Trust as an Entry Barrier: Evidence from FinTech Adoption

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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 the credit markets. The empirical setting exploits the outburst of the Wells Fargo scandal as a negative shock to the 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 more trust erosion has a larger increase in FinTech share relative to a county experiencing less trust erosion. Treatment effect heterogeneity estimations from both OLS and generic machine learning inference suggests that trust is less critical in FinTech adoption for African American borrowers.

Keywords: FinTech, FinTech Adoption, Trust in Bank, Bank Scandal, Belief Heterogeneity, Machine Learning, Causal Inference, Race

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1 Introduction

Technological innovation has always been intertwined with the financial industry. New technologies, including artificial intelligence, enable institutions to digitize most of their financial services. The current wave of FinTech innovation is revolutionizing the credit markets. 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 affects overall credit market conditions and credit accessibility. [1] In the U.S. residential mortgage market, online mortgage origination platform Quicken Loans has overtaken banking juggernauts such as Wells Fargo, becoming the largest retail mortgage originator.

However, FinTech adoption is not universal. Different regions have immensely different FinTech adoption rates. In some counties in the U.S., more than 75% mortgage origination services are performed online, while in others, FinTech services have never been used (see figure 1).

What are the potential entry barriers faced by FinTech lenders? This paper studies a potential entry barrier to FinTech lenders – trust in the incumbent lenders (banks). Trust, as defined in Guiso et al. (2008), an individual's subjective belief of the probability of being cheated, is at the heart of economic transactions. The role of trust in household financial decisions has been well documented in the literature. Giannetti and Wang (2016) find that the erosion of trust in corporations reduces household participation in the stock market. Rossi and Utkus (2020) perform a large-scale survey of investors' demand for financial advisor services, and find that trust is the most critical factor among all types of investors[2] and is one of the most significant barriers to using robo-advising.

Therefore, when FinTech lenders enter the market as new entrants, individuals with limited information about their service quality and creditability are unlikely to choose

[1] Fuster et al. (2018) 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.

[2] Including traditionally-advised, robo-advised, and unadvised investors. Robo-advising is a FinTech financial advising tool that delivers automated financial advice to individual investors.

them as the financial services providers. This could be particularly true for individuals who have high trust in traditional lenders. If the differences in the trust that individuals place on different financial institutions affect their choices of different types of lenders, then a decrease in the trust in banks could lead to an increase in the probability of choosing FinTech lenders.

However, 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.

To address these challenges, I exploit the Wells Fargo account fraud scandal as a negative shock to households' 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 inappropriately charging extension fees. The Wells Fargo fraud offers several advantages in my study. First, most of the fraudulent behaviors dated back to as early as 2005, and thus were unlikely to be a reaction to the recent episode of 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 good variation in the exposure to this fraud across geographic areas.

County-level household exposure to the Wells Fargo scandal is measured 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. To find support of this assumption, I use the Gallup survey data to measure the level of trust that households place on banks. Using a difference-in-differences strategy, I show that a one standard deviation increase in the exposure to the Wells Fargo scandal in a county leads to a 10% decrease relative to the average probability of trusting the banks.

Using the same difference-in-differences strategy, 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 contained 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. This result is consistent with the argument that the Wells Fargo scandal operates as a negative shock to trust in the banking sector as a whole, not just a shock to trust in Wells Fargo.

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.

To do so, I explore the substantial heterogeneity in households' responses to the Wells Fargo scandal conditional on an area's exposure to the 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. Because the Gallup Survey data is not a 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 provide further support for the argument that the exposure to bank scandals affects FinTech adoption through the erosion of trust in banks.

My conclusions rely on several assumptions. First, the level of exposure measured by the Wells Fargo deposits share should be uncorrelated with local shocks that may affect FinTech adoption. For example, D'Acunto and Rossi (2017) shows that large banks have been exiting some segments of the mortgage lending market since 2009. It is thus 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 region before the revelation of the Wells Fargo scandal. I find that both the 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 JPMorgan Chase bank deposit share 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 has 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 for most types of lenders, the percentage of mortgages rejected by lenders does not change after exposure to the Wells Fargo shock. 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 the exposure to the Wells Fargo scandal affects loan pricing. I follow Scharfstein and Sunderam (2016) to purge mortgage rate variations due to borrowers' credit risk, and find that FinTech lenders and non-Wells Fargo banks do not change their mortgage rates after the 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.

Having documented trust as a crucial entry barrier, I then examine the role of trust in FinTech adoption for borrowers from different race groups, given that FinTech lending reduces interest rate discrimination again the minority borrowers (Bartlett et al. (2019)). I explore the heterogeneous responses by using a generic machine learning inference approach proposed by Chernozhukov et al. (2020) to estimate the heterogeneous treatment effects. I compute the group average treatment effects of the exposure to the Wells Fargo scandal across different race groups and find that African American borrowers have a smaller and statistically insignificant increase in FinTech adoption, compared to other borrowers. The results suggest that the trust is less critical in FinTech adoption for the African American borrowers.

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

Recent studies in FinTech examine how FinTech adoption affects the overall credit market conditions and credit accessibility, and what drives the increasing growth of 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. (2018) find no correlation between improved internet access and FinTech adoption. Several papers focus on what types of borrowers FinTech lenders lend to and whether FinTech lenders extend credit to under-served borrowers (e.g., Tang (2018), Di Maggio and Yao (2020)). This is the first to study the role of trust in banks as an entry barrier to FinTech adoption and sheds new light on cross-regional differences in FinTech adoption.

This paper also contributes to the literature that documents the role of trust in finance, pioneered by Guiso et al. (2004), which 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)) , in the credit market (Brown et al. (2019), Thakor and Merton (2018)), in the financial advisory market (Gennaioli et al. (2015), Gurun et al. (2018)), and in 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 relation between bank misconduct and FinTech lending and examines the role of trust in banks as an entry barrier for FinTech adoption.

2 Data Description

2.1 Defining FinTech Lenders

The definition of a FinTech lender is central to my research question. Following existing literature studying FinTech lending in the residential mortgage origination market (Buchak et al. (2018), Fuster et al. (2018)), 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 our primary analysis sample, no bank falls into our strict definition of FinTech. For some banks, even though people can submit their documents online, they have to meet a banker in person to finalize the lending process.

The first key feature in the definition of FinTech is the scope of technology innovation. The lenders' ability to process fully-online mortgage origination services represents technology advancement in both "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 algorithm 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 information processing time and labor intensity.

Through the adoption of full-scale online lending technology initiated by mortgage companies, e.g., Quicken Loan's Rocket Mortgage, it is possible that some banks also provide complete online mortgage originations services. Also, 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.[3] 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 nearly two years after the treatment effect, and 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.

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

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

The number of mortgage loans can be defined as either the number of loan originations or the number of total loan applications. The number of total applications reflects households' demand for FinTech services, while the number of originated loans reflects equilibrium results of supply and demand. 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 answer different perspectives of the same question; we will use both in our analyses. If the supply of FinTech loans is elastic, these two measures should produce similar results.

2.2 U.S. Residential Mortgage Data

The Home Mortgage Disclosure Act (HMDA) requires all depository and non-depository lenders to disclosure 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 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)." 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. [4] In this project, instead of measuring aggregate demand for mortgage, I need to measure mortgage demand for different types of lenders (in different regions). However, the vagueness in defining "loan origination" and "loan purchase" in HMDA may bias the measurement. When a loan is originated by a retail originator and purchased by another institution in the same year, the loan may be double-counted in HMDA. I therefore 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. I therefore 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 one percent of 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.

[4] Fuster et al. (2018) 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.

Despite documentation as early as in 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 the regulators issued the enforcement actions. I therefore 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 some exposure to the Wells Fargo scandal prior to 2016 due to the news reported by *Los Angeles Times*. To explore this, I examine Google searches only from 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 pay attention to 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 branch office of all FDIC-insured institution, 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).[5] For each county, the Wells Fargo deposits share is calculated as the total amount of deposits in Wells Fargo branches in that

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

county over the total amount of deposits by all FDIC insured institution,

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

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 surveys, "Trust in Institutions." In the surveys, Gallup Analytics randomly interviewed around 1000 individuals across the U.S. about their confidence in U.S. institutions, from 1981 to 2018. The respondent's 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 are sampled proportional to the regional population.

Respondents report their confidence in institutions among 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 Small 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 the 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 obtain county-year and MSA-year level demographic data from the US Census American Community Survey(ACS) 1-year estimates [6] between 2014 to 2018. ACS 1-year estimates are only available for areas with a population larger than 65,000, so I restrict my sample to counties with a population larger than 65,000.

County-level political affiliation data are from the MIT Election Data and Science Lab[7]. 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 the independent candidates. I measure party affiliation for Non-republican as the total share of votes for the Democratic and the 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 variable 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 be correlated with both unobservable local banking industry shocks and local economic conditions. If one region experienced an unobservable banking industry shock, the banks' quality of services might

[6] 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.

[7] 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' 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 the FinTech adoption between an area with higher initial Wells Fargo deposit 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,

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

WF Exposure is the percentage of Wells Fargo deposits in county c in 2015. Post is a dummy equal to 1 after 2016, and 0 otherwise. I include county fixed effects λ_c and time fixed effects δ_t. County-level control variables are from Buchak et al. (2018), which I will discuss when presenting the results. Since the American Community Survey one-year estimates only reports 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 mortgage 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 choosing 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 Wells Fargo deposits share is uncorrelated with unobservable shocks that affect FinTech adoption. If there is an unobserved shock that only affects areas with a high initial Wells Fargo deposit shares, we should see the FinTech shares evolve differently between treated and less-treated regions before the revelation of the Wells Fargo scandal. We will thus examine the dynamic effects of the exposures to the Wells Fargo scandal on FinTech adoption between 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 relation between the 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 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 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. Though 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 $(= 10.4 *$

-0.279) in the probability to report trust in banks, which is a 10% decrease from the average probability to report trust in banks (29.6).

Column (2) includes several respondent-level control variables, including 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 economic magnitude remains similar. Heterogeneity in respondent characteristics and local economic conditions does not explain away 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 the trust in general businesses to measure the trust in FinTech companies. In the Gallup survey, individuals were surveyed on their confidences in big business, small business, and banks. Since FinTech companies do not belong to the traditional definition of bank lenders, the survey questions on trust in big business and trust in small business are the best available proxies for trust in FinTech companies. In columns (4) (5) (6) (7), I re-do all of the analyses using trust in big businesses and trust in small businesses as dependent variables. The results show that exposure to the Wells Fargo scandal does not decrease trust in big business or trust in small business. 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 A1, 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 affiliation is large and significant. On average, people who reported as affiliated with the Republican Party have much higher trust in banks. Being affiliated with the Republican Party increases the probability of reporting trust in banks by 6.5-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

I next 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) (2) include only originated loans, while columns (3) (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) (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 0.15-percentage-point increase $(= 10.4 * 0.013)$ in the probability of choosing a FinTech lender, which is a 2% increase from the average probability to choose 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. Comparing 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 Top 4 lenders as a measure of competition.[8] 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) (4) show the results using all mortgage loan applications to measure FinTech adoption.[9] 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 of credit supply. Later in section 4.5, I will further show that lenders' credit supply is not affected by the exposure to the Wells Fargo scandal.

