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Do FinTech Mortgage Lenders Fill the Credit Gap? Evidence from Natural Disasters

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Abstract

After exogenous demand shocks caused by natural disasters, FinTech lenders are more responsive to increased demand for reconstruction mortgages than traditional banks and non-FinTech shadow banks. Both FinTech and traditional banks increase credit supply, but FinTech supply is more elastic without increases in risk-adjusted interest rates or delinquency rates. Comparing lending supply channels, banks respond to regulatory incentives to lend to damaged areas, whereas FinTech lenders supply more credit when traditional banks rely more on balance sheet financing and physical branch networks. Compared to traditional banks, FinTech lenders increase supply elasticity more aggressively in response to local competitive pressure.

I. Introduction

FinTech lenders have "rocketed" into the residential mortgage market by disrupting the mortgage application and underwriting process, with Quicken Loans emerging as the largest mortgage lender in the United States.[1] While previous

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[1]According to the Home Mortgage Disclosure Act data, Quicken Loans originated more than 1.1 million loans worth $314 billion in 2020, leading all other mortgage lenders by a large margin.

literature explores how banking regulation and financial technology contributed to the FinTech revolution over recent years (Buchak, Matvos, Piskorski, and Seru (2018a), Fuster, Plosser, Schnabl, and Vickery (2019)), it remains unclear whether these technology-equipped lenders can fill the credit gap when a local mortgage market faces unanticipated and temporary demand pressure. In this article, we exploit natural disasters as exogenous demand shocks to local residential mortgage markets as in Cortés and Strahan (2017) and Dlugosz, Gam, Gopalan, and Skrastins (2022), and study how FinTech and non-FinTech lenders respond to the surge in credit demand for reconstruction of damaged or destroyed property. More importantly, we compare the relative competitive positions of FinTech and traditional bank lenders in local areas, and explore the potential channels that explain how financial intermediaries fill the local credit gap amid unanticipated demand shocks. In so doing, we contribute to a nascent literature investigating the competition between FinTech lenders and traditional banks (e.g., Balyuk, Berger, and Hackney (2020)).

We find that, although mortgage applications surged after natural disasters for all lender types (i.e., mortgage applications increased between 5.0% and 7.8% in disaster-affected counties), only FinTech and traditional bank lenders filled the postdisaster credit gap by significantly increasing their supply of mortgage loans. The likelihood of approval increased by 6.9% for FinTech loans and 4.7% for traditional bank loans, equivalent to 8.7% and 6.0% of the sample mean likelihood of approval. In contrast, we find no increase in the likelihood of approval for non-FinTech shadow banks following natural disasters.

To better understand how mortgage credit is allocated, we examine whether mortgage lenders adjust credit underwriting standards in the wake of natural disasters. This analysis is particularly important in our context as natural disasters may disrupt local economic conditions, thereby impairing the creditworthiness of impacted borrowers. Increased uncertainty, tighter capacity constraints, and higher processing costs may induce lenders to tighten their credit underwriting standards. We compare credit underwriting standards across lender types using the loan-to-income ratio (LTI) on approved and denied mortgage loans. Mortgages with higher LTIs are considered riskier because the borrower's mortgage debt burden is heavier relative to their income. We find that although both FinTech and traditional bank lenders loosen underwriting standards (increase LTI), FinTech lenders did so more aggressively than banks. For example, the LTI on postdisaster mortgages approved by FinTech lenders increases by 7.8% more than the LTI on postdisaster mortgages approved by traditional banks.

Upon establishing that increases in both bank and FinTech lenders' supply satisfy the sudden, exogenous increase in credit demand both along the extensive margin (as indicated by increases in approvals) and the intensive margin (as indicated by higher LTIs), we examine mortgage pricing. It is possible that FinTech lenders charge a premium in exchange for the enhanced credit availability that they provide in the wake of natural disasters. FinTech lenders may also raise interest rates if their funding costs increase during the turbulent times associated with disaster

In contrast, Wells Fargo, the largest bank mortgage lender, originated 320,026 loans worth $137 billion in 2020.

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emergencies. Thus, we examine postdisaster mortgage pricing while controlling for all observable borrower and loan characteristics. In other words, we investigate whether there is any change in postdisaster loan rates that cannot be explained by observable risk factors. We find no significant increases in loan rates charged by FinTech lenders as compared to other lenders, suggesting that FinTech lenders do not alter their risk-adjusted interest rates in postdisaster lending.[2]

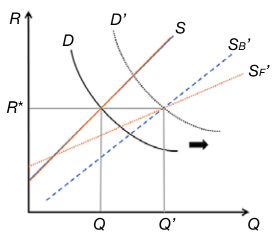
FinTech lenders' expansive postdisaster lending behavior may introduce adverse changes in risks that are unobservable to econometricians and are not fully captured by loan interest rates. If so, we should observe abnormally deteriorating performance for FinTech postdisaster loans after controlling for interest rates and observable risk factors. However, we do not find a significantly higher likelihood of delinquency on FinTech postdisaster loans. This suggests that FinTech lenders fill the credit gap during a turbulent time without their loan performance being impaired by unpriced or underpriced risk factors.

Our clean empirical setting allows us to disentangle the dynamics of demand and supply for different types of lenders without the confounding effects of fundamentals or other background noise, thereby allowing us to draw inferences about mortgage supply that can be generalized to other circumstances. We illustrate the economics behind our results using the simplified demand and supply curves shown in Figure 1, where the horizontal axis indicates loan volume and the vertical axis indicates risk-adjusted loan rates. Given that our focus is to compare the changes in lending decisions by different types of lenders in the wake of natural disasters, we allow the predisaster supply curves of different lender types to overlap (i.e., same slope and location) to simplify the illustration. The exogenous surge in postdisaster mortgage applications suggests a rightward shift in the demand curve from D to D'. If there were no rightward shifts in mortgage supply curves, the increase in demand would generate an increase in quantity supplied at higher mortgage rates (as long as the predisaster supply is not perfectly elastic). Since we do not find evidence

FIGURE 1

Mortgage Demand and Supply Curves in the Wake of Natural Disasters

Figure 1 presents the mortgage demand (supply) curves for FinTech and traditional bank lenders. The curve labeled D (S) represents the predisaster mortgage demand (supply) curve for both FinTech and traditional bank lenders. For simplicity, the predisaster supply and demand curves (and hence the equilibrium quantity supplied Q) are shown to be the same for FinTech and traditional bank lenders. The curve labeled D' represents the postdisaster demand curve for mortgages, that is, the exogenous demand shock. S'_B (S'_F) represents the postdisaster mortgage supply curve for traditional bank (FinTech) lenders.



[2]However, our results are consistent with a secular trend toward lower mortgage rates at Fintech lenders.

consistent with increases in mortgage rates for any lenders, we infer that lender supply curves shift rightward in response to the natural disaster demand shock. Thus, Figure 1 shows that both FinTech and traditional banks shift their mortgage supply curves in order to fulfill higher postdisaster credit demand at predisaster risk-adjusted loan rates (R^*).

Further, our results indicate that both FinTech and traditional bank lenders (but not non-FinTech shadow banks) increase credit supply at both the extensive margin (as indicated by increases in approvals) and the intensive margin (as indicated by higher LTI). Increased lending along the extensive margin suggests a rightward shift in the supply curve, whereas increased credit supply along the intensive margin implies an increase in supply elasticity, which is inconsistent with an infinitely elastic predisaster supply curve. This is shown in Figure 1 as flatter supply curves for both bank and FinTech supply curves ($S_{B'}$ and $S_{F'}$). Moreover, since our results show that FinTech lenders increase LTI more than traditional banks, the postdisaster Fintech supply curve $S_{F'}$ is flatter (more elastic) than the postdisaster mortgage supply of traditional banks $S_{B'}$.

We relate our analysis to these theoretical supply and demand curves as follows: The natural disaster shock induces a subsequent rightward shift in demand for mortgages for rebuilding. Thus, we interpret our finding of an increase in loan applications for refinancing and home improvement as an indication of the rightward shift in demand shown in Figure 1. If there were no concomitant supply curve shifts, then we would find increased mortgage lending at higher rates, that is, a shift along a stationary supply curve to a higher quantity demanded. Our findings are inconsistent with this, thereby indicating that lender supply curves shift rightward in the wake of natural disasters. We analyze mortgage approvals in order to identify supply curve shifts by different lender types. That is, our finding that postdisaster refinancing and home improvement mortgage approvals increase at both FinTech and traditional bank lenders (but not at shadow banks) is consistent with the supply curve shifts shown in Figure 1. Finally, the depiction of the decreased slope of the postdisaster lender supply curves is obtained from our analysis of LTI, which shows increased supply elasticity for both FinTech and traditional bank lenders after natural disasters (inconsistent with an infinitely elastic predisaster supply curve for all lender types).

Generalizing from our natural disaster empirical setting, our findings suggest that FinTech lenders may have some certain advantages or incentives that enable them to increase supply in response to exogenous demand shocks. We draw general inferences about the competitive economics in the U.S. mortgage market and investigate the economic mechanisms through which mortgage lenders expand credit supply along both the extensive and intensive margins. Specifically, we contrast the competitive channels of FinTech lenders relative to traditional banks in local markets along three dimensions: i) regulatory incentives, as measured by whether the county is dominated by highly regulated (i.e., stress-tested) traditional banks; ii) funding sources, as indicated by whether local traditional banks are dependent upon on-balance sheet lending as opposed to securitization to fund mortgage lending; and iii) reliance on the brick-and-mortar business model, as measured by the density of local physical bank branch networks as opposed to FinTechs' online access.

We first test the oft-cited hypothesis (e.g., Acharya, Berger, and Roman (2018), Buchak, Matvos, Piskorski, and Seru (2018b), Calem, Correa, and Lee (2020), and De Roure, Pelizzon, and Thakor (2022)) that regulatory oversight restricts bank lending activity, particularly in the highly regulated mortgage lending arena during the post-Dodd Frank era. Contrary to this regulatory restrictions hypothesis, however, we find that counties dominated by stress-tested, traditional banks saw a greater increase in mortgage lending in the wake of natural disasters. We argue that this results from favorable regulatory treatment for banks that contribute to community recovery. For example, banks receive Community Reinvestment Act (CRA) consideration if they grant community development loans in federally designated disaster areas.[3] This credit is particularly important for large stress-tested banks that may provide limited community lending support, but require high CRA grades for regulatory approval of mergers and acquisitions (Berger, Klapper, and Udell (2001), Dahl, Evanoff, and Spivey (2010)). Thus, the regulatory inducements provide a competitive advantage for stress-tested traditional banks, thereby incentivizing them to fill the mortgage credit gap.

In contrast, we find that the postdisaster FinTech shifts in supply emanate from counties in which traditional banks are dependent upon on-balance sheet lending and physical branch networks. In these markets, FinTech lenders have a competitive advantage due to their reliance on securitization and online access. This allows FinTechs to exploit market-building opportunities and step in to fill the mortgage credit gap left by traditional banks reliant upon balance sheet lending and branch networks.

Moreover, we find that FinTech lenders tend to more aggressively relax underwriting standards in regions with more competitive traditional banks. Specifically, FinTech lenders loosen their requirements on borrower LTI more aggressively in areas dominated by stress-tested traditional banks and areas where banks are less dependent on branch networks or balance sheet lending. In sum, our results suggest that FinTech lenders increase credit availability when they have a competitive advantage and relax underwriting standards when they are under competitive pressure from traditional banks. However, our findings suggest that traditional banks do not respond to competition from FinTech lenders by relaxing their underwriting standards, consistent with the finding in Jiang (2020) that traditional banks actually fund their local shadow bank competitors' mortgage lending via securitization warehouse facilities.

To our knowledge, this is the first article to compare the mortgage supply responses by traditional banks, non-FinTech shadow banks, and FinTech lenders to exogenous demand shocks emanating from local natural disasters. Besides the econometric advantage of disentangling demand from supply, the empirical setting of natural disasters enables us to examine the channels used to fill the credit gap resulting from unanticipated, urgent, and temporary demand pressure in local mortgage markets. In this regard, our empirical setting complements earlier work examining the response of FinTech and non-FinTech lenders to time-series variations in total mortgage applications in the United States (e.g., Buchak et al. (2018a),

[3]For example, see the FDIC Financial Institution Letter for Hurricane Sally, https://www.fdic.gov/news/financial-institution-letters/2020/fil20092.html.

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Fuster et al. (2019)). Our article also echos the methodology of Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton (2020), Erel and Liebersohn (2020), and Li, Strahan, and Zhang (2020) who exploit exogenous demand shocks (e.g., the extraordinary COVID-19 Paycheck Protection Program) to draw inferences about credit supply in the small business loan market. In addition, our article generalizes the work of Gopal and Schnabl (2022) which finds that FinTech lenders and finance companies increase small business lending in response to reductions in bank lending in the wake of the 2008 financial crisis.

Moreover, our article extends the literature on the competition between FinTech and traditional lenders in the mortgage market (Buchak et al. (2018a), Fuster et al. (2019), and Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021)), the consumer credit market (Tang (2019), De Roure et al. (2022)), and the small business lending market (Balyuk et al. (2020), Erel and Liebersohn (2020), and Gopal and Schnabl (2022)). We add nuance to the literature demonstrating a widespread withdrawal of the largest U.S. banks from mortgage lending during the post-2009 period (Chen, Hanson, and Stein (2017), Begley and Srinivasan (2021)) by examining the role of previously overlooked CRA regulatory incentives to encourage postdisaster mortgage credit supply.

Finally, our analysis of three loan supply channels offers us an opportunity to examine the competitive supply responses of FinTech lenders and traditional banks to sudden surges in demand for mortgage loans. In particular, we examine the use of credit underwriting standards as a competitive tool. That is, we examine the question of whether FinTech firms that are under competitive pressure from traditional banks increase supply elasticity by relaxing credit standards. To the best of our knowledge, we are the first to empirically analyze this question, although traditional banking literature examines the use of credit standards as a tool of competition.[4] In the context of FinTech lenders, our empirical setting also allows us to extend work by Tang (2019) and Balyuk et al. (2020) that examine the impact of FinTech entry on credit quality.

II. Literature Review and Hypothesis Development

In this article, we contrast the agility and efficiency of FinTech lenders to the deliberative pace of the regulated traditional banking sector. FinTech lenders adopt fully-automated algorithms that integrate machine learning and artificial intelligence to process credit information, especially hard information, more efficiently than traditional lenders (Balyuk et al. (2020), Berg, Burg, Gombović, and Puri (2020), Agarwal, Alok, Ghosh, and Gupta (2021), and Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022)). This competitive advantage is more pronounced in the securitized mortgage lending market characterized by a large amount of hard information. Indeed, Fuster et al. (2019) find that FinTech mortgage lenders process applications 20% faster than other lenders. The algorithm-driven approaches also allow FinTech lenders to better identify underbanked, but creditworthy borrowers

[4]For example, Boot and Thakor (2000) model interbank competition as a force that limits rents from relationship banking, thereby inducing a shift to higher quality, more transparent borrowers.

