Trust as an Entry Barrier: Evidence from FinTech Adoption

(Job Market Paper)

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Abstract

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.

Key Words: FinTech, FinTech Adoption, Trust in Bank, Bank Scandal, Belief Heterogeneity, Machine Learning and Causal Inference, Race
JEL Classification: G2, G41, G5

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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. [1] 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, defined as an individual's subjective belief of the probability of being cheated, is at the heart of every economic transaction. When FinTech lenders enter the market as new entrants, individuals with limited information about their service quality and creditability are unlikely to choose them as the financial services providers due to the lack of trust. This could be particularly true when FinTech transactions lack human interaction. 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. (Forthcoming)).

I exploit the outbreak of the Wells Fargo scandal as a negative shock to trust in banks. 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, misplacing collateral and auto protection insurance to customers, and inappro-

[1] 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.

priately 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 2% 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.

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 the 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 10% 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 in the trustworthiness of the information. Thus, conditional on the exposure to the Wells Fargo scandal, individuals with lower ex-ante trust in banks will likely experience a larger decrease 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 the trust in banks but also a larger increase in FinTech adoption. These 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, Demirer, Duflo and Fernandez-Val (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 omitted variable 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 characteristics. 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 and Freddie Mac 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 credit supply after the scandal.

To rule out the credit supply channel, I examine both the amount of bank deposits and mortgage rejection rates. I find that exposure to the Wells Fargo scandal had a minimal effect on bank deposits. Since deposits are the most critical funding source for banks, banks do not have to reduce their credit supply because of financial constraints. I further 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.

This paper contributes to the fast-growing literature on FinTech.

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. My paper is the first to study the role of trust in banks as an entry barrier affecting the competition between banks and FinTech lenders.

Recent studies in FinTech examine how FinTech adoption affects the 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. (Forthcoming)). This paper highlights trust in traditional financial intermediaries such as banks as an entry barrier to financial innovation.

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 lending usage. Compared to Bertsch et al. (2020), this paper takes up the challenge of assessing potential endogeneity in the relationship between bank misconduct and FinTech lending and examines the role of trust in banks as an entry barrier for FinTech adoption.

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 a non-depository institution that provides full-scale, comprehensive online mortgage origination services. A lender is classified as either a bank, a non-FinTech shadow bank, or a FinTech lender. 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 Fin-

Tech. For some banks, even though people can submit their documents online, they must meet a banker in person to finalize the lending process.

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.

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 complete online mortgage originations services. Additionally, since most of the initial financial technology advancement happened outside the banking sector, it is natural to first focus on FinTech adoption of non-banks.

The definition is consistent with Buchak et al. (2018)'s FinTech classification, which can be downloaded from their website.[2] One caveat is that some companies classified as non-FinTech lenders in 2017 could fit into the definition of FinTech lender in 2018. 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 happened approximately two years after the treatment effect and was only indirectly affected by the scandal, not classifying these lenders as FinTech only makes the treatment effects less likely to be significant.

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

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

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

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. 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.

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. [3] In this project, instead of measuring aggregate demand for mortgages, I need to measure mortgage demand for different types of lenders (in different regions). However,

[3] 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.

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 and Freddie Mac single-family loan performance dataset provides origination and performance data on a subset of Fannie Mae and Freddie Mac’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.

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, force-placing collateral, and auto protection insurance to customers, 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” and “Wells Fargo Scandal” to provide time series trends of public attention to the scandal. 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. 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. Figure 3 shows that there are not 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 (figure 4).[4] For each county, the Wells Fargo deposits share is calculated as the total amount of deposits in Wells Fargo branches in that

[4]The results are consistent if I use the 2013, 2014, 2015 average share.

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. 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 Figure 5. Figures 4 and 5 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. I use the Google Trend Index as an alternative measure of exposure to the Wells Fargo scandal.

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 2018. 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 [5] between 2014 and 2018. 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[6]. 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. Although Figure 2 shows that FinTech adoption is faster in states with lower trust in banks, 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

[5] 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.

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

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 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,

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

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 65000, 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.

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 equation (1), I estimate the effects of exposure to the bank scandal on trust in banks.

$$y_{i,c,t} = \beta WFExposure_c \times Post_t + Control_{i,c,t} + \delta_t + \varepsilon_{c,t} \tag{2}$$

The dependent variable is an individual's trust in banks, which is measured using 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. 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 three-percentage-point decrease $(= 10.4 *$

-0.267) in the probability of reporting trust in banks, which is a 10% decrease from the average probability of reporting trust in banks (29.6).

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

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 (4), (5), (6), and (7), 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 A3, I use an alternative measure of exposure to the Wells Fargo scandal. $WFExposure_c$ is instead measured using 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. 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 being affiliated with the Republican Party had much higher trust in banks. Being affiliated with the Republican Party increases the probability of reporting trust in banks by 6.7-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 4.3 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 Equation (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 0.12-percentage-point increase $(= 10.4 * 0.011)$ in the probability of choosing a FinTech lender, which is a 2% increase from the average probability of choosing a FinTech lender, (7.6). 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 less likely to choose FinTech lenders than males. People with Hispanic backgrounds are less likely to choose FinTech lenders. Compared to White, Asians and African Americans are also less 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.[7] 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.[8] 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 4.6, I will further show that lenders' credit supply is not affected by exposure to the Wells Fargo scandal.

In Table A1, I use an alternative measure of the exposure to the Wells Fargo scandal. $WFExposure_c$ is instead measured using Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. I find that a one standard deviation (32.4) increase in the exposure to the Wells Fargo scandal in a county also leads to a 0.2-percentage-point decrease in the probability of reporting trust in banks, the magnitude of which is similar to exposure measured using the Wells Fargo deposit share.

[7] 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

[8] 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.

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,

$$y_{i,c,t} = \beta WFExposure_c \times \sum_{t=2015, t\neq 2015}^{2018} Dummy_t + Control_{i,t} + Control_{c,t} + \sigma_t + \eta_c + \varepsilon_{i,t}$$

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.

Figure 7 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 shock related to FinTech adoption.

The publicly available HMDA dataset is at an annual frequency, so my dynamic analysis is at an annual frequency. Figure 3 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 and Freddie Mac'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.

Figure 8 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 Choice of other lenders

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, including Wells Fargo banks, Non-Wells Fargo (non-WF) banks, all banks, non-FinTech shadow banks, and all shadow banks.

The dependent variable in Table 5 is a dummy variable equal to 100 if the lender is a FinTech lender, or Wells Fargo, or a non-Wells Fargo bank, or non-FinTech shadow bank, respectively. Table 5 presents that a one-standard-deviation increase in the exposure of the Wells Fargo scandal leads to a $0.5\%(= 0.022 * 10.4/43.22)$ 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. Moreover, exposure to the Wells Fargo scandal also increases the probability of choosing non-FinTech shadow banks. A one-standard-deviation increase in the exposure of Wells Fargo scandal leads to a $0.7\% (= 0.031 * 10.4/44)$ 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 0.12% increase from the average probability to choose a FinTech lender, the results suggest that FinTech lending is more affected by trust erosion in banks, compared with non-FinTech shadow bank lending.

4.3 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 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 in the trustworthiness of the information. Thus, conditional on the exposure to the Wells Fargo scandal, individuals with lower ex-ante trust in banks will likely experience a larger decrease in their trust in banks after the scandal. Thus, 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 interact respondents' reported political affiliation with the Wells Fargo scandal exposure and the post-2016 dummy, and estimate the following model:

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

$NonRep_c$ is a dummy variable that equals to one if the individual self-reports to be affiliated with the Democratic Party or independent.

The coefficient of interest here is β, the effect from the triple interaction term $WFExposure_c \times Post_t \times NonRep_c$. β captures the additional change in trust in banks for individuals not affiliated with the Republican Party. The interaction term $WFExposure_c \times Post_t$ captures the average change in trust in banks for all respondents exposed to the Wells Fargo scandal in the years after the scandal. Since the Wells Fargo scandal coincides with the 2016 national election, it is possible that different updating of beliefs about the future of the US economy may affect trust in banks. Including the term $NonRep_c \times Post_t$ lets me tease out the potentially confounding change in the trust in banks. Alternatively, I re-run analyses in Table 2, but split the sample into two groups, by the respondents' political affiliations (Republican vs. non-Republican).

The results are presented in Table 6. Column (1) shows the triple-difference effect on trust in banks. The coefficient is statistically significant and has a value of -0.332. In terms of economic magnitude, a one-standard-deviation increase in the exposure to the Wells Fargo scandal for a non-Republican individual leads to a $3.5(0.332*10.4)$-percentage-point larger decrease in the probability of reporting trust in banks compared to a Republican respondent. The results are consistent when we split the sample into Republican vs non-Republican respondents. Column (2) shows that for the non-Republican respondents, a one-standard-deviation increase in the exposure to the Wells Fargo scandal leads to a $5.0(0.483 * 10.4)$-percentage-point decrease in the probability of reporting trust in banks, which is a 20% decrease from the non-Republican's average probability of reporting trust in banks (25.3). In contrast, column (3) shows that the average Republican respondents have only a 1.0-percentage-point decrease in the probability of reporting trust in banks, and the decrease is not statistically significant.

In columns (4) - (6), I re-do all analyses using trust in big business as dependent variables. The results show that exposure to the Wells Fargo scandal does not decrease trust in big business more for non-Republican individuals. The trust that households place on FinTech and non-FinTech shadow banks do not change differently between Republican and non-Republican individuals after exposure to the Wells Fargo scandal. The triple-difference results correspond to the relative difference between trust in banks and trust in FinTech decreasing after the scandal.

Overall, we see that the non-Republicans and the Republicans have different ex-ante trust in banks and react differently to the Wells Fargo scandal.

4.4 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 7 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 0.058. 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 0.6-percentage-point $(= 10.4 * 0.058)$ increase in the probability of choosing a FinTech lender, which is approximately a $9\% (= 0.6/6.94)$ increase relative to the sample mean. The effect is similar when the FinTech share is measured using mortgage applications (column [4]), and stronger than the average effects reported in table 3. 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.

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 ($\geq$ 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 figure 10. 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 6 lends further support to the interpretation that the exposure to the bank scandal affects FinTech adoption through the erosion of trust in banks.

4.5 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 the 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.[9]. The estimation details are presented in the appendix B.1. 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. We 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 omitted variable 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 characteristics. 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 characteristics of the most and least affected groups. One advantage of the Gallup and HMDA data is that both datasets contain individual-

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

level information on race, ethnicity, and gender. I follow Bartlett et al. (2021), defining African American and Hispanic borrower as minority borrower.[10] 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 8 compares the average characteristics of the most and least affected group by the Wells Fargo scandal. In Table 8a, 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. Column (2) shows the average characteristics of the survey respondents who have the largest decrease in trust in banks. The machine learning algorithm identifies that non-Republican survey respondents' trust in banks is more responsive to the Wells Fargo scandal, consistent with our OLS results. Moreover, the machine learning algorithm 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 decrease in trust in banks.

In Table 8b, the dependent variable is FinTech adoption. This is consistent with previous findings. I find that female borrowers have a smaller decrease in trust in banks and a smaller increase in FinTech adoption. Moreover, I find that minority borrowers are significantly less likely to respond to the Wells Fargo scandal, both in trust in banks and FinTech adoption. The 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 the 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

[10]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

borrowers.[11] The results suggest that minority borrowers are less affected by the bank scandal.

4.6 Robustness

4.6.1 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.[12] 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 9b 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 9a 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' participation in mortgage origination and other structural changes in big banks.

[11] 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.

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

4.6.2 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 acceptance rates and total bank deposits do not change.

Table 10a shows that the percentage of mortgage rejected does not significantly increase for all types of lenders after exposure to the Wells Fargo shock, consistent with the credit supply channel. The rejection rate for non-Wells Fargo banks decreases slightly after exposure to the Wells Fargo scandal (column [3]).

Deposits are a key source of funding for banks and therefore an important factor affecting credit supply. As argued by Thakor and Merton (2018), the trust gives lenders access to cheaper credit. Thus, it is crucial to examine how the erosion of trust in banks affects bank deposits. Table 10b examines how exposure to the Wells Fargo scandal affects per capita deposits of Wells Fargo, and per capita deposits of other banks.