In Table A2, 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.

[8]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

[9]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) shows that large banks have been exiting some mortgage lending market segments since 2009. To rule out the alternative channel, I estimate a 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 to 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. Year 2015 is omitted, as the reference year.

Figure 7 shows the dynamic effects of the exposure to the Wells Fargo scandal on FinTech adoption. The treatment dynamics are consistent with the parallel trends assumption. The increase in FinTech adoption happens in the treated areas only after the scandal in 2016, and there exist no pre-trends before the scandal. The results indicate that the Wells Fargo deposits in county c in 2015 is unlikely to be correlated with potential confounding unobservable shock related to FinTech adoption.

The public available HMDA dataset is at annual frequency, so my dynamic analysis is at annual frequency. Figure 3 shows an intensive search of "Wells Fargo Account Fraud Scandal" started in September 2016 when the regulators issued the enforcement actions. So in our primary annual-level analysis, the treatment year started in 2016. Ideally, we would like to see the treatment effect starts in September 2016. To explore the finer time trends, I turn to Fannie Mae and Freddie Mac 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 to one after the third quarter of 2016. 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 quarterly frequency. There is no significant differences between the more and the 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 exist 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 similar empirical analysis on the mortgage origination activitivies 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 shows that a one-standard-deviation increase in the exposure of Wells Fargo scandal leads to a $0.5\%(= 0.02 * 10.4/43.22)$ decrease in the probability of choosing a non-Wells Fargo bank, $0.7\%(= 0.03 * 10.4/44)$ increase in the probability of choosing a non-FinTech shadow bank. Although the bank scandal focuses on Wells Fargo, there exists 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 comparing to banks other than Wells Fargo. Moreover, exposure to the Wells Fargo scandal also increases the probability of choosing non-FinTech shadow banks, indicating that erosion of the trust in banks also benefits other types of non-bank lenders.

4.3 Heterogeneous effects of scandal on Trust in banks

In this section, I explore the heterogeneous effects of the Wells Fargo scandal on trust in banks to further sharpen the underlying mechanism of the documented effects. A large literature has documented the role of belief differences in household's financial decisions (e.g. Meeuwis et al. (2018), Giglio et al. (2019)). In particular, Meeuwis et al. (2018) uses political affiliation to measure ex-ante belief heterogeneity of investors. Tables 1 and 2 show that people with different political affiliations have different prior beliefs on 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, while 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), which find that individuals who do not prefer government ownership of businesses and who 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 respondent's 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 1 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 of trust in banks for individuals not affiliated with the Republican Party. The interaction term $WFExposure_c \times Post_t$ captures the average change in the 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 $NonRep_c \times Post_t$ allows me to tease out the potentially confounding change of 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 reported in Table 6. Column (1) shows the triple-difference effect on trust in banks. The coefficient is statistically significant and has a value of -0.195. In terms of economic magnitudes, a one-standard-deviation increase in the exposure to the Wells Fargo scandal for a non-Republican individual leads to a 2.0-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 3.0-percentage-point decrease in the probability to report trust in banks, which is a 11% decrease from the non-Republican's average probability of reporting trust in banks (26.1). In contrast, column (3) shows that the average Republican respondents has only 1.0-percentage-point decrease in the probability of reporting trust in banks, and the decrease is not statistically significant.

In columns (4) - (9), I re-do all of the analyses using trust in big business and trust in small business as dependent variables. The results show that exposure to the Wells Fargo scandal does not decrease trust in big business or trust in small 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.

I also conduct similar analyses but split survey respondents by their gender and ideology, as shown in figure 9. The pictures show that for more liberal survey respondents, the individuals who resided in treated counties reported larger decreases in trust in banks, and there is no heterogeneous response between female and male survey respondents. The results suggest that heterogeneous responses do not exist in random sample split, but are driven by individuals' different priors.

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

4.4 Heterogeneous effects of scandal and FinTech Adoption

In the previous section, I document 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. If the Wells Fargo scandal affects FinTech adoption through the erosion of trust in banks, then individuals leaning towards the non-Republican Party should be more likely to choose FinTech lenders than others with the same exposures 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 the household's probability to be 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. I measure county-level FinTech adoption using the share of loans by FinTech lenders. Consistently with the loan level analysis, I analyze both loan application and loan origination.

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 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, it is possible that different updating of beliefs about the future of the US economy may affect FinTech adoption. Including the term $NonRep_c \times Post_t$ allows me to 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 of 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 roughly 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 share ($\geq 45\%$, the sample median) and with low non-Republican share. 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. The result thus 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 prior to 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 Robustness

4.5.1 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 the 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 of 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.[10] JPMorgan Chase is the fourth largest residential mortgage originator and has a similar origination volume as Wells Fargo. If the positive relationship between FinTech adoption and exposure to the Wells Fargo scandal reflects decline of big banks' participation in mortgage origination, then we should see a positive relationship between the JPMorgan Chase share and FinTech adoption.

Results shown in table 8a 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, results in table 8b show that a higher exposure to JPMorgan Chase bank is not accompanied by a larger decrease in the trust in banks. The falsification tests suggest that our results are unlikely to be driven by the nation-wide decline of big banks' participation in mortgage origination and other structural change in big banks.

4.5.2 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 exposures 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

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

originations to measure FinTech adoption, I now more formally rule out the supply side interpretation by showing that both mortgage acceptance rates and total bank deposits do not change.

Table 9a shows that the percentage of mortgage rejected does not significantly increase for all types of lenders after the exposure to the Wells Fargo shock, which is consistent with the credit supply channel. The rejection rate for non-Wells Fargo banks even 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), trust gives lenders access to cheaper credit. It is thus crucial to examine how the erosion of trust in banks affects bank deposits. Table 9b examines how the exposure to the Wells Fargo scandal affects per capita deposits of Wells Fargo, and per capita deposits of other banks.

I find that the 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, though deposits per capita in column (6) does 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 9a, suggesting that total credit supply from banks unlikely 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 its access to financing.

Moreover, Table A4 further analyzes the effect of the scandal on banks' credit supply using the triple differences specification. In the previous section, I show 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 9 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 post the scandal.

4.5.3 Loan Pricing

The evidences so far have shown that the erosion of trust in banks leads to an increase in FinTech adoption in local mortgage markets. However, it is possible that borrowers 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)[11] 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) and the GSE 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 is determined solely by FICO score, LTV, and loan type, according to a Loan Level Price Adjustments (LLPAs) matrix. As a result, any interest rate deviation from the guarantee fee reflects the lenders' different overhead costs and strategic price positioning. Specifically, I run the following regressions,

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

where $Rate_{ijcm}$ is 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 captures the variation in LLPAs matrix. I restrict the sample to 30-year, full amortizing, full documentation, single-family, and conventional fixed rate mortgage with FICO scores above 660 to achieve maximal comparability.

For each MSA c at each quarter t , we compute the average residual rate charged by

[11] The method is pioneered by Hurst et al. (2016), and similarly used in Bartlett et al. (2019).

different types of lenders as our variables of interest.

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

where $LenderType$ can be FinTech, Wells Fargo bank, or non-Wells Fargo bank. All measured are done separately for home purchase mortgage and refinance mortgage.

I estimate a similar difference-in-differences model as before, but use the average residual rate charged by different types of lenders as the dependent variables. I include several MSA-level characteristics as control variables, and the results are shown in Table 10. In columns (1) and (2), the dependent variables are average home purchasing mortgage rate and refinance mortgage rate charged by the 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. Result in columns (3) shows that for home purchase loans, the Wells Fargo charges a significantly higher interest rate after losing clients due to the erosion of trust in banks. The increases in 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 the 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.

5 Heterogeneous Responses of Different Race Groups

One argument in support of the FinTech adoption is that the FinTech lending can reduce face-to-face bias against minority borrowers. For example, Bartlett et al. (2019) find that FinTech lending reduces discrimination in interest rate against Latinx and African-

American borrowers.[12] Since the previous results in the paper have documented the role of trust as a crucial entry barrier, I further investigate how different race groups response to the Wells Fargo scandal heterogeneously.

One advantage of the Gallup and the HMDA data is that both datasets contain individual-level information on race and ethnicity. In this section, I focus on the difference between African American borrower and non-Hispanic White borrower. [13] 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.

To better understand the borrowers' heterogeneous responses to the Wells Fargo scandal in FinTech adoption, in additional 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. 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.[14]. The estimation details are shown in the appendix B.1.

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

[12] 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.

[13] The results for White-Hispanic borrowers are provided in the appendix. The results for White-Hispanic borrowers are inconsistent across different specifications, which suggests that there are other unobservable factors that may affect White-Hispanic borrowers' behavior. Moreover, given the caveat in Buchak et al. (2018) and Fuster et al. (2018), since the HMDA has missing values on race and ethnicity, one need to be cautious in interpreting the results.

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

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 after the exposure to the Wells Fargo scandal, conditional on the individual's characteristics.

Before examining FinTech adoption, I begin by investigating whether African American borrowers have different decrease in trust in banks after the exposure to the Wells Fargo scandal. In columns (1) - (3) of Table 11a, the dependent variables are individuals' trust in banks. I include only non-Hispanic White survey respondents in column (1) and only African Ameircan survey respondents in column (2). Both DID coefficients in columns (1) and (2) are negative. However, the DID coefficient is not significant for African American, which is possibly due to the small variation in the outcome variables after controling for county and year fixed effects. In column (3), the triple interaction term $WFExposure_c \times Post_t \times AfricanAmerican$ captures the additional change of trust in banks for the African American borrower. The triple interaction coefficient is not statistically significant. Overall, the results suggest that the African American borrowers do not have a statistically significant difference in trust erosion after the exposure to the Wells Fargo scandal.

Table 11b reports the results of FinTech adoption. The dependent variable is a dummy variable that equals to one hundred if the lender is a FinTech lender. In columns (1) - (3) of table 11a, coefficients are estimated from traditional OLS (difference-in-differences) estimations. In columns (4) - (5) of table 11b, coefficients are estimated from CDDF treatment effects heterogeneity estimations. In column (1), the interaction between $WFExposure_c \times Post_t$ is positive and statistically significant for non-Hispanic White borrowers. Given tha non-Hispanic White borrowers are the majority group in our sample, the result is consistent with the average treatment effect documented in Table 3. In column (2), the DID coefficient is positive but not significant. In column (3), the triple interaction term $WFExposure_c \times Post_t \times AfricanAmerican$ is negative and statistically significant, suggesting that the effect of the Wells Fargo scandal on FinTech adoption is less pronounced for the African American borrowers.