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who may be perceived to be riskier under traditional measures of credit risk (Jagtiani and Lemieux (2019)). This advantage may be particularly important in the wake of natural disasters when lenders face increased uncertainty, tighter capacity constraints, and higher processing costs. To avoid legal liabilities for riskier loans (e.g., costs of failure to meet the government-sponsored enterprises' (GSEs) representation and warranty conditions), traditional lenders may introduce credit overlays in the form of stricter credit standards. In line with this conjecture, Bedayo, Jiménez, Peydró, and Sánchez (2020) find that traditional banks expedite loan approval and origination during boom periods, but delay them during times of high volatility. In contrast, FinTech lenders may configure algorithms to identify creditworthy borrowers without tightening underwriting standards. These advantages allow FinTech lenders to better exploit market-building opportunities in the wake of demand shocks. Thus, we first hypothesize that:

Hypothesis 1A. In response to increased demand for mortgages in the wake of natural disasters, FinTech lenders increase mortgage supply and supply credit more elastically.

Nevertheless, traditional banks still possess some unique advantages and incentives that enable them to enhance the supply of credit following natural disasters. Notably, a key function served by traditional banks is intertemporal credit smoothing, such that the high loan rates and low deposit rates offered by banks imply an implicit guarantee of enhanced credit availability during stressed periods. For example, Bolton, Freixas, Gambacorta, and Mistrulli (2016) show that relationship banks charge higher spreads in exchange for the provision of credit at favorable terms during economic downturns. Further, Dia (2013) proposes a dynamic model showing that banks smooth the impact of interest rate shocks on their customers, and Berger, Bouwman, Norden, Roman, Udell, and Wang (2022) document intertemporal smoothing in credit card loans to consumers and small businesses. Indeed, the long-standing and personalized customer relationships provide traditional banks, especially community banks, with private information that ensure a stable source of mortgage financing in both good and bad times (DeYoung, Hunter, and Udell (2004)). Consistent with this argument, Cortés and Strahan (2017) find that traditional banks are incentivized to direct their balance sheet resources to their disaster-impacted local communities in order to preserve monopoly rents.

Moreover, regulators provide various forms of regulatory relief and assistance to traditional banks in order to facilitate postdisaster recovery. For example, the FDIC encourages banks to increase the supply of credit to disaster-impacted areas by offering banks CRA consideration and expediting any request to operate temporary banking facilities. The FDIC may also exempt banks' relaxation of loan terms in disaster-impacted areas from examiner criticism. The Federal Reserve Board can also exercise its authority to waive real estate-related appraisal regulations and extend CRA consideration to activities that revitalize disaster areas. Similarly, the Office of the Comptroller of the Currency, the National Credit Union Administration, the Conference of State Bank Supervisors, and the Farm Credit Administration also issue press releases that encourage regulated financial institutions to assist postdisaster recovery.[5] Given that these factors only apply to traditional banks, we hypothesize that:

Hypothesis 1B. In response to increased demand for mortgages in the wake of natural disasters, traditional banks increase mortgage supply and supply credit more elastically.

Finally, we examine non-FinTech shadow banks' response to postdisaster increases in mortgage demand. Similar to FinTech lenders, non-FinTech shadow banks rely on securitization (by selling to GSEs) to fund their mortgage originations. Hence they are less likely to face credit constraints when increasing their supply of mortgages as compared to lenders that hold a significantly higher fraction of mortgages on their balance sheets. However, unlike FinTech lenders, non-FinTech shadow banks rely heavily on "brick and mortar" branch networks (a feature that non-FinTech shadow banks and traditional banks share in common). As a result, their processing capacity may be more constrained when they face postdisaster demand shocks. For example, the lack of personnel to handle mortgage applications at physical branches following natural disasters could introduce significant delays and setbacks to the mortgage origination process. Given these conflicting advantages and disadvantages, we do not expect an increase in credit supply by non-FinTech shadow banks as conjectured for other lender types. We hypothesize that:

Hypothesis 1C. Following the increased demand for mortgages in the wake of natural disasters, there is no significant increase in mortgage supply or the elasticity of mortgage supply by non-FinTech shadow banks.

We evaluate Hypotheses 1A, 1B, and 1C by testing both the changes in loan approval rates in order to measure different lenders' mortgage supply at the extensive margin, and the changes in mortgage LTI in order to measure different lenders' mortgage supply at the intensive margin. The tests allow us to draw inferences on the dynamics of credit supply for each lender type during the postdisaster period. These hypotheses focus on lender supply-side responses to exogenous demand curve shifts. However, natural disaster shocks may induce divergent demand-side shifts for different lender types. For example, borrowers may value the convenience and speed of processing of FinTech lenders more in the wake of natural disasters, thereby inducing them to direct their applications to their preferred provider. We test this conjecture by analyzing loan applications, and find that all lender types experience significant increases in loan applications, with no statistically significant difference in coefficients across lender types. Thus, we find no distinction in demand shifts by lender types, which ensures the comparability of the supply effects across lender types and allows us to perform a meaningful evaluation of Hypotheses 1A, 1B, and 1C.

[5]A counterargument is that traditional banks' mortgage supply is limited by postfinancial crisis regulations (e.g., Dodd-Frank Act and Basel III capital adequacy requirements) that impose stringent rules on mortgage underwriting activities. These effects of regulatory constraints may be intensified following natural disasters that increase economic uncertainty.

We supplement the analysis of the postdisaster mortgage supply dynamics by analyzing equilibrium mortgage rates. FinTech firms provide an online mortgage application and underwriting process that is more convenient and efficient. Borrowers who value convenience might be willing to pay for the convenience offered by FinTech lenders. Indeed, Buchak et al. (2018a) find that FinTech lenders appear to charge a convenience premium of 14–16 basis points. Fuster et al. (2019) also find FinTech lenders demand a higher premium among borrowers who value convenience. These features may be more valuable during disaster emergencies, such that FinTech lenders may charge a higher convenience premium in the aftermath of disasters.

Moreover, mortgage rates also depend on lenders' funding and processing costs, which may increase after natural disasters. For traditional banks that mainly rely on deposits to extend loans, the cost of funding may rise because they have to either bid up deposit rates in disaster-affected areas (Dlugosz et al. (2022)) or transfer credit from other areas to the affected areas (Cortés and Strahan (2017)). Funding costs may increase even more for shadow banks (FinTech and non-FinTech) who typically rely on lines of credit from banks (i.e., warehouse lines) to finance mortgage originations, since traditional banks' higher funding costs may be transmitted to their shadow bank customers. Processing costs may also increase for traditional banks and non-FinTech shadow banks if they face temporary labor and facility constraints in the wake of natural disasters. This is less of a concern for FinTech lenders whose automated operations allow them to expand their processing capacity without higher processing costs. Thus, mortgage rates may increase if lenders pass on their higher funding or processing costs to borrowers.

Lastly, in the face of increasing economic uncertainty and a deteriorating informational environment, lenders may be more risk-averse and raise the risk premium on postdisaster loans. This concern is intensified by the stringent GSE representation and warranty framework which increases buyback risk. However, FinTech lenders' usage of nontraditional data sources and algorithm-driven operations may allow them to better measure credit risk and identify creditworthy borrowers (Jagtiani and Lemieux (2019), Berg et al. (2020), and Agarwal et al. (2021)), thereby mitigating an increase in mortgage risk premiums. Based on the above arguments, we test the hypothesis that:

Hypothesis 2. Relative to other lenders, FinTech lenders charge higher interest rates for postdisaster mortgage loans.

Next, we consider the ex post performance of postdisaster loans. Natural disasters may introduce adverse changes in risks that are neither observable to econometricians nor fully captured by interest rates. For example, natural disasters may negatively impact borrowers' future income. If mortgage lenders still rely on, or assign a static weight to, borrowers' past income data, without incorporating the increased uncertainty about their future income, then their credit models may derive overly optimistic outcomes, leading to a lower-than-expected loan performance (after controlling for interest rate and observable borrower and loan characteristics). Given that FinTech lenders rely on a centralized loan processing facility (e.g., in Detroit for Quicken Loans), they are more likely to neglect such adverse changes in local unobservable risks. The losses incurred by this underpricing of risk may be even higher if FinTech lenders are more expansive in their postdisaster lending activity. Thus, we test the following hypothesis:

Hypothesis 3. FinTech postdisaster loans experience higher delinquency rates than those originated by other lenders.

Our empirical setting allows us to examine three possible economic channels for the transmission of mortgage loans by different lender types. We explore mortgage lenders' heterogeneous supply responses across different markets, thereby investigating the channels through which mortgage lenders respond to demand shocks and competitive pressure. First, we examine the regulatory channel. Although all traditional banks faced increased regulatory burdens after 2008, systemically important banks are subject to more rigorous regulatory scrutiny. For example, the Dodd-Frank Act introduced mandatory stress testing to promote sufficient capitalization of the largest bank holding companies. Companies failing the stress test may be required to cut dividend payouts, buy back shares, and submit capital plans. The lack of stress test evaluation transparency also induces some banks to retain more capital than necessary in case of poor evaluation outcomes. As a result, recent empirical studies find that stress tests on large bank holding companies have led to more cautious lending by traditional banks, resulting in lower credit supply, especially to riskier borrowers (Acharya et al. (2018), Cortés, Demyanyk, Li, Loutskina, and Strahan (2020)). Thus, in markets with a prevalence of highly regulated traditional banks that must undergo rigorous annual stress tests, traditional banks may be unable to compete effectively with less-constrained FinTech lenders.

Alternatively, however, despite their higher regulatory burden, stress-tested banks may also be endowed with regulatory incentives that actually encourage postdisaster lending. This favorable postdisaster regulatory assistance and relief may be more valuable for banks that are more heavily regulated exante. For example, the CRA consideration is particularly important for large stress-tested banks that provide limited community lending support during normal times, but require high CRA grades for regulatory approval of mergers and acquisitions (Berger et al. (2001), Dahl et al. (2010)). In this case, stress-tested banks may take advantage of the postdisaster regulatory relief to extend more credit to their underserved customers. Thus, we formulate the following hypothesis which is tested for traditional bank lenders:

Hypothesis 4A. Regulatory incentives encourage traditional banks to increase postdisaster mortgage supply.

The second credit supply channel studied is the impact of securitization versus on-balance sheet lending on postdisaster mortgage lending. Traditional banks that are highly dependent on local deposit (and other sources) of funds to finance on-balance sheet mortgages may find themselves constrained by deposit outflows in the wake of natural disasters. In contrast, shadow banks (especially FinTech lenders) fund mortgages using the securitization process by selling mortgages to geographically dispersed GSEs. To study this, we identify areas in which there is a prevalence of traditional banks that are more dependent on balance sheet lending as opposed to securitization in order to fund mortgage loan supply. We hypothesize that:

Hypothesis 4B. FinTech lenders' postdisaster mortgage supply is higher in impacted areas where banks rely more heavily on on-balance sheet lending as opposed to securitization.

The third credit supply channel investigates the impact of physical branch networks as opposed to online access to mortgage loans. Traditional banks and non-FinTech shadow banks rely on "brick and mortar" branches that may constrain lending due to credit constraints, capital allocation constraints, and managerial limitations (Cortes (2014), Cortés and Strahan (2017), and Dlugosz et al. (2022)). For example, banks' postdisaster lending may require the establishment of temporary loan offices and personnel, a process that can be sluggish and costly. In contrast, a key feature of the FinTech lending model is an end-to-end online mortgage application platform, as well as centralized mortgage underwriting and processing. The centralized and automated operations allow customers to complete the entire application and approval process online through the company's website and call centers without meeting any local officer or visiting any local branch. Thus, FinTech lenders are less constrained than traditional lenders that rely heavily on physical branch networks. Thus, we hypothesize that:

Hypothesis 4C. FinTech lenders' postdisaster mortgage supply is higher in impacted areas where traditional banks rely more heavily on physical branch networks.

Upon establishing our earlier hypotheses, we posit that the elasticity of FinTech lenders' postdisaster mortgage supply depends on local competitive pressure from traditional banks. Integrating the three supply-side postdisaster lending channels, we evaluate the overall competitive environment across local mortgage markets. In particular, based on our earlier hypotheses, we posit that traditional banks that benefit the most from regulatory incentives and are least reliant upon branch networks and on-balance sheet lending are most poised to fill the credit gap left in the wake of natural disasters. That is, traditional banks should be most competitive in local areas where there is a preponderance of stress-tested banks with fewer physical branches per capita that are less likely to retain mortgage loans on their balance sheets. When facing competitive traditional banks, in order to maintain or enhance their local market presence, FinTech lenders may choose to more aggressively loosen underwriting standards by increasing LTI. We test whether FinTech lenders relax their credit standards, thereby increasing supply elasticity as a competitive response to bank competitiveness in the following hypothesis:

Hypothesis 5. FinTech lenders loosen their credit standards and increase the elasticity of credit supply more in markets with higher competitive pressure from traditional banks.

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III. Data and Descriptive Statistics

A. Natural Disasters and Disaster Relief

We obtain natural disaster data for the period between 2010 and 2017 from the Federal Emergency Management Agency (FEMA) Disaster Declarations Database. The FEMA Disaster Declarations Database reports all natural disasters that were declared by the President of the United States (Presidential Declared Disasters, or PDDs) and provides their incident dates, disaster types, and affected counties. In a PDD, the severity of the damage is found to be beyond the combined capability of the state and local governments so that supplemental federal assistance is needed. We only consider PDDs to ensure that the damage to property is severe enough to shift local mortgage demand.[6]

Table 1 lists the frequency of each type of natural disaster, with the corresponding number of affected counties during the period between 2010 and 2017. Our sample includes 275 unique natural disasters which affect 4,808 counties in total. On average, 17.8 counties are affected by each natural disaster. The three most frequent types of disaster are severe storms (135 incidents), floods (74 incidents), and hurricanes (28 incidents). Severe storms, the most frequent type of natural disaster, affected a total of 2,148 counties, with each incident affecting 15.91 counties on average. Hurricanes and severe ice storms affected the largest number of counties per incident (27.79 counties and 31.00 counties, respectively).

Figure 2 shows the heat map of population density (Graph A) and the distribution of natural disasters (Graph B) at the county level. Although disasters are not

TABLE 1

Frequency of Natural Disasters and Affected Counties

Table 1 reports the frequency of natural disasters and the number of affected counties in our sample during the period between 2010 and 2017.