I find that exposure to the Wells Fargo scandal has a minimal effect on bank deposits. All coefficients are insignificant except in column (3), where the logarithm value of total deposits for non-Wells Fargo even increases slightly, although deposits per capita in column (6) do not. Deposits may have shifted from Wells Fargo to non-Wells Fargo banks after the scandal; however, total deposits in the banking sector did not change. This result is consistent with what we find in Table 10a, suggesting that the total credit supply from banks is unlikely to have changed after the scandal. 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.

Moreover, Table A4 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 Table 10 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 in Tables 10 and A4 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.

4.6.3 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)[13] 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:

$$Rate_{ijcm} = \alpha_m + \beta_m X_{im} + \eta_{icm} \tag{3}$$

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

where $Rate_{ijcm}$ is the mortgage rate on a loan i from lender j in MSA c in month m, and X_{im} 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.

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.

$$R_{ct}^{LenderType} = \frac{1}{N_{ct}^{LenderType}} \sum_{(i,m)\in\{c,t\},j\in\{LenderTypeType\}} \eta_{icm} \tag{4}$$

where $LenderType$ can be FinTech, Wells Fargo Bank, or non-Wells Fargo bank. 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. Several MSA-level characteristics are included as control variables, and the results are shown in Table 11. 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) show that the Wells Fargo charges a significantly higher interest rate after losing clients for home purchase loans due to the erosion of trust in banks. The increases in the mortgage rate are not significant for other non-Wells Fargo 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. For refinancing mortgage borrowers who are more sensitive to price changes, the pricing strategy does not change.

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

4.7 Discussion

This section discusses how my empirical results substantiate the identification of trust as an entry barrier. 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) and Gennaioli et al. (2015)). [14]

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 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) and Gennaioli et al. (2015))

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

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.

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Figure 1: Heterogeneity in FinTech Adoption

This figure displays county-level FinTech adoption measured as the share of mortgage loans originated by FinTech lenders in 2017.

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

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.

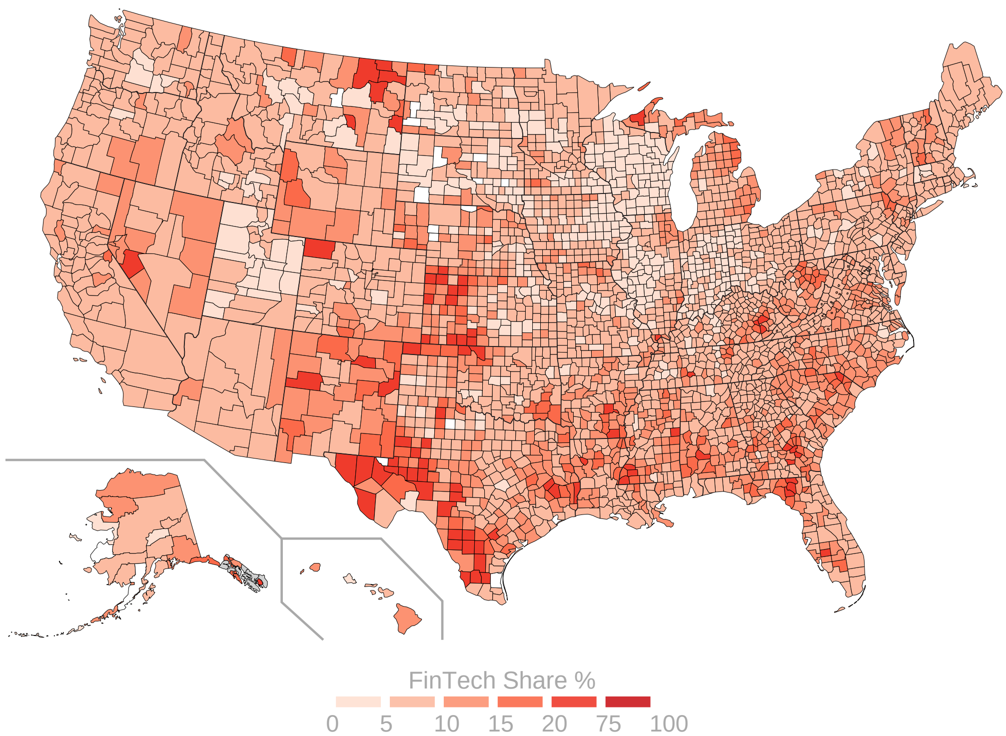

Figure 2: FinTech Adoption in Low and High "Trust in Banks" States

This figure plots a time series of FinTech adoption for states with low "Trust in Banks" and high "Trust in Banks." High "Trust in Banks" states are those with 2011–2015 average trust in banks higher than the median (27%). FinTech share is measured as the number of loans originated by FinTech lenders. Time series plots of FinTech shares are provided for both loan origination and loan applications.

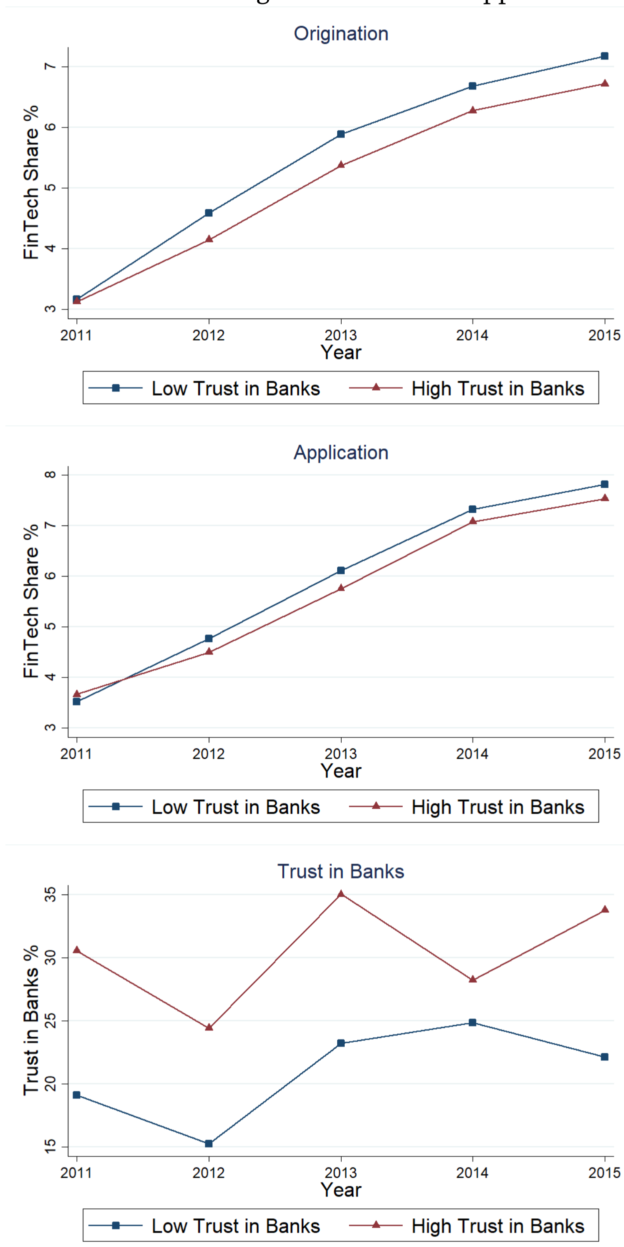

Figure 3: Google Search Intensity Trend of the Wells Fargo Scandal

This figure displays Google search topic trends for "Wells Fargo Account Fraud Scandal" and "Wells Fargo Scandal" from 2013 January to 2018 December. The first row shows the google search volume of the topic "Wells Fargo Account Fraud Scandal" from users across the U.S. (left) and Californian users (right), respectively. The second row shows the google search volume of the term "Wells Fargo Scandal" from U.S. users (left) and Californian users (right). The Google search index is normalized to 100, the index value when the topic has the highest search intensity volume.

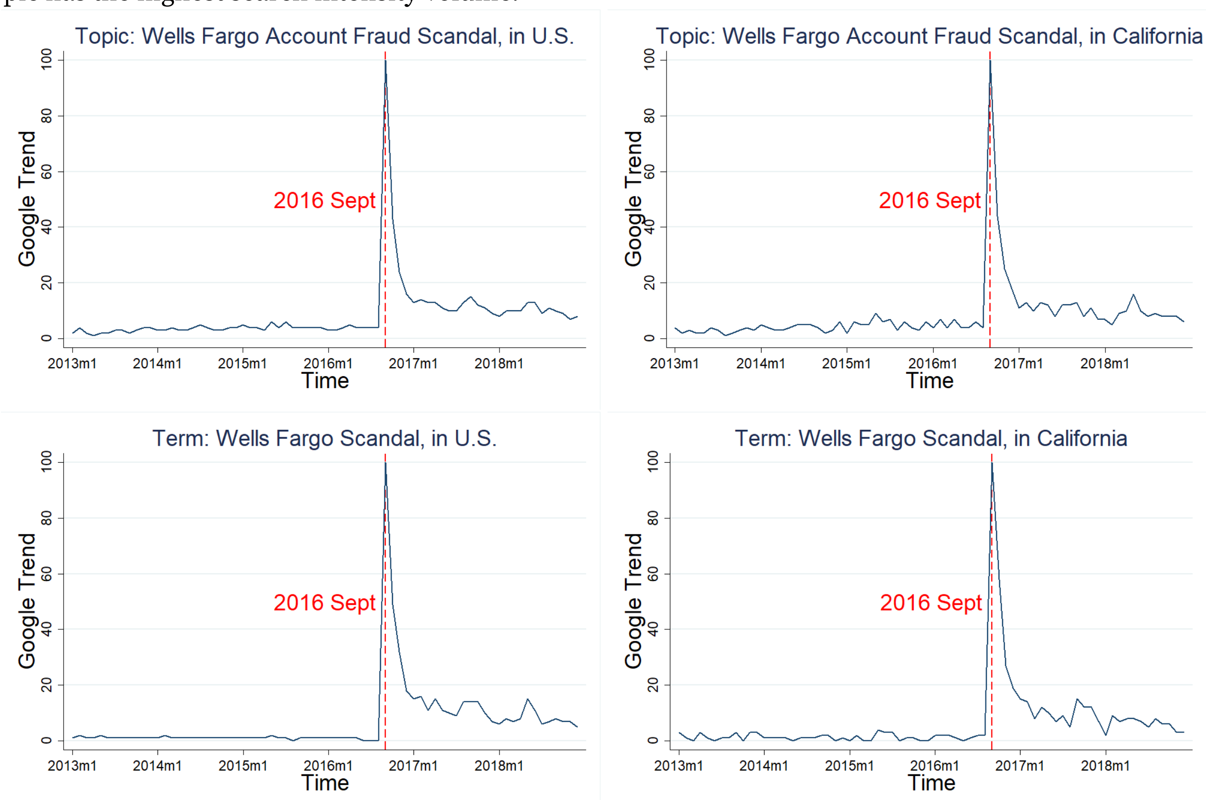

Figure 4: Household Exposure to the Wells Fargo Scandal

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).

