draw similar conclusions. Because it absorbs all time-series variation, this alternative specification does not allow us to observe the uninteracted coefficient on aggregate application volume.

33 Like Fuster et al. (2017b), we use the 10-year Treasury rate rather than a market rate on new mortgages to prevent endogeneity to concurrent supply conditions in the mortgage market.

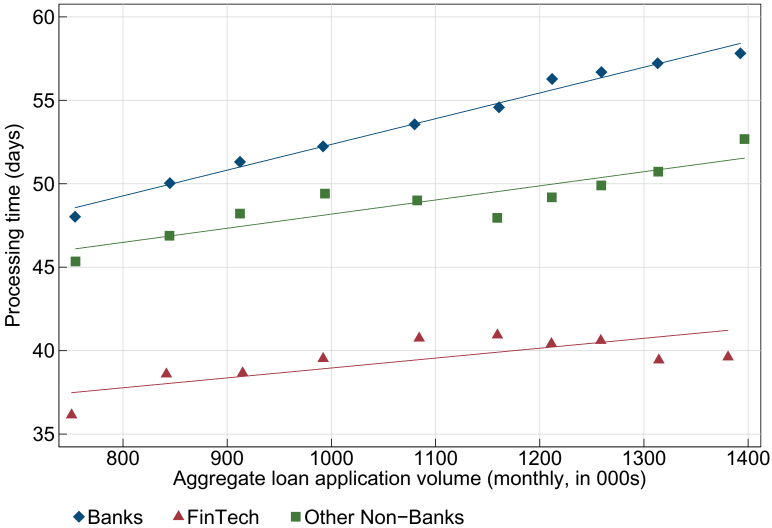

Figure 3
Illustrating differences in processing times and elasticity to demand across lender types
This figure shows binned scatter plot (with linear fit) of processing times of originated loans against the volume of aggregate loan applications by lender type, all measured in HMDA 2010-2016:Q2. Processing times and application volume are first residualized with respect to the following variables: census tract indicators, calendar month indicators, the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans and jumbo loans, applicant race, gender, whether the loan is a refinance, whether the loan has a coapplicant, whether a preapproval was requested, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Application volumes are then grouped into 10 bins, and for each bin the mean of the residualized processing time is calculated and the mean processing time is added, separately for the three lender types in our analysis.

As a second alternative approach, we also construct a "Bartik-style" index of exposure to local fluctuations in mortgage application volume based on the geography of lender activity. The index is calculated as the log of the weighted sum of county-level mortgage applications in month t, where the weights are the lender's average market shares in each county measured over the entire sample period. The identification assumption is that application volumes in a geographic area are exogenous to any given market participant's share. Panel B of Table A.4 in the Internet Appendix presents the results. Processing times are positively correlated with the proxy, although once again, less so for FinTech lenders when we compare to all lenders. Comparing to nonbanks only, effects are not quite significant for all originated loans and all applications (Columns 4 and 6), although coefficients are negative and of substantial magnitude, consistent with our broader findings.

In sum, results based on two alternative measures of loan demand indicate that FinTech lenders are less sensitive to exogenous demand shocks than other lenders, particularly for refinances, supporting our main findings in Table 6.

Table 7
Elasticity of mortgage application denial probabilities with respect to variation in aggregate demand for loans : FinTech versus other lenders.

	(1)	(2)	(3)	(4)
ln(app. vol.)	−0.067***	−0.105***	−0.066***	−0.123***
	(0.009)	(0.011)	(0.017)	(0.023)
ln(app. vol.) × FinTech	−0.108***	−0.087***	−0.109***	−0.072***
	(0.018)	(0.011)	(0.023)	(0.023)
Loan controls	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes
Census tract FEs	Yes	Yes	Yes	Yes
R^2	.18	.19	.27	.30
Observations	68,793,029	44,727,774	23,537,946	13,327,482
Application sample	All	Refi	All	Refi
Lender sample	All	All	Nonbanks	Nonbanks

Table reports regressions of indicator for loan application denial on the log of aggregate application volume, an interaction with the FinTech indicator, loan controls, lender fixed effects, census-tract fixed effects, and calendar month fixed effects. Data source: HMDA. The sample is restricted to application dates from 2010 to 2016:Q2. Applications are included if they result in a loan origination, in the application being approved by the lender, but not accepted by the borrower, or an application denial. The sample of lenders includes all lender types in Columns 1 and 2 and nonbanks only in Columns 3 and 4. Loan controls include the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans, and jumbo loans, applicant race, gender, whether the loan has a coapplicant, whether a preapproval was obtained, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Standard errors reported in parentheses are clustered by lender. *$p<.1$; **$p<.05$; ***$p<.01$.

4.3 Demand shocks and application denial rates

A possible concern is that our results may reflect credit rationing. If FinTech lenders avoid capacity constraints by becoming more selective and rationing credit when total mortgage demand rises, their processing times may seem less sensitive to demand even if they are not actually more elastic. We test this hypothesis by examining whether denial rates for FinTech lenders are differentially sensitive to aggregate application volume. The regression specification is identical to Equation (3), except that the left-hand-side variable is an indicator variable equal to 1 if a loan application was denied and zero otherwise. The sample includes all applications that were either approved or denied.

Table 7 presents the results. We find that, in fact, FinTech lenders differentially *reduce* denial rates by 1.1% percentage points for each 10% increase in application volume (Column 1). The effect is similar when focusing on refinances (Column 2), restricting the sample to nonbanks (Column 3), and focusing on refinance mortgages among nonbanks (Column 4).[34] These results are inconsistent with credit rationing and, if anything, instead provide further evidence that FinTech lenders' credit supply is more elastic than those of other lenders.[35]

[34] The direct effect of application volume on denial rates is negative across all specifications. Although this may seem counterintuitive, it likely reflects the fact that when applications rise because of lower interest rates, the average credit quality of applicants improves. In line with this interpretation, Fuster and Willen (2010) show that denial probabilities fell for all income levels in the wake of the first MBS purchase announcement by the Federal Reserve in late 2008 (when application volumes surged), and average FICO scores increased.

