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Trust as an entry barrier: Evidence from FinTech adoption

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A R T I C L E I N F O

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A B S T R A C T

This paper studies the role of trust in incumbent lenders (banks) as an entry barrier to emerging FinTech lenders in credit markets. The empirical setting exploits the outbreak of the Wells Fargo scandal as a negative shock to borrowers' trust in banks. Using a difference-in-differences framework, I find that increased exposure to the Wells Fargo scandal leads to an increase in the probability of borrowers using FinTech as mortgage originators. Utilizing political affiliation to proxy for the magnitude of trust erosion in banks in a triple-differences specification, I find that, conditional on the same exposure to the scandal, a county experiencing a greater erosion of trust has a larger increase in FinTech share relative to a county experiencing less of an erosion of trust. Estimating treatment effect heterogeneity using generic machine learning inference suggests that borrowers with the greatest decrease in trust in banks and the greatest increase in FinTech adoption have similar characteristics.

1. Introduction

Financial Technology (FinTech) has been increasingly replacing bank lending in credit markets. In the U.S., the market share of FinTech mortgage lending increased from 2% in 2010 to 8% in 2016. FinTech lenders provide efficient and convenient services to borrowers. They use machine learning techniques to process online loan applications, largely reducing processing time compared to traditional banks. Moreover, the increasing growth of FinTech firms competes with bank lending, affecting overall credit market conditions and credit accessibility.[2] However, FinTech adoption is not universal. Different local residential mortgage markets have immensely different FinTech adoption rates. The ability of FinTech lenders to effectively compete against banks is not well understood. What are the factors that affect the competition between banks and FinTech lenders?

This paper studies trust in the incumbent lenders (banks) as a potential entry barrier to FinTech lenders. Trust is at the heart of every economic transaction (Arrow, 1974; Tirole, 2017). Guiso et al. (2008) define trust as an individual's subjective belief of the probability of being cheated. Gennaioli et al. (2015) think of trust as inducing a tighter, or lower volatility of, perceived distribution of financial returns. Both these two aspects of trust could serve as the underlying mechanisms through which trust affects borrowers' choice of FinTech lenders. More trust placed on FinTech lenders could indicate that FinTech lenders have a lower perceived probability of cheating. Borrowers could also choose FinTech lenders because trust in FinTech lenders tightens the perceived distribution of the probability of being cheated. Therefore, the role of trust may not be absolute but relative. Households need to use intermediaries to transact, even if they trust them very little. As a

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[2] Fuster et al. (2019) show that FinTech lenders process mortgage loans faster than traditional banks without incurring higher default rates. Tang (2018) finds that peer-to-peer lending platforms only expand credit to existing bank borrowers, while Di Maggio and Yao (2020) show that FinTech lenders lend to high risk borrowers first when they enter the market. Hong et al. (2020) find that FinTech adoption improves household risk-taking.

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result, erosions of trust can shift demand away from traditional lenders toward new ones, such as FinTech lenders.[3]

Trust could be important for borrowers to enter financial contracts with lenders due to the complex financial contracts issue. Mortgage loans are complex transactions involving multiple parties and dozens of pages of legal documents, and most borrowers do not thoroughly learn the financial terms. In most predatory lending cases, lenders not only misled borrowers before contracts were finalized but also altered the documents after they were signed. Therefore, trust could be crucial for borrowers to enter financial contracts with lenders. Whether trust affects households' choice between banks and FinTech is a crucial real-world consideration. The question is further motivated by the literature studying the impact of trust on household financial decisions (e.g., Guiso et al., 2008; Giannetti and Wang, 2016; Brown et al., 2019; Gennaioli et al., 2015; Gurun et al., 2018; D'Acunto et al., 2020; Gennaioli et al., 2022).

However, empirically identifying the impact of trust on FinTech adoption poses significant challenges. Firstly, we need a shock to trust in banks to address the identification challenge, as trust in banks may be correlated with unobservable local economic conditions that also affect FinTech adoptions. Secondly, a comprehensive identification of all lenders in the market is necessary to compare the credit supply and pricing strategies of FinTech and non-FinTech lenders. Thirdly, the empirical setting must account for alternative factors contributing to FinTech adoption, such as convenience of FinTech service. This paper tackles these challenges by leveraging the Wells Fargo scandal outbreak as a negative shock to trust in banks relative to FinTech lenders and using the U.S. residential mortgage market as a lab to study the question.

As one of the most prominent bank scandals after the financial crisis, the Wells Fargo account fraud scandal involved the creation of millions of fraudulent saving and checking accounts, issuing unwanted collateral and auto insurance, and inappropriately charging extension fees. I measure county-level household exposure to the Wells Fargo scandal using the share of Wells Fargo branch deposits over deposits in all commercial bank branches in a given county. As bank branches play an important role in local financial services (Célerier and Matray, 2019; Nguyen, 2019), households residing in areas where Wells Fargo branches operate would be more likely to experience fraudulent financial services. In areas where Wells Fargo operates more intensively, local media would also likely have greater news coverage of the scandal, which intensifies the exposure. The revelation of the Wells Fargo account fraud scandal thus could serve as a negative shock to households' trust in banks in the exposed (treated) areas. Using a difference-in-differences framework, I compare FinTech adoption in regions with a higher initial Wells Fargo deposit share to regions with a lower initial Wells Fargo deposits share before and after the revelation of the scandal in 2016. I find that a one standard deviation increase in exposure to the Wells Fargo scandal leads to a 4.1% increase in the average probability of a household choosing a FinTech lender. I further establish that this effect is not just confined to Wells Fargo. An increase in an area's exposure to the Wells Fargo scandal also leads to a decrease in the probability of borrowers in that area choosing non-Wells Fargo banks.

I analyze the channels through which trust affects FinTech adoption by examining how the Wells Fargo scandal affects borrowers' choices of non-FinTech shadow banks. I first test a "non-bank lender" channel. Trust creates additional utility gain for borrowers when matching with trusted lenders who are perceived to have a lower probability of cheating. The utility loss of matching with traditional banks due to the trust erosion in the banking sector would lead to a relative increase in the utility gain when matching with non-bank lenders. I find that exposure to the Wells Fargo scandal also increases the probability of choosing non-FinTech shadow banks, suggesting that the non-bank feature makes FinTech lenders more appealing after the erosion of trust in the banking sector.

Trust erosion in the banking sector could also affect FinTech adoption due to FinTech lenders' online nature of customer-lender interaction. FinTech borrowers face homogeneous decision-making processes when submitting mortgage applications through online platforms. When customers borrow from lenders who have yet to adopt online lending platforms, the qualities and outcomes of the loan application processes have more significant variations because customers may interact with different human agents. After the Wells Fargo scandal, lenders with online platforms are less likely to experience increased perceived volatility of cheating due to standardization. Borrowers would be more likely to borrow from lenders adopting online platforms because of the relatively higher utility from the lower perceived volatility of being cheated. I test this channel by comparing the effect of the scandal on the choice of FinTech with that of non-FinTech shadow banks. I find that FinTech lending is more affected by trust erosion in banks, compared with non-FinTech shadow bank lending. Therefore, the online customer-lender interaction feature also plays a vital role in FinTech adoption when trust in existing bank lenders erodes.

Examining the relationship between trust and FinTech adoption offers several empirical challenges. Trust in financial institutions could be correlated with other unobservable factors that also affect FinTech adoption. For example, suppose that one region experiences an unobservable banking industry shock, which affects banks' credit supply and thus the demand for alternative lenders. At the same time, the banking industry shock leads to deterioration in banks' quality of services, lowering households' trust in banks. It is also possible that increased FinTech penetration makes banks act more aggressively to compete with FinTech lenders, leading to fraudulent or reckless behavior that would erode people's trust in banks. In both scenarios, trust in banks would be negatively correlated with FinTech adoption.

The setting of the Wells Fargo account fraud scandal allows me to address these challenges due to the nature of the shock. First, most of the fraudulent behaviors dated back to as early as 2005, and thus were unlikely to be a reaction to FinTech penetration. Second, the revelation of this fraud in late 2016, when federal regulators fined the bank $ 185 million, was not correlated with any banking industry shock. Third, there is a large degree of variation in the exposure to this fraud across geographic areas.

Having established that the exposure to the Wells Fargo scandal has a causal effect on the probability of choosing a FinTech lender, I next provide further evidence suggesting that the effect is likely going through the channel of an erosion of trust in banks. First, I use Gallup survey data to measure the level of trust that households place on banks, and show that the Wells Fargo scandal directly reduced trust in banks. I show that a one standard deviation increase in the exposure to the Wells Fargo scandal in a county leads to a 6% decrease in the probability of trusting banks relative to the average. Second, I explore the heterogeneity in households' responses to the Wells Fargo scandal. Thakor and Merton (2018) theorize that an individual's response to public information is affected by the individual's ex-ante belief. Thus, conditional on the exposure to the Wells Fargo scandal, individuals with different ex-ante beliefs in trust in banks will likely experience different decreases in their trust in banks after the scandal. Since the Gallup Survey data are not panel data of households' beliefs, I use households' political affiliations to proxy for their ex-ante level of trust in banks. The Gallup survey shows that, on average, non-Republican survey respondents tend to have lower trust in banks. I find that conditional on the exposure to the Wells Fargo scandal, counties with more non-Republican voters not only experience a larger decrease in trust in banks but also a larger increase in FinTech adoption. These

[3] This paper does not take a stand on whether FinTech lenders complement or substitute traditional banks. As long as the relative trust shifts, we expect a change in demand for different lenders.

results further support the argument that exposure to bank scandals affects FinTech adoption through the erosion of trust in banks.

Furthermore, I explore the treatment effect heterogeneity by using a generic machine learning inference approach proposed by Chernozhukov et al. (2020) (CDDF) to provide additional support for the trust channel. The CDDF approach allows researchers to sort observations into groups with different levels of treatment effects based on a machine learning proxy predictor without pre-specifying the possible characteristics, and make inferences on the average characteristics of the sorted groups. The generic machine learning approach has several advantages. First, it provides a systematic way to perform treatment effects heterogeneity analysis. The approach allows me to stay agnostic about the borrowers' characteristics ex-ante and let the machine learning algorithm choose the characteristics that will be the most affected. Second, the sample splitting feature in the method overcomes the *overfitting* concern in the subgroup analysis. For example, one may argue that the non-Republican borrowers responded to the Wells Fargo scandal differently due to unobserved random variation. The CDDF method solves this issue by randomly splitting observations within the treatment group, thus teasing out the effect of any random variation.

Specifically, I analyze the treatment effects heterogeneity of the Wells Fargo scandal on both trust in banks and FinTech adoption. I sort observations into five groups based on the magnitude of treatment effects, and compute the average characteristics of the most and least affected groups. I then compare the differences in individual characteristics between the most affected group and the least affected group. If the individuals that have the greatest decrease in trust in banks and those that have the greatest increase in FinTech adoption share similar characteristics, then it is unlikely that the Wells Fargo scandal affects FinTech adoption through channels other than trust. I find that female borrowers have a smaller decrease in trust in banks and a smaller increase in FinTech adoption. Similarly, I find that minority borrowers, defined as either African American or Hispanic borrowers, have a smaller decrease in trust in banks and a smaller increase in FinTech adoption. Given that the individuals who have the greatest decrease in trust in banks have similar characteristics to individuals who have the greatest increase in FinTech adoption, the machine learning results further support the trust channel.

My conclusions rely on several assumptions. First, the level of exposure measured by the Wells Fargo deposit share should be uncorrelated with local shocks that may affect FinTech adoption. For example, D'Acunto and Rossi (2017) show that large banks have been exiting some segments of the mortgage lending market since 2009. Thus, it is crucial to show that such time trends do not drive my results.

To address this possibility, I examine the dynamic effects of exposure to the Wells Fargo scandal on the trust in banks and FinTech adoption. The idea is that if there is an unobservable shock that only affects an area with a high initial Wells Fargo deposit share, we should see that the FinTech share evolves differently between treated and less treated regions before the revelation of the Wells Fargo scandal. I find that trust in banks and FinTech adoption are not significantly different between more- and less-treated regions before the scandal at an annual level. To provide finer evidence on the dynamic effects, I also use the Fannie Mae single-family loan dataset to show that FinTech adoptions are not different between more- and less-treated regions until the third quarter of 2016, which corresponds to the timing of the Wells Fargo scandal. Additionally, the parallel trends assumption is not violated in the triple-differences setup involving households' political orientations.

Moreover, I use the deposit share of a placebo bank that was not directly affected by the Wells Fargo scandal to conduct falsification tests. I find that counties with higher JPMorgan Chase deposit shares do not experience larger increases in FinTech adoption. As JPMorgan Chase Bank is one of the largest mortgage originators and has a similar mortgage origination volume as Wells Fargo bank, it rules out the possibility that the results are driven by the nation-wide decline of big banks' participation in mortgage origination.

The second identifying assumption is that exposure to the Wells Fargo scandal affects FinTech adoption only through decreased trust in banks. Even assuming that exposure to the Wells Fargo scandal is uncorrelated with unobserved local shocks, FinTech adoption may increase because banks operating in areas with more exposure to the Wells Fargo scandal reduced local credit supply after the scandal.

To rule out the credit supply channel, I examine mortgage rejection rates. I find that the percentage of mortgages rejected by lenders does not change after exposure to the Wells Fargo shock for most types of lenders. Moreover, treated counties with higher non-Republican shares do not seem to experience a greater credit supply reduction by banks. Thus, the results of the Wells Fargo scandal on FinTech adoption are unlikely to be driven by a reduction in banks' credit supply.

Furthermore, I study how exposure to the Wells Fargo scandal affects loan pricing. I follow Scharfstein and Sunderam (2016) to examine mortgage rate variation not due to credit risk, and find that FinTech lenders and non-Wells Fargo banks do not change their mortgage rates after exposure to the scandal. This finding suggests that the increase in FinTech adoption is unlikely to result from the different pricing strategies between banks and FinTech lenders.

As previous literature (Buchak et al., 2018; Fuster et al., 2019) have documented, the relative convenience of online lenders matters for FinTech adoption. One may be concerned that a significant loss of trust in the Wells Fargo banks could prompt Wells Fargo customers to seek other options. In this scenario, the ease and accessibility of FinTech platforms play a crucial role in driving the higher demand for FinTech loans because FinTech loans can be initiated without the need for any human interaction. To address this possibility, I examine the reaction of "online" banks after the Wells Fargo scandal. I find that exposure to the Wells Fargo scandal has a negative and statistically significant impact on the probability of choosing "online" banks. If our results were purely driven by the convenience channel and not the trust channel, we would observe similar effects of the scandal on FinTech lenders and "online" banks. Therefore, this evidence suggests that it is unlikely the findings are purely driven by the convenience channel.