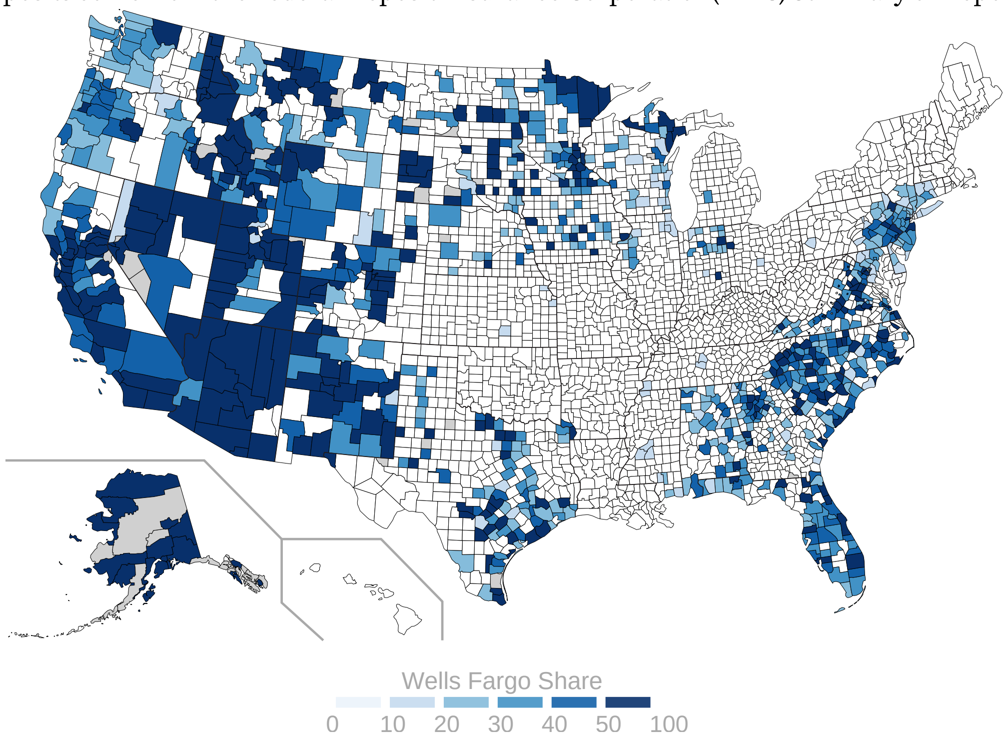

Figure 5: Google Search Intensity

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.

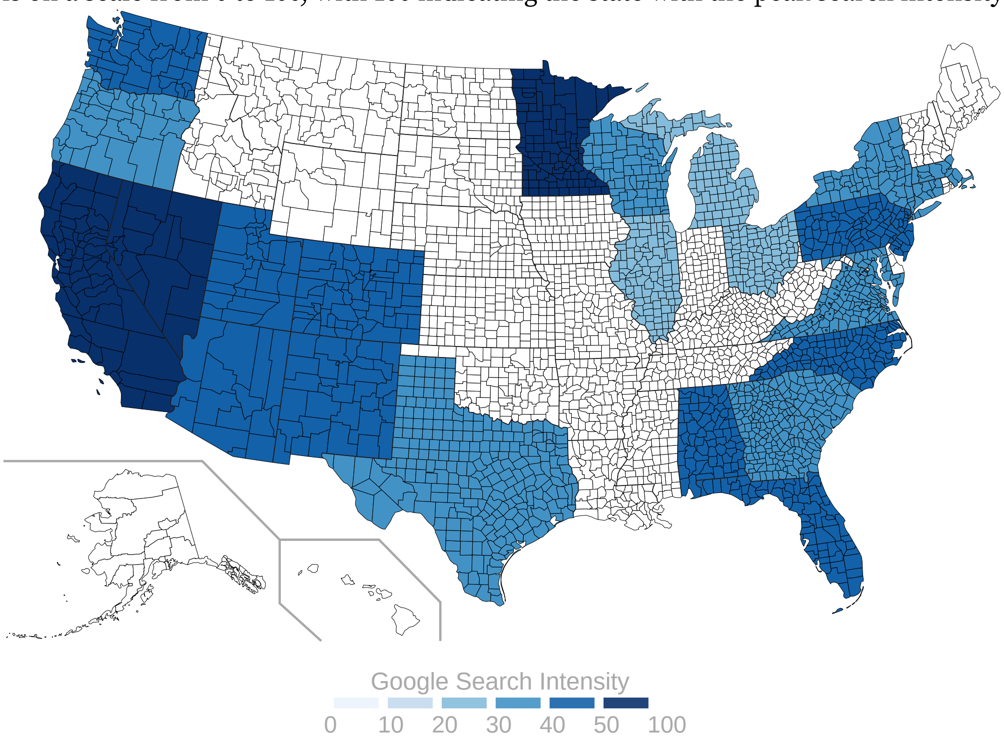

Figure 6: Political Affiliation

This figure displays county-level political affiliation, measured as the percentage of votes for the Democratic Party and the independent candidates in the 2016 presidential election. The county-level presidential election results data are obtained from the MIT Election Data and Science Lab.

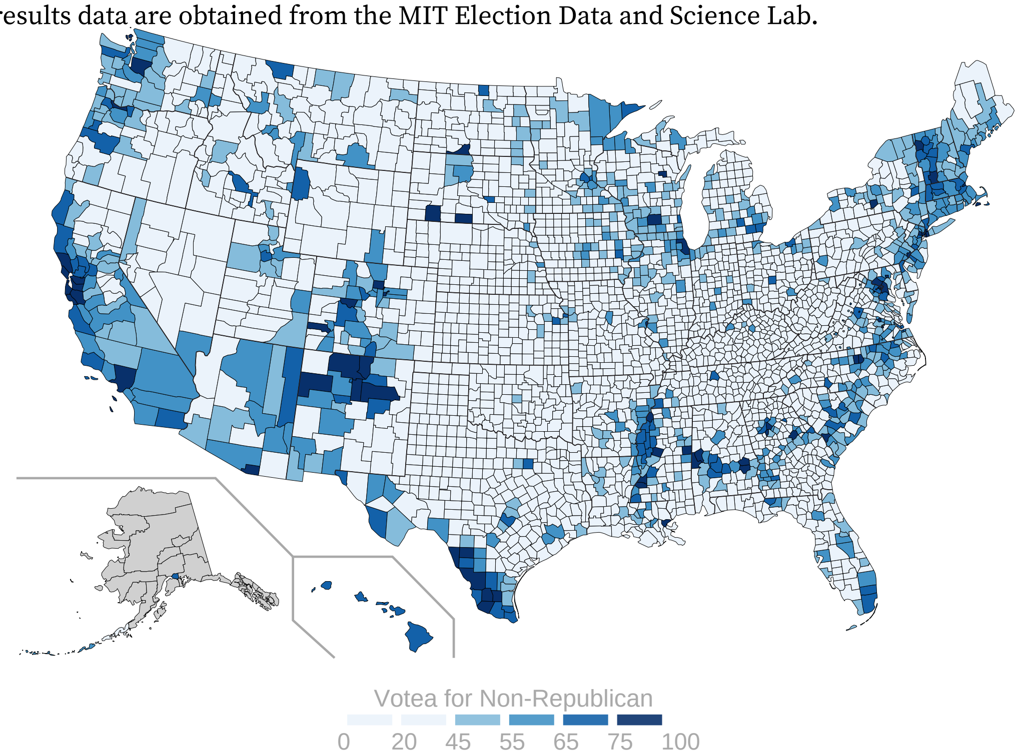

Figure 7: Dynamic effects of the Wells Fargo scandal revelation on FinTech adoption

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 2014 to 2018.

$$y_{i,s,c,t} = \beta WFExposure_c \times \sum_{t=2015,t\neq 2015}^{2018} Dummy_t + Control_{i,t} + \lambda_z + \sigma_t \times \eta_s + \varepsilon_{i,t}$$

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 and include both originated and rejected loans. 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.

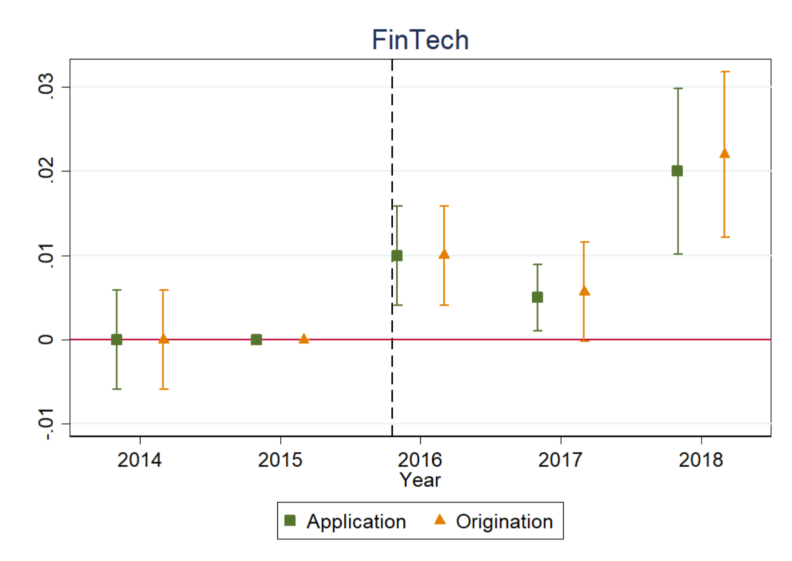

Figure 8: Dynamic effects of the Wells Fargo scandal on FinTech adoption: Fannie Mae and Freddie Mac Loans

This figure reports the dynamic effects of the revelation of bank misconduct on mortgage loan origination using Fannie Mae and Freddie Mac loans. The plotted coefficients are estimated from the following regression, using MSA-year-quarter-level data from 2014Q3 to 2018Q2.

$$y_{c,t} = \beta WFExposure_c \times \sum_{t=2014Q3,t\neq 2016Q2}^{2018Q2} Dummy_t + Control_{c,t} + \varepsilon_{c,t}$$

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. MSA and Year-Quarter fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at the 5% level.

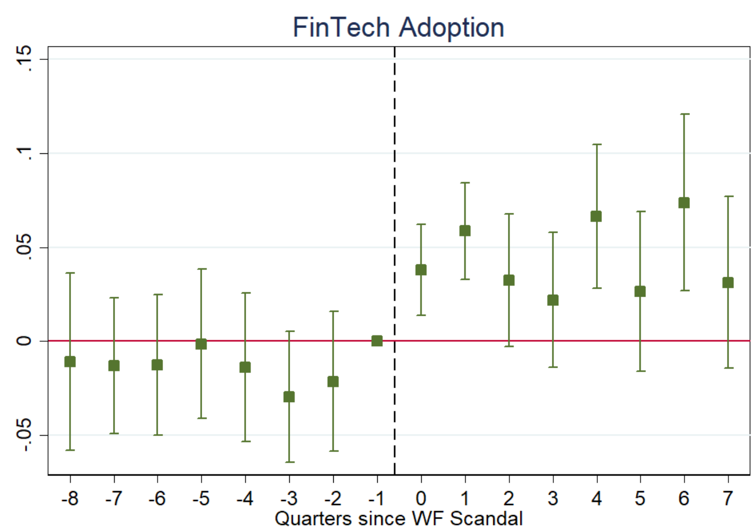

Figure 9: The effect of the revelation of the Wells Fargo scandal on Trust in Banks

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 2015 to 2018. The plotted coefficients are estimated from the following regression.

$$y_{i,c,t} = \beta WFExposure_c \times \sum_{t=2015,t\neq 2015}^{2018} Dummy_t + Control_{i,c,t} + \lambda_c + \eta_t + \varepsilon_{i,t}$$

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 regressions are run in subsamples, split into "Republican" or "Non-Republican" respondents. 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.

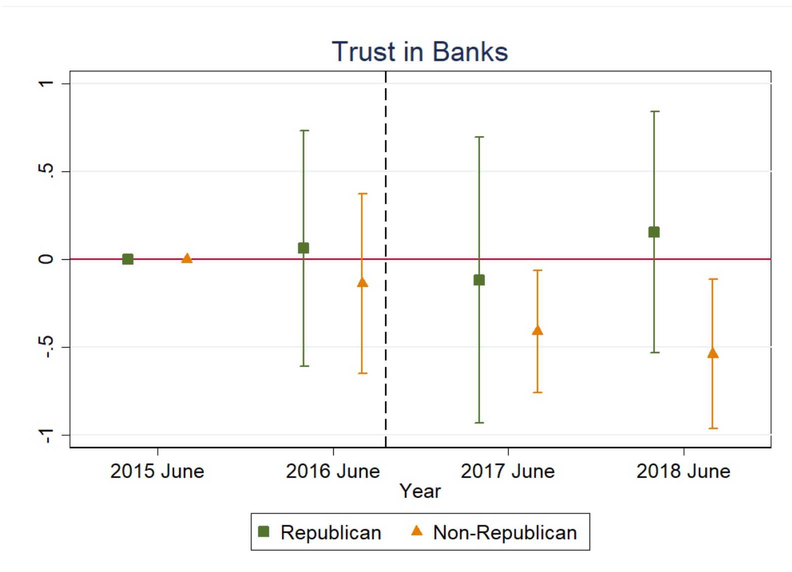

Figure 10: Dynamic triple effects of the revelation of the Wells Fargo scandal on FinTech adoption

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 2014 to 2018.

$$y_{c,t} = \beta WFExposure_c \times NonRep_c \times \sum_{t=2014,t\neq 2015}^{2018} Dummy_t + \beta Treated_c \times Post_t + NonRep_c \times Post_t + Control_{i,t} + \sigma_t + \eta_c + \varepsilon_{c,t}$$

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. 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.