I also find significant heterogeneous responses to the Wells Fargo scandal across different race groups in the CDDF estimation results. In column (4), for non-Hispanic White mortgage borrower, being exposed to the Wells Fargo scandal leads to 1.447-percentage-point increase in the probability of choosing a FinTech lender. However, as shown in column (5), for African American, the treatment effect of the exposure to the Wells Fargo scandal is smaller, and not statistically significant. The results are consistent with the OLS evidence in columns (1)-(3). Altogether, the results seem to suggest that African American borrowers do not respond significantly to the Wells Fargo scandal.

What explains the heterogeneous response of different borrowers? Given that Bartlett et al. (2019) find that African American borrowers are less discriminated by FinTech lenders, it is possible that trust as an entry barrier is less crucial for those who would benefit more from adopting FinTech lenders. This interpretation is consistent with our finding in Table 3 that African American borrowers use more FinTech lenders compared with non-Hispanic White borrowers.

6 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 show 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 compared to 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.

I find that trust is less critical in FinTech adoption for the African American borrowers. The result can help policymakers to design more suitable policies to promote FinTech adoption among financially under-served communities.

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Figures

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

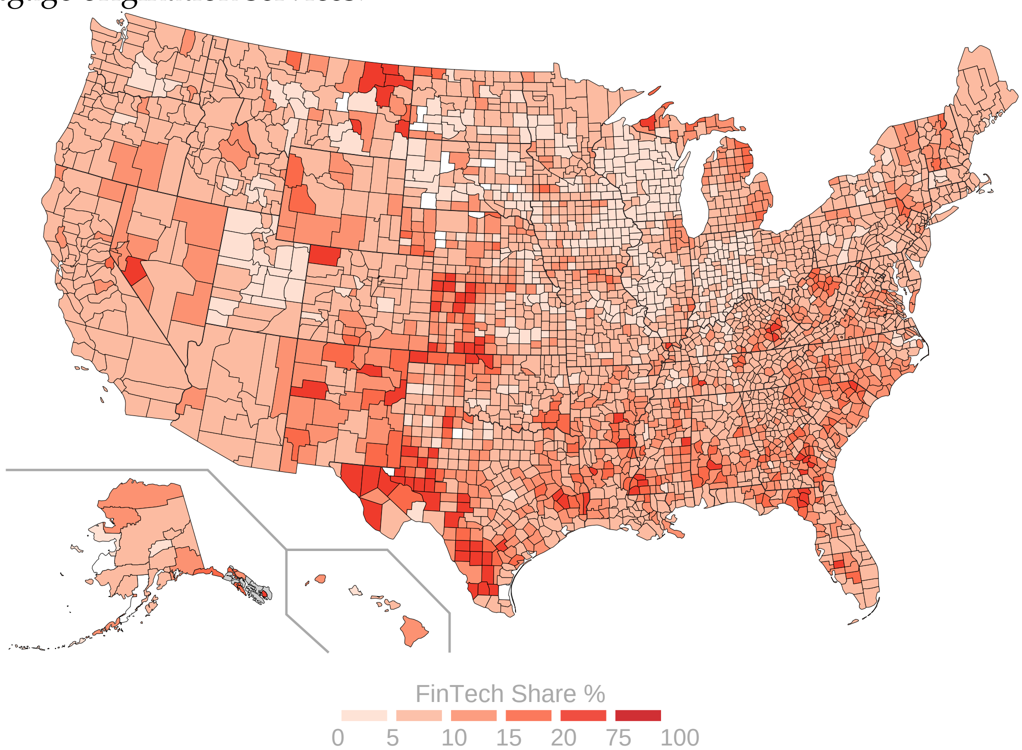

Figure 2: FinTech Adoption in Low and High "Trust in Banks" States

This figure plots a time series of FinTech adoption for states with low "Trust in Banks" and states with 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 share are provided for both loan origination and loan applications.

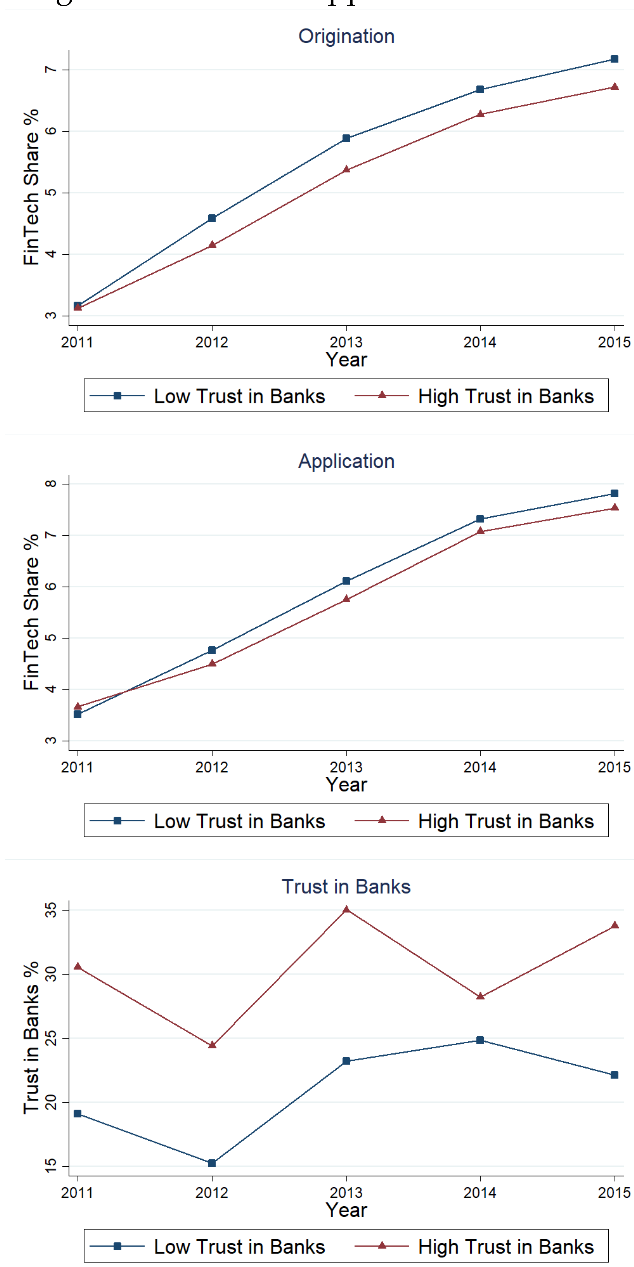

Figure 3: Google Search Intensity Trend of the Wells Fargo Scandal

This figure displays Google search topic trends for "Wells Fargo Account Fraud Scandal" and "Wells Fargo Scandal" from 2013 Jan to 2018 Dec. 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), respectively. The Google search index is normalized to 100, which is the index value when the topic has the highest search intensity volume.

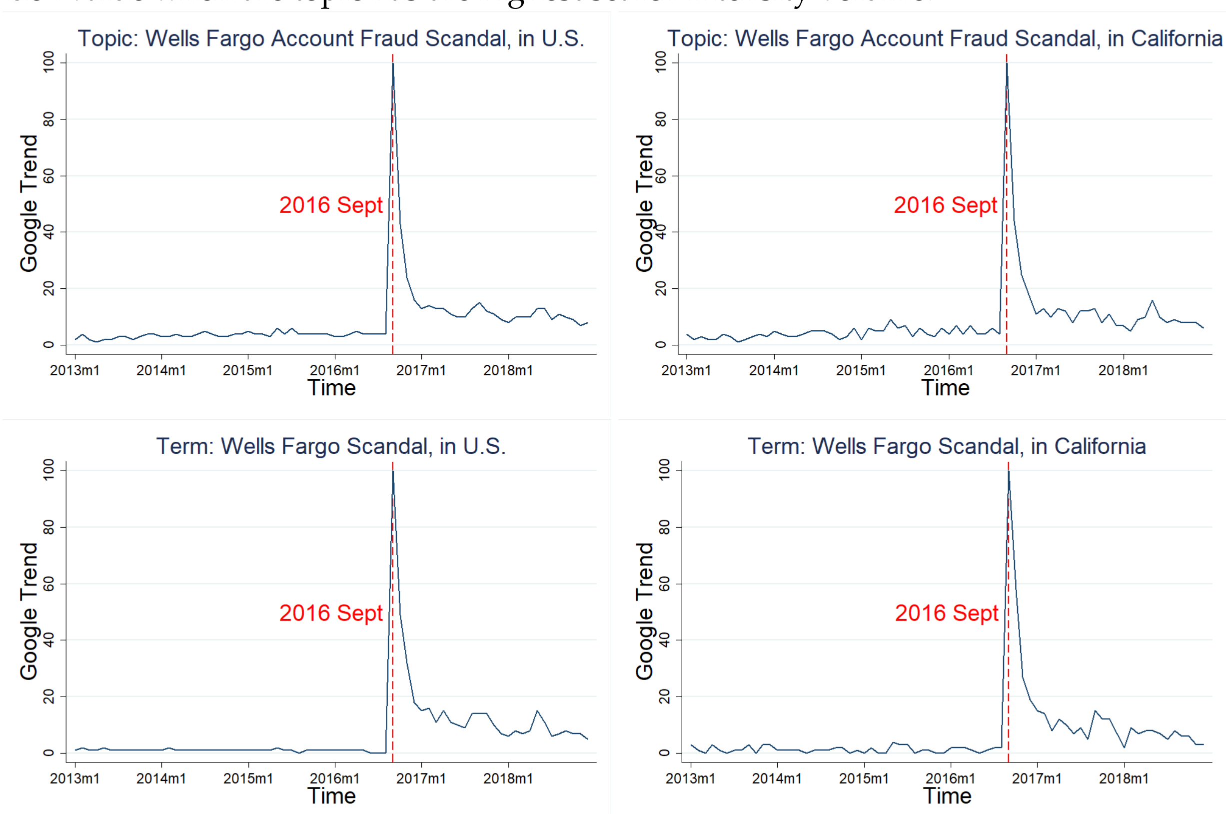

Figure 4: Household Exposure to the Wells Fargo Scandal

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).