[35] In unreported results, we find that FinTech lenders on average have a roughly 2.5 percentage point higher denial rate than banks (though the difference is statistically insignificant), and a 3.5 percentage higher denial rate than

4.4 Demand shocks and origination volumes

We also analyze whether mortgage origination volumes for FinTech lenders respond differentially to changes in total applications. Analyzing quantities over our short sample period is difficult because of differential trends in application volumes across lender types and across individual firms within a type. We estimate a model in first differences to partial out these trends:

$$\Delta \text{Originations}_{jt} = \gamma\, \Delta \text{Applications}_t + \beta\, \Delta \text{Applications}_t \times \text{FinTech}_j + \alpha_j + \epsilon_{jt},$$

where Originations_{jt} is the log of originated applications (by lender j for applications in month t) and Applications_t is the log of aggregate application volume. Lender origination changes are winsorized at the top and bottom 1% to mitigate the impact of extreme outliers. We include lender fixed effects, α_j, to allow for lender-specific differences in the average growth rate over the analysis period. We restrict the sample to lenders who rank in the top 500 in volume at some point during the sample period.

We find no meaningful difference in origination sensitivity for FinTech lenders. As shown in Table 8, FinTech origination volume appears equally sensitive to changes in aggregate application volumes as those of all other lenders (Columns 1 and 2) and nonbanks (Columns 3 and 4). Hence, similar to our results on denials, we find no evidence that the lower sensitivity of FinTech lender processing times comes at the expense of lower originations due to credit rationing; conversely, though, we do not see an obvious increase in origination growth for FinTech lenders when application volume rises. Overall, we are cautious about drawing strong conclusions from this analysis as it is quite difficult to establish lender-type specific effects given the strong and nonlinear upward trend in the FinTech lender market share during this period.

5. FinTech and Mortgage Refinancing

This section examines whether the presence of FinTech lenders affects mortgage refinancing behavior by borrowers. Prior work has shown that many borrowers do not refinance their fixed-rate mortgages optimally; they commit errors either by failing to refinance when it is in their financial interest to do so or by refinancing even though the costs of doing so exceed the benefits (e.g., Campbell 2006; Agarwal et al. 2015; Andersen et al. 2015; Keys et al. 2016). In addition to behavioral factors, intermediation frictions in the mortgage market also contribute to inefficient refinancing patterns (e.g., Agarwal et al. 2017; Bond et al. 2017; Scharfstein and Sunderam 2016). These frictions weaken the "refinancing channel" of monetary policy (e.g., Beraja et al. 2019; Di Maggio et al. 2016; Wong 2018). Examining the effect of FinTech

other nonbank lenders (significant at $p < .1$), conditional on our typical set of controls. This could reflect more stringent screening, or alternatively that with online applications, there is no "filtering" by a loan officer that may discourage borrowers from applying when their chances of approval are low.

Table 8
Elasticity of originations with respect to changes in aggregate volume: FinTech versus other lenders

	(1)	(2)	(3)	(4)
Δ ln(app. vol.)	1.14***	1.86***	1.12***	2.07***
	(0.01)	(0.01)	(0.02)	(0.02)
Δ ln(app. vol.) × FinTech	0.02	0.06	0.02	−0.08
	(0.08)	(0.13)	(0.09)	(0.13)
Observations	52,030	51,311	24,450	23,831
R^2	.36	.39	.33	.39
Month FEs	Yes	Yes	Yes	Yes
Application sample	Originated	Refi	Originated	Refi
Lender sample	All	All	Nonbanks	Nonbanks

Table reports regressions of the log change in lender-level originated loans on the log change in aggregate application volumes, an interaction with the FinTech indicator, lender fixed effects, and calendar month fixed effects. The unit of observation is lender-month. Data source: HMDA. The sample is restricted to 2010 through 2016:Q2. Columns 1 and 3 include all originated loans; Columns 2 and 4 included originated refinancing loans. The sample of lenders includes all lender types in Columns 1 and 2 and nonbanks only in Columns 3 and 4. Standard errors reported in parentheses are White-Huber standard errors. $*p<.1$; $**p<.05$; $***p<.01$.

on refinancing is thus important, since this is one channel through which technological progress in the mortgage industry may have real effects on the economy.

Industry reports and academic research indicate that mortgage-backed securities backed by FinTech loans do exhibit faster prepayment speeds than pools from other lenders, consistent with an effect of FinTech on the speed of refinancing (e.g., Goldman Sachs Research 2016; Buchak et al. 2018). However, it is unclear whether this fact reflects faster-prepaying borrowers selecting into mortgages from FinTech lenders, or whether FinTech lending directly affects the likelihood of refinancing, thereby potentially affecting aggregate refinancing behavior. If FinTech mortgage lending does affect the market-wide propensity to refinance, an important follow-up question is whether this is due to a reduction in errors of omission (meaning that more borrowers who should refinance do so), or instead reflects an increase in errors of commission (more borrowers refinance even when they should not). Below, we assess this based on the optimal refinancing decision rule of Agarwal, Driscoll, and Laibson (2013).

To measure refinancing behavior, we use data from Equifax's Credit Risk Insight Servicing McDash (CRISM) data set, which merges McDash mortgage servicing records from Black Knight with credit bureau data from Equifax. The sample period is January 2010 through June 2016. The CRISM data set provides information on loan and borrower characteristics, such as FICO score, CLTV, interest rate, and loan term, and features borrower identifiers that allow us to track a borrower across loans and thereby identify mortgage refinancing.[36] We focus on the 500 largest counties by loan volume. Details on the sample construction and how we measure refinancing are provided in Section E of the Internet Appendix, where we also confirm that the average refinance propensity

[36] CRISM has been previously used by Beraja et al. (2019) and Di Maggio et al. (2016) to study refinancing.

we measure in our data is closely aligned with variation over time in the volume of refinancing loans in HMDA.