Incident Type	Frequency	Total No. of Counties Affected	Avg. No. of Affected Counties Per Incident
Severe storm	135	2,148	15.91
Flood	74	1,251	16.91
Hurricane	28	778	27.79
Snow	12	281	23.42
Severe ice storm	8	248	31.00
Tornado	7	65	9.29
Mud/Landslide	4	7	1.75
Tsunami	3	9	3.00
Earthquake	2	12	6.00
Coastal storm	1	8	8.00
Volcano	1	1	1.00
Total	275	4,808	17.48

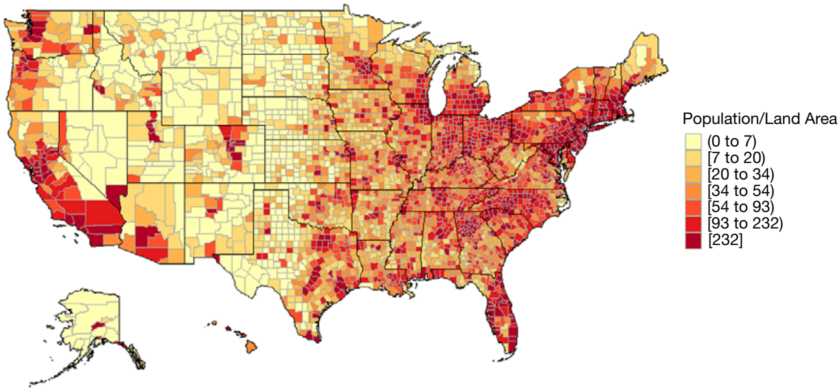
[6]PDDs consist of two types of declarations: major disaster declarations and emergency declarations. Although both declarations authorize the President to provide supplemental federal disaster assistance, there are differences in the incident type, disaster scope, and amount of assistance between the two types of declarations. While the President can declare an emergency for any occasion or instance (not limited to natural disasters), he can declare a major disaster only for natural events. There is also more public and private assistance available for major disaster declarations. Our sample includes both emergency and major disaster declarations, but we focus our analysis on natural disasters only.

FIGURE 2

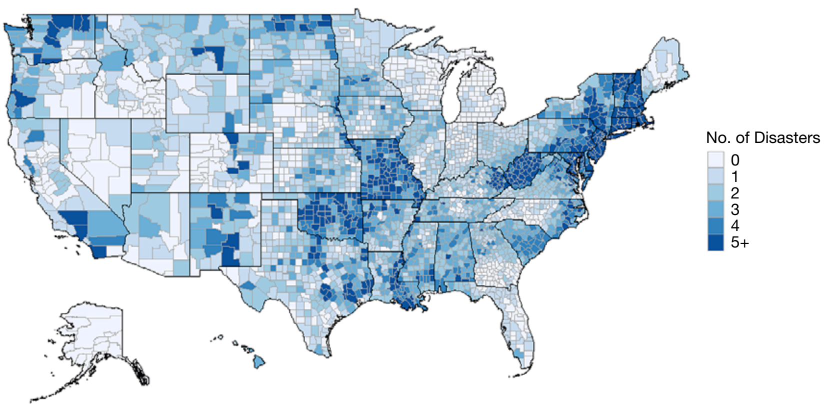
Distribution of Population and Natural Disasters

Graph A of Figure 2 presents the heat map of population density (thousand population per square mile as of 2010). Graph B presents the distribution of natural disasters during the period between 2010 and 2017.

Graph A. Population Density



Graph B. Disaster Frequency



evenly distributed across all states and counties, they cover the vast majority of U.S. regions. In additional untabulated figures, we find that the disasters that hit the middle states are mainly severe storms and floods, whereas the disasters that hit the northeastern and southeastern states are more likely to be snow storms and hurricanes. Moreover, disaster declarations do not appear to be correlated with population density, thereby mitigating an endogeneity concern that the propensity to declare a disaster is higher in densely populated areas.

Mortgage demand may surge after natural disasters because affected residents must rebuild or replace damaged homes and businesses. The first avenue to repair or replace damaged homes or businesses is to submit a homeowner insurance claim. However, many homeowners in the United States are underinsured against natural disasters, particularly for flooding damage, which is not covered under most privately provided property insurance policies.[7] Since many homeowners are underinsured, insurance generally covers only a fraction of the money needed to repair, replace, or rebuild damaged property. Affected residents can also obtain funds directly from FEMA and the Small Business Administration through various finance assistance programs (for temporary housing, repair, and replacement) and direct assistance programs (i.e., construction assistance). However, most of the programs only provide temporary assistance and do not offer sufficient funds to return the property to its predisaster condition. In cases where these assistance programs leave a gap in funds required to rebuild after natural disasters, there will be an increase in the local demand for mortgage loans. For example, a household may take a refinancing loan to either reduce principal or interest payments or convert home equity into cash in order to pay for home repairs.

B. Data on Mortgage Application, Origination, and Performance

We collect mortgage application and approval data for our sample period between 2010 and 2017 from the Home Mortgage Disclosure Act (HMDA) database. The HMDA data include the vast majority of residential mortgage applications in the United States, and provide information about lender identity, property location, loan type, loan purpose, loan amount, applicant income, race, and ethnicity.[8] Moreover, HMDA records whether the originator retains the loan on its balance sheet or sells the loan within the calendar year of origination. In this article, we restrict our sample to a subset of the HMDA database that only includes conventional loans (any loan other than Federal Housing Administration, Department of Veterans Affairs, Farm Service Agency, or Rural Housing Service loans) for 1 to 4-family residential properties (other than manufactured housing). HMDA records the outcomes of applications, such as loan originated or application denied by the financial institution. In the calculation of mortgage demand and approval, we only include applications that were i) approved and originated, ii) approved but not accepted by the applicant, and iii) denied by the financial institution, thereby dropping incomplete applications that were denied without full credit underwriting. We consider an application to be approved if its outcome is either originated or approved but not accepted.

Since the information on loan interest rate and performance is not available from the HMDA database, we augment the HMDA data with conforming mortgage origination and performance data obtained from two GSE databases: the Fannie Mae Single-Family Loan Performance Data (Fannie Mae) and the Freddie Mac Single-Family Loan-Level data set (Freddie Mac). The Fannie Mae data set provides loan-level monthly origination and performance information for Fannie Mae's 30-year, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages, which is the predominant conforming mortgage type in the

[7]The 2018 Insurance Information Institute Pulse survey found that only about 15% of American homeowners had a flood insurance policy, so that uncovered water damage accounted for 45% of all property damage. See "Facts+Statistics: Flood insurance," https://www.iii.org/fact-statistic/facts-statistics-flood-insurance.

[8]As of 2017, there were 5,697 financial institutions with nonmissing Federal Reserve IDs (RSSD IDs) reporting to HMDA.

United States.[9] Similarly, the Freddie Mac data set provides loan-level monthly origination, performance, and actual loss data for a subset of Freddie Mac's 15-, 20-, and 30-year fully amortizing, full documentation, single-family mortgages. Combining the Fannie Mae and Freddie Mac data provides coverage of the majority of conforming loans issued in the United States.[10] We construct the following variables using the GSE data: interest rate (INT_RATE), the borrower's credit score (FICO), the debt-to-income (DTI) ratio, the combined loan-to-value (CLTV) ratio, the term of the loan (TERM), and the natural logarithm of the loan amount (ln(AMT)). The performance data set provides monthly payment history and delinquency status. Accordingly, we construct a dummy variable DELQ, which equals 1 if a loan has at least one record showing payment that is 30 days (or longer) delinquent within 6 months after origination, and 0 otherwise.[11]

C. Classifying Lenders

According to the definition by the Financial Stability Board, we define all "deposit-taking corporations" as traditional banks and all "credit intermediation involving entities outside the regular banking system" as shadow banks. We describe the method of categorizing traditional banks versus shadow banks in the Supplementary Material. Within the group of shadow banks, we follow Buchak et al. (2018a) and classify a lender as a FinTech shadow bank (FinTech lender, hereafter) if it enables mortgage applicants to obtain preapprovals online, and as a non-FinTech shadow bank otherwise. Following this definition, we identify twelve FinTech lenders: Quicken Loans, Guaranteed Rate Inc, Amerisave Mortgage Corporation, Movement Mortgage LLC, Cashcall Inc, Cardinal Financial Company, American Internet Mortgage Inc, Homeward Residential Inc, NTFN Inc, NE Moves Mortgage LLC, James B Nutter & Co, and 21st Mortgage. This classification matches up well with firms considered by industry observers and the media to be at the frontier of technology-based mortgage lending. We identify the highly regulated (i.e., stress-tested) banks using the list of bank-holding companies included in the 2009 Supervisory Capital Assessment Program (SCAP) and the subsequent annual Comprehensive Capital Analysis and Review (CCAR).[12]

[9]Conforming mortgages are mortgages with an original balance equal to or less than the dollar amount established by the conforming loan limit set by the Federal Housing Finance Agency so as to meet the funding criteria of Freddie Mac and Fannie Mae.

[10]Fannie Mae and Freddie Mac only disclose the names of lenders who account for 1% or more of volume within a given acquisition quarter as determined by loans' aggregate original unpaid principal balance.

[11]The GSE data segment mortgage originations by the method used to deliver the loan to the seller. There are three major loan delivery mechanisms: retail, correspondent, and broker. A mortgage loan is classified as retail if the mortgage loan seller takes and processes the application, as well as underwrites, funds, and delivers the loan to the GSE. A correspondent loan is originated by a party other than the mortgage loan seller and is then sold to the seller. A broker loan is originated through a broker. We restrict our sample to the retail GSE loans to focus on the underwriting decisions of the actual originators.

[12]The first formal stress test was the 2009 SCAP, conducted by the Federal Reserve for 19 bank holding companies with assets exceeding $100 billion. Most of the banks were included in the subsequent annual CCAR from 2011 to 2014, with the exception of one firm that was delisted as a bank holding company in 2013. Starting in 2014, the CCAR was conducted for a wider set of bank holding

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D. Area-Level Control Variables

Local mortgage demand and borrower credit risk can be affected by a variety of local socioeconomic and demographic characteristics, as well as competitive factors such as the presence of traditional banks. We obtain county-level census data from the American Community Survey (ACS) to control for the local unemployment rate (UNEMP), population (POP), the share of white people in the local population (WHITE), the share of females in the local population (FEMALE), the share of people with at least high school education in the total population over 25 years old (EDUCATION), the share of the population that is over 65 years old (SENIOR), income per capita (INCOME_PER_CAP), the share of the labor force that works in the manufacturing industry (MANUFACTURE) or the information industry (INFORMATION).

We obtain local bank presence data from the FDIC Summary of Deposits and extract two bank presence measures and two bank competition measures. The bank presence measures include the number of local bank branches per capita (BRANCH) and deposits per capita (DEPOSITS). Bank competition measures include the Herfindahl–Hirschman index of deposits in local bank branches (HHI) and the share of deposits of the top 3 bank branches (C3) within the county. Further, FinTech penetration can be affected by local access to the Internet. Thus, we also control for local internet access using the Form 477 County Data on Internet Access Services from the Federal Communication Commission. Internet access (INTERNET) is the share of local households with residential fixed high-speed connections over 200 kbps in at least one direction. All variable definitions are listed in the Appendix.

E. Summary Statistics

We merge the geographic locations of HMDA and GSE mortgages with disaster declaration data from FEMA to obtain the HMDA–FEMA merged application and approval sample and the GSE-FEMA merged sample.[13] Table 2 presents summary statistics for the HMDA–FEMA merged application sample (Panel A), the HMDA–FEMA merged approval sample (Panel B), and the GSE–FEMA merged sample (Panel C).

Panel A of Table 2 shows that FinTech mortgage applications account for 5.46% of the total number of applications during the sample period, whereas non-FinTech shadow bank applications and traditional bank applications account for 23.36% and 71.17%, respectively. The approval rate (all originated plus approved

companies with assets exceeding $50 billion until the asset threshold for mandatory annual tests increased to $250 billion in 2018.

[13]The geographic locations of HMDA mortgages and FEMA disaster declarations are identified at the county level, whereas the locations of GSE mortgages are identified at the 3-digit ZIP Code level. To match disaster-affected counties with their 3-digit ZIP Codes, we first link 3-digit ZIP Codes to 3-digit ZIP Code Tabulation Areas (ZCTAs) using the ZIP Code-ZCTA crosswalk data from the Missouri Census Data Center (MCDC). Then ZCTAs are matched with counties using the ZCTA-County crosswalk data from the MCDC. A 3-digit ZIP Code will be considered a disaster-affected (unaffected) area only if 100% of its population reside within the disaster-affected (unaffected) counties.

TABLE 2
Summary Statistics

Table 2 presents the descriptive statistics for the HMDA–FEMA merged application sample (Panel A) and approval sample (Panel B), and the GSE-FEMA merged sample (Panel C). All variables are defined in the Appendix.

Variables	FinTech	Shadow Bank	Trad. Bank	All Lenders
Panel A. HMDA–FEMA Merged Application Sample				
No. of loans	1,408,528	6,023,702	18,349,774	25,782,004
No. of loans (% of total)	5.46	23.36	71.17	100.00
Loan volume ($bil)	291.65	1,343.61	3,443.93	5,079.19
Loan volume (% of total)	5.74	26.45	67.80	100.00
Loan purposes (share in %)				
Home purchase	21.04	42.87	29.35	32.05
Refinancing	78.38	55.67	58.33	58.80
Home improvement	0.58	1.46	12.32	9.14
Action taken (share in %)				
Loan originated	75.13	74.39	73.01	73.45
Application approved but not accepted	3.76	5.41	4.77	4.87
Application denied by financial institution	21.10	20.20	22.22	21.69
Risk attributes (Mean)				
AMT ($k)	207.06	223.05	187.68	197.01
INCOME ($k)	104.43	107.95	109.72	109.00
LTI (%)	241.12	257.44	198.17	214.65
Panel B. HMDA–FEMA Merged Approval Sample				
No. of loans	1,111,266	4,807,101	14,272,800	20,191,167
No. of loans (% of total)	5.50	23.81	70.69	100.00
Loan volume ($bil)	231.48	1,098.18	2,796.51	4,126.17
Loan volume (% of total)	5.61	26.62	67.77	100.00
Loan purposes (share in %)				
Home purchase	22.46	49.24	32.78	36.13
Refinancing	77.16	49.24	57.86	56.87
Home improvement	0.37	1.52	9.35	6.99
Risk attributes (Mean)				
AMT ($k)	208.30	228.45	195.93	204.36
INCOME ($k)	106.26	112.19	115.45	114.13
LTI (%)	236.29	244.70	194.63	209.21
Panel C. GSE–FEMA Merged Sample				
No. of loans	119,949	277,203	578,700	975,852
No. of loans (% of total)	12.29	28.41	59.30	100.00
Loan volume ($bil)	26.67	65.38	128.20	220.25
Loan volume (% of total)	12.11	29.69	58.20	100.00
Loan purposes (share in %)				
Purchase	26.84	52.38	51.32	48.61
Cash-out refinance	33.17	20.14	20.75	22.11
No-cash-out refinance	39.98	27.48	27.92	29.28
Origination channel (share in %)				
Retail	91.83	30.96	46.90	47.90
Broker	6.96	20.82	2.50	8.25
Correspondent	1.20	48.22	50.60	43.85
Risk attributes (Mean)				
AMT ($k)	222.38	235.86	221.52	225.70
INT_RATE (%)	4.03	3.99	3.97	3.99
DELQ (%)	3.04	2.60	1.70	2.10
DTI (%)	34.35	33.47	32.65	33.09
FICO	746.18	753.93	757.69	755.21
CLTV (%)	72.29	74.82	73.57	73.77
TERM (Months)	296.02	314.81	309.91	309.59

but not accepted loans), when calculated using the number of loans, is 78.90 (1,111,126/1,408,528 = 78.90%) % for FinTech lenders, 79.80 (4,807,101/6,023,702 = 79.80%) % for non-FinTech shadow banks, and 77.78 (14,272,800/18,349,774 = 77.78%) % for traditional banks. Panel B shows that the average original loan balances for approved loans are $208,300 for FinTech lenders,

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$228,450 for non-FinTech shadow banks, and $195,930 for traditional banks. The average income of FinTech borrowers is $106,260, lower than that of non-FinTech shadow bank ($112,190) and traditional bank ($115,450) borrowers. Compared with non-FinTech shadow banks and traditional banks, FinTech lenders focus more on refinancing loans. The share of refinancing loans in the HMDA database is 77.16% for FinTech lenders, 49.24% for non-FinTech shadow banks, and 57.86% for traditional banks.