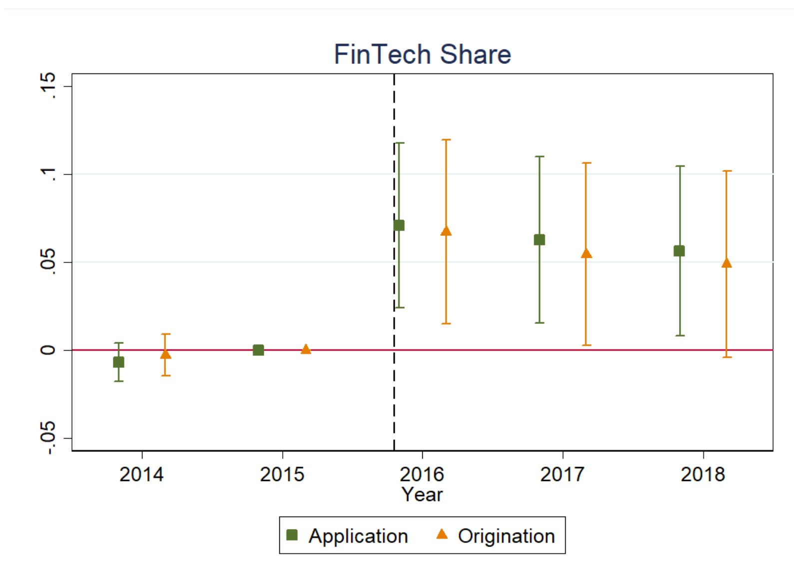

Table 1: Summary Statistics

This table reports the summary statistics of the key variables. Tables A and B present summary statistics for counties with populations larger than 65000. The U.S. Residential Mortgage Data 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 2014 to 2018. Trust in institutions data is obtained from the Gallup Analytics surveys.

Table A: Mortgage Share	Mean	Median	Std Dev	25%	75%	N
Mortgage Origination						
FinTech	7.35	6.94	2.97	5.42	8.89	4164
+NonFinTech Shadow Bank	38.38	38.34	13.18	29.21	47.96	4164
=Shadow Bank	45.73	46.49	14.24	35.89	56.18	4164
Wells Fargo	4.33	3.68	2.97	2.07	6.02	4164
+Non-Wells Fargo Bank	40.09	37.97	14.67	29.41	49.51	4164
=Bank	54.27	53.51	14.24	43.82	64.11	4164
Mortgage Application						
FinTech	8.18	7.83	3.13	6.22	9.75	4164
+NonFinTech Shadow Bank	37.65	37.83	11.79	29.49	46.15	4164
= Shadow Bank	45.83	46.78	12.88	36.81	55.27	4164
Wells Fargo	4.85	4.35	3.10	2.38	6.65	4164
+Non-Wells Fargo Bank	39.72	37.94	13.69	29.80	48.04	4164
=Bank	54.17	53.22	12.88	44.73	63.19	4164

Table B: County Characteristics: 2014 - 2018	Mean	Median	Std Dev	25%	75%	N
Treated (Wells Fargo Deposits Share in 2015)	9.01	5.28	10.40	0.00	16.53	4164
Treated× Post	5.43	0.00	9.21	0.00	9.46	4164
Democrat Share	0.42	0.39	0.15	0.30	0.51	4164
Treated× Post×NonRep	2.43	0.00	4.51	0.00	3.51	4164
Google Search Intensity	51.08	66.00	32.38	33.00	75.00	4164
Top 4 Share	0.31	0.28	0.10	0.23	0.36	4164
American Community Survey: 1 Year						
Population (000s)	330.87	156.84	583.75	94.76	328.26	4164
% Female	50.76	50.80	1.23	50.20	51.50	4164
% African American	12.43	8.00	12.64	3.60	16.40	4164
% Hispanic	12.92	6.90	16.66	4.00	14.30	4164
% over 21	72.95	73.10	3.26	70.90	74.80	4164
% over 65	15.88	15.50	4.18	13.20	17.80	4164
% with less than 12th grade education	11.26	10.40	5.02	7.90	13.60	4164
% with bachelor degree or higher	29.25	27.80	10.50	21.40	35.10	4164
% living in the same house last year	84.87	85.40	4.44	82.40	87.90	4164
Median Household Income	57750.23	54451.50	16082.09	46942.50	65345.50	4164
Unemployment Rate	6.00	5.60	2.56	4.30	7.10	4164
% with less than 35K income	31.71	31.60	9.54	25.20	37.80	4164

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Table 1: continued

...
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Table C: Gallup Individuals, 2015 - 2018	Mean	Median	Std Dev	25%	75%	N
Trust in Banks	29.00	0.00	45.38	0.00	100.00	4686
Trust in Big Business	21.68	0.00	41.21	0.00	0.00	4686
Trust in Media	22.25	0.00	34.77	0.00	50.00	4686
NonRepublican	0.55	1.00	0.50	0.00	1.00	4686
Age	53.31	55.00	18.67	38.00	68.00	4686
Female	0.47	0.00	0.50	0.00	1.00	4686
College Education	0.75	1.00	0.43	0.00	1.00	4686
High Income	0.36	0.00	0.48	0.00	1.00	4686
White	0.77	1.00	0.42	1.00	1.00	4686
Hispanic	0.07	0.00	0.26	0.00	0.00	4686
Black	0.10	0.00	0.30	0.00	0.00	4686
Protestant	0.43	0.00	0.50	0.00	1.00	4686
Jewish	0.02	0.00	0.14	0.00	0.00	4686
Trust in Banks (NonRepublican)	25.23	0.00	43.44	0.00	100.00	2572
Trust in Banks (Republican)	33.59	0.00	47.24	0.00	100.00	2114

Table D: Loan Characteristics	Mean	Median	Std Dev	25%	75%	N
Mortgage Origination						
FinTech	7.63	0.00	26.54	0.00	0.00	32260458
Wells Fargo	5.13	0.00	22.06	0.00	0.00	32260458
Non-Wells Fargo Bank	43.22	0.00	49.54	0.00	100.00	32260458
Bank	48.35	0.00	49.97	0.00	100.00	32260458
NonFinTech Shadow Bank	44.02	0.00	49.64	0.00	100.00	32260458
Shadow Bank	51.65	100.00	49.97	0.00	100.00	32260458
Mortgage Application						
FinTech	8.15	0.00	27.36	0.00	0.00	41903693
Wells Fargo	5.70	0.00	23.19	0.00	0.00	41903693
Non-Wells Fargo Bankk	43.58	0.00	49.59	0.00	100.00	41903693
Bank	49.29	0.00	49.99	0.00	100.00	41903693
NonFinTech Shadow Bank	42.56	0.00	49.44	0.00	100.00	41903693
Shadow Bank	50.71	100.00	49.99	0.00	100.00	41903693

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

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 2015 to 2018. The coefficients are estimated using following regressions.

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

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.

	Trust in Banks				Trust in Big Business			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WF Exposure× Post	-0.267**	-0.290**	-0.350***	-0.281**	0.008	-0.028	-0.066	-0.001
	(-2.1)	(-2.2)	(-2.7)	(-2.1)	(0.1)	(-0.2)	(-0.6)	(-0.0)
NonRep		-6.731***	-12.760***	-13.418***		-15.136***	-18.963***	-19.799***
		(-3.9)	(-7.4)	(-7.5)		(-9.8)	(-12.0)	(-12.1)
Age		-0.059	-0.125***	-0.125***		0.080*	0.038	0.032
		(-1.3)	(-2.8)	(-2.7)		(1.9)	(0.9)	(0.8)
Female		2.780*	2.300	1.666		-5.394***	-5.699***	-5.645***
		(1.7)	(1.5)	(1.0)		(-3.7)	(-4.0)	(-3.8)
College Education		-2.875	-1.980	-2.247		-3.987**	-3.419**	-3.318*
		(-1.5)	(-1.1)	(-1.1)		(-2.3)	(-2.0)	(-1.8)
High Income		2.030	2.168	2.351		3.618**	3.706**	3.744**
		(1.2)	(1.3)	(1.4)		(2.4)	(2.5)	(2.4)
White		-4.161	-3.180	-3.474		-4.871	-4.248	-4.818
		(-1.3)	(-1.0)	(-1.1)		(-1.6)	(-1.4)	(-1.6)
Hispanic		-1.258	-0.328	-0.342		-0.215	0.375	0.402
		(-0.3)	(-0.1)	(-0.1)		(-0.1)	(0.1)	(0.1)
Black		-5.722	-3.991	-4.522		-3.433	-2.334	-2.990
		(-1.4)	(-1.0)	(-1.1)		(-0.9)	(-0.6)	(-0.8)
Protestant		4.371**	4.266**	4.103**		0.434	0.367	-0.014
		(2.5)	(2.5)	(2.4)		(0.3)	(0.2)	(-0.0)
Jewish		-1.197	-2.215	-2.190		-2.689	-3.335	-3.218
		(-0.2)	(-0.4)	(-0.4)		(-0.6)	(-0.7)	(-0.7)
Trust in Media			0.324***	0.328***			0.205***	0.201***
			(14.3)	(14.1)			(9.9)	(9.4)
% with less than 35K income				-1.346**				-1.015
				(-2.0)				(-1.6)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4026	4026	4026	3683	4026	4026	4026	3683
Adjusted R^2	0.000	0.008	0.066	0.064	0.004	0.044	0.071	0.072

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

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 2014 to 2018 from the HMDA.

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

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. 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.

	Origination		Application	
	FinTech	FinTech	FinTech	FinTech
	(1)	(2)	(3)	(4)
WF Exposure× Post	0.011***	0.010**	0.010***	0.009**
	(3.0)	(2.4)	(2.8)	(2.4)
Population		0.001		0.002
		(0.8)		(1.4)
Median Household Income		0.000		-0.000
		(1.1)		(-1.2)
Unemployment Rate		-0.053*		-0.054**
		(-1.9)		(-2.1)
% with less than 35K income		-0.012		-0.036**
		(-0.8)		(-2.4)
Top 4 Share		-2.265***		-2.418***
		(-3.7)		(-4.1)
Income	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.5)	(-6.4)	(-5.8)	(-5.6)
Loanamt	-0.001***	-0.001***	-0.001***	-0.001***
	(-5.2)	(-4.8)	(-4.8)	(-4.4)
Type (Omitted Category = Conventional)				
FHA	2.527***	2.243***	4.041***	3.715***
	(15.4)	(13.5)	(21.5)	(18.8)
VA	0.225*	0.183	1.545***	1.458***
	(1.9)	(1.5)	(11.8)	(10.1)
FSA/RHS	-2.001***	-1.499***	-1.894***	-1.175***
	(-11.2)	(-7.2)	(-12.3)	(-6.2)
Type (Omitted Category = Home Purchase)				
Home Improvement	-1.359***	-1.102***	-4.495***	-3.877***
	(-12.4)	(-8.6)	(-31.8)	(-25.1)
Refinance	6.807***	6.971***	5.952***	6.338***
	(42.3)	(37.8)	(46.0)	(43.2)