5.1 Refinancing propensity

We measure the effect of FinTech lending on monthly refinancing propensities using the following OLS regression:

$$\text{Refi Propensity}_{c,t} = \alpha_c + \alpha_t + \beta \cdot \text{FinTechShare}_{c,t-s} + \Gamma \cdot \mathbf{X}_{c,t} + \epsilon_{c,t}, \tag{4}$$

where Refi Propensity$_{c,t}$ is the share of mortgages in county c in month t that are refinanced and FinTechShare$_{c,t-s}$ is the one-quarter-lagged four-quarter moving average market share of FinTech mortgage lenders among refinance loans in a county. We include county fixed effects, α_c, to control for fixed unobservable differences in refinancing speeds across counties and month fixed effects, α_t, to control for aggregate conditions.[37] The time-varying county-level controls $\mathbf{X}_{c,t}$ include average FICO score, average CLTV, the average interest rate on outstanding loans, and the share of outstanding loans that are FHA or VA loans. We run the regressions separately for the sample of all outstanding loans, and restricting to 30-year FRMs only. We cluster standard errors by county.

Table 9 shows a positive and strongly statistically significant association between refinancing propensities and FinTech market share. The estimate of 0.689 in Column 2 implies that an 8-percentage-point increase in FinTech market share (corresponding to moving from the 10th to 90th percentile of county averages in 2015) is associated with a 0.055-percentage-point increase in the refinancing propensity, about a 10% increase relative to the average monthly refinancing propensity over this time period of 0.54%. Thus, the magnitude of the effect is economically meaningful.[38]

Figure 4 further illustrates the effect. Here, we sort the counties into fixed terciles based on their FinTech market share in the middle of our sample period (between mid-2012 to mid-2013). We then plot the average refinance propensity in each tercile over time. We see that in 2010, before the growth in FinTech lending, the tercile of counties where FinTech lenders subsequently gained the most market share has the slowest refinancing speeds. The refinancing propensity across the three terciles converge over time, however, coincident with the growth in FinTech lending. This suggests that FinTech mortgage lenders have helped "slow" refinancing counties to "catch up."

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[37] Market shares are calculated based on HMDA. Results are similar if we use all loans, rather than just refinances, to calculate the market share (although we view this alternative approach as less conceptually appealing, because composition effects imply that the overall FinTech market share will be affected by the relative volume of purchase loans versus refinances, which in turn is related to our outcome variable). Market shares are calculated on a volume-weighted basis, although results are similar if we use loan-count weighted shares instead. Similarly, our results are robust to using alternative timing conventions, such as the share over the previous calendar year.

[38] We have also replicated these regressions using HMDA data, where we use the log of the number of refinance loans originated in a county-month as the dependent variable. The lagged FinTech market share (controlling for county and month fixed effects) is again positively and significantly associated with refinance originations, and the magnitude of the effect is comparable to the estimates in Table 9.

Table 9
FinTech market share and refinancing propensities: County-level results

	(1) All	(2) All	(3) 30yr FRM	(4) 30yr FRM
FinTech share$_{Q-1}$ (MA)	1.121***	0.689***	1.195***	0.706***
	(0.204)	(0.142)	(0.223)	(0.157)
Average FICO/10		0.067***		0.071***
		(0.012)		(0.013)
Average CLTV/10		−0.094***		−0.104***
		(0.007)		(0.008)
Average current rate		1.135***		1.202***
		(0.059)		(0.062)
FHA/VA share		0.190		0.185
		(0.315)		(0.332)
County fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Mean of dep. var.	0.54	0.54	0.59	0.59
R^2	.78	.81	.76	.79
Obs.	39,000	39,000	39,000	39,000

This table reports regressions of county-level monthly refinancing propensities (defined as the share of outstanding mortgages in month $t-1$ that are refinanced in month t, in percentage points) on the FinTech share in a county (4-quarter rolling average, lagged one quarter; range [0,1]), county fixed effects, month fixed effects, and average characteristics of outstanding loans in the county: FICO, updated combined loan-to-value ratios (CLTV), average coupon rate, and the share of FHA/VA mortgages. Data sources: CRISM for refinancing propensities and loan characteristics, HMDA for FinTech market shares. In Columns 1 and 2, refinancing propensities are calculated based on all loans; in Columns 3 and 4, based on 30-year fixed-rate mortgages only. Sample covers January 2010 through June 2016 for the largest 500 counties by count of outstanding mortgages in December 2013 (see Internet Appendix E for details). Standard errors reported in parentheses are clustered by county. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

In summary, our results show that the faster prepayment speeds on FinTech mortgages are also reflected in overall market-wide local refinancing propensities, rather than just being due to within-region selection of "fast" borrowers into FinTech loans. As a caveat on our results, we note that, although our regressions condition on county and time fixed effects, the differential growth in FinTech market share across counties may not be exogenous with respect to refinancing propensities. For instance, it is possible that FinTech lenders predicted correctly which geographic regions still had the most potential for higher refinancing volumes, and advertised and expanded most intensively there. At the least, however, our results suggest that a higher presence of FinTech lending leads to faster mortgage refinancing, perhaps by reducing the transaction or time costs of refinancing.[39]

5.2 Refinancing optimality

Next, we examine whether the increase in refinancing speeds documented above is associated with more *optimal* refinancing decisions. In other words, is it driven by additional refinancing by borrowers with a high current mortgage rate relative to the available rate on new loans, who realize large savings in interest

39 Our findings here have an interesting parallel to earlier work by Bennett et al. (2001), who find that technological innovation in the 1990s reduced refinancing frictions and increased mortgage refinancing speeds.

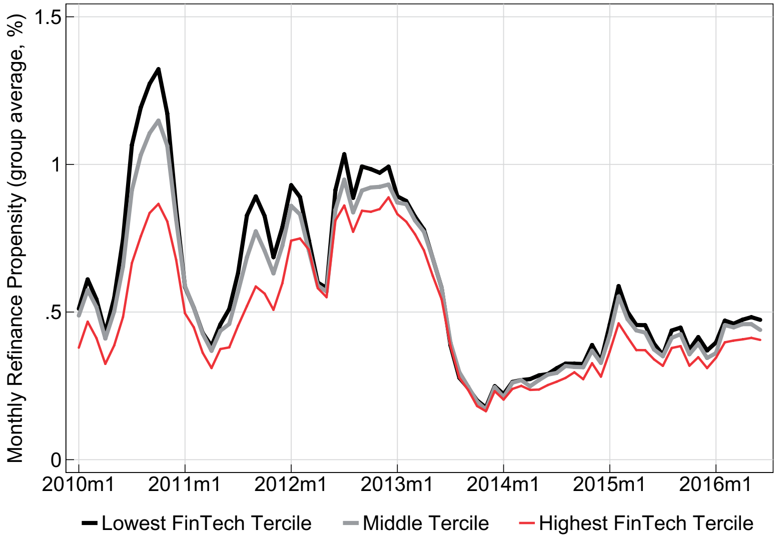

Figure 4
Refinancing propensities across counties with different levels of FinTech market share
This figure shows average monthly refinance propensities across three groups of counties, sorted based on county-level FinTech market shares (among refinance loans) over mid-2012 to mid-2013. Data source: CRISM.

costs by refinancing (fewer errors of omission)? Or is it largely due to borrower who refinance even though the interest savings are small and outweighed by the costs of refinancing (more errors of commission)?