My paper contributes to the literature on the role of trust in the FinTech growth. Rossi and Utkus (2020) find that trust emerges as the most critical factor among the most significant barriers to robo-advising adoption. Bertsch et al. (2020) use Consumer Financial Protection Bureau complaint data to proxy for bank misconduct, finding a positive association between bank misconduct and online peer-to-peer (P2P) lending usage. Saiedi et al. (2022) also documents the role of trust and FinTech adoption in the P2P lending. Okat et al. (2022) uses survey and experiment evidence and find that the relationship between trust and FinTech adoption is ambiguous.

This paper makes significant contributions to the literature in three aspects. Firstly, it leverages the Wells Fargo scandal and Gallup survey to directly identify a substantial negative impact on trust in banks and demonstrates how this directly affects FinTech adoption. By doing so, it addresses concerns in the literature regarding the correlation between trust in banks and FinTech adoption. This correlation could be influenced by unobservable characteristics or reverse causal factors, which is not addressed in existing literature. Secondly, the paper takes advantage of the U.S. residential mortgage market's unique features, allowing for the identification of the complete universe of mortgage originations and rejections, along with lender information. Unlike studies using P2P lender platforms (Saiedi et al., 2022; Bertsch et al., 2020), which cannot observe this complete universe, this paper can address crucial concerns related to loan origination and rejection. Additionally, the paper addresses the potential influence of pricing strategies, which might not be easily observable through survey evidence.

My paper contributes to a strand of literature studying the factors that drive the increasing growth of FinTech lenders and affect the competition between banks and FinTech lenders. For example, Buchak et al. (2018) show that both technology advantages and lower regulatory pressure contribute to the growth of FinTech lending. Fuster et al. (2019) find no correlation between improved internet access and FinTech adoption. Previous research studies the differences in cost of capital (Thakor and Merton, 2018; Donaldson et al., 2019) and the differences in regulatory burden (Buchak et al., 2018; Chrétien and Lyonnet, 2021) between banks and non-bank lenders. Buchak et al. (2018) and Fuster et al. (2019) have documented, the relative convenience of online lenders matters for FinTech adoption. My paper is the first to study and empirically identify the role of trust in banks as an entry barrier affecting the competition between banks and FinTech lenders. The paper also rules out the potential convenience channel.

Recent studies in FinTech examine how FinTech adoption affects overall credit market conditions and credit accessibility. Several papers focus on identifying the types of borrowers FinTech lenders lend to and examine whether FinTech lenders extend credit to under-served borrowers (e.g., Tang, 2018; Di Maggio and Yao, 2020; De Roure et al., 2021). My paper sheds light on cross-regional differences in FinTech adoption, suggesting that lack of trust from potential borrowers could affect FinTech lenders' credit expansion.

This paper also contributes to the literature that documents the role of trust in finance, pioneered by Guiso et al. (2004), who show that social capital plays a vital role in financial development. Researchers have examined the role of trust in the stock market (Guiso et al., 2008; Giannetti and Wang, 2016), credit market (Brown et al., 2019; Thakor and Merton, 2018), financial advisory market (Gennaioli et al., 2015; Gurun et al., 2018), and contract design (D'Acunto et al., 2020; Gennaioli et al., 2022). This paper highlights trust in traditional financial intermediaries such as banks as an entry barrier to financial innovation.

Finally, this paper contributes to the use of machine learning in finance. The recent literature at the intersection between econometrics and machine learning has developed several applications of using machine learning for causal inference, especially for heterogeneous treatment effects estimation (e.g., Athey and Imbens, 2016; Athey and Wager, 2019; Chernozhukov et al., 2020). This paper designs an empirical framework that uses a generic machine learning method in a difference-in-difference setup. By estimating the average characteristics of the most and least treated groups and comparing the differences in the average characteristics for different outcome variables, the research design can be applied for studying the underline mechanisms of a quasi-experiment.

2. Data description

2.1. Defining FinTech lenders

The definition of a FinTech lender is central to my research question. Following existing literature on FinTech lending in the residential mortgage origination market (Buchak et al., 2018; Fuster et al., 2019), I define a FinTech lender as an institution that provides full-scale, comprehensive online mortgage origination services. A bank is defined as a depository institution, and a shadow bank is defined as a non-depository institution. In my primary analysis sample, no bank falls into my strict definition of FinTech. For some banks, even though people can submit their documents online, they must meet a banker in person to finalize the lending process. Therefore, a lender is classified as either a bank, a non-FinTech shadow bank, or a FinTech lender.

The first key feature in the definition of FinTech is the scope of technological innovation. The lenders' ability to process fully online mortgage origination services represents technological advancement in both the "front-end" and "back-end". At the "front-end", the online application platform can electronically collect borrowers' documents, including financial statements and tax returns. At the "back-end", software and algorithms have been developed to process and verify collected information. For example, the system can identify potentially fraudulent applications by flagging inconsistent data. Such a degree of automation reduces the information processing time and labor intensity. I define FinTech lender based on the "front-end", the nature of customer lender interaction. Some anecdotal evidence also suggests that lender which employ the online lending platform are also likely to use more advanced technology to screen and monitor borrowers.

Through the adoption of full-scale online lending technology initiated by mortgage companies, such as, Quicken Loan's Rocket Mortgage, it is possible that some banks also provide some level of online mortgage origination services. No bank falls into my strict definition of FinTech in my sample. However, some banks are adopting more customer-lender interaction than others. More information can be uploaded and processed on their website than on other banks. I classify banks with a high degree of automation in their online mortgage application process as "online" banks.[4]

The definition is consistent with Buchak et al. (2018)'s FinTech classification, which can be downloaded from their website.[5] One caveat is that some companies classified as non-FinTech lenders in 2017 could fit into the definition of FinTech lender in 2019. Though such transition may correlate with trust erosion in banks, I do not classify these lenders as FinTech in the primary analysis mostly because it was only indirectly affected by the scandal.

Define FinTech adoption. County-level FinTech adoption is measured as the share of mortgage loans handled by FinTech lenders.

$$\text{FinTech adoption}_{ct} = \frac{\sum_{i \in \text{FinTech}} \text{Num of Loans}_{ict}}{\sum_{i \in \text{All Lenders}} \text{Num of Loans}_{ict}}$$

The number of mortgage loans can be defined as either the number of loan originations or the number of total loan applications. The number of total applications reflects households' demand for FinTech services, whereas the number of originated loans reflects supply and demand equilibrium results. Both measures are essential when examining FinTech adoption. FinTech adoption measured using total applications allows researchers to assess household demand and how trust affects household demand for FinTech. FinTech adoption measured using originated loans directly measures the actual degree of FinTech adoption, which matters for welfare analysis (see Fig. 1). These two measures respond to different perspectives of the same question; I will use both in my analyses. If the supply of FinTech loans is elastic, these two measures should produce similar results. Similar results using total loan amount instead of total number of loans are provided in the appendix.

2.2. United States residential mortgage data

The Home Mortgage Disclosure Act (HMDA) requires all depository and non-depository lenders to disclose information on housing-related loans. This loan-level mortgage application dataset covers most home mortgage applications in the U.S.. The dataset provides information including the lender name, year of application, property location, application outcome, loan amount, loan type, loan purpose, loan purchaser type, gender, income, race, and ethnicity of the applicant.

The application outcome is named as the "Type of Action" in the HMDA dataset, indicating the type of action taken on the application, including "Loan originated", "Application approved but not accepted", "Application denied", "Application withdrawn", "File closed for incompleteness", "Loan purchased by your institution", "Preapproval request denied", "Preapproval request approved but not accepted (optional reporting)". The originated loan is defined as a loan with "Type of Action" equals to "Loan Originated".

A direct measure of household demand for mortgages is the total number of applications.[6] In this project, instead of measuring aggregate demand for mortgages, I need to measure mortgage demand for

[4] Although these online banks did not fully qualify as FinTech lenders, some studies, such as Buchak et al. (2018), classified them as FinTech banks in 2019. In this paper, however, I classify them as "online" banks, as their bankers tend to engage directly with borrowers.

[5] https://sites.google.com/view/fintech-and-shadow-banks.

different types of lenders (in different regions). However, the vagueness in defining "loan origination" and "loan purchase" in HMDA may bias the measurement. When a loan is originated from a retail originator and is purchased by another institution in the same year, the loan may be double-counted in the HMDA. Therefore, I exclude "loan purchase" when measuring total applications. Furthermore, action types such as "Application approved but not accepted" (3%), "Application withdrawn" (9%), "File closed for incompleteness" (3%), "Preapproval request denied" (0.4%), "Preapproval request approved but not accepted (optional reporting)" (0.2%) are also excluded because they do not necessarily represent mortgage demand. Since FinTech lenders are online lenders and are convenient to apply to, there may be more "File closed for incompleteness" cases. Therefore, I do not include those records in "total applications".

The Fannie Mae single-family loan performance dataset provides origination and performance data on a subset of Fannie Mae's 30-year and less, full-documentation, single-family, conventional fixed-rate mortgages. The origination (acquisition) dataset provides information including: the name of the entity that delivered the mortgage loan, month of origination, loan amount, original interest rate, months to maturity, original loan to value, debt to income ratio, borrower FICO score, the property's metropolitan statistical area (MSA) code. Sellers' names are available only for entities representing more than 1% of the unpaid principal volume within a given quarter. I focus on the Fannie Mae sample from 2014 to 2020 because Fannie Mae indicates that it used the same MSA definition from 2014 to 2020, and Fannie Mae offered several forms of COVID relief[7] to mortgage owners during COVID, which could affect the incentives for securitization among different types of mortgage lenders.[8]

2.3. Wells Fargo Account Fraud

The Wells Fargo account fraud scandal is one of the most prominent corporate scandals after the 2008 financial crisis. Wells Fargo was engaged in creating millions of fraudulent saving and checking accounts, issuing unwanted collateral and auto insurance, and inappropriately charging mortgage rate lock extension fees, dating back to as early as 2005.

Despite documentation as early as 2013 by *Los Angeles Times*, the controversy received national attention only in September 2016 after the bank was fined $ 185 million by the regulators. Following Giannetti and Wang (2020), I plot the Google search topic trends for "Wells Fargo Account Fraud Scandal" to provide time series trends of public attention to the scandal in Fig. 2. The Google search index is normalized to 100, which is the index value when the topic has the highest search intensity volume. The highest search intensity occurred in September 2016 when regulators issued enforcement actions. In Fig. 2, I also plot the number of local newspaper articles covering the Wells Fargo scandal each month from 2013 to 2018. Consistent with the patterns observed using Google Search Intensity data, I find that local newspaper massively cover the Wells Fargo scandal began in the third quarter of 2016. Therefore, I use 2016 as the year when households are exposed to the Wells Fargo scandal, particularly after the third quarter of 2016. One potential concern is that California might have had some exposure to the Wells Fargo scandal before 2016 due to the news reported by *Los Angeles Times*. To explore this, I examine Google searches only from the users in California. The second row from Fig. 2 shows that there are no significant differences in Google search intensity between California and other states.

Having established that the revelation of the Wells Fargo scandal is an arguably exogenous event following the massive media attention, I use the location and deposits share of Wells Fargo banks to measure cross-regional differences in the exposures to the Wells Fargo exposure. As bank branches play an important role in local financial services (Célerier and Matray, 2019; Nguyen, 2019), households residing in areas where Wells Fargo branches operate would be more likely to experience fraudulent financial services. In areas where Wells Fargo operates more intensively, local media would also be more likely to notice the scandal, which intensifies the effect.

Data on deposits come from the Federal Deposit Insurance Corporation(FDIC) Summary of Deposits (SOD). The Summary of Deposits is the annual survey for all FDIC-insured institutions of branch office deposits as of June 30. This data provide the physical location of the branch office of all FDIC-insured institutions, and the deposits as of June 30 in that branch.

I measure the county-level household exposure to the Wells Fargo scandal using the Wells Fargo deposit share on June 30, 2015 (Fig. 3). For each county, the Wells Fargo deposits share is calculated as the total amount of deposits in Wells Fargo branches in that county over the total amount of deposits by all FDIC insured institution,

$$\text{Wells Fargo(WF) Exposure}_c = \frac{\sum_{i \in \text{Wells Fargo}} \text{Deposits}_{ic}}{\sum_{i \in \text{All Banks}} \text{Deposits}_{ic}}$$

Another way to measure the cross-region differences is to use the geographic variation of public attention in the Wells Fargo scandal, which can be measured using the Google Trend data and local newspaper data. Google Trend provides a state-level index called "Interest by subregion". The index is on a scale from 0 to 100, with 100 indicating the month in the state with the peak search intensity, while 0 indicates no data for the search. I measure state-level attention to the "Wells Fargo scandal" using the Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017 and plot it in Fig. 4. Figs. 3 and 4 suggest that the public attention was mostly concentrated in states with high Wells Fargo deposits share. People in states without Wells Fargo branches were not exposed to the Wells Fargo scandal.

Public attention can also be measured using local newspaper coverage of the Wells Fargo scandal. I focus on local newspapers because they serve as a centralized source of information for households (Gentzkow and Shapiro, 2010). Additionally, newspaper coverage complements the analysis of digital media, as measured by the Google Search Intensity Index. I collect news coverage of the Wells Fargo Account Fraud scandal across all daily newspapers available in the Factiva ProQuest database. Following Gentzkow and Shapiro (2010), I exclude four newspapers — The New York Times, The Wall Street Journal, The Christian Science Monitor, and USA Today — due to the lack of a well-defined local market for these publications. The Factiva ProQuest data identify the Metropolitan Statistical Area (MSA) of each newspaper's headquarters, which I match to counties using the City-County Crosswalk data from City County Crosswalk.[9] The sample includes a total of 333 daily newspapers from 156 counties. I search for articles covering the Wells Fargo Account Fraud scandal within this set of 333 newspapers.

I use both the Google Trend Index and local newspaper coverage as alternative measures of exposure to the Wells Fargo scandal. However, since the local newspaper coverage database includes only a small subset of the counties in our sample, I use the local newspaper coverage measure as a robustness check.

[6] Fuster et al. (2019) use two ways to measure time-series change of *aggregate* mortgage demand. One measure is the total mortgage application from HMDA, and another one is the weighted average coupon rate on fixed-rate mortgage-backed securities less than 10-year Treasury yield.

[7] https://www.fanniemae.com/newsroom/fannie-mae-news/understand-your-covid-19-mortgage-options.

[8] The HMDA sample is less of a concern because it covers a broader sample of mortgage applications and originations.

[9] https://simplemaps.com/data/us-cities.