Panel C of Table 2 shows that FinTech lenders originate 12.29% of GSE loans. In comparison, non-FinTech shadow banks and traditional banks originate 28.41% and 59.30% of GSEs loans, respectively. Refinancing loans (both cash-out refinance and no-cash-out refinancing) account for a large portion of FinTech-originated GSE loans. FinTech lenders' share of refinancing loans is 73.15% (33.17% for cash-out refinance and 39.98% for no-cash-out refinance); 47.62% (20.14% for cash-out refinance and 27.48% for no-cash-out refinance) for non-FinTech shadow banks; and 48.67% (20.75% for cash-out refinance and 27.92% for no-cash-out refinance) for traditional banks. The average conventional loan size is $235,860 for non-FinTech shadow banks, followed by that of FinTech lenders ($222,380) and traditional banks ($221,520). Compared with loans by the other two types of lenders, the descriptive statistics suggest that a typical FinTech GSE loan has a higher interest rate, higher debt-to-income ratio, lower FICO, lower combined loan-to-value ratio, and shorter loan term.

IV. Mortgage Demand Shocks: Analysis of Mortgage Applications

We first examine whether natural disasters introduce positive shocks to local mortgage demand. We use a difference-in-differences (DID) framework that compares mortgage applications in disaster-affected counties (treatment counties, TREAT = 1) relative to unaffected, nonadjacent counties in the same state (control counties, TREAT = 0) over a 2-year window, comprised of the year of the disaster (treatment year, POST = 1) and the preceding year (control year, POST = 0). Specifically, a county is considered a treatment county if it was hit by at least one natural disaster during the treatment year and did not experience any natural disasters during the control year. We consolidate all natural disasters occurring in the treatment year so that counties experiencing multiple natural disasters are designated as treatment counties in the same way as counties having just one disaster during the year. A county is considered a control county if it is in the same state, but not adjacent to the treatment counties, and no disaster occurred in it during either the treatment year or the control year.[14] Thus, the first difference is between the treatment and control counties (TREAT), and the second difference is between the predisaster year and the disaster year (POST). We then estimate the

[14]We exclude adjacent counties from the control sample in order to eliminate the spill-over effect of natural disasters. For example, after their homes are damaged, residents may need to find a new place to live, and they may typically stay within local areas to remain close to family, job, and their familiar community. This can affect the housing market in unaffected, but adjacent counties.

following DID regression of mortgage applications for each lender type and borrowing purpose[15]:

$$\text{(1)}\quad \text{APPLICATIONS}_{i,t} = \beta_1 \text{TREAT}_i \times \text{POST}_t + \beta_2 \text{TREAT}_i + \beta_3 \text{POST}_t + \beta_4 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,t},$$

where subscripts i and t index county and year. $\text{APPLICATIONS}_{i,t}$ is the natural logarithm of the total number of mortgage applications in county i during year t. TREAT_i is a dummy variable that equals 1 for treatment counties, and 0 for control counties. POST_t is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. $\mathbf{X}_{i,t}$ is a vector of county-level control variables including bank presence and competition variables and local socioeconomic and demographic characteristics (see Section III.D for a complete description of control variables). For each treatment or control county, there is one observation for the year of the disaster and one for the preceding year.[16] We employ state by disaster year fixed effects to compare the mortgage demand only between within-state counties during the disaster incident window. We cluster standard errors by county to address any common unobserved random shocks that may lead to correlations in applications within each county.

An important assumption underlying the DID design is that the predisaster trends of mortgage demand should move in parallel patterns for both the treatment and control counties. To check the validity of this assumption, we estimate the following year-by-year DID regression of mortgage applications for each lender type:

$$\text{(2)}\quad \begin{aligned} \text{APPLICATIONS}_{i,t} = {} & \beta_1 \text{TREAT}_i \times D_{i,t}^{-2} + \beta_2 \text{TREAT}_i \times D_{i,t}^{0} + \beta_3 \text{TREAT}_i + \beta_4 D_{i,t}^{-2} \\ & + \beta_5 D_{i,t}^{0} + \beta_6 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,t}, \end{aligned}$$

where subscripts i and t index county and year, respectively. For each treatment or control county, there are three observations: one for the year of the disaster (year 0) and two for the two preceding years (year -2 and -1). Event-time indicators ($D_{i,t}^{k}$) run from year -2 ($k = -2$, 2 years before the disaster) to year 0 ($k = 0$, the year of the disaster). β_1 measures the difference in mortgage applications between the treatment and control counties in year -2 relative to that in year -1. β_2 measures the difference in mortgage applications between the treatment and control counties in year 0 relative to that in year -1. As in equation (1), we add a vector of county-level control variables ($\mathbf{X}_{i,t}$) and state by disaster year fixed effects, and cluster the standard errors by county.

[15]For each lender type and loan purpose, we exclude areas where there are less than 20 applications in the predisaster year. The purpose is to identify areas with sufficient potential mortgage demand so that natural disasters can generate meaningful changes in mortgage applications.

[16]We drop disasters occurring in December since their impacts on mortgage demand can hardly be observed during the year of the disaster. We do not distinguish between disasters that occur earlier or later in the year. Thus, the disaster year may include some time period prior to the disaster incident, which biases against finding any results. Therefore, our estimate of demand shocks is a conservative one. Further, we perform robustness checks on the timing of the response to natural disasters by excluding all natural disasters that occur within the fourth quarter of the year following Cortés and Strahan (2017) who find disaster responses end within 6 months. Supplementary Table IA1 shows that the results of our analysis are robust to this change.

FIGURE 3

Dynamics of Mortgage Demand Before and After Natural Disasters

Figure 3 presents the dynamics of mortgage demand (mortgage applications per capita) in treatment and control counties in year 0 (the year of disaster incident) and year −2, relative to that in year −1. The graphs plot the point estimates and 95% confidence intervals for the coefficients of the interaction terms between TREAT and D^k, where TREAT is a dummy variable that equals one for disaster-affected counties, and zero for control counties, and D^k is a set of event-time indicators that run from year −2 to year 0 (year −1 is omitted).

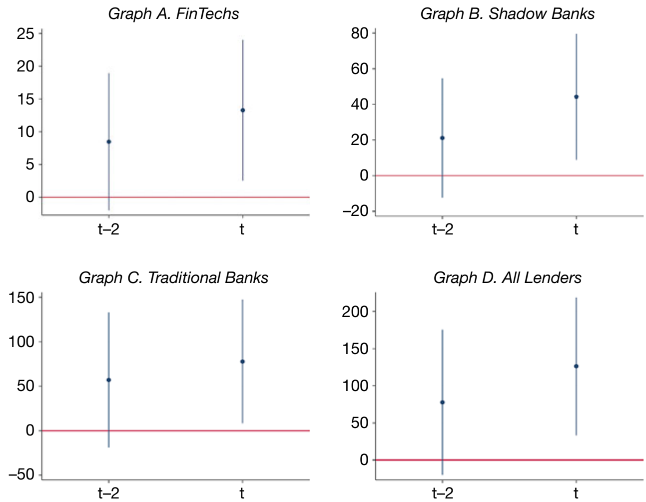

Figure 3 reports the coefficients on the interaction terms (β_1 and β_2) from our estimation of equation (2), along with the 95% confidence interval boundaries for the estimates. Figure 3 shows a negative point estimate but no significant difference in mortgage applications between year −2 and year −1 for all lender types, suggesting that absent natural disasters, mortgage applications in treatment and control counties would have evolved along the same path. The change in mortgage applications from year −1 to year 0 is positive and significant for all lender types and all lenders combined, consistent with an unexpected and exogenous increase in loan demand due to natural disasters.

We present the results of estimating equation (1) using the refinance and home improvement mortgages in Table 3 and using mortgages of all purposes in Supplementary Table IA2. We report results for each type of lender using the natural logarithm of the annual number of mortgage applications, APPLICATIONS, as the dependent variable.[17] For all lenders, the coefficient on the interaction term TREAT × POST is positive and statistically significant at the 1% level, consistent with a postdisaster surge in mortgage demand and indicated by an rightward shift in the mortgage demand curve as shown in Figure 1. Economically, compared with those in control counties, loan applications in treatment counties during the disaster year

[17] As robustness tests, we consider alternative measures of mortgage demand in Supplementary Table IA2, such as the natural logarithm of the total dollar volume of mortgage applications, the number of mortgages scaled by population, or the total dollar volume of mortgage applications scaled by population. Supplementary Table IA2 shows that our results are robust to these alternative measures of mortgage demand.

TABLE 3

Mortgage Demand Curve Shifts: Postdisaster Applications

Table 3 identifies the postdisaster exogenous demand shocks. APPLICATIONS is the natural logarithm of the annual number of refinancing and home improvement mortgage applications by county. TREAT is a dummy variable that equals 1 for disaster-affected counties, and 0 for control counties. POST is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. BRANCH is the number of bank branches per 1,000 population by county. DEPOSITS is the amount of deposits per capita by county. HHI is the Herfindahl–Hirschmann index of deposits by county. C3 is the share of deposits in the 3 largest banks by county. UNEMP is the share of the labor force that is unemployed by county. POP is the population by county. WHITE is the share of white people by county. FEMALE is the share of female people by county. EDUCATION is the share of population over 25 years that is with high school or higher education. INCOME_PER_CAP is income per capita. SENIOR is the share of population that is over 65 years old. MANUFACTURE is the share of the labor force working in the manufacturing industry. INFORMATION is the share of the labor force working in the information industry. INTERNET is the share of households with residential fixed connections over 200kbps in at least one direction. Standard errors are clustered at the county level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	APPLICATIONS			
	FinTechs	Shadow Banks	Trad. Banks	All Lenders
	1	2	3	4
TREAT × POST	0.078***	0.055***	0.050***	0.048***
	(4.069)	(3.394)	(5.454)	(5.464)
TREAT	0.041	0.049*	0.041**	0.044**
	(1.387)	(1.891)	(2.007)	(2.147)
POST	−0.136***	−0.265***	−0.225***	−0.204***
	(−11.665)	(−26.282)	(−34.105)	(−32.351)
BRANCH	−0.002***	−0.002***	−0.002***	−0.002***
	(−12.618)	(−17.534)	(−23.255)	(−23.814)
DEPOSITS	0.014***	0.009***	0.008***	0.006**
	(5.615)	(3.286)	(3.507)	(2.547)
HHI	−0.178	−0.566***	−0.978***	−1.159***
	(−0.759)	(−3.552)	(−7.985)	(−9.864)
C3	−2.037***	−2.171***	−2.550***	−2.505***
	(−10.969)	(−14.679)	(−20.607)	(−20.818)
UNEMP	3.565***	2.299***	2.894***	3.112***
	(4.150)	(3.227)	(5.811)	(6.185)
POP	1.324***	1.563***	1.548***	1.628***
	(9.155)	(9.217)	(9.427)	(9.625)
WHITE	0.346*	−0.116	0.426***	0.403***
	(1.923)	(−0.774)	(3.211)	(3.052)
FEMALE	8.439***	4.901***	5.339***	4.967***
	(7.781)	(5.542)	(8.313)	(7.567)
EDUCATION	1.546**	1.421**	2.837***	2.833***
	(2.469)	(2.522)	(7.592)	(7.511)
INCOME_PER_CAP	0.042***	0.054***	0.035***	0.041***
	(4.873)	(5.598)	(5.884)	(6.662)
SENIOR	−2.708***	−2.401***	−4.037***	−3.693***
	(−5.539)	(−5.051)	(−9.576)	(−8.638)
MANUFACTURE	−0.461	−0.452*	0.189	0.295
	(−1.396)	(−1.768)	(0.784)	(1.289)
INFORMATION	9.082**	12.131***	4.140**	4.377**
	(2.366)	(3.832)	(2.240)	(2.386)
INTERNET	0.215***	0.246***	0.170***	0.179***
	(7.970)	(10.491)	(9.389)	(10.089)
State × disaster year FE	Yes	Yes	Yes	Yes
No. of obs.	4,586	7,968	11,296	11,562
Adj. R^2	0.810	0.811	0.848	0.861

increase by 7.8% for FinTech lenders, 5.5% for non-FinTech shadow banks, and 5.0% for traditional banks. Compared to the results for the sample of refinance and home improvement mortgages, columns 1–4 of Supplementary Table IA2 show a positive, but weaker, demand shock for the full sample including loans for all purposes.[18]

The results of Table 3 and Supplementary Table IA2 suggest that postdisaster mortgage demand shocks are mainly driven by refinance and home improvement loan applications, whereas home purchase mortgage applications play a less important role, consistent with Sheldon and Zhan (2019) who find a 3%–5% decrease in home ownership rates among households that migrate to disaster-affected areas.[19] In the wake of natural disasters, the demand for home improvement loans to rebuild damaged property is expected to increase. However, the demand for refinancing loans also increases because borrowers either want to reduce principle or interest payments or convert home equity into cash in order to pay for home repairs. Most importantly, refinancing loans may be used to fund property repair since the HMDA mortgage applications database does not distinguish cash-out from noncash-out refinancing. We confirm the conjecture that a substantial increase in postdisaster mortgage demand is for loans for refinancing and home improvement rather than home purchases in Supplementary Table IA3 which reports the results of a multinomial logit regression distinguishing among loan purposes (new purchase, refinancing, or home improvement) for traditional bank mortgage applications.[20] We only include bank mortgages in this analysis because there are few applications for home improvement mortgages for FinTech and non-FinTech shadow banks, who specialized primarily in refinancing mortgages during our sample period. The results show that the postdisaster demand increase in bank mortgage applications for refinancing or home improvement loans is significantly higher than for new purchase loans. Thus, in the remainder of the article, we focus our attention specifically on refinance and home improvement loans.

Finally, we perform additional robustness tests to capture the effects of the most destructive natural disasters. Over past decades, water-related disasters (i.e., severe storms, floods, and hurricanes) top the list of natural disasters with the highest human losses and property damage.[21] Additionally, as of 2018, only 15% of American homeowners had a flood insurance policy (see footnote 7), thereby requiring many homeowners to apply for mortgages to repair water-damaged property that is under-insured. Thus, as a further robustness test, Supplementary Table IA4 presents the results of limiting our sample to water-related disasters, which are consistent with our baseline results in Table 3.