To determine the breakeven interest rate differential beyond which a borrower should refinance, we use the "square-root rule" of Agarwal et al. (2013), henceforth ADL.[40] For this analysis, we restrict the sample to 30-year FRMs, since the ADL optimality calculation was derived for FRMs and does not apply to adjustable-rate loans. We note that the ADL calculation embeds a number of assumptions about the costs and benefits of refinancing; among these, it does not account for other common refinancing motives, such as cashing out home equity, shortening the term of the loan, or refinancing from a mortgage type that requires mortgage insurance (such as FHA loans) into one that does not. Although the ADL benchmark is very useful, it is ultimately a simplification.

Based on the ADL rule, we find, similar to Keys et al. (2016), that at certain points over our sample period, a lot of borrowers should refinance. For instance, in late 2012, about 60% of all 30-year FRM borrowers in our sample should have refinanced according to the ADL benchmark, yet only a significantly smaller percentage did so. However, similar to Agarwal et al. (2015), we find that among

40 The square-root rule is a second-order approximation that comes close to the (more complicated) optimal decision rule derived by ADL. As inputs to the calculation, we require assumptions on discount rates, tax rates, moving probabilities, interest rate volatility, and (most importantly) the upfront costs associated with refinancing; we use the same parameter values as ADL's baseline calibration (following also Keys et al. 2016).

Table 10
FinTech market share and refinancing propensities, by refinancing incentive bins

Refi incentive (ADL)	(1) <-1	(2) $[-1,-0.5)$	(3) $[-0.5,0)$	(4) $[0,0.5)$	(5) $[0.5,1)$	(6) ≥ 1	(7) All
FT share$_{Q-1}$ (MA)	−0.140*	1.028***	2.008***	1.985***	1.444***	0.507*	1.436***
	(0.073)	(0.200)	(0.304)	(0.353)	(0.347)	(0.267)	(0.229)
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	0.12	0.46	0.85	1.04	1.05	0.78	0.59
R^2	.00	.00	.01	.01	.01	.01	.00
Obs.	64,866,392	42,085,823	38,988,748	29,249,088	19,039,098	20,745,039	214,996,787

Table reports regressions of indicator for whether a borrower refinanced their loan in a given month on the FinTech share in a county (4-quarter rolling average, lagged one quarter), county fixed effects, month fixed effects, and the following loan controls: 5-point bins of CLTV, 20-point bins of FICO, a cubic function in the age of the refinanced loan, the log of the balance of the refinanced loan, and an indicator for whether the refinanced loan was an FHA/VA loan. Data sources: CRISM for refinancing propensities and loan characteristics, HMDA for FinTech market shares. For Columns 1–6, borrowers are separated into six bins depending on their refinancing incentive based on the Agarwal, Driscoll, and Laibson (2013) (ADL) calculation. Negative incentives (expressed in percentage points of interest rates) mean that according to ADL a borrower should not refinance; positive incentives mean they should refinance. Column 7 pools all bins. Sample includes 30-year fixed-rate mortgages only. Standard errors reported in parentheses are clustered by county. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

refinances that do occur, more than half are executed at a rate differential that is *too small* when assessed against the ADL rule. Thus, at least when compared to this benchmark, there is substantial scope for enhanced refinancing efficiency.

In Table 10, we estimate loan-level regressions similar to the county-level specifications from above, but now separating outstanding mortgages into different bins depending on how "in the money" the refinancing option is. Specifically, the "refi incentive" shown in the table is equal to the difference between the outstanding mortgage rate and current market rate, minus the optimal refinancing differential according to ADL.[41] For instance, if a borrower is currently paying 6.5%, the market interest rate is at 4.5%, and the optimal refinancing differential is 1.5% based on the ADL formula, the borrower would have a 0.5% positive refinancing incentive. If the market rate increases to 5.5%, the refinancing incentive would become negative. Even though a refinancing in this situation would still reduce the borrower's monthly payments, the savings would not be sufficient to outweigh the transaction costs of refinancing and the loss of option value.

Column 1 shows that for borrowers where the refinancing option is more than 1 percentage point out of the money, a higher local FinTech share has a marginally *negative* effect on the likelihood of refinancing. The effect of a higher FinTech share then becomes positive, and is highest for borrowers that are within 50 bps of their optimal refinancing differential (Columns 3 and 4). The effect size then decreases again somewhat for borrowers that have a large refinancing incentive according to ADL. These borrowers in many cases

41 The FRM market rate is measured using the 30-year FRM rate from Freddie Mac's Primary Mortgage Market Survey, which is a standard source for academic research and policy analysis.

have suboptimally failed to refinance for a long period of time (given that the refinancing incentive is driven by market interest rates, which drift only slowly through time). In industry jargon, these borrowers are sometimes called "woodheads" (Deng and Quigley 2012).

The results imply that an increased presence of FinTech lenders is most strongly associated with higher refinancing when the borrower's incentive to refinance is either "at the money" or just "in the money," meaning refinancing is (at least close to) optimal. It does not appear that FinTech lenders induce an increase in grossly inefficient refinancings (if anything, the reverse is true). However, they also do not spur a large increase in refinancing for the borrowers who would gain the most from doing so, and may induce additional suboptimal refinancing among a subset of borrowers.