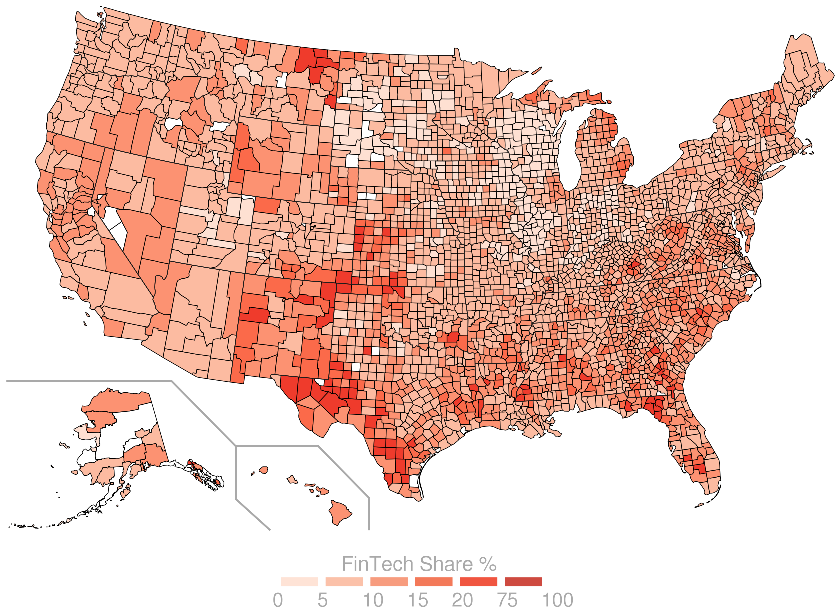

Fig. 1. Heterogeneity in FinTech adoption.
This figure displays county-level FinTech adoption measured as the average share of mortgage loans originated by FinTech lenders from 2012 to 2021.

$$\text{FinTech adoption}_{ct} = \frac{\sum_{i \in \text{FinTech}} \text{Num of Loans}_{ict}}{\sum_{i \in \text{All Lenders}} \text{Num of Loans}_{ict}}$$

The mortgage origination data are obtained from the Home Mortgage Disclosure Act (HMDA). A mortgage lender is classified as a FinTech lender if it provides full-scale, comprehensive online mortgage origination services.

2.4. *Trust in banks*

Trust in Banks is measured using the Gallup Analytics Survey, "Trust in Institutions". In the surveys, Gallup Analytics randomly interviewed approximately 1000 individuals across the U.S. about their confidence in U.S. institutions, from 1981 to 2021. The respondents' age, income, gender, education, race, political affiliation, religion, and county of residence are recorded. The surveys are conducted in June or July each year, and the geographical distribution of individual respondents is sampled proportional to the regional population.

Respondents report their confidence in institutions on five scales: "a great deal", "a lot", "very little", "some", or "none". I define a dummy variable *Trust in Banks*, that is equal to one hundred if the individual reported a level of confidence in banks as "a great deal" or "a lot", and zero otherwise. I apply the same definition to *Trust in Big Business*, *Trust in Newspapers*, and *Trust in Television News*. Since there is no direct survey question asking about the confidence level in the U.S. media, I take the average trust level of newspaper and TV news as a proxy for trust in media. Respondents were asked to report their political affiliation as "Republican", "Lean Republican", "Independent", "Lean Democrat", or "Democrat". I define a dummy variable *Non-Republican* that equals to one if the respondents reported their party affiliations as "Independent", "Lean Democrat", or "Democrat".

2.5. *Other variables*

I obtained county-year and MSA-year level demographic data from the U.S. Census American Community Survey(ACS) 1-year estimates[10] between 2012 and 2021. ACS 1-year estimates are only available for areas with a population larger than 65,000, so I restrict my sample to counties larger than 65,000.

County-level political affiliation data are from the MIT Election Data and Science Lab.[11] The dataset includes county-level results for the 2016 presidential election, in terms of county-level total votes, votes for the Democratic, the Republican, and independent candidates. I measure party affiliation for non-Republican as the total share of votes for the Democratic and independent candidates.

3. Empirical methodology

The main challenges for estimating the causal effect of the erosion of trust in banks on the propensity to choose FinTech mortgage lenders are the issues of omitted variables and reverse causality. Trust in banks and FinTech adoption may correlate with unobservable local banking industry shocks and local economic conditions. If one region experienced an unobservable banking industry shock, the banks' quality of services might deteriorate, and households may be less likely to trust banks. It is also possible that increased FinTech penetration makes banks act more aggressively to compete with FinTech lenders, leading to fraudulent or reckless behavior that would erode people's trust in banks. In both scenarios, trust in banks would be negatively correlated with FinTech adoption. Moreover, higher trust in banks does not imply a larger difference between trust in banks and trust in FinTech. The higher probability of choosing FinTech lending may not result from a larger difference between trust in banks and trust in FinTech.

I use the geographic variation of exposure to the Wells Fargo scandal to estimate the causal effect. I compare FinTech adoption between an area with higher initial Wells Fargo deposits share to an area with lower Wells Fargo deposits share before and after massive media attention

[10] US Census American Community Survey(ACS) 1-year estimates data is a part of American Community Survey, a survey program that provides demographics information at many geographic summary levels. "1-year estimates" denotes the data collecting period. For example, 2019 ACS 1-year estimates use data collected between January 1, 2019 and December 31, 2019.2015–2019 ACS 5-year estimates use date collected between January 1, 2015 and December 31, 2019. Therefore, 1-year estimates data is the most current data.

[11] https://electionlab.mit.edu/data.

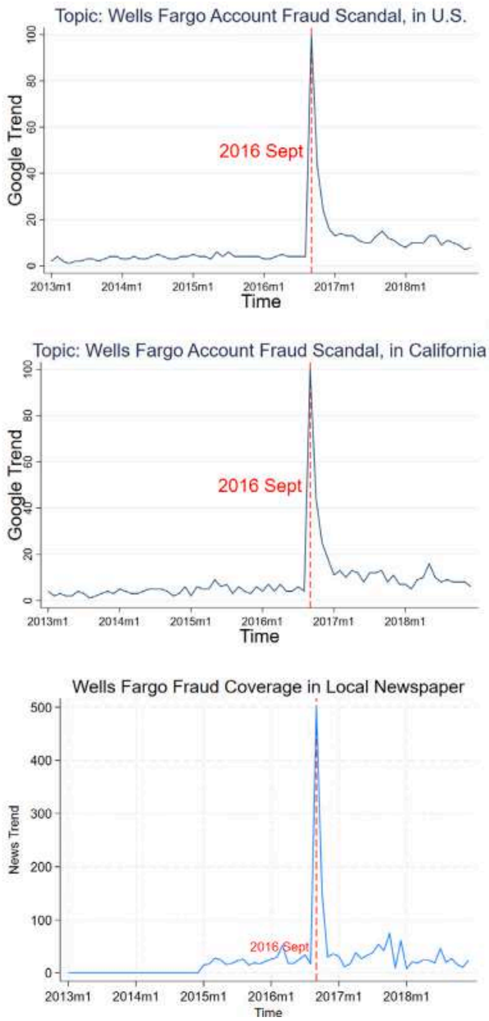

Fig. 2. Media coverage of the Wells Fargo Scandal.
This figure displays Google search topic trends for "Wells Fargo Account Fraud Scandal" from 2013 January to 2018 December, and the number of local newspaper articles covering the Wells Fargo scandal each month from 2013 January to 2018 December. The first and second rows show the Google search volume for the topic "Wells Fargo Account Fraud Scandal" from users across the U.S. and California, respectively. The third row displays the number of local newspaper articles covering the Wells Fargo scandal each month. The Google search index is normalized to 100, the index value when the topic has the highest search intensity volume.

in 2016. The empirical strategy is akin to a difference-in-differences approach, and most of the analysis is a variation of the following form,

$$y_{(i),c,t} = \beta WFExposure_c \times Post_t + Control_{(i),c,t} + \lambda_c + \delta_t + \varepsilon_{(i),c,t} \quad (1)$$

WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is a dummy equal to 1 after 2016, and 0 otherwise. I include county fixed effects λ_c and time fixed effects δ_t. County-level control variables are from Buchak et al. (2018), which I will discuss when presenting the results. Since the American Community Survey one-year estimates only report annual county characteristics for counties with a population larger than 65 000, I only include those counties in our sample. It is robust when extending the sample to all counties. In the loan-level analysis, the dependent variable is an indicator variable equal to 100 if the mortgage lender is a FinTech lender. In the county-level analysis, the dependent variable is the share of mortgages originated by FinTech lenders.

The parameter of interest β measures the incremental effects of the increased household exposure to the Wells Fargo scandal on the propensity of the household to choose a FinTech mortgage lender. Interpreting β as a causal effect of the erosion of trust in banks on the probability of choosing FinTech lenders relies on two assumptions.

The first assumption is that the level of exposure measured by the Wells Fargo deposits share is uncorrelated with unobservable shocks that affect FinTech adoption. Suppose there is an unobserved shock that only affects areas with high initial Wells Fargo deposit shares, I should see the FinTech shares evolve differently between treated and less-treated regions before the revelation of the Wells Fargo scandal. I will thus examine the dynamic effects of exposure to the Wells Fargo scandal on FinTech adoption in different areas.

The second assumption is that the Wells Fargo scandal generates a negative shock to households' trust in banks, through which the scandal affects households' FinTech adoption. I will first establish a causal relationship between exposure to the scandal and households' trust in banks. Then I will present evidence that the erosion of trust in banks is the most likely mechanism through which the scandal affects households' FinTech adoption.

One caveat is that my empirical setting does not assume whether FinTech lenders complement or substitute traditional banks. The results document the *relative* probability of choosing FinTech or traditional banks. The relative probability change could come from FinTech both complementing and substituting bank lenders.

4. Results

4.1. The revelation of wells Fargo Account Fraud and trust in banks

Before establishing the relationship between the exposure to the bank scandal and the probability of choosing a FinTech lender, I first show that the Wells Fargo scandal erodes trust in banks. Using a difference-in-differences model similar to Eq. (1), I estimate the effects of exposure to the bank scandal on trust in banks.

$$y_{i,c,t} = \beta WFExposure_c \times Post_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t} \quad (2)$$

The dependent variable is an individual's trust in banks, which is measured using the Gallup survey data from June 2012 to June 2021.[12] Trust in Banks is a dummy variable equaling to one hundred if the respondent reports "a great deal" or "a lot of" confidence in banks. Since Gallup does not provide an individual identifier, one cannot identify individuals who repeatedly responded in different years. Although I cannot add individual fixed effects, I control for a wide range of respondent characteristics and compare individuals' reported trust in banks before and after the scandal.

Column (1) of Table 2 shows that exposure to bank scandals leads to a decrease in the probability of reporting trust in banks. A one-standard-deviation increase in the exposure to the Wells Fargo scandal in a county leads to a 1.67-percentage-point decrease ($= -10.4 * 0.163$) in the probability of reporting trust in banks, which is a 6% decrease from the average probability of reporting trust in banks (29).

Column (2) includes several respondent-level control variables: age, gender, education, income, race, ethnicity, religion, and political affiliation. Column (3) includes trust in media. Column (4) includes local economic conditions.[13] The point estimate remains significant, and the economic magnitude remains similar. Heterogeneity in respondent characteristics and local economic conditions does not explain the results.

[12] The Gallup surveys are conducted in June or July each year. Therefore, we have five-year observations (June 2012, 2013, 2014, 2015, and 2016) before the scandal and five-year observations (June 2017, 2018, 2019, 2020, and 2021) after the scandal.

[13] There are fewer observations in Column (4) because local economic condition measure is not available for counties with total population larger than 65 000.

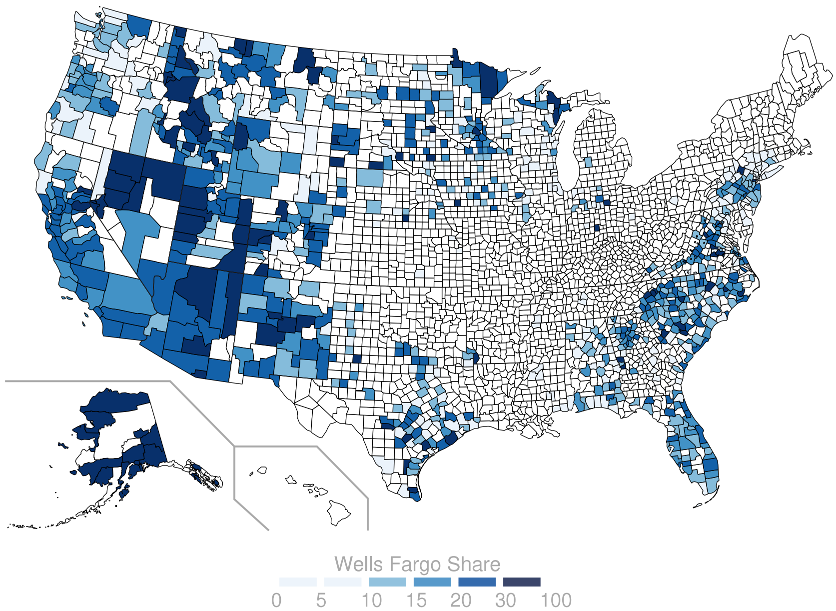

Fig. 3. Household exposure to the Wells Fargo Scandal.
This figure displays county-level household exposure to the Wells Fargo scandal using the Wells Fargo deposit share in 2015. For each county, the Wells Fargo deposits share is calculated as the total amount of deposits in Wells Fargo branches in that county over the total amount of deposits by all FDIC-insured institution.

$$\text{Wells Fargo(WF) Exposure}_c = \frac{\sum_{i \in \text{Wells Fargo}} \text{Deposits}_{ic}}{\sum_{i \in \text{All Banks}} \text{Deposits}_{ic}}$$

Data on deposits come from the Federal Deposit Insurance Corporation(FDIC) Summary of Deposits (SOD).

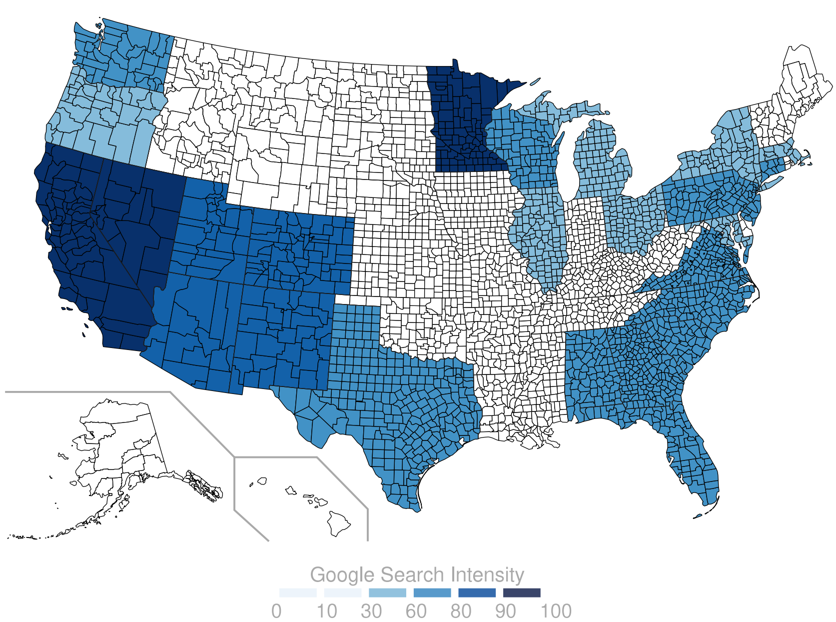

Fig. 4. Google search intensity.
This figure displays state-level exposure to the Wells Fargo scandal using the Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. The index is on a scale from 0 to 100, with 100 indicating the state with the peak search intensity.