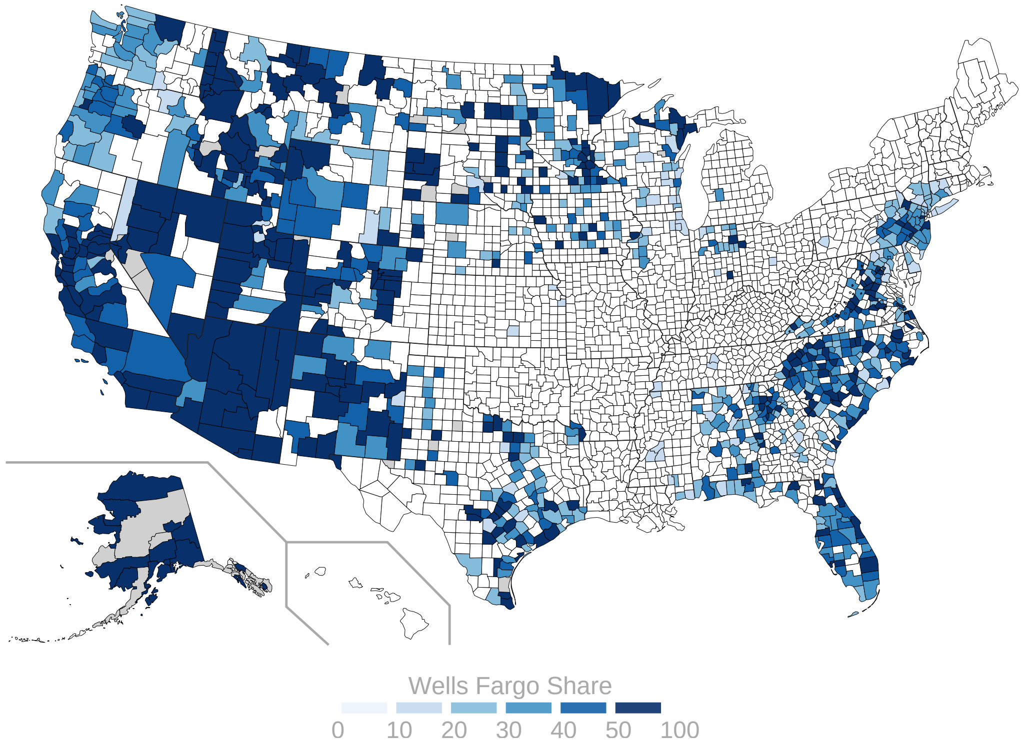

Figure 5: Google Search Intensity

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.

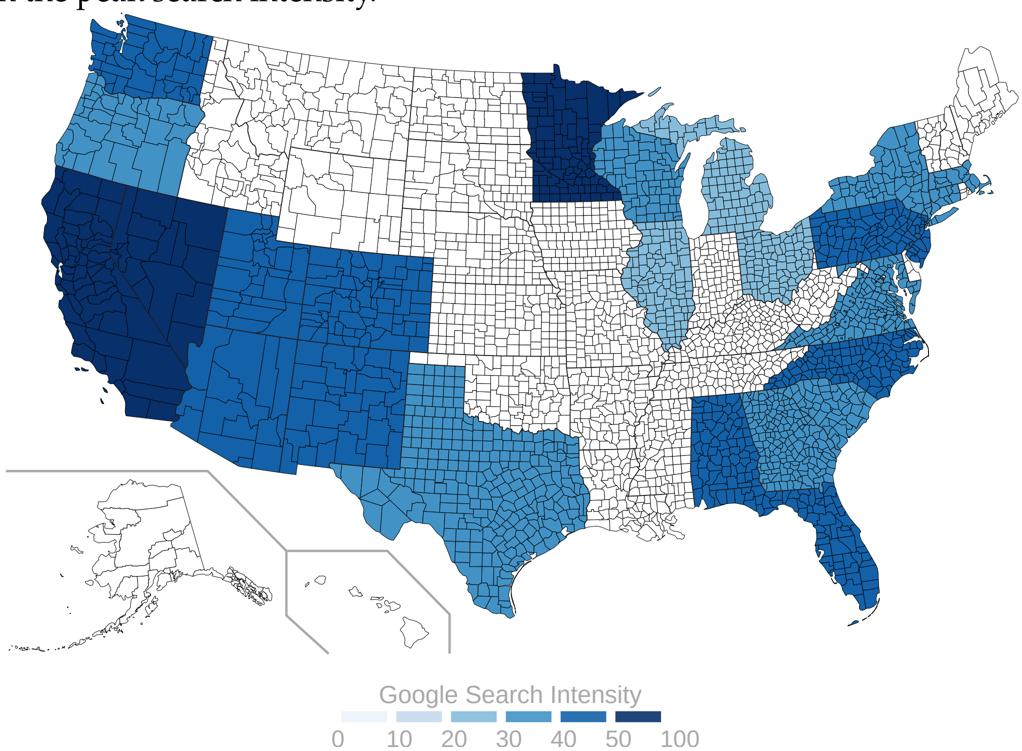

Figure 6: Political Affiliation

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

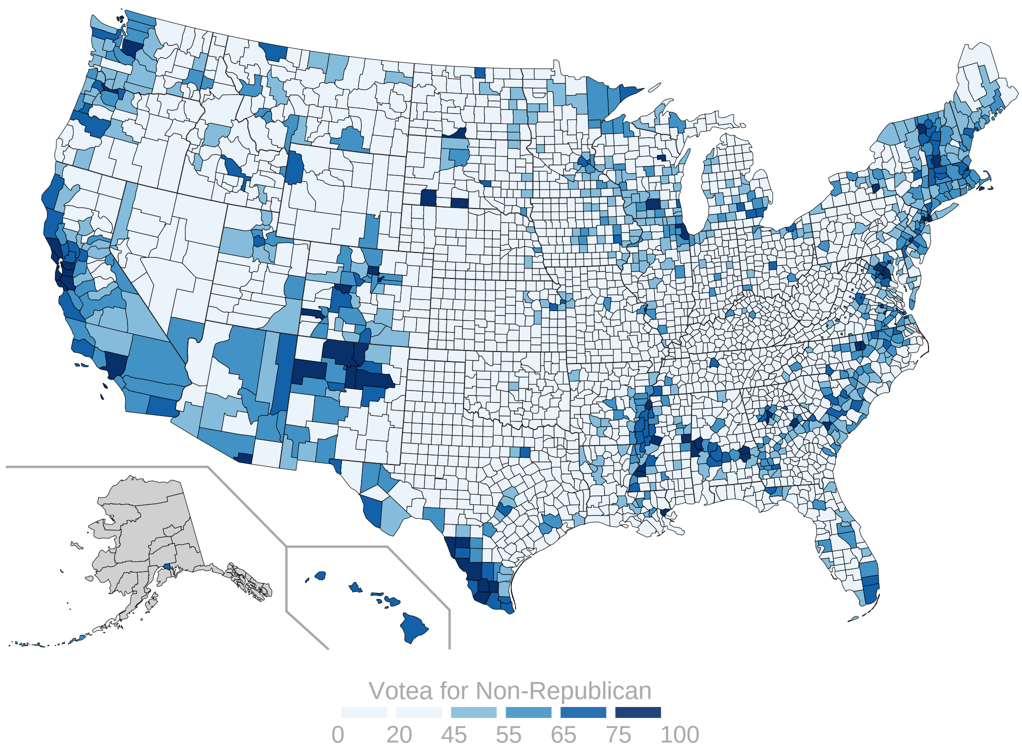

Figure 7: Dynamic effects of the Wells Fargo scandal revelation on FinTech adoption

This figure shows the dynamic effects of the exposure to the Wells Fargo scandal on FinTech adoption. Coefficients are estimated from the follow 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 to 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. Year 2015 is omitted, as the reference year. Results including only originated loans and including both originated and rejected loans are provided. County and Year fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at 5% level.

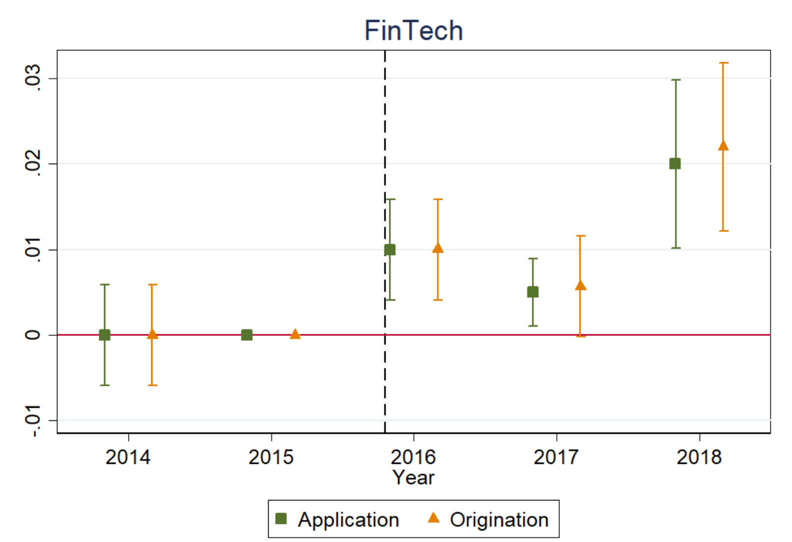

Figure 8: Dynamic effects of the Wells Fargo scandal on FinTech adoption: Fannie Mae and Freddie Mac Loans

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. 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 5% level.

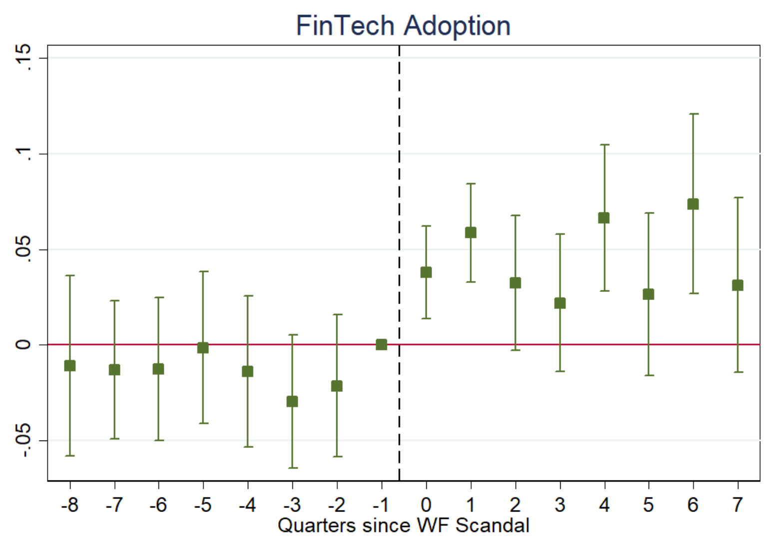

Figure 9: The effect of the revelation of the Wells Fargo scandal on Trust in Banks

This figure reports the effects of the Wells Fargo account fraud scandal revelation 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.

$$y_{i,c,t} = \beta WFExposure_c \times \sum_{t=2015,t\neq2015}^{2018} Dummy_t + Control_{i,c,t} + \lambda_c + \eta_t + \varepsilon_{i,t}$$

The dependent variable is 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, 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 equaling one at year t. Year 2015 is omitted, as the reference year. The regressions are run in subsamples, split into "Republican" or "Non-Republican" respondents, "Conservative" or "Liberal" respondents, "Male" or "Female" respondents. County and Year fixed effects are included in all regressions. Standard errors are clustered at the county level; confidence intervals are calculated at 5% level.