Table A.5 of the Internet Appendix presents additional evidence to examine refinances from 30-year FRMs to new 30-year FRMs. Consistent with Table 10, we find that a higher local FinTech share is associated with a larger fraction of refinances that are classified as optimal by the Agarwal et al. rule. A higher local FinTech share is also associated with larger average decreases in the borrower's interest rate at the point of refinancing, and a higher fraction of cash-out refinances.

In sum, the results suggest that a higher share of FinTech lending is associated not just with faster refinancing, but also more optimal refinancing decisions, at least on average. This effect, however, appears somewhat weaker for the borrowers that would benefit most from refinancing. Such borrowers may be less financially literate; we show in the next section that proxies for financial literacy are positively correlated with FinTech mortgage borrowing. In some cases seemingly "woodhead" borrowers may face other obstacles that prevent refinancing (e.g., a significant drop in income since the original mortgage was obtained).

We note that, to the extent that future growth of FinTech in the mortgage market continues to lead to faster refinancing, it is in fact possible that borrowers who themselves are limited in their sophistication or are otherwise unable to refinance may be worse off. In equilibrium faster prepayment speeds will be priced in MBS valuations, which could feed through to higher mortgage interest rates.

6. Who Borrows from FinTech Lenders?

The market share of FinTech lenders varies significantly by geography and across segments of the mortgage market.[42] In this section we estimate a simple model of the likelihood of borrowing from a FinTech mortgage lender as a

[42] Table 2 provides univariate summary statistics about the characteristics of mortgages from FinTech lenders. Figure A.3 in the Internet Appendix maps the FinTech market share of mortgage originations in 2010 and 2016. This map highlights the substantial geographic variation in the market share of FinTech lenders, as well as the widespread growth in technology-based lending over our sample period. One limitation of HMDA is that market

function of loan, borrower and location characteristics. We then compare the cross-sectional patterns in the data to hypotheses about the drivers of the growth in FinTech mortgage borrowing.

We estimate a loan-level linear probability model using pooled HMDA data on mortgage originations from 2010 to 2016:

$$\text{FinTech}_{i,c,t} = \alpha_t + \beta \cdot \text{Controls}_{i,c,t} + \Gamma \cdot \text{location}_c + \epsilon_{l,c,t}, \tag{5}$$

where $\text{FinTech}_{i,c,t}$ is equal to 100 if mortgage i in census tract c originated at time t was originated by a FinTech lender and zero otherwise, α_t is a vector of time dummies, $\text{Controls}_{i,c,t}$ is a set of loan and borrower characteristics drawn from HMDA, and location_c is a set of local geographic and socioeconomic variables measured at the census tract or county level, drawn from a variety of sources including the U.S. Census, American Community Survey and the FRBNY consumer credit panel. These location variables are measured in 2010, or otherwise as early in time as possible, to minimize any concerns about reverse causality. We provide data definitions and sources in Appendix Table A.

We estimate this model separately for purchase mortgages and refinances, because the determinants of demand may be quite different between the two, and because the market share of FinTech lenders is significantly higher for refinances (Table 2). Since differences in borrower characteristics between FinTech lenders and banks may be driven by regulatory factors, we present each specification both including and excluding mortgages from banks. In the specifications excluding banks, FinTech lenders are compared to other nonbanks, who are regulated similarly and have the same funding model.

6.1 Results

Table 11 presents the estimates. Each continuous right-hand-side variable is normalized to have a standard deviation of one, so that magnitudes can be compared across variables.[43] Below, we discuss the cross-sectional patterns relative to the predictions of four sets of potential drivers of the growth in FinTech mortgage lending: (1) access to finance, (2) technology adoption and financial literacy, (3) Internet access, and (4) local mortgage and housing market conditions.

coverage outside of MSAs may be more limited, because very small lenders and lenders that do not operate in MSAs do not need to report. However, our regression results in this section are robust to restricting the sample to MSAs.

43 Beyond the main variables of interest reported in the table, regressions also control for loan size (in logs), dummies for loan type (jumbo, FHA, VA), dummies for coapplicant and investor loan, additional individual-level race dummies, state dummies, month-year dummies, and dummies for missing values for each variable with incomplete data coverage. See Internet Appendix G for a full table of results including these variables. The table in the Internet Appendix also presents results of univariate regressions in which the FinTech dummy is regressed individually on each right-hand-side variable. The only additional control included in these univariate regressions is the vector of time dummies. Comparing the univariate and multivariate results helps to show which results are robust to the inclusion or exclusion of other variables.

Table 11
Who borrows from FinTech mortgage lenders?