[18]It is possible that natural disaster shocks may induce divergent demand side shifts for different lender types. For example, borrowers may value the convenience and speed of processing of FinTech lenders more in the wake of natural disasters, thereby directing their applications to their preferred provider. Thus, we perform a statistical test on the equality of the coefficients on the interaction term TREAT $\times$ POST across lender types, and find that the coefficients are not statistically different, suggesting no distinction in demand shifts by lender type.

[19]In untabulated results, we find that postdisaster home purchase loans do not experience a significant demand increase.

[20]The dependent variable in Supplementary Table IA3 is an indicator variable that is equal to 0 if the purpose of the loan is new purchase, 1 if the purpose of the loan is refinance, and 2 if the purpose of the loan is home improvement.

[21]"The Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970–2019)," World Meteorological Organization.

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V. Lender Supply of Postdisaster Mortgages

A. Shifts in Lender Supply Curves Along the Extensive Margin

In this section, we examine lenders' mortgage approval rates to determine how lender supply curves shift after natural disasters. We first examine supply curve shifts along the extensive margin. Specifically, we perform the following logit DID analysis of loan approval for each type of lenders:

$$\text{(3)} \qquad \text{APPROVED}_{i,j,t} = \beta_1 \text{TREAT}_i \times \text{POST}_t + \beta_2 \text{TREAT}_i + \beta_3 \text{POST}_t + \beta_4 \mathbf{L}_{i,j,t} + \beta_5 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,j,t},$$

where subscripts i, j, and t index county, loan application, and year. $\text{APPROVED}_{i,j,t}$ is a dummy variable that equals 1 if the application outcome is either "loan originated" or "approved but not accepted," and 0 otherwise. $\mathbf{L}_{i,j,t}$ denotes loan application level characteristics, including the natural logarithm of applicant income (ln(INCOME)) and the natural logarithm of the mortgage amount (ln(AMT)). $\mathbf{X}_{i,t}$ represents a vector of county-level control variables as in equation (1). Besides state by disaster year fixed effects, we also employ borrower ethnicity, race, and gender fixed effects to control for any unobservable sociodemographic and other individual characteristics. Standard errors are clustered by county.

Table 4 presents the estimation results of equation (3) for postdisaster refinancing and home improvement mortgages. We find an increase in postdisaster mortgage approval rates for FinTech and traditional banks, but not for non-FinTech shadow banks. The coefficients on the interaction term in columns 1 and 3 are positive and statistically significant at the 1% or 5% levels for FinTech and traditional bank loan applications. Economically, compared with that in control counties, the likelihood of approval in treatment counties in the disaster year increases by 6.9% for FinTech lenders and 4.7% for traditional banks, equivalent to 8.7% (0.069/0.789 = 8.7%) and 6.0% (0.047/0.778 = 6.0%) of the sample mean likelihood of approval. In contrast, there is no significant change in the postdisaster approval likelihood by non-FinTech shadow banks (as shown by the insignificant interaction term coefficient in column 2 of Table 4).[22] Thus, our results provide support for Hypotheses 1A, 1B, and 1C in that only FinTech and traditional bank lenders increase credit supply along the extensive margin in the wake of natural disasters.[23]

[22]Our difference-in-differences empirical framework tests for negative as well as positive supply shocks. However, we find no evidence of negative supply responses for any lender type, even non-FinTech shadow banks.

[23]In Supplementary Table IA5, we show similar results for loans of all purposes in columns 1–3 in Panel A. In Panel B, we perform pairwise comparisons to examine whether the change in the likelihood of approval is different across lender types by introducing one more difference, FINTECH, to the interaction term in equation (3). FINTECH is a dummy variable that equals 1 for FinTech loan applications, and 0 otherwise. Columns 1 and 3 in Panel B use the subsample of FinTech and non-FinTech shadow bank loan applications, while columns 2 and 4 in Panel B use the subsample of FinTech and traditional bank applications. Our results show that the likelihood of approval for FinTech loan applications increases significantly more than that of non-FinTech shadow bank loan applications, as indicated by the positive and statistically significant coefficient on the triple interaction term, TREAT × POST × FINTECH, in columns 1 and 3 (marginally). The likelihood of approval for FinTech loan applications also increases more than that of traditional bank loan applications, although the difference is not statistically significant (columns 2 and 4).

TABLE 4

Mortgage Supply Curve Shifts: Postdisaster Approvals

Table 4 reports the logit regressions of mortgage approvals. APPROVED is a dummy variable that equals 1 if the outcome of the mortgage application is either originated or approved but not accepted, and 0 if the application is denied. TREAT is a dummy variable that equals 1 for disaster-affected counties, and 0 for control counties. POST is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. ln(INCOME) is the natural logarithm of the applicant's annual income. ln(AMT) is the natural logarithm of the mortgage amount. BRANCH is the number of bank branches per 1,000 population by county. DEPOSITS is the amount of deposits per capita by county. HHI is the Herfindahl–Hirschmann index of deposits by county. C3 is the share of deposits in the 3 largest banks by county. UNEMP is the share of the labor force that is unemployed. POP is the population by county. WHITE is the share of white people by county. FEMALE is the share of female people by county. EDUCATION is the share of population over 25 years that is with high school or higher education. INCOME_PER_CAP is income per capita. SENIOR is the share of population that is over 65 years old. MANUFACTURE is the share of the labor force working in the manufacturing industry. INFORMATION is the share of the labor force working in the information industry. INTERNET is the share of households with residential fixed connections over 200 kbps in at least one direction. Standard errors are clustered at the county level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	APPROVED		
	FinTechs	Shadow Banks	Trad. Banks
	1	2	3
TREAT × POST	0.069**	0.001	0.047***
	(2.249)	(0.023)	(3.165)
TREAT	−0.005	0.051*	0.002
	(−0.212)	(1.755)	(0.165)
POST	−0.214***	−0.116***	−0.070***
	(−12.073)	(−3.890)	(−8.121)
ln(INCOME)	0.339***	0.662***	0.456***
	(21.836)	(70.684)	(48.649)
ln(AMT)	−0.089***	−0.013	0.188***
	(−4.923)	(−0.985)	(20.126)
BRANCH	−0.001***	−0.001***	0.000
	(−6.094)	(−5.136)	(0.530)
DEPOSITS	0.001	0.002*	0.001
	(0.702)	(1.758)	(0.910)
HHI	0.091	0.085	0.106
	(1.006)	(0.593)	(1.309)
C3	−0.215*	−0.413***	0.010
	(−1.853)	(−3.449)	(0.138)
UNEMP	−0.601	−0.944	−2.466***
	(−0.853)	(−1.501)	(−5.851)
POP	0.030**	0.007	−0.023***
	(2.142)	(0.435)	(−2.638)
WHITE	0.128	−0.139	0.151*
	(1.453)	(−1.272)	(1.847)
FEMALE	2.571***	2.072**	1.390***
	(3.924)	(2.197)	(2.723)
EDUCATION	0.658**	0.808**	1.620***
	(1.987)	(2.471)	(8.185)
INCOME_PER_CAP	0.011***	0.013***	−0.007***
	(2.812)	(4.004)	(−4.187)
SENIOR	−0.910***	−0.574	−0.919***
	(−2.970)	(−1.196)	(−4.379)
MANUFACTURE	0.301*	0.395*	1.094***
	(1.862)	(1.844)	(7.820)
INFORMATION	2.272	9.220***	−0.907
	(1.473)	(4.902)	(−0.829)
INTERNET	0.016	0.022	−0.037***
	(1.005)	(1.198)	(−3.206)
State × disaster year FE	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes
No. of obs.	1,094,721	3,248,888	12,054,996
Pseudo-R^2	0.030	0.101	0.065

Buchak et al. (2018b) show that traditional banks specialize in jumbo mortgage loans that are more likely to be funded by deposits and held on balance sheets. It is reasonable to conjecture that banks facing local deposit outflows after natural disasters would be more constrained in meeting the increased postdisaster mortgage demand for jumbo as opposed to conventional loans.[24] To examine this, we construct a sample of bank applications for jumbo and conventional mortgages and estimate the following logit triple DID regressions of loan approval:

$$\text{(4)}\quad \begin{aligned}\text{APPROVED}_{i,j,t} = {} & \beta_1 \text{TREAT}_i \times \text{POST}_t \times \text{JUMBO}_{i,j,t} + \beta_2 \text{TREAT}_i \times \text{POST}_t \\ & + \beta_3 \text{TREAT}_i \times \text{JUMBO}_{i,j,t} + \beta_4 \text{POST} \times \text{JUMBO}_{i,j,t} + \beta_5 \text{TREAT}_i \\ & + \beta_6 \text{POST}_t + \beta_7 \text{JUMBO}_{i,j,t} + \beta_8 \mathbf{L}_{i,j,t} + \beta_9 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,j,t},\end{aligned}$$

where subscripts i, j, and t index county, loan application, and year. JUMBO is a dummy variable that equals 1 if the loan amount is higher than the conforming loan limits and 0 otherwise. All the other independent variables are defined the same way as in equation (3). The results of this estimation are shown in Supplementary Table IA6, where column 1 (2) shows the results for loans for all purposes (refinance and home improvement). The coefficient estimates on the interaction term TREAT × POST are positive and statistically significant at the 1% levels in both columns, indicating that traditional banks increase conforming loan availability after natural disasters, consistent with our previous results. The coefficient estimate on the triple interaction term is also positive and statistically significant at the 5% level for the refinancing and home improvement loan sample only (column 2), suggesting that the increase in jumbo mortgage credit availability is even higher, consistent with Buchak et al. (2018b) showing bank specialization in nonconventional mortgages even though these loans may be more costly to securitize in the wake of natural disasters.

B. Postdisaster Supply Elasticity: Loan to Income

In this subsection, we examine how mortgage lenders adjust their credit supply along the intensive margin by examining LTI, therefore, drawing inferences on the elasticity of the mortgage supply curve. Supply elasticity, as represented by the slope of the mortgage supply curve, reflects the costs of credit for each lender type. In addition to the cost of funds, an important component of lender costs is the loss from loan defaults and delays in contractual payments. That is, each lender analyzes the loan amount that can be supported by the borrower's financial resources. In the case of mortgages, the most important source of repayment is borrower income. Thus, we measure the elasticity of the mortgage supply function using LTI offered by each lender type on postdisaster mortgages. That is, the greater the mortgage loan amount per dollar of borrower income, ceteris paribus, the more elastic is the lender's supply of mortgages, and the looser the lender's underwriting standards (see Gaudóncio, Mazany, and Schwarz (2019)). Thus, if lenders approve a higher LTI, they are offering a larger loan per dollar of income; represented by a higher elasticity of supply in Figure 1. Similarly, if the cutoff LTI in the denial sample of mortgages is higher, then the lender is more elastically offering loans up until a

[24]We are indebted to an anonymous referee for this suggestion.

maximum loan amount per dollar of income. Thus, the higher this cutoff on the denial subsample, the more elastic is loan supply.

In this section, we use LTI to measure supply elasticity in order to test Hypotheses 1A, 1B, and 1C along the intensive margin of each lender type's supply curve. Specifically, we estimate the following triple DID regressions of borrower LTI to perform pairwise comparisons between FinTech and non-FinTech shadow bank lenders and between FinTech and traditional bank lenders:

$$(5)\quad \mathrm{LTI}_{i,j,t} = \beta_1 \mathrm{TREAT}_i \times \mathrm{POST}_t \times \mathrm{FINTECH}_{i,j,t} + \beta_2 \mathrm{TREAT}_i \times \mathrm{POST}_t + \beta_3 \mathrm{TREAT}_i \times \mathrm{FINTECH}_{i,j,t} + \beta_4 \mathrm{POST}_t \times \mathrm{FINTECH}_{i,j,t} + \beta_5 \mathrm{TREAT}_i + \beta_6 \mathrm{POST}_t + \beta_7 \mathrm{FINTECH}_{i,j,t} + \beta_8 \mathbf{X}_{i,t} + \mathrm{FE} + \varepsilon_{i,j,t},$$

where subscript i, j, and t index county, loan application, and year. $\mathrm{FINTECH}_{i,j,t}$ is a dummy variable that equals 1 if the application is submitted to a FinTech lender, and 0 otherwise. The coefficient on the triple interaction term, β_1, measures how the supply elasticity for FinTech loans changes relative other lender types' post-disaster mortgage supply. $\mathbf{X}_{i,t}$ is a vector of county-level control variables same as in equation (1). We employ state by disaster year, ethnicity, race, and gender fixed effects, and cluster the standard errors by county.

Table 5 reports the estimation results for the applications sample (columns 1 and 2), denial sample (columns 3 and 4), and approval sample (columns 5 and 6). Columns 1, 3, and 5 use the subsample of FinTech and shadow bank loans, whereas columns 2, 4, and 6 use the subsample of FinTech and traditional bank loans. The coefficient on TREAT × POST is positive and significant in column 2, suggesting that both FinTechs and traditional banks receive applications requesting higher LTI after natural disasters. However, the positive and significant (at the 1% level) coefficient on TREAT × POST × FINTECH in column 2 suggests that FinTech lenders receive applications requesting even higher LTI relative to traditional banks. Further, the positively significant (at the 1% level) coefficient on the TREAT × POST term in column 6 shows that both FinTech and traditional bank lenders satisfy these customer requests by approving loans with higher LTI than on post-disaster loans, consistent with an increase in supply elasticity for both lender types. Additionally, the positively significant (at the 1% level) coefficient on the triple interaction term in column 6 implies that FinTech lenders satisfy these customer requests by approving loans with higher LTI than on postdisaster loans offered by traditional banks, suggesting that supply elasticity at FinTech lenders is more expansive (i.e., increased LTI for more lending at the intensive margin) as compared to traditional banks. Economically, FinTech lenders raise the LTI of their approved postdisaster loans by 7.8% more than traditional banks. Consistently, for the denial sample in column 4, the positive and statistically significant (at the 5% level) coefficient on the triple interaction term suggests that only the highest LTI mortgages are denied by FinTech lenders after natural disasters. To be denied by a FinTech lender, the LTI must be 3.8% higher than for mortgages denied by traditional banks.[25] The results suggest that FinTech lenders loosen underwriting standards as compared to traditional banks, consistent with Hypothesis 1A.

[25]In Supplementary Table IA7, we show similar results using the full sample including loans of all purposes.