As previously noted, the Gallup survey does not survey individuals' confidence in other types of financial institutions. Thus, a reliable cross-regional measure of trust in FinTech is not available. Instead, I use trust in general businesses to measure the trust in FinTech companies. In the Gallup survey, individuals were surveyed on their confidence in big businesses and banks. Since FinTech companies do not belong to the traditional definition of bank lenders, the survey questions on trust in big businesses are the best available proxies for trust in FinTech companies. In columns (5), (6), (7), and (8), I re-do all of the analyses using trust in big businesses as dependent variables. The results show that exposure to the Wells Fargo scandal does not decrease trust in big businesses. The trust that households place on FinTech and non-FinTech shadow banks do not change after exposure to the Wells Fargo scandal. This is therefore consistent with the relative difference between trust in banks and trust in FinTech decreasing after the scandal.

In the Appendix Table A6, I use an alternative measure of exposure to the Wells Fargo scandal. $WFExposure_c$ is instead measured using

Table 1
Summary statistics.

Table A: Mortgage share						
	Mean	Median	Std Dev	25%	75%	N
Mortgage origination						
FinTech	7.79	7.22	3.54	5.28	9.76	8 229
+ NonFinTech shadow bank	38.31	37.94	13.98	28.36	48.29	8 229
= Shadow bank	46.10	45.89	15.86	34.79	57.51	8 229
Wells Fargo	4.77	3.41	4.12	1.84	6.33	8 229
+ Non-Wells Fargo bank	49.13	48.40	15.71	37.49	60.30	8 229
Bank	53.90	54.11	15.86	42.49	65.21	8 229
Mortgage application						
FinTech	8.46	7.89	3.74	5.86	10.50	8 229
+ NonFinTech shadow bank	37.21	36.83	12.59	28.24	46.16	8 229
= Shadow bank	45.66	45.52	14.56	35.07	56.13	8 229
Wells Fargo	5.26	4.02	4.16	2.21	6.96	8 229
+ Non-Wells Fargo bank	49.08	48.39	14.51	38.41	59.50	8 229
Bank	54.34	54.48	14.56	43.87	64.93	8 229
Table B: County characteristics: 2012–2021						
	Mean	Median	Std Dev	25%	75%	N
Treated (Wells Fargo deposits share in 2015)	9.13	5.94	10.41	0.00	16.65	8 229
Treated × post	5.52	0.00	9.26	0.00	9.89	8 229
Non-Republican (NonRep) share	0.47	0.46	0.15	0.36	0.57	8 229
Treated × Post × NonRep	2.80	0.00	5.14	0.00	4.12	8 229
Google search intensity	51.11	66.00	32.41	33.00	75.00	8 229
Top 4 share	0.31	0.29	0.10	0.23	0.36	8 229
American Community Survey: 1 Year						
Population (000s)	333.88	158.77	584.28	96.19	333.75	8 229
Median household income	60 055.46	56 482.00	16 951.45	47 999.00	68 424.00	8 229
Unemployment rate	6.29	5.80	2.68	4.40	7.70	8 229
% with less than 35K income	30.44	30.40	9.02	23.90	36.90	8 229
Table C: Gallup individuals, 2012–2021						
	Mean	Median	Std Dev	25%	75%	N
Trust in banks	29.27	0.00	45.50	0.00	100.00	11 372
Trust in big business	21.15	0.00	40.84	0.00	0.00	11 372
Trust in media	21.68	0.00	34.18	0.00	50.00	11 372
NonRep	0.56	1.00	0.50	0.00	1.00	11 372
Age	53.13	55.00	18.75	38.00	68.00	11 372
Female	0.47	0.00	0.50	0.00	1.00	11 372
College	0.76	1.00	0.43	1.00	1.00	11 372
High income	0.34	0.00	0.47	0.00	1.00	11 372
White	0.74	1.00	0.44	0.00	1.00	11 372
Hispanic	0.08	0.00	0.27	0.00	0.00	11 372
Black	0.13	0.00	0.33	0.00	0.00	11 372
Protestant	0.37	0.00	0.48	0.00	1.00	11 372
Jewish	0.02	0.00	0.14	0.00	0.00	11 372
Trust in banks (NonRep)	25.74	0.00	43.72	0.00	100.00	6 318
Trust in banks (Republican)	33.70	0.00	47.27	0.00	100.00	5 054
Table D: Loan characteristics						
	Mean	Median	Std Dev	25%	75%	N
Mortgage origination						
FinTech	8.84	0.00	28.38	0.00	0.00	86 860 239
Wells Fargo	4.97	0.00	21.72	0.00	0.00	86 860 239
Non-Wells Fargo bank	43.73	0.00	49.61	0.00	100.00	86 860 239
Bank	48.70	0.00	49.98	0.00	100.00	86 860 239
NonFinTech shadow bank	42.47	0.00	49.43	0.00	100.00	86 860 239
Shadow bank	51.30	100.00	49.98	0.00	100.00	86 860 239
Mortgage application						
FinTech	9.25	0.00	28.97	0.00	0.00	110 071 472
Wells Fargo	5.52	0.00	22.83	0.00	0.00	110 071 472
Non-Wells Fargo bank	44.84	0.00	49.73	0.00	100.00	110 071 472
Bank	50.36	100.00	50.00	0.00	100.00	110 071 472
NonFinTech shadow bank	40.39	0.00	49.07	0.00	100.00	110 071 472
Shadow bank	49.64	0.00	50.00	0.00	100.00	110 071 472

This table reports the summary statistics of the key variables. Tables A and B present summary statistics for counties with populations larger than 65 000. Table C presents the characteristics of Gallup survey individuals. Table D reports the U.S. residential mortgage loan characteristics. The U.S. Residential Mortgage Data are obtained from the HMDA. County-year level demographic data from the U.S. Census American Community Survey(ACS) 1-year estimates 6 between 2012 to 2021. Trust in institutions data is obtained from the Gallup Analytics surveys.

Table 2
The effect of the revelation of the Well Fargo scandal on trust in banks.

	Trust in banks				Trust in big business			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WF exposure	−0.163**	−0.169**	−0.214***	−0.178**	0.024	0.017	−0.010	0.032
	(−2.0)	(−2.1)	(−2.9)	(−2.3)	(0.3)	(0.2)	(−0.1)	(0.4)
NonRep		−7.373***	−13.115***	−13.238***		−17.255***	−20.656***	−20.967***
		(−7.0)	(−12.7)	(−12.1)		(−17.1)	(−21.0)	(−20.0)
Age		−0.009	−0.061**	−0.072***		0.020	−0.010	−0.012
		(−0.3)	(−2.3)	(−2.6)		(0.8)	(−0.4)	(−0.5)
Female		2.785***	2.379***	2.011**		−5.268***	−5.508***	−5.504***
		(3.0)	(2.7)	(2.1)		(−6.6)	(−7.0)	(−6.7)
College		−2.685**	−1.681	−1.337		−3.101***	−2.506**	−1.921*
		(−2.4)	(−1.6)	(−1.2)		(−3.1)	(−2.5)	(−1.8)
High income		1.277	1.485	1.509		2.864***	2.988***	2.991***
		(1.3)	(1.6)	(1.5)		(3.0)	(3.3)	(3.2)
White		−4.741**	−4.659**	−5.654**		−5.177***	−5.128***	−5.805***
		(−2.1)	(−2.1)	(−2.5)		(−2.7)	(−2.8)	(−3.0)
Hispanic		−3.209	−3.197	−4.052		−1.297	−1.290	−1.442
		(−1.2)	(−1.2)	(−1.5)		(−0.6)	(−0.6)	(−0.7)
Black		−4.786*	−4.600*	−5.519**		−1.883	−1.773	−2.774
		(−1.9)	(−1.8)	(−2.1)		(−0.8)	(−0.8)	(−1.2)
Protestant		5.929***	5.648***	5.649***		−0.233	−0.399	−0.433
		(5.9)	(5.7)	(5.4)		(−0.2)	(−0.4)	(−0.4)
Jewish		2.959	1.539	1.728		−0.283	−1.124	−0.846
		(1.0)	(0.5)	(0.6)		(−0.1)	(−0.4)	(−0.3)
Trust in media			0.317***	0.316***			0.188***	0.184***
			(21.9)	(20.6)			(14.1)	(13.1)
% with less than 35K income				0.095				−0.243
				(0.3)				(−1.0)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10 687	10 687	10 687	9303	10 687	10 687	10 687	9303
Adjusted R^2	0.028	0.039	0.091	0.081	0.007	0.056	0.078	0.078

This table reports the effects of the Wells Fargo scandal revelation on trust in banks, using "Confidence in Institution" survey data from Gallup Analytics from 2012 to 2021. The coefficients are estimated using following regressions.

$y_{i,c,t} = \beta WFExposure_c \times Post_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$

The dependent variable is respondent's trust in banks and trust in big business, which equal to one hundred if the respondent reports the level of confidence as "a great deal" or "a lot", zero if reports "very little", "some" or "none". $WFExposure_c$ is the percentage of Wells Fargo deposits in county c in 2015. $Post_t$ is a dummy variable that equals to 1 after September 2016. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

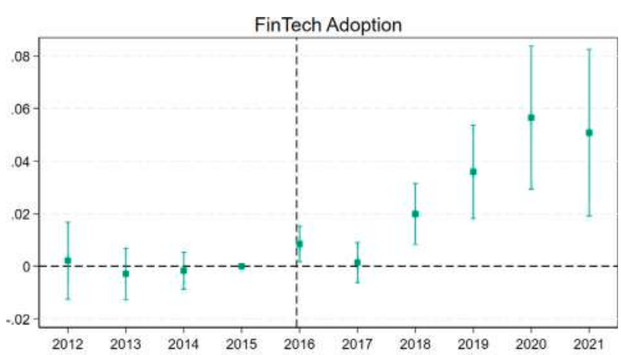

Fig. 5. Dynamic effects of the Wells Fargo scandal revelation on FinTech adoption.
This figure shows the dynamic effects of exposure to the Wells Fargo scandal on FinTech adoption. Coefficients are estimated from the following regression using HMDA loan-level data from 2012 to 2021.

$y_{i,c,t} = \beta_t WFExposure_c \times \sum_{t=2012,t\neq 2015}^{2021} Dummy_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$

The dependent variable is a dummy variable that equals 100 if the lender is FinTech, and 0 otherwise. WF Exposure is the share of Wells Fargo deposits in county c in 2015. Year dummy t is a dummy variable that equals 1 at year t and 0 otherwise. The year 2015 is omitted as the reference year. The result include only originated loans. The constant term, county and year fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at the 5% level.

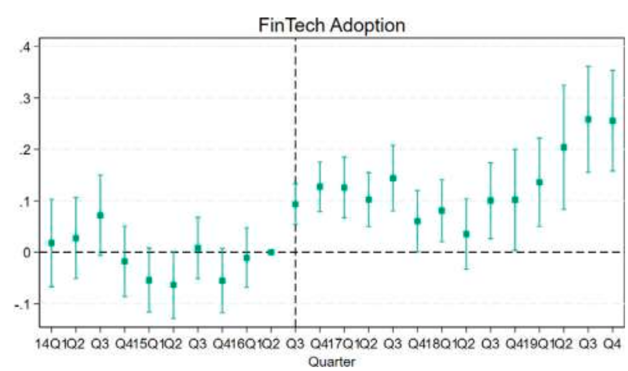

Fig. 6. Dynamic effects of the Wells Fargo scandal revelation on FinTech adoption: Fannie Mae Loans.
This figure reports the dynamic effects of exposure to the Wells Fargo scandal on mortgage loan origination using Fannie Mae loans. The plotted coefficients are estimated from the following regression, using MSA-year-quarter-level data from 2014Q1 to 2019Q4.

$y_{c,t} = \beta_t WFExposure_c \times \sum_{t=2014Q1,t\neq 2016Q2}^{2019Q4} Dummy_t + Control_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t}$

The dependent variable is the share of the number of mortgages originated by FinTech lenders at the MSA level. WF Exposure is the percentage of Wells Fargo deposits in MSA c in 2015. Post is a dummy variable that equals to one after the third quarter of 2016. The 2016 Q2 dummy is the reference period, and is thus omitted. The constant term, MSA and year-quarter fixed effects are included in all regressions. Standard errors are clustered at the MSA level; confidence intervals are calculated at the 5% level.

Table 3
The effect of the revelation of the Well Fargo scandal on FinTech adoption.

	Origination		Application	
	FinTech	FinTech	FinTech	FinTech
	(1)	(2)	(3)	(4)
WF exposure × post	0.035***	0.033***	0.030***	0.032***
	(3.4)	(3.2)	(3.5)	(3.4)
Population		−0.004**		−0.003*
		(−2.6)		(−1.9)
Median household income		0.000***		0.000***
		(5.3)		(4.4)
Unemployment rate		−0.033		−0.011
		(−1.0)		(−0.4)
% with less than 35K income		0.032		0.021
		(1.4)		(1.0)
Top 4 share		−0.103		−0.678
		(−0.1)		(−0.6)
Income	−0.000*	−0.000*	0.000	0.000
	(−1.7)	(−1.8)	(0.0)	(0.1)
Loan Amount	−0.001***	−0.001***	−0.001***	−0.001***
	(−5.4)	(−4.8)	(−5.3)	(−4.8)
Loan type (Omitted category = Conventional)				
FHA	3.790***	3.541***	4.744***	4.493***
	(22.9)	(20.8)	(25.5)	(22.7)
VA	1.578***	1.600***	2.154***	2.172***
	(14.3)	(13.5)	(16.9)	(15.3)
FSA/RHS	−0.033	0.470**	−0.437***	0.334*
	(−0.2)	(2.2)	(−2.8)	(1.8)
Loan purpose (Omitted category = Home purchase)				
Home improvement	−1.008***	−0.821***	−4.152***	−3.610***
	(−10.2)	(−7.1)	(−33.0)	(−26.3)
Refinance	6.096***	6.233***	5.623***	5.988***
	(42.5)	(38.0)	(45.0)	(42.7)
Purchaser type (Omitted category = Held)				
Fannie Mae	11.659***	11.901***	8.486***	8.815***
	(61.8)	(56.9)	(46.3)	(44.4)
Ginnie Mae	9.102***	8.836***	4.842***	4.767***
	(37.1)	(32.2)	(26.2)	(22.8)
Freddie Mac	8.863***	9.065***	5.698***	5.986***
	(38.2)	(34.8)	(23.8)	(22.6)
Farmer Mac	−0.895***	−1.242***	−4.206***	−4.473***
	(−4.1)	(−4.5)	(−20.1)	(−16.8)
Private securitization	0.965***	1.331***	−2.407***	−1.900***
	(2.9)	(3.8)	(−7.0)	(−5.3)
Bank	2.083***	2.455***	−1.317***	−0.807**
	(5.6)	(6.1)	(−3.5)	(−2.0)
Insurance	−1.120***	−0.780***	−4.756***	−4.262***
	(−6.8)	(−4.5)	(−30.1)	(−26.4)
Affiliate	−2.950***	−2.734***	−6.093***	−5.806***
	(−17.1)	(−14.7)	(−34.2)	(−30.0)
Other	−0.218	0.170	−3.835***	−3.294***
	(−1.4)	(1.0)	(−24.4)	(−19.9)
Gender (Omitted category = Male)				
Female	0.532***	0.430***	0.769***	0.610***
	(15.4)	(12.0)	(21.5)	(17.6)
N.A.	11.212***	11.056***	10.587***	10.686***
	(35.2)	(32.1)	(39.7)	(36.2)
Ethnicity (Omitted category = Non-Hispanic)				
Hispanic	−0.943***	−1.049***	−0.314*	−0.505***
	(−6.0)	(−6.5)	(−1.8)	(−2.9)
Other	1.141***	0.613***	2.480***	1.479***
	(8.8)	(4.8)	(14.1)	(9.9)
Race (Omitted category = White)				
Native American	1.473***	1.565***	1.770***	1.780***
	(13.6)	(12.8)	(16.7)	(14.6)
Asian	0.441**	0.337*	0.435**	0.339*
	(2.2)	(1.7)	(2.4)	(1.9)
Black	0.825***	0.741***	1.266***	0.920***
	(9.6)	(8.3)	(13.2)	(10.1)
Hawaiian	0.494***	0.468***	0.539***	0.500***

(*continued on next page*)

Table 3 (*continued*).