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Table 3: continued

	Origination		Application	
	(1) FinTech	(2) FinTech	(3) FinTech	(4) FinTech
...				
To continue				
Purchaser (Omitted Category = Held)				
Fannie Mae	10.881***	11.101***	7.644***	7.949***
	(55.7)	(50.9)	(40.8)	(38.9)
Ginnie Mae	11.231***	11.005***	6.222***	6.192***
	(41.6)	(36.1)	(31.6)	(27.7)
Freddie Mac	9.099***	9.297***	5.894***	6.180***
	(30.6)	(27.7)	(19.4)	(18.3)
Farmer Mac	-0.065	-0.200	-3.754***	-3.836***
	(-0.2)	(-0.5)	(-13.0)	(-10.3)
Private securitization	1.480***	1.817***	-2.372***	-1.857***
	(4.7)	(5.4)	(-7.0)	(-5.2)
Bank	2.875***	3.227***	-0.937**	-0.429
	(7.7)	(8.0)	(-2.5)	(-1.1)
Insurance	1.164***	1.530***	-2.963***	-2.430***
	(5.8)	(7.1)	(-14.9)	(-11.8)
Affiliate	-2.909***	-2.653***	-6.279***	-5.946***
	(-16.3)	(-14.1)	(-31.8)	(-28.1)
Other	0.828***	1.210***	-3.265***	-2.726***
	(4.4)	(5.9)	(-17.7)	(-13.8)
Sex (Omitted Category = Male)				
Female	0.720***	0.610***	0.973***	0.812***
	(24.3)	(19.5)	(29.9)	(24.8)
NA	11.003***	11.013***	10.263***	10.645***
	(34.3)	(31.4)	(35.9)	(34.1)
Ethnicity (Omitted Category = Non-Hispanic)				
Hispanic	-1.215***	-1.371***	-0.515***	-0.769***
	(-7.0)	(-7.7)	(-2.9)	(-4.2)
NA	0.929***	-0.194	3.600***	1.779***
	(3.3)	(-0.8)	(10.2)	(5.8)
Race (Omitted Category = White)				
Native American	1.533***	1.665***	1.790***	1.881***
	(11.9)	(11.2)	(15.3)	(13.8)
Asian	-0.056	-0.175	-0.092	-0.200
	(-0.3)	(-1.0)	(-0.6)	(-1.2)
Black	0.360***	0.244**	0.849***	0.520***
	(3.8)	(2.5)	(8.4)	(5.2)
Hawaiian	0.619***	0.575***	0.701***	0.641***
	(4.2)	(3.8)	(4.9)	(4.4)
NA	6.167***	6.423***	4.801***	5.411***
	(34.8)	(34.6)	(24.9)	(27.9)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34179861	29985964	44856156	39029308
Adjusted R^2	0.096	0.093	0.080	0.077

Table 4: Dynamic effects of the Wells Fargo scandal revelation on FinTech adoption: Fannie Mae and Freddie Mac Loans

This table reports the dynamic effects of the Wells Fargo scandal revelation on mortgage loan origination using Fannie Mae and Freddie Mac loans. Coefficients are estimated from the following regression, using MSA - year-quarter level data from 2014Q3 to 2018Q2.

$$y_{c,t} = \beta WFExposure_c \times \sum_{t=2014Q3, t\neq 2016Q2}^{2018Q2} Dummy_t + Control_{c,t} + \varepsilon_{c,t}$$

The dependent variable is the share of the number of mortgages originated by FinTech lenders at the MSA level. $WFExposure_c$ is the percentage of Wells Fargo deposits in MSA c in 2015. The Year-Quarter dummy variable t is equal to one at Year-Quarter t. 2016Q2 dummy is omitted, as the reference quarter. 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.

	FinTech (1)	FinTech (2)
WF Exposure×		
2014 Q3	-0.015	-0.011
	(-0.6)	(-0.5)
2014 Q4	-0.017	-0.013
	(-0.9)	(-0.7)
2015 Q1	-0.016	-0.013
	(-0.8)	(-0.7)
2015 Q2	-0.005	-0.002
	(-0.2)	(-0.1)
2015 Q3	-0.018	-0.015
	(-0.8)	(-0.7)
2015 Q4	-0.033*	-0.030*
	(-1.8)	(-1.7)
2016 Q1	-0.022	-0.022
	(-1.1)	(-1.1)
2016 Q2		
2016 Q3	0.038***	0.038***
	(3.1)	(3.1)
2016 Q4	0.059***	0.059***
	(4.5)	(4.5)
2017 Q1	0.031*	0.032*
	(1.7)	(1.8)
2017 Q2	0.019	0.020
	(1.0)	(1.1)
2017 Q3	0.064***	0.065***
	(3.2)	(3.3)
2017 Q4	0.025	0.026
	(1.1)	(1.2)
2018 Q1	0.070***	0.073***
	(3.1)	(3.1)
2018 Q2	0.026	0.029
	(1.1)	(1.2)
MSA Level Char.	No	Yes
MSA FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	5888	5888
Adjusted R^2	0.751	0.752

Table 5: The effect of the Wells Fargo scandal revelation on lender choice

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 2014 to 2018 in the HMDA.

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

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.

	FinTech	Wells Fargo	Non-WF Bank	Bank	Non-FinTech ShadowBank	ShadowBank
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure$\times$ Post	0.011***	-0.020***	-0.022**	-0.042***	0.031***	0.042***
	(2.7)	(-6.1)	(-2.6)	(-4.7)	(3.6)	(4.7)
Income	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000***
	(-6.9)	(-2.8)	(-3.3)	(-3.8)	(4.9)	(3.8)
Loan Amount	-0.001***	0.003***	-0.002***	0.001*	0.000	-0.001*
	(-4.9)	(4.6)	(-4.1)	(1.7)	(0.3)	(-1.7)
Population	0.002	0.002**	-0.008***	-0.005**	0.004**	0.005**
	(1.0)	(2.5)	(-3.0)	(-2.4)	(2.3)	(2.4)
Median Household Income	0.000	0.000	0.000***	0.000***	-0.000***	-0.000***
	(1.3)	(0.4)	(8.3)	(6.8)	(-7.2)	(-6.8)
Unemployment Rate	-0.058**	0.077***	0.124**	0.201***	-0.143**	-0.201***
	(-2.1)	(4.3)	(2.3)	(3.6)	(-2.6)	(-3.6)
% with less than 35K income	-0.013	0.007	0.219***	0.226***	-0.213***	-0.226***
	(-0.8)	(0.5)	(6.2)	(5.8)	(-5.6)	(-5.8)
Top 4 Share	-2.360***	2.410***	-0.536	1.874	0.485	-1.874
	(-3.8)	(3.8)	(-0.4)	(1.3)	(0.3)	(-1.3)
Loan Char.	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29985964	29985964	29985964	29985964	29985964	29985964
Adjusted R^2	0.069	0.043	0.309	0.329	0.295	0.329

Table 6: The heterogeneous effects of revelation of Well Fargo scandal on trust in banks

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on trust in banks and trust in big business, using "Confidence in Institution" survey data from Gallup Analytics from 2015 to 2018. The coefficients are estimated using the following regressions.

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

The dependent variable is the respondent's trust in banks and trust in big business, that 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." WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is a dummy variable equaling to one after 2016. NonRep is a dummy variable equal to one if the respondent reports party affiliation as "Republican" or "Independent." In columns (2) (3) (5) (6), the sample is divided into respondents not affiliated with the Republican party and those affiliated with the Republican party. 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.

	Trust in Banks			Trust in Big Business		
		NonRep	Rep		NonRep	Rep
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure× Post× NonRep	-0.332*			-0.149		
	(-1.9)			(-1.5)		
WF Exposure× Post	-0.068	-0.483***	-0.041	0.094	-0.035	0.055
	(-0.4)	(-3.5)	(-0.2)	(1.0)	(-0.4)	(0.4)
NonRep× Post	3.505			-1.760		
	(0.9)			(-0.8)		
NonRep	-14.808***			-14.306***		
	(-4.5)			(-8.8)		
Respondent 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	3683	1964	1456	3683	1964	1456
Adjusted R^2	0.062	0.074	0.042	0.124	0.078	0.048

Table 7: The heterogeneous effects of the Wells Fargo scandal revelation on FinTech Adoption

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 2014 to 2018.

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

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.

	Origination			Application		
		High NonRepublican Share	Low NonRepublican Share		High NonRepublican Share	Low NonRepublican Share
	FinTech (1)	FinTech (2)	FinTech (3)	FinTech (4)	FinTech (5)	FinTech (6)
WF Exposure× Post× NonRep	0.058**			0.067***		
	(2.2)			(2.8)		
WF Exposure× Post	-0.024	0.014***	-0.005	-0.030**	0.012***	-0.007
	(-1.6)	(3.0)	(-0.7)	(-2.2)	(2.9)	(-0.9)
NonRep× Post	-1.317***			-1.350***		
	(-3.6)			(-4.1)		
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	4054	2096	1968	4054	2096	1968
Adjusted R^2	0.871	0.899	0.847	0.892	0.910	0.877

Table 8: Treatment Effects Heterogeneity Analysis using Machine Learning

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 8a, the dependent variable is the respondent's trust in banks, which equal 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 8b, the dependent variable is a dummy variable equal to one hundred if the lender is a FinTech lender and zero otherwise. Borrowers are sorted into five groups with different level of treatment effects based on a machine learning proxy predictor. 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 resides in a county with an above-median level of the Wells Fargo deposits share ($> 10\%$). 90% confidence intervals are in parentheses. The p-values are provided in the parentheses.

(a) Trust in Banks

	Least Affected		Most Affected		Difference	
	β	p-value	β	p-value	β	p-value
NonRep	0.508	(0.0)	0.540	(0.0)	0.0297	(0.0)
	[0.457,0.559]		[0.49,0.644]		[-0.04,0.10]	
Female	0.526	(0.0)	0.432	(0.0)	-0.093	(0.0)
	[0.475,0.578]		[0.383,0.480]		[-0.164,-0.022]	
Minority	0.247	(0.0)	0.242	(0.0)	-0.007	(0.1)
	[0.202,0.291]		[0.200,0.285]		[-0.068,0.055]	

(b) FinTech Adoption

	Least Affected		Most Affected		Difference	
	β	p-value	β	p-value	β	p-value
Female	0.280	(0.0)	0.262	(0.0)	-0.018	(0.0)
	[0.279, 0.280]		[0.261, 0.262]		[-0.019, -0.017]	
Minority	0.131	(0.0)	0.094	(0.0)	-0.036	(0.0)
	[0.131,0.132]		[0.093,0.095]		[-0.036,-0.034]	

Table 9: Falsification Tests: Use JPMorgan Chase Deposit Share

This table reports how JPMorgan deposits share affect FinTech adoption and trust in banks. The coefficients are estimated using the following regressions.

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

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 9a, 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 9b, the dependent variable is the share of the number of mortgages handled by FinTech lenders for both origination and application. 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.

(a) Trust in Banks

	Trust in Banks (1)	Trust in Big Businesss (2)
Chase Exposure $\times$ Post	0.102	-0.078
	(0.4)	(-0.7)
Respondent Char.	Yes	Yes
County Char.	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	3683	3683
Adjusted R^2	-0.001	0.015

(b) FinTech Adoption

	Origination (1)	Application (2)
Chase Exposure $\times$ Post	-0.011	-0.010*
	(-1.6)	(-1.7)
Loan Char.	Yes	Yes
County Char.	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	4054	4054
Adjusted R^2	0.882	0.889

Table 10: The effect of the revelation of the Wells Fargo scandal on lenders' credit supply and banks' deposits

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 2014 to 2018.

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

In Table 10a, the dependent variable is the percentage of mortgage applications denied by different types of lenders. In Table 10b, 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, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics are in parentheses.

(a) Loan Denial Rate

	All Lenders	Wells Fargo	Non-Wells Fargo Bank	All Banks	FinTech	Shadow Bank	Non-FinTech ShadowBank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WF Exposure$\times$ Post	-0.004	-0.019	-0.017**	-0.011	0.001	0.010	0.012
	(-0.7)	(-1.1)	(-2.4)	(-1.5)	(0.0)	(1.1)	(1.1)
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	4064	4064	4064	4064	4064	4064	4064
Adjusted R^2	0.936	0.753	0.899	0.909	0.842	0.925	0.905

(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$\times$ Post	0.001	0.001	0.001***	0.140	0.220	-0.080
	(1.4)	(1.1)	(2.8)	(0.8)	(1.0)	(-1.5)
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	4064	4064	4064	4064	4064	4064
Adjusted R^2	0.996	0.996	0.995	0.980	0.896	0.985

Table 11: Wells Fargo Scandal and Loan Pricing

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 2013Q4 to 2018Q4. 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 county level, and t statistics are in parentheses.