TABLE 5

Mortgage Supply Elasticity Shifts: Postdisaster Loan-to-Income Ratios

Table 5 examines postdisaster mortgage supply elasticity by measuring loan-to-income ratios. LTI is the loan-to-income ratio on approved mortgages, calculated as the mortgage amount divided by the borrower's annual income. TREAT is a dummy variable that equals 1 for disaster-affected counties, and 0 for control counties. POST is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. FINTECH is a dummy variable that equals 1 if the application is submitted to a FinTech lender, and 0 otherwise. BRANCH is the number of bank branches per 1,000 population by county. DEPOSITS is the amount of deposits per capita by county. HHI is the Herfindahl–Hirschman index of deposits by county. C3 is the share of deposits in the 3 largest banks by county. UNEMP is the share of the labor force that is unemployed. POP is the population by county. WHITE is the share of white people by county. FEMALE is the share of female people by county. EDUCATION is the share of population over 25 years that is with high school or higher education. INCOME_PER_CAP is income per capita. SENIOR is the share of population that is over 65 years old. MANUFACTURE is the share of the labor force working in the manufacturing industry. INFORMATION is the share of the labor force working in the information industry. INTERNET is the share of households with residential fixed connections over 200 kbps in at least one direction. Standard errors are clustered at the county level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	LTI					
	Application Sample		Denial Sample		Approval Sample	
	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech
	1	2	3	4	5	6
TREAT × POST × FINTECH	0.073***	0.069***	0.027	0.038**	0.100***	0.078***
	(2.893)	(3.367)	(0.905)	(2.345)	(3.684)	(3.211)
TREAT × POST	0.007	0.024***	0.042	0.035***	−0.014	0.023***
	(0.455)	(2.839)	(1.599)	(3.035)	(−1.424)	(2.925)
TREAT × FINTECH	−0.064**	−0.036	−0.068*	0.010	−0.050**	−0.046
	(−2.315)	(−0.987)	(−1.827)	(0.399)	(−1.993)	(−1.201)
POST × FINTECH	−0.128***	0.023	−0.186***	0.005	−0.096***	0.018
	(−8.032)	(1.412)	(−8.180)	(0.391)	(−5.771)	(0.929)
TREAT	−0.020	−0.002	−0.030	−0.030	−0.010	0.010
	(−0.876)	(−0.131)	(−0.960)	(−1.241)	(−0.459)	(0.669)
POST	0.058***	−0.089***	0.066***	−0.119***	0.038***	−0.083***
	(5.026)	(−19.742)	(3.448)	(−18.663)	(5.278)	(−19.479)
FINTECH	−0.106***	0.564***	−0.338***	0.692***	0.009	0.531***
	(−4.993)	(24.007)	(−11.877)	(38.990)	(0.408)	(20.630)
BRANCH	−0.000	0.000	−0.000	0.000**	−0.000	0.000
	(−0.493)	(0.879)	(−0.827)	(2.085)	(−1.264)	(0.208)
DEPOSITS	−0.003***	−0.002*	−0.004***	−0.003*	−0.003***	−0.001
	(−3.141)	(−1.649)	(−3.322)	(−1.956)	(−2.701)	(−1.437)
HHI	0.080	0.095	0.131	0.241*	0.096	0.049
	(0.748)	(1.024)	(1.021)	(1.937)	(0.882)	(0.579)
C3	−0.110	−0.243***	−0.156	−0.340***	−0.149	−0.213***
	(−1.104)	(−2.792)	(−1.306)	(−2.770)	(−1.474)	(−2.763)
UNEMP	−2.156***	−0.617	−3.394***	−2.716***	−1.808***	−0.009
	(−3.057)	(−1.081)	(−3.854)	(−3.370)	(−2.641)	(−0.020)
POP	0.041**	0.070***	0.061**	0.072***	0.037**	0.068***
	(2.433)	(4.407)	(2.427)	(3.299)	(2.453)	(4.887)
WHITE	−0.063	0.058	−0.192	−0.096	−0.036	0.101
	(−0.420)	(0.452)	(−1.043)	(−0.517)	(−0.253)	(0.990)
FEMALE	−0.824	−1.150**	−0.242	−1.330*	−0.784	−0.935*
	(−1.068)	(−2.029)	(−0.316)	(−1.780)	(−0.985)	(−1.816)
EDUCATION	−1.116***	−0.912***	−1.690***	−1.610***	−0.902***	−0.610**
	(−3.710)	(−3.209)	(−4.745)	(−4.303)	(−2.948)	(−2.483)
INCOME_PER_CAP	0.009***	0.022***	0.019***	0.029***	0.010***	0.019***
	(3.499)	(9.159)	(5.191)	(8.230)	(3.800)	(9.377)
SENIOR	1.468***	0.643**	1.742***	0.734**	1.198***	0.537**
	(3.971)	(2.524)	(4.168)	(2.035)	(3.521)	(2.417)
MANUFACTURE	−0.452***	−0.467***	−0.669***	−0.589***	−0.343**	−0.377***
	(−2.904)	(−3.490)	(−3.533)	(−3.516)	(−2.146)	(−2.919)
INFORMATION	4.707**	3.469**	7.437***	4.658*	4.935***	3.081**
	(2.325)	(2.025)	(2.857)	(1.869)	(2.579)	(2.140)
INTERNET	0.011	0.018	0.044**	0.018	0.001	0.019*
	(0.750)	(1.549)	(2.168)	(1.087)	(0.036)	(1.783)
State × disaster year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,343,193	13,145,645	1,145,870	3,378,952	3,197,012	9,766,693
Adj. R^2	0.061	0.082	0.054	0.080	0.081	0.095

In contrast, we do not observe a significant change in borrower LTI for the non-FinTech shadow bank sample, as indicated by the insignificant coefficient on TREAT × POST in column 5. These results are consistent with Hypothesis 1C. Moreover, the positive and significant (at the 1% level) coefficient on the triple interaction term in column 5 further indicates that FinTech lenders raise the LTI of their approved loans as compared to non-FinTech shadow banks. Economically, the increase in the LTI of approved FinTech loans is 10% higher than that of non-FinTech shadow bank loans.

C. Loan Pricing

In this subsection, we use the GSE-FEMA merged sample to examine how mortgage lenders adjust mortgage interest rates in response to demand shocks. As in our earlier analysis, we examine postdisaster loan pricing across the three types of lenders using triple DID regressions with mortgage interest rates as the dependent variable. Instead of the annual observations in the HMDA database, the GSE data provide the month of mortgage origination. Given that Cortés and Strahan (2017) document that demand shocks usually dissipate after 6 months following natural disasters, the GSE data allow us to employ an even more restrictive comparison within a shorter time window. Specifically, we focus on loans originated in the 6-month period before each natural disaster and in the 6-month period after each natural disaster. We then perform two pairwise comparisons between FinTech lenders and non-FinTech shadow banks and between FinTech lenders and traditional banks as follows:

$$\begin{aligned}(6)\quad \text{INT\_RATE}_{i,j,t} = {} & \beta_1 \text{TREAT}_i \times \text{POST}_t \times \text{FINTECH}_{i,j,t} + \beta_2 \text{TREAT}_i \times \text{POST}_t \\ & + \beta_3 \text{TREAT}_i \times \text{FINTECH}_{i,j,t} + \beta_4 \text{POST}_t \times \text{FINTECH}_{i,j,t} \\ & + \beta_5 \text{TREAT}_i + \beta_6 \text{POST}_t + \beta_7 \text{FINTECH}_{i,j,t} \\ & + \beta_8 \mathbf{G}_{i,j,t} + \beta_9 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,j,t},\end{aligned}$$

where INT_RATE is the original mortgage interest rate minus the return on the 10-year Treasury note. $\mathbf{G}_{i,j,t}$ is a set of loan-level control variables available in the GSE but not the HMDA database, including DTI, FICO, CLTV, TERM, and ln(AMT). $\mathbf{X}_{i,t}$ is a vector of county-level control variables same as in equation (1). We employ state by disaster year fixed effects and cluster the standard errors by 3-digit ZIP Code.[26] The coefficient on the triple interaction term, β_1, examines the changes in interest rates charged on FinTech loans as compared to that charged on loans by other lender types.

The GSE-FEMA database allows identification of mortgage loans for refinancing, cash-out refinancing, and noncash-out refinancing. Table 6 presents the estimation results of equation (6) for these three loan subsamples.[27] Examining the interest rates charged on FinTech loans as compared to those charged on traditional bank loans, the coefficient on the triple interaction term is negative and

[26]GSEs report the location of the property at the 3-digit-ZIP Code level, instead of the county level. Please see footnote 13.

[27]The complete Table 6 including control variables is shown in Supplementary Table IA8.

TABLE 6

Postdisaster Mortgage Pricing

Table 6 examines how mortgage lenders adjust mortgage loan interest rates after natural disasters. INT_RATE is the postdisaster mortgage interest rate minus the contemporaneous return on the 10-year U.S. Treasury note. TREAT is a dummy variable that equals 1 for disaster-affected areas, and 0 for control areas. POST is a dummy variable that equals 1 for the 6 months following the natural disaster, and 0 for the 6 months before the natural disaster. FINTECH is a dummy variable that equals 1 for FinTech loans, and 0 otherwise. Standard errors are clustered at the 3-digit ZIP Code level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	INT_RATE					
	Refinance		Cash-Out Refinance		Noncash-Out Refinance	
	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech
	1	2	3	4	5	6
TREAT × POST × FINTECH	6.214*	−5.715	4.657	−6.656*	6.147	−5.586
	(1.807)	(−1.252)	(1.410)	(−1.779)	(1.525)	(−0.953)
TREAT × POST	−17.643***	−6.023	−19.182***	−8.044	−15.254**	−3.708
	(−3.077)	(−0.999)	(−3.355)	(−1.541)	(−2.511)	(−0.506)
TREAT × FINTECH	−2.106	−0.276	−0.299	0.731	−3.176	−0.167
	(−0.837)	(−0.107)	(−0.107)	(0.307)	(−1.238)	(−0.052)
POST × FINTECH	−6.640***	−7.219***	−7.097***	−7.083***	−4.895*	−6.154**
	(−2.716)	(−3.533)	(−2.975)	(−4.239)	(−1.701)	(−2.240)
TREAT	6.964**	3.845	7.509**	4.910*	6.324*	2.392
	(2.138)	(1.271)	(2.171)	(1.816)	(1.860)	(0.655)
POST	3.468	4.878	7.228**	7.758**	−0.538	1.396
	(0.943)	(1.346)	(2.017)	(2.559)	(−0.137)	(0.323)
FINTECH	13.339***	14.793***	7.413***	9.978***	17.359***	18.470***
	(8.005)	(10.578)	(3.539)	(6.753)	(10.649)	(11.774)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State × disaster Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	128,989	233,046	58,453	107,027	69,317	125,020
Adj. R^2	0.561	0.550	0.552	0.550	0.577	0.553

insignificant in column 2. When we divide the sample into cash-out refinance and noncash-out refinance subsamples, the coefficient on the triple interaction term for cash-out refinance loans is weakly significant at the 10% level (column 4), and is insignificant for noncash-out refinance loans (column 6). Turning to the comparison between FinTech loans and non-FinTech shadow bank loans, the difference is positive but only weakly significant at the 10% level and insignificant for the cash-out and noncash-out refinancing subsamples. Although cash-out refinancing may appear to be more useful for rebuilding in the wake of natural disasters, even noncash-out refinancing mortgages may offer resources to property owners. First, noncash-out refinancing may reduce borrowers' debt burden by lowering principal and interest payments, which can be especially valuable to borrowers who are faced with cash shortages postdisaster. Second, since cash-out refinancing is more difficult to obtain than noncash-out refinancing (particularly after the economic disruption caused by natural disasters), there may be some substitution between these types of mortgages, thereby limiting their usefulness as an identification strategy. In Supplementary Table IA9, we report the results of multinomial logit regressions of loan purposes (new purchase, cash-out refinancing, or noncash-out refinancing) using the GSE sample. The results show that the likelihood of a loan being cash-out refinancing increases relative to new purchases in the wake of natural disasters for all lenders. Similar results are found for noncash-out refinancing loans. In untabulated tests, we find that the increase in

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the likelihood relative to new purchases is similar between cash-out refinancing and noncash-out refinancing. Therefore, the inferences about postdisaster loan rates presented in Table 6 apply to the postdisaster increase in supply of both cash-out and noncash-out refinancing mortgages. Taken together, therefore, the results in Table 6 suggest that FinTech lenders do not seem to charge higher interest rates despite their more expansive postdisaster lending, inconsistent with Hypothesis 2.

D. Loan Performance

In the previous subsections, we document that FinTech lenders are able to expand lending in the wake of demand shocks caused by natural disasters while relaxing underwriting standards (increasing LTI) without increasing interest rates compared to both traditional banks and non-FinTech shadow banks. In this subsection, we further investigate underwriting standards by examining ex post loan performance. In particular, we test how postdisaster loans granted by FinTech lenders perform relative to loans granted by other lender types. We utilize the GSE database which contains data on loan delinquency that are unavailable in the HMDA database.

Using a DID analysis, we compare delinquencies on loans originated after the natural disasters with those originated before. However, since we consider delinquencies up to 6 months after origination, predisaster mortgages originated in treatment areas within 6 months prior to the disaster will experience the economic dislocation associated with natural disasters, thereby biasing our results. To cleanly differentiate the performance of pre and postdisaster mortgages, we alter the loan performance evaluation window by comparing the 6-month performance of loans originated in months $\tau-12$ to $\tau-7$ (in which month τ is the month of the disaster) with the 6-month performance of loans originated in months $\tau+1$ to $\tau+6$. This performance evaluation time window eliminates the economic impact of the natural disaster on the performance of predisaster loans. We estimate the following triple DID regression using delinquencies as our dependent variable:

$$\begin{aligned}(7)\qquad \mathrm{DELQ}_{i,j,t} = {} & \beta_1 \mathrm{TREAT}_i \times \mathrm{POST}_t \times \mathrm{FINTECH}_{i,j,t} + \beta_2 \mathrm{TREAT}_i \times \mathrm{POST}_t \\ & + \beta_3 \mathrm{TREAT}_i \times \mathrm{FINTECH}_{i,j,t} + \beta_4 \mathrm{POST}_t \times \mathrm{FINTECH}_{i,j,t} \\ & + \beta_5 \mathrm{TREAT}_i + \beta_6 \mathrm{POST}_t + \beta_7 \mathrm{FINTECH}_{i,j,t} + \beta_8 \mathrm{INT\_RATE} \\ & + \beta_9 \mathbf{G}_{i,j,t} + \beta_{10} \mathbf{X}_{i,t} + \mathrm{FE} + \varepsilon_{i,j,t},\end{aligned}$$

where $\mathrm{DELQ}_{i,j,t}$ is a dummry variable that equals 1 if loan j has at least one record of 30 days (or longer) delinquent within 6 months of origination, and 0 otherwise. $\mathbf{G}_{i,j,t}$ is a vector of loan-level control variables same as in equation (6). $\mathbf{X}_{i,t}$ is a vector of county-level control variables same as in equation (1). We include state by disaster year fixed effects and cluster the standard errors by 3-digit ZIP Code.

Table 7 presents some results of the estimation of equation (7).[28] Columns 1 and 2 show that the coefficient on the triple interaction term is marginally significant at the 10% level. However, separating these loans into the cash-out and noncash-out refinancing subsamples results in an insignificant coefficient for the

[28]The complete Table 7 including control variables is shown in Supplementary Table IA10.