Dependent variable: = 100 if originator is FinTech lender, = 0 otherwise

	Purchases		Refinances	
	All	Nonbanks	All	Nonbanks
Borrower income and demography				
log(income)	0.104***	0.701***	−0.833***	−0.159***
	(0.00650)	(0.0173)	(0.00725)	(0.0275)
Gender:				
Female	0.0592***	0.184***	0.756***	3.056***
	(0.00947)	(0.0208)	(0.0126)	(0.0379)
Unknown	2.887***	10.13***	6.728***	24.99***
	(0.0421)	(0.117)	(0.0437)	(0.100)
Race and ethnicity:				
Black	−0.306***	−0.387***	−0.415***	1.166***
	(0.0254)	(0.0495)	(0.0291)	(0.0814)
Hispanic	−0.880***	−1.577***	−1.432***	−1.982***
	(0.0200)	(0.0391)	(0.0250)	(0.0629)
Unknown	1.551***	3.220***	3.632***	6.540***
	(0.0294)	(0.0658)	(0.0310)	(0.0710)
% black or hispanic$^{\mathrm{TRACT}}$	−0.228***	−1.064***	−0.256***	−2.273***
	(0.0166)	(0.0394)	(0.0165)	(0.0501)
Access to finance				
Credit score$^{\mathrm{TRACT}}$	−0.279***	−0.731***	−1.068***	−3.002***
	(0.0192)	(0.0468)	(0.0193)	(0.0618)
Bank branch density$^{\mathrm{TRACT}}$	0.467***	0.954***	0.275***	0.479***
	(0.0262)	(0.0574)	(0.0201)	(0.0530)
Technology diffusion and adoption				
Population density$^{\mathrm{TRACT}}$	0.141***	0.920***	−0.0691***	0.421***
	(0.0275)	(0.0697)	(0.0236)	(0.0607)
Borrower age$^{\mathrm{TRACT}}$	0.119***	0.340***	0.263***	0.869***
	(0.0168)	(0.0400)	(0.0169)	(0.0502)
% bachelor degree$^{\mathrm{TRACT}}$	0.307***	0.920***	0.262***	0.690***
	(0.0213)	(0.0529)	(0.0180)	(0.0553)
Internet access				
% high speed coverage$^{\mathrm{TRACT}}$	0.101***	0.255***	0.0689***	0.371***
	(0.0127)	(0.0316)	(0.0127)	(0.0461)
% with broadband subscription$^{\mathrm{CTY}}$	−0.132***	−0.487***	−0.0344**	−0.0551
	(0.0179)	(0.0460)	(0.0167)	(0.0555)
Local housing market conditions				
% home price appreciation$^{\mathrm{CTY}}$	−0.0362***	−0.836***	0.277***	−1.258***
	(0.0114)	(0.0258)	(0.0132)	(0.0382)
Processing time coefficients$^{\mathrm{TRACT}}$	0.0182	0.205***	0.588***	1.599***
	(0.0111)	(0.0269)	(0.0119)	(0.0397)
log(2010 home price)$^{\mathrm{CTY}}$	−0.127***	−0.688***	−0.812***	−2.993***
	(0.0188)	(0.0471)	(0.0213)	(0.0675)
Additional controls	Yes	Yes	Yes	Yes
Observations	20,790,255	8,901,875	32,936,746	9,888,845
Mean of dependent variable	2.888	6.745	6.129	20.41

Linear probability model based on HMDA data from 2010-16. All continuous right-hand size variables normalized to have mean of zero and standard deviation of one. Superscripts $^{\mathrm{TRACT}}$ and $^{\mathrm{CTY}}$ indicate variable is measured at the census tract or county level of aggregation, respectively, rather than at the loan level. Robust standard errors in parentheses, clustered by census tract. Regressions include year-month dummies as well as controls for loan size, loan type, dummies for jumbo loan, coapplicant, owner occupied, other race categories, and missing values for any variable with positive incidence of missing values. See the Internet Appendix for full results including coefficients on these variables as well as univariate regressions. See Appendix Table A for variable definitions and sources. *$p<.1$; **$p<.05$; ***$p<.01$.

6.1.1 Access to finance. We find no strong evidence that FinTech lenders disproportionately cater to financially constrained borrowers (e.g., borrowers with low incomes or poor credit histories), particularly compared to other nonbanks. Although the FinTech market share is higher in census tracts where mortgage borrowers have lower average credit scores, the results for income and the share of FHA/VA-insured mortgages are mixed depending on the type of loan and comparison group.[44] As shown in Section 3, FinTech mortgages also have comparatively lower default rates on FHA loans, suggesting they are not targeting the riskiest borrowers. Nonbank lenders overall, including FinTech lenders, originate a significantly higher share of FHA and VA loans than banks, however (see Table 2 or the Internet Appendix). Buchak et al. (2018) attribute the low levels of bank FHA lending to regulatory and legal factors. FinTech lenders attract a higher share of female borrowers, although the share of black or hispanic borrowers is lower in most specifications.[45]

Also related to access to finance, we test whether FinTech borrowing is higher in census tracts with few physical bank branches. We measure branch access as the number of bank branches within a 25 mile radius of the geographic midpoint of the census tract, based on FDIC Summary of Deposits data. Even though the FinTech business model is focused on online applications, we find that the share of FinTech borrowing is *increasing* in bank branch density.

6.1.2 Technology adoption and financial literacy. Early technology adoption is often concentrated in urban areas as well as among younger and more educated consumers. Indeed, we find that the FinTech market share is higher in more urban neighborhoods, measured by population density, although only for purchase mortgages (for refinances, the coefficient flips sign across specifications).

Examining education and age directly, we find that the FinTech market share is increasing in the fraction of adults with at least a bachelor's degree. Interestingly, however, the share of FinTech borrowing is *increasing* with average mortgage borrower age. Although this may seem counterintuitive, we have been told by industry practitioners that first-time mortgage borrowers often prefer to interact face-to-face with a mortgage broker or loan officer, rather than applying online, because they are less familiar with the steps involved; in other words they

[44] Among purchase mortgages, FinTech borrowers have higher incomes either compared to all lenders or just nonbanks and are also less likely to be FHA/VA-guaranteed than are loans from other nonbanks. For refinances, FinTech borrowers have lower incomes and the fraction of FHA/VA insured loans is generally higher (see Internet Appendix G for the FHA and VA coefficients).

[45] Our estimates for borrowers' gender and race should be treated with caution, because, as discussed earlier, a significant fraction of race and gender fields in HMDA are coded as missing or "NA" for FinTech lenders. As a result, the measured shares of female and minority borrowers are likely to be a lower bound. Using census tract variation in minority population from the 2010 Census, we find that the FinTech share is lower in tracts with a high share of minority borrowers, although this is not always true in the univariate specifications in the Internet Appendix.

are less financially experienced and literate (consistent with Agarwal et al. 2009, who find that financial literacy increases with age up to individuals' mid-50's).

6.1.3 Internet access. As online services become more ubiquitous, the "digital divide" becomes a growing concern, meaning that inequality in access to Internet services may be exacerbating income and wealth inequality. We examine whether the availability of high-speed Internet is a constraint on FinTech mortgage borrowing (where applications are generally completed online), using two data sources: first, the fraction of households with high-speed Internet access from the Census Bureau American Community Survey (available from 2013 by county); second, census-block data from the FCC and NTIA for the ten largest states by population on the fraction of households with the option to connect to fiber or cable Internet, which we aggregate by census tract.

Empirically, these two variables have opposite signs, and the coefficients are generally small in magnitude. We conclude that lack of access to adequate Internet does not appear to be a significant constraint on the diffusion of technology-based mortgage lending. This interpretation is also consistent with more detailed analysis described below about the staggered rollout of Google Fiber in one local market.