	(4.1)	(3.9)	(4.5)	(4.1)
N.A.	3.571***	3.634***	3.174***	3.466***
	(31.6)	(30.0)	(25.3)	(26.7)
Constant	−1.009***	−3.908*	2.350***	0.243
	(−6.5)	(−1.8)	(17.3)	(0.1)
Observations	86 860 239	76 809 340	110 071 472	96 648 461
Adjusted R^2	0.090	0.088	0.078	0.076

This table reports the effect of the Well Fargo scandal revelation on FinTech adoption. Coefficients are estimated from the following regression, using loan-level data from 2012 to 2021 from the HMDA.

$y_{i,c,t} = \beta_t WFExposure_c \times Post_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$

The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender and zero otherwise. $WFExposure_c$ is the percentage points of Wells Fargo deposits in county c in 2015. $Post_t$ is a dummy variable that equals to one after 2016. $Control_{i,c,t}$ include both county-level and loan-level control variables. Columns (1) and (2) only include originated loans, and columns (3) and (4) include all applications. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. I find a very similar result that exposure to the bank scandal leads to a decrease in the probability of reporting trust in banks.[14] This result suggests that these two are both valid measures of the exposure to the Wells Fargo scandal and that cross-sectional variation in the exposure to the scandal creates cross-sectional variation in the changes of trust in banks.

Moreover, the coefficient controlling for individuals' political affiliations is large and significant. On average, people who reported not being affiliated with the Republican Party had much lower trust in banks. Not being affiliated with the Republican Party decreases the probability of reporting trust in banks by 7.4-percentage-points, a nontrivial effect. Survey evidence shows that people behave heterogeneously in terms of their trust in banks, which will be further investigated in Section 4.4 to sharpen the trust channel.

4.2. Wells Fargo Account Fraud and FinTech adoption

4.2.1. Baseline results

Next, I relate the exposure to the Wells Fargo scandal to FinTech adoption, comparing FinTech adoption in regions with high initial Wells Fargo deposit share to regions with low Wells Fargo deposits share before and after the outburst of the scandal in 2016. I estimate the difference-in-differences model specified in Eq. (1).

In Table 3 the dependent variable is a dummy variable equal to 100 if the lender is FinTech. Regressions in Columns (1) and (2) include only originated loans, whereas Columns (3) and (4) include all applications (originated + denied loans). As previously noted, total applications of mortgage loans is a direct measure of household ***demand*** for different types of mortgage lenders, while the total number of originated mortgages is a result of both credit supply and demand. Later I will show that the lender's credit supply does not affect our results.

I begin by focusing on origination in Columns (1) and (2). Column (1) shows that an increased exposure to the Wells Fargo scandal leads to an increase in the probability of choosing a FinTech lender. A one-standard-deviation increase in exposure to the Wells Fargo scandal in a county leads to a 0.36-percentage-point increase ($= 10.4 * 0.035$) in the probability of choosing a FinTech lender, which is a 4.1% increase from the average probability of choosing a FinTech lender (8.84). The result is significant at the 1% level. Since individual characteristics and types of loans may also affect lender choice, I include applicant and loan characteristics in the regression. Women are more likely to choose FinTech lenders than men. Compared to White, African Americans are also more likely to choose FinTech lenders.

Since local economic and market conditions may also affect the probability of choosing a FinTech lender, I add county-level economic controls from the American Community Survey one-year estimates. I lose some observations since the county-year level economic data are only available for counties with a population larger than 65,000. Scharfstein and Sunderam (2016) and Liebersohn (2017) show that market power plays an important role in mortgage lending. To control for local credit market conditions, I use the total share of the top 4 lenders as a measure of competition.[15] Column (2) shows that an increased exposure to the Wells Fargo scandal has a positive and significant effect on the probability of choosing a FinTech lender, even after controlling for county-level demographics, economic conditions, and local credit market conditions. The economic magnitude is similar.

Columns (3) and (4) show the results using all mortgage loan applications to measure FinTech adoption.[16] The coefficients are all statistically significant and have values similar to the results for loan origination. An increased exposure to the Wells Fargo scandal leads to an increase in the probability of choosing a FinTech lender among approved and rejected borrowers. Since rejected loans are included in the regression, the positive coefficient reflects the increase in household demand for FinTech lenders. Overall, these results suggest that the effects of exposure to the Wells Fargo scandal on FinTech adoption are not driven by changes in credit supply. Later in Section 4.7, I will further show that lenders' credit supply is not affected by exposure to the Wells Fargo scandal.

In the Appendix Tables A4 and A5, I use two alternative measures of exposure to the Wells Fargo scandal. $WFExposure_c$ is measured using Google Trend's "Interest by subregion" index for the search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. $LocalNews_c$ represents the number of local newspaper articles covering the Wells Fargo scandal in county c in 2016, expressed in logarithmic form as $log(NumberofNews+1)$. I find that a one-standard-deviation increase in exposure to the Wells Fargo scandal, measured using Google Search Intensity in a county, leads to a 0.2-percentage-point decrease in the probability of choosing FinTech. Similarly, a

[14] The results based on Google Trends data, measured at the state level, may exhibit reduced statistical significance due to the lack of within-state variation. This limitation likely contributes to the observed discrepancy in statistical significance between the Google Trends data and the deposit share exposure data. I do not use the local newspaper coverage measure due to the low overlap between the Gallup survey and counties covered by local newspaper markets. I used a shorter sample from 2014 to 2018 due to the well-documented short-term effect of scandals on trust, which will be explained further in Section 4.4.

[15] Stanton et al. (2014) discussed that concentration in the US mortgage market might be underestimated; the results are robust using either the Herfindahl index or share of Top 4 lenders.

[16] However, many individuals rely on real estate agents to purchase homes and apply for mortgages, and the incentive of real estate agents may distort individuals' choice of mortgage lender. Although we do not observe the real estate agencies in HMDA data, most real estate agencies are local. Thus they should be exposed to trust shock similarly to individuals who were shopping for the mortgage.

one-standard-deviation increase in exposure to local news coverage of the Wells Fargo scandal leads to a 0.18-percentage-point increase in FinTech shares. Both magnitudes are comparable to the effects of exposure measured using the Wells Fargo deposit share.

Our findings demonstrate consistent effects of exposure to the Wells Fargo scandal, whether measured using county-level Wells Fargo deposit shares, the Google Search Index, or local newspaper coverage. Overall, these results suggest that the effects observed through media coverage are as significant as those derived from deposit share exposure to Wells Fargo prior to the scandal.

4.2.2. Parallel trends

One possible concern of the causal interpretation is that the results may be driven by the different trends of FinTech adoption among areas with different Wells Fargo scandal exposure. If this is the case, we should see that the FinTech share evolved differently between more- and less-treated regions before the revelation of the Wells Fargo scandal. Furthermore, the parallel trends assumption is critical to rule out alternative channels when studying FinTech adoption. For example, D'Acunto and Rossi (2017) show that large banks have been exiting some mortgage lending market segments since 2009. To rule out the alternative channel, I estimate the dynamic treatment effect models in the following forms,

$$y_{i,c,t} = \beta_t WFExposure_c \times \sum_{t=2012,t\neq 2015}^{2021} Dummy_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$$

The dependent variable is a dummy variable that equals 100 if the lender is FinTech, and 0 otherwise. WF Exposure is the share of Wells Fargo deposits in county c in 2015. Year dummy t is a dummy variable that equals to 1 at year t, and 0 otherwise. The year 2015 is omitted, as the reference year.

Fig. 5 shows the dynamic effects of exposure to the Wells Fargo scandal on FinTech adoption. The treatment dynamics are consistent with the parallel trends assumption. The increase in FinTech adoption occurred in the treated areas only after the scandal in 2016, and there existed no pre-trends before the scandal. The results indicate that the Wells Fargo deposits in county c in 2015 are unlikely to be correlated with potential confounding unobservable shocks related to FinTech adoption.

The treatment effect in 2017 is positive but not statistically significant, possibly due to the loan-level empirical specification used to estimate the treatment dynamics. The estimates in Fig. 5 are based on regression analysis using HMDA loan-level data. If counties with greater decreases in trust in banks experienced fewer loan originations in 2017, a loan-level analysis could attenuate the treatment effects observed for that year. I calculate the total number of loans in counties with high exposure to the Wells Fargo scandal. In 2017, Counties with high exposure to the Wells Fargo scandal recorded the lowest number of loan applications and originations during the six post-treatment years (2016, 2017, 2018, 2019, 2020, and 2021). From 2016 to 2017, the total number of loan decreased 12% in regions with low exposure to the Wells Fargo scandal, and 18% decrease in regions with high exposure to the Wells Fargo scandal. We indeed find that the number of loan originations decline more sharply in 2017 in high exposure counties, compared to low exposure counties. In Appendix Figure A1, I present the dynamic effects of the Wells Fargo scandal revelation on FinTech adoption, with coefficients estimated using county-year-level data from 2012 to 2021. In this county-level dynamic effect analysis, with equal weights assigned to each county, the treatment effects in 2016 and 2017 have similar magnitudes and are both statistically significant.

The publicly available HMDA dataset is at an annual frequency, so my dynamic analysis is at an annual frequency. Fig. 2 shows an intensive search of the "Wells Fargo Account Fraud Scandal" that started in September 2016 when the regulators issued enforcement actions. Therefore, in our primary annual-level analysis, the treatment year started in 2016. Ideally, we would like to see that the treatment effect started in September 2016. To explore the finer time trends, I turn to Fannie Mae's single-family loan datasets, which provide loan origination at the quarterly frequency. Since these datasets provide only the first three digits or the MSA codes of the property location, I conduct a similar dynamic difference-in-differences estimates at the year-quarter-MSA level. Post is a dummy variable that equals one after the third quarter of 2016. The 2016 Q2 dummy is the reference period, and is thus omitted.

Fig. 6 shows the dynamic effects of the exposure to the Wells Fargo scandal on FinTech adoption at a quarterly frequency. There are no significant differences between the more and less treated regions before Q3 of 2016. The treatment effect is strong and significant right after the scandal outburst in Q3 of 2016 and remains positive and significant later. Overall, the results show that there existed no pre-trends before the scandal.

4.2.3. The spillover effect of the scandal

The previous results show a causal relationship between the exposure to the Wells Fargo scandal and FinTech adoption. However, it is unclear which types of lenders failed to retain the borrowers after the outburst of the Wells Fargo scandal. Moreover, since the scandal focuses on Wells Fargo bank, one may be concerned that the increase in FinTech adoption is simply a shift from Wells Fargo to FinTech, rather than a more general shift from banks to FinTech firms. To address this concern, I conduct a similar empirical analysis of the mortgage origination activities of all types of lenders in Table 4.

The dependent variable in Table 4a is a dummy variable equal to 100 if the lender is a Wells Fargo, a non-Wells Fargo bank, or any bank, respectively. Table 4a presents that a one-standard-deviation increase in the exposure of the Wells Fargo scandal leads to a $1\%(= 0.043 * 10.4/43.76)$ decrease in the probability of choosing a non-Wells Fargo bank. Although the bank scandal focuses on Wells Fargo, there is a significant spillover effect on other banks. The increase in FinTech adoption did not only result from a switch from Wells Fargo to other lenders; individuals are also more likely to choose FinTech compared to banks other than Wells Fargo.

4.3. How trust affects FinTech adoption?

In this section, I analyze the channels through which trust affect FinTech adoption by examining the how the Wells Fargo scandal affects borrowers' choices of non-FinTech shadow banks.

There are two perspectives of trust that could affect economic agents' decision makings. Guiso et al. (2008) define trust as an individual's subjective belief of the probability of being cheated. Gennaioli et al. (2015) think of trust as inducing a tighter, or lower volatility of, perceived distribution of financial returns. Both these two aspects of trust could serve as the underlying mechanisms through which trust affects borrowers' choice of FinTech lenders. More trust placed on FinTech lenders could indicate that FinTech lenders have a lower perceived probability of cheating. Borrowers who trust FinTech more would choose FinTech lenders because they are less likely to be cheated by FinTech lenders. Borrowers could also choose FinTech lenders because trust in FinTech lenders tightens the perceived distribution of the probability of being cheated. Risk-averse borrowers who trust FinTech more would be more likely to choose FinTech lenders because they experience less anxiety from the likelihood of being cheated. Therefore, the role of trust may not be absolute but relative. Households need to use intermediaries to transact, even if they trust them very little. As a result, erosions of trust can shift demand away from traditional lenders toward new ones, such as FinTech lenders.

Given the two perspectives, I test two channels through which the erosion of trust in banks could affect FinTech adoption. First, trust erosion in the banking sector affects FinTech adoption because FinTech

Table 4
The effect of the Wells Fargo scandal revelation on lender choice.

(a) Other banks

	Wells Fargo (1)	Non-WF bank (2)	All bank (3)
WF exposure × post	−0.121***	−0.043**	−0.164***
	(−18.0)	(−2.5)	(−7.9)
Loan Char.	Yes	Yes	Yes
County Char.	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	86 860 239	86 860 239	86 860 239
Adjusted R-squared	0.058	0.305	0.324

(b) Other shadow banks and online banks

	FinTech (1)	Non-FinTech shadow bank (2)	All shadow banks (3)	"Online" bank (4)
WF exposure × post	0.035***	0.129***	0.164***	−0.045***
	(3.4)	(6.5)	(7.9)	(−5.8)
Loan Char.	Yes	Yes	Yes	Yes
County Char.	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	86 860 239	86 860 239	86 860 239	86 860 239
Adjusted R^2	0.090	0.281	0.324	0.053

This table reports the effect of the Wells Fargo scandal revelation on mortgage lender choice. Coefficients are estimated from the following regression, using loan-level data from 2012 to 2021 in the HMDA.