TABLE 7

Performance of Postdisaster Mortgages

Table 7 examines the performance of loans originated after natural disasters. DELQ is a dummy variable that equals 1 if the loan has at least one record of 30 days (or longer) delinquent status within 6 months of origination, and 0 otherwise. TREAT is a dummy variable that equals 1 for disaster-affected areas, and 0 for control areas. POST is a dummy variable that equals 1 for the 6 months following the natural disaster, and 0 for the 6 months before the natural disaster. FINTECH is a dummy variable that equals 1 if the application is submitted to a FinTech lender, and 0 otherwise. Standard errors are clustered at the 3-digit ZIP Code level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	DELQ					
	Refinance		Cash-Out Refinance		Noncash-Out Refinance	
	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech	Shadow Bank and FinTech	Bank and FinTech
	1	2	3	4	5	6
TREAT × POST × FINTECH	0.420*	0.413*	0.372	0.322	0.412	0.484*
	(1.822)	(1.953)	(1.311)	(1.237)	(1.452)	(1.958)
TREAT × POST	0.021	−0.021	0.072	0.082	0.021	−0.110
	(0.146)	(−0.180)	(0.380)	(0.521)	(0.098)	(−0.663)
TREAT × FINTECH	−0.422**	−0.576***	−0.305	−0.429**	−0.485*	−0.673***
	(−1.980)	(−3.601)	(−1.329)	(−2.112)	(−1.919)	(−3.739)
POST × FINTECH	−0.568***	−0.405***	−0.532***	−0.375**	−0.568***	−0.443***
	(−3.842)	(−3.258)	(−2.904)	(−2.260)	(−2.893)	(−2.916)
TREAT	0.065	0.231**	0.031	0.147	0.058	0.273*
	(0.416)	(2.055)	(0.183)	(1.112)	(0.293)	(1.709)
POST	0.140	−0.024	0.125	−0.013	0.140	−0.028
	(1.267)	(−0.250)	(0.900)	(−0.117)	(0.799)	(−0.190)
FINTECH	0.372***	1.214***	0.300**	1.109***	0.393**	1.305***
	(2.660)	(11.348)	(2.009)	(7.842)	(2.328)	(11.390)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State × Disaster year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	122,993	230,079	54,364	104,435	66,913	124,246
Adj. R^2	0.042	0.056	0.049	0.055	0.042	0.065

triple interaction term in columns 3 to 6. If disaster lending carries any negative consequences on the performance of loans, we would expect a higher likelihood of observing such an effect on cash-out refinancing loans. That is, borrowers on cash-out refinancing mortgages are more likely to be liquidity constrained, thereby potentially limiting their ability to make timely repayments on their mortgages. The results on the triple interaction term presented in columns 3 to 6 of Table 7 suggest that the delinquency rates on FinTech loans do not change significantly as compared to loans originated by either traditional or non-FinTech shadow banks. Thus, despite the more relaxed underwriting standards imposed by FinTech lenders in disaster-affected areas, our results suggest that FinTech postdisaster loans do not seem to introduce any adverse changes in risks unobservable to econometricians that are not fully captured by loan interest rates and observable borrower and loan characteristics, inconsistent with Hypothesis 3.

VI. Channels of Lending Supply

In this section, we exploit the cross-sectional patterns of local credit markets in order to investigate the lending supply behaviors of FinTech and traditional bank lenders. Since our previous results show that non-FinTech shadow banks fail to meet the postdisaster demand shock by expanding loan supply, we only focus our attention on FinTech lenders and traditional banks in this section. Our empirical results allow us to draw inferences regarding postdisaster supply-side shifts for different types of lenders. That is, equilibrium outcomes observed after the exogenous demand shocks trace out different lenders' supply responses, thereby offering insights into the shapes of mortgage supply curves. Thus, we believe that our article provides inferences about mortgage supply that extend beyond the special circumstances associated with natural disasters.

What are the aggregate supply-side insights that we have observed thus far? Our finding of increases in mortgage supply along the extensive margin (i.e., increased loan approval rates) implies that the mortgage supply function shifts to the right for both traditional banks and FinTech lenders, but not for non-FinTech shadow banks, as illustrated by the rightward shift in the aggregate mortgage supply function from S_B (S_F) to S'_B (S'_F) in Figure 1. Further, our finding that both traditional banks and FinTech lenders increase loan supply at the intensive margin (i.e., higher LTI ratios without an increase in either risk-adjusted delinquencies or mortgage interest rates) implies a postdisaster increase in supply elasticity shown by the flatter postdisaster supply curves for banks and FinTech lenders in Figure 1. Finally, although supply elasticity of postdisaster mortgages increases for both banks and FinTechs, our results indicate a greater increase in FinTech lenders' supply elasticity as shown in Figure 1.

Using natural disasters as our empirical setting provides an ideal opportunity to decompose these supply schedules and investigate the economic channels through which lenders supply mortgages to meet postdisaster, local demand surges. Not only does the exogenous nature of the demand shock disentangle supply and demand, but the stress associated with natural disasters also intensifies the impact of our three lending channels: regulation, on-balance sheet lending, and branch networks. However, one may conjecture that the unexpected and transitory nature of natural disasters might limit the supply reactions to lenders that can rapidly respond to intense demand shocks. That is, even if traditional banks do not react as expeditiously as do FinTech lenders, they may more gradually adjust over time, thereby closing the credit gap in a more deliberative manner. However, the findings presented in this section suggest that the greater supply elasticity of FinTech lenders vis a vis traditional banks induces competitive responses that are not transitory, but rather are consistent with the observed increase in FinTech market share in the U.S. mortgage market over time.

A. Three Economic Channels of Credit Supply Curve Shifts

In this subsection, we examine credit supply curve shifts along the extensive margin for each of our three lending channels. First, we test the impact of regulation (Hypothesis 4A) by constructing a county-year level dummy variable measuring the market share (with regard to residential mortgages) of highly regulated (i.e., stress-tested) banks. Specifically, the dummy variable, STRESS_TEST, is set equal to 1 if the market share of stress-tested banks in a county is above the median market share among all counties in a given year, and 0 if it is below the median.

Second, we examine the channel that FinTech lenders are better able to compete in markets with a higher proportion of banks dependent upon on-balance sheet lending (Hypothesis 4B). That is, FinTech lenders' reliance on securitization allows them to expand credit supply in areas where traditional banks are limited by their reliance on on-balance sheet lending. We construct a county-year level dummy variable, RETENTION_RATIO, which equals 1 if the fraction of newly originated bank mortgages that are held on bank balance sheets in a county is above the median fraction among all counties in a given year, and 0 if it is below median. A higher RETENTION_RATIO indicates that local traditional banks are more dependent upon on-balance sheet lending as opposed to securitization to fund mortgage lending.

Finally, our third channel examines banks' dependence on physical branch networks. If traditional banks relying on extensive physical branch networks have stronger incentives to preserve informational rents from long-term depositor relationships, then they may have a comparative advantage in expanding their postdisaster lending. Alternatively, FinTech lenders may have a comparative advantage in expanding their postdisaster lending because their centralized online delivery systems make them less subject to capacity constraints associated with "brick and mortar" bank branches that can be incapacitated by natural disasters (Hypothesis 4C). To test this hypothesis, we construct a county-year dummy variable, BRANCH_NETWORK, that equals 1 if the number of branches per capita in a county is above the median number of branches per capita among all counties in a given year, and 0 otherwise.

We examine how lenders supply mortgage credit through the three channels using the following triple DID regression separately for FinTech and traditional bank loans:

$$
\begin{aligned}
(8)\quad \text{LOANS}_{i,t} = {} & \beta_1 \text{TREAT}_i \times \text{POST}_t \times \text{CHANNEL}_{i,t-1} + \beta_2 \text{TREAT}_i \times \text{POST}_t \\
& + \beta_3 \text{TREAT}_i \times \text{CHANNEL}_{i,t-1} + \beta_4 \text{POST}_t \times \text{CHANNEL}_{i,t-1} \\
& + \beta_5 \text{TREAT}_i + \beta_6 \text{POST}_t + \beta_7 \text{CHANNEL}_{i,t-1} + \beta_8 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,t},
\end{aligned}
$$

where LOANS is the natural logarithm of the number of approved loans. CHANNEL is one of the time-varying county-level market competition variables (STRESS_TEST, RETENTION_RATIO, or BRANCH_NETWORK). We use 1-year lagged CHANNEL so that the structure of the local banking market is predetermined before the disaster strikes.

Table 8 presents the results of estimating equation (8). Columns 1 and 2 show the results of the regulation channel. In column 2, the interaction term TREAT × POST is insignificant and the triple interaction term is positive and statistically significant at the 5% level, suggesting that traditional banks increase postdisaster credit supply mainly in counties with a higher presence of stress-tested banks.[29] Economically, the increase in the number of loans approved by traditional banks in counties with a high proportion of stress-tested banks is 6.4% greater than the increase in counties with a low proportion. These results are *not* supportive of the

[29]The negative and statistically significant coefficients on CHANNEL and TREAT × CHANNEL in column 2 suggest that counties with higher market share of stress-tested banks indeed saw lower levels of mortgage lending during nondisaster periods, consistent with Acharya et al. (2018), Buchak et al. (2018b), Calem et al. (2020), and De Roure et al. (2022).

TABLE 8

Postdisaster Supply Curve Shifts Across Different Local Competitive Markets

Table 8 examines shifts in postdisaster mortgage supply across different markets for FinTech and traditional bank lenders. LOANS is the natural logarithm of the annual number of approved mortgage applications by county. TREAT is a dummy variable that equals 1 for disaster-affected counties, and 0 for control counties. POST is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. CHANNEL is a time-varying county-level market structure variable, which is STRESS_TEST in columns 1 and 2 and RETENTION_RATIO in columns 3 and 4, BRANCH_NETWORK in columns 5 and 6. STRESS_TEST is a dummy variable that equals 1 if the market share (with regard to mortgages) of stress-tested banks in a county is above the median among all counties in a given year, and 0 if it is below median. RETENTION_RATIO is a dummy variable that equals 1 if the share of newly originated bank mortgages that are held on the balance sheets in a county is above the median among all counties in a given year, and 0 if it is below median, BRANCH_NETWORK is a dummy variable that equals 1 if the number of branches per capita in a county is above median among all counties in a given year, and 0 if it is below median. Standard errors are clustered at the county level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	LOANS					
Channel Variable	STRESS_TEST		RETENTION_RATIO		BRANCH_NETWORK	
	FinTechs	Trad. Banks	FinTechs	Trad. Banks	FinTechs	Trad. Banks
	1	2	3	4	5	6
TREAT × POST × CHANNEL	0.038	0.064**	0.164***	0.023	0.131**	0.027
	(0.793)	(2.300)	(2.622)	(0.717)	(2.317)	(1.143)
TREAT × POST	0.063*	0.022	0.033	0.050***	0.038	0.046***
	(1.852)	(1.390)	(1.106)	(2.591)	(1.306)	(3.248)
TREAT × CHANNEL	−0.103***	−0.113***	−0.104***	0.050**	−0.125***	−0.032**
	(−3.584)	(−6.662)	(−3.054)	(2.525)	(−4.359)	(−2.229)
POST × CHANNEL	−0.032	−0.028	−0.066	−0.044	−0.056	0.011
	(−0.597)	(−0.786)	(−1.206)	(−1.323)	(−1.002)	(0.333)
TREAT	0.061	0.051*	0.056	0.050*	0.061*	0.025
	(1.384)	(1.774)	(1.557)	(1.786)	(1.677)	(0.921)
POST	−0.114***	−0.196***	−0.145***	−0.275***	−0.140***	−0.235***
	(−4.848)	(−18.419)	(−7.830)	(−21.750)	(−8.294)	(−24.168)
CHANNEL	0.225***	−0.110***	−0.150***	−0.038	−0.047	−0.045
	(5.252)	(−3.665)	(−3.853)	(−1.303)	(−0.896)	(−1.209)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State × Disaster year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	3,706	10,900	3,706	10,900	3,706	10,900
Adj. R^2	0.800	0.834	0.803	0.832	0.799	0.832

hypothesis that regulations restrict lending by traditional banks, thereby creating greater competitive opportunities for FinTech lenders. Rather, our findings are consistent with Hypothesis 4A that stress-tested traditional banks meet the demand for credit in the wake of natural disasters in order to benefit from competitive advantages created by favorable regulatory treatment. In contrast, FinTech lenders do not benefit from these regulatory incentives, and thereby do not exhibit differential changes in credit supply between the two markets, as indicated by the insignificant coefficient on the triple interaction term in column 1.

Columns 3 and 4 of Table 8 report the results of tests of the securitization channel. In column 3, the coefficient on the interaction term TREAT × POST is insignificant and the triple interaction term is positive and statistically significant at the 1% level, suggesting that FinTech lenders increase credit supply more in counties where on-balance sheet lending is more prevalent among traditional banks. Economically, the increase in the number of FinTech loans in high bank retention ratio counties is 16.4% higher than that in low bank retention ratio counties. This is consistent with Hypothesis 4B, suggesting that FinTech lenders exploit their competitive advantage vis a vis banks dependent upon on-balance sheet lending. In contrast, column 4 presents the coefficients on the TREAT × POST interactive term

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(positive and significant at the 1% level) and the triple interaction term (positive but statistically insignificant), indicating that traditional banks increase their postdisaster supply of mortgages in markets with both high and low levels of securitization, with no special advantages relating to their securitization levels.

Columns 5 and 6 of Table 8 report the results of the physical branch network channel. In column 6, the interaction term TREAT × POST is positive and statistically significant at the 1% level, whereas the triple interaction term is statistically insignificant, suggesting that traditional banks increase their postdisaster mortgage supply in all markets with no special advantages relating to the densities of branch networks.[30] In contrast, FinTech lenders target their loan supply to exploit bank vulnerability. The significant (at the 5% level) triple interaction term in column 5 suggests that FinTech lenders utilize their online advantage to increase their postdisaster mortgage lending in areas characterized by denser physical branch networks, consistent with Hypothesis 4C. Economically, the increase in the number of FinTech loans in high branch network counties is 13.1% higher than the increase in low branch network counties. These results suggest that the online advantages of FinTech lenders offset the absence of a geographic presence in supplying credit to disaster-impacted regions. Indeed, our results show that the only channel that offers traditional banks an added competitive advantage in expanding their supply of postdisaster mortgage lending is in areas with regulatory incentives.

B. Three Economic Channels of Supply Elasticity Shifts

In the previous subsection, we investigate supply curve shifts along the extensive margin for each of the three lending supply channels. Our analysis suggests that FinTech lenders have a competitive advantage in the supply of postdisaster mortgage loans stemming from their use of securitization and online delivery. In contrast, traditional banks have a competitive advantage obtained from regulatory incentives to lend to disaster-impacted areas. In this subsection, we compare the LTIs for FinTech and traditional bank lenders in order to investigate how each of the three credit supply channels affect mortgage underwriting standards along the intensive margin. That is, we examine whether the elasticity of FinTech lenders' supply of mortgages is impacted by competitive pressures from traditional banks. We pose the question whether FinTech lenders relax credit underwriting standards when traditional banks have a competitive advantage (i.e., due to regulatory incentives) or instead when traditional banks lose their competitive advantage (i.e., due to reliance upon on-balance sheet lending and physical branch networks).