6.1.4 Local mortgage and housing market conditions. As FinTech lending becomes more widely available, it may be particularly beneficial in areas with long processing times. Indeed, we find a higher share of FinTech mortgage borrowing in census tracts where mortgage processing times were slow ex ante, measured in 2010 prior to the growth in FinTech lending.[46] This result suggests that borrowers have turned to FinTech lenders in part to alleviate origination bottlenecks associated with "traditional" mortgage lenders.[47]

We also examine whether FinTech mortgage borrowing is more prevalent in "hot" real estate markets where prices are rising rapidly and quick closing may be more important. Anecdotal evidence suggests that borrowers may be particularly attracted to the convenience and fast processing speeds of FinTech lenders in such markets.[48] We find no empirical support for this hypothesis; in fact, home price growth is negatively correlated with the market share of

[46] We measure average processing time in 2010 conditional on borrower characteristics. Using 2010 HMDA data, we regress processing time on loan and borrower characteristics. We then take the residuals from this regression and aggregate them to the census tract level.

[47] As discussed in Section 2, the sign of this correlation also speaks against concerns that our earlier processing time results are due to selection effects. If "fast processor" borrowers (conditional on observables) are attracted to FinTech lenders, we would have expected a higher ex post FinTech share in neighborhoods where 2010 processing times were faster than would be expected based on observables. In fact, however, we find that the opposite correlation is true in the data.

[48] For example, Powell (2015) highlights the shorter closing times of online lenders, and includes the following quote from the CEO of the lender Bank of the Internet: "We have very short underwriting term times and that's a plus for our purchase oriented borrowers – we give quick answers," Garrabrants said. "In a really hot market, that's important."

FinTech lending for purchase mortgages (which are the relevant group to consider for this hypothesis).

Finally, we test whether the FinTech share is lower in neighborhoods with high average home prices (measured in 2010). This hypothesis is motivated by the fact that FinTech lenders rely on securitization for funding mortgages; as a result these lenders originate few jumbo loans, which are difficult to securitize. This in turn means that FinTech lenders may advertise less in high-home-price markets where jumbo mortgages predominate. There also may be less social learning about the FinTech mortgage lending model in such markets. We do indeed find that the likelihood of borrowing from a FinTech lender is lower in high home price areas, conditional on loan size and other observables.

6.2 Interpretation

We interpret our evidence as supporting the view that FinTech mortgage borrowers are attracted to the faster processing times and greater convenience involved with online applications and partial automation of mortgage underwriting. This is consistent with the faster growth of FinTech in census tracts with previously long mortgage processing cycle times and the higher incomes and education of FinTech borrowers. It is also consistent with the high share of refinances for FinTech lenders.[49] We find no empirical support for the hypothesis that FinTech lenders have grown by disproportionately targeting risky, marginal borrowers. Despite the emphasis of the FinTech lending model on online applications and interactions, we also find no evidence that younger borrowers or borrowers located in census tracts with better Internet access are more likely to borrow from FinTech lenders.

We emphasize that we do not attach a strong causal interpretation to our results, given the reduced-form nature of our analysis. Yet, we believe that the empirical relationships documented here are a useful benchmark for further analysis.[50]

6.3 Evidence from Google Fiber rollout

In addition to our reduced-form analysis, we also conduct an in-depth empirical analysis of the potential causal effect of improved Internet access on FinTech lending. We exploit the staggered entry of a new high-speed Internet provider in a single market, namely the entry of Google Fiber in Kansas City starting in late 2012. Google Fiber is a large-scale initiative by Google to establish a new

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49 The more standardized set of tasks involved in refinancing a mortgage may be the best fit for FinTech lending at the current state of technology.

50 We note that, where comparable, our results are generally consistent with Buchak et al. (2018), who estimate similar reduced-form regressions of the determinants of borrowing from FinTech lenders and other nonbanks. For example, Buchak et al. (2018) also find that FinTech lenders originate a significantly higher share of refinances compared to purchase mortgages, and have a high incidence of missing race and gender. Besides differences in modelling choices, we also examine a number of determinants of FinTech demand which Buchak et al. (2018) do not (e.g., bank branch density, borrower age, or Internet access).

Internet service provider. Kansas City was the first metro area that Google Fiber entered.[51] A key factor behind the selection of Kansas City was that households had poor access to high-speed Internet prior to the entry of Google Fiber. There was subsequently a rapid expansion in high-speed Internet access from 2012 to 2015 as Google Fiber became widely available and as competitors improved their own services.

Using HMDA data, we analyze how the market share of FinTech lenders across different neighborhoods in the Kansas City MSA evolved over this period, exploiting the staggered rollout of Google Fiber across census tracts and controlling for time and census-tract fixed effects. Internet Appendix H presents the results. Our main finding is that the discrete improvements in Internet access generated by the entry of Google Fiber did not induce a higher share of FinTech borrowing. The results are often not statistically significant, and in the cases where they are significant they have the opposite sign to that predicted, due to a migration in mortgage lending from nonbanks to banks.

Consistent with our earlier evidence, these results indicate that adequate Internet access is unlikely to be a significant constraint on the diffusion of online mortgage lending, mitigating concerns about the "digital divide" in this setting.

7. Conclusion

This paper presents new evidence on how technology is reshaping the U.S. mortgage market by studying the vanguard of technology-based lenders. We find that FinTech lenders offer a faster origination process that is less sensitive to capacity constraints. FinTech lending is also associated with an increase in the propensity to refinance, especially among borrowers that are likely to benefit from it. We find no evidence that FinTech lenders originate riskier loans or screen borrowers less effectively; in fact, FHA mortgages from FinTech lenders have *lower* default rates than do similar loans from other originators.

Going forward, we expect that banks and other lenders will seek to replicate the "FinTech model" characterized by an online application process and centralized, semiautomated underwriting and processing. Indeed, online mortgage lending has continued to expand rapidly since the end of our sample period in 2016. 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. Banks are likely to be less nimble than specialist nonbank mortgage lenders, because they are more highly regulated and organizationally complex, and often have complex legacy processes and information systems. On the other hand, banks also have significant competitive advantages, including access to low-cost

[51] This area consists of Johnson, Leavenworth, and Wyandotte counties in Kansas and Cass, Clay, Jackson, and Platte counties in Missouri.

deposit funding, cross-selling opportunities, and the availability of branches for those borrowers preferring a mix of online and face-to-face interactions.