$y_{i,c,t} = \beta_t WFExposure_c \times Post_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$

The dependent variable is a dummy variable that equals to one hundred if the lender is the indicated type and zero otherwise. $WFExposure_c$ is the percentage points of Wells Fargo deposits in county c in 2015. $Post_t$ is a dummy variable that equals to one after 2016. The constant term is included, and the control variables and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

Table 5
The heterogeneous effects of the Wells Fargo scandal revelation on FinTech adoption.

	Origination			Application		
		High	Low		High	Low
		NonRepublican share			NonRepublican share	
	FinTech (1)	FinTech (2)	FinTech (3)	FinTech (4)	FinTech (5)	FinTech (6)
WF exposure × post × nonRep	0.080**			0.082**		
	(2.4)			(2.2)		
WF exposure × post	−0.023	0.024***	0.003	−0.021	0.027***	0.008
	(−1.2)	(3.7)	(0.3)	(−1.0)	(3.8)	(0.8)
NonRep × post	−1.966***			−1.960***		
	(−3.7)			(−3.7)		
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes
County Char.	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7335	3779	3574	7335	3779	3574
Adjusted R^2	0.873	0.886	0.867	0.837	0.860	0.820

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on FinTech adoption. Coefficients are estimated from the following regression, using county-year level data from 2012 to 2021.

$$y_{c,t} = \beta WFExposure_c \times Post_t \times NonRep_c + \gamma_1 WFExposure_c \times Post_t + \gamma_2 Post_t \times NonRep_c + Control_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t}$$

The dependent variable is the share of the number of mortgages handled by FinTech lenders for both origination and application. $WFExposure_c$ is the percentage of Wells Fargo deposits in county c in 2015. $Post_t$ is a dummy variable that equals one after 2016. NonRep is the percentage of share voted for non-Republican candidates in the 2016 presidential election. In columns (2), (3), (5), and (6), the sample is divided into counties with higher than and lower than median Non-Republican voting shares. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

lenders are new entrants. Following Guiso et al. (2008)'s argument, trust creates additional utility loss for borrowers when matching with distrusted lenders, who are perceived to have a higher probability of cheating. The utility loss of matching with traditional banks due to the trust erosion in the banking sector would lead to a relative increase in the utility gain of matching with non-bank lenders. Therefore, FinTech lenders, as new non-bank entrants, could gain market share due to the relative utility increase. I test this hypothesis by studying the choice of non-FinTech shadow banks after exposure to the Wells Fargo scandal in Table 4b. Similar to Table 4a, the dependent variable in Table 4b is a dummy variable equal to 100 if the lender is a FinTech lender, non-FinTech shadow bank, or any shadow bank, respectively. The coefficient in column (2) of Table 4b is positive and statistically significant, showing that exposure to the Wells Fargo scandal also increases the

Table 6
Treatment effects heterogeneity analysis using machine learning.

(a) Trust in banks

	Least decrease	Most decrease	Difference	
	β (1)	β (2)	β (3)	p-value
Female	0.510	0.439	−0.076	0.016
	[0.464, 0.555]	[0.394, 0.484]	[−0.140, −0.012]	
Minority	0.262	0.219	−0.044	0.025
	[0.222, 0.302]	[0.181, 0.256]	[−0.099, 0.011]	

(b) FinTech adoption

	Least increase	Most increase	Difference	
	β (1)	β (2)	β (3)	p-value
Female	0.280	0.258	−0.020	0.000
	[0.279, 0.281]	[0.258, 0.259]	[−0.021, −0.019]	
Minority	0.130	0.093	−0.034	0.000
	[0.130, 0.131]	[0.092, 0.094]	[−0.034,−0.033]	

This table reports the average characteristics of the most and least affected groups, from Chernozhukov et al. (2020) treatment effects heterogeneity estimates for the effects of exposure to the Wells Fargo scandal. In Table 6a, the dependent variable is the respondent's trust in banks. In Table 6b, the dependent variable is a dummy variable equal to one hundred if the lender is a FinTech lender and zero otherwise. A borrower belongs to the treatment group if she resides in a county with an above-median level of the Wells Fargo deposits share (> 10%). Borrowers are sorted into five groups with different levels of treatment effects based on the machine learning estimations. Column (1) of Table 6a (or Table 6b) shows the average characteristics of survey respondents who have the smallest decrease in trust in banks (or smallest increase in FinTech adoption) after exposure to the Wells Fargo scandal. Column (2) of Table 6a (or Table 6b) shows the average characteristics of the survey respondents who have the largest decrease in trust in banks (or largest increase in FinTech adoption). Column (3) of Table 6a (or Table 6b) shows the difference in average characteristics between survey respondents who have the largest decrease in trust in banks(or largest increase in FinTech adoption) and those who have the smallest decrease in trust in banks(or smallest increase in FinTech adoption). The Chernozhukov et al. (2020) algorithm is applied to estimate the average group characteristics β. 0.51 indicates that 51% of the group individuals are female. The 90% confidence intervals of β are in parentheses.

probability of choosing non-FinTech shadow banks. Therefore, trust erosion in banks leads to a higher probability of choosing any non-bank lender. This result supports the channel of new non-bank entrants.

Second, trust erosion in the banking sector affects FinTech adoption due to FinTech lenders' online nature of customer-lender interaction. FinTech borrowers face homogeneous decision-making processes when submitting mortgage applications through online platforms. For traditional offline lenders, customers interact with human agents. When customers borrow from lenders who have yet to adopt the online customer-lender interaction platform, the qualities and outcomes of the loan application processes experience more significant variations because customers may interact with immensely different human agents. Therefore, the online customer-lender interaction could tighten, or lower the volatility of, the perceived distribution of being targeted as fraud victims.[17] After the trust erosion in the banking sector, borrowers would be more likely to borrow from lenders adopting online platforms because of the higher utility gain created by lower perceived volatility of being cheated. This applies to both banks and non-bank lenders with online platforms. Bank lenders with online platforms are less likely to have an increase in perceived volatility of cheating after the Wells Fargo scandal due to standardization. Since the Wells Fargo scandal could have a spillover effect on the perceived volatility of cheating by non-bank lenders,[18] the increase in perceived volatility would also affect non-bank lenders with online lending platforms less.

To test this channel, I compare the effect of the scandal on the choice of FinTech with that of non-FinTech shadow banks. A one-standard-deviation increase in the exposure of the Wells Fargo scandal leads to a $3.1\%(= 0.129 * 10.4/42.47)$ increase in the probability of choosing a non-FinTech shadow bank, indicating that erosion of trust in banks also benefits other types of non-bank lenders. Given that the Wells Fargo scandal leads 4.1% increase from the average probability of choosing a FinTech lender, the results suggest that FinTech lending is more affected by trust erosion in banks, compared with non-FinTech shadow bank lending. Therefore, the online customer-lender interaction feature also makes FinTech lenders more appealing.

However, as previous literature (Buchak et al., 2018; Fuster et al., 2019) have documented, the relative convenience of online lenders matters for FinTech adoption. One may be concerned that a significant loss of trust in traditional banks could prompt Wells Fargo customers to seek other options. In this scenario, the ease and accessibility of FinTech platforms play a crucial role in driving the higher demand for FinTech loans. This is because FinTech loans can be initiated without the need for any human interaction. To address this possibility, I exploit the heterogeneity in bank lenders by studying banks close to adopting online customer-lender interaction platforms. In my sample period, some banks were adopting online customer-lender interaction more. More information can be uploaded and processed on these banks' websites than on other banks. I classify banks with a high degree of online automation in their mortgage application process as "online" banks. A majority part of the loan application processes can be done online for these "online" banks.[19] I then examine the choice of these "online" banks after exposure to the Wells Fargo scandal. The result is presented in column (4) of Table 4b.[20]

The coefficient is negative, showing that exposure to the Wells Fargo scandal does not increase the probability of choosing "online" banks. If our results were purely driven by the convenience channel and not the trust channel, we would observe similar effects of the scandal on FinTech lenders and "online" banks. Therefore, our result suggest that it is unlikely the findings are purely driven by the convenience channel. This result also suggest that the negative trust effect overweights the positive "online" feature for "online" banks. Combining these three pieces of evidence, I conclude that both the non-bank and online customer-lender interaction features serve as underlying mechanisms through which trust affects FinTech adoption. Our empirical evidence is not due to alternative advantages that contribute to FinTech adoption, such as convenience.

4.4. Heterogeneous effects of scandal on trust in banks

In this section, I further explore the heterogeneous effects of the Wells Fargo scandal on trust in banks to sharpen the documented effects' underlying mechanism. Many studies have documented the role of belief differences in households' financial decisions (e.g. Meeuwis et al., 2018; Giglio et al., 2019). Particularly, Meeuwis et al. (2018) uses political affiliation to measure investors' ex-ante belief heterogeneity. Tables 1 and 2 present that people with different political affiliations have different prior beliefs about the trustworthiness of banks. People not affiliated with the Republican Party are less likely to report trust

[17] The idea is similar to the (Gennaioli et al., 2015). They model trust as reducing the perceived volatility of financial returns in the context of financial advisors.

[18] Because trust is relative, not absolute. The Wells Fargo scandal can lead to an overall increase in the perceived volatility of cheating for all lenders, but much higher increase for banks than non-bank lenders.

[19] These "online" banks were not classified as FinTech lenders because borrowers needed to meet with bankers offline before getting the loans approved.

[20] In the regression, if one of the "online" banks originated loans before 2018, I also classify these loans as "online" bank loans because we want to compare the changes in loan origination for these banks before and after the scandal.

in banks. On average, 34% of Republican survey respondents reported trust in banks, whereas only 26% of non-Republican survey respondents reported trust in banks. This evidence is consistent with a cross-country analysis by Fungáčová et al. (2019), who find that individuals who do not prefer government ownership of businesses and prefer competition in the economy are more likely to report trust in banks. These different prior beliefs on banks' trustworthiness may lead to different responses to the Wells Fargo bank scandal.

Thakor and Merton (2018) theorize that an individual's response to public information is affected by the individual's ex-ante belief. Thus, conditional on the exposure to the Wells Fargo scandal, individuals with different ex-ante beliefs in trust in banks will likely experience different decreases in their trust in banks after the scandal.[21] I use individuals' political affiliation to proxy for their ex-ante trust in banks, since the Gallup survey does not allow the identification of repeated respondents in different years. To test the theoretical prediction, I estimate the dynamic treatment effect of the Wells Fargo scandal on trust in banks separately for Republican survey respondents and non-Republican survey respondents.

$$y_{i,c,t} = \beta_t WFExposure_c \times \sum_{t=2012, t\neq 2015}^{2021} Dummy_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$$

The dependent variable is an individual's trust in banks, measured by the Gallup survey data. Trust in Banks is a dummy variable equaling to one hundred if the respondent reports "a great deal" or "a lot of" confidence in banks, zero if reports "very little" or "some" or "none". WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Dummy is a dummy variable equal to one at year t. The year 2015 is omitted, as the reference year. The scandal happened in September 2016. Therefore, the observations in 2016 were surveyed before the treatment. The regressions are run in subsamples, split into "Republican" or "Non-Republican" respondents.

The results are presented in Fig. 8. For both Republican and non-Republican survey respondents, the treatment dynamics align with the parallel trends assumption, with no evidence of pre-trends before the scandal. Among Republican survey respondents, no significant decline in trust in banks is observed after the scandal. For non-Republican respondents, statistically significant decreases in trust in banks are evident in 2017 and 2018. However, no significant differences in trust are observed in regions with high exposure to the Wells Fargo scandal during 2019, 2020, or 2021.

The decaying effects of the Wells Fargo scandal on trust in banks align with prior findings on the influence of scandals on household financial decisions. For example, Gurun et al. (2018) examines the impact of the December 2008 revelation of the Madoff Ponzi scheme on the investment advisory industry. The study finds the effect of exposure to the Madoff scandal on the assets under management of registered investment advisers is negative and statistically significant only in 2009, and negative though statistically insignificant in 2010. The impact of the revelation of the Madoff Ponzi scheme persists for just two years after the scandal (see Figure 5 in Gurun et al., 2018). Our findings also align with the memory decay effects observed in how individuals form beliefs. For instance, both psychology and behavioral economics literature document individuals' tendency to overweight recently sampled information (Hertwig et al., 2004; Malmendier and Nagel, 2011).

Overall, the findings indicate that non-Republicans and Republicans exhibit different levels of ex-ante trust in banks and respond differently to the Wells Fargo scandal. The decline in trust in banks among non-Republicans lasts around three years.[22]

[21] Here, I do not predict whether individual with ex-ante low trust in banks will have a greater or less decrease in trust in banks. I rely on the empirical findings to conclude.

4.5. Heterogeneous effects of scandal and FinTech adoption

The previous section documents the heterogeneous effects of the bank scandal on trust in banks of Republican-leaning individuals versus others. I now utilize this heterogeneity to sharpen the role of trust in explaining the effect of the Wells Fargo scandal on FinTech adoption. Suppose the Wells Fargo scandal affects FinTech adoption through the erosion of trust in banks. In that case, individuals leaning towards the non-Republican Party should be more likely to choose FinTech lenders than others with the same exposure to the scandal.

Neither HMDA nor any other mortgage origination dataset reports party affiliation of the originator. Thus it is not possible to identify the exact party affiliation of the mortgage originator. Meeuwis et al. (2018) uses zip code level political contribution to measure a household's probability of being Democrats at the zip code level. Since the Wells Fargo scandal measure is at the county level, I instead measure county-level political affiliation using the 2016 presidential election results, assuming that individuals who live in counties with a higher share of non-Republican votes have a higher probability of holding beliefs similar to non-Republicans, and are thus more likely to be affected by the scandal. County-level FinTech adoption is measured using the share of loans by FinTech lenders. Consistently with the loan level analysis, both loan application and loan origination were analyzed.

More specifically, I run the following triple-differences specification:

$$\begin{aligned} y_{c,t} &= \beta WFExposure_c \times Post_t \times NonRep_c \\ &+ \gamma_1 WFExposure_c \times Post_t + \gamma_2 NonRep_c \times Post_t \\ &+ Control_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t} \end{aligned}$$

where the dependent variable is the county-level FinTech share. $NonRep_c$ is the percentage of votes for non-Republican candidates in county c in the 2016 presidential election.

The interaction term $WFExposure_c \times Post_t$ captures the average change in the FinTech share for all counties exposed to the Wells Fargo scandal in the years after the scandal. Since the Wells Fargo scandal coincides with the 2016 national election, different updates of beliefs about the future of the US economy may affect FinTech adoption. Including the term $NonRep_c \times Post_t$ lets me tease out the potentially confounding change of the FinTech share for counties with high non-Republican share after the scandal. I include year and county fixed effects, which capture county-invariant effects and time effects.