	FinTech		Wells Fargo		Non-Wells Fargo Bank	
	Purchase	Refinance	Purchase	Refinance	Purchase	Refinance
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure$\times$ Post	0.016	0.009	0.101***	0.030	0.104	0.060
	(0.3)	(0.3)	(3.0)	(0.7)	(1.6)	(1.0)
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
Observations	5367	5808	5953	5610	5540	4968
adjusted R^2	0.665	0.783	0.812	0.697	0.712	0.620

Online Appendices for *"Trust as an Entry Barrier: Evidence from FinTech Adoption"*

Appendix A: Appendix Table

Appendix B: Chernozhukov, Demirer, Duflo, and Fernández-Val

Appendix C: Models of Trust

A Appendix Table

Table A1: The effect of the revelation of the Well Fargo scandal on FinTech adoption

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 2014 to 2018 from the HMDA.

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

The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. $WFExposure_c$ is Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. $Post_t$ is a dummy variable that equals to one after 2016. Columns (1) (2) only include originated loans, and columns (3) (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 in parentheses.

	Origination		Application	
	(1) FinTech	(2) FinTech	(3) FinTech	(4) FinTech
WF Exposure$\times$ Post	0.005***	0.005**	0.004**	0.005**
	(2.8)	(2.3)	(2.6)	(2.3)
Population		0.001		0.002
		(0.8)		(1.4)
Median Household Income		0.000		-0.000
		(0.9)		(-1.5)
Unemployment Rate		-0.045*		-0.046*
		(-1.7)		(-1.9)
% with less than 35K income		-0.014		-0.038**
		(-0.9)		(-2.6)
Top 4 Share		-2.284***		-2.425***
		(-3.8)		(-4.2)
Income	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.5)	(-6.3)	(-5.8)	(-5.6)
Loanamt	-0.001***	-0.001***	-0.001***	-0.001***
	(-5.2)	(-4.8)	(-4.8)	(-4.4)
Loan Char.	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34179861	29985964	44856156	39029308
Adjusted R^2	0.096	0.093	0.080	0.077

Table A2: The heterogeneous effects of the Wells Fargo scandal revelation on FinTech Adoption

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 2014 to 2018.

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

The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. $WFExposure_c$ is the Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. $Post_t$ is a dummy variable equaling to one after 2016. NonRep is the percentage of share voted for Non-Republican candidates in the 2016 presidential election. In columns (2) (3) (5) (6), the samples are divided into counties with larger 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 in parentheses.

	Origination			Application		
		High NonRepublican Share	Low NonRepublican Share		High NonRepublican Share	Low NonRepublican Share
	(1) FinTech	(2) FinTech	(3) FinTech	(4) FinTech	(5) FinTech	(6) FinTech
WF Exposure× Post× NonRep	0.028**			0.030**		
	(2.3)			(2.4)		
WF Exposure× Post	-0.012**	0.006***	-0.001	-0.012**	0.007***	-0.000
	(-2.0)	(2.9)	(-0.7)	(-2.0)	(3.0)	(-0.1)
NonRep× Post	-1.574**			-1.681**		
	(-2.5)			(-2.6)		
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	4049	2081	1968	4049	2081	1968
Adjusted R^2	0.907	0.926	0.859	0.910	0.925	0.880

Table A3: The effect of the revelation of the Well Fargo scandal on trust in banks

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 2015 to 2018. Coefficients are estimated from the following regressions.

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

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" or "some" or "None". $WFExposure_c$ is the Google Trend "Interest by subregion" index of search topic "Wells Fargo Account Fraud Scandal" from August 2016 to August 2017. Post is a dummy variable that equals to 1 after 2016 Sept. The sample is split into individuals not affiliated with the Republican Party, and those affiliated with the Republican Party. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and *t* statistics in parentheses.

	Trust in Banks		Trust in Big Business	
	NonRep	Rep	NonRep	Rep
	(1)	(2)	(3)	(4)
WF Exposure× Post	-0.121*	0.067	0.017	0.093
	(-1.7)	(0.7)	(0.3)	(1.0)
Respondent Char.	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2042	1574	2042	1574
Adjusted R^2	0.077	0.040	0.058	0.035

Table A4: The triple-differences effects of the revelation of the Wells Fargo scandal on lenders' credit supply and deposits

This table reports the effect of the revelation of bank misconduct on lenders' credit supply. Coefficients are estimated from the following regression, using county - year level data from 2014 to 2018.

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

In table A4a, the dependent variable is the percentage of mortgage denied by different lenders. In table A4b, the dependent variables are per capita deposits and the logarithm of deposits in county c at time t. $WFExposure_c$ is the percentage of Wells Fargo deposits in county c in 2015. Post is a dummy variable equaling to one after 2016. NonRep is the percentage of share voted for Non-Republican candidates in the 2016 presidential election. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and *t* statistics in parentheses.

(a) Loan Denial Rate

	(1) All Lenders	(2) Wells Fargo	(3) Non-Wells Fargo Bank	(4) All Banks	(5) FinTech	(6) Shadow Bank	(7) Non-FinTech ShadowBank
WF Exposure× Post× NonRep	-0.023	0.065	-0.013	-0.012	0.059	0.021	0.022
	(-0.6)	(0.5)	(-0.3)	(-0.3)	(0.7)	(0.4)	(0.4)
WF Exposure× Post	0.010	-0.053	-0.008	-0.001	-0.031	-0.005	-0.003
	(0.5)	(-0.9)	(-0.4)	(-0.1)	(-0.7)	(-0.2)	(-0.1)
NonRep× Post	-0.387	-0.316	-1.217*	-1.213*	2.532*	0.801	0.308
	(-0.7)	(-0.2)	(-1.7)	(-1.8)	(1.8)	(0.9)	(0.3)
County Control	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4054	4054	4054	4054	4054	4054	4054
Adjusted R^2	0.936	0.753	0.899	0.910	0.843	0.925	0.905

(b) Bank Deposits

	Log Value Deposits			Deposits Per Capita		
	(1) Total	(2) Wells Fargo	(3) Non-Wells Fargo	(4) Total	(5) Wells Fargo	(6) Non-Wells Fargo
WF Exposure× Post× NonRep	-0.005**	-0.015*	-0.003	-0.841	-0.700	-0.141
	(-2.0)	(-1.8)	(-1.4)	(-1.5)	(-1.1)	(-0.5)
WF Exposure× Post	0.003***	0.008***	0.002**	0.508	0.543	-0.035
	(2.7)	(3.0)	(2.4)	(1.3)	(1.1)	(-0.2)
NonRep× Post	0.101***	0.262	0.087***	15.188**	4.865	10.323*
	(3.0)	(1.6)	(2.7)	(2.2)	(1.2)	(1.7)
County Control	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	4064	4064	4064	4064	4064	4064
Adjusted R^2	0.996	0.996	0.995	0.980	0.896	0.985

Table A5: The effect of the revelation of the Well Fargo scandal on trust in banks

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 2015 to 2018. Coefficients are estimated from the following regressions.

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

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 a dummy variable that equals to one if the percentage of Wells Fargo deposits in county c in 2015 is greater than 10. $Post_t$ is a dummy variable that equals to 1 after 2016 Sept. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and *t* statistics in parentheses.

	Trust in Banks				Trust in Big Business			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WF Exposure× Post	-6.197*	-6.707**	-7.630**	-6.825**	0.134	-0.529	-1.115	-0.007
	(-1.9)	(-2.2)	(-2.5)	(-2.2)	(0.0)	(-0.2)	(-0.4)	(-0.0)
NonRep		-6.720***	-12.730***	-13.414***		-15.134***	-18.954***	-19.798***
		(-3.9)	(-7.4)	(-7.5)		(-9.8)	(-12.0)	(-12.1)
Age		-0.058	-0.124***	-0.125***		0.080*	0.038	0.032
		(-1.3)	(-2.8)	(-2.7)		(1.9)	(0.9)	(0.8)
Female		2.822*	2.352	1.711		-5.390***	-5.689***	-5.645***
		(1.8)	(1.5)	(1.1)		(-3.7)	(-4.0)	(-3.8)
College Education		-2.924	-2.034	-2.306		-3.989**	-3.423**	-3.318*
		(-1.5)	(-1.1)	(-1.2)		(-2.3)	(-2.0)	(-1.8)
High Income		2.051	2.191	2.381		3.619**	3.708**	3.744**
		(1.2)	(1.3)	(1.4)		(2.4)	(2.5)	(2.4)
White		-4.240	-3.276	-3.567		-4.878	-4.266	-4.818
		(-1.3)	(-1.0)	(-1.1)		(-1.6)	(-1.4)	(-1.6)
Hispanic		-1.332	-0.419	-0.424		-0.222	0.358	0.402
		(-0.3)	(-0.1)	(-0.1)		(-0.1)	(0.1)	(0.1)
Black		-5.743	-4.023	-4.539		-3.435	-2.342	-2.990
		(-1.4)	(-1.0)	(-1.1)		(-0.9)	(-0.6)	(-0.8)
Protestant		4.338**	4.221**	4.069**		0.430	0.356	-0.015
		(2.5)	(2.5)	(2.3)		(0.3)	(0.2)	(-0.0)
Jewish		-1.249	-2.288	-2.218		-2.697	-3.357	-3.219
		(-0.2)	(-0.4)	(-0.4)		(-0.6)	(-0.7)	(-0.7)
Trust in Media			0.323***	0.327***			0.205***	0.201***
			(14.3)	(14.1)			(9.9)	(9.4)
% with less than 35K income				-1.424**				-1.014
				(-2.1)				(-1.6)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4026	4026	4026	3683	4026	4026	4026	3683
Adjusted R^2	0.000	0.008	0.065	0.064	0.004	0.044	0.071	0.072

Table A6: The effect of the revelation of the Well Fargo scandal on FinTech adoption

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 2014 to 2018 from the HMDA.

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

The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. $WFExposure_c$ is a dummy variable that equals to one if the percentage of Wells Fargo deposits in county c in 2015 is greater than 10. $Post_t$ is a dummy variable that equals to one after 2016. Columns (1) (2) only include originated loans, and columns (3) (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 in parentheses.

	Origination		Application	
	(1) FinTech	(2) FinTech	(3) FinTech	(4) FinTech
WF Exposure× Post	0.305***	0.302***	0.276***	0.291**
	(3.0)	(2.6)	(2.8)	(2.5)
Population		0.001		0.002
		(0.7)		(1.3)
Median Household Income		0.000		-0.000
		(1.0)		(-1.3)
Unemployment Rate		-0.050*		-0.051**
		(-1.8)		(-2.0)
% with less than 35K income		-0.010		-0.033**
		(-0.6)		(-2.3)
Top 4 Share		-3.021***		-3.360***
		(-2.7)		(-3.3)
Income	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.5)	(-6.3)	(-5.8)	(-5.6)
Loanamt	-0.001***	-0.001***	-0.001***	-0.001***
	(-5.2)	(-4.8)	(-4.8)	(-4.4)
Loan Char.	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34174869	29985964	44831361	39029308
Adjusted R^2	0.096	0.093	0.080	0.077

Table A7: Falsification Tests: Use JPMorgan Chase Deposit Share

This table reports how JPMorgan deposits share affect FinTech Adoption and trust in banks. Coefficients are estimated from the following regressions.

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

In table A7a, the dependent variable is the share of the number of mortgages handled by FinTech lenders for both origination and application. In table A7b, 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." 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 A7a, NonRep is the percentage of share voted for Non-Republican candidates in the 2016 presidential election. In table A7b, NonRep is a dummy variable equaling to one if respondent reports party affiliation as Non-Republican. In the table A7a columns (3) (4) (7) (8) , the samples are divided into counties with higher than and lower than median Non-Republican voting shares. In table B columns (3) (4) (7) (8) (11) (12), the samples are divided into respondents not affiliated with the Republican Party and those affiliated with the Republican party. The constant term is included, and fixed effects are indicated in the table. Standard errors are clustered at the county level, and t statistics in parentheses.