From an industrial organization perspective, the shift to online lending raises particular challenges for smaller lenders, given the economies of scale associated with developing and maintaining an online lending platform. The end result could be a more concentrated mortgage market dominated by those firms that can afford to innovate and invest in technology.

From a consumer perspective, we believe our results shed light on how mortgage credit supply is likely to evolve in the future. Specifically, our results suggest that technological diffusion will speed up the mortgage origination process and reduce the influence of capacity constraints during periods of peak demand, thereby strengthening the transmission of monetary policy to households via the mortgage market. Our findings also imply that technological diffusion may lead to more efficient refinancing decisions, which could have significant benefits to U.S. households.

Our results must be considered in the prevailing institutional context of the U.S. mortgage market. Specifically, at the time of our study FinTech lenders are nonbanks that securitize their mortgages and do not take deposits. It remains to be seen whether we find the benefits of FinTech lending prevail as the model spreads to deposit-taking banks and their borrowers. Changes in regulation or the housing finance system may significantly affect FinTech lending going forward. Furthermore, the benefits we document stem from innovations that rely on hard information; as these innovations spread, they may affect access to credit for borrowers with applications that involve soft information or that require face-to-face communication with a loan officer. We leave these issues for future research.

Appendix

Table A
Data sources and variable definitions

Variable	Definition	Level of aggregation
HMDA		
log(income)	Logarithm of borrower income	Individual
log(loan size)	Logarithm of loan amount	Individual
Loan-to-income (LTI)	Loan amount divided by borrower income	Individual
Jumbo loan [0,1]	Indicator variable equal to 1 if loan amount exceeds FHFA conforming loan limit for the month of origination	Individual
Loan type [0,1]	Indicator variables for conventional, FHA, and VA loans. Conventional is omitted category in regressions	Individual
Loan purpose [0,1]	Indicator variables for whether whether loan is a home purchase loan or a refinancing	Individual
No coapplicant [0,1]	Indicator variable equal to 1 if no coapplicant on the mortgage application	Individual

Table A
Continued

Variable	Definition	Level of aggregation
Owner occupied [0,1]	Indicator for the property being the borrower's principal dwelling	Individual
Gender [0,1]	Indicators for borrower gender being female, male, or unknown (unreported). Male is omitted category in regressions	Individual
Race and ethnicity [0,1]	Indicators for race and ethnicity. Nonhispanic white is omitted category in regressions	Individual
Processing time	Number of calendar days between the application date and action date of a loan (based on restricted-use version of HMDA data)	Individual
log(application volume)	Logarithm of aggregate application volume	National
U.S. Census		
% Black or Hispanic	Percentage of population identifying as Black, Hispanic, or both in 2010	Tract
Population density	Thousands of residents in thousands per square mile in 2010	Tract
American Community Survey		
% bachelor degree	Percentage of population 25 years or older with a bachelor's or higher degree in 2010	Tract
% with broadband subscription	Percentage of population with an Internet subscription other than dial-up (including DSL, cable, fiber optic, mobile broadband, satellite, or fixed wireless) in 2010	County
Equifax		
Credit score	Mean credit score of all individuals with a positive mortgage balance (measured as of 2014Q3)	Tract
Age	Median age of individuals with a positive mortgage balance (measured as of 2014Q3)	Tract
Zillow		
Home price appreciation	Home price appreciation over the 12 months up to the month of loan origination	County
log(2010 home price)	Logarithm of average home price as of January 2010	County
NTIA/FCC		
High-speed internet coverage	Percentage of households with access to either cable or fiber services, or Google Fiber, measured at a half-yearly frequency. Data were collected from the NTIA from 2011 to mid-2014 and from the FCC from end-2014 to end-2016. Data are only available for the ten largest U.S. states	Tract
FDIC Summary of Deposits		
Bank branch density	Number of bank branches (in 000s) within a 25 mile radius of the center of census tract in 2010	Tract
FHA Neighborhood Watch Early Warning System		
One- and two-year comparative default rate	Default rate (90+ days delinquent or teriminated in a claim as the percentage of loans) for FinTech lender *i* measured as the percent deviation from the default rate for all FHA loans in the same geography and time period. One-year default rate considers only defaults occurring in the first year of the mortgage life. For most analysis, performance is measured over the sample period 2015:Q3 to 2017:Q3	MSA, state or national
Mix-adjusted 2-year default rate	Based on the FHA supplementary performance measure (SPM, equal to the ratio of the lender's two-year default rate to a benchmark default rate for a portfolio of loans with the same mix of credit scores.) Mix-adjusted default rate is the ratio of the lender's SPM to the SPM for all FHA loans in the same geography and time period	MSA, state or national
Ginnie Mae loan-level data		
Default	Indicator variable for whether FHA mortgage enters 90+ days delinquency	Individual
FICO	Borrower credit score at origination	Individual
LTV	Ratio of loan amount to appraised property value	Individual
DTI	Ratio of total debt payment to borrower income	Individual

Table A
Continued

Variable	Definition	Level of aggregation
Equifax CRISM borrower-level data		
Coupon minus 10-year Treasury yield	Difference between average coupon rate on outstanding mortgages and 10-year Treasury bond yield (used in Figure 2)	National
Refinancing propensity	Share of outstanding mortgages in month *t* that are refinanced in month *t+1*	County
FICO	Borrower credit score (updated monthly), county average	County
CLTV	Combined loan-to-value ratio (sum of all mortgage liens, divided by updated home value)	County
Average current rate	Current mortgage coupon rate, county average	County
FHA/VA share	Share of FHA/VA mortgages in county	County
Author-derived variables		
2010 conditional processing time	Average processing time in 2010 (census tract average, residual after regressing processing time in days on HMDA borrower and loan characteristics)	Tract
Refinancing incentive	Difference between coupon rate and rate at which borrower would be indifferent between refinancing and not refinancing based on the "square root rule" of Agarwal, Driscoll, and Laibson (2013)	Individual

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