To answer this question, we utilize our triple DID methodology to test Hypotheses 4A, 4B, and 4C along the intensive margin, as specified by equation (8) with LTI as the outcome variable. That is, we estimate the following loan-level regression for subsamples of mortgages approved in high or low channel variable (STRESS_TEST, RETENTION_RATIO, or BRANCH_NETWORK) areas:

[30] Although traditional banks do not decrease their supply of mortgages, they also do not exhibit any extra expansion of their supply of postdisaster mortgages in areas where they are dependent on balance sheet lending and physical branches as might be expected if relationship banking is driving credit allocation as in Cortés and Strahan (2017).

$$\text{(9)}\quad \text{LTI}_{i,j,t} = \beta_1 \text{TREAT}_i \times \text{POST}_t \times \text{FINTECH}_{i,j,t} + \beta_2 \text{TREAT}_i \times \text{POST}_t + \beta_3 \text{TREAT}_i \times \text{FINTECH}_i + \beta_4 \text{POST}_t \times \text{FINTECH}_{i,j,t} + \beta_5 \text{TREAT}_i + \beta_6 \text{POST}_t + \beta_7 \text{FINTECH}_{i,j,t} + \beta_8 \mathbf{X}_{i,t} + \text{FE} + \varepsilon_{i,j,t}.$$

Table 9 presents the estimation results for equation (9). Columns 1 and 2 test Hypothesis 4A by comparing FinTech and traditional banks' underwriting standards in areas with above and below median mortgage lending market share held by stress-tested banks. Columns 3 and 4 test Hypothesis 4B by comparing FinTech and traditional banks' underwriting standards in areas where traditional banks hold above and below median percent of mortgages on their balance sheets (i.e., high and low retention ratios, respectively). Hypothesis 4C is tested in columns 5 and 6 which compare areas with above and below median physical branches per capita.

The positive and significant (at the 1% level) coefficients in columns 2, 3, and 5 of Table 9 suggest that FinTech lenders are more aggressive than banks in relaxing credit standards in areas where banks receive regulatory incentives and are less reliant on balance sheet lending and physical branches. That is, FinTech lenders

TABLE 9

Postdisaster Changes in Supply Elasticity Across Different Local Competitive Markets

Table 9 examines shifts in postdisaster mortgage supply elasticity across different markets for FinTech and traditional bank lenders. LTI is the loan-to-income ratio, calculated as the mortgage amount divided by the borrower's annual income. TREAT is a dummy variable that equals 1 for disaster-affected counties, and 0 for control counties. POST is a dummy variable that equals 1 for the year of the disaster, and 0 for the preceding year. FINTECH is a dummy variable that equals 1 for FinTech loans, and 0 otherwise. Low (high) stress test counties are those where the market share (with regard to mortgages) of stress-tested banks is below (above) the median among all counties in a given year. Low (high) retention ratio counties are those where the share of newly originated bank mortgages that are held on the lender's balance sheet is below (above) the median among all counties in a given year. Low (high) branch network counties are those where the number of physical branches per capita is below (above) median among all counties in a given year. Low (high) bank competition areas are markets with a lower (higher) market share of stress-tested banks, higher (lower) bank mortgage retention ratios, and higher (lower) branch networks. Standard errors are clustered at the county level and *t*-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	LTI							
	Low Stress Test	High Stress Test	Low Retention Ratio	High Retention Ratio	Low Branch Network	High Branch Network	Low Bank Competition	High Bank Competition
	1	2	3	4	5	6	7	8
TREAT × POST × FINTECH	−0.047**	0.101***	0.094***	0.016	0.062***	0.110**	−0.055	0.112***
	(−2.460)	(3.595)	(3.576)	(0.248)	(2.604)	(2.003)	(−1.020)	(4.571)
TREAT × POST	0.018	0.027***	0.022**	0.031*	0.018**	0.038**	0.014	0.009
	(1.499)	(2.684)	(2.243)	(1.929)	(2.091)	(2.000)	(0.900)	(0.706)
TREAT × FINTECH	0.066***	0.009	−0.002	0.075	0.025	0.006	0.071*	−0.025
	(6.022)	(0.400)	(−0.113)	(1.246)	(1.252)	(0.138)	(1.829)	(−1.265)
POST × FINTECH	0.027	−0.063	−0.058	0.047	−0.066	0.013	0.093**	−0.111**
	(0.966)	(−1.468)	(−1.407)	(0.608)	(−1.420)	(0.232)	(2.110)	(−2.109)
TREAT	0.019	0.007	−0.003	0.014	0.005	−0.014	0.042**	−0.001
	(1.312)	(0.367)	(−0.152)	(0.687)	(0.242)	(−0.780)	(2.074)	(−0.047)
POST	−0.063***	−0.090***	−0.079***	−0.081***	−0.076***	−0.091***	−0.061***	−0.076***
	(−10.349)	(−15.657)	(−14.081)	(−8.443)	(−14.711)	(−11.302)	(−5.331)	(−9.859)
FINTECH	0.631***	0.505***	0.517***	0.564***	0.522***	0.542***	0.676***	0.479***
	(29.646)	(17.712)	(19.733)	(8.463)	(18.774)	(10.278)	(19.472)	(19.874)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Disaster Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,671,603	7,098,826	7,446,576	2,323,837	6,953,128	2,817,303	291,462	3,555,625
Adj. R^2	0.094	0.081	0.080	0.143	0.093	0.101	0.073	0.071

respond to bank competitive pressure by increasing supply elasticity, consistent with Hypotheses 4A, 4B, and 4C. Specifically, in high stress-test counties where stress-tested banks increase the availability of postdisaster credit along the extensive margin (as shown in Table 8), FinTech lenders compete by loosening credit standards and increasing supply elasticity more than banks, as suggested by the positive and statistically significant (at the 1% level) coefficient on the triple interaction term in column 2. Economically, the LTI of FinTech loans increases by 10.1% more than that of traditional bank mortgage loans in markets with the greatest proportion of stress-tested banks, consistent with Hypothesis 4A. Further, column 3 shows that FinTech firms are more aggressive in relaxing credit standards, increasing LTI by 9.4% relative to traditional banks in counties with banks that have low retention ratios (Hypothesis 4B). Finally, results in column 5 indicate that FinTech lenders increase supply elasticity in regions with fewer branches per capita (consistent with Hypothesis 4C).[31] Additionally, when FinTech lenders are not under high competitive pressure from banks, they do not appear to relax credit standards, and indeed may actually tighten their credit standards. That is, the negative and significant coefficient on the triple interaction term in column 1 of Table 9 indicates that the LTI on FinTech loans actually decreases in markets with a lower market share of stress-tested banks.

To examine the overall competitive impact of market structure on FinTech lenders' credit standards and supply elasticity, we integrate all three lending channels. We segment our sample into regions with the most and the least competitive banks relative to FinTech lenders. The results on the individual lending channels in Table 9 indicate that traditional banks are least competitive in markets with lower market shares of stress-tested banks, with banks that have higher retention ratios and more physical branches per capita (columns 1, 4, and 6). In contrast, traditional banks are most competitive in markets with higher market shares of stress-tested banks and with banks that have low loan retention ratios and fewer physical branches per capita (i.e., columns 2, 3, and 5). That is, traditional banks have the most advantageous conditions relative to FinTechs when they can avail themselves of regulatory benefits and when they can mimic the online and securitization technologies of FinTech lenders. Thus, we characterize high (low) bank competition areas as markets with a higher (lower) market share of stress-tested banks, lower (higher) bank mortgage retention ratios, and less (more) dense branch network.

The last two columns of Table 9 contrast FinTech lenders' credit standards in markets with the least competitive traditional banks (column 7) versus the most competitive ones (column 8) in order to test Hypothesis 5. The results show that FinTech lenders relax credit standards only when they are under competitive pressure from traditional banks. The positive and statistically significant (at the 1% level) coefficient on the triple interaction term in column 8 suggests that the LTI on FinTech loans increases more than banks' LTI in markets with more

[31]The positive and 5% significant coefficient on the TREAT $\times$ POST term in column 6 of Table 9 is consistent with greater bank elasticity of supply in regions with denser branch networks indicative of long-term customer relationships. However, the positive and 5% significant coefficient on the triple interaction term in column 6 indicates that FinTech supply curves are more elastic than bank supply curves even in these regions. The empirical results indicate that the increase in LTI on FinTech postdisaster mortgages is 11.0% higher than that of traditional bank mortgages in these areas.

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competitive banks, but not in markets where banks are least competitive (as shown by the negative and insignificant coefficient in column 7 of Table 9). Economically, the LTI of FinTech loans increases by 11.2% more than that of traditional bank loans in markets with the most competitive traditional banks. Thus, although FinTech lenders meet the funding gap left by natural disasters by expanding the quantity of mortgage loans supplied, it is the pressure from traditional banks that pushes them to relax credit standards and extend credit supply more elastically along the intensive margin, consistent with Hypothesis 5.

However, traditional banks do not respond to their less advantageous conditions by increasing their supply elasticity as a reaction to FinTech competition (as indicated by the insignificant coefficient on the interaction term TREAT × POST in column 7). Thus, our findings suggest that traditional banks cede market share to FinTech lenders by not aggressively competing via underwriting standards. That is, the lower supply elasticity of traditional banks vis a vis FinTech lenders reduces bank competitiveness in contested markets that may persist beyond the circumstances of natural disaster shocks.

VII. Conclusion

The financial services sector is undergoing a profound transformation. FinTech is redefining and reshaping the sector in fundamental ways. This article focuses on the impact of FinTech lenders on the consumer mortgage market, the largest consumer loan market in the United States. We utilize natural disasters as exogenous shocks to demand for mortgage loans, and investigate how FinTech, non-FinTech shadow bank, and traditional bank lenders respond to the shocks. Our results show that both FinTech and traditional bank lenders (but not non-FinTech shadow banks) increase credit supply after natural disasters. FinTech lenders ease credit standards more than other types of lenders do, along both the extensive and intensive margins. Our results suggest that FinTech's greater elasticity of supply emanates from their online business model as well as their ability to securitize loans to underbanked, but creditworthy borrowers using nontraditional data sources and machine learning. We do not find evidence that FinTech lenders charge higher interest rates as a convenience premium in their postdisaster lending. Further, FinTech postdisaster loans do not experience higher delinquency rates than other loans, suggesting that FinTech loans do not underprice any adverse changes in unobservable risks that may impair loan performance.

Our empirical setting allows us to explore the economic channels of credit supply and understand FinTech lenders' competitive advantages in the residential mortgage market in order to generalize our results beyond the setting of natural disasters. We find that FinTech postdisaster lenders benefit from their usage of securitization and online lending. That is, FinTech lenders expand lending more in areas dominated by banks dependent upon on-balance sheet lending and physical branch networks. In contrast, traditional banks increase lending to disaster-affected areas because of regulatory inducements to provide postdisaster community assistance that are most beneficial to stress-tested banks.

We also find that FinTech lenders increase supply elasticity by relaxing underwriting standards more in markets where they are confronted with competitive pressure from traditional banks. Specifically, the loan-to-income ratio on postdisaster mortgages approved by FinTech lenders is highest in markets where traditional banks are most competitive, that is, where stress-tested banks have a higher market share and where banks are less reliant on balance sheet lending and physical branch networks. Thus, the competitive pressure by traditional banks appears to induce FinTech firms to approve more generous lending terms, consistent with expanding credit supply elasticity along the intensive margin. In contrast, we find that traditional banks do not aggressively loosen credit standards in markets where they have fewer competitive advantages. Thus, traditional banks cede market share to FinTech lenders when they have no built-in advantages and incentives.

Appendix. Variable Definitions

Loan-Level Variables

APPROVED: A dummy variable that equals 1 if the outcome of the mortgage application is either originated or approved but not accepted, and 0 if the application is denied.

FINTECH: A dummy variable that equals 1 if the application is submitted to a FinTech lender, and 0 otherwise.

ln(INCOME): The natural logarithm of the applicant's annual income.

ln(AMT): The natural logarithm of the mortgage amount.

LTI: The borrower's loan-to-income ratio, calculated as the mortgage amount divided by the borrower's annual income.

INT_RATE: The interest rate on a mortgage.

DTI: The borrower's debt-to-income ratio, calculated as the borrower's monthly obligations (including housing expense) divided by her stable monthly income.

FICO: The borrower's FICO score.

CLTV: The borrower's combined loan-to-value ratio, calculated as all loans secured by the mortgaged property divided by the mortgage amount.

TERM: The number of months in which regularly scheduled borrower payments are due under the terms of the related mortgage documents.

FEMALE: A dummy variable that equals 1 for female borrowers, and 0 otherwise.

DELQ: A dummy variable that equals 1 if the loan has at least one record of 30 days (or longer) delinquent within 6 months of origination, and 0 otherwise.

JUMBO: A dummy variable that equals 1 if the loan amount is higher than the conforming loan limits and 0 otherwise.

Area-Level Variables

APPLICATIONS: The natural logarithm of the annual number of mortgage applications in a county.

LOANS: The natural logarithm of the annual number of approved mortgage applications in a county.

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VOLUME: The natural logarithm of the total dollar value of mortgage applications.

APL_PER_CAP: The number of mortgage applications scaled by local population.

VOLUME_PER_CAP: The dollar value of mortgage applications per capita.

TREAT: A dummy variable that equals 1 for disaster-affected counties, and 0 for control counties.

POST: A dummy variable that equals 1 for the disaster incident year, and 0 for the preceding year.

BRANCH: The number of bank branches per 1,000 population in a county.

DEPOSITS: The amount of deposits per capita in a county.

HHI: The Herfindahl–Hirschmann index of deposits in a county.

C3: The share of deposits in the 3 largest banks in a county.

UNEMP: The share of the labor force that is jobless.

POP: The population in a county.

WHITE: The share of white people in a county.

FEMALE: The share of female people in a county.

EDUCATION: The share of population over 25 years that is with high school or higher education.

INCOME_PER_CAP: Income per capita.

SENIOR: The share of population that is over 65 years old.

MANUFACTURE: The share of the labor force working in the manufacturing industry.

INFORMATION: The share of the labor force working in the information industry.

INTERNET: The share of households with residential fixed connections over 200 kbps in at least one direction.

STRESS_TEST: A dummy variable that equals 1 if the market share (with regard to mortgages) of stress-tested banks in a county is above the median among all counties in a given year, and 0 if it is below median.

RETENTION_RATIO: A dummy variable that equals 1 if the share of newly originated bank mortgages that are held on the balance sheets in a county is above the median among all counties in a given year, and 0 if it is below median.

BRANCH_NETWORK: A dummy variable that equals 1 if the number of branches per capita in a county is above median among all counties in a given year, and 0 if it is below median.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S002210902200120X.

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