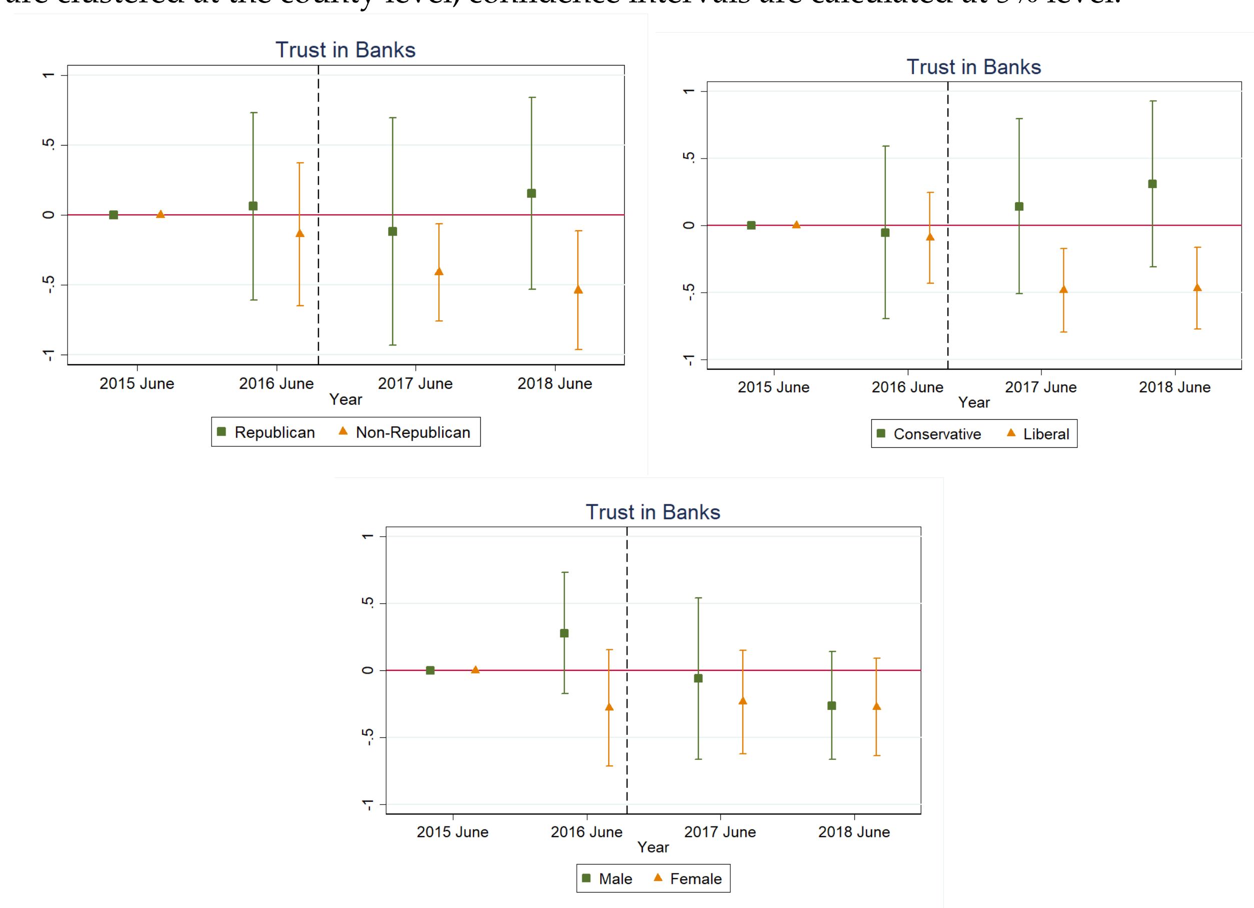

Figure 10: Dynamic triple effects of the revelation of the Wells Fargo scandal on FinTech adoption

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 share voted for Non-Republican candidates in the 2016 election. A dummy variable is equaling 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 5% level.

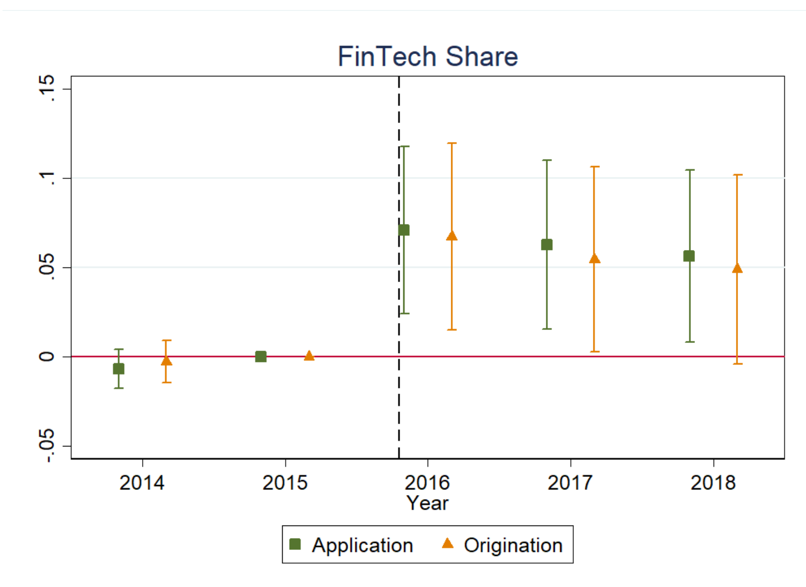

Table 1: Summary Statistics

This table report the summary statistics of key variables. Table A and table B present summary statistics for counties with populations larger than 65000. The U.S. Residential Mortgage Data data is from 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 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	29.66	0.00	45.68	0.00	100.00	4851
Trust in Big Business	66.88	100.00	47.07	0.00	100.00	4713
Trust in Small Business	69.79	100.00	45.91	0.00	100.00	4713
Trust in Media	46.12	50.00	23.38	20.00	65.00	4745
Republican	0.45	0.00	0.50	0.00	1.00	4851
Age	53.68	56.00	18.80	38.00	68.00	4765
Male	1.47	1.00	0.50	1.00	2.00	4851
College Education	0.74	1.00	0.44	0.00	1.00	4851
High Income	0.35	0.00	0.48	0.00	1.00	4851
White	0.77	1.00	0.42	1.00	1.00	4851
Black	0.07	0.00	0.25	0.00	0.00	4851
Hispanic	0.10	0.00	0.30	0.00	0.00	4851
Protestant	0.43	0.00	0.50	0.00	1.00	4851
Jewish	0.02	0.00	0.14	0.00	0.00	4851
Republican						
Trust in Banks	33.97	0.00	47.37	0.00	100.00	2193
Trust in Media	37.97	35.00	20.70	20.00	50.00	2147
Non-Republican						
Trust in Banks	26.11	0.00	43.93	0.00	100.00	2658
Trust in Media	52.86	50.00	23.32	35.00	65.00	2598

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. 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, trust in big business, and trust in small 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 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		Trust in Small Business	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WF Exposure× Post	-0.279**	-0.257*	-0.272**	0.028	-0.006	0.040	0.029
	(-2.1)	(-1.9)	(-2.2)	(0.4)	(-0.1)	(0.6)	(0.4)
NonRepublican		-14.287***	-5.546***		-16.412***		-5.311***
		(-8.0)	(-3.0)		(-17.5)		(-6.2)
Age		-0.112**	-0.114**		0.006		-0.086***
		(-2.5)	(-2.4)		(0.3)		(-3.5)
Female		1.190	3.346**		-3.727***		-3.357***
		(0.7)	(2.1)		(-4.1)		(-4.1)
College Education		-2.288	-1.561		-1.213		3.013***
		(-1.2)	(-0.9)		(-1.1)		(2.8)
High Income		2.112	0.402		3.101***		2.233***
		(1.3)	(0.3)		(3.3)		(2.9)
White		-3.994	-2.221		-2.960		4.470**
		(-1.2)	(-0.7)		(-1.5)		(2.3)
Black		-0.298	0.181		-0.762		-1.802
		(-0.1)	(0.0)		(-0.3)		(-0.7)
Hispanic		-4.238	-3.616		-1.239		-0.602
		(-1.1)	(-0.9)		(-0.5)		(-0.3)
Protestant		3.865**	3.499**		0.960		0.490
		(2.2)	(2.3)		(1.0)		(0.6)
Jewish		-1.710	-0.591		-2.278		-0.176
		(-0.3)	(-0.1)		(-0.9)		(-0.1)
% with less than 35K income		-1.355**	-0.957		-0.696**		0.348
		(-2.0)	(-1.5)		(-2.0)		(1.0)
Trust in Media		0.436***	0.328***		0.190***		0.056***
		(14.0)	(10.3)		(9.6)		(3.4)
Trust in Big Business			0.536***				
			(16.6)				
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4255	3720	3693	4237	3715	4266	3729
Adjusted R^2	0.003	0.060	0.142	0.019	0.121	0.016	0.043

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, 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) (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)	(2)	(3)	(4)
	FinTech	FinTech	FinTech	FinTech
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	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
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 MSA level. $WFExposure_c$ is the percentage of Wells Fargo deposits in MSA c in 2015. The Year-Quarter dummy variable t is equaling 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 in parentheses.

	FinTech (1)	FinTech (2)
WF Exposure×		
2014 Q3	-0.015	-0.011
	(-0.6)	(-0.4)
2014 Q4	-0.017	-0.013
	(-0.9)	(-0.7)
2015 Q1	-0.016	-0.013
	(-0.8)	(-0.7)
2015 Q2	-0.005	-0.001
	(-0.2)	(-0.1)
2015 Q3	-0.018	-0.014
	(-0.8)	(-0.7)
2015 Q4	-0.033*	-0.029*
	(-1.8)	(-1.7)
2016 Q1	-0.022	-0.021
	(-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*	0.033*
	(1.7)	(1.8)
2017 Q2	0.019	0.022
	(1.0)	(1.2)
2017 Q3	0.064***	0.067***
	(3.2)	(3.4)
2017 Q4	0.025	0.027
	(1.1)	(1.2)
2018 Q1	0.070***	0.074***
	(3.1)	(3.1)
2018 Q2	0.026	0.031
	(1.1)	(1.3)
MSA Level Controls	N	Y
MSA FE	Y	Y
Year-Quarter FE	Y	Y
N	5888	5840
adj. R^2	0.751	0.753

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 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, 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 control variables and fixed effects are indicated in the table. Standard errors are clustered at the county level, and *t* statistics in parentheses.

	(1) FinTech	(2) Wells Fargo	(3) Non-WF Bank	(4) Bank	(5) Non-FinTech ShadowBank	(6) ShadowBank
WF Exposure× 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 Level Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
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, trust in big business, and trust in small business, using "Confidence in Institution" survey data from Gallup Analytics from 2015 to 2018. Coefficients are estimated from the following regressions.

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

The dependent variable is the respondent's trust in banks, trust in big business, and trust in small 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 equaling to one if the respondent reports party affiliation as "Republican" or "Independent". In columns (2) (3) (5) (6) (8) (9), 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 in parentheses.