The coefficient of interest here is β, the effect from triple interaction term $WFExposure_c \times Post_t \times NonRep_c$. Conditional on the exposure to the Wells Fargo scandal, β captures the additional change in FinTech share for counties with higher non-Republican shares.

Table 5 presents results adding triple interaction. Column (1) shows the effect on FinTech adoption measured using mortgage origination. The coefficient estimate for β is statistically significant and has a value of 0.080. In terms of the economic magnitudes, a one-standard-deviation increase in the exposure to the Wells Fargo scandal for a non-Republican individual leads to a 0.8= $(10.4 * 0.080)$-percentage-point increase in the probability of choosing a FinTech lender, which is approximately a 9%$(= 0.8/8.84)$ increase relative to the sample mean. The effect is similar when the FinTech share is measured using mortgage applications (column [4]). The positive and significant triple-differences coefficient suggests that areas with a larger drop in the trust in banks also experience a larger increase in FinTech adoption.

[22] The technology adoption literature documents that even when the removal of the barrier to adoption is temporary or limited to a subset of a population, the spatial interaction and network effects among neighbors imply that adoption spills over to the neighbors, making the adoption rate permanently high in a treated population (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Carter et al., 2014; Comin and Mestieri, 2014; Beaman et al., 2021).

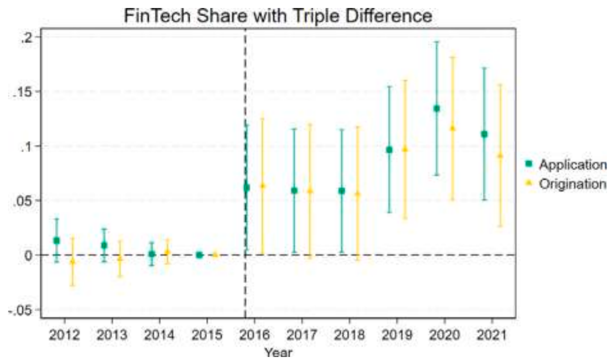

Fig. 7. Dynamic heterogeneous effects of the revelation of the Wells Fargo scandal on FinTech adoption.
This figure reports the dynamic effects of the Wells Fargo scandal revelation on mortgage loan origination. Coefficients are estimated from the following regression, using county-year level data from 2012 to 2021.

$$y_{c,t} = \beta_t WFExposure_c \times NonRep_c \times \sum_{t=2012,t\neq 2015}^{2021} Dummy_t + \gamma_1 WFExposure_c \times Post_t + \gamma_2 NonRep_c \times Post_t + Control_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t}$$

The dependent variable is the share of the number of mortgages handled by FinTech lenders for both origination and application. WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. NonRep is the percentage of shares voted for non-Republican candidates in the 2016 election. A dummy variable is equal to one at year t. Year 2015 is omitted, as the reference year. The constant term, county and year fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at the 5% level.

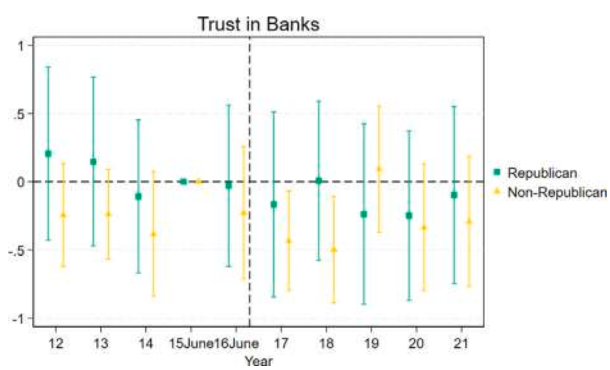

Fig. 8. The effect of the revelation of the Wells Fargo scandal on trust in banks.
This figure reports the effects of the Wells Fargo account fraud scandal on trust in banks using "Confidence in Institution" survey data from Gallup Analytics from 2012 to 2021. The plotted coefficients are estimated from the following regression.

$$y_{i,c,t} = \beta_t WFExposure_c \times \sum_{t=2012,t\neq 2015}^{2021} Dummy_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$$

The dependent variable is an individual's trust in banks, measured by the Gallup survey data. Trust in Banks is a dummy variable equaling to one hundred if the respondent reports "a great deal" or "a lot of" confidence in banks, zero if reports "very little" or "some" or "none". WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Dummy is a dummy variable equal to one at year t. The year 2015 is omitted, as the reference year. The scandal happened in September 2016. Therefore, the observations in 2016 were surveyed before the treatment. The regressions are run in subsamples, split into "Republican" or "Non-Republican" respondents. The constant term, county and year fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at the 5% level.

In columns (2)–(3) and (5)–(6), I exploit heterogeneity by conducting difference-in-differences analyses in sub-samples. The sample is split into counties with high non-Republican shares (≥45%, the sample median) and with low non-Republican shares. The results suggest that the exposure to the Wells Fargo scandal leads to an increase in FinTech adoption only in counties with high non-Republican shares.

Moreover, although I already show that, on average, there are no different time trends between more- and less-treated regions, it is possible that conditional on the same exposure to the Wells Fargo scandal, FinTech adoption in counties with more non-Republican voters evolved differently from counties with fewer non-Republican voters. If so, the significant triple differences could result from distinct time trends of FinTech adoption, rather than from different reactions to the Wells Fargo scandal. Thus, the results would not validate the trust channel. I estimate a dynamic triple-differences model, the results of which are shown in Fig. 7. The dynamic triple-differences estimates show no differences in FinTech adoption between high non-Republican share counties and low non-Republican share counties, conditioning on the same amount of exposure before the treatment. The parallel trends assumption is not violated in the triple-difference setup. After being exposed to the Wells Fargo scandal, counties with more non-Republican voters experience a larger increase in FinTech share, compared to counties with the same level of scandal exposure but more Republican voters.

Overall, the results in Table 5 and Fig. 7 lend further support to the interpretation that the exposure to the bank scandal affects FinTech adoption through the erosion of trust in banks.

4.6. Heterogeneity analysis using machine learning

To provide additional support of the trust channel and better understand the borrowers' heterogeneous responses to the Wells Fargo scandal, in addition to the OLS (difference-in-differences) estimations, I exploit a generic machine learning inference approach proposed by Chernozhukov et al. (2020) (CDDF) to estimate treatment effect heterogeneity. One advantage of using the machine learning method in heterogeneity analysis is that we do not need pre-specific subgroups. The Chernozhukov et al. (2020) approach allows me to ex-ante stay agnostic about the characteristics of borrowers that will be more affected by the Wells Fargo scandal and let the machine learning algorithm choose those who will be more affected. Afterwards, I could compare the differences in characteristics between the most affected group and the least affected group.

The CDDF method develops a method of generic machine learning inference on heterogeneous treatment effects in randomized experiments. I apply the method to understand the heterogeneous treatment effect of the exposure to the Wells Fargo scandal, a quasi-experiment setting.[23] The estimation details are presented in Appendix B. The CDDF method allows us to sort observations into groups with different levels of treatment effects based on a machine learning proxy predictor. The method also provide a consistent estimation of the average characteristics of the most and least affected groups. I follow Chernozhukov et al. (2020), sort observations into five groups, and compute the average characteristics of the most and least affected groups.

The generic machine learning approach has several advantages. First, it provides a systematic way to perform treatment effects heterogeneity analysis. The approach allows researchers to stay agnostic about the borrowers characteristics ex-ante and let the machine learning algorithm choose the characteristics that will be more affected. Given that there are various ways to perform subgroup analysis, this approach provides a disciplined process. Second, the sample splitting feature in the method overcomes the *overfitting* concern in the subgroup analysis. For example, one may argue that the non-Republican borrowers responded to the Wells Fargo scandal differently due to unobserved random variation. The CDDF method solves this issue by randomly splitting observations within the treatment group, thus teasing out the effect of any random variation.

I analyze the treatment effect heterogeneity of the Wells Fargo scandal on trust in banks and FinTech adoption. I sort observations into five groups based on the magnitude of treatment and compute the average

[23] For example, Deryugina et al. (2019) also applies the method in a quasi-experiment setting.

characteristics of the most and least affected groups. One advantage of the Gallup and HMDA data is that both datasets contain individual-level information on race, ethnicity, and gender. I follow Bartlett et al. (2021), defining African American and Hispanic borrower as minority borrower.[24] Considering that several important borrowers' credit risk metrics are not available in the HMDA data, I restrict the HMDA sample to the conforming loans purchased by Fannie Mae and Freddie Mac, to ensure that the loans are maximally comparable.

Table 6 compares the average characteristics of the most and least affected groups by the Wells Fargo scandal. In this heterogeneity analysis, I focus on a shorter sample period from 2014 to 2018 to ensure that the effect of the Wells Fargo scandal on trust in banks is statistically significant throughout the post-treatment period in the sample. In Table 6a, the dependent variable is trust in banks. Column (1) shows the average characteristics of survey respondents who have the smallest decrease in trust in banks after exposure to the Wells Fargo scandal. In the group with the smallest increase in trust in banks, 51.0% are female and 26.2% are minority. Column (2) shows the average characteristics of the survey respondents who have the largest decrease in trust in banks. In the group with the largest increase in trust in banks, 43.9% are female and 21.9% are minority. Column (3) shows the difference in average characteristics between survey respondents who have the largest decrease in trust in banks and those who have the smallest decrease in trust in banks. The differences in means between most and least affected group for the percentage of females and minorities are negative and statistically significant. The machine learning inference suggests that compared to female survey respondents, males are more responsive to the Wells Fargo scandal with respect to their decrease in trust in banks. Moreover, I find that non-minority borrowers are more responsive to the Wells Fargo scandal. Minority borrowers have a smaller probability of reporting a decrease in trust in banks.

In Table 6b, the dependent variable is FinTech adoption. Column (3) of Table 6b shows that female and minority borrowers have a smaller decrease in trust in banks and a smaller increase in FinTech adoption. Therefore, female and minority borrowers are significantly less likely to respond to the Wells Fargo scandal, both in trust in banks and FinTech adoption. The female and minority borrowers have a smaller decrease in trust in banks and a smaller increase in FinTech adoption. Given that the individuals who have the highest decrease in trust in banks have similar characteristics to those who have the highest increase in FinTech adoption, the machine learning results validate the trust channel.

One argument in support of FinTech adoption is that FinTech lending can reduce face-to-face bias against minority borrowers. For example, Bartlett et al. (2021) find that FinTech lending reduces discrimination in interest rates against Latinx and African-American borrowers.[25] However, the treatment effect heterogeneity results suggest that trust erosion (building) is more difficult for minority and female borrowers. This imposes potential challenges to fostering financial inclusion with new technologies.

[24] Given that the Gallup survey have little coverage on Asian, I do not include Asian borrower in the minority borrower. Moreover, given the caveat in Buchak et al. (2018) and Fuster et al. (2019), this broader definition alleviate the concern that since the HMDA has missing values on race and ethnicity.

[25] They find that Latinx and African-American borrowers pay 7.9 bp more in home-purchase mortgage interest and 3.6 bp more in refinance mortgage interest, after controlling for all credit risk. However, for mortgages originated by FinTech lenders, Latinx and African-American borrowers only 5.3 bp more for home-purchase mortgage interest, and 2.0 bp more for refinance mortgages. Moreover, traditional lenders reject 6% more Latinx and African-American borrowers for GSE guaranteed loans.

Table 7
Falsification tests: Use JPMorgan chase deposit share.

(a) Trust in banks

	Trust in banks		Trust in big business	
	(1)	(2)	(3)	(4)
Chase exposure × post	−0.107	−0.077	−0.094	−0.070
	(−0.9)	(−0.6)	(−0.9)	(−0.6)
Respondent Char.	Yes	Yes	Yes	Yes
County Char.	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7386	6558	7386	6558
Adjusted R^2	0.075	0.072	0.070	0.072

(b) FinTech adoption

	Origination		Application	
	FinTech (1)	FinTech (2)	FinTech (3)	FinTech (4)
Chase exposure × post	−0.010	−0.007	−0.007	−0.003
	(−1.3)	(−0.8)	(−1.0)	(−0.3)
Loan Char.	Yes	Yes	Yes	Yes
County Char.	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	73 043 669	64 462 683	93 579 405	81 984 842
Adjusted R^2	0.087	0.084	0.074	0.072

This table reports how JPMorgan deposits share affect FinTech adoption and trust in banks. The coefficients are estimated using the following regressions.
$y_{i,c,t} = \beta ChaseExposure_c \times Post_t + Control_{i,c,t} + \lambda_c + \delta_t + \varepsilon_{i,c,t}$
Chase Exposure is the percentage of JPMorgan Chase deposits in county c in 2015. Post is a dummy variable that equals to one after 2016. In Table 7a, the dependent variable is the respondent's trust in banks and trust in big business, which equal to one hundred if the individual reports the level of confidence as "a great deal" or "a lot," zero if reports "very little" or "some" or "none." In Table 7b, the dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender and zero otherwise. The constant term is included. Control variables and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

4.7. Robustness

4.7.1. Falsification test using JPMorgan chase share

The difference-in-differences design is based on the localized exposure to the Wells Fargo scandal. A potential concern is that exposure to the scandal may also capture exposures to some nation-wide structural change in the banking industry. For example, the deposits share of Wells Fargo may coincide with the decline in big banks' participation in mortgage origination. To address this concern, I construct the deposit share of another big national bank — JPMorgan Chase — in 2015 and examine how the deposits share of JPMorgan Chase affects trust in banks and FinTech adoption after 2016.[26] JPMorgan Chase is the fourth largest residential mortgage originator and has a similar origination volume as Wells Fargo. Suppose the positive relationship between FinTech adoption and exposure to the Wells Fargo scandal reflects a decline in big banks' participation in mortgage origination. In that case, we should see a positive relationship between the JPMorgan Chase share and FinTech adoption.

The results presented in Table 7b suggest that counties with higher exposure to JPMorgan Chase shares do not experience larger increases in FinTech adoption after 2015 relative to counties with lower JPMorgan Chase shares. Moreover, the results in Table 7a show that higher exposure to JPMorgan Chase Bank is not accompanied by a larger decrease in trust in banks. The falsification tests suggest that our results are unlikely to be driven by the nationwide decline in big banks'

[26] D'Acunto et al. (2020) use similar falsification tests to dismiss concerns about confounding time varying trends in consulting industry.

Table 8
The effect of the revelation of the Wells Fargo scandal on lenders' credit supply and banks' deposits.