(a) FinTech Adoption

	Origination			Application		
		High NonRep	Low Share		High NonRep	Low Share
	(1)	(2)	(3)	(4)	(5)	(6)
Chase Exposure× Post	-0.026	-0.003	-0.023	-0.008	-0.006	-0.007
	(-1.1)	(-0.4)	(-1.3)	(-0.4)	(-1.1)	(-0.6)
Chase Exposure× Post× NonRep	0.032			0.003		
	-0.9			-0.1		
NonRep× Post	-0.791**			-0.736**		
	(-2.0)			(-2.0)		
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	4039	2066	1943	4039	2066	1943
Adjusted R^2	0.883	0.909	0.857	0.889	0.914	0.859

(b) Trust in Banks

	Trust in Banks			Trust in Big Business		
	(1)	(2)	(3)	(4)	(5)	(6)
Chase Exposure× Post	0.162	0.181	-0.070	0.090	0.016	-0.326
	(0.7)	(0.7)	(-0.2)	(0.5)	(0.1)	(-1.4)
Chase Exposure× Post× NonRep	-0.105			-0.297*		
	(-0.5)			(-1.8)		
NonRep× Post	-3.044			-3.629		
	(-0.8)			(-1.1)		
NonRep	-5.323**			-13.010***		
	(-2.2)			(-6.2)		
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	3683	1964	1456	3683	1964	1456
Adjusted R^2	0.004	0.007	-0.019	0.047	0.016	0.013

Table A8: Summary Statistics by Race

This table report the summary statistics of key variables by race.

Panel A: Trust in Banks	Full		Before Treatment		After Treatment	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
White	28.99	45.38	26.61	44.20	31.42	46.43
Observations	3598		1819		1779	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Hispanic	32.02	46.73	26.19	44.10	38.04	48.70
Observations	331		168		163	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
African American	26.20	44.02	21.40	41.10	31.09	46.38
Observations	481		243		238	

Panel B: FinTech Adoption

	Full		Before Treatment		After Treatment	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
White Non Hispanic	11.11	31.42	10.29	30.38	11.65	32.08
Observations	6949757		2754899		4194858	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
White Hispanic	9.27	29.01	8.06	27.22	9.97	29.97
Observations	754221		275147		479074	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
African American	13.97	34.67	12.11	32.62	15.03	35.73
	399483		144309		255174	

Table A9: FinTech Adoption Across Race Groups

This table reports the number share of FinTech loans used by borrowers from different race groups. The sample include HMDA loans purchased by Fannie Mae or Freddie Mac from 2014 to 2018.

	White Non-Hispanic	White Hispanic	African American	Asian	Pacific Islander/ Native American
FinTech Share %	11.11	9.27	13.97	9.72	13.83

Table A10: Do minority borrowers react differently to the Wells Fargo scandal?

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on trust in banks (table A10b) and FinTech adoption (table A10b). In table A10a, the dependent variable is the respondent's trust in banks and trust in big business, that 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 A10b, the dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. The DID is estimated across different racial subgroups, indicated above. $WFExposure_c$ is a dummy variable that equals to one if the percentage of Wells Fargo deposits in county c in 2015 is greater than 10. Post is a dummy variable equaling to one after 2016. Individual and county controls, County and Year fixed effects are included. Standard errors are clustered at the county level, and t statistics in parentheses.

(a) Treatment Effect on Trust in Banks

	Trust in Banks			Trust in Big Business		
	White Non-Hispanic	Hispanic	African American	White Non-Hispanic	Hispanic	African American
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure$\times$ Post	-0.285**	1.000	-1.101*	-0.034	0.561	-0.180
	(-2.1)	(1.5)	(-1.8)	(-0.3)	(0.8)	(-0.4)
Individual Char.	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2962	192	319	2962	192	319
Adjusted R^2	0.017	0.067	0.005	0.080	0.063	0.126

(b) Treatment Effect on FinTech Adoption

	FinTech		
	White Non-Hispanic	White Hispanic	African American
	(1)	(2)	(3)
	0.050***	0.018	0.029**
	(4.99)	(1.09)	(1.99)
County Char.	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6737208	737262	384230
Adjusted R^2	0.04	0.03	0.03

Table A11: CDDF Heterogeneity Analysis

This table reports the CDDF treatment effects heterogeneity estimates for the effects of exposure to the Wells Fargo scandal on FinTech adoption across different race groups. Table A11a reports the effects on trust in banks. Table A11b reports the effects on FinTech adoption. The first four columns reports best linear predictors of the conditional treatment. The last four columns reports the group average treatment for the least affected group and the most affected group. The groups are sorted into five groups based on the machine learning treatment proxy. The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. A borrower belongs to the treatment group if she resides in a county resides in a county with above-median level of the Wells Fargo deposits share ($> 10\%$). The adjusted p-values are provided in the brackets.

(a) Trust in Banks

BLP				GATE			
ATE (β_1)		HET (β_2)		Least Affected		Most Affected	
β	p-value	β	p-value	β	p-value	β	p-value
-0.59	(0.6)	0.075	(0.6)	1.089	(0.5)	-4.293	(0.6)
[-9.585,8.095]		[-0.339,0.472]		[-20.404,22.722]		[-22.767,14.809]	

(b) FinTech Adoption

BLP				GATE			
ATE (β_1)		HET (β_2)		Least Affected		Most Affected	
β	p-value	β	p-value	β	p-value	β	p-value
0.730	(0.0)	1.587	(0.0)	-4.552	(0.0)	5.328	(0.0)
[0.395,1.063]		[1.403,1.770]		[-5.596,-3.521]		[4.512,6.149]	

B Chernozhukov, Demirer, Duflo, and Fernández-Val

To better understand the borrowers' heterogeneous responses to the Wells Fargo scandal, I exploit a generic machine learning inference approach proposed by Chernozhukov et al. (2020) (CDDF) to estimate treatment effect heterogeneity. CDDF develop a method of generic machine learning inference on heterogeneous treatment effects in randomized experiments. The sample splitting feature of the CDDF method largely solves the out-of-sample validity issue in heterogeneous treatment effect estimation. I apply the method in understanding the heterogeneous treatment effect of the exposure to the Wells Fargo scandal, which is a quasi-experiment setting.[15]

The CDDF method applies to binary treatment, therefore I partition the Wells Fargo exposure into "treatment" ($T = 1$) and "control" groups ($T = 0$), assigning an individual to the treatment group if the individual resides in a county with above-median level of the Wells Fargo deposits share after 2016. Let Y be the variable of interest, the FinTech dummy variable, and Z be the vector of covariates. Conditional on the individuals' characteristics Z, the average treatment effect (ATE) becomes a conditional average treatment effect (CATE), which is denoted as $s_o(Z) = E(Y|T = 1, Z) - E(Y|T = 0, Z)$. In our setting, the conditional treatment effect is the increase in an individual's probability of choosing FinTech as mortgage originator(decrease in individual's probability of reporting trust in banks) after the exposure to the Wells Fargo scandal, conditional on the individual's characteristics.

CDDF argues that we can use generic machine learning method to construct an imperfect estimator $\hat{s}(Z)$ of the CATE $s_o(Z)$, and use this measure to sort observations into groups that are most and least treated, study the average characteristics of the groups,

$$\delta_1 = E[g(Y, Z)|G_1] \quad \text{and} \quad \delta_K = E[g(Y, Z)|G_K]$$

where G_1 is the least affected group of observations, G_K is the most affected group of observations, and $g(Y, Z)$ is the characteristics vector of an observation.

The estimation procedure can be summarized as the following. First, we partition

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

the sample into a "main" sample and an "auxiliary". Second, we train a machine learning model using all control variables (Z) to predict FinTech adoption (Y), for only the treatment group of the auxiliary sample. Then apply this model to make predictions on the main sample, which are the predicted treated effects. Third, train the machine learning model for only the control group of the auxiliary sample. Then apply this model to make predictions on the main sample, which are the predicted baseline effects. The difference between the predicted treatment effects and predicted baseline effects is our estimated conditional treatment effects $\hat{s}(Z)$. Next, we run a weighted OLS regression using $\hat{s}(Z)$ to compute the group average treatment effects $E[s_o(Z)|G_k]$ and sort observations into groups that are least affected and most affected. Last, we calculate the average characteristics of groups who are most and least treated. To overcome the randomness brought by the sample splitting, we then repeat the above steps several times and take the medians of the point estimates and the p-values.

Before computing the group average treatment effects, CDDF suggest to first calculate the best linear predictor (BLP) of the conditional average treatment effects. The BLP takes the form

$$
\begin{aligned}
BLP[s_0(Z)|S(Z)] &= \arg \min_{f(z) \in \text{Span}(1, S(Z))} E[s_0(Z) - f(Z)]^2 \\
&= \beta_1 + \beta_2(S(Z) - ES)
\end{aligned}
$$

The BLP results are shown in Table A11, with adjusted p-values reported in the parenthesis. Column (1) shows that the average treatment effects β_1, which is positive and statistically significant. Being exposed to the Wells Fargo scandal (high Wells Fargo scandal exposure) leads to a 1-percentage-point increase in the probability of choosing FinTech lenders. The magnitude is slightly smaller than the reduce-form DID estimate in Table A6. The heterogeneous effects coefficient β_2 is statistically significant. Therefore, I strongly reject that the null hypothesis that $S(Z)$ is a complete noise proxy for $s_0(Z)$, and reject that there is heterogeneity in $s_0(Z)$.

The BLP results have validated that the CDDF estimator is a reasonable proxy for the conditional treatment effect with respect to FinTech adoption, and there exits treatment effects heterogeneity. The results are less significant for trust in banks, probably due to the small number of observations (less than 4000). Next I compute the average treatment effects of exposure to the Wells Fargo scandal across different race groups, shown in A11.

B.1 Estimation Procedure

Chernozhukov et al. (2020) (CDDF) develops a generic machine learning inference on heterogeneous treatment effects in randomized experiment.[16] In this section, I outline the setting and in their paper and my estimation procedures.

I follow Deryugina et al. (2019), applying CDDF in a quais-experiment framework. In my main setting, the treatment effect is a continuous variable. Given that the CDDF method applies only to binary treatment, I partition the Wells Fargo exposure into "treatment" ($T = 1$) and "control" groups ($T = 0$), assigning an individual to the treatment group if the individual resides in a county with above-median level of the Wells Fargo deposits share after 2016.

Let Y be the variable of interest and Z be the vector of covariates. In their natural experiment setting, researchers are interested in comparing the outcomes of two (or more) randomly assigned groups. Each data point is randomly assigned to a treatment group ($T = 1$) or a control group ($T = 0$). The probability of assigning to the treatment group is known to the researcher, denoted as the propensity score $p(Z)$, which is a function of the observed covariates. Researchers are interested in the treatment effect heterogeneity, the conditional average treatment effect (CATE).

$$s_o(Z) = E(Y|T = 1, Z) - E(Y|T = 0, Z)$$

Though it is difficult to construct an unbiased and consistent estimator of the CATE $s_o(Z)$, CDDF argues that we can use generic machine learning method to construct an imperfect estimator $\hat{s}(Z)$, and use this measure to study some properties of the CATE $s_o(Z)$. Before explaining how to construct the estimator $\hat{s}(Z)$, I first talk about the three

[16] Some research, for example, Athey and Imbens (2016) and Athey and Wager (2019), focus on more sperfici tools

properties of the CATE that can be derived using the new method.

- Best Linear Predictor (BLP) of the CATE $s_o(Z)$ using $S(Z)$ The BLP of the CATE $s_o(Z)$ using $S(Z)$ is defined as the following:

$$\begin{aligned} BLP[s_0(Z)|S(Z)] &= \arg \min_{f(z)\in \text{Span}(1,S(Z))} E[s_0(Z) - f(Z)]^2 \\ &= \beta_1 + \beta_2(S(Z) - ES) \end{aligned}$$

  If $S(Z)$ is a complete noise proxy for $s_0(Z)$, then we have $\beta_2 = 0$. Furthermore, if there exits no heterogeneity, which means $s_0(Z) = s$, then $\beta_2 = 0$. Therefore, rejecting $\beta_2 = 0$ means that $S(Z)$ is a relevant estimator of $s_0(Z)$, and that there is heterogeneity in $s_0(Z)$.