	Trust in Banks			Trust in Big Business			Trust in Small Business		
		NonRep	Rep		NonRep	Rep		NonRep	Rep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
WF Exposure× Post× NonRep	-0.341**			-0.147			-0.119		
	(-2.0)			(-1.5)			(-1.5)		
WF Exposure× Post	-0.056	-0.463***	-0.023	0.079	-0.043	0.032	0.099	0.021	0.062
	(-0.3)	(-3.4)	(-0.1)	(0.8)	(-0.4)	(0.2)	(1.3)	(0.2)	(0.5)
NonRep× Post	3.064			-1.900			0.323		
	(0.8)			(-0.9)			(0.2)		
Age	-0.108**	-0.111*	-0.059	0.006	-0.032	0.097**	-0.085***	-0.128***	-0.010
	(-2.2)	(-1.7)	(-0.7)	(0.3)	(-1.0)	(2.3)	(-3.5)	(-3.5)	(-0.3)
Female	1.188	0.451	-0.398	-3.688***	-2.517**	-6.480***	-3.347***	-3.069***	-5.080***
	(0.7)	(0.2)	(-0.1)	(-4.1)	(-2.2)	(-4.0)	(-4.1)	(-2.6)	(-4.2)
College Education	-2.308	-2.561	-1.226	-1.151	-3.049**	2.186	3.027***	3.894**	1.344
	(-1.2)	(-1.0)	(-0.4)	(-1.0)	(-2.1)	(1.2)	(2.8)	(2.2)	(1.0)
High Income	2.165	-1.949	6.573**	3.076***	0.779	5.773***	2.240***	0.948	3.407***
	(1.3)	(-0.9)	(2.2)	(3.2)	(0.6)	(3.6)	(2.9)	(0.8)	(3.1)
White	-3.852	-4.671	-6.497	-2.910	-5.738**	-0.029	4.518**	5.414**	2.954
	(-1.1)	(-1.0)	(-1.0)	(-1.5)	(-2.5)	(-0.0)	(2.3)	(2.3)	(1.0)
Black	-0.024	0.995	-9.744	-0.668	-1.048	-2.856	-1.713	0.928	-4.909
	(-0.0)	(0.2)	(-1.2)	(-0.3)	(-0.4)	(-0.6)	(-0.6)	(0.3)	(-1.2)
Hispanic	-4.228	-6.004	-13.973	-1.298	-2.265	-6.271	-0.611	-0.154	3.265
	(-1.0)	(-1.2)	(-1.5)	(-0.5)	(-0.8)	(-1.0)	(-0.3)	(-0.1)	(0.8)
Protestant	3.840**	5.089**	3.268	0.964	2.200	-1.102	0.487	1.147	-0.464
	(2.4)	(2.2)	(1.0)	(1.0)	(1.5)	(-0.7)	(0.6)	(0.9)	(-0.4)
Jewish	-1.750	-8.106	15.624	-2.348	-3.596	-0.780	-0.202	-1.376	-0.336
	(-0.4)	(-1.6)	(1.5)	(-0.9)	(-1.1)	(-0.1)	(-0.1)	(-0.6)	(-0.1)
% with less than 35K income	-1.321**	-1.690*	-1.601	-0.689*	-0.415	-1.178*	0.357	-0.805	0.921*
	(-2.0)	(-1.8)	(-1.2)	(-2.0)	(-0.8)	(-1.9)	(1.0)	(-1.4)	(1.8)
NonRep	-14.312***			-14.169***			-4.795***		
	(-4.3)			(-8.8)			(-3.2)		
Trust in Media	0.437***	0.412***	0.539***	0.193***	0.213***	0.190***	0.057***	0.093***	-0.012
	(13.5)	(10.9)	(9.0)	(9.7)	(8.9)	(4.9)	(3.5)	(4.2)	(-0.4)
Observations	3720	1985	1472	3715	1976	1474	3729	1988	1479
Adjusted R^2	0.060	0.076	0.039	0.121	0.077	0.044	0.043	0.047	0.015

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 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 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 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	0.058**			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)		
Population	0.001	0.001	0.004	0.001	0.002	0.001
	(0.9)	(0.8)	(0.6)	(0.8)	(1.4)	(0.2)
% Female	0.012	0.172*	-0.097	0.021	0.126*	-0.059
	(0.2)	(1.9)	(-1.6)	(0.4)	(1.7)	(-0.9)
% African American	0.045	0.083	-0.019	0.023	0.077*	-0.045
	(1.1)	(1.6)	(-0.3)	(0.6)	(1.7)	(-0.8)
% Hispanic	0.017	0.055	-0.028	0.100	0.068	0.142
	(0.2)	(0.6)	(-0.1)	(1.0)	(0.7)	(0.8)
% over 21	0.063	-0.012	0.114**	0.027	-0.008	0.051
	(1.6)	(-0.2)	(2.1)	(0.8)	(-0.2)	(1.0)
% over 65	-0.012	0.026	-0.043	-0.108	0.034	-0.167*
	(-0.2)	(0.2)	(-0.5)	(-1.5)	(0.3)	(-1.8)
% with less than 12th grade education	-0.010	0.023	-0.030	-0.030	-0.007	-0.037
	(-0.5)	(0.8)	(-1.1)	(-1.6)	(-0.2)	(-1.5)
% with bachelor degree or higher	-0.031**	-0.019	-0.034	-0.053***	-0.029	-0.063***
	(-2.1)	(-0.9)	(-1.6)	(-3.6)	(-1.5)	(-3.1)
% living in the same house last year	-0.017*	0.005	-0.033**	-0.014	0.022	-0.037***
	(-1.7)	(0.3)	(-2.5)	(-1.4)	(1.5)	(-2.7)
Median Household Income	-0.000*	-0.000***	-0.000	-0.000***	-0.000***	-0.000
	(-1.9)	(-3.1)	(-0.1)	(-3.2)	(-4.9)	(-0.4)
Unemployment Rate	-0.050**	-0.018	-0.067**	-0.060***	-0.030	-0.078***
	(-2.3)	(-0.6)	(-2.2)	(-2.9)	(-1.2)	(-2.7)
% with less than 35K income	-0.035***	-0.028*	-0.030*	-0.043***	-0.040**	-0.032*
	(-3.0)	(-1.7)	(-1.9)	(-3.7)	(-2.5)	(-1.9)
Top 4 Share	-1.752***	-0.185	-3.037***	-1.894***	-0.521	-3.137***
	(-3.1)	(-0.2)	(-4.2)	(-3.7)	(-0.6)	(-4.7)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	4054	2096	1968	4054	2096	1968
Adjusted R^2	0.871	0.899	0.847	0.892	0.910	0.877

Table 8: 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 8a, the dependent variable is the share of the number of mortgages handled by FinTech lenders for both origination and application. In table 8b, the dependent variable is the respondent's trust in banks, trust in big business, and trust in small 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 8a, NonRep is the percentage of share voted for Non-Republican candidates in the 2016 presidential election. In table 8b, NonRep is a dummy variable equaling to one if respondent reports party affiliation as Non-Republican. In the table 8a 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 NonRepublican Share	Low NonRepublican Share			High NonRepublican Share	Low NonRepublican Share
	(1) FinTech	(2) FinTech	(3) FinTech	(4) FinTech	(5) FinTech	(6) FinTech	(7) FinTech	(8) FinTech
Chase Exposure× Post	-0.011	-0.026	-0.003	-0.023	-0.010*	-0.008	-0.006	-0.007
	(-1.6)	(-1.1)	(-0.4)	(-1.3)	(-1.7)	(-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 Control	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4054	4039	2066	1943	4054	4039	2066	1943
Adjusted R^2	0.882	0.883	0.909	0.857	0.889	0.889	0.914	0.859

(b) Trust in Banks

	Trust in Banks				Trust in Big Business				Trust in Small Business			
			NonRep	Rep			NonRep	Rep			NonRep	Rep
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Chase Exposure× Post	0.026	0.110	-0.331	0.227	-0.071	0.001	-0.173	-0.063	-0.146*	-0.000	-0.119	-0.190
	(0.1)	(0.5)	(-1.0)	(0.8)	(-1.0)	(0.0)	(-1.1)	(-0.7)	(-1.8)	(-0.0)	(-1.3)	(-1.5)
Chase Exposure× Post × NonRep		-0.158				-0.139				-0.246**		
		(-0.7)				(-1.4)				(-2.2)		
NonRep× Post		4.530				-1.233				1.321		
		(1.0)				(-0.6)				(0.7)		
County Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3426	3426	1360	1801	3427	3427	1365	1795	3440	3440	1371	1807
Adjusted R^2	0.006	0.000	-0.021	0.010	0.094	0.038	0.029	0.022	0.047	0.038	0.045	0.033

Table 9: 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. 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 9a, the dependent variable is the percentage of mortgage application denied by different types of lenders. In table 9b, 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 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	-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 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	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		
	(1) Total	(2) Wells Fargo	(3) Non-Wells Fargo	(4) Total	(5) Wells Fargo	(6) Non-Wells Fargo
WF Exposure× 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 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 10: 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. Coefficients are estimated from 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.Mortage 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 equaling to one after 2016Q3. All regressions are done 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 in parentheses.

	FinTech		Wells Fargo		Non-Wells Fargo Bank	
	Purchase	Refinance	Purchase	Refinance	Purchase	Refinance
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure× 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 Level Control	Y	Y	Y	Y	Y	Y
MSA FE	Y	Y	Y	Y	Y	Y
Year-Quarter FE	Y	Y	Y	Y	Y	Y
Observations	5367	5808	5953	5610	5540	4968
adj. R^2	0.665	0.783	0.812	0.697	0.712	0.620

Table 11: 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, big business, small business (table 11a) , and FinTech adoption (table 11b). In table 11a and columns (1) - (3) of table 11a, coefficients are estimated from OLS. In columns (4) - (5) of table 11b, coefficients are estimated from CDDF treatment effects heterogeneity estimates. The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. In columns (1) (4) (7) of table 11a and column (1) of table 11b, only White Non-Hispanic borrowers are included in the sample. In columns (2) (5) (8) of table 11a and column (1) of table 11b, only African American borrowers are included in the sample. "Both" indicates that both White Non-Hispanic borrowers and African American borrowers are included in the sample. $WFExposure_c$ 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. For OLS regresions, standard errors are clustered at the county level, and t statistics in parentheses. For CDDF estimations, median p-values is reported in effects.