(a) Loan denial rate

	All lenders	Wells Fargo	Non-Wells Fargo bank	All banks	FinTech	Non-FinTech shadow bank	Shadow bank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WF exposure × post	−0.010**	−0.036***	0.013	0.013	0.002	0.009	0.004
	(−2.0)	(−2.7)	(1.5)	(1.5)	(0.2)	(1.1)	(0.5)
County Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8194	8194	8194	8194	8194	8194	8194
Adjusted R^2	0.954	0.899	0.924	0.934	0.901	0.931	0.943

(b) Bank deposits

	Log value deposits			Deposits per capita		
	Total	Wells Fargo	Non-Wells Fargo	Total	Wells Fargo	Non-Wells Fargo
	(1)	(2)	(3)	(4)	(5)	(6)
WF exposure × post	−0.001	0.204***	−0.006***	0.420	0.698	−0.278**
	(−0.5)	(17.5)	(−3.2)	(0.6)	(1.3)	(−2.2)
County Char.	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8194	8194	8194	8194	8194	8194
Adjusted R^2	0.994	0.872	0.994	0.874	0.710	0.911

This table reports the effect of the Wells Fargo scandal on lenders' credit supply and banks' deposits. The coefficients are estimated from the following regression using county-year level data from 2012 to 2021.

$y_{c,t} = \beta WFExposure_c \times Post_t + Control_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t}$

In Table 8a, the dependent variable is the percentage of mortgage applications denied by different types of lenders. In Table 8b, the dependent variable is per capita deposits and the logarithm of deposits of different banks in county c at time t. WF Exposure is the percentage point of Wells Fargo deposits in county c in 2015. Post is a dummy variable equaling to one after 2016. The constant term is included. Control variables and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

Table 9
Wells Fargo scandal and loan pricing.

	FinTech		Wells Fargo		Non-Wells Fargo bank	
	Purchase	Refinance	Purchase	Refinance	Purchase	Refinance
	(1)	(2)	(3)	(4)	(5)	(6)
WF exposure × post	−0.082	−0.045	0.068**	0.133***	0.086	0.081
	(−1.4)	(−1.4)	(2.5)	(3.7)	(1.2)	(1.6)
MSA Char.	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
	6481	6481	6481	6481	6481	6481
Adjusted R^2	0.823	0.898	0.947	0.855	0.847	0.772

This table reports the effects of the Wells Fargo scandal revelation on loan pricing, using Fannie Mae single-family data. The sample is at the MSA-year-quarter level from 2014Q1 to 2019Q4. The coefficients are estimated using the following regressions.

$y_{c,t} = \beta WFExposure_c \times Post_t + MSAControl_{c,t} + \lambda_c + \delta_t + \varepsilon_{c,t}$

The dependent variable $y_{c,t}$ is the average mortgage rate by FinTech lenders, Wells Fargo, and non-Wells Fargo banks. Mortgage rates are residualized with respect to FICO and LTV in each MSA-quarter following procedure used in Scharfstein and Sunderam (2016). WF Exposure is the percentage of Wells Fargo deposits in MSA c in 2015. Post is a dummy variable equal to one after 2016Q3. All regressions are performed separately for home purchase loans and refinance loans. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the MSA level, and t statistics are in parentheses.

participation in mortgage origination and other structural changes in big banks.

4.7.2. Supply of credit

One underlying assumption for my identification strategy is that the exposure to the Wells Fargo scandal affects FinTech adoption only through decreased trust in banks. An alternative possibility is that the FinTech share may change because banks in areas with more exposure to the Wells Fargo scandal may reduce their credit supply more after the scandal. Although my baseline results are robust to using mortgage applications rather than originations to measure FinTech adoption, I now more formally rule out the supply side interpretation by showing that mortgage rejection rates do not change.

Table 8a reports how exposure to the Wells Fargo scandal affects county-level mortgage rejection rates. The results show that the percentages of mortgage rejected do not significantly increase for all types of lenders after exposure to the Wells Fargo shock, except in the case of Wells Fargo itself. The results rule out the supply-side interpretation.

Next, I examine the effect of the Wells Fargo scandal on bank deposits because deposits are a key source of funding for banks and, therefore, an important factor affecting credit supply. Table 8b examines how exposure to the Wells Fargo scandal affects the deposits of Wells Fargo and other banks. I find that the scandal has a minimal effect on bank deposits. The coefficients in columns (1) and (4) are insignificant, indicating that the total deposits in the banking sector did not change following the Wells Fargo scandal. This result is consistent with what we find in Table 8a. As deposits are held as safe assets for households, the total amount of deposits is not affected by the Wells Fargo scandal, probably due to the protection from deposit insurance.[27]

However, we cannot examine county-level changes in other types of bank liabilities due to data limitations. The trust shock may affect banks' more vulnerable liabilities at the *aggregate* level. Since our difference-in-differences framework compares the local FinTech usage, the aggregate change in bank liabilities would not invalidate the credit demand channel as long as the local credit supply is not affected by the Wells Fargo scandal, as shown in Table 8a.

Moreover, Appendix Table A9 further analyzes the scandal's effect on banks' credit supply using the triple differences specification. The previous section shows that conditional on the exposure to the Wells Fargo scandal, counties with more non-Republican voters experience a larger increase in FinTech adoption; the increased FinTech share may be due to a decrease in credit supply rather than an erosion of trust in counties with larger share of non-Republican voters. However, the results in Appendix Table A9 do not support this alternative interpretation. Conditional on the scandal exposures, counties with higher non-Republican shares do not experience a larger credit supply reduction by banks, proxied by the mortgage rejection rate, relative to counties with lower non-Republican shares.

Overall, the results suggest that the effects of the Wells Fargo scandal on FinTech adoption are unlikely to be driven by a reduction in banks' credit supply after the scandal.

4.7.3. Loan pricing

The evidence so far has shown that the erosion of trust in banks leads to an increase in FinTech adoption in local mortgage markets. However, borrowers may choose to use FinTech lenders due to the differences in pricing strategies between banks and FinTech lenders.

I investigate the effects of the revelation of the Wells Fargo scandal on loan pricing in local mortgage markets, using the Fannie Mae single-family loan dataset. I follow the procedure used in Scharfstein and Sunderam (2016)[28] to purge mortgage rate variations due to borrowers' credit risk. The mortgage loans from the Fannie Mae single-family loan dataset are sold to the government-sponsored enterprise (GSE), which charges the lender a guarantee fee to cover the projected borrower default cost. Therefore, the lender who originates the mortgage is not exposed to the borrower's credit risk when the mortgage defaults. Since March 2008, the guarantee fee has been determined solely by the FICO score, LTV, and loan type, according to a Loan Level Price Adjustments (LLPAs) matrix. Consequently, any interest rate deviation from the guarantee fee reflects the lenders' different overhead costs and strategic price positioning. Specifically, I run the following regression:

$$Rate_{i,j,c,m} = \alpha_m + \beta_m X_{i,m} + \eta_{i,j,c,m} \tag{3}$$

where $Rate_{i,j,c,m}$ is the mortgage rate on a loan i from lender j in MSA c in month m, and $X_{i,m}$ is a series of FICO and LTV dummy variables that capture the variation in LLPAs matrix. To achieve maximal comparability, I restrict the sample to 30-year, full amortization, full documentation, single-family, and conventional fixed rate mortgage with FICO scores above 660. We denote the estimated residuals as $\hat{\eta}_{i,j,c,m}$.

For each MSA c at each quarter t, we compute the average residual rate charged by different types of lenders as our variables of interest.

$$R^{LenderType}_{c,t} = \frac{1}{N^{LenderType}_{c,t}} \sum_{m\in t, j\in\{LenderTypeType\}} \hat{\eta}_{i,j,c,m} \tag{4}$$

where $LenderType$ can be FinTech, Wells Fargo Bank, or non-Wells Fargo bank.[29] All measures are performed separately for home purchase mortgages and refinance mortgages.

I estimate a similar difference-in-differences model as before, but use the average residual rate charged by different lenders as the dependent variables. MSA-level characteristics are included as control variables, and the results are shown in Table 9. In columns (1) and (2), the dependent variables are the average home purchasing mortgage rate and refinance mortgage rate charged by FinTech lenders. The coefficients are not statistically significant, suggesting that the FinTech lenders do not change their strategic pricing after one region experiences a decrease in trust in banks and an increase in FinTech adoption. The result in columns (3) and (4) show that the Wells Fargo charges a significantly higher interest rate after losing clients due to the erosion of trust in banks. Given that the borrowers who stayed with the Wells Fargo bank after the erosion of trust in banks are loyal customers who are less likely to shop around for rates, the Wells Fargo bank may exploit the clientele and strategically increase the mortgage rate to offset the profit loss. I do not observe non-Wells Fargo lenders charging different rates.

This finding suggests that the increase in FinTech adoption is unlikely to result from the different pricing strategies between banks and FinTech lenders.

4.8. Discussion

This section discuses how my empirical results substantiate the identification of trust as an entry barrier and the magnitude of the trust effect.

4.8.1. The identification of trust

Following Guiso et al. (2008), trust is defined as borrowers' subjective beliefs about the lender types—whether lenders will cheat or not. I test whether trust enters borrowers' expected utility (Guiso et al., 2008; Gennaioli et al., 2015).[30]

First, the Wells Fargo shock should be uncorrelated with unobservable factors that affect the borrower's utility to achieve the identification. Even under the circumstances that the Wells Fargo scandal does not affect unobservable factors that affect the borrower's utility, the change in a lender's market share may be driven by borrowers' trust in the lender and the interest rate charged by the lender. I empirically observe that the treatment effect of the Wells Fargo scandal on loan pricing is not significant. Therefore, it is trust, not the interest rate, that affects the borrower's probability of choosing a FinTech lender. Moreover, the supply shock may affect FinTech adoption through channels other than the interest rate. To rule out this possibility, I empirically test whether lenders' credit supply does not change. To further identify the trust channel and rule out the possibility that the Wells Fargo scandal affects unobservable factors, markets with different levels of trust erosion are compared. If the shock affects through unobservable factors other than trust, a variation in the trust will not lead to a variation in market share s_i. My heterogeneity treatment effects analysis further rules out this possible explanation.

Moreover, there is a concept closely related to trust – reputation. Trust and reputation are indistinguishable in a non-dynamic setting. They are both economic agents' subjective beliefs. In a dynamic setting, as argued by Thakor and Merton (2018), if we define trust as an investor (borrower)'s perceived probability of the lender's type

[27] This result is also consistent with the theoretical prediction by Thakor and Merton (2018); erosion of trust for banks does not affect their access to financing.

[28] The method is pioneered by Hurst et al. (2016), and similarly used in Bartlett et al. (2021).

[29] I did not add back the time dummies $\hat{\alpha}_m$ to $R^{LenderType}_{c,t}$ because we use this average residual rate in a difference-in-differences framework. Therefore, there is no need to consider the time-invariant time-series change in the residual price.

[30] The idea is formalized in Appendix C, using a simple logit demand system with trust to formalize the idea.

and economic agents in the model update their beliefs following the Bayesian rule, trust and reputation are still mostly indistinguishable. My empirical results do not distinguish between trust and reputation. They are all modeled as the borrowers' perceived belief about the lenders' type, and enter borrowers' utility function. (Similarly in Guiso et al., 2008; Gennaioli et al., 2015)

4.8.2. The magnitude of the trust effect

To summarize the effects documented in the trust literature and compare the magnitudes reported in this paper with those in the existing studies, I focus on research examining the impact of trust on household financial decisions, particularly two relevant empirical papers that analyze the effect of corporate scandals on households' financial choices.

Giannetti and Wang (2016) investigate how decreases in trust in the stock market influence household stock market participation. They find that "a one-standard-deviation increase in the state's fraud revelation intensity (2.2 percentage points) decreases the probability that a household participates in the stock market by about 1.23 percentage points. Since approximately 30% of the sample households participate in the stock market, this implies an almost 4% decrease in the probability of household stock market participation".

Gurun et al. (2018) examine the impact of the Madoff Ponzi scheme on the investment advisory industry. Their findings indicate that, following the revelation of the fraud in December 2008, residents in affected communities shifted their assets away from investment advisers and toward bank deposits. They report that "a one-standard-deviation increase in the log number of victims leads to a decrease in AUM of 8.8%".

In this paper, I find that a one-standard-deviation increase in exposure to the Wells Fargo scandal leads to a 4.1% increase in the average probability of a household choosing a FinTech lender. The magnitude of this effect aligns closely with the findings reported in the broader trust literature.

Moreover, only a few studies have utilized survey-based trust measures on the same scale as those used in our paper. To provide further insights, we focus on Giannetti and Wang (2016), which also employed a Gallup-based survey measure of trust. Specifically, we examine the magnitudes associated with the Gallup-based trust survey in greater detail.

Giannetti and Wang (2016) find that "a one-standard-deviation increase in fraud revelation corresponds to a 7-percentage-point decrease in the fraction of respondents reporting high confidence in big business". Their estimates suggest that a one-percentage-point decrease in the likelihood of reporting high confidence in big business leads to a 0.18-percentage-point reduction in household stock market participation, equivalent to a 0.6% decrease.

In this paper, I find that a 1.67-percentage-point decrease ($=0.163 * 10.4$) in the probability of reporting trust in banks corresponds to a 0.33-percentage-point increase ($=0.032 * 10.4$) in the probability of using FinTech as mortgage lenders, which is a 4.1% increase in the average probability of a household choosing a FinTech lender. My results suggest that a one-percentage-point decrease in the probability of reporting trust in banks leads to a 0.2-percentage-point increase in the likelihood of using FinTech as mortgage lenders, representing an approximately 2.5% increase. Trust appears to play a slightly more significant role in FinTech adoption compared to stock market participation, perhaps due to the critical importance of trust in banking relationships.

Overall, the findings indicate that the effects of trust on FinTech adoption are consistent with those documented in the broader trust literature. Furthermore, I find that the magnitude of this effect closely aligns with the results reported in existing studies.

5. Conclusion

This paper analyzes the role of trust in incumbent financial institutions in deterring new entrants with innovative technology. Using the Wells Fargo scandal as a negative shock to households' trust in banks, I document that areas with larger exposures to the Wells Fargo scandal leads to an increase in the probability of choosing a FinTech mortgage lender. My analysis further shows that the erosion of trust in banks relative to other financial institutions is the most likely channel through which the exposure to the Wells Fargo scandal affects FinTech adoption.

I utilize this heterogeneity to sharpen the identification strategy in studying the effect of the Wells Fargo scandal on FinTech adoption. After exposure to the Wells Fargo scandal, counties with more non-Republican voters have a larger increase in FinTech lending share than others with the same level of scandal exposure. Since non-Republic respondents reduced their trust in banks more than Republican respondents after exposure to the scandal, the results corroborate that exposure to the scandal affects FinTech adoption through the erosion of trust in banks. Specifically, I compute the treatment effect heterogeneity of the Wells Fargo scandal on trust in banks and FinTech adoption. I find that female borrowers have a smaller decrease in trust in banks and smaller increase in FinTech adoption. The treatment effect heterogeneity by using a generic machine learning inference approach proposed by Chernozhukov et al. (2020), I find that female and minority borrowers are less likely to respond to the Wells Fargo scandal, both in trust in banks and FinTech adoption. Given that individuals who have the highest decrease in trust in banks have similar characteristics to individuals who have the highest increase in FinTech adoption, the machine learning results further support the trust channel.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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