- Sorted Group Average Treatment Effects (GATE)

$$E[s_0(Z)|G_k]$$

  where $\{G_k\}_{k=1}^K$ are non-overlapping intervals that span the support of S, and CDDF impose the monotonicity restriction that

$$E[s_o(Z)|G_1] \leq ... \leq E[s_o(Z)|G_K]$$

- Classification Analysis (CLAN)
  When BLP and GATES show that there exits substantial heterogeneity, we can examine the properties of the subpopulation of the most and least affected group, G_1 and G_K. Denote $g(Y, Z)$ as a characteristics vector of an observation. It is interesting to know the average characteristics of the most and least affected groups.

$$\delta_1 = E[g(Y,Z)|G_1] \quad \text{and} \quad \delta_K = E[g(Y,Z)|G_K]$$

To study the three properties of the treatment effect heterogeneity $s_0(Z)$, CDDF propose the following algorithm.

Step 1 Split sample equally into the main sample M, and the auxiliary sample A. Randomly split is S times (e.g., S = 100), each split is indexed by i. So we generate S random splits of the sample, denoted as $\{M_i, S_i\}_{i=1}^{S}$. Choose significant level α

Step 2 For each split $i = 1, ..., S$, we repeat the following steps:

1. Given the main sample M_i, and the auxiliary sample A_i. The propensity score $p(Z)$ is known by the researcher. (we ignore the subscription i later)
2. Use the auxiliary sample A to train a machine learning (ML) model. First, predict Y_A using Z_A using only treatment group of the auxiliary sample, which is treatment effect $TR()$. Second, predict Y_A using Z_A using only control group of the auxiliary sample, which is baseline effect $B()$. Here we follow Deryugina et al. (2019), using gradient boosted decision trees (XGBoost) implemented by Chen and Guestrin (2016).
3. Use the two models trained on the auxiliary sample to make predictions on the main sample. Predicted treatment effect is $Y^{\hat{T}=1} = TR(Z_M)$, predicted baseline effect is $Y^{\hat{T}=0} = B(Z_M)$.
4. **On the main sample**, calculate the difference between treatment effect and baseline effect as proxy predictors, $\hat{S}(Z) = Y^{\hat{T}=1} - Y^{\hat{T}=0}$.
   Note that $\hat{S}(Z)$ is an estimator for the conditional average treatment effect $s_o(Z) = E(Y|T=1, Z) - E(Y|T=0, Z)$. The estimator is possibly a biased and inconsistent estimator. Nevertheless, CDDF shows that the estimator can be used easily to derive some important properties of $s_o(Z)$.

   (a) BLP

   The BLP parameters are estimated by a weighted OLS

$$Y = \alpha X_1 + \beta_1(T - p(Z)) + \beta_2(T - p(Z))(\hat{S}(Z) - E[\hat{S}(Z)]) + \varepsilon$$

   where the weights are $w(Z) = \frac{1}{p(Z)(1-p(Z))}$, $X_1 = \{1, Y^{\hat{T}=0}, Y^{\hat{T}=1}\}$ includes a constant, predicted baseline effect, and predicted treatment effect.

(b) GATE

The GATE parameters are estimated by a weighted OLS

$$Y = \alpha X_1 + \sum_{k=1}^{K} (T - p(Z)) \cdot 1(S \in G_k) + \varepsilon$$

where the weights $w(Z)$ and controls X_1 are the same as below. The monotonic groups are sorted by $\hat{S}(Z)$. For example, G_k is the k-quintiles of $\hat{S}(Z)$.

(c) CLAN

$$\hat{\delta}_k = \hat{E}[g(Y, Z) | S \in G_k]$$

where $g(Y, Z)$ is a characteristics vector of an observation.

Step 3 Compute the final adjusted parameters

The reason why we conducted S random split in step 2 is to overcome the splitting uncertainty induced by random splitting. We report the median of all S estimated coefficient as our adjusted parameters of interest. For example, for heterogeneity parameter β_1, we have S estimated $\{\hat{\beta}_1^i\}_{i=1}^S$. Given significant level α, we have S estimated confident intervals $\{\hat{\beta}_{1,L}^i, \hat{\beta}_{1,U}^i\}_{i=1}^S$. The final adjusted estimates of $\hat{\beta}_1 = \text{Median}\{\hat{\beta}_1^i\}_{i=1}^S$, the final adjusted confidence interval has adjusted significant level 2α, and adjusted confidence interval is $\{\hat{\beta}_{1,L}^i, \hat{\beta}_{1,U}^i\} = \{\text{Median}\{\hat{\beta}_{1,L}^i\}_{i=1}^S, \text{Median}\{\hat{\beta}_{1,U}^i\}_{i=1}^S\}$.

C Models of Trust

In this section, I discuss various definitions of trust in the literature and how each definition relates to households' financial choices. In addition, I discuss how trust relates to reputation and stickiness and explore distinguishing these different concepts. I also provide a parsimonious model to fix ideas and how my empirical results are related to the parsimonious model.

C.1 Different Models of Trust

Guiso et al. (2008) defines trust as an individual's subjective belief of the probability of being cheated. When the firm cheats, the individual gets zero return from investing its stock. Gennaioli et al. (2015) defines distrust as the anxiety suffered by an investor for bearing risk. Trust reduces the risk aversion of the investor. Thakor and Merton (2018) defines trust as the belief about whether a lender is trustworthy and competent. Trust is an agent's subjective belief over the lender's type.

Both Guiso et al. (2008) and Gennaioli et al. (2015) directly embed trust into investors' expected utility. In Guiso et al. (2008), the dis-utility is directly modeled as utility loss due to a decrease in the value of the risky asset's payoff. In Gennaioli et al. (2015), trust in investment advisors can help reduce the level of risk-averse in the risky asset recommended by the investment advisors. The utility loss is due to a higher risk-averse when investing in low trust investment advisors. This is a different way of inserting trust in the utility function, but the general idea is quite similar. In the online appendix, Bertsch et al. (2020) models trust as the additional utility gain for the borrowers, similarly to Guiso et al. (2008). Thakor and Merton (2018) models trust similarly, but with more structure. The variations in trust in lenders are the variations in the beliefs of lenders' types. The belief affects investor's choice in the model through the investor's utility function.

C.2 A Simple Logit Demand System with Trust

I follow the definition of trust in Guiso et al. (2008) and use a simple logit demand system (Berry (1994), Buchak et al. (2018)) to illustrate the role of trust in determining the market share of FinTech lenders. Trust is defined as borrowers' subjective beliefs of the types of the lender – whether lenders will cheat or not. I follow Guiso et al. (2008) and Gennaioli et al. (2015), directly embed trust into borrowers' expected utility.

Demand There is a mass of borrowers, scaled to one. The utility for borrower b borrowing from lender i is the following:

$$u_{b,i} = -\alpha r_i + \lambda_i + \mu_i + \varepsilon_{b,i}$$

A borrower's utility is made up of three components. The first part is the interest rate charged by the lender; the second part $\lambda_i + \mu_i$ is the borrower's non-pricing-related preference for the lender, where λ_i is the trust placed on the lender and μ_i is other non-trust related factor. $\varepsilon_{b,i}$ is assumed to be i.i.d and follow a standard logit distribution.

Supply Each lender i is a price setter, maximize its expected profit

$$\pi_i = (r_i - \rho_i)s_i F - c_i$$

where s_i is the market share of lender i, ρ is the funding cost of lender i, F is the size of the market, and c_i be the entry cost for lender i.

The lender only enters the market if earning positive net profit $\pi_i \geq 0$. For simplicity, we assume that each lender has the same non-trust related entry cost.

Equilibrium I define a symmetric equilibrium following Buchak et al. (2018)

1. borrowers maximize utility, taking price as given

2. lender set interest rate to maximize profit, taking the price of other lenders as given (we can relax this assumption by assuming an oligopolistic competition, the only

difference will be lender's maximization problem).

Under the assumption of the logit demand system, the market share of lender i is the following

$$s_i = \frac{\exp(-\alpha r_i + \lambda_i + \mu_i)}{\sum_{j=1}^{N} \exp(\alpha r_j + \lambda_j + \mu_j)} \tag{5}$$

The lender's profit maximization gives the standard results for the interest rate

$$r_i - \rho_i = \frac{1}{\alpha}\frac{1}{1 - s_i} \tag{6}$$

the entry condition for the lender is that

$$(r_i^{\star} - \rho_i)s_i F - c \geq 0 \tag{7}$$

Aggregation There are three ways to aggregate the model. The first way is to simply sum all market share of FinTech lenders.

$$s_{\text{FinTech}} = \frac{\sum_{i \in \text{FinTech}} \exp(-\alpha r_{\text{i}} + \lambda_{\text{i}} + \mu_{\text{i}})}{\sum_{j=1}^{N} \exp(\alpha r_j + \lambda_j + \mu_j)} \tag{8}$$

In the simple logit demand model, a decrease in the borrower's trust in banks leads to an increase in FinTech's market share (probability of borrowing from FinTech).

The second way to aggregate is to assume that there is only one FinTech lender that competes with other lenders. The third way is to assume that this is a model of oligopolistic competition– the FinTech industry competes with the banking industry. i represents one particular industry rather than one lender. All three methods yield similar results.

C.2.1 Identifying Trust Channel in the Demand System

I test whether the market share of the lender s_i responds to *ceteris paribus* variation in borrowers' trust in the lender λ_i.

According to equation 8, trust can affect market share in three channels. In channel 1, trust affects households' demand through utility gain of trust λ_i in equation 8. In channel 2, trust affects households through both utility gain of trust λ_i and interest rate r_i. In channel 3, λ_i does not enter the utility function; the trust shock affects s_i only through the interest rate. In channel 4, λ_i does not enter the utility function; the trust shock affects s_i only through other unobserved variables μ_i. Channel 1 and Channel 2 are both the effects of trust. We first rule out the possibility of channel 4, that the trust shock affects FinTech adoption through other unobserved variables μ_i. However, empirically, even if we rule out the possibility that the trust shock affects other unobserved variables μ_i (channel 4), it isn't easy to distinguish between channel 2 and channel 3. To empirically test whether the trust will enter borrowers' utility function, I test whether channel 1 holds and rule out channels 2 and 3. [17]

My empirical results speak to the parsimonious model as the following:

1. To achieve my identification, the Wells Fargo shock should be uncorrelated with μ_i, which is unobservable factor that affects borrower's utility.

2. Given that the Wells Fargo scandal does not affect μ_i, in the model, the change in a lender's market share is driven by borrowers' trust in the lender and the interest rate charged by the lender. I empirically observe the positive average treatment effect of the Wells Fargo scandal on FinTech adoption. Therefore, the shock validates the existence of channels 1, 2, and 3.

3. I empirically observe the none treatment effect of the Wells Fargo scandal on loan pricing. Therefore, the shock rules out channels 2 and 3. My empirical results show that it is trust, not the interest rate, that affects the probability of choosing FinTech. One caveat is that my empirical results shows that *average* interest does not change after the Wells Fargo scandal. To perfectly match to the simple demand system, one can think of the model as a industry competition model, therefore the interest rate r_i in $exp(-\alpha r_i + \lambda_i)$ represents the average interest rate of each type of lender.

4. Moreover, in the parsimonious model, the supply shock only affects market share through the interest rate channel. The credit supply may affect the market share of

[17] My identification challenge is slightly different from the usual identification challenge in the demand system as discussed in Berry and Haile (2021). When estimating demand elasticity, the ideal shock is to variate price while keeping all other factors fixed. While in my setting, I could achieve identification (that trust enters households' utility function) by fixing the price variation.

the lender through channels other than the interest rate, which was not modeled (e.g., entry cost c). To rule out this possibility, I empirically test that the lenders' credit supply does not change.

5. To further identify the trust channel λ_i and rule out the possibility that the Wells Fargo scandal affects unobservable factor μ_i, I compare markets with different levels of trust erosion. If the shock affects s_i through unobservable factor μ_i other than trust λ_i, a variation in trust λ_i will not lead to a variation in market share s_i. My heterogeneity treatment effects analysis further rules out this possible explanation (channel 4).

6. To achieve equation 6, it is possible that the funding cost of the FinTech lenders decreased after the Wells Fargo scandal. However, we can not directly observe it in the data.

7. The model can partially speak to the stickiness (a shock to outside option) explanation: borrowers with different levels of trust erosion will have different changes in the probability of choosing FinTech loans.