(a) Group Average Treatment Effect on Trust in Banks

	Trust in Banks			Trust in Big Business			Trust in Small Business		
	White Non-Hispanic	African American	Both	White Non-Hispanic	African American	Both	White Non-Hispanic	African American	Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
WF Exposure× Post	-7.376*	-5.699	-6.354*	0.015	1.661	0.217	-0.227	15.292**	1.524
	(-2.0)	(-0.5)	(-1.8)	(0.0)	(0.3)	(0.1)	(-0.1)	(2.4)	(1.0)
WF Exposure× Post ×African American			-2.933			2.836			3.921
			(-0.5)			(0.6)			(1.3)
African American× Post			6.259			-2.260			-2.975
			(1.2)			(-0.7)			(-0.9)
Observations	2716	319	3162	2714	319	3159	2723	321	3168
Adjusted R^2	0.063	0.100	0.062	0.140	0.151	0.123	0.027	0.014	0.044

(b) Group Average Treatment Effect on FinTech Adoption

	OLS			CDDF	
	White Non-Hispanic	African American	Both	White Non-Hispanic	African American
	(1)	(2)	(3)	(4)	(5)
WF Exposure× Post	1.390***	0.551	1.407***	1.447***	1.251
	(6.7)	(1.5)	(6.6)	[0.013]	[0.301]
WF Exposure× Post×African American			-1.218**		
			(-2.4)		
African American× Post			2.398***		
			(8.7)		
Observations	6737208	384230	7121438	6737208	384230
Adjusted R^2	0.037	0.030	0.037		

A Appendix Table

Table A1: 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, trust in big business, and trust in small 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		Trust in Small Business	
	NonRep	Rep	NonRep	Rep	NonRep	Rep
	(1)	(2)	(3)	(4)	(5)	(6)
WF Exposure× Post	-0.148**	-0.098	-0.023	-0.028	-0.082*	-0.084
	(-2.0)	(-0.8)	(-0.5)	(-0.5)	(-1.7)	(-1.2)
Age	-0.109*	-0.045	-0.028	0.091**	-0.149***	0.010
	(-1.7)	(-0.6)	(-0.9)	(2.2)	(-4.3)	(0.4)
Female	1.331	0.634	-2.613**	-5.842***	-3.479***	-5.343***
	(0.6)	(0.2)	(-2.3)	(-3.8)	(-2.7)	(-4.3)
College Education	-2.279	-0.912	-3.055**	1.854	3.723*	1.582
	(-0.9)	(-0.3)	(-2.2)	(1.0)	(1.9)	(0.9)
High Income	-2.105	6.282**	0.652	5.655***	1.450	3.847***
	(-1.0)	(2.2)	(0.5)	(3.6)	(1.1)	(3.6)
White	-4.636	-4.664	-5.577**	0.019	4.901*	0.837
	(-1.0)	(-0.7)	(-2.4)	(0.0)	(1.9)	(0.2)
Black	0.344	-6.855	-0.760	-3.076	-0.050	-5.718
	(0.1)	(-0.9)	(-0.3)	(-0.6)	(-0.0)	(-1.6)
Hispanic	-5.636	-12.006	-2.177	-6.542	-0.708	2.197
	(-1.1)	(-1.2)	(-0.8)	(-1.1)	(-0.2)	(0.5)
Protestant	4.751**	2.704	2.429*	-0.654	0.904	-0.642
	(2.1)	(0.9)	(1.7)	(-0.4)	(0.7)	(-0.4)
Jewish	-8.794*	14.621	-3.706	-1.063	-1.937	-1.496
	(-1.7)	(1.4)	(-1.2)	(-0.2)	(-0.9)	(-0.4)
Trust in Media	0.412***	0.536***	0.221***	0.178***	0.097***	-0.018
	(11.1)	(9.1)	(9.3)	(4.6)	(4.1)	(-0.6)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	2067	1592	2056	1592	2043	1577
Adjusted R^2	0.075	0.048	0.083	0.049	0.036	-0.071

Table A2: 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)	(2)	(3)	(4)
	FinTech	FinTech	FinTech	FinTech
WF Exposure× 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)
Type (Omitted Category = Conventional)				
FHA	2.527***	2.242***	4.041***	3.715***
	(15.4)	(13.5)	(21.5)	(18.8)
VA	0.225*	0.182	1.545***	1.459***
	(1.9)	(1.5)	(11.8)	(10.1)
FSA/RHS	-2.002***	-1.500***	-1.894***	-1.176***
	(-11.2)	(-7.2)	(-12.3)	(-6.2)
Type (Omitted Category = Home Purchase)				
Home Improvement	-1.360***	-1.102***	-4.495***	-3.877***
	(-12.4)	(-8.6)	(-31.8)	(-25.1)
Refinance	6.807***	6.971***	5.953***	6.338***
	(42.3)	(37.8)	(46.0)	(43.2)

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Table A2: continued

	Origination		Application	
	(1)	(2)	(3)	(4)
	FinTech	FinTech	FinTech	
...				
To continue				
Purchaser (Omitted Category = Held)				
Fannie Mae	10.882***	11.101***	7.644***	7.950***
	(55.7)	(50.9)	(40.8)	(38.9)
Ginnie Mae	11.233***	11.006***	6.223***	6.193***
	(41.7)	(36.1)	(31.6)	(27.7)
Freddie Mac	9.100***	9.298***	5.895***	6.180***
	(30.6)	(27.7)	(19.4)	(18.3)
Farmer Mac	-0.065	-0.195	-3.755***	-3.832***
	(-0.2)	(-0.5)	(-12.9)	(-10.3)
Private securitization	1.479***	1.816***	-2.373***	-1.858***
	(4.7)	(5.4)	(-7.0)	(-5.3)
Bank	2.875***	3.227***	-0.937**	-0.429
	(7.7)	(8.0)	(-2.5)	(-1.1)
Insurance	1.165***	1.530***	-2.963***	-2.430***
	(5.8)	(7.1)	(-14.9)	(-11.8)
Affiliate	-2.909***	-2.654***	-6.280***	-5.947***
	(-16.3)	(-14.1)	(-31.8)	(-28.1)
Other	0.829***	1.210***	-3.264***	-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***	11.012***	10.263***	10.644***
	(34.3)	(31.4)	(35.9)	(34.1)
Ethnicity (Omitted Category =)				
Hispanic	-1.215***	-1.372***	-0.516***	-0.769***
	(-7.0)	(-7.7)	(-2.9)	(-4.2)
NA	0.930***	-0.193	3.600***	1.779***
	(3.3)	(-0.8)	(10.2)	(5.8)
Race (Omitted Category = White)				
Native American	1.533***	1.666***	1.790***	1.881***
	(11.9)	(11.2)	(15.3)	(13.8)
Asian	-0.057	-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	6.166***	6.422***	4.800***	5.410***
	(34.8)	(34.6)	(24.9)	(27.9)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3417986162	29985964	44856156	39029308
Adjusted R^2	0.096	0.093	0.080	0.077

Table A3: 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	Low		High	Low
		NonRepublican Share			NonRepublican Share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FinTech	FinTech	FinTech	FinTech	FinTech	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)		
Population	0.002	0.002	0.010**	0.002	0.002	0.006
	(1.6)	(1.4)	(2.1)	(1.6)	(1.5)	(1.3)
% Female	0.066	0.226***	-0.089	0.075	0.181**	-0.046
	(1.3)	(2.7)	(-1.4)	(1.5)	(2.5)	(-0.7)
% African American	0.033	0.020	-0.017	-0.003	-0.015	-0.045
	(0.8)	(0.4)	(-0.3)	(-0.1)	(-0.3)	(-0.8)
% Hispanic	0.069	0.090	-0.184	0.114	0.120	-0.040
	(0.8)	(1.0)	(-0.9)	(1.5)	(1.4)	(-0.2)
% over 21	0.062*	0.020	0.119**	0.030	0.022	0.061
	(1.7)	(0.4)	(2.3)	(0.8)	(0.4)	(1.2)
% over 65	0.011	-0.006	-0.049	-0.094	-0.057	-0.185*
	(0.1)	(-0.1)	(-0.5)	(-1.2)	(-0.5)	(-1.9)
% with less than 12th grade education	-0.014	0.020	-0.055*	-0.030	0.001	-0.062**
	(-0.7)	(0.7)	(-1.9)	(-1.6)	(0.0)	(-2.3)
% with bachelor degree or higher	-0.025	-0.016	-0.035*	-0.045***	-0.028	-0.060***
	(-1.6)	(-0.8)	(-1.7)	(-3.0)	(-1.4)	(-2.9)
% living in the same house last year	-0.002	0.018	-0.019	0.003	0.031*	-0.022
	(-0.2)	(1.0)	(-1.4)	(0.2)	(1.7)	(-1.6)
Median Household Income	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000
	(-3.8)	(-3.5)	(-1.2)	(-5.3)	(-5.1)	(-1.3)
Unemployment Rate	-0.051**	-0.046	-0.060*	-0.053**	-0.045	-0.072**
	(-2.2)	(-1.4)	(-1.9)	(-2.4)	(-1.4)	(-2.3)
% with less than 35K income	-0.064***	-0.060***	-0.041**	-0.078***	-0.076***	-0.040**
	(-4.1)	(-2.6)	(-2.4)	(-5.3)	(-3.7)	(-2.2)
Top 4 Share	-1.512***	-1.132	-2.583***	-1.511***	-1.178*	-2.789***
	(-2.7)	(-1.6)	(-3.6)	(-2.9)	(-1.8)	(-4.1)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	4049	2081	1968	4049	2081	1968
Adjusted R^2	0.907	0.926	0.859	0.910	0.925	0.880

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, trust in big business, and trust in small 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		Trust in Small Business	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WF Exposure× Post	-6.686**	-6.305**	-6.957**	1.006	0.551	1.200	1.262
	(-2.0)	(-2.0)	(-2.1)	(0.6)	(0.3)	(0.8)	(0.8)
NonRepublican		-14.281***	-5.534***		-16.402***		-5.304***
		(-8.0)	(-3.0)		(-17.4)		(-6.2)
Age		-0.112**	-0.114**		0.007		-0.086***
		(-2.5)	(-2.4)		(0.3)		(-3.5)
Female		1.233	3.392**		-3.725***		-3.361***
		(0.8)	(2.2)		(-4.1)		(-4.1)
College Education		-2.339	-1.626		-1.202		3.029***
		(-1.2)	(-0.9)		(-1.1)		(2.8)
High Income		2.141	0.431		3.098***		2.227***
		(1.3)	(0.3)		(3.2)		(2.9)
White		-4.073	-2.310		-2.960		4.478**
		(-1.2)	(-0.7)		(-1.5)		(2.3)
Black		-0.372	0.100		-0.763		-1.795
		(-0.1)	(0.0)		(-0.3)		(-0.7)
Hispanic		-4.250	-3.634		-1.245		-0.610
		(-1.1)	(-0.9)		(-0.5)		(-0.3)
Protestant		3.833**	3.468**		0.955		0.489
		(2.2)	(2.2)		(1.0)		(0.6)
Jewish		-1.725	-0.596		-2.306		-0.192
		(-0.3)	(-0.1)		(-0.9)		(-0.1)
% with less than 35K income		-1.430**	-1.042		-0.679*		0.371
		(-2.1)	(-1.6)		(-1.9)		(1.1)
Trust in Media		0.435***	0.328***		0.190***		0.056***
		(14.0)	(10.2)		(9.6)		(3.4)
Trust in Big Business			0.537***				
			(16.6)				
Constant	30.267***	68.836***	29.796	47.262***	71.380***	79.620***	69.612***
	(38.2)	(3.5)	(1.6)	(118.7)	(7.0)	(225.5)	(6.8)
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4255	3720	3693	4237	3715	4266	3729
Adjusted R^2	0.003	0.060	0.142	0.019	0.121	0.016	0.043

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)	(2)	(3)	(4)
	FinTech	FinTech	FinTech	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)
Type (Omitted Category = Conventional)				
FHA	2.527***	2.242***	4.045***	3.714***
	(15.4)	(13.5)	(21.5)	(18.8)
VA	0.225*	0.182	1.546***	1.458***
	(1.9)	(1.5)	(11.8)	(10.1)
FSA/RHS	-2.002***	-1.499***	-1.898***	-1.175***
	(-11.2)	(-7.2)	(-12.3)	(-6.2)
Type (Omitted Category = Home Purchase)				
Home Improvement	-1.360***	-1.103***	-4.495***	-3.877***
	(-12.4)	(-8.6)	(-31.8)	(-25.1)
Refinance	6.808***	6.971***	5.953***	6.338***
	(42.3)	(37.8)	(46.0)	(43.2)

...

Continued on next page

Table A6: continued

	Origination		Application	
	(1) FinTech	(2) FinTech	(3) FinTech	(4)
...				
To continue				
Purchaser (Omitted Category = Held)				
Fannie Mae	10.882***	11.101***	7.645***	7.949***
	(55.7)	(50.9)	(40.8)	(38.9)
Ginnie Mae	11.231***	11.005***	6.220***	6.193***
	(41.6)	(36.1)	(31.6)	(27.7)
Freddie Mac	9.100***	9.297***	5.895***	6.180***
	(30.6)	(27.7)	(19.4)	(18.3)
Farmer Mac	-0.060	-0.191	-3.749***	-3.829***
	(-0.2)	(-0.5)	(-12.9)	(-10.3)
Private securitization	1.478***	1.815***	-2.373***	-1.859***
	(4.7)	(5.4)	(-7.0)	(-5.3)
Bank	2.875***	3.226***	-0.936**	-0.430
	(7.7)	(8.0)	(-2.5)	(-1.1)
Insurance	1.165***	1.530***	-2.963***	-2.429***
	(5.8)	(7.1)	(-14.9)	(-11.8)
Affiliate	-2.909***	-2.654***	-6.279***	-5.947***
	(-16.3)	(-14.1)	(-31.8)	(-28.1)
Other	0.827***	1.209***	-3.265***	-2.727***
	(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	11.004***	11.013***	10.265***	10.645***
	(34.3)	(31.4)	(35.9)	(34.1)
Ethnicity (Omitted Category =)				
Hispanic	-1.215***	-1.371***	-0.516***	-0.769***
	(-7.0)	(-7.8)	(-2.9)	(-4.2)
NA	0.930***	-0.193	3.602***	1.779***
	(3.3)	(-0.8)	(10.2)	(5.8)
Race (Omitted Category = White)				
Native American	1.534***	1.666***	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)	(5.3)
Hawaiian	0.618***	0.575***	0.701***	0.641***
	(4.2)	(3.8)	(4.9)	(4.4)
NA	6.167***	6.422***	4.804***	5.410***
	(34.8)	(34.6)	(24.9)	(27.9)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	34174869	29985964	44831361	39029308
Adjusted R^2	0.096	0.093	0.080	0.077

Table A7: 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.

	All	White Non-Hispanic	White Hispanic	Native American	Asian	African American	Hawaii/ Pac Isl
FinTech	1,559,777	859,525	72,909	8,586	81,064	58,408	5,374
Non-FinTech	9,925,655	6,973,174	711,488	49,136	753,749	358,593	36,739
FinTech Share	13.58	10.97	9.29	14.87	9.71	14.01	12.76

Table A8: Do minority borrowers react differently to the Wells Fargo scandal?

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 A8a reports best linear predictors of the conditional treatment. Table A8b reports the group average treatment. 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) Best Linear Projection on FinTech Adoption

ATE (β_1)	HET (β_2)
0.968	2.750
(0.080)	(0.000)

(b) Group Average Treatment Effect on FinTech Adoption

White Non-Hispanic	White Hispanic	Native American	Asian	African American	Hawaii/Pac Isl
1.447	2.618	0.970	3.663	1.251	4.559
(0.013)	(0.041)	(0.605)	(0.076)	(0.301)	(0.091)

Table A9: FinTech Adoption Across Race Groups

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on FinTech adoption. Coefficients are estimated from the following regressions.

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

The dependent variable is a dummy variable equaling to one hundred if the lender is a FinTech lender, zero otherwise. $WFExposure_c$ is 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. Post is dummy equaling to 1 after 2016. Each race category indicates that only borrowers belong to that race group are included in the regression. The sample include HMDA loans purchased by Fannie Mae or Freddie Mac from 2014 to 2018. 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.

	FinTech					
	(1) White-NonHis	(2) White-Hispanic	(3) Native American	(4) Asian	(5) African American	(6) Hawaii
WF Exposure× Post	1.390***	1.039***	0.833	1.123**	0.551	2.311***
	(6.2)	(2.9)	(0.9)	(2.1)	(1.5)	(2.6)
Loan Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	6737208	737262	49041	812956	384230	39707
Adjusted R^2	0.037	0.026	0.133	0.039	0.030	0.033

Table A10: Do different race groups react differently to the Wells Fargo scandal regarding trust in banks?

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on trust in banks, big business, small business. Coefficients are estimated from the following regressions.

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

The dependent variable is the respondent's trust in banks, trust in big business, and trust in small business, which equal to one hundred if the individual reports level of confidence as "a great deal" or "a lot," zero if reports "very little" or "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 is a dummy variable equaling to one after 2016. Post is dummy equaling to 1 after 2016. Each race category indicates that only borrowers belong to that race group are included in the regression. 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				Trust in Small Business			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	White Non-His	Hispanic	African American	Asian	White Non-His	Hispanic	African American	Asian	White Non-His	Hispanic	African American	Asian
WF Exposure× Post× Race	0.224	0.055	-0.162	-0.613	0.116	-0.216	-0.024	0.032	0.094	-0.248	0.220	-0.012
	(1.0)	(0.2)	(-0.5)	(-1.0)	(1.1)	(-1.4)	(-0.1)	(0.1)	(0.8)	(-1.3)	(1.4)	(-0.0)
Race× Post	-12.295***	9.611	5.189	19.081**	-1.238	0.568	-1.676	9.659**	2.036	0.581	-2.576	0.551
	(-2.9)	(1.5)	(1.0)	(2.1)	(-0.5)	(0.2)	(-0.5)	(2.3)	(0.8)	(0.1)	(-0.7)	(0.1)
WF Exposure× Post	-0.433*	-0.273*	-0.242*	-0.247*	-0.097	0.015	-0.007	-0.009	-0.045	0.053	0.015	0.030
	(-1.9)	(-2.0)	(-1.7)	(-1.7)	(-0.8)	(0.2)	(-0.1)	(-0.1)	(-0.4)	(0.7)	(0.2)	(0.4)
Respondent Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3720	3720	3720	3720	3715	3715	3715	3715	3729	3729	3729	3729
Adjusted R-squared	0.062	0.060	0.059	0.061	0.120	0.121	0.120	0.122	0.044	0.044	0.043	0.043

Table A11: Do different race groups react differently to the Wells Fargo scandal regarding trust in banks?

This table reports the heterogeneous effects of the Wells Fargo scandal revelation on trust in banks, big business, small business. Coefficients are estimated from the following regressions.

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

The dependent variable is the respondent's trust in banks, trust in big business, and trust in small business, which equal to one hundred if the individual reports level of confidence as "a great deal" or "a lot," zero if reports "very little" or "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 is a dummy variable equaling to one after 2016. $Race_i$ is a dummy variable equaling to one if the individual belongs to the race groups as indicated. Post is dummy equaling to 1 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 in parentheses.

	Trust in Banks				Trust in Big Business				Trust in Small Business			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	White Non-His	Hispanic	African American	Asian	White Non-His	Hispanic	African American	Asian	White Non-His	Hispanic	African American	Asian
WF Exposure× Post	-6.013	-12.040	8.367	-10.998	0.343	-1.425	17.821*	25.803	0.065	13.577**	7.064	-14.140
	(-1.6)	(-1.1)	(0.5)	(-0.3)	(0.2)	(-0.3)	(1.7)	(1.4)	(0.0)	(2.1)	(0.8)	(-1.0)
Respondent Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2767	328	192	64	2761	328	193	62	2773	330	194	64
Adjusted R^2	0.006	0.020	-0.033	-0.017	0.113	0.078	0.009	-0.241	0.029	0.021	0.028	-0.011

B Chernozhukov, Demirer, Duflo, and Fernández-Val

To better understand the borrowers' heterogeneous responses to the Wells Fargo scandal across different race groups, 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 after the exposure to the Wells Fargo scandal, conditional on the individual's characteristics.

Given that we are interested in the treatment effects heterogeneity between difference race groups, we estimate the group average treatment effects (GATE) across different race groups,

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

where $\{G_k\}_{k=1}^{K}$ are non-overlapping race groups (Non-Hispanc White, Hispanic White, Native American, Asian, African American, Hawaiian or Other Pacific Islander).

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 study the group average treatment effects $E[s_o(Z)|G_k]$. The estimation procedure can be summarized as the follow-

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

ing. First, we partition 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 $\hat{s}(Z)$. Last, we run a weighted OLS regression using $\hat{s}(Z)$ to compute the group average treatment effects $E[s_o(Z)|G_k]$. 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.

The results of the CDDF estimation are shown in Table A8. 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

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

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 $s_0(Z)$.

The BLP results are shown in Table A8a, 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 0.968-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, and there exits treatment effects heterogeneity. Next I compute the average treatment effects of exposure to the Wells Fargo scandal across different race groups, shown in A8b.

B.1 CDDF

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 properties

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

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

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

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 $\{\hat{\beta}_{1,L}^i, \hat{\beta}_{1,U}^i\} = \{\text{Median}\{\hat{\beta}_{1,L}^i\}_{i=1}^S, \text{Median}\{\hat{\beta}_{1,U}^i\}_{i=1}^S\}$.

I focus on group average treatment effects instead of sorted group average treatment effects. For the estimation method proposed to estimate $E[s_0(Z)|G_k]$ (Theorem 3.3 in CDDF) to be valid, the monotonicity restriction that $E[s_o(Z)|G_1] \leq ... \leq E[s_o(Z)|G_K]$ is not required. Moreover, the estimator is valid as long as $[1(G_k)_{k=1}^K]'$ are orthogonal. Therefore, we can split the observations into orthogonal but not monotonic groups and compute the GATE